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**Book**

## Quantitative analysis of financial market infrastructures: further perspectives on financial stability

Scientific monographs, No. E:50

**Provided in Cooperation with:**

Bank of Finland, Helsinki

*Suggested Citation:* Laine, Tatu (Ed.) (2015) : Quantitative analysis of financial market infrastructures: further perspectives on financial stability, Scientific monographs, No. E:50, ISBN 978-952-323-084-2, Bank of Finland, Helsinki,  
<https://nbn-resolving.de/urn:nbn:fi:b0f-201512221501>

This Version is available at:

<https://hdl.handle.net/10419/212983>

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# **Quantitative analysis of financial market infrastructures: further perspectives on financial stability**

**E:50 • 2015**

**Scientific monographs**

*Tatu Laine (ed.)*

The views expressed in this study are those of the authors  
and do not necessarily reflect the views of the Bank of Finland.

ISBN 978-952-323-084-2  
ISSN 1798-1085  
(online)

Helsinki 2015

# Abstract

This simulator seminar book includes twelve chapters dealing with various aspects of quantitative analysis of financial market infrastructures. The topics include, among others, systemic risks, participant behavior, and new monitoring methods of various payment systems. The methodologies vary from payment system simulations to other types of quantitative analysis based e.g. on artificial neural networks as well as GARCH models. These studies have been presented in the Bank of Finland's simulator seminars during 2012–2014.

Keywords: simulation, payment system, settlement system, liquidity, systemic risk, indicators, free riding, behavioral modeling, RTGS

JEL classification numbers: C15, C81, C92, D53, D70, E42, E58, G01, G21

# Tiivistelmä

Simulaattoriseminaarikirja sisältää kaksitoista lukua, joissa käsitellään rahoitusmarkkinainfrastruktuurin kvantitatiivista analyysia. Kirjassa esitellään tutkimuksia mm. maksujärjestelmien systeemiriskistä, osapuolten käyttäytymisestä ja uusien monitorointimetodien hyödyntämisestä. Metodologiat vaihtelevat maksujärjestelmäsimulaatioista muihin kvantitatiivisiin menetelmiin kuten esimerkiksi neuroverkkoonalyyseihin ja GARCH-mallinnuksiin. Kirjan tutkimukset on esitetty Suomen Pankin simulaattoriseminaareissa vuosina 2012–2014.

Asiasanat: simulointi, maksu- ja selvitysjärjestelmä, likviditeetti, systeemiriski, indikaattorit, vapaamatkustuksen ongelma, käyttäytymismallinnus, RTGS-järjestelmät

JEL-luokittelu: C15, C81, C92, D53, D70, E42, E58, G01, G21

# Preface

Safe and efficient financial market infrastructures are crucial for a well-functioning financial system. That is why quantitative oversight analysis has become more important in recent years. Systems are interdependent and risks need to be analyzed with the help of sophisticated quantitative methods.

The BoF-PSS2 simulator can be used to replicate and simulate different scenarios for payment and securities settlement systems. Originally, the simulator was developed at the Bank of Finland to study impacts on local payment systems when Finland was joining the European Monetary Union.

Today, over a hundred licenses have been granted worldwide. The simulator is available free of charge for noncommercial research and operational analysis of infrastructures. Simulation studies have dealt with such topics as stress testing, liquidity shocks, and specific feature analyses of various systems.

The Bank of Finland arranges an annual simulator seminar to support the analytical work connected with the simulator. The seminar provides a venue for presenting new ideas and getting feedback from colleagues. This book, which covers the main topics of the simulator seminars over the years 2012–2014, follows in the wake of four other books that were published between 2005 and 2012.

Many of the articles here have also been published in various journals. This in itself tells us that this research field has achieved a mature state over a period of ten years. The quantitative analysis of financial market infrastructures is not only important in itself but it has come to be appreciated in the broader financial stability research community.

We are grateful to Esa Jokivuolle, Jouko Vilmunen and Otso Manninen, who served as an editorial board, and Tatu Laine who was the main editor of this seminar book. We also thank the language and publication services for their helpful expertise. Several specialists in the Financial Stability and Statistics Department have provided useful comments for this publication.

The future of quantitative analysis of infrastructures looks promising. The annual simulator seminars are set to be continued in the future. All new and current users of the simulator are welcome to submit research proposals. The simulator seminar not only provides a great chance for networking but it is also an excellent forum for receiving personal feedback and for sharing and testing ideas for future research topics.

Helsinki, December 2015  
Erkki Liikanen  
Governor  
Bank of Finland

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# Chapter 1

## Introduction

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*Tatu Laine*

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# 1 Introduction

The quantitative analysis of financial market infrastructures has advanced and has become better able to provide further perspectives on a wider sweep of financial stability analysis. Oversight work aims at ensuring the reliability and efficiency of infrastructures. To fulfil this task, innovative and well-founded quantitative methods are needed to gain a deeper understanding of the dynamics of the financial markets.

Quantitative analysis of infrastructures is also highlighted in the Principles for financial market infrastructures (BIS 2012)<sup>1</sup>. Various new methodologies and techniques can be applied to analyze payment and securities settlement systems. Information from such analyses needs to be assessed so as to formulate potential policies and make recommendations.

The August 2015 simulator seminar included a special panel session entitled “Quantitative Financial Market Infrastructures Analysis: Trends, Challenges and Opportunities”. The panel session provided insights into the current status of quantitative market infrastructure analysis and laid out a path for future research.

One trend has been to combine data from different sources and to expand the range of utilization of the data. For example, payment system data can be used not only to estimate systemic risks but also to forecast the state of the economy. The financial infrastructure data contain rich information on payment flows. These are high-frequency data that offer ample possibilities to gain further perspectives via timely financial stability analysis. One important challenge is to combine macroprudential analyses and quantitative financial market infrastructure (FMI) analyses to obtain a more comprehensive view of systemic risk issues. Accordingly, there should be a closer dialogue between macroprudential and oversight analysts.

The above-described challenge also opens up many opportunities. For example, it is important to recognize relevant interlinkages and behavioral elements embedded in FMI data. Infrastructures are interlinked, and same entities participate in several systems. Therefore, changes in a participant’s behavior may have effects in several infrastructures as well as on other participants in the network.

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<sup>1</sup> CPSS-IOSCO: Principles for financial market infrastructures  
(<http://www.bis.org/cpmi/publ/d101a.pdf>)

Efficient interactive and visualized analysis can help in detecting these effects.

This book includes a collection of research studies presented in the simulator seminars in the years 2012–2014. The overall structure of this book is as follows. Chapters 2–5 present studies in which payment systems and their risks are estimated using quantitative analysis. Chapters 6–8 analyze participant behavior in payment systems. Chapter 9 studies collateral requirement changes in an existing payment system, and chapter 10 presents ways to improve simulations by aggregating low-value payments. Finally, chapters 11–13 propose new tools and methods for overseers and operators.

Chapter 2 (Diehl and Müller) analyzes the use and impact of limits in TARGET2 where bilateral and multilateral limits can be used for liquidity management purposes. The analysis reveals that the limits are rarely used and not actively managed in practice. However, the simulation results show that when limits apply to late payers, the burden of additional delay is systemically shifted towards late players. This clearly benefits the limit setters and punishes late payers.

Chapter 3 (Cepeda and Ortega) presents the methodology to estimate intraday liquidity in the Colombian large value payment system. It analyzes different cases where each systemically important financial institution must confront simulated failures-to-pay via its main discretionary liquidity supplier. A dynamic approach to intraday liquidity needs is presented, and the BoF-PSS2 simulator is used to estimate different effects: direct effect, second-round effect and feedback effect. The results confirm a non-linear relationship between the initial failure-to-pay by a specific institution and by the failure-to-pay by the rest of the system.

Chapter 4 (Heijmans, Hernández and Heuver) investigates unsecured money market loans in the Dutch interbank market. It analyzes how conventional and unconventional changes in the monetary policy framework have affected the overnight money market lending rate during tranquil and crisis times. The volatility of the rate is studied using an EGARCH model. The results show that the volatility of the rate depends on the monetary policy framework, and unconventional measures implemented after 2008 have also affected banks' behavior. The method used enables central banks to monitor the volatility of the interest rate and to measure the impact of changes in policy for the euro area.

Chapter 5 (Alexandrova-Kabadjova and Ochoa) analyzes Mexican large value payment system data. Transactional data are used to build and analyze networks for two types of payments, namely payments initiated by third parties, i.e. nonbank financial institutions, and by

participants, ie. private or public banks. The main findings are that both networks have (i) a core-periphery structure, common for financial services networks, and (ii) very similar dynamics in terms of the values of the operations.

Chapter 6 (Diehl) investigates free riding (postponing outgoing payments at incoming payments' expense) in the German component of TARGET2. It addresses the question of how free riding in a payment system should be measured. In addition to the traditional measures of free riding, new measures originally designed for econometric studies are applied. These measures have the advantage of being independent of size, composition and other special features of the payment system. The empirical results suggest that free riding is rather limited for the most important participants.

Chapter 7 (Heemeijer and Heijmans) studies the behavior of banks in an artificial large value payment system using an experimental game approach. It studies the reactions of banks to disruptions in the payment system as well as to incentive changes imposed by the central bank. The results show that a positive or negative incentive to pay late steers payments to the inefficient or efficient equilibrium, respectively.

Chapter 8 (Nielsen) simulates various shocks to the Danish interbank market. The participants are allowed to react dynamically to the shocks via a binary reaction function. Facilitating smooth payment settlements and limiting the need for liquidity reserves requires a high degree of coordination among the participants. This leads to mutual reliance across the banks and poses a potential systemic risk because a sudden incident may spread to the rest of the system. The results show that the systemic risk is currently low due to the fact that the participants are holding ample liquidity reserves.

Chapter 9 (Embree and Taylor) examines the implications of full collateralization in the Canadian large value transfer system using the BoF-PSS2 simulator. The results indicate that, at the system level, such an increase in collateral requirements is not unreasonable given the total collateral currently available in the system. However, at a participant level, the results indicate that some participants are more strongly impacted than others, and some even see lower collateral requirements relative to what they currently pledge.

Chapter 10 (Heuver and Heijmans) addresses the problem of long simulation times when performing simulations on the TARGET2 platform. This is due to the lack of computational power on the platform. The amount of transaction data can be huge, leading to the simulation times varying from a single day up to several months, depending on the type of scenario. To tackle this problem, a method to

aggregate low value payment transactions is proposed. The simulation results show that the method can be used without compromising the reliability of the analysis. Depending on the liquidity level in simulations, the processing time can be reduced to less than one percent of the original.

Chapter 11 (Hellqvist, Leinonen and Maslinarskis) presents an idea for and implementation of a testing framework for early warning indicators derived from large value payment system data. These indicators could warn in advance of adverse changes in the behavior of separate LVPS participants or crystallization of risks in the financial market. The paper also describes a signaling analysis methodology for payment systems data.

Chapter 12 (Sadornas) forecasts the time series of intraday throughput of selected participants in the Philippine large value payment system using artificial neural networks (ANN). This preliminary work shows the potential of ANNs in forecasting the throughput of individual participants in a large value payment system. The ANN models generally approximate the trend and seasonality of the throughput data of the selected participants, although the forecast errors remain significant.

Chapter 13 (León) addresses the measurement of large value payment system intraday liquidity risk. The core of the model is the Monte Carlo simulation of bivariate Poisson random variables for the intraday arrival of executed and received payments. Modelling the uncertainty of intraday payments enables the overseeing of participants' intraday behavior, to assess their ability to fulfill intraday payments at a certain confidence level, to identify participants that are nonresilient to changes in payment timing mismatches, and to estimate intraday liquidity buffers.

These studies include useful examples of research applications in which simulations and other quantitative analyses can provide further insight into oversight and financial stability work. We have brought together in this book a cross-section of research activities in the field of quantitative FMI analysis. In addition, the book seeks to serve food for thought for future research. The Bank of Finland continues to contribute, for its own part, to open and fruitful discussions and debates on potential applications of simulation and other quantitative methods by continuing to arrange simulator seminars also in the future.

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# Chapter 2

## Analysis of the use and impact of limits

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*Martin Diehl – Alexander Müller*

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\* This article first appeared in Journal of Financial Market Infrastructures, 30 September 2014. The publisher gratefully acknowledges the permission to reprint this article.

## **Analysis of the use and impact of limits**

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(Received April 2, 2014; revised June 24, 2014; accepted July 23, 2014)

*In this paper, we analyze the use and impact of limits in TARGET2. Limits in the form of bilateral or multilateral debit limits are a liquidity management feature in TARGET2. The analysis of the use of limits reveals that they are rarely used and not actively managed. In quantifying the different impacts of limits on the performance of TARGET2 via the simulation of various stress scenarios, this paper contributes to the overall assessment of limits. The paper quantifies the first-round effect of limits (longer queues and more delay) and the partially offsetting second-round effect, which is caused by the liquidity redirection of effective limits. It is shown that the net effect is significantly smaller in the case of a more severe stress scenario. Moreover, it can be proven that in applying limits to late payers the burden of additional delay is systematically shifted toward the late payers. This clearly benefits the limit setters and punishes free riders.*

### **1 INTRODUCTION**

This paper analyzes the use and impact of limits in TARGET2. Limits are one of the many liquidity management features in TARGET2. The detailed use of liquidity management features is of particular interest when it comes to understanding the payment behavior of banks and participants in payment systems and analyzing

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The authors acknowledge helpful comments on earlier drafts by the participants of the Bank of Finland Payments and Settlements Simulation Seminar in August 2013. This paper represents the judgments and views of the authors and does not necessarily reflect the opinion of the Deutsche Bundesbank.

the functionality of real time gross settlement (RTGS) systems. This is because liquidity management features have been introduced to relax the liquidity needs for settlement without sacrificing the safety of RTGS systems. Given the importance of TARGET2 as the main financial market infrastructure for euro transactions, it is in the interest of overseers, operators and participants to understand how the various features of the system are used. Moreover, the use of different features may indicate a reaction to market developments. Therefore, the possible usefulness of the use of limits as an early warning indicator is an issue. Beyond the descriptive aspects, the question of whether the use of limits is beneficial to the overall settlement in terms of liquidity efficiency and settlement speed has hitherto not been addressed on a reliable basis. We aim to answer that question by running various simulations with and without stress and comparing the outcome depending on the use of limits.

Therefore, the analysis has three objectives:

- to analyze the use of a limit feature in payment systems in general, as well as describing the use of the specific limit feature of TARGET2 in particular, thereby contributing to the establishment of stylized facts about payment behavior of banks in TARGET2 and assessing the suitability of the use of limits as a crisis indicator;
- to quantify via simulation the theoretically ambiguous impacts of the use of limits on settlement efficiency;
- to derive recommendations for or against the use of limits in TARGET2.

The detailed assessment of these objectives based on real data has not been addressed so far in the literature. Closest to our analysis is the simulation study on payment system design and participant operational disruptions in Australia's RTGS system by Clarke and Hancock (2014).

The use of limits is analyzed by descriptive analysis of the full data set of limits set by participants in TARGET2 for the observation period from November 19, 2007 (the start of TARGET2) to May 31, 2013. The impact of limits is analyzed via simulations of various scenarios using the TARGET2-Simulator. Section 2 will first describe how limits are generally used in TARGET2 and other payment systems. Section 3 is the descriptive analysis of the use of limits in TARGET2, including the assessment of limits as crisis indicators. Section 4 covers the theoretical impact of limits based on the literature and our own considerations. The analysis of the impact of limits via simulations is covered in Section 5. Finally, Section 6 gives our conclusions and recommendations for payment system policy.

## 2 THE USE OF LIMITS IN TARGET2 AND OTHER PAYMENT SYSTEMS

TARGET2 offers a wide range of liquidity management features:

- priorities (normal, urgent, highly urgent),
- reservations for different priorities,
- dedications of liquidity to specific use (eg, for ancillary systems),
- manual intervention via the information and control module (ICM), and
- bilateral and multilateral limits.

The limits in TARGET2 are debit limits, not credit limits. The effect of a limit is described in the TARGET2 user detailed functional specification (UDFS):

With the bilateral limit, the direct PM [payment module] participant restricts the use of liquidity when submitting normal payments for another direct PM participant.

Whereas,

with the multilateral limit, the direct PM participant restricts the use of liquidity, when submitting normal payments for any other direct PM participant for which a bilateral limit has not been set.

3CB (2011, p. 70)

Limits are effective only for normal payments. The treatment of urgent and highly urgent payments is not affected by limits in order to enable a special treatment of payments by the single participants that is not conditioned by any action of any other participant. If a participant disposes of enough liquidity, they can, by setting a higher priority (and maybe shifting a payment in the queue), almost enforce the immediate settlement of their payment, notwithstanding any actions of others. The use of limits can be considered a market-based tool, since it is totally at the discretion of a participant whether to use limits or not (3CB 2011, p. 8).

The use of limits in the way described for TARGET2 is not widespread in RTGS systems around the world and can be considered unique in that particular form. Nevertheless, limits are often mentioned as being a feature of many different payment systems. A detailed assessment of the setup of the limit feature in other payment systems shows that they are based on distinct definitions of the term “limits”.

Principle 3 (“Framework for the comprehensive management of risks”) of the Principles for Financial Market Infrastructures (CPSS 2012b, p. 33) mentions limits as a tool for risk management.

According to that, limits are seen as especially suitable for netting systems, in which their risk-containing ability is treasured. They are used in many netting systems, albeit not always at the discretion of the limit setter.

In the Mexican retail payment system (RPS), the central bank sets a limit on the amount of any individual credit line that a bank may grant to another bank. It also sets a limit on the aggregate amount of the credit lines a bank may grant to all other banks (see CPSS 2011, p. 269).

EURO1, the payment system operated by the European Banking Association, requires participants to define bilateral limits for all other participants (restricted to a range). On the basis of these bilateral limits set against a participant, the operator determines the multilateral debit cap for this participant (see CPSS 2012a, p. 101).

Another example is Bacs, the United Kingdom's main retail payment system, which allows every member to set individual item and account limits as actionable referrals. This means that, depending on the limit, a specific payment will be halted, requiring a prior action by the user before being processed (see CPSS 2012a, p. 455).

In the United Kingdom's Faster Payments Service, a net sender cap is defined for each participant by the operator, so it works in a similar way to a multilateral debit limit (see CPSS 2012a, p. 456).

Similarly, the CLS bank, based in the United States, applies member-specific account position limits (aggregate short position limits and currency-specific short position limits) (see CPSS 2012a, p. 518).

The setting of limits by participants is possible in, for example, the Russian large-value payment system (LVPS), the Banking Electronic Speed Payment (BESP) system. It allows participants to set bilateral and multilateral limits on payments to other participants, and it gives the operator the ability to cancel payment limits in case of a gridlock (see CPSS 2011, pp. 311, 313).

The Canadian LVPS uses self-defined net debit caps of participants in combination with bilateral credit limits, which are granted to the participant by others, to calculate the necessary amount of collateral (see CPSS 2011, p. 128). The aim is that the system can handle the failure of the participant with the largest net debit position. Therefore, in Tranche 2 a multilateral net debit cap is calculated for each participant proportional to the sum of all bilateral credit limits granted to them (see CPSS 2011, p. 129).

The overall usefulness of limits at the participant level draws attention to the possibility that banks may apply internal bilateral limits in order to withhold the submission of payments to payment systems. There have been several endeavors to find evidence of the existence of internal limits. Whereas Hellqvist (2009) does not identify significant internal limits for the eighteen Finnish participants in TARGET2, Heijmans and Heuver (2012, p. 107) observe the use of internal limits and even counterlimits within the somewhat larger Dutch component of TARGET2.

Ball *et al* (2011), referring to the Clearing House Automated Payment System (CHAPS), also explain that many participants use internal schedulers to apply bilateral limits.

This discussion of the definition of the limit feature in different payment systems has shown that the term “limits” in payment systems can have different meanings. Our analysis focuses on the definition of limits as debit limits, as is the case in TARGET2.

### 3 DESCRIPTIVE ANALYSIS

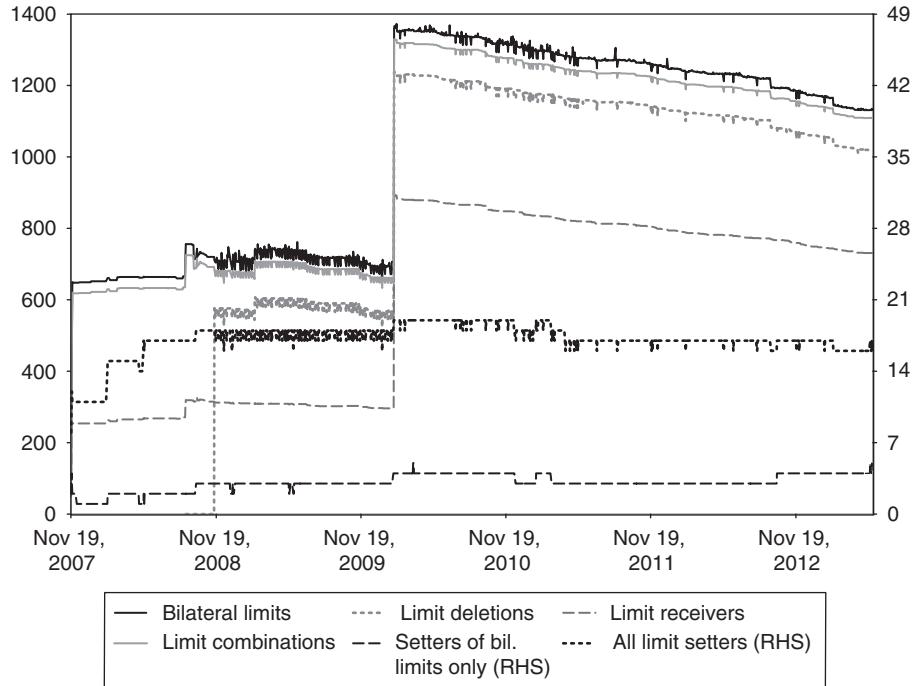
The descriptive analysis of the use of limits in TARGET2 is split into three areas. First, we analyze time series of daily statistics and calculate data for the whole time period. Therefore, we match limit data with transaction data (regular payments in TARGET2) in order to assess the importance of limits. Second, we focus on the network characteristics by identifying the time series of the reciprocal limits. Third, we analyze the intraday patterns of limit setting by using a daily timing indicator.

The objective of the descriptive analysis is to find reasons for the limit setting behavior, which in turn may be interpreted as an indicator for financial market developments, ideally for changes in market stress. Moreover, an understanding of the use of limits contributes to the overall objective of deriving stylized facts about the payment behavior of participants.

The number of limits set over time is depicted in Figure 1 on the next page. The main contents are summarized as follows.

- The daily number of bilateral limits stays between 600 and 800 until February 9, 2010, then jumps to almost 1400 before decreasing again, reaching a value of 1133 at the end of the observation period. Detailed investigations reveal that the jump on February 10, 2010 is caused by a dramatic increase in the number of bilateral limits of a small group of institutes and does not have any systemic meaning.
- The daily number of distinct limit combinations reaches on average more than 96% of all bilateral limits. This difference between the number of limits and limit combinations is caused by reciprocal limits (see explanation to Figure 3 on page 40).
- Only 1% of total activity (setting, changing and deleting limits) is changing of limits during the day in reaction to ongoing development of bilateral balances (not shown in Figure 1 on the next page).
- Since the deletion of limits has been possible (since November 19, 2008), more than 80% (in more recent times, more than 90%) of all bilateral limits have been deleted during the course of the day.
- The number of limit setters is stable in the medium term, and slightly decreasing in the long term; it never surpasses twenty. The number of setters of bilateral limits only is five or below.

**FIGURE 1** Time series of number of limits, number of limit setters and receivers.

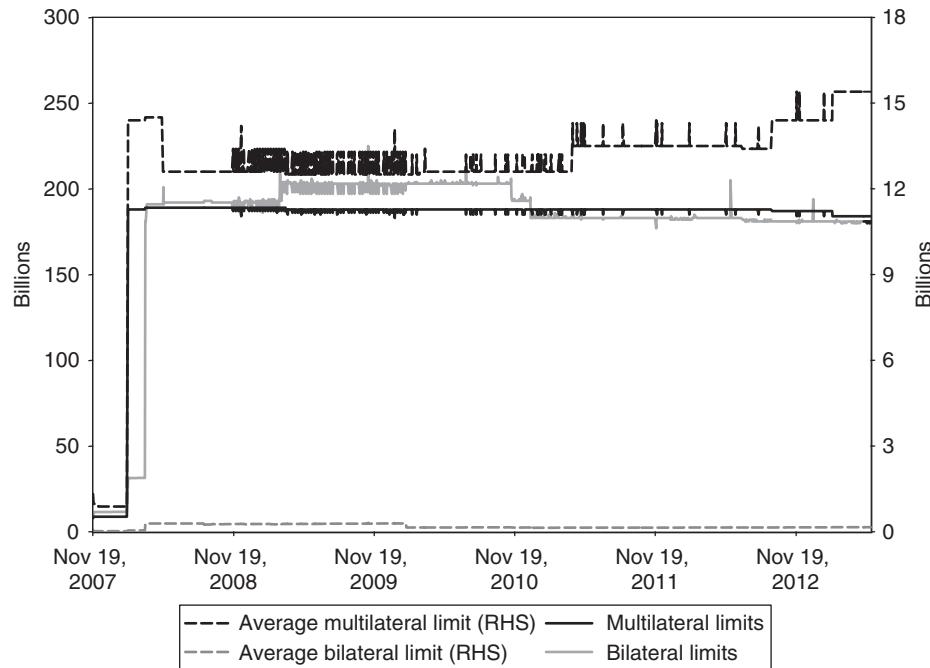


Data from TARGET2. Observation period: November 19, 2007–May 31, 2013.

- The number of distinct limit receivers displays the same structural feature as the number of bilateral limits or limit combinations and stays above 1000 at the more recent end of the observation period.

The value of limits is depicted in Figure 2 on the facing page. Some features stand out.

- The value of all multilateral limits and the value of all bilateral limits are, after an initial phase, rather stable over time and stand at roughly the same level (more than €180 billion).
- The average multilateral limit usually displays remarkable stable tendencies over many days and rises over time to around €15 billion.
- The average bilateral limit is even more stable over time and stays at €160 million. This is really remarkable given the high number of bilateral limits and the changes in that number over time.

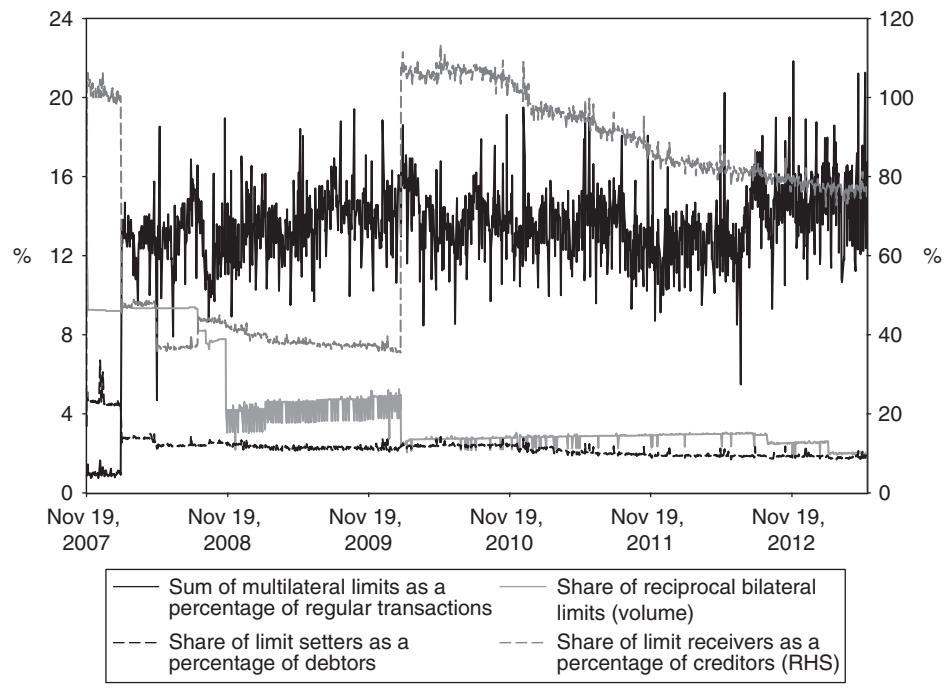
**FIGURE 2** Time series of limit values.

Data from TARGET2. Observation period: November 19, 2007–May 31, 2013.

Further, we have related the limits to the value of transactions and the number of limit setters to creditors and debtors of regular payments (interbank payments and payments on behalf of customers), as is shown in Figure 3 on the next page.

- The ratio of the value of all multilateral limits (or of all bilateral limits) to all regular transactions is very volatile. On average, the ratio is 13% with no clear trend over time.
- Less than 2% of all debtors use limits, whereas on average almost 75% of creditors are subject to a limit set against them. At times in 2010 this share reached above 100%, since some banks obviously applied limits against accounts that had not been credited by regular payments on that day.
- The share of reciprocal limits (a limit between two banks setting limits against each other) is declining over time and falls below 2% at the more recent end of the period. This is clearly too low to warrant a further structural analysis as for related network features.

**FIGURE 3** Limits' relative importance.

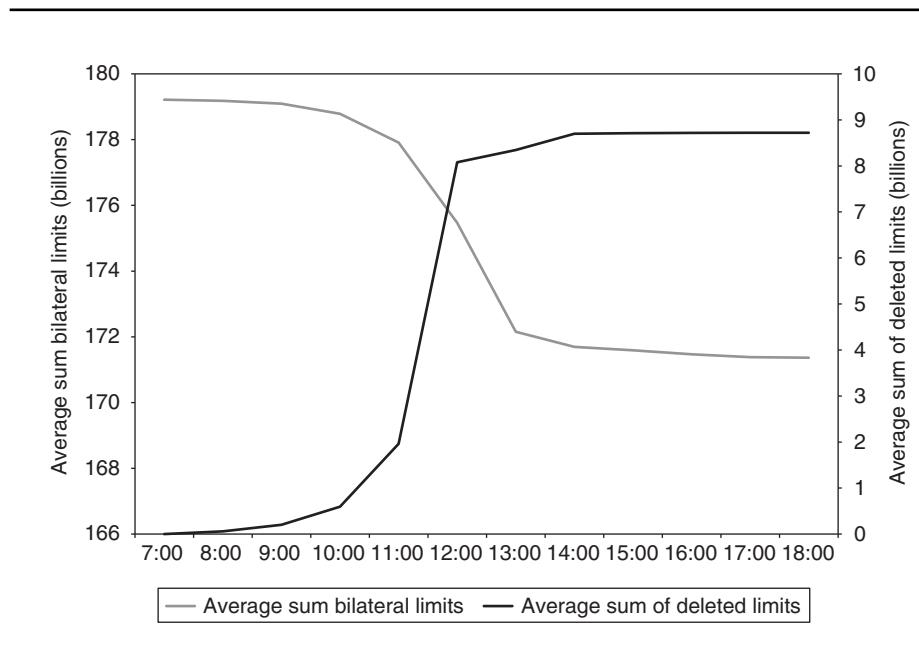


Data from TARGET2. Observation period: November 19, 2007–May 31, 2013.

Besides the time series and the structural features, we have investigated the timing of limits. In this respect only the time of deletion of a bilateral limit is of interest. Multilateral limits have never been deleted separately, and, since only very few institutes apply intraday changes of limits, we forwent their further analysis.

Figure 4 on the facing page displays the average daily timing profile of deletions and of the remaining sum of bilateral limits, respectively. At 07:00 no deletions could have occurred; therefore, the sum of bilateral limits stays at its predefined level. During the course of the day only a few limit increases take place, such that the valid sum of bilateral limits decreases as more limits become deleted. The figure clearly shows that the bulk of limit deletions occurs between 11:00 and 12:00, leading to a significant drop in the still-valid bilateral limits. However, the share of limit deletions in terms of volume is (see Figure 1 on page 38) far higher than in terms of value, meaning that especially large limits are more often remaining and not being deleted.

We constructed a timing indicator of bilateral limits and limit deletions to track the time series of the timing of deletions. The timing of deletions is volatile, but stable in

**FIGURE 4** Average daily timing profile.

Data from TARGET2. Observation period: November 19, 2007–May 31, 2013.

trend until summer 2012. In June 2012 a regime shift occurred and the timing index of deletions fell, indicating that deletions were, on average, set later. Detailed analysis revealed that this shift was due to a technical change in the average deletion time of a limited number of institutes without reference to market developments.

As for the nominal values of multilateral limits, round lots are clearly preferred. The most common value is €500 million, accounting for more than one-fifth of all multilateral limits. The range of limits spreads enormously: that of multilateral limits far more than that of bilateral limits. Whereas the highest bilateral limit reaches 23 700 times the level of the lowest one, the respective factor for multilateral limits is 149 000.

What do the features about the use of limits described above tell us? The use of limits in TARGET2 is rather low, displays remarkably stable features over time and does not in any discernible way react to financial market developments. Even the few institutes that use limits do not seem to actively manage them in reaction to transaction values or business environments. The limits are overwhelmingly set by standing orders and only rarely reviewed. Detailed analyses of the use of limits by single participants support this perception of a limited usefulness of the use of limits as crisis indicators. Hypotheses of active management and of differentiated use of values of limits or of deletions and their timing must be rejected. Nevertheless, these

features are an interesting tessera in the larger mosaic that is banks' use of liquidity management features or – thinking on a larger scale – banks' payment behavior.

In addition, we take this result as a hint that banks may use internal limits before submission of payments to TARGET2 in order to reduce the risk of dissipating liquidity.

#### 4 THE IMPACT OF LIMITS IN THEORY

After having analyzed the use of different setups of a limit feature in payment systems in general, as well as the use of the specific limit feature in TARGET2 in particular, we now turn to the analysis of the impact of limits, focusing on limits in TARGET2. We first derive the theoretical impact of limits in TARGET2 based on theoretical considerations, of which some are based on the literature, and then evaluate this empirically via simulation. The intended impacts of the use of limits for TARGET2 are described in the UDFS as follows.

The setting of these limits enables the direct PM participant:

- to prevent unbalanced dissipation of liquidity with regard to other direct PM participants.
- to avoid free-riding on the liquidity of a direct PM participant by another participant.
- to synchronise the payment flow with other direct PM participants, and to promote its early submission.

(3CB 2011, p. 70)

The different impacts of limits could have two origins. First, there is the technical impact of limits on the flow of a given list of submitted payments, when payments to participants against whom the limit is exhausted are delayed and the liquidity is redirected to other participants against whom the limit is not exhausted. Second, given the existence of limits, a behavioral impact on the submission time is assumed when participants anticipate the effect of limits and change their behavior.

Limits have to be evaluated from both a participant's perspective and an operator's perspective.<sup>1</sup> The participant may benefit in particular from a risk reduction because an unbalanced dissipation of liquidity is prevented. The system operator may have a particular interest in a more synchronized flow of liquidity, which should by itself speed up the settlement process. Still, the aspects of risk and settlement speed are objectives for both participants and operators. A systematic categorization has therefore to take into account the impacts of behavioral and technical effects on risk and settlement speed.

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<sup>1</sup> In the context of our analysis, the objectives of an overseer are close to the objectives of the operator and will not be treated separately.

From the point of view of a single participant, setting limits has the advantage of reducing counterparty risks. Missing offsetting payments that could be caused by liquidity or solvency problems or an operational failure of a counterparty will automatically lead this participant to hold back their own payments toward this counterparty, and the amount of liquidity sunk will also be reduced (Becher *et al* 2008, p. 120, footnote 12).

The use of limits protects the limit setter against an undue outflow of liquidity and limits its claims on others. This holds particularly for bilateral limits. This technical impact is therefore clearly beneficial from a risk perspective.

Besides the clearly beneficial effect for the single participant, this risk reduction effect also bears a systemic effect. The studies of Mazars and Woelfel (2005) and Glaser and Haene (2009) point out that bilateral limits can be a powerful instrument for containing the systemic effects of a participant-level disruption in interbank payment systems. The containment, however, is restricted to the setter of a limit. Participants not setting their own limits against a “delinquent”<sup>2</sup> participant will be hit harder by the disruptions, since their net balance against this participant will *ceteris paribus* drop lower. This is because the delinquent participant lacks funds when they exhaust the limits set against them by others (Ball *et al* 2011, p. 8).

The behavioral impact of the existence of limits – we are inclined to call it the educational impact – is well understood. Becher *et al* (2008) have modeled this effect as an interperiod spillover, in which a participant punishes the late payer in the next period by applying bilateral limits, thereby increasing the delay costs for that bank. Therefore, they consider the bilateral limit a mechanism to enforce discipline (see Becher *et al* 2008, p. 113 and the Appendix on p. 129).

It can be assumed that the educational impact of limits is caused by an incentive for general, earlier submission and by an incentive to avoid excessive net balances with specific counterparties in order not to exhaust the limit set by the counterparty. However, the educational impact of limits is hard to measure empirically without having data about the differences between the time when a payment instruction reaches the liquidity manager and the time when they submit it to the payment system. Moreover, deriving this impact of limits via simulation by simply deleting the limits and running the algorithms again is not possible, since we must assume that limits have had an impact on the submission time that is not observable by the operator.

What about the impact on settlement speed, which is of particular interest from an operator’s view? The “educational impact” works unambiguously positively: earlier submissions by all or most participants reduce the overall level of liquidity needed and

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<sup>2</sup> The adjective “delinquent” is here used to capture all cases where a participant deviates significantly from the due flow of liquidity, eg, by withholding incoming funds, delaying outgoing payments or an operational failure that leads to a liquidity sink.

enhance liquidity efficiency. Only a participant who used to submit late and refinance their payments only by incoming payments, instead of providing a minimum of their own liquidity, may suffer in terms of liquidity costs and lower liquidity efficiency. However, their costs will be low since they benefit from overall early submission. Moreover, the interests of late payers deserve no special protection by system design. This effect works better the more bilateral limits are set with the reasonable assumption that limit levels are not below the value of individual payments.

Theory is, however, inconclusive when it comes to judging whether the technical impact on settlement speed given a predetermined submission time for all payments is positive or negative overall. Effective limits – and only effective limits are relevant – are obviously an obstacle for the settlement of transactions because they increase in a first-round effect the number of queued payments (or even unsettled payments, if queuing does not work). More queuing means slower settlement and lower liquidity efficiency. In the second round, the remaining liquidity of the limit setter can be used to finance their payments to others more quickly than would have been possible if the limit receiver had received the now queued payment: the above-mentioned redirection effect. This is a countervailing effect. In the case of effective limits, those others – not limit receivers or limit setters, but so-called third parties – receive payments from the limit setters earlier but payments from the limit receivers later than in the case without limits.

Again, the more bilateral limits that are set, and the more they are set against notorious late payers, the better the chances are that this positive countervailing effect will outweigh the negative first-round effect. Effects on value and volume of queued payments could also be different, since queuing of one large value payment could allow the settlement of many other lower value payments. However, the overall effect on timing and amount of queued payments remains unclear and subject to the specific matrix of payments between the various parties, as well as the vector of submission times.

Having mentioned the term “effective limit”, we should be more explicit about what this means. First, a limit should not be too high given the normal development of bilateral balances, and it should be related to the expected bilateral flow of liquidity. More precisely, a bilateral limit that exceeds the total gross flow to the respective participant is too high, whereas a bilateral limit that falls short of the net flow to the respective participant is too low. The latter will still be effective and possibly meaningful if the limit is deleted or the amount is raised later in the day. Second, limits below the amount of single payments to the respective participant could possibly cause an overall gridlock. However, splitting a large payment into smaller payments could solve this problem. Third, in very tight liquidity conditions of the limit setter, the limits can be of less importance overall, since payments have to be queued before the limits are reached (see Mazars and Woelfel 2005, p. 121).

**TABLE 1** Effect of a bilateral limit in different liquidity conditions.

(a) Limit set against participant A			
Payment	High liquidity	Medium liquidity	Low liquidity
Payment to A	Queued due to limit	Queued due to limit	Queued due to lack of liquidity
Payment to B	Settled	Settled	Queued due to lack of liquidity
(b) No limit set			
Payment	High liquidity	Medium liquidity	Low liquidity
Payment to A	Settled	Settled	Queued due to lack of liquidity
Payment to B	Settled	Queued due to lack of liquidity	Queued due to lack of liquidity

The following example illustrates the effect of liquidity conditions on the efficacy of limits. Assume that participant X wants to settle two payments: the first one to participant A and the second one to participant B. We distinguish the following three levels of liquidity for participant X.

- (1) High liquidity means that both payments can be settled.
- (2) Medium liquidity means that only one payment can be settled.
- (3) Low liquidity means that no payment can be settled.

Table 1 shows which payments would be settled directly with and without a limit against participant A, assuming that the payment to A is higher than the free limit.

Even in this very simple example the overall effect of limits is ambiguous. A positive redirection effect can be observed in the scenario with medium liquidity and under the assumption of A being a late and B being an early payer. In the situation with high liquidity, the risk of participant X is mitigated, but the technical first-round effect on settlement delay is negative (meaning settlement delay will increase). In the scenario with low liquidity the limit is not effective at all. This shows the importance of empirical analysis of the effects of limits.

Table 2 on the next page summarizes the discussed behavioral and technical impacts of limits on settlement speed and risk. Table 3 on page 48 provides an overview of the

**TABLE 2** Theoretically derived impacts of limits.

(a) Behavioral effects		
	Settlement speed	Risk
Earlier submission	+	(+)
Reduced net balances	(+)	+

(b) Technical effects		
	Settlement speed	Risk
Limit net transfers (first-round effect)	-	+
Liquidity redirection (second-round effect)	+	(+)

+ means positive impact, ie, settlement speed is increased and risk is reduced; - means the opposite; (+) means the impact is indirectly positive.

three impacts of limits discussed and their effects on the limit setters, limit receivers and third parties.

As can be seen by studying the various effects, the multilateral limit definitely has fewer positive impacts than the bilateral one. A multilateral limit just reduces the undue dissipation of liquidity and can be seen as risk reducing for the single participant. A multilateral limit neither redirects liquidity to early payers nor gives any special incentive for early submission. However, multilateral limits have been designed as an addendum to bilateral limits. The tool enables participants to limit the unwanted overall liquidity outflow without having to set bilateral limits against all possible participants.

The impacts of limits are particularly relevant if the assumption that some banks may be inclined to behave as free riders by postponing the submission of payments in order to use less of their own liquidity and reuse more incoming liquidity is justified. Two empirical studies tried to measure free riding. Denbee *et al* (2012) provided a first proposal for the measurement of free riding in CHAPS and concluded that strategic delay does not pose a problem at a system-wide level. However, at the level of individual participants the usage of liquidity seems to differ. In an extension of that, Diehl (2013) argued based on an axiomatic approach that the measurement of free riding should rely on a set of various measures to capture the different aspects of free riding. In calculating the measures for some large participants in TARGET2-BBk, he showed that patterns of different behavior in the timing of payment submission can be found, but that the differences in general are small. In explaining these outcomes, we have to consider the following three aspects.

- (1) The incentive to postpone the submission of payments and to free ride may, in practice, be outweighed by the endeavor to be perceived as an early payer, if that helps to restore and uphold credibility. So, during the financial crisis the latter may have become more important, supported by the fact that liquidity became extremely cheap and – for some participants – rather abundant.
- (2) Even if the incentive to free ride can still be assumed, peer pressure may limit the chances – especially for large participants – to follow that incentive.
- (3) Moreover, some existing institutional features limit the possibilities to free ride, such as the throughput rules in CHAPS and the bilateral limits in TARGET2.

Therefore, not having measured a significant magnitude of free riding is in the given contexts no proof for the non-existence of the incentive to free ride. It may well be the outcome of a properly designed payment system in combination with working market pressure.

## 5 SIMULATIONS OF THE IMPACT OF LIMITS

The aim of the simulations is to quantify the ambiguous effects of limits that have been discussed in the theoretical part. The simulations undertaken make use of the TARGET2-Simulator. This tool is the best known replication of the real system TARGET2. In order to derive the impact of limits for a basis scenario, we re-ran real business days with and without limits. In re-running a real business day in TARGET2, we made use of the full data set (ie, all participants; transactions; liquidity transfers or intraday credits; opening balances; reservations; system parameters, such as specificities of algorithm; and so on) of that respective day and changed only the setting of limits. Afterward, we compared the outcomes of the simulated day with limits and the simulated day without limits. Furthermore, we created four stress scenarios and compared again the outcomes of the simulation with and without limits. In these scenarios we changed some of the real input data to derive the impact of limits under changing conditions (for an overview, see Table 4 on page 50).

The assessment of the impact of limits on the system level focuses on the efficiency of the settlement. The main indicators used are, therefore, the number of queued payments and the overall delay measured by a value and time-weighted delay indicator. For the simulation we used the original data of January and May 2013. In this paper we report results from January 2013, since data from May 2013 is often missing.<sup>3</sup>

The first parameter to be set for the input data of the simulations is the limit data, in order to investigate the effect of limits in a given scenario. In the first set of scenarios, we compared no limit setups to setups with unchanged limits (ie, limits as set in the

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<sup>3</sup> The results that are available for May 2013 confirm the results for January 2013.

**TABLE 3** Theoretically derived impacts of bilateral limits on the limit setter, the limit receiver and on third parties. [Table continues on next page.]

(a) Impact: technical effect and behavioral effect of limited net balances			
	<b>Limit setter</b>	<b>Limit receiver</b>	<b>Third parties</b>
<b>Effects</b>	Risk reduction	Risk enhancement	Risk enhancement
<b>Explanation</b>	Only if limit is set against the delinquent participant	Restriction of available liquidity to weather a temporary shortage	Net balance against delinquent participant drops because of others' limits against them
(b) Impact: technical effect of limited net transfers and liquidity redirection			
	<b>Limit setter</b>	<b>Limit receiver</b>	<b>Third parties</b>
<b>Effects</b>	Slower settlement for payments to limit receiver Faster settlement of payments to non-limit-receivers	Slower settlement Need to rely more on own liquidity	Faster reception of payments from limit setters Slower reception of payments from limit receivers
<b>Explanation</b>	Overall effect on timing is unclear More bilateral limits against the late payer lower the overall settlement time	Settlement time increases with more limits against limit receiver	Overall effect on timing is unclear More bilateral limits against the late payer lower the overall overall settlement time

**TABLE 3** Continued.

(c) Impact: behavioral effect of earlier submission			
	<b>Limit setter</b>	<b>Limit receiver</b>	<b>Third parties</b>
<b>Effects</b>	Reduced liquidity needs because of overall earlier submission Risk reduction	Reduced liquidity needs because of overall earlier submission Risk reduction	Reduced liquidity needs because of overall earlier submission Risk reduction
<b>Explanation</b>	Best if limits are set against potential late payers	Overall early submission may enforce behavioral change because of peer pressure	Benefit as long as “threat” of limits is credible

**TABLE 4** Overview of simulation setups.

<b>Simulation setups</b>	<b>Transaction data</b>	<b>Intraday credit data</b>	<b>Opening balances</b>	<b>Limit data</b>
Basis scenario	Unchanged	Unchanged	Unchanged	Unchanged limits compared to no limits scenario
Stress scenario 1: reduced intraday credits	Unchanged	Proportional cut to 10% of original value	Unchanged	Unchanged limits compared to no limits scenario
Stress scenario 2: reduced opening balances	Unchanged	Unchanged	Set to zero	Unchanged limits compared to no limits scenario
Stress scenario 3: delayed payments	All payments of a group of participants delayed Data restricted to large value payments (>€50,000)	Unchanged	Unchanged	Artificial limits of a group of participants against late payers compared to no limits scenario
Stress scenario 4: delayed payments with reduced intraday credits	All payments of a group of participants delayed Data restricted to large value payments (>€50,000)	Proportional cut to 10% of original value	Unchanged	Artificial limits of a group of participants against late payers compared to no limits scenario

real TARGET2 environment were used). In the second set of scenarios, we compared no limits setups to setups with artificially fixed limits set by the participants who also regularly set limits in the real TARGET2 environment. Other scenarios with artificial limits are possible, such as setting a “standard limit” (eg, in relation to the average transaction sums) for every participant and could be investigated in a future project.

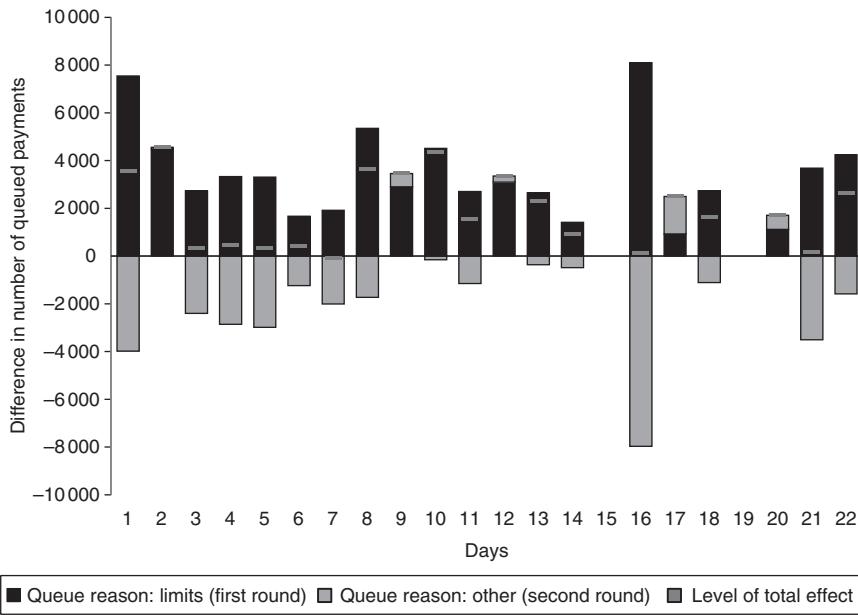
The second parameter to be set for the input data of the simulations is the setup of different scenarios based on changes to the other input data tables. We have simulated a basis scenario without changes to other data, and several stress scenarios. In a first stress scenario, the intraday credits were reduced, with a proportional cut of their value to 10% of the original value. In a second stress scenario, the opening balances were set to zero. Both scenarios thereby reduce the level of available liquidity. Since some participants do not have their intraday credit lines and opening balances on the TARGET2 platform but use proprietary home accounts, this is an asymmetric shock. Since the correlation between participants using the proprietary home account and intensively using limits is high, the implicit consequence is that the liquidity conditions of limit setters are less affected. In a third stress scenario – the delayed payments scenario – we simulated a substantial delay of the payments of a group of participants. In this scenario, artificial limits were used. They were defined as participants who use limits intensively in the real data having limits against the participants whose payment’s submission has been modified to reflect late paying. Thus, we created a group of late payers and applied limits by all usual limit setters against them. In this way, we are able to focus on the impact of limits on settlement time given the existence of notorious late payers. In a fourth stress scenario, we combined the late-payer scenario with the restricted liquidity conditions of the first stress scenarios. We achieved this by adding a proportional cut of the value of the intraday credits to 10% of the original value to the third stress scenarios.

The main method of examining the results was to compare the changes in the setups with and without limits for the respective scenarios. Nevertheless, comparisons of the results over different scenarios and between different groups of participants also led to important results.

The results of the simulations for January 2013 for stress scenario 1 (reduced intraday credits) are shown in Figure 5 on the next page. The figure shows the differences in the number of queued payments in a setup with limits compared with a setup without limits (ie, a positive value means more queued payments in the scenario with limits). We distinguish two causes for queues: (i) because of an exhausted limit and (ii) due to lack of liquidity. We do not take into account the third possible queue reason, payments queued due to technical reasons, since the payments affected are identical in setups with and without limits.

The number of payments queued due to limits shows the strength of the first-round effect, while the difference in payments queued due to a lack of liquidity shows

**FIGURE 5** Differences in number of queued payments with and without limits, stress scenario 1.

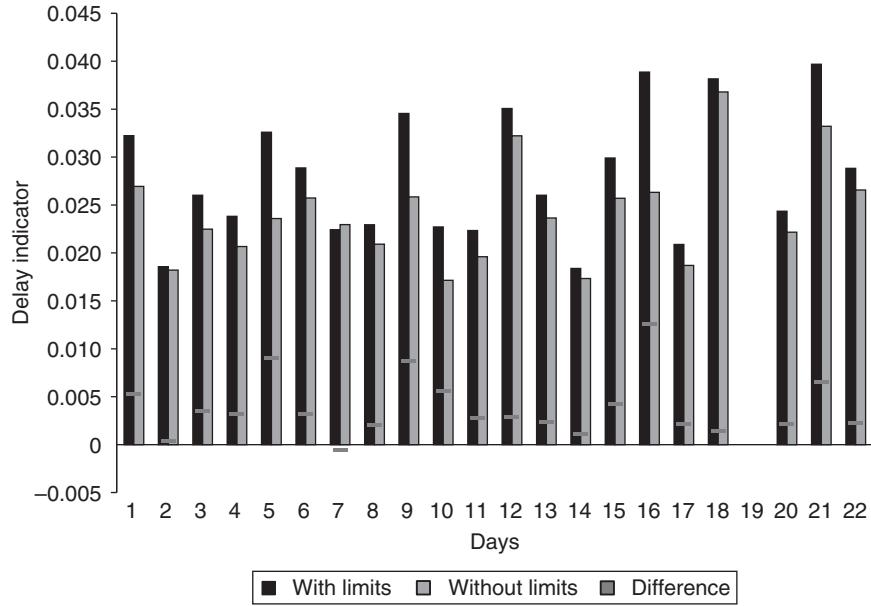


Simulated period: January 2013. Missing values are caused by failing simulations for the respective day.

the strength of the second-round effect caused by the redirection of liquidity and its possible reuse. The total effect is the sum of both effects: ie, the total difference in the number of queued payments.

We can clearly see that limits directly cause more queued payments, but that this effect is at least partially offset by a reduction in the number of queued payments due to a lack of liquidity. Nevertheless, this offsetting is only partial in almost every case. The results do not differ significantly for the different stress scenarios.

The result of a partial offsetting is confirmed by the calculation of a delay indicator. The delay indicator is not restricted to the number of queued payments, but it also takes into account the time spent in queue and the value of the queued payments. In addition, the delay indicator includes all payments, not only those queued, and is therefore able to capture a much broader aspect of settlement efficiency than the number of queued payments. The delay indicator has been developed as a joint work of Matti Hellqvist (European Central Bank), Alexandros Kalontzoglou (Bank of Greece) and Alexander Müller (Deutsche Bundesbank).

**FIGURE 6** Delay indicator with and without limits, stress scenario 2.

Simulated period: January 2013. Missing values are caused by failing simulations for the respective day.

The delay indicator is defined as

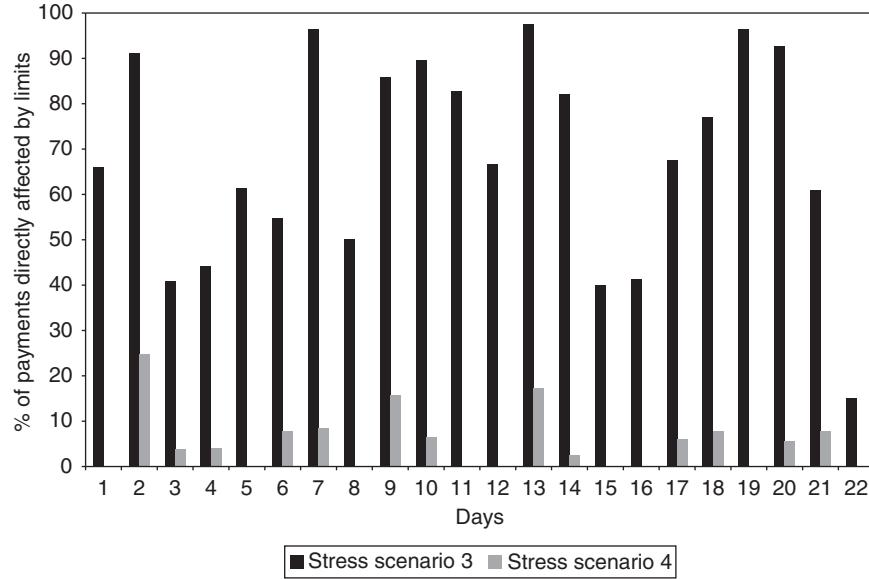
$$\frac{\sum_{i=1}^n \text{value}_i (\text{actual settlement time}_i - \text{introduction time}_i)}{\sum_{i=1}^n \text{value}_i (\text{latest possible settlement time}_i - \text{introduction time}_i)}.$$

The latest possible settlement time is defined as the end of the business day. It distinguishes for the different cut-off times for customer and interbank payments in TARGET2. For unsettled payments, the actual settlement time is set equal to the latest possible settlement time. The delay indicator only takes into account interbank and customer payments (payment types 1.1 and 1.2). Its value ranges between 0, which means that every payment is directly settled, and 1, which means that every payment is settled only at the latest possible moment or remains unsettled.

Figure 6 shows that the delay indicator is higher in the setup with limits in almost all cases. The results do not differ significantly for the different stress scenarios. The delay indicator is very low in general, which proves the efficiency of TARGET2's settlement engine.

We have to be aware of the fact that the simulations do not take into account behavioral changes of the participants when parameters are changed. The overall

**FIGURE 7** Additional queued payments due to limits.



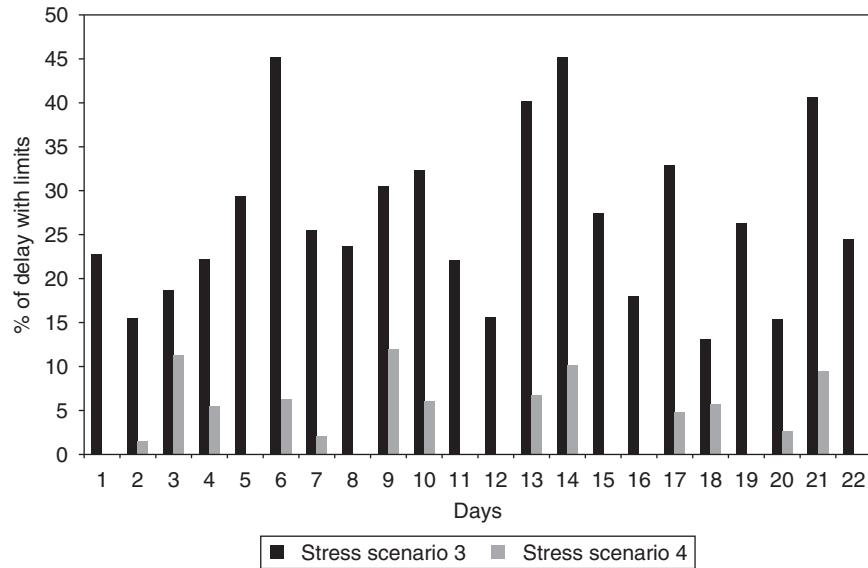
Simulated period: January 2013. Missing values for scenario 4 on days 1, 5, 8, 11, 12, 15, 16, 19, 22 are caused by failing simulations for the respective day.

positive effect of limits is therefore underestimated, since the educational impact is not reflected. The design of stress scenarios 3 and 4 takes this shortcoming into account. We create an artificial scenario with a group of participants being notoriously late payers. We are then able to investigate the effect of limits in a scenario with the assumption of a reduced educational impact.

The results of the analysis of differences in the number of queued payments and the delay indicator from stress scenarios 1 and 2, as shown in Figure 5 on page 52 and Figure 6 on the preceding page, is confirmed by the stress scenarios 3 and 4. We can again distinguish a first-round effect that is partially offset by a second-round effect.<sup>4</sup>

More important conclusions can be drawn from the comparison of the results in stress scenarios 3 and 4. While scenario 3 has delayed payments as the only stress component, scenario 4 has reduced intraday credits as an additional stress factor. The effect of limits can then be compared between environments with different levels of stress. The results are shown in Figure 7 and Figure 8 on the facing page.

<sup>4</sup> The comparison of the level of both effects in scenarios 1 and 2 with 3 and 4 is misleading, since the input of transactions has been restricted to large value payments.

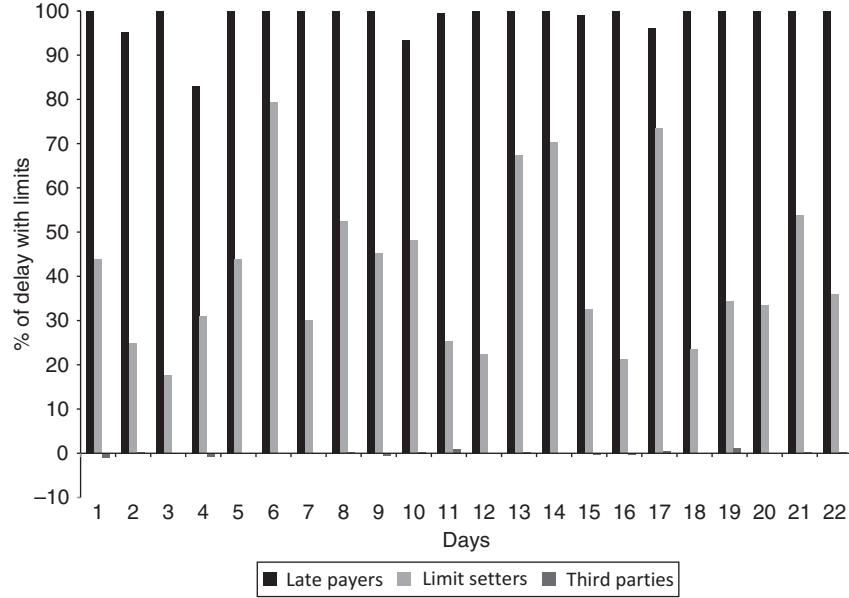
**FIGURE 8** Additional delays due to limits.

Simulated period: January 2013. Missing values for scenario 4 on days 1, 5, 8, 11, 12, 15, 16, 19, 22 are caused by failing simulations for the respective day.

Figure 7 on the facing page shows the difference in the number of queued payments in both scenarios. This is calculated as the percentage difference between the first- and second-round effect (ie, the total effect of limits). The figure can be interpreted as the share of the first-round effect that is not offset by the second-round effect.

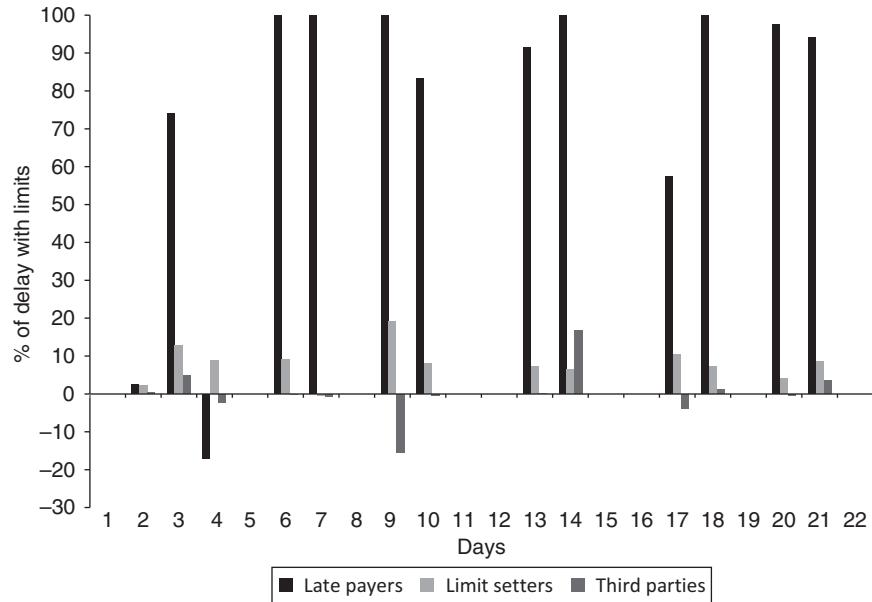
Figure 8 shows the additional delay that is caused by limits. It is calculated as the difference of the delay indicator between the setup with and without limits as a percentage of the value of the delay indicator in the setup with limits. It can be interpreted as the share of delay in the setup with limits that is caused by the limits. Both figures clearly show that the additional delay due to limits is much smaller in the scenario with a higher level of stress. The first-round effect is offset by the second-round effect to a much larger degree, and the increase in the delay indicator is much smaller.

We have also investigated the effect of limits on different groups of participants in scenarios 3 and 4: in particular, the group of limit setters, the group of late payers against whom limits are set and the group of third parties (other participants). The results are shown in Figure 9 on the next page and Figure 10 on page 57.

**FIGURE 9** Additional delay due to limits by participant groups, stress scenario 3.

Simulated period: January 2013.

The figures clearly show that the late payers against whom the limits are set are mainly affected by the additional delay due to limits. This indicates that these participants are highly reliant on the liquidity from the limit setters. This illustrates the working of the intended effect of limits toward avoiding free riding. The effect on limit setters is much lower. Its highest value in stress scenario 3 is 79%. This is still below the lowest value of the late payers, which is 83%. This difference is even more clear-cut in stress scenario 4, which involves a higher level of stress. On average, the value is 76% for the late payers and only 8% for the limit setters. This is caused by the different liquidity environment, as was discussed in the example in Table 1 on page 45. While in the first case most of the payments of the limit setters could have been settled in the environment with high liquidity and delays are only caused by limits, the saving of liquidity by effective limits for other payments takes effect in the second case. The effect for third parties is almost zero in stress scenario 3, and ambiguous in stress scenario 4. This seems at first to indicate a small effect of redirected and reused liquidity. However, the effect on the group of limit setters is not only caused by a setter's own limits but also by the limits of the other setters. The redirection effect is therefore probably also part of the observed positive impact.

**FIGURE 10** Additional delay due to limits by participant groups, stress scenario 4.

Simulated period: January 2013. Missing values on days 1, 5, 8, 11, 12, 15, 16, 19, 22 are caused by failing simulations for the respective day.

for limit setters. In addition, in our simulation the groups of late payers and limit setters are fairly small, much smaller than the group of third parties. A more equal distribution of group sizes would have been needed to make the redirection effect more clearly visible.

To complete the picture, the differences between scenarios with and without limits have been investigated in more detail for a single day of the simulations. While the overall results are confirmed, the complex effects of limits are revealed here. For example, we do also observe a few payments that are settled later due to lack of liquidity in a scenario with limits. Since these effects are very small, we can still maintain the argument with first-round and second-round effects, as they are the dominating causes of changes in settlement time. The detailed analysis also confirms that, on the whole, the payments of the late payers are settled later in a scenario without limits. Again, we can also observe some small unexpected effects, ie, some payments of late payers being settled even earlier in the setup with limits, which nevertheless do not contradict the main line of our argument. The analysis of different transaction classes shows that all are affected by whether limits are set or not.

Summing up the results of the simulations, we can clearly observe the expected first- and second-round effects in the number of queued payments. The second-round effect is only partially offsetting the first-round effect. This result is confirmed by the delay indicator, which shows higher delays in payments weighted by the time of delay and value of the delayed payment in the scenarios with limits. When comparing the effect of limits in scenarios with different levels of stress, we can show that, in scenarios with a higher level of stress, the positive impact of limits is higher. We can also show that the participants who are negatively affected by limits are predominantly the limit receivers. This is even more pronounced in times of heightened stress.

## 6 DISCUSSION AND RECOMMENDATION

We have comprehensively described the use of bilateral and multilateral limits in TARGET2 over the observation period from November 19, 2007 to May 31, 2013. While data on the use of limits can obviously not be used as indicators for the detection of financial market stress, it may well serve as one tessera in the overall mosaic of payment behavior of participants in TARGET2. The limited usefulness of data on the use of limits as crisis indicators hints at the possibility that banks may use internal limit systems before submission of payments to limit the risk of dissipating liquidity. The use and impact of those internal limit systems constitutes an area of future research. It would require, however, at least partial access to data outside the domain of operators.

What is more interesting from the view of operators is the impact of limits on the performance of TARGET2, especially in times of heightened stress. The results of our simulation analysis can be used to support the further existence of limits as a liquidity management tool in TARGET2. From the view of a single participant, limits clearly fulfill the objective of limiting outstanding balances to single counterparties (bilateral limits) and to the rest of the whole market (multilateral limit). Obviously, the mere existence of potential limits may have an educational effect and prompt participants to submit payments earlier in order not to become subject to strict limits by others. However, as has been shown in the theoretical considerations, the other effect of limits is to some extent ambiguous. Nevertheless, the quantification of the effects of limits on queue length and settlement delay, as has been done by this study, leads to an overall positive assessment of limits from the perspective of an operator. The negative effects of limits in the first round are partially offset by the second-round effects. The offsetting works better in times of stress, and the negative impact of limits is, to a large extent, to be borne by limit receivers in the case that they are truly late payers. So, overall, the limits do their job of contributing to avoiding free riding.

All these results, however, do not hold for multilateral limits. These cannot be focused on perceived late payers, they do not redirect liquidity and they cannot cause a second-round effect. However, multilateral limits have been designed as an additional

tool to enable participants to limit the unwanted overall liquidity outflow without having to set bilateral limits against all possible participants. Against this background the tool is warranted as an addendum to bilateral limits.

From the analysis above it is also clear that the positive effects of limits will significantly increase by the more extensive use of limits by more participants. Although we do not have an indication that free riding is a serious problem in TARGET2, we would call upon participants to make more active use of limits. Operators should, in their market communication, spread the arguments for a wider use of bilateral limits, which can in times of stress or operational failure serve well as a tool to prevent harm and to keep up a high settlement efficiency.

TARGET2 has the advantage of this tool being available. Other systems must rely on other tools to prevent free riding, such as throughput rules or different fees according to submission times. However, bilateral limits – as they are defined in TARGET2 – have significant advantages over those alternatives. First, limits are a market-based tool. The use of them is decided by participants based on their individual needs and assessments. No regular check by operators, and no punishment in the case of noncompliance, has to be considered. Second, and even more importantly, bilateral limits work automatically. If they are set, they will do the job in the case of a sudden stress situation (most stress situations are unexpected). Once they are set they work: a throughput rule may be set, but compliance cannot be enforced in real time. In addition, different payment fees for late submissions do not contribute to any liquidity redirection.

All in all, there are good reasons for bilateral limits to be used on a wider scale.

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# Chapter 3

## A dynamic approach to intraday liquidity needs

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*Freddy Cepeda L. – Fabio Ortega C.*

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\* This article first appeared in Journal of Financial Market Infrastructures, 17 June 2015. The publisher gratefully acknowledges the permission to reprint this article.

# A dynamic approach to intraday liquidity needs <sup>‡</sup>

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## Abstract

This paper presents a methodology to estimate intraday liquidity that, in order to fulfill its obligations, systemically important financial institutions need to confront simulated failures-to-pay by its main discretionary liquidity supplier. To this purpose, the Bank of Finland's BoF-PSS2 simulator and fund transfer data from the Colombian large value payment system (CUD) are used to achieve a dynamic estimation distinguishing three types of effects (direct effect, second-round effect and feedback effect). The procedure of identifying and selecting of systemically important institutions to be subject of simulated attacks is based on network analysis.

The results confirm a non-linear relationship between the initial failure-to-pay by a specific institution and the failure-to-pay by the rest of the system.

An Intraday Liquidity Sufficiency Index (ILSI) is proposed to establish the amount of additional liquidity that financial institutions participants in the system need to fulfill its obligations in a timely fashion without generating second-round effects. The proposed methodology could contribute to the efficiency and security of the payment system, and therefore, contribute to financial stability.

**Key Words:** Large value payment system, intraday liquidity, counterparty stress test, discretionary payments, simulation, direct effect, second-round effect, feedback effect, network topology.

**Classification JEL:** D53, D85, E51, C63, G21, G23

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<sup>‡</sup> The opinions and statements in this article are the sole responsibility of the authors and do not represent those of Banco de la República. Comments and suggestions from Clara Lía Machado, Carlos León, Ben Craig, Hernando Vargas and Pamela Cardozo are appreciated. Helpful assistance from Carlos Cadena in estimating the sovereign securities balances and Santiago Hernandez in building some graphics.

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## 1. Introduction

As result of the growing importance of intraday liquidity risk management there have been significant changes in international regulations. In this regard, Basel Committee on Banking Supervision (2008) formulates as eighth principle: "A bank should actively manage its intraday liquidity positions and risks to meet payment and settlement obligations on a timely basis under both normal and stressed conditions and thus contribute to the smooth functioning of payment and settlement systems".

The cited document mentions that the inability of a financial institution to effectively manage intraday liquidity could leave it unable to meet its payment obligations at the expected time, thereby affecting its own liquidity position and that of other parties. First, particularly in the face of credit concerns or general market stress, counterparties may view the failure to settle payments when expected as a sign of financial weakness. They could, in that case, withhold or delay payments to the financial institution that initially failed to meet its obligations and thus cause additional liquidity pressures. Second, it could also cause counterparties unexpectedly short of funds, impair those counterparties' ability to meet payment obligations, and disrupt the smooth functioning of payment and settlement systems. In this sense, given the interdependence that exists among systems, a financial institution's failure to meet certain critical payments could lead to liquidity dislocations that cascade quickly across many systems and institutions.

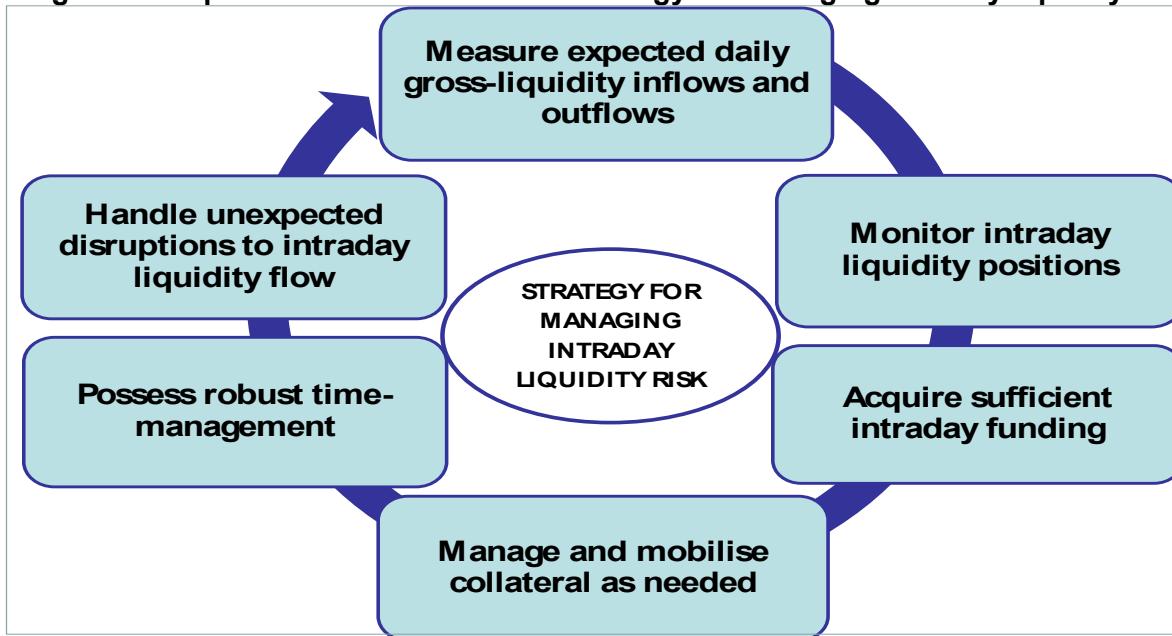
Diagram 1 shows six operational elements that according to the Principle 8 should be included in the strategy management of intraday liquidity.

The same Basel Committee on Banking Supervision (BCBS) issued the document "Monitoring tools for intraday liquidity management" in April 2013. It recommends to have the capacity to monitor the following set of indicators for each participant in the payment system: i) daily maximum intraday liquidity usage; ii) available intraday liquidity at the start of the business day; iii) total daily payments; iv) time-specific obligations or critical time payments; v) value of payments made on behalf of correspondent banking customers and credit lines granted to them; and vi) percentage of intraday payment processing done at specific points throughout the day. It further suggests four possible intraday liquidity stress scenarios to quantify the availability and use of intraday liquidity under conditions of non-normality, one of which is counterparty stress.

So that the purpose of this document is to design and develop a methodology to respond to "how" to address certain recommendations issued by the, and more specifically, "how" to implement counterparty stress scenarios in order to reliably quantify the impact and systemic effects of liquidity risk. Additionally the analysis performed let us to formulate effective policy recommendations that could mitigate their potential impact.

Therefore, the developed methodology identifies the systemically important entities and considers their discretionary payments. The discretionary payments, correspond to the transfer of funds for which the responsibility to settle is not exercised by a clearing and settlement infrastructure, but depends on the willingness of the originating entity to make the payment. Among there are uncollateralized interbank loans, for which there is evidence that, in times of crisis, the liquidity vanishes since lending providers for precautionary reasons retain this liquidity source or reduce it.

**Diagram 1 – Operational elements in the strategy for managing intraday liquidity**



Source: Authors based on Basel Committee on Banking Supervision, Monitoring tools for intraday liquidity management.

The proposed methodology makes it possible to answer several questions related to the "how" already mentioned, namely: i) how to select systemically important entities that could be subjected to simulated attacks; ii) how to identify the main liquidity provider counterparty for discretionary payments for each systemically important entity; iii) how to simulate attacks on systemically important entities in counterparty stress scenarios; iv) how to quantify the direct, second-round, and feedback effects; and v) how to establish policies to mitigate the impact of systemic risk caused by stress of intraday liquidity.

## 2. Theoretical framework

Liquidity is a broad concept, which manifests itself in different ways: i) Market Liquidity that corresponds to the ability to quickly buy or sell without causing significant changes in prices. This is related to the maturity and depth of financial markets; ii) Liquidity funding or financing understood as ability to obtain funds when required to meet obligations; iii) Intraday Liquidity that means the ability to make payments when they are due or to get access to funds during the business day usually to make payments in real time (Committee on Payment and Settlement Systems 2003).

Although each of the concepts of liquidity is different from the theoretical point of view, they tend to interact, especially in times of stress. For example, a problem with intraday or market liquidity can quickly become a problem of funding liquidity, or vice versa.

The recent global financial crisis has led to a growing consensus on the importance of liquidity risk management within financial institutions, financial infrastructure, and the financial system as a whole. Within that consensus, the importance of having a stable,

reliable, and diversified funding base that contributes to mitigating liquidity risks caused by failures in the interbank market, stock market, and long-term securitizations has been highlighted.

Therefore, international institutions and individual studies have diagnosed and made new recommendations to address the systemic effect of a liquidity crisis. Among these we quote: i) Ackerman (2008), who mentions that as in a market-based financial system liquidity crises are more likely than solvency crises, liquidity management is a better response than higher capital cushions; ii) Tirole (2009) who, considering the systemic risk and under the externality-based rationale, insists that banks have to hold enough liquidity to not expose the rest of the financial system to a widespread crisis; iii) Borio (2009), who said that to better prevent liquidity crises the cushion system needs to be improved and the macro-prudential orientation of regulation and supervision must be reinforced; iv) French et al. (2010), who stated that regulators should enforce and monitor liquidity requirements for systemically important banks and broker-dealers; v) IMF (2010a), which says enhancing liquidity buffers and lowering maturity mismatches between assets and liabilities will help to reduce the possibility that an individual institution will fall into liquidity difficulties.

In the same vein, as recognized by several authors (IMF, 2010b; Tucker, 2009; León, 2012), even though a liquidity regulatory framework and some tools for managing liquidity risk exist, they are only at an early stage of development and discussion. In addition, the prevailing concept of liquidity in the literature and in regulation corresponds to the ability to generate cash from the asset and liability positions on institutions' balance sheets (i.e. market liquidity and funding liquidity), so risk management liquidity has traditionally focused on the mismatch between liquid assets and short term liabilities.

Although a consensus on the need to improve the management of liquidity risk became apparent after the 2008 financial crisis, the emergence of a particular type of risk mentioned very little in the past—Intraday liquidity risk—is remarkable.

As a result of the growing importance of risk management, there have been significant changes in the international regulation of intraday liquidity. In this regard, several examples should be noted. One of them was the inclusion of the eighth principle, cited before, by Basel Committee on Banking Supervision (2008).

The same Committee in April 2013 issued a document entitled "Monitoring tools for intraday liquidity management" in which they recommended to develop four possible stress scenarios (not exhaustive) to quantify the availability and use of intraday liquidity under conditions of non-normality, one of which is counterparty stress.

Another example is the inclusion of intraday liquidity requirements for financial institutions, banks, and non-banks by the Financial Services Authority (FSA) in the UK. As described by Ball et al. (2011), the new FSA liquidity regime includes intraday liquidity risk as a key factor that requires banks to calibrate their liquidity reserves based on their intraday liquidity needs under normal and stress circumstances.

In Colombia, in particular, the last evaluation done by the IMF and the World Bank (Financial Sector Assessment Program-FSAP, 2013) included recommendations aimed at improving other aspects. One is to tighten liquidity standards for broker-dealers and other non-bank financial intermediaries (NBFIs), and another is to adopt more rigorous stress testing for broker-dealers and other NBFIs.

On October 24, 2013, the Federal Reserve Board proposed a rule to strengthen liquidity positions of large financial institutions. The proposal creates a standardized minimum liquidity requirement for the first time. This requirement applies to both large and internationally active banking organizations, and systemically important non-bank financial companies. These institutions would be required to maintain minimum amounts of high quality liquid assets such as reserves at the central bank, and government and corporate bonds that can be easily and quickly converted into cash to guard against restrictions on funding in times of financial turmoil.

As recognized by Ball et al. (2011), prior to the 2008 financial crisis regulators were not focused on intraday liquidity risk, and there were no standardized measures for monitoring or managing it. Before the crisis, there were only general principles and recommendations (not requirements) with respect to the benefit of a proper management of intraday liquidity. However, even though the crisis revealed the importance of this type of liquidity, this importance arises from the progressive structural change that large value payment systems (LVPS) have experienced worldwide. This has resulted in the transition from a system of deferred net settlement payments to real time gross settlement (RTGS).<sup>1</sup>

The implementation of the RTGS, which consists of continuous settlement (in real time) by transferring funds or securities individually (i.e. one at a time), received intense support from the banking authorities as an effort to reduce settlement risk and systemic risk (Committee on Payments and Settlement Systems 1997). However, mitigating settlement risk occurs at the expense of: i) an increase in the liquidity needs of the entities involved in the payment system, and ii) an increase in the entities' dependency on recirculation liquidity within the payment system, which carries a higher liquidity risk.

As a result of the increased demand for liquidity that an RTGS system causes, participants may choose between the following (non-exclusive) alternative sources to meet payments during the day: i) use the available balance in deposit accounts in the central bank; ii) use the money market (with - without collateral); iii) use central bank liquidity, and iv) use payments received from other participants (recirculation of balances).

The participant's preference for one or more of these alternatives depends mainly on the related cost each one has. In this regard, one participant that seeks to minimize the cost of getting liquidity to meet the intraday obligations prefers a resource that has no cost, such as the use of payments received from other participants (recirculation of balances). A participant's preference for one of the other sources is determined by the trade-off between the opportunity cost of keeping cash in the accounts and the financial cost of using assets as collateral with third parties such as the central bank and other financial institutions.<sup>2</sup>

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<sup>1</sup> Bech (2008) documents that the number of central banks that had implemented a payment system based on large value RTGS went from 3 in 1985 to 93 at the end of 2006. According to the World Bank (2011), 116 central banks (out of 139) had an RTGS implemented for the payment system. Also 17 central banks in Latin America and the Caribbean with a total of 20 respondents had implemented this type of settlement in their payment systems.

<sup>2</sup> The cost incurred in participating in systems where the central bank provides liquidity support without a collateral requirement corresponds to setting an explicit fee for overdraft. When it comes to providing collateralized liquidity, this refers to the sum of the opportunity cost of immobilized securities and explicit cost at which the central bank provides that liquidity. The same calculation is applied when estimating the cost of funds in the money market.

Now, while obtaining liquidity by receiving payments from other participants in the system carries no charge, it has the disadvantage of being subject to uncertainty and, therefore, may result in delays in meeting one's own payments. In addition, due to the existence of timing mismatches between incoming and outgoing flows, any tension that exacerbates these mismatches can lead to significant increases in intraday liquidity needs.

Therefore, we can say that the main source of uncertainty with respect to the intraday liquidity needs of a participant in an RTGS system is the timing mismatch between the receipt of liquidity and its use. That is, if the reception is not timely (i.e. the reception does not occur before the entity is required to make payments), the entity may face difficulties in meeting its own payments. This could result in delays in the payment system and negatively impact other participants that, in turn, would not have enough liquidity to meet their payment obligations. This negative externality can lead to higher liquidity requirements for the system as a whole and possibly a higher level of systemic risk.

Once the relevance of the intraday liquidity risk is recognized, a methodological approach to dynamically estimating intraday liquidity needs should be designed and developed. This approach must consider the failure-to-pay (simulated) by the participant's main liquidity provider counterparty through discretionary payments. The purpose of this document is to contribute to this effort.

Simulation exercises were done using the simulator developed by the Bank of Finland BoF-PSS2 and with information on fund transfers that financial institutions make through the Colombian large value payment system (CUD-RTGS).

### **3. Methodology**

In order to follow the recommendations of Basel Committee on Banking Supervision (2013) to develop counterparty stress scenarios with respect to intraday liquidity, the methodological proposal described in this document will take advantage of two technical tools – simulation and network topology. While the network topology allows us to identify those critical participants in the system from the point of view of connectivity, simulation enriches the analysis by allowing us to identify and quantify the impacts exerted by the failure to pay and critical entities on the amount paid in the system.

Simulation scenarios were purposefully designed to impact a set of systemically important entities with failures in the delivery of discretionary payments from their primary counterparties.

These scenarios were created considering as opening balances for each entity<sup>3</sup>, the existing balance in deposit accounts of the participants in the CUD-RTGS plus the estimated minimum intraday balance of local sovereign debt securities (TES) in proprietary portfolio<sup>4</sup> in securities central depository DCV.<sup>5</sup>

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<sup>3</sup> Other scenarios were developed taken as opening balances just the existing in deposit accounts in CUD, but their results are not shown in this document because they are considered as extreme stress test, given the possibility that entities have to get additional liquidity with the central bank using their local sovereign debt securities as collateral.

<sup>4</sup> The average haircut estimated to these sovereign bonds was 2.2%.

<sup>5</sup> DCV is central depository of securities for local sovereign debt, which is owned and managed by Banco de la República.

The reason for adding the TES balance is that it can be easily converted into cash through the liquidity facilities offered by the central bank as the owner/manager of large value payment system CUD-RTGS and in its task to achieve the payment system's stability. The inclusion of these intraday TES balances rests on the assumption that voluntarily the institutions would use these idle daily minimum balances as collateral to fund their payments.

Diagram 2 summarizes the sequence of steps for the simulation scenario carried out. The information sample that was considered in our analysis corresponds to the fund transfers that financial institutions made through the CUD system for the months of April 2012 and 2013. These two months were used because April 2012 turned out to have a daily average that was the closest to the one calculated for the annual average, and the same month in 2013 was chosen to eliminate seasonality effects.

For the selection of systemically important entities within the universe of participants in the system, we first considered the types of entities with greater participation in the total value of payments sent so that the aggregate reach 85% of the whole system. By this way were selected types of entities such as commercial banks (CB), financial corporations (FC), brokerage firms (BF) and trust companies (TC).

Once these types of entities were selected, we proceeded to identify within each type the systemically important entities. The identification procedure combines two criteria, one relative to topology network to capture the importance of the entities in the payments network, and another related to the value of sent payments.

The metric used to capture the connectivity and substitutability of the entities in the LVPS network was the hub centrality index estimated with the HITS (hyperlink induced topic search) algorithm designed by Kleinberg (1999). According to Langville and Meyer (2012), this index has the ability to measure the importance of a node recognizing the interdependent relationship origin-destination that reinforces itself. Therefore, it could be inferred that a central distributor (hub-central) node that will point to the higher authority node, and likewise, a central authority node will be the one receiving connections of the largest distributors.<sup>6</sup>

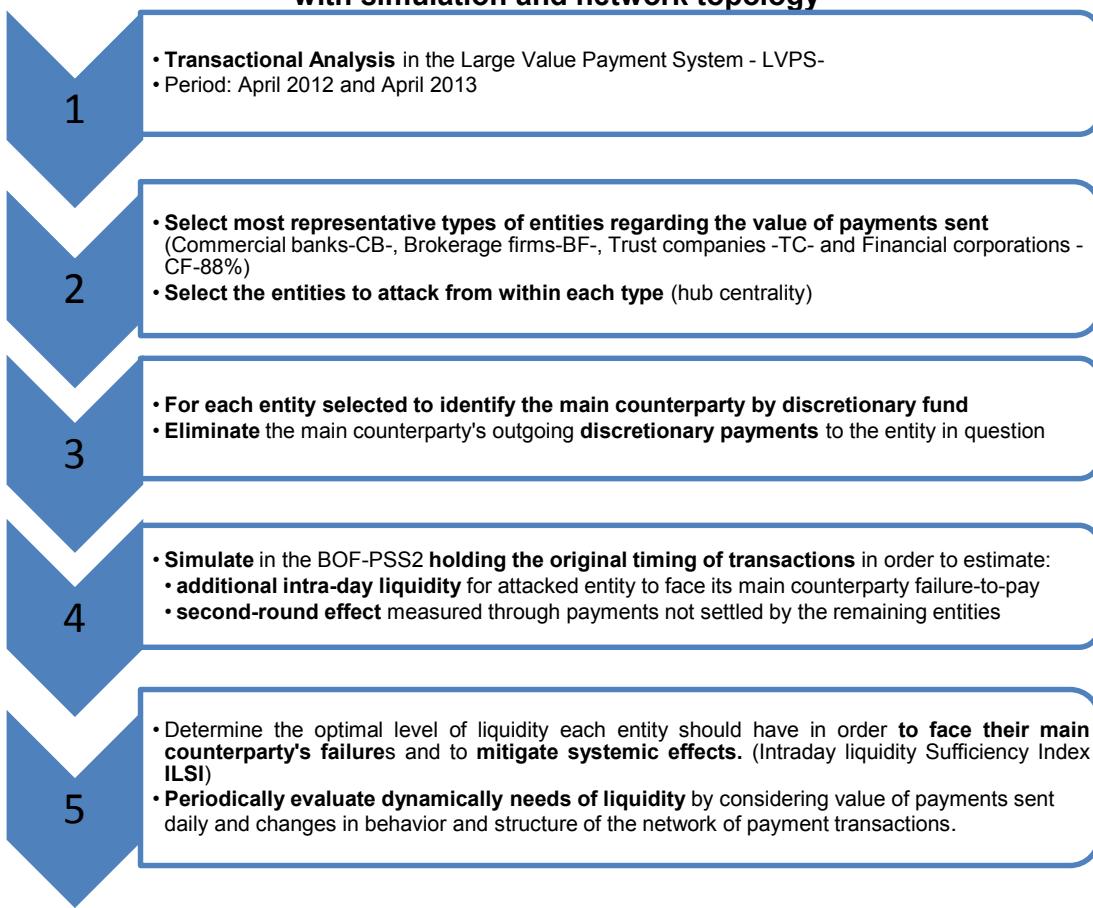
Once we estimated the hub centrality indices of entities inside of each type, we selected those with higher index until completing the 80% of payments sent by the respective group. These chosen entities were subjected to failure-to-pay from its main counterparty by discretionary payment concept. Henceforth we define this failure-to-pay as an "attack". In this way, as shown in Table 1, the number of participants chosen to be attacked in April 2012 (April 2013) was 31 (27).<sup>7</sup>

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<sup>6</sup> Leon and Pérez (2014) used the hub-centrality to analyze the centrality in the net exposures in the money market and in the Colombian LVPS.

<sup>7</sup> Their payments exceeded 75% (72%) of the total excluded from value paid by the National Treasury and Central Bank.

**Diagram 2**  
**Methodology for stress-testing counterparty failures**  
**with simulation and network topology**



To implement the simulated attacks we eliminated the corresponding discretionary payment transactions from our daily payment data sample of CUD-RTGS. This way we built the input information for the simulation exercises done with the BoF-PSS2 simulator under RTGS settlement configuration (1183 scenarios).

**Table 1**  
**Entities selected by type for the simulated counterparty attack**

Institution type	April 2012		April 2013		
	Number of selected entities	% share in outgoing payments		Number of selected entities	% share in outgoing payments
		By type	Total System*		
Commercial banks	10	85.22%	45.4%	9	81.72% 47.6%
Financial corporations	2	96.41%	8.7%	2	87.05% 6.4%
Trust companies	11	82.73%	5.6%	9	83.27% 6.3%
Brokerage firms	8	82.59%	15.4%	7	81.58% 12.6%
<b>Selected entities</b>	<b>31</b>		<b>75.2%</b>	<b>27</b>	
					<b>72.9%</b>

\* This does not include outgoing payments from National Treasury or Banco de la República

Source: Authors with information from CUD-RTGS

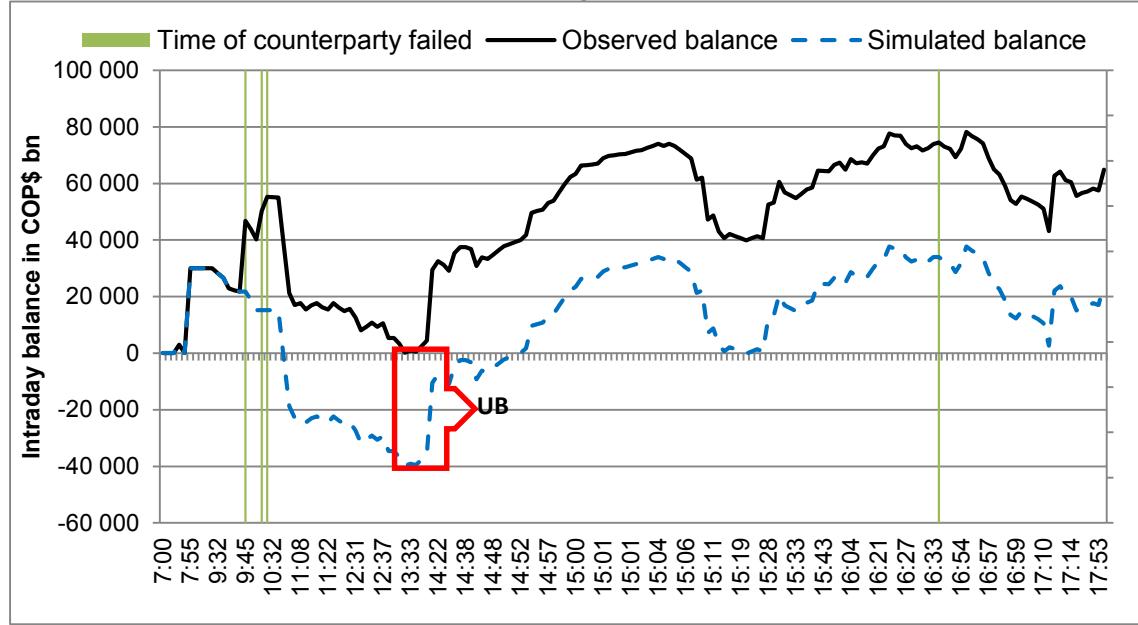
The simulated attack scenarios were carried out against 31 (27) entities for 19 (22) days in April 2012 (2013) thus making it possible to obtain the value of the payments each participant failed to settle and to calculate the minimum liquidity amount that each one should maintain to settle all its payment obligations in a timely fashion. Koponen and Soramäki (1998) defined this concept as Upper-Bound balance (UB) in equation (1)

$$UB = \min(0; \min \sum_{j=0}^t P_j^I - P_j^O); \quad \forall t [0, T] \quad (1)$$

where  $P_j^I$  and  $P_j^O$  correspond to incoming and outgoing payments, respectively

Graph 1 let us to compare for one entity, the intraday trajectories of observed balance (including TES) and simulated balance when its primary counterparty by discretionary concept fails to pay (failures-to-pay are identified by green bars). As can be seen from the observed intraday trajectory, despite having low initial balances, high coordination of incoming and outgoing payments enables the entity to comply with its payment obligations (i.e. intraday balance greater than zero). As this situation vanishes when failures-to-pay are simulated, the simulated trajectory indicates that the entity should get additional resources equivalent to UB.

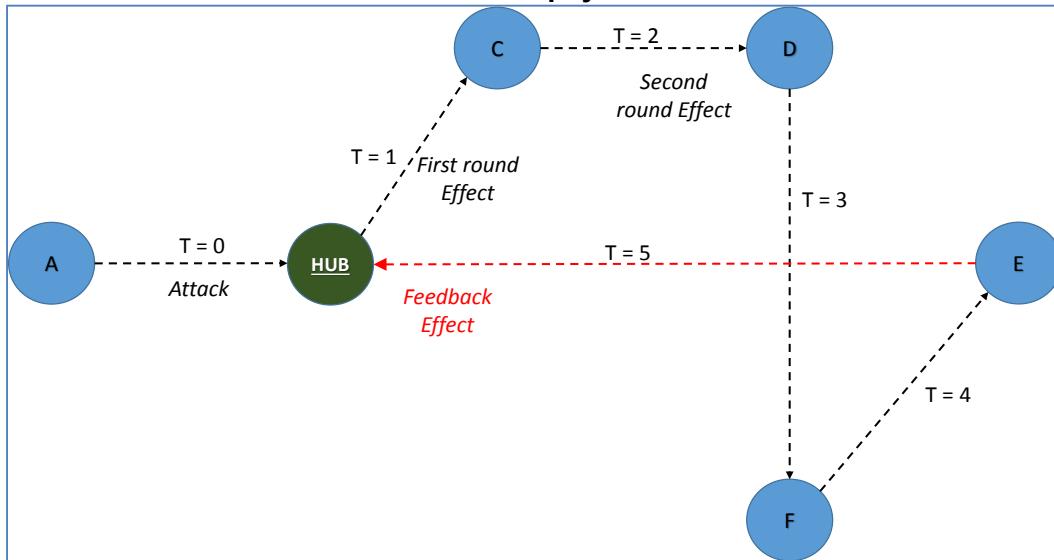
**Graph 1**  
**Intraday trajectories of observed balance and simulated balance when carried counterparty attack out**



Source: Authors

The Diagram 3 exemplified a possible sequence of effects after the simulated attack. The failure to send discretionary payments from the main counterparty (entity A) to one particular entity (entity B) in time  $T=0$ , can impede to this latter entity in time  $T=1$  fulfill its payment order to others (direct effect), and thus cause a string of failures to pay affecting other entities (second-round effect) in times  $T=2, 3$  and  $4$ . This failures to pay chain could as consequence of non-settled payments by second-round effect even result in a feedback effect, in which the attacked entity (entity B) as receiver of payments ends up being affected too in time  $T=5$ .

Diagram 3  
Effects of failures on payment settlement



Source: Authors

Based on these Upper-Bound balances estimated through simulations and on the observed daily opening balances plus the minimum value of local debt sovereign securities (TES), it is possible to establish the percentage by which an entity should increase its initial balance in order to opportunely meet all its mandatory payments. Using these prior concepts, an Intraday Liquidity Sufficiency Index -ILSI- was proposed in equation (2) to measure the ratio between the observed opening balance -OB- and estimated UB balance of each entity j,

$$ILSI_j = \frac{OB_j}{UB_j}; \quad (2)$$

so that  $\begin{cases} ILSI_j < 1; & \text{additional required liquidity } UB_j - OB_j \\ ILSI_j \geq 1, & \text{sufficient liquidity to meet its payment obligations in a timely fashion} \end{cases}$

Note that the value of this index depends on the value and the timing<sup>8</sup> of payments made by each entity and the liquidity available from alternate sources (Bernal et al., 2012).

As the value of UB is highly sensitive to changes in the sequence of payment order (timing), entities with an observed opening balance that is normally much higher than required to meet all their payments promptly (UB), (i.e. high ILSIs) could find themselves unable to meet them. This would be the result of being denied liquidity by simulated failures-to-pay from its counterparties.

The new  $\widehat{UB}_j$ s were estimated using the Bof-PSS2 simulator when the attacked entities experienced the reduction in discretionary incoming payments as a result of failures-to-pay

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<sup>8</sup> The “timing” in this context means that the original schedule of payments (observed) holds in the simulation scenarios that imply that we are not assuming behavioral changes of the entities as reaction after the attacks and their effects.

by their major counterparts (Graph 1). Given this scenario, the  $\widehat{UB}$  balance of attacked entities shall be,

$$\widehat{UB} = \min(0; \min \sum_{j=0}^t \widehat{P}_j^I - P_j^O) = \min(0; \sum_{j=0}^T \widehat{P}_j^I - P_j^O); \quad \forall t [0, T] \quad (3)$$

Where  $\widehat{P}_j^I$  is the value of the simulated incoming payments (funds not received from the main counterparty) and  $P_j^O$  represents out-going payments (which correspond to all the payments the entity should have sent). In this kind of scenario where just incoming payments were eliminated, it is possible to demonstrate that simulated  $\widehat{UB}$ s will be equivalent to the net value of the observed outgoing payments and simulated incoming payments as can be seen in the last part of this equation (3).

Given that the timing of payment orders is decisive in these transfer payment networks, the failure to pay of a participant can spillover failures-to-pay to the remaining participants, increasing the  $\widehat{UB}$ s. This situation could happen even if the value of payments of one participant is relatively small with respect to the total sent by the system. The systemic impact increases even more if incoming payments constitute the main source of liquidity not only for this participant but also for a large share of their counterparties and other participants.

This analysis allows to quantify intraday liquidity that each financial institution should hold to deal with a failure on the part of its main counterparty liquidity provider without generating effects on whole system. The results of this exercise provide valuable elements that could support the financial authorities' decision-making and the design of macro-prudential policies to mitigate liquidity risk and systemic risk.

#### 4. Results

In order to keep reserved individual identity of entities considered, the main results obtained from the simulation exercises are summarized below as averages by type of institution. They reflect the direct, second-round and feedback effects with information from April 2012 and 2013.

For April 2012, Table 2 shows the results of the simulation scenarios are carried out when the minimum intraday TES balance had in proprietary holding was added to the observed opening balance in deposit accounts of the Colombian LVPS to meet its obligations. Lines in shadow gray correspond to simulations which results show the nonexistence of systemic effects, given that attacked entities had enough average liquidity to confront failure-to-pay from main counterparty.

For example, commercial banks were able to pay all their obligations without generating an effect on other entities (i.e. no direct effect or second round effects) although they had stopped receiving on average COP\$86 billion (bn<sup>9</sup>) from its main counterparty daily, which accounted for 0.23% of the average total payments settled daily in the system.

Another type of entity, that with their beginning of day balance plus TES, were able to pay all their obligations timely were financial corporations. The amount average of liquidity left to receive by this type COP\$35.0 bn, which is equivalent to 0.09% of the daily average total payments settled in the system.

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<sup>9</sup> Billions (bn) correspond to nine zeros.

The results for commercial banks and financial corporations could be explained by the reserves requirement which these types of entities are subjected.

Meantime, in the same Table 2 as result of the attack, in average the brokerage firms stopped receiving from their corresponding main counterparties, a daily average of COP\$43 bn during 19 simulated days, representing 0.11% of the daily average total payments settled in the system. As a consequence of not receiving these funds for 12 of the 19 days with simulated failures, the brokerage firms could not meet part of their obligations that amounted to COP\$210.3 bn as a daily average (direct effect), which represented 0.55% of the average total payments settled in the system daily.

The brokerage firms failure generated second-round effects. It affected an average of 9 entities in the system, which in turn were unable to fulfill part of their obligations amounting to a daily average of COP \$527.2 bn which represented 1.38% of the daily average total payments settled in the system. Following the same type of entity and as result of the effects mentioned above, we can see that for 6 of the 19 simulated days some entities in the system failed to send payments that they owed to brokerage firms, amounting to COP\$12.3 bn (Feedback effect).

As can be seen from our results, an initial minimal failure of COP\$43 bn (0.11% of the payments in the whole system) finally generated an extended impact of failures to pay that impeded to settle on average COP\$749.7 bn (1.97% of payments settled) in the system. This was due to the concurrency of the three effects mentioned above (direct, second round, and feedback).

In the case of trust companies our results show after the attack of its main counterpart, equivalent to an average of 0.10% of total payments sent by the system, that although the three types mentioned effects were generated, its impact on the system was modest, this is on average 0.26% of total payments.

A comparative analysis of our results makes it possible to recognize that by type of institution, brokerage firms generate on average the most intense effects on the whole system after the attack<sup>10</sup>.

It can be seen that under this scenario, banks and financial corporations have no difficulty making their payments after the attack of their major counterparties and are, therefore, not generating any effect on the system (Direct, second round, and feedback). For brokerage firms and trust companies, our results show on average by type of entity the existence of direct, second-round, and feedback effects.

These results show that the addition of minimum intraday TES balance to the balance in deposit accounts could operate as a mechanism to mitigate systemic risk; however, caution is advised because the decision to take the liquidity provided by the central bank depends on the willingness of the financial institution to use this liquidity source.

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<sup>10</sup> For April 2013, in the same terms such entities generated a reduced systemic impact corresponding to an average 0.98%. (See Appendix Table A1)

Table 2  
**Effects of simulated attack on the settlement of payments  
with observed opening balance + TES (April 2012)**

Number of Attacked Entities <sup>1</sup>	Number of days simulated <sup>2</sup>	Amount of liquidity left to receive by attacked entity from its main counterpart		Payments not settled by attacked entity (First-round effect)			Payments not settled by remaining affected entities in the system (Second-round effect)			Payments not received by attacked entity (Feedback effect)			Total average of unsettled payments as % of total payments sent for settlement
		Average daily value (in thousands of millions of COP\$)	as % of average total value settled in the system	Number of days <sup>3</sup>	Average daily value (in thousands of millions of COP\$)	as % of average total value settled in the system	Number of affected entities <sup>4</sup>	Average daily value (in thousands of millions of COP\$)	as % of average total value settled in the system	Number of days <sup>5</sup>	Average daily value (in thousands of millions of COP\$)	as % of total value settled in the system	
<b>Commercial banks</b>													
10	19	86	0.23%	0	0.0	0.00%	0	0.0	0.00%	0	0.0	0.00%	
<b>Financial corporations</b>													
2	17	35	0.09%	0	0.0	0.00%	0	0.0	0.00%	0	0.0	0.00%	
<b>Brokerage firms</b>													
8	19	43	0.11%	12	210.3	0.55%	9	527.2	1.38%	6	12.3	0.03%	
<b>Trust companies</b>													
11	18	39	0.10%	12	80.0	0.21%	1	16.8	0.05%	0	0.0	0.00%	
<sup>1</sup> Hub entity that was subjected to failure-to-pay from its main counterparty by discretionary payment concept.													
<sup>2</sup> Number of days when simulations were done. For some entities, this number was lower than the observed days in the sample (19 for April 2012), because during some days these entities did not receive funds by discretionary payment concept from anyone participant.													
<sup>3</sup> Number of days when attacked entity was not able to fulfill all its payment obligations after the failure-to-pay from its main counterparty.													
<sup>4</sup> Corresponds to the remaining affected entities, which did not fulfill some of their payments obligations after the failure-to-pay of the attacked entity.													
<sup>5</sup> Number of days when attacked entity did not receive some payment from the remaining affected entities.													

Source: Authors' calculations

As for the banks, high ILSIs are related to minor impacts on the system. For trust companies and brokerage firms this relationship does not apply. It could also disrupt payment synchronization given the weight that the funds not received from their main counterparty have as a liquidity source to meet their obligations.

The results of average observed and average estimated ILSIs presented in Tables 3 make possible to recognize the following facts<sup>11</sup>.

Based on the observed payment timing, commercial banks have on average a daily opening balance that far exceeds the UB balance (i.e. the balance required to settle all of its obligations in a timely fashion) in 117%. By their side, financial corporations and trust companies had an average daily opening balances that barely fit the UB balance. Respect to the eleven brokerage firms considered here, the average observed daily opening balance was 18% greater than UB estimated.

It is worth recognize that the average values estimated by type of entity result from adding individual estimation of entities with high and low balances at the beginning of the day, so that there could exist entities that because hold liquidity balances very close to UB liquidity are highly exposed to shortage of liquidity by failure-to-pay of their counterparties.

Such situations are exhibited for brokerage firms and trust companies in Table 3 when failure-to-pay by discretionary concepts were simulated. In effect after the attack during 12 days the estimated ILSIs were on average lower than one for brokerage firms (0.449) and trust companies (0.380). These results mean additional liquidity needs, which in terms of average weighted by submitted payments are equivalent to 5.5% and 15.6% for brokerage firms and trust companies respectively.

**Table 3  
Intraday Liquidity Sufficiency Index (ILSI) and required liquidity  
to face simulated counterparty failure to pay - April 2012**

Number of Attacked Entities	Number of days simulated	ILSI estimated for original observed payments	Simulated attack of counterparty failure with observed opening balance + TES		
			Number of days	ILSI estimated	Additional required liquidity (as % of payment sent)
<b>Commercial banks</b>					
10	19	2.17	0	>1	0.0%
<b>Financial corporations</b>					
2	17	1.04	0	>1	0.0%
<b>Brokerage firms</b>					
8	19	1.18	12	0.449	5.5%
<b>Trust companies</b>					
11	18	1.08	12	0.380	15.6%

Source: Authors' calculations.

As can be seen, despite the fact that on average brokerage firms register observed ILSIs (opening balances observed greater 18% than its UB), once they are subjected to simulated failures-to-pay from their main counterparty, they do not have enough liquidity to comply

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<sup>11</sup> The results for April 2013 show in Appendix Table A2.

with their payment obligations. This fact can be explained by i) the timing of the funds that were not received in their payment sequence and ii) the weight that these resources represent with respect to the payment obligations.

So if each entity remains frozen as additional liquidity the amount of resources that by concept of discretionary payments would cease to receive for failure-to-pay from its main counterpart, could mitigate or even eliminate the extended impact of failures-to-pay in the system.

## 5. Conclusions

When the minimum intraday balance of an entity's proprietary position in sovereign securities (TES) in the DCV discounted by a haircut is added to the opening balance in deposit accounts, the results show that on average commercial banks and financial corporations would have sufficient liquidity to settle their payment obligations without generating any impact on the system.

Based on our results, the average amount of additional resources from their proprietary position in TES would allow trust companies and brokerage firms to mitigate but not to eliminate, the impact of the failure on the settlement of payments of the entire system. This result may be due to the particular nature of their business.

Indeed, when we take into account the TES balances above mentioned together opening balance in deposit account, for 2012 (2013) the average minimum liquidity required to fulfill the total payment obligations in a timely manner, as weighted percentage of its submitted payments, would be 15.6% (24.6%) for trust companies and 5.5% (8.4%) for brokerage firms for 2012 (2013). Note that as intraday liquidity requirements can exceed the estimated "average" values, systemic effects of individual failures-to-pay of intraday liquidity could persist.

These facts, together with the dynamic nature and the network structure of this kind of system make possible to recognize the existence of complexities. These reveal a non-linear relationship between liquidity that has not been received by a particular systemically important participant as a result of the attack and the total liquidity that has not been delivered by the remaining participants.

It is valuable to identify those systemically important entities because if their major counterparties fail to send the discretionary payments, this failures-to-pay to an individual entity could magnify the impact on the liquidity of the rest of the system in a non-linear fashion. Then if each entity remains frozen as additional liquidity the amount of resources that by concept of discretionary payments would cease to receive for failure-to-pay from its main counterpart, could mitigate or even eliminate the systemic impact of failures-to-pay in the system.

As a result of our simulation of counterparty stress scenarios (attack) it is possible to distinguish and to quantify the value of failures-to-pay i) that originated from the entity subject to attack (direct effect); ii) that occurred between other entities (second-round effect); and iii) in which the attacked entity is the recipient of other participants' defaults (feedback effect).

Recognizing potential effects of network externalities in these systems is valuable because it creates awareness of how an entity's individual actions may cause problems to other

participants in the system and, in the end, affects itself. In addition to quantifying the amount of payments that was not received from a primary counterparty, it is possible to estimate how much additional liquidity each attacked entity should have in order to face these failures without causing illiquidity problems to spill over into the system.<sup>12</sup>

As our figures of estimated liquidity requirements needed to meet these counterparty stress scenarios are the result of estimated average values, it may be the case that the additional required liquidity will not be sufficient in non-typical scenarios. Setting the level of liquidity required to confront these kinds of failure-to-pay situations should, among other considerations, take into account both the cost of liquidity the participants must incur and the coverage degree desired to shield the system in extreme situations.

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<sup>12</sup> As forthcoming research related to this issue, would be useful carry out simulation exercises to identify effects on the liquidity of each of the participants and the liquidity of the aggregate system when one or more entities considered systemically important (as example hubs) stop sending payments. Another possibility in this area, which could contribute as novel tool for monitoring financial market infrastructure and its participants, would be use network topology to analyze the structure the network of defaults that result from stress-test exercises.

## Appendix

Table A1  
**Effects of simulated attack on the settlement of payments  
with opening balance observed + TES - April 2013**

Number of Attacked Entities <sup>1</sup>	Number of days simulated <sup>2</sup>	Amount of liquidity left to receive by attacked entity from its main counterpart		Payments not settled by attacked entity (First-round effect)			Payments not settled by remaining affected entities in the system (Second-round effect)			Payments not received by attacked entity (Feedback effect)			Total average of unsettled payments as % of total payments sent for settlement
		Average daily value (in thousands of millions of COP\$)	as % of average total value settled in the system	Number of days <sup>3</sup>	Average daily value (in thousands of millions of COP\$)	as % of average total value settled in the system	Number of affected entities <sup>4</sup>	Average daily value (in thousands of millions of COP\$)	as % of average total value settled in the system	Number of days <sup>5</sup>	Average daily value (in thousands of millions of COP\$)	as % of total value settled in the system	
<b>Commercial banks</b>													
9	22	111.1	0.29%	0	0.0	0.00%	0	0.0	0.00%	0	0.0	0.00%	
<b>Financial corporations</b>													
2	17	49.0	0.13%	0	0.0	0.00%	0	0.0	0.00%	0	0.0	0.00%	
<b>Brokerage firms</b>													
7	22	60.0	0.16%	15	167.8	0.44%	5	200.3	0.52%	6	4.9	0.01%	
<b>Trust companies</b>													
9	21	66.0	0.17%	17	135.9	0.35%	1	17.9	0.05%	0	0.0	0.00%	

<sup>1</sup> Hub entity that was subjected to failure-to-pay from its main counterparty by discretionary payment concept.

<sup>2</sup> Number of days when simulations were done. For some entities, this number was lower than the observed days in the sample (19 for April 2012), because during some days these entities did not receive funds by discretionary payment concept from anyone participant.

<sup>3</sup> Number of days when attacked entity was not able to fulfill all its payment obligations after the failure-to-pay from its main counterparty.

<sup>4</sup> Corresponds to the remaining affected entities, which did not fulfill some of their payments obligations after the failure-to-pay of the attacked entity.

<sup>5</sup> Number of days when attacked entity did not receive some payment from the remaining affected entities.

Source: Authors' calculations

Table A2  
**Intraday Liquidity Sufficiency Index (ILSI) and required liquidity  
 to face simulated counterparty failure to pay**  
**April 2013**

Number of Attacked Entities	Number of days simulated	ILSI estimated for original observed payments	Simulated attack of counterparty failure with observed opening balance + TES		
			Number of days	ILSI estimated	Additional required liquidity (as % of payment sent)
<b>Commercial banks</b>					
9	22	2.77	0	>1	0.0%
<b>Financial corporations</b>					
2	17	1.10	0	>1	0.0%
<b>Brokerage firms</b>					
7	22	2.18	15	0.334	8.4%
<b>Trust companies</b>					
9	21	1.10	17	0.240	26.4%

Source: Authors' calculations.

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# Chapter 4

## Determinants of the rate of the Dutch unsecured overnight money market

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\* This article first appeared in DNB Working Paper series, no. 374, 21 March 2013. The publisher gratefully acknowledges the permission to reprint this article.

# Determinants of the rate of the Dutch unsecured overnight money market

Thursday 6<sup>th</sup> August, 2015

## Abstract

This empirical paper investigates how conventional and unconventional changes in the monetary policy framework have affected the overnight money market lending rate for the Dutch segment of the euro area during tranquil and crisis times. We use a long time series of the Dutch interbank money market rate ranging from the start of the euro in 1999 to May 2012. We present an EGARCH model on the volatility of the overnight lending rate. The results show that modifications of the monetary policy framework in 2004 decreased the volatility of the rate. Since the turmoil of the crisis the volatility increased again. Unconventional changes introduced in 2008 not only had an effect on the lending rate but have also modified banks' behavior within maintenance periods. Our method makes it possible for central banks to monitor the volatility of the rate and to measure the impact of changes in the policy for the euro area.

**Key Words:** financial stability, unsecured interbank money market, EONIA, monetary policy

**JEL Codes:** E42, E43 E44, E52 G20

## 1 Introduction

An efficient interbank money market plays an important role in the transmission of the monetary policy of a central bank. One of the aims of the policy is to steer the overnight interbank money market rates close to the refinancing rate set by the central bank. With this rate the central bank steers the rate at which banks lend liquidity to the real economy. Its importance was well illustrated by the financial crisis, that erupted in the summer of 2007. Especially after the failure of Lehman Brothers, in the fall of 2008, banks became very reluctant to lend liquidity to each other. For some banks this reluctance made it difficult (read expensive) or even impossible to obtain the desired liquidity from the interbank money market. To reduce counterparty risk banks reduced their bilateral limits and required high quality collateral for their loans (ECB, 2010). Central banks world-wide, including the European Central Bank (ECB), feared that the (un)secured money market would dry up. To prevent this, the ECB intervened by providing relatively inexpensive liquidity to the financial sector, resulting in a strong downward effect on the interest rate paid in the money market, see e.g. Heijmans et al. (2010) who studied the Dutch part of the euro interbank money market and Arciero et al. (2015) who studied the entire euro area interbank money market from June 2008. In many cases banks preferred depositing their surpluses at the ECB overnight deposit facility over lending in the money market. Banks that suffered from shortage preferred using the ECB lending facilities to obtain the required liquidity, so as to avoid the appearance of illiquidity among peers, and the associated stigma effect (Cappelletti et al., 2011).

The introduction of the euro in 1999 marked the start of the euro area monetary policy. Since then several modifications and adjustments have been made. In the initial framework, starting in 1999, the reserve maintenance period started on the 24<sup>th</sup> and ended on the 23<sup>rd</sup> of every month. The beginning or end of this period could fall on a weekend or a public holiday. The Main Refinancing Operations (MROs) provided by the ECB ran for two weeks, and were carried out every week, which resulted in an overlap between successive tenders. The ECB initially decided on the main refinancing rate every two weeks. In March 2004 the ECB introduced several modifications to the policy framework (ECB, 2004). The reason for these modifications was to decrease the disturbing impact of rate change expectations on the EONIA rate (ECB, 2004), (as high interest rate volatility is perceived as risky). The ECB changed the maturity of its main refinancing operations (from 2 weeks to 1 week) and synchronised the timing of the reserve maintenance periods with the interest rate decisions by the Governing Council. ECB (2006) and Durré and Nardelli (2008) argue that the modified operational framework decreased the volatility of EONIA. The contribution of our paper is to shed light on the behaviour of the modified framework during crisis times and to investigate how it has affected the overnight lending rate and its volatility. Besides making formal changes to the framework, the ECB also began to carry out more fine-tuning operations, to provide liquidity to the market as the need arose. These fine-tuning operations were already provided for in the initial framework, but very few had been carried out. As the crisis persisted, the ECB further adjusted its policy several times to support the financial system, see e.g. ECB (2010) or Cassola and Huetl (2010). Initially, the ECB allowed euro area banks to draw the full amount of liquidity they required at the main refinancing rate. In the months following August 2007, the ECB allowed tenders of 6 months. After the failure

of Lehman Brothers in September 2008, central banks world-wide, including the ECB, feared the total collapse of the financial system. To prevent potential spill-over from the financial markets to the real economy, central banks lowered their main policy rates rapidly and introduced unconventional policy measures. The ECB decreased the tender rate by 325 basis points to 1.00% between October 2008 and May 2009. As the first amongst other (unconventional) measures taken since October 2008, it introduced fixed rate full allotment tender procedures.<sup>1</sup> Secondly, it extended the list of eligible assets, to make it easier for banks to access the ECB's liquidity tenders. Lastly, it provided tenders with maturities up to 12 months starting July 2009 and 3-year tenders starting in December 2011.<sup>2</sup>

The research question of this paper is: How have changes in the monetary policy framework affected the (interbank) lending rate in the Dutch overnight unsecured money market? For this analysis we use the daily totals of the lending value and the value weighed average interest rate of all individual trades identified by the Heijmans et al. (2010)'s algorithm. In particular, we zoom in on the effect of the modifications in the framework on the rate since the start of the crisis. Although the ECB tries to steer the entire euro area market rather than just the Dutch segment of that market, we shed light on the extent to which the ECB's policy is effective in a subset of the euro money market. As the ECB aims to steer the overnight money market rate close to the main refinancing rate, we expect volatility to decrease after the modification to the initial framework and after further changes to the modified framework. The analysis in this paper only focusses on the unsecured money market due to lack of data on the secured part of this market. In order to gain a better understanding of the fluctuation of the overnight lending rate, we first study the effects on the rate with respect to calendar effects (end of month, end of quarter, public holidays, etc), maintenance period effects (periodic movements towards the end of a maintenance period, and several other variables regarding the composition of the market, such as number of lenders and borrowers, amount of excess liquidity, etc. Secondly, we look at the impact which major changes in the monetary policy instrument have had on the volatility of the rate. We distinguish four periods in our analysis, which are linked to the major changes in the way the money market functioned that occurred after modifications in the operational framework of the European Monetary Union:

- I. Initial framework: January 1<sup>st</sup> 1999 to March 9<sup>th</sup> 2004.
- II. Modified framework until the start of turmoil: March 10<sup>th</sup> 2004 to July 31<sup>st</sup> 2007.
- III. Start of the turmoil period: August 1<sup>st</sup> 2007 to October 7<sup>th</sup> 2008.
- IV. Crisis period: October 8<sup>th</sup> 2008 to May 31<sup>st</sup> 2012. It refers to the period after the collapse of Lehman Brothers and the following introduction of the fixed rate full allotment (FRFA) policy.

Our paper relates to the literature in the following way. Hamilton (1996) initiated the empirical literature on overnight rates. He introduced an approach to measuring the volatility of Federal Funds rate, taking into account the tails and infrequent spikes that characterise such rate changes. He finds

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<sup>1</sup>Initially the ECB provided tenders at a minimum bid rate.

<sup>2</sup>National governments also supported their financial systems by providing state support to systemically important financial institutions or even nationalising them. For an overview of the euro area's fiscal policy measures during the crisis, see van Riet (2010).

that the behaviour of the federal funds rate turns out to be close to a martingale over the reserve maintenance period, though there is enough predictability in daily movements of the federal funds rate to reject the martingale hypothesis over the reserve maintenance period.<sup>3</sup>

Gaspar et al. (2004) use an EGARCH model to analyse the individual interest rates reported by the banks contained in the EONIA panel. Bartolini and Prati (2006) analyse the volatility of the daily overnight rates for a set of countries, including the euro area. They study how interest rate volatility is affected by national differences in monetary policy implementation. Soares and Rodrigues (2011) model the volatility of the EONIA spread as an EGARCH model.<sup>4</sup> They state that the nature of the EGARCH will be different in the period before the fixed-rate full allotment (FRFA) policy where they follow Hamilton (1996). They find, for the period after the introduction of FRFA (2008-2009), that a conventional EGARCH is sufficient to capture the behaviour of volatility. Their results suggest a greater difficulty for the ECB to steer the level of the EONIA spread during the turmoil relative to the main refinancing rate. They also find that the liquidity effect declined from 2007 and in particular since the FRFA policy. Nautz and Offermans (2006) empirically investigate the transmission of EONIA volatility to longer term money market rates.<sup>5</sup> Würtz (2003) presents a model on the spread between the euro overnight rate and the key policy rate of the ECB. He shows that the most important variables driving the level and the volatility of the spread are expectations at the end of the reserve maintenance period. His research focusses on data between April 1999 and April 2002. Pérez-Quirós and Mendizábal (2006) state that the range of the standing facilities and the degree of asymmetry relative to the main reference rate influences the market interest rate. A reduction in the amplitude of the corridor allows EONIA to be more stable and closer to the policy rate. Pérez-Quirós and Mendizábal (2010) argue that if banks have a strong preference for liquidity due to expectations of tight liquidity conditions in the future, the corridor amplitude will only impact the demand for reserves if the corridor is asymmetric relative to the main reference rate. Cassola and Huetl (2010) analyse the impact of the beginning of the crisis, summer of 2007 to August 2008, on EONIA and interbank market trading and assess the effectiveness of the ECB liquidity policy in this period. They build their model on Pérez-Quirós and Mendizábal (2006). Facing this uncertainty about the end-of-day liquidity shocks, banks manage their reserves by trading on the interbank market in such a way as to minimise the cost of borrowing liquidity shortages from or lending surpluses to the ECB. They find that liquidity frontloading is a small scale central bank intervention which is capable of stabilising interest rates in both frictionless and distorted markets.<sup>6</sup> Their simulations suggest that without frontloading the EONIA would have been, on average, 23 basis points above the policy rate. With frontloading the overnight rate is, on average, equal to the policy rate. Acharya and Merrouche (2013) study liquidity demand of large settlement banks in the United Kingdom and its effect on the Sterling money markets before and during the sub-prime crisis of 2007 and 2008. They use the

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<sup>3</sup>The martingale is a stochastic process in which the conditional expectation of future values remains constant in time.

<sup>4</sup>Their data set ranges from March 2004 until December 2009.

<sup>5</sup>Their data set ranges from July 2000 until August 2006. This period includes the introduction of the ECB's new operational framework (NOF).

<sup>6</sup>Frontloading liquidity policy: additional liquidity was provided via allotments above benchmark, which is the amount of refinancing that allows banks to fulfil their reserve requirements smoothly over the reserve period, during the early stage of the reserve maintenance period with the surplus gradually reduced throughout the reserve maintenance period either through allotments below benchmark or via liquidity draining fine-tuning operations.

algorithm developed by Furfine (1999) to identify loans from large value payment systems (LVPS) data. One of their findings is that the liquidity demand by settlement banks caused overnight interbank rates to rise.

We follow the approach of e.g. Gaspar et al. (2004) and Soares and Rodrigues (2011) by using an EGARCH model to analyse the volatility of the overnight lending rate in the Dutch segment of the euro money market. Like Acharya and Merrouche (2013) we use an algorithm (Heijmans et al., 2010) to identify unsecured loans from LVPS transaction data. In contrast to other papers we make use of a long time series, ranging from January 1999 until May 2012. This includes the start of the euro area, the introduction of the modified operational framework, the start of the turmoil period of the crisis and the failure of Lehman Brothers. Unlike previous analysis on EONIA, we include all banks active in the Dutch overnight money market, instead of only the panel banks which contribute to calculating the euro area-wide EONIA rate.

Our results indicate that the 2004 modifications in the monetary policy framework decreased the volatility of the interest rate, as expected. However, the unconventional measures during the turmoil period and after the collapse of Lehman Brothers has not made the rate less volatile. On the contrary, during the turmoil the rate became more volatile and during the crisis period volatility persistence remained high. Although during the financial crisis the primary concern of the ECB has not been to control volatility but to save the financial system from collapse, the increase in volatility can be considered as the price of preserving relative financial stability.

The outline of this paper is as follows. Section 2 describes the large value payment system and its data. Section 3 describes the developments of the (volatility of the) rate. Section 4 describes the model and section 5 describes the results of the developments of the volatility analysis. Section 6 concludes.

## 2 Payment Systems Data

### 2.1 TARGET

TARGET2 is the main euro area real time gross settlement system (RTGS). Currently, all the euro area countries and six non-euro area countries are connected to TARGET2.<sup>7</sup><sup>8</sup> It has been designed to handle large value transaction in euro in a reliable and efficient manner. TARGET2 complements the Eurosystem's operational framework for the implementation of monetary policy and falls within the responsibility of the Governing Council of the ECB. TARGET2 handles the transactions of roughly 4,500 credit institutions and of other financial institutions, that meet the access criteria, directly or indirectly. As TARGET2 is an RTGS, each transaction is settled directly (in real time) and individually (gross). Apart from processing transactions between (in)direct participants, it is also used for settlement payments of many other payment systems.

TARGET2 has several advantages for commercial banks. 1) Payments are made immediately (in real time) and irrevocably. Due to the irrevocability of the payment, a payment can never be made undone,

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<sup>7</sup>Trans European Real Time Gross Settlement Express Transfer

<sup>8</sup>The six non euro area countries are Bulgaria, Denmark, Latvia, Lithuania, Poland and Romania. (status July 2012).

Table 1: Statistics on TARGET2-NL and TOP.

Year	Number of participants	Number of direct participants	Average daily number of transactions (thousands)	Average daily value of transactions (EUR billion)
1999	158	108	12.5	71.2
2000	163	105	14.9	83.1
2001	166	108	16.2	94.9
2002	166	108	18.7	97.9
2003	155	106	19.3	103.1
2004	161	102	18.1	116.4
2005	155	102	18.4	120.4
2006	148	99	18.7	125.5
2007	132	90	28.5	153.1
2008	102	60	36.3	230.9
2009	103	61	36.8	249.7
2010	99	55	33.7	303.8
2011	100	54	32.7	310.6
2012	100	53	32.3	314.0

not even in case of bankruptcy. 2) TARGET2 puts no limits on the amount of a payment whether for domestic or for cross-border transactions. 3) It provides a uniform cost structure for the same services thus ensuring a level playing field across all participating countries. This is of particular advantage to banks operating in more than one euro country.

Each transaction in TARGET2 involves two participants (mainly banks) and/or two central banks. Each bank is assigned to one of the central banks. Although banks are free to choose any central bank in the Euro-system to handle their account, most banks choose (at least) the central bank in which they have their headquarter. Many banks hold accounts at more than one central bank. The payment takes place between accounts held at two central banks. The sending bank must have sufficient liquidity in its central bank account. Banks are allowed to obtain free collateralised overdrafts, which they have to repay by the end of the business day, otherwise an overnight fee will apply to the overdraft. The balance on the account can be obtained either from monetary policy refinancing operations or from incoming payments. An important incoming payment type is unsecured interbank loans, which we are looking for in this paper.

Another RTGS system in euro is EURO1, which is a privately owned payment system for domestic and cross-border single payments in euro between banks operating in the European Union.<sup>9</sup> Although EURO1 offers the opportunity to settle interbank money market loans, most of such loans and refunds are settled through TARGET2. The daily turnover of TARGET2 (EUR 4005 billion) far outstrips that of EURO1 (EUR 238 billion).<sup>10</sup>

<sup>9</sup>This system numbers 65 participating (mainly large) banks.

<sup>10</sup>see <https://www.ebaclearing.eu/Statistics-on-EURO1%2fSTEP1-N=E1statistics-L=EN.aspx>

## 2.2 Statistics on large value payment systems

We use transaction data from two payment systems operating throughout the past twelve years, corresponding to our sample period. The first one called TOP existed from the start of our sample, the 1st of January 1999 until the 17th of February 2008. The second system is TARGET2-NL, introduced on the 18th of February 2008. Table 1 shows statistics on the Dutch segment of TARGET2: number of participants, number of transactions and value settled. The table shows that the number of direct participants drops from 90 in 2007 to 60 in 2008. The drop is mainly related to the introduction of TARGET2 as the new payment system. Some TOP participants did not meet the access criteria of TARGET2. Some (international) banks, which used the account in TOP mainly for their reserve requirements, have since the introduction of TARGET2-NL been able to hold these reserves in the so-called Home Accounting Module (HAM). These HAM account holders, which can reach direct participants in TARGET2, do not count towards the (in)direct number of participants of TARGET2.<sup>11</sup> Although the number of participants since the introduction of TARGET2-NL (2008) is much lower, we do not expect this decrease to cause a decrease in active lenders and borrowers. This is because most of the large and active participants in the Dutch money market remain present from the change-over from TOP/TARGET to the new TARGET2-NL system. Many former participants in TOP that no longer participate directly in TARGET2-NL did not operate as (active) traders in the Dutch money market.

The daily average number of all transactions in TOP/TARGET and TARGET2-NL shows an increase over the years until 2009, from 12,500 to 36,800.<sup>12</sup> The value increased every year across the investigated period. Even though the number of direct participants decreased with the introduction of TARGET2, the average daily number and corresponding value of transactions continued to increase. This is because some large British banks participate in TARGET2-NL.<sup>13</sup> Some of these banks used to be either absent or inactive in the days of TOP. Therefore, our sample is not constant over the investigated period.

## 3 Developments of the interest rate

### 3.1 Statistics on Dutch unsecured interbank money market

The unsecured money market loans are identified distinguished from other transaction data present in the TOP and TARGET2-NL systems, using by means of an algorithm developed by Heijmans et al. (2010). This algorithm is able to identify the lender, borrower, maturity, interest rate and loan value.<sup>14</sup> In our analysis we focus on participants active in TARGET2-NL. In case a TARGET2-NL

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<sup>11</sup>Transactions between HAM account holders and TARGET participants are mainly liquidity transfers.

<sup>12</sup>The increase of the number of transactions in 2007 is mainly caused by the introduction of an urgent retail payment system mid 2007. They are high in volume but relatively low in value.

<sup>13</sup>These British banks are relatively large ones in TARGET2-NL.

<sup>14</sup>Furfine (1999) was the first to develop an algorithm for identification of unsecured interbank loans from large value payment system's data. His algorithm was suitable for the US market. The algorithm of Heijmans et al. (2010) is suitable for the Dutch part of the euro area. Their algorithm uses a corridor around EONIA for overnight rates. The algorithm is able to identify loans with maturities up to one year. However, in this analysis we focus on the overnight money market. Around the EONIA rate a corridor of 50 bps is placed for most of the investigated period. For the pre-crisis period of the

participant borrows from or lends to a non-TARGET2-NL participant, e.g. with a participant in the Italian part of TARGET2, we do not see the Italian counterparty. However, we do not have data on all loans from and to this Italian counterparty. Therefore we analyse the money market from a lending perspective. This means that we look at transactions where at least the lender is a TARGET2-NL participant. Most TARGET2-NL consists mainly of participants are Dutch banks, however although there are some foreign banks also present participants in TOP and TARGET2-NL systems, which are either registered branches or subsidiaryies in the Netherlands.<sup>15</sup> Some of these foreign banks, with headquarters in the UK, and are relatively large participants in TARGET2-NL.

The algorithm filtering the loans, identifies individual trades. However, our analysis focuses on daily totals. This means that the lending value is the aggregate of all individual trades of that particular day. The lending rate is the value weighted average interest rate.

### 3.1.1 Number of lenders and borrowers

Figure 1 shows the number of lenders and borrowers (Figure 1,top graph) and the corresponding lending value/volume (Figure 1, bottom graph) of all TOP and TARGET2-NL participants. The top graph of Figure 1 illustrates that the numbers of lenders and borrowers hover around 30 until 2002. From 2003 until the end of 2008 the number of lenders is larger than the number of borrowers. This difference is caused by trades with banks in other euro countries (not being part of TOP or TARGET2-NL). After the collapse of Lehman Brothers, banks became more reluctant to lend to each other due to increased perceived counterparty risk. There were banks which could not obtain liquidity easily from the market and therefore dropped out of the market. At the same time the ECB introduced unconventional measures such as fixed-rate full allotment in the weekly MROs. This means that banks that need liquidity can obtain it from the ECB at a fixed price. As a consequence both the number of lenders and borrowers decreased from roughly 20 in the fourth quarter of 2008 to just above 10 in mid-2009. The number of lenders and borrowers increased again from around 10 (second half of 2010) to just below 20 (mid-2011). Since the political problems in Italy started (August 2011) these numbers fell back to 10 again. Part of the interbank money market loans (not shown in the figure) are loans extended at rates below the ECB overnight deposit rate, by parties that do not have access to the ECB standing facilities and that prefer low interest rate (below overnight deposit) above no interest at all. These parties could either be non-euro banks within the European Economic Area having access to TARGET2 through the Dutch central bank, or non-banks, e.g. large companies or pension funds, which instruct their banks to execute payments on their behalf.

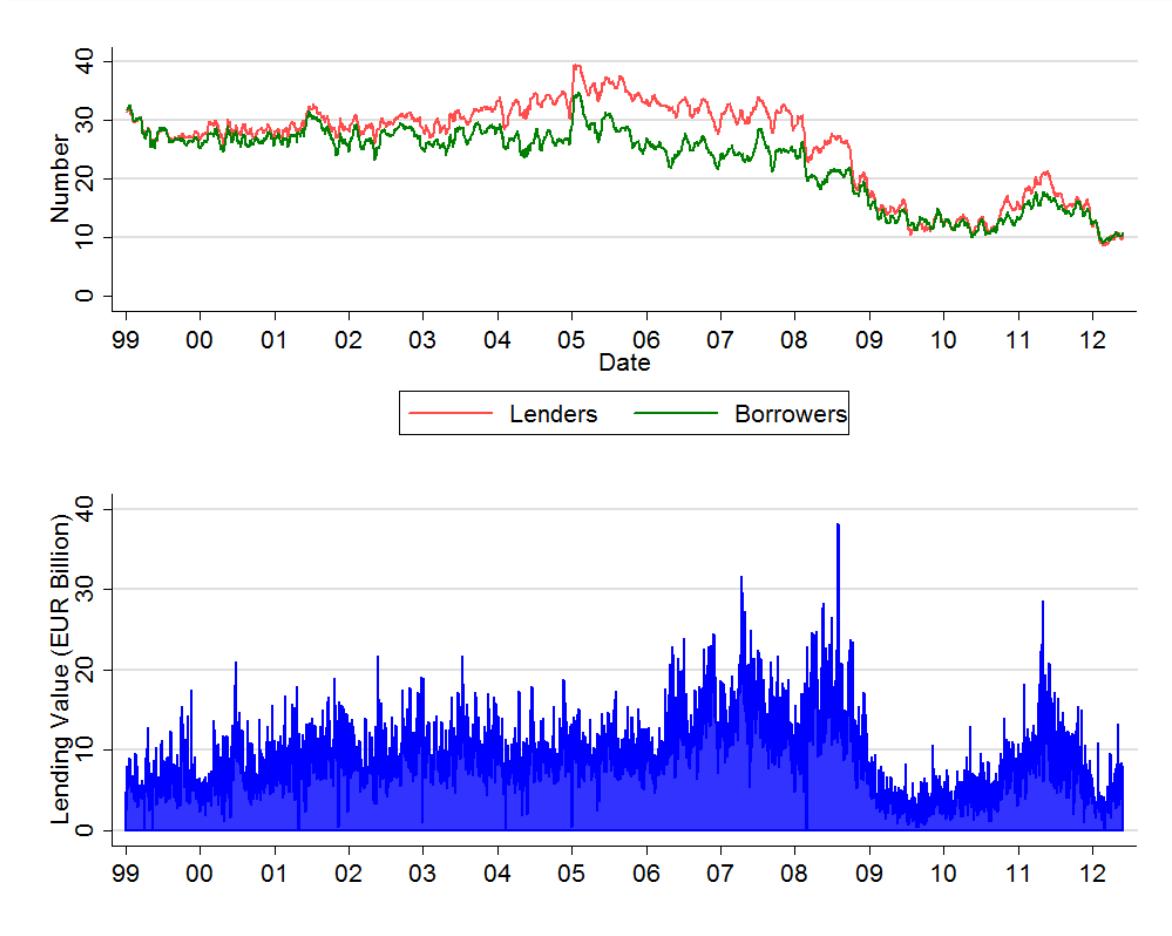
The group of lenders and borrowers changes over the years. Some banks joined or left TOP/TARGET2-NL. Especially at the introduction of TARGET2-NL some large British banks joined TARGET2-NL that were not part of the TOP system or were much smaller participants (in terms of turnover and money market activity) in TOP. Even within a maintenance period the group of lenders and borrowers

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modified framework Heijmans et al. (2010) extended the lower bound of the corridor to 100 bps due to the deviation from EONIA for the Dutch market. The algorithm is not without uncertainty. However, it provides a representative picture of the money market, especially for short maturities.

<sup>15</sup>Dutch banks refers to those that have their headquarters in the Netherlands and are supervised by the Dutch central bank.

Figure 1: Daily number of lenders and borrowers (bottom graph) and turnover (top graph) for the Dutch part of TARGET (1999 - 2012). Both represent one-month moving averages.



can change from day to day. Not every bank will be active in the money market every day, either as lender nor as borrower. It might be that some banks are more active at certain parts of the reserve maintenance period (e.g. on the last day).

### 3.1.2 Total loan value

The lower graph of Figure 1 shows the total overnight lending amount of banks in the Dutch payment system. The daily turnover and the number of lenders follow similar trends. Especially after the collapse of Lehman Brothers, the number of lenders follows the trend of the overnight value quite closely. The amount ranges from approximately EUR 8 to EUR 22 billion from 1999 to 2006. The loan value showed higher values (between EUR 15 and EUR 38 billion) from the beginning of 2006 until the collapse of Lehman Brothers in September 2008. After this date the activity in the Dutch unsecured money market decreased. Simultaneously, the number of lenders and borrowers also decreased. The value decreased to below EUR 5 billion, which is lower than the turnover at the time of the introduction of the euro in 1999. This low turnover can partly be explained by the first one-year

liquidity providing tender of the ECB, which was used by many banks as a security against potential future shocks. The Dutch market showed some signs of recovery, with ups and downs, until the summer of 2011. After the contagion of the Italian sovereign debt crisis in August 2011, the turnover in the Dutch market decreased again to low values similar to those of mid 2009.

### 3.2 The overnight lending rate and its volatility

Figure 2 shows the evolution of the overnight lending rate in TARGET2-NL here referred as the rate) relative to the Main Refinancing Operation (MRO) rate and ECB's standing facilities since February 1999.<sup>16</sup>

Under the initial operational framework, the lending rate was characterised by high levels and great jumps. The introduction of the modified monetary policy framework implied significant changes in the way the overnight money market works. Figure 3 shows the rate change (with respect to the previous business day) from the introduction of the modified framework onwards. As can be seen, it is characterised by large swings most of the time; however the volatility increases dramatically as of August 2007. The volatility shown here is only for the Dutch overnight money market. The Eurosystem, however, will judge the effectiveness of its policy not from the Dutch case but by looking at the whole euro area. Arciero et al. (2015) developed a method to filter the unsecured interbank loans from TARGET2 data. Their results show that the differences in the rates paid by banks vary significantly between the different countries in the euro area. This suggests that the volatility of the rate is likely to be higher for the Eurosystem as a whole than for just the Dutch overnight money market.

### 3.3 Evolution of the overnight lending

The behaviour of the change of the rate ( $\Delta r$ ) was relatively stable until the start of the financial crisis. Although the rate experienced its largest increase under the initial operational framework (reaching a maximum increase of about 116 basis points) the change in the rate was characterised by the occurrence of occasional jumps, mainly linked to the reserve maintenance period calendar. With the introduction of the Modified Operational Framework in 2004 the volatility decreased, meaning the changes in the monetary framework resulted in a lower volatility. In other words, the ECB was better able to steer the interest rates in the money market, thus achieving its policy aim of reducing volatility in the money market. The rate showed a clear change in behaviour from August 2007, when it turned much more volatile. Table 2 shows the descriptive statistics of the different behaviour of the rate and its first difference during the periods under analysis. From the amplitude of the first difference interval (maximum - minimum) one can notice a clear increase in the dispersion of  $\Delta r$  after the implementation of the Fixed Rate Full Allotment tender procedure. The pre-crisis period of the modified operational framework presents the lowest value of the standard deviation of  $\Delta r$ , which increased after the FRFA policy. This last period shows a daily average standard deviation of around

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<sup>16</sup>DEONIA or Dutch EONIA refers to the quoted EONIA of the EONIA panel banks. The overnight lending rate is a weighted average of all loans identified with an algorithm of all TARGET2-NL participants.

Figure 2: Overnight lending rate and ECB rates, from January 1999 to May 2012.

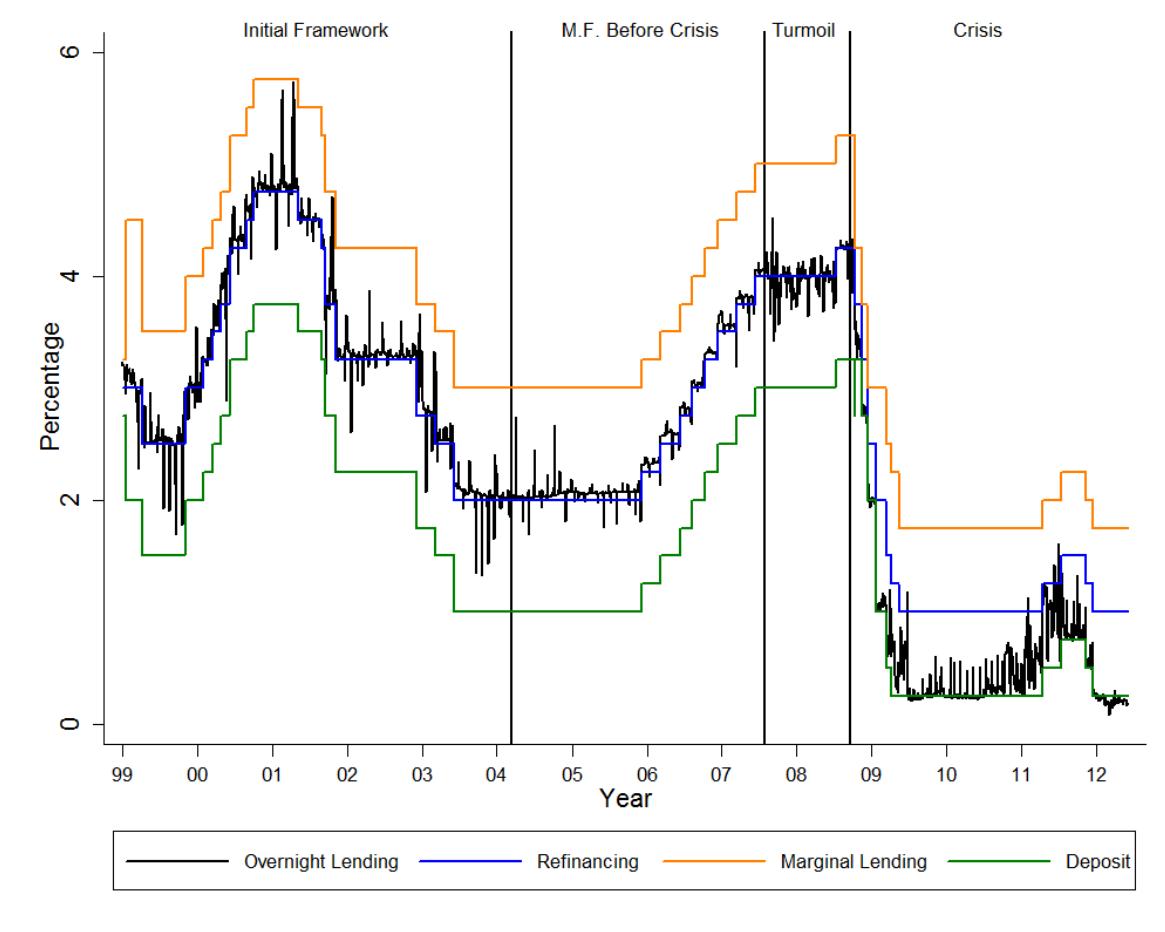


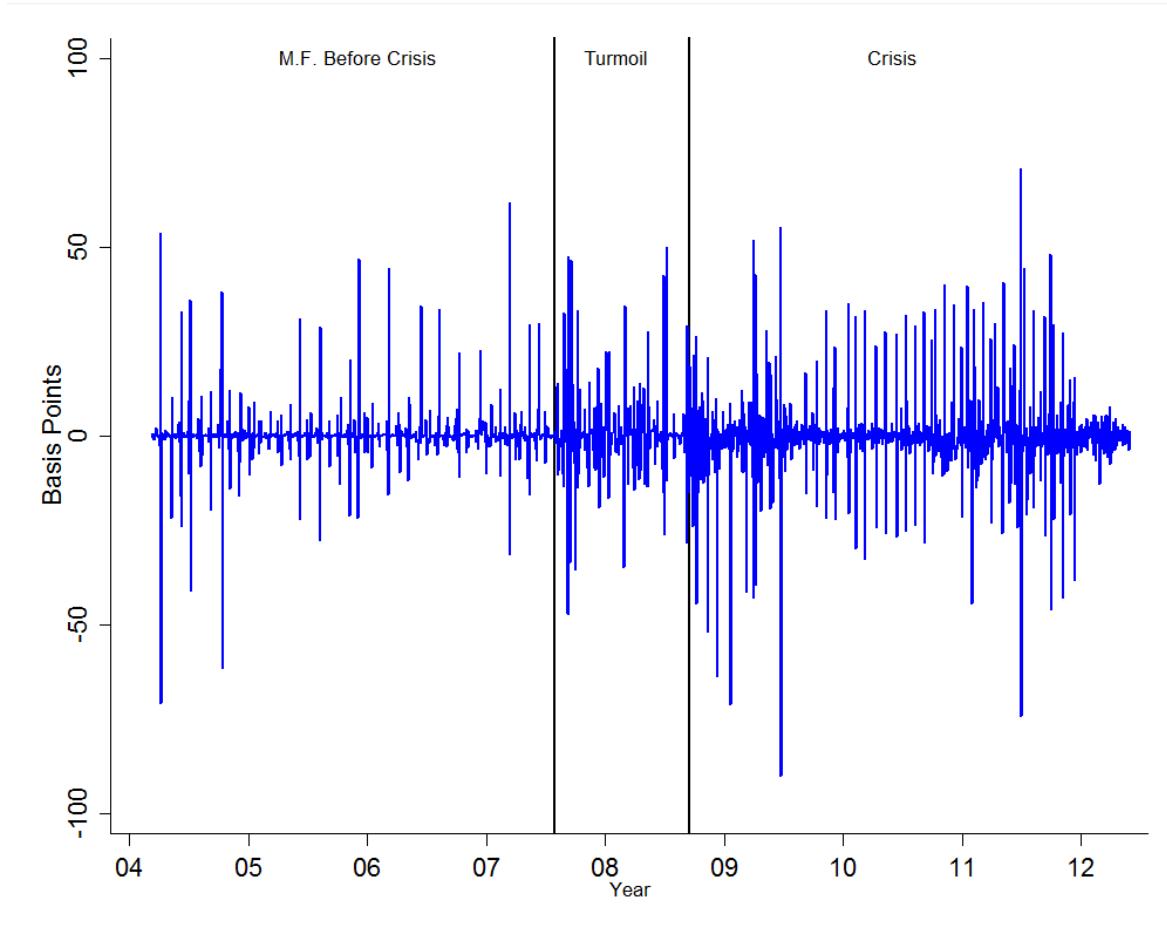
Table 2: Descriptive statistics of the overnight lending rate 1999-2012 ( $\Delta r$  in bp).

	Initial framework		M.F. before crisis		turmoil		Crisis	
	r	$\Delta r$	r	$\Delta r$	r	$\Delta r$	r	$\Delta r$
Mean	3.31	-0.09	2.58	0.24	4.01	0.09	0.77	-0.43
Median	3.28	-0.18	2.14	0	4.01	-0.08	0.41	-0.3
Minimum	1.33	-95.74	1.7	-71.05	3.42	-47.29	0.08	-90.07
Maximum	5.73	115.96	4.12	61.65	4.52	49.8	4.33	70.73
Std. Dev	0.92	12.96	0.67	7.18	0.16	10.84	0.9	11.41

11 basis points and a ( $\Delta r$ ) interval range of of 160 basis points - turning into the widest range for the past eight years.

Figure 4 shows the average change of the rate over the reserve maintenance period (MP). Under the initial operational framework (top left graph of Figure 4), the rate shows greater variations within a maintenance period. During the pre-crisis period of the modified framework a more stable pattern

Figure 3: Volatility of the overnight lending rate after the implementation of the Modified Framework. The volatility of the rate refers to the first difference of the rate.

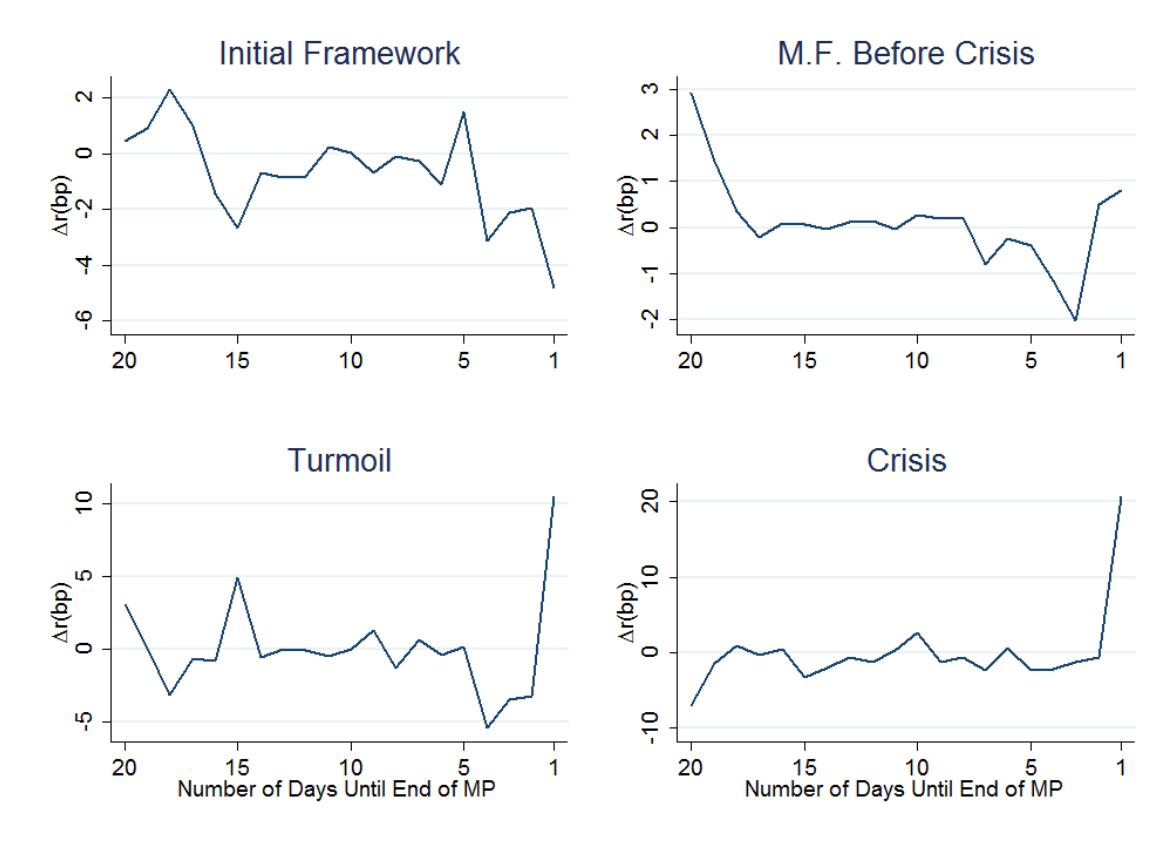


appears within the MP (top right graph of Figure 4). It started with higher changes at the beginning of the period followed by a decrease that led ( $\Delta r$ ) to oscillate around zero up to one week before the last day, when it showed negative changes. During pre-crisis period, the rate increased until one day before the end of the maintenance period.

During the initial turmoil of the crisis (bottom left graph of Figure 4), the rate varied substantially with positive and negative changes until the last day of the maintenance period, when it underwent a significant increase. Unlike the pre-crisis period, after the introduction of the Fixed Rate Full Allotment policy the behaviour of the rate shows negative changes from the beginning of the MP until two weeks before the end (bottom right graph of Figure 4). It appears that the rate moves by very small increments in the second half of the MP but barely varies until the last day of the maintenance period when it has a sharp increase of, on average, 20 basis points.

The sudden increase of the lending rate can be partly explained by the liquidity absorbing tenders of the ECB on the last day of the maintenance period. On this day, banks that have access to the ECB facilities can deposit their excess liquidity at the ECB at a higher rate than the overnight deposit,

Figure 4: Average change of the rate over the reserve maintenance period.



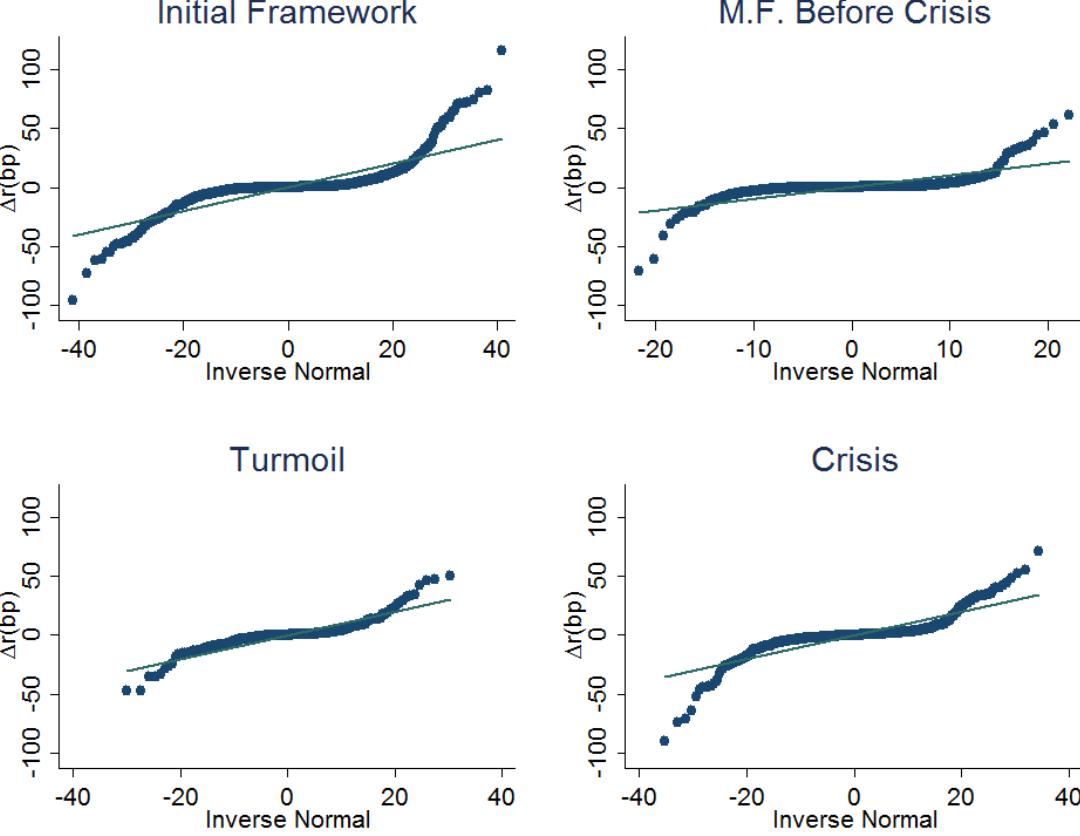
which results in a more attractive option for banks with a surplus of funds. Consequently, the supply of money in the market drops, resulting in an increase of the interest rate in the money market.

### 3.4 Distributional characteristics of the data

To test distributional characteristics of the data two methods were used. As a first approach, graphical analysis was applied. Distributional diagnostic plots and histograms in Figures 5 and 6 suggest that the overnight lending rate does not follow a normal distribution. Figure 5 plots the quantiles of the rate against quantiles of the normal distribution per sample period. If the data were distributed perfectly normally, the dots should all be on the 45 degree line. As shown in the graph, the lending rate diverges from this line; implying that it does not follow a normal distribution. On closer observations more points appear to fall on the 45 degree line during the second and third period, suggesting that the rate is perhaps closer to a normal distribution during these periods. Furthermore, Figure 6 presents the histograms of the overnight lending rate showing high levels of asymmetry and leptokurtosis. Additional to graphical analysis, the skewness and kurtosis tests were used to check the distribution of the rate and its first difference. The null and alternative hypothesis are:

$$H_0 = \text{The data follows a normal distribution}$$

Figure 5: Normal quantile plot.



$H_1 = \text{The data does not follows a normal distribution}$

Results in Table 3 lead us to reject the null hypothesis that the sample is normally distributed. The excess kurtosis estimate of the first difference of the rate (see Table 3) also implies that the distribution of returns has fat tails (leptokurtosis) relative to the normal distribution. This shows that neither the rate or its first difference follow a normal distribution.

## 4 Methodology

We consider a GARCH model to study the overnight lending rate for the Dutch overnight money market. The standard GARCH model allows the conditional variance to be dependent upon previous own lags. However, there are some limitations: GARCH models have the disadvantage of not allowing for asymmetric shocks in the conditional volatility. Since the distribution of the overnight lending series is stated as non-linear, we apply the asymmetric Exponential GARCH (EGARCH) analysis of Nelson (1991) instead. Two essential strengths of this model are highlighted in the literature. First, the

Figure 6: Histogram of the overnight lending rates.

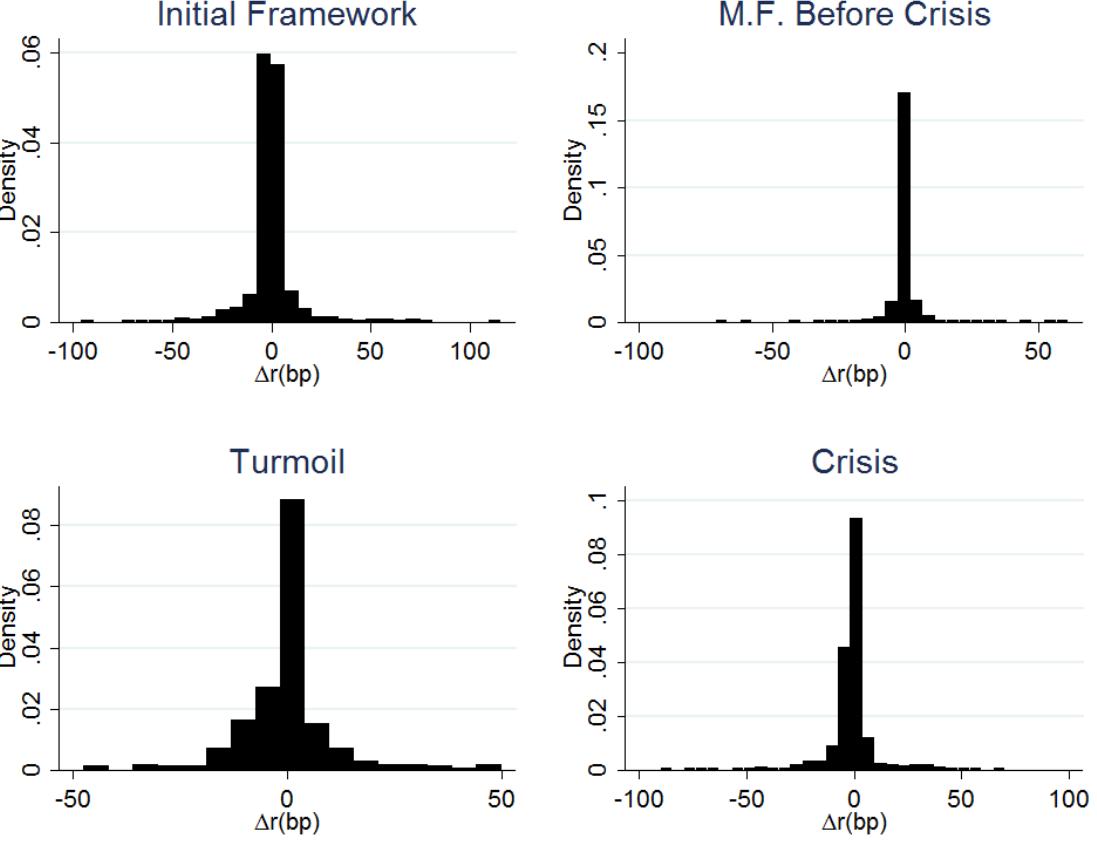


Table 3: Skewness and kurtosis test ( $\Delta r$  in bp).

	Initial framework				M.F. before crisis			
	r		$\Delta r$		r		$\Delta r$	
Skewness	0.32	***	1.13	***	0.9	***	0.37	***
Kurtosis	2.1	***	20.92	***	2.31	***	38.68	***
	Turmoil				Crisis			
	r		$\Delta r$		r		$\Delta r$	
Skewness	-0.29	*	0.54	***	2.54	***	-0.58	***
Kurtosis	4.08	**	10.61	***	8.97	***	16.69	***

limitations of positive constraints on the ARCH and GARCH coefficients are eased by using the exponential formulation. Second, an EGARCH model has the ability to capture the negative asymmetry that is commonly observed in financial time series.

The following AR(p) EGARCH model is conducted to scrutinise the relationship between the con-

ditional volatility of the Dutch overnight lending rate and seasonal, calendar and monetary policy effects by considering asymmetric effects. The econometric implementation of the model is built on the methodology of studies in the US and European markets (see e.g. Hamilton, 1996; Prati et al., 2002). The empirical model has the form:

$$\Delta r_t = \mu_t + \sigma_t v_t \quad (1)$$

where  $r$  is the rate change (in basis points),  $\mu$  is the conditional mean,  $v$  is a mean-zero, unit variance, i.i.d error term and standard deviation  $\sigma_t$  of  $\mu_t$  evolve over time.

Conditional mean of the interest rate has the form:

$$\mu = c + \Delta r_{t-1} + \delta mp_t + \delta c_t + \alpha' h_t + \varepsilon_{t-1} \quad (2)$$

Where  $c$  is a constant,  $\Delta r_{t-1}$  is the first lag of the rate,  $\delta mp_t$  the maintenance period effect,  $\delta c_t$  calendar effects (end of month, holidays) and the vector  $h$  controls for specific changes in monetary policy (like the unlimited fixed rate full allotment LTROs for shorter and longer term tenders).

$$\log(\sigma_t)^2 = c + \lambda [\log(\sigma_{t-1}^2)] + \phi \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \theta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (3)$$

The specification allows for fixed calendar effects, denoted by  $\xi mp_t$  and  $\xi' c_t$ , for maintenance period days and holidays respectively. The set of variables exploring maintenance period effects refer to the last five days of the maintenance period and an additional dummy variable to capture any effect in the middle stretch of the maintenance period. Calendar effects are captured by dummy variables for before and after the end of 1) the month, 2) the quarter, 3) the year and 4) holidays. The vector  $h_t$  captures the effect of specific monetary policies as the ECB's refinancing rate, standing facilities (marginal lending and deposit rate) and long-term liquidity providing tenders. Other explanatory variables include the growth rate of deposits at the European Central Bank and the number of lenders participating each day in the overnight money market (see section 3.1.1). The variance equation allows for "Exponential GARCH" effects (see Nelson, 1991) to capture persistent deviations of the log conditional variance from its unconditional expected value. Residual analysis reveals that an EGARCH (1,1) model is appropriate.

#### 4.1 Model comparison: Gaussian vs Student-t distribution

In order to investigate what model best fits financial time series on Dutch overnight lending, we compared EGARCH (1,1) models with alternative probability density functions for the error term. Specifically, the analysis was carried out using normal and Student-t distribution. The criteria used to determine the performance of a model include the comparison of the log likelihood value and the likelihood ratio test (Alexander, 2009). We propose an EGARCH model using Student-t distribution since the prevailing concern about the distributional characteristics of the Dutch overnight lending rate, presenting fat tails and high levels of skewness and kurtosis. Table 4 reports the log-likelihood values for each estimated model. Those models based on the Student-t distribution produced the largest val-

Table 4: Log-likelihood value and likelihood ratio test.

	EGARCH Gaussian	EGARCH Student-t	Student-t $LR^{EGARCH}$	
Initial framework	-4494.49	-3851.08	1286.83	***
Modified framework: before crisis	-1846.5	-1601.73	489.54	***
Turmoil	-1028.54	-950.35	156.39	***
Crisis	-3040.56	-2791.22	501.3	***
Alternative period: Initial framework	-4494.49	-3851.08	1286.83	***
Alternative period: Modified framework	-6581.75	-5693.06	1679.4	***

Note: First two columns refer to the log-likelihood values of EGARCH models following a Gaussian and Student-t distribution.  $LR^{EGARCH}$  refers to the Likelihood ratio test of an EGARCH model following a Student-t distribution.

ues. On the contrary, models assuming a Gaussian distribution were consistently outperformed by those associated with the Student-t distribution. This test demonstrates that the alternative leptokurtic alternative of adopting the Student-t distribution performs better in modeling overnight lending data. The second phase of residual diagnostics consisted in determining whether the results under the assumption of the t-distributions were statistically different from those obtained under the normal distribution. To do this, we calculated likelihood ratio statistics following the definition given by Brooks (2008):

$$LR = -2(L_R - l_u) \chi^2(1) \quad (4)$$

$L_u$  denotes the given maximised log likelihood value of the Gaussian model while  $L_R$  comes from the model following a Student-t distribution. Basically  $LR$  statistic follows a Chi-square distribution. Table 5 reports the likelihood ratio test between EGARCH models for each period and their Gaussian counterparts. Results show that an EGARCH model with student-t distribution is more fit to the sample data.

Additional to the first two phases of residuals diagnostics, we conduct the ARCH-LM test in order to test whether the model adequately captures the persistence of volatility and there is no ARCH effect left in the residuals. Results in Table 5 show high probability values indicating there is no serial correlation in the residuals. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The Obs\*R-squared statistic is Engel's Lagrange Multiplier (LM) test statistic for the null hypothesis of no serial correlations. Furthermore, the results of the diagnostic tests show that the EGARCH models are specified correctly. The standardised residuals and standardised square residuals have been diagnosed, while Q-statistics show that both the mean and variance equations for each sub-sample period are specified correctly. All statistics are insignificant with high p-values, suggesting that the EGARCH models are successful at modeling the serial correlation structure in conditional means and conditional variances.

Table 5: ARCH-LM test.

Period	F-statistic	Obs*R-squared
Initial framework	1.27 -0.26	1.27 -0.26
Modified framework: before crisis	0.15 -0.7	0.15 -0.7
Turmoil	0.36 -0.55	0.37 -0.55
Crisis	0.46 -0.5	0.46 -0.5

Note: Probability values are in parentheses.

All of our tests indicate that the EGARCH model with student-t distribution is the best fit for the Dutch overnight lending rate as it fully captures the leptokurtosis and the serial correlation of the standardised residuals.

## 5 Results

Table 6 presents the results of the model, defined in section 4 for four sample periods between 1999 and May 2012. We observe changes in the pattern of behavior between the four different periods, with significant changes of direction soon after the collapse of Lehman Brothers and the subsequent adoption of the fixed rate full allotment policy. A distinction can be made between results before the start of the turmoil period and after it.

The overnight lending rate followed a (somewhat) similar pattern during the first two sample periods. The introduction of the modified framework increased the ECB's ability to steer the overnight lending rate, witness a decrease in volatility. Whereas under the initial operational framework the ECB's refinancing rate had a negative near-zero effect on the rate, during the second period the effect of the refinancing rate increased the overnight lending rate by more than one basis point. Results for the turmoil and crisis period show ECB's decreased capacity to influence the market and an increase in the volatility of the overnight lending rate. In comparison to the pre-crisis period, the effect of the refinancing rate decreases to around zero (0.6 basis points) during the crisis period.

Until the summer of 2007, the effect of the number of lenders participating in the overnight money market is as expected. During the first two periods, the number of lenders has a negative effect on the lending rate, unlike during the turmoil and crisis periods, when the number of lenders participating in the market stop showing statistically significant effects. During the crisis the growth rate of ECB deposits first begins to have negative effects on the overnight lending rate (specifically, a small but statistically significant effect of -0.05 basis points).

During the first two periods, the rate increases at the beginning of the reserve maintenance period

(MP) and decreases at the end of it. However, with the arrival of the crisis this pattern is reversed.

Under the initial operational framework the rate increases by roughly 2 basis points (bps) at the beginning and decreases by more than 3 bps at the end of the maintenance period. Half way through the MP, the rate already presents a small but statistically significant negative effect, turning positive until 2 days before the end of the MP. Although more subdued, the direction at the beginning (+ 0.9 bps) and end (- 0.7 bps) of the maintenance period is the same for the modified operational framework before the crisis period. During this period the negative effect at the end of the MP would be apparent from one week before the end date, although only significant for 5, 3 and 1 day before the end of the MP. A potential explanation for this could be that banks apply frontloading in the first half of the MP to make sure that they can fulfil the reserve requirements. In the second half of the period they have a (small) surplus which they lend again in the market to obtain a return on it. If there are enough banks, using the frontloading strategy, this will lead to an increase of the rates in the first half of the MP and consequently there will be a downward pressure on the rate in the second half. Dialogue with commercial banks has taught us that some banks did in fact actively pursue this strategy before the crisis erupted.

Maintenance period effects show a change of direction after the onset of the turmoil period, suggesting a change of behaviour within the reserve maintenance period. During the turmoil period the rate decreases more than 3 bps at the beginning of the maintenance period and increases three times more on the last day (by almost 10 bps). In the following crisis period the rate presents an abrupt decrease of 20 bps at the beginning of the maintenance period and an increase of almost 19 bps at the end of it. This would suggest that there is a potential arbitrage effect, in that banks use the opportunity to lend on the last day, when rates are significantly higher. A possible explanation of the increase at the end of the maintenance period could have been the extensive use of the liquidity absorbing tenders on the last day of the maintenance period, yielding rates above the market rates of the preceding days. These tenders offer an alternative opportunity of ‘investment’ at no risk to banks that have access to ECB standing facilities. Banks that require liquidity at the end of the maintenance period would have to pay a higher price that day. However, this effect is not significant. Another possible explanation could be that banks do not want to lend to certain counterparties. However, we have not investigated this possibility. The stronger decrease on the first day is partly because of the strong increase on the last day of the previous maintenance period. It should be noted that trading volumes vary within a maintenance period, intimating that the alleged arbitrage effect may be non-existent.

The liquidity providing 1-year and 3-year tenders did not have a significant effect on the rate. Conceivably, injection of an enormous amount of liquidity in the system might have a decreasing effect on the rate. However, the first 1-year tender settled mid 2009 was used by many banks as a precautionary measure. Due to the uncertainty in the market at that time, banks took the loan from the central bank as a precautionary measure even though most banks did not need it. At the same time, banks used this relatively cheap liquidity as an investment opportunity. This means that the liquidity does not stay on the bank’s account and therefore cannot be lent to other commercial banks, which is a potential reason behind the 3-year tender. However, further research explore this phenomenon. A side-effect of the abundant low cost liquidity provided by the central bank has been a diminishing stigma to its

use. Unlike in previous times, borrowing from the central bank is no longer considered a sign of a bank's problems per se.

Table 6 shows consistent results for the calendar effects across all sample periods. The initial operational framework presented stronger calendar effects tending to increase by almost 5 bps at the end of the month, around 4 bps at the end of the quarter and 17 bps on the last day of the year. The pre-crisis period of the modified framework showed effects in the same direction, although much smaller. Like the initial operational framework period, the turmoil period exhibits one of the largest calendar variations, increasing almost 7 bps at the end of the month, 12 bps at the end of the quarter and 11 bps the day after the end of the year. Holiday effects show contrary patterns between the period under the modified operational framework and the crisis period. In the first period the rate decreases before holidays (1.9 bps) and increases the day after (2 bps). However, during the crisis period the rate tends to increase by 1.92 bps before holidays.

As with the holiday effect, the rest of calendar effects in the crisis period are smaller than in previous years but have the same direction. During the crisis the rate decreases at the end of the month (2 bps) and before the end of the year (7 bps). While it increases 5bps at the end of a quarter.

The (EGARCH[1]) parameter measures the persistence in conditional volatility irrespective of anything happening in the market. Under the initial operational framework, volatility was more persistent (0.61). The value of the parameter decreases with the introduction of the modified monetary policy framework. However, with the start of the turmoil period, volatility persistence increased and remained fairly high (0.51) showing the capacity of past volatility to explain current volatility.

## 6 Conclusions

This paper investigates the changes in the interbank overnight lending rate of the euro area unsecured money market for the Dutch segment of TARGET2. We describe the movements of the rate by splitting up the sample from 1999 to 2012 into four different periods corresponding to the most important changes in the monetary policy framework of the euro area.

To study the rate movements we look in detail at the calendar effects, the day within the maintenance period, the number of lenders as a proxy for lending volume and the effect of the excess liquidity provided by the Eurosystem. In order to capture the effect of the rate changes we present an EGARCH model which best fits the characteristics of the overnight lending rate. This model can also be used in the future to measure the effect of changes in the monetary policy framework on the volatility of the rate. In order to measure the volatility from a Eurosystem point of view it is essential to look at all banks in the euro area instead of just the Dutch part of it.

The modifications in the monetary policy framework in 2004 succeeded in reducing the volatility of the interest rate, as expected. However, the unconventional measures during the turmoil period and after the collapse of Lehman Brothers, such as the fixed rate full allotment policy, including the long term refinancing operations with 1-year and 3-years maturities has not been able to reduce the volatility of the rate. On the contrary, the volatility increased during the turmoil, although the spikes did not. During the crisis period, volatility remained high as did the volatility compared to the

Table 6: Mean and variance equation. The rate changes are in basis points.

	Initial framework	M.F. before crisis	Turmoil	Crisis
mean equation:				
Constant	-0.08	-0.05	-0.74	-0.12
Delta Refinance	-0.64 **	1.33 ***	2.11	0.66 ***
Delta Marginal lending	0.34 ***			
Delta Deposit rate	0.5 ***			
Growth rate of ECB deposits	0	0	0	-0.05 ***
Number of lenders	-0.02 *	-0.01 *	0.08	0.04
Begin MP	2.09 ***	0.9 ***	-3.37 **	-20.28 ***
End MP	-3.22 ***	-0.72 ***	9.76 ***	18.77 ***
Day 2 from end of MP	0.58 **	-0.03	2.42 ***	0.33
Day 3 from end of MP	0.15	-0.65 ***	-0.22	-0.11
Day 4 from end of MP	-0.18	-0.01	-0.22	-0.37
Day 5 from end of MP	-0.2	-0.24 **	1.45	0.21
Half of MP	-0.32 **	0.07	0.77	0.05
Settlement 1-year tender				0.62
Settlement 3-year tender				-1.51
Before end of the month	0.56 *	0.01	1.2	0.24
End of the month	4.64 ***	1.54 ***	6.86 ***	0.79
After end of the month	-4.2 ***	-1.53 ***	-4.02 ***	-1.69 ***
First day of the quarter	-5.73 ***	-3.21 ***	-12.71 ***	0.59
Last day of the quarter	3.68 ***	2.72 ***	12.18 ***	5.21 ***
Day before end of the year	17.28 ***	0.73	-17.82	-7.39 ***
Day after end of the year	-1.71	-0.71	11.25	-0.79
Before holidays	-1.91 **	-0.19	0.94	1.93 **
After holidays	2.14 **	0.23	1.27	1.21
variance equation:				
Constant	2.27 ***	2.06	2.82	2.49 **
—RES—/SQR[GARCH](1)	10.54	9.1	5.52	3.63
RES/SQR[GARCH](1)	-1	1.62	-0.33	-0.09
EGARCH(1)	0.61 ***	0.48 ***	0.51 ***	0.46 ***
Log likelihood	-3851	-1602	-950	-2791.22

previous periods since the start of the modified operational framework in 2004. Note that the primary concern of the policy since the start of the crisis has not been controlling volatility, but preventing the collapse of the financial system. The increase in volatility can be considered as the price of preserving (relative) financial stability.

Since the turmoil started the interest rate decreased significantly on the last day of every maintenance period, jumping up 10 basis points during the turmoil period and 20 basis points during the crisis

period. Banks aware of this jump, would prefer to lend on the last day of the maintenance period while banks that need to borrow would do so before the last day. This ‘behaviour’ would not cause jumps on the last day. Part of the jump in the crisis period is due to the liquidity absorbing tenders of the Eurosystem, which is used extensively by the banks. Such tenders offers banks an opportunity to deposit their excess liquidity at the ECB at rates above the overnight deposit rate. As banks used this overnight deposit facility extensively during the crisis period, this was a logical and very secure alternative ‘investement’ opportunity for banks on the last day of the maintenance period. Possibly, banks are aware of the higher interest rate on the last day, but do not see this as a suitable investment option given the uncertainty in the market. It might also be the case that the subset of the banks borrowing on the last day differs significantly from banks lending or borrowing during the rest of the maintenance period. However, this is still to be investigated, as we have not looked into the data at bank level.

The calendar effects are consistent across the four different periods. The initial operational framework caused stronger effects (increases of around 5, 4 and 17 basis points at the end of the month, quarter and year, respectively). The pre-crisis period shows similar but smaller results. The turmoil period shows some of the strongest calendar effects increasing in around 7, 12 and 11 basis points at the end of the month, end of the quarter and on the last day of the year, respectively). Holiday effects make for different results. In the first period there was a decrease of 1.9 basis points before the public holiday and an increase after, by 2 basis points. During the crisis period the rate increases by 1.9 basis points before the holidays.

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# Chapter 5

## The tale of two networks in SPEI: Insights from structural indicators

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*Biliana Alexandrova-Kabadjova – Liliana García Ochoa*

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# The tale of two networks in SPEI: Insights from structural indicators

Biliana Alexandrova-Kabadjova<sup>1</sup>  
Liliana García Ochoa<sup>2</sup>

**Abstract.** In the present study we use transactional data of the Mexican Large Value Payment System, SPEI, for the period of one year (2013) to build networks for two types of payments, namely payments initiated by third parties and by participants. Our aim is to identify the structural similarity and differences between these networks, given that currently there are 95 direct participants in SPEI classified under two categories (sectors) – credit institutions, which are private multiple purpose banks (commercial banks) and public development banks, and nonbank financial institutions, which are brokerages and other nonbank financial institutions. Our main finding is that both networks have a core-periphery structure, common for financial services networks and very similar dynamics in terms of value of the operations. Nevertheless third party payments help to increase connectivity at the core, without exhibiting strong pressure on the daily volume of payments.

## 1 Introduction and literature review

Efficient processing and clearing of electronic payments transactions have economic value (FIS, 2013). In the last two decades, the platforms in charge of those activities have evolved into complex digital infrastructures, most commonly referred to as (financial) market infrastructures (FMIs). The design of the FMIs, guided by the Principles of FMIs established in CPSS-IOSCO (2012), is aimed to strengthen the stability of the financial system, increase the security of the services provided, and achieve broader effectiveness through the adequate integration of processes of payments and securities settlement. These requirements are not trivial to fulfill. Among them efficient processing and clearing of payment and financial transactions is the one that has been among the top priorities in the last decade. Many reasons lay behind this growing interest - it matters to economic growth, to cost reduction in the businesses processes of corporations and medium- and small-size enterprises, and to saving customers time on a broader scale.

The FMIs are commonly referred as the backbone of financial system (Diehl, 2015). Certainly with the structure of the spinal column, nature gives us an unequivocal example of how stability and efficiency could coexist, and how the disadvantages of the carapace's design could be overcome. Specifically, the design of shell guarantees stability, but not mobility and for our modern society being mobile is becoming a crucial factor for economic development. By mobile we refer to being easily transported from one place to another. In the particular case of FMIs, this feature could be assured by efficient processing and clearing of payment and financial transactions in real time than include not only large value, but also retail payments. In fact, real time or near real time settlement of retail payments has a strong impact on mobility.

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Payments architectures across the globe are in a renewing process in order to become faster, more efficient and more effective. Speed is only one of the factors involved in this transformation, nevertheless is worth going into the details of the implications that this improvement could have in boosting the economy. Currently there are at least three categories of speedy payments. For instance, since 2014, in Australia direct credit and debit transactions are settled the same day (APCA, 2014). Further in India, the National Payments Corporation of India settled transaction in near real time (within the span of a few hours) through the Immediate Payment Service (IMPS). Finally, Faster Payments in the United Kingdom is, since 2008, offering low value payments settlement services in real time (15 seconds) for banks and non-bank financial institutions that are direct members. In the three cases, the payment service is offered through auxiliary systems that connect to Real Time Gross Settlement (RTGS) payment system, in charge to settle large value payments. Other countries that offer similar fast payments solutions are Germany (GiroPay and Sofortüberweisung), Pakistan (via 1Link) and Singapore (G3).

Alternatively, integrating the settlement of high value and low value payments in real time could also be feasible. To achieve this, settlement engines need to ensure that time sensitive payment orders are not delayed due to the use of available liquidity by the retail payments. To this end, payment systems need to incorporate a liquidity saving mechanism (LSM) and establish timely and liquidity efficient operational rules.

One of the best known examples of a RTGS that settles both high value financial market payments and retail payments is the Swiss Interbank Clearing (SIC) system. In 2013 the system settled 420.07 million transactions with approximate value of 29,967.43 billion EUR. In terms of number of the transactions, these figures are many times higher in comparison to TARGET2 components of other developed countries like Germany (43.80 million) and France (9.12 million), but in terms of value is indeed lower - 224,328.7 billion EUR for Germany and 87,565.1 billion EUR in the case of France (CPMI, 2014). Other countries like the Czech Republic, Mexico, Serbia, Slovakia, Turkey and Ukraine also settle large value payments together with retail payments in real time through their RTGS (Allsopp et al. 2009).

In the case of Mexico, since more than a decade, low value direct credit electronic transactions have been settled in real time through a RTGS-equivalent payment system SPEI. These transactions are initiated by third party and are received by third party. SPEI on average settled around 853,000 transactions daily during 2013. More than 91% of the obligations are payments with a value lower than 10,000 EUR, whereas around 0.5% of the transactions are above million EUR. This feature gives us an opportunity to study how the direct participants' behavior regarding to liquidity management has evolved over time.

In the last decade network theory has become a widely used method to model social relationships. Particularly after the financial crisis, Large Value Payment Systems (LVPS) are among the most studied complex social structures using network modeling. Some of the most relevant studies are: Soramäki et al. (2006), Bech and Atalay, (2008), Becher et. al (2008), Rordam and Bech (2008), Pröpper et. al (2008). In only few years, network theory has gained momentum and has attracted financial authorities' attention as it gives the possibility of having a systemic view of the interconnectivity among financial institutions, and the network paradigm allows gaining insights regarding the dominant participants. Network structure and behavior are closely connected and in the case of payment systems the liquidity behavior has been studied in deep (Adams et al., 2010). For instance in Heijmans and Heuver (2014) the authors analyze the possible disruptions

inTARGET2, whereas in Alexandrova and Solis (2012) the liquidity management and the settlement rules of SPEI have been approached. There are also studies that have investigated network structures based on different types of financial participants' interactions, e.g. the interbank exposures and the payment systems (Martinez-Jaramillo et al., 2014).

The diversity of business relations among institutions determines the multidimensional nature of the financial system. Modeling this complex phenomena have to mayor challenges - to establish the multiplex or multilayer networks that most accurately represent the financial institutions' relationships and to identify the relevant players. In some jurisdictions the number of institutions that formed the financial system is relatively small (e.g Brazil, Canada, Mexico, the Netherlands and Russia only to mention some). In these cases, it could be relatively easy to distinguish the dominant players, even though it could be considerably more complex to find out which are the most relevant business relationships that should be incorporated into the network analysis. In the cases, in which the number of notes in the network increases (e.g. Germany and United States of America), the complexity in finding the dominant player also increases.

In the present study we use the network paradigm to evaluate in structural terms, the impact of processing retail payments in real time (every 3 seconds) in SPEI. To that end, we split the twelve different types of payments settled in SPEI in two categories – payments initiated by third party and payments initiated by participants. We analyze the network structure formed by the two categories of transactions. We made a detailed comparison between different topological indicators and find correlation between the spikes observed in the daily volume and the peaks of external funds used to cover participants' payments. Similar high points are not observed in the daily volume and external funds used for third party payments.

The rest of the paper is organized as follows – in the next section we present the institutional framework and operational rules of SPEI; in section three we present a detailed comparison between the two network structures and we finalize with the conclusions and recommendations for future research in section four.

## 2 Institutional framework

In this section we briefly explain the institutional framework and what measurements we have applied to evaluate the structure of the two networks.

SPEI is operated by Banco de México and receives payment instructions continuously during the day. It starts operation at 19:00 of the previous day and closes at 17:35. During operation time, a settlement process (SP) is executed every 3 seconds. Payment instructions, which are not settled in a certain SP are kept in a queue and are considered for settlement in the subsequent processes. After execution of the latest SP before the operation is closed, payments in the queue are cancelled. During the period, in which we perform our analysis, there were nighy-five direct participants in SPEI.<sup>1</sup> Those are identified under four categories: (i) private multiple-purpose banks or commercial banks (CBs), (ii) public development banks (DBs)<sup>2</sup>, (iii) brokerages (Bs), and (iv) other nonbank

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<sup>1</sup> For this study we have excluded the connectivity with other FMIs.

<sup>2</sup> The legal arrangement of the commercial and development banks is established by the Credit Institutions Act.

financial institutions (NBFI). For this study we look at the overall emerging structure without putting particular emphasis into the intra sectorial aspects.

Payments in SPEI are categorized in twelve different types. In order to build the two type of network we have used all direct participants' transactions and we have split the different types of payments in two mayor sets – the first incorporates payments initiated by a third party and the second includes payments initiated by participants + income payments. Let for each type of payment  $tp$  the two networks for a given day be defined as weighted directed graph (weighted digraph),  $G_{tp}(N, A)$ . The nodes  $N$  are direct participants and the arcs  $A$  are the set of ordered pairs from  $N$ , which represent the existence of specific type of payments' flow between two insittutions on a given day. Furhter  $W$  represents the total daily flow between two direct participants according to the type of payment used and it is refered as the weight of the arc. For example, let  $i, j \in N$  represent two institutions; the arc  $a = (i, j)$  exists in the specific type of payment network if the flow of these payments is greater than zero between nodes  $i$  and  $j$ . We define the set of values for a type of payment as  $tp = \{P, T\}$ .

Furthermore, let  $C$  be the set of cycles in one day. For each  $i \in N$  we define  $F_{ic\_tp}$  as the amount of own funds for each  $i \in N$  in each  $c \in C$  per type of payment calculated according to the transactional data, given that  $F_{i0\_t} = 0$  and  $F_{i0\_p} = 0$  for all  $i$ . We define  $F_t$  as the proportion of external funds used by institutions to cover payments initiated by third party to the total payments made, and  $F_p$  as the proportion of aggregated level of external funds used by participants to cover payments initiated by them to the total of payments made. Further, we denote  $F_T$  and  $F_P$  as the value of external funds used for the corresponding type of payment. A detailed analysis how in general external funds are calculated from the historical data could be found in Alexandrova-Kabadjova et al. (2015) and for the case of different type of payment in Alexandrova-Kabadjova (2015). For the present study in subsection 3.3 we have analyzed the correlation between the daily volume, obtained as an indicator for both networks and the proportion and value of external funds per type of payments, i.e.  $F_t$ ,  $F_p$ ,  $F_T$  and  $F_P$ .

### 3 Comparison based on structural indicators

In this section we present our findings on the comparison of the two structures, built from the transactions initiated by third party  $G_T(N, A)$  and the transactions initiated by participants  $G_P(N, A)$ . We have divided the section in four parts. In the first subsection we present our descriptive analysis based on the empirical general topological indicators, in the second subsection the indicators related to the structure of the network obtained by the test of the core-periphery and the algorithm of the giant strongly connected component (GSCC) are analyzed<sup>1</sup>, further in the third subsection we present the correlation of external funds per type of payments with respect to the daily volume and the average straight of the two networks. Finally in subsection four we made observation with regards to the semi connected and disconnected nodes in each network.

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<sup>1</sup> For more details on the formal definition of the core-periphery model refer to Craig and von Peter (2010) and with respect to the GSCC see Dorogovstev et al. (2001).

### 3.1 Topological measures

We start our analysis by comparing topological indicators for both networks, such as average degree, reciprocity, number of arcs and completeness index.

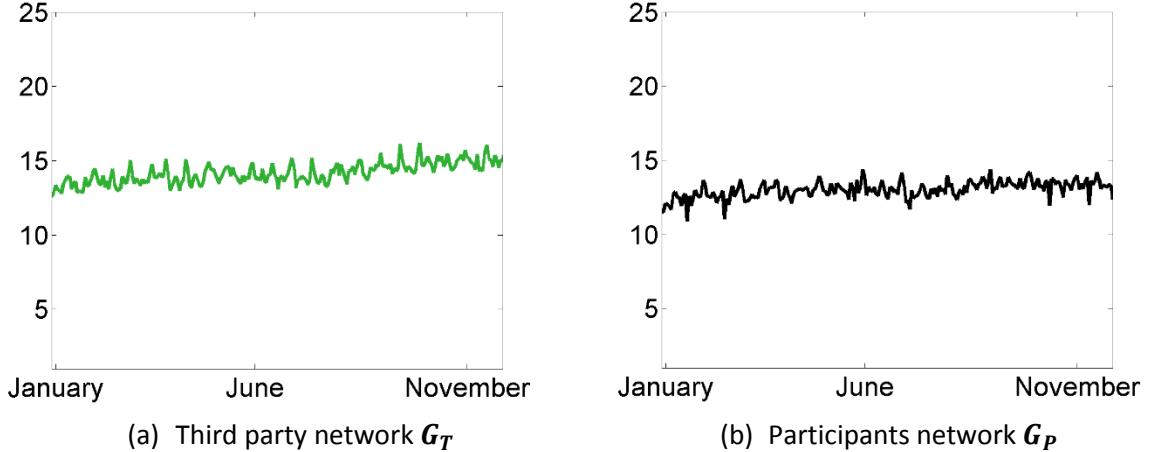


Figure 1. Average Degree

The patterns observed in Figure 1, representing the average degree for each network, show that the average number of contra parties per participants is similar in the two cases – 14 for  $G_T$  and 12 in the case of  $G_P$ . Nevertheless the graphs exhibit different relationships among institutions. For instance, as it is shown in Figure 2, in the case of  $G_T$  the average reciprocity is 0.7, which implies that the majority of links corresponding to the 14 counterparties on average for each node are bilateral. Oppositely, in the case of  $G_P$  the average reciprocity is 0.4, which means that less than a half of the links, corresponding to the average degree of 12, are bilateral.

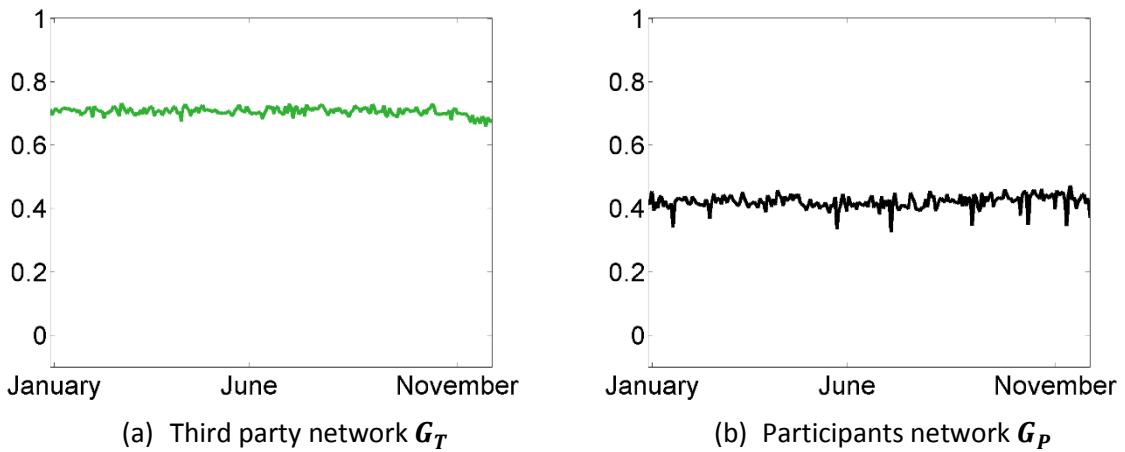


Figure 2. Reciprocity

Further, in Figure 3 we present the number of arcs. This indicator is consistent with the average degree shown in Figure 1, as small differences are observed between the two networks. Regarding the number of arcs, from possible 17860 links we observe that in the case of  $G_T$  only around 1050

arcs are active, whereas in the case of  $G_P$  the number of existing connections is less than a 800. This set the Completeness Index for both networks at around 5%.

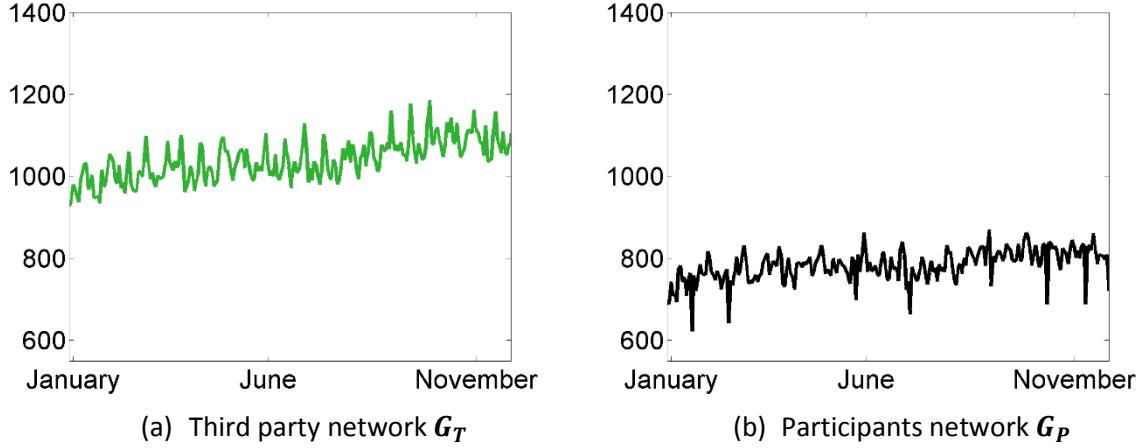


Figure 3. Number of Arcs

### 3.2 Structural tests

In this section we analyze the results obtained by the two structural tests applied to the networks. The first algorithm, under deterministic approach, was run to identify the giant strongly connected component (GSCC) in the two graphs. From this perspective, the networks exhibit very similar characteristics, as it is shown in Figure 4. The interval, in which the GSCC is formed, is between [50 – 61] for  $G_T$  and between [47 – 62] for  $G_P$ . Further, despite the fact that both time series exhibit certain degree of volatility, in the case of the third party payments network we observe that the size of the GSCC slowly increased toward the end of the year, whereas the size of the GSCC in the participants' payment network is stationary.

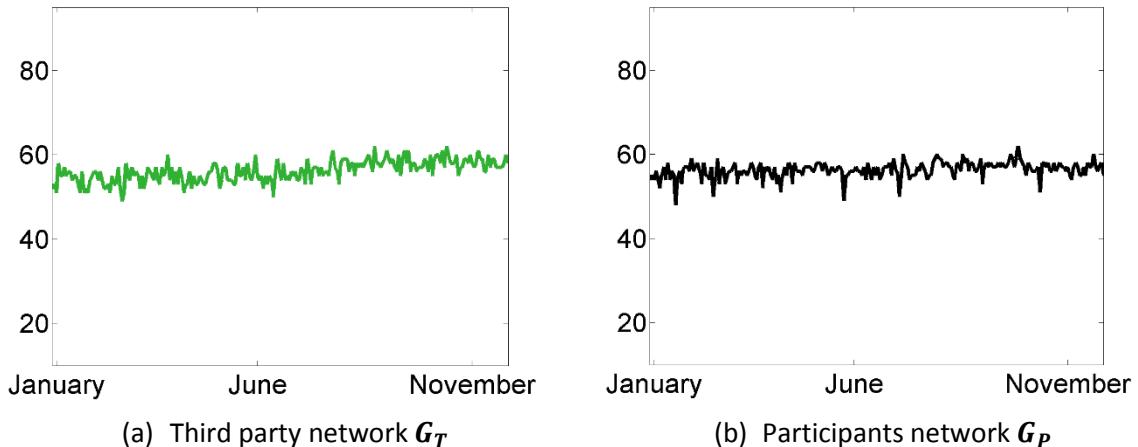


Figure 4. Giant Strongly Connected Component

Further, we perform a test for a core-periphery structure, in which the algorithm follows an optimization approach in order to find the core of the network. The outcome of the test shows that both networks exhibit core-periphery features. In figure 5 is presented the findings of the algorithm in terms of the size of the core for the studied period. We observe that in the case of  $G_T$ , the size of the core varies between 17 – 20 nodes, but it is stable during the year as the majority of times is formed by 18 – 19. In the case of  $G_P$ , the size of the core fluctuated between 12 and 17, presenting higher variation than the  $G_T$  for the studied period.

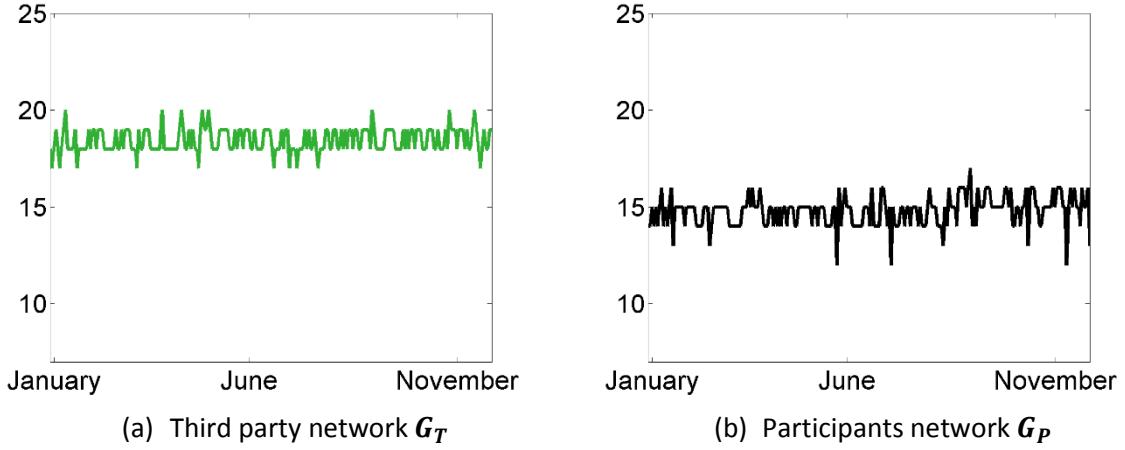


Figure 5. Core Size

From our observation of Figure 5, we can conclude that the size of the core of both graphs is not very distant. Nevertheless the dynamic observed throughout the study period is different. This remark takes us to our next questions. To what extent the core of both graphs is a complete network and how similar the two networks are in this regard. In order to answer these questions, in Figure 6, we present our calculation of completeness index of the core in the two cases of study.

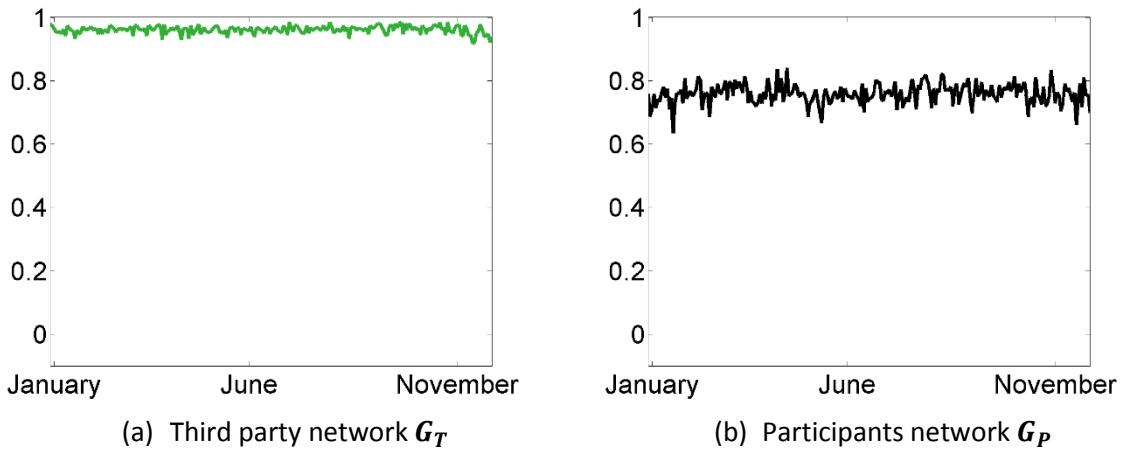


Figure 6. Completeness Index of the Core

We observe that the degree of connectivity inside the core is different for the two graphs. This suggests that payments made by third party increase the size of the core and increase the degree of connectivity among the nodes that are forming the core.

### 3.3 External Funds vs Daily Volume

In this subsection we make a comparison between the network indicator daily volume and the measure of external funds  $F_t$  and  $F_p$ , which we have taken from the study on funds used to cover different type of payments in Alexandrova-Kabadjova (2015). We start our analysis by comparing the daily volume of the two networks, which is followed by the observation related to the correlation between the overall volume and the corresponding to the type of payment external funds.

In Figure 7 we present the daily volume observed in the two graphs for the period January – November 2013. We notice that daily volume is very similar in terms of overall size and in both cases represent a stationary series. This is an important point as SPEI is a RTGS-equivalent and it is not a common feature of RTGS. Further, there are nine points in Figure 7(b), in which unusual fluctuations are observed. One of these movements is upwards and it presents a change of more than doubled average daily volume in the system, whereas the other eight points are downwards. In those points the registered volume is less than the half of the average one. These kinds of fluctuations are not observed in the Figure 7(a). It implies that the flow of third party's payments is persistent, whereas payments initiated by participants do not always have the same turn round.

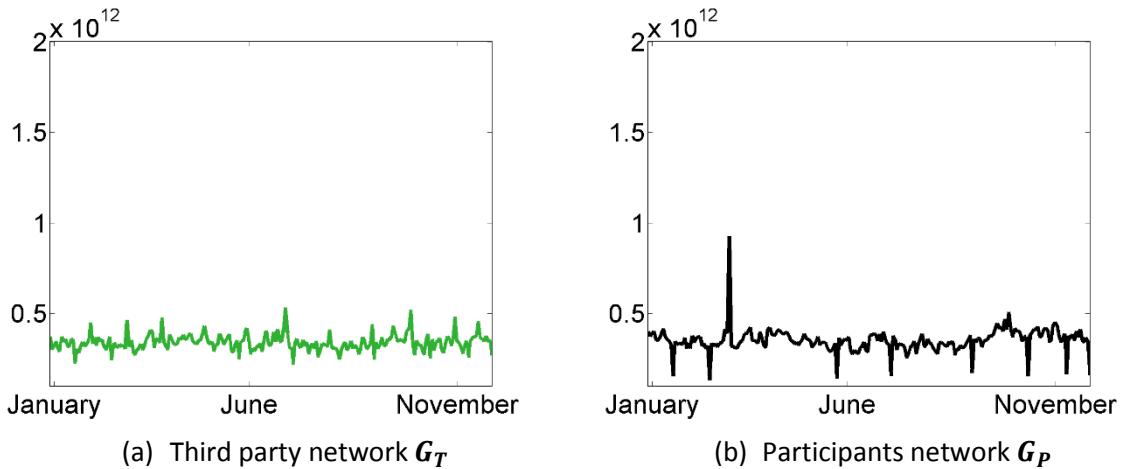


Figure 7. Daily Volume

Moreover, at comparing the daily volume with the series that represent the proportion of external funds used and the value to cover payment obligations  $F_t$ ,  $F_p$ ,  $F_T$  and  $F_P$  presented in Figures 8 and 9 respectively, we gain more insights in finding possible explanation of the fluctuations observed in the flow of participants' initiated payments. In particular, in Figure 8(b) we observe nine points with pronounced upward movements, which march with the eight points with downwards movements and the one point with strong upward movement. This indicates that significant changes in the daily volume imply an increase in the use of the proportion of external funds. In the case of transactions initiated by third party such noticeable movements are not observed.

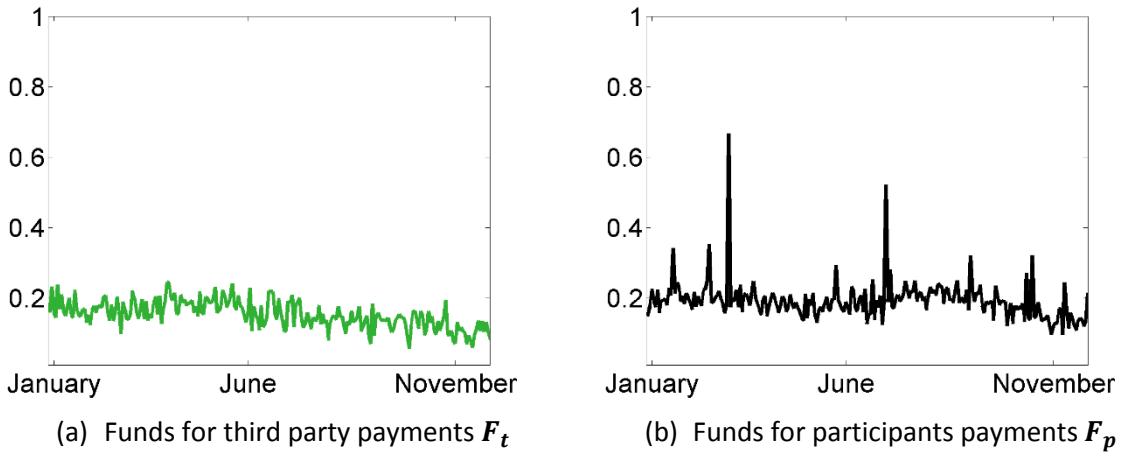


Figure 8. Proportion of External Funds

Finally we compare in Figure 9 the value of external funds  $F_T$  and  $F_P$ . We notice that both series are stable, with three remarkable points with upward movements only in the case of participants' initiated payments presented in Figure 9(b). The absence of such huge jumps in the case of Figure 9(a) is an indication of the urgency with which participants' payments have to be settled. The elevated points in Figure 9(b) match three of the highlighted dots in Figure 8(b). From this observation we conclude that for the rest six occasions, in which an increased in the proportion of funds is observed in Figure 8(b) is due to a reduction of the total number of payments settled in the system. This is also consistent with our observations from Figure 7(b).

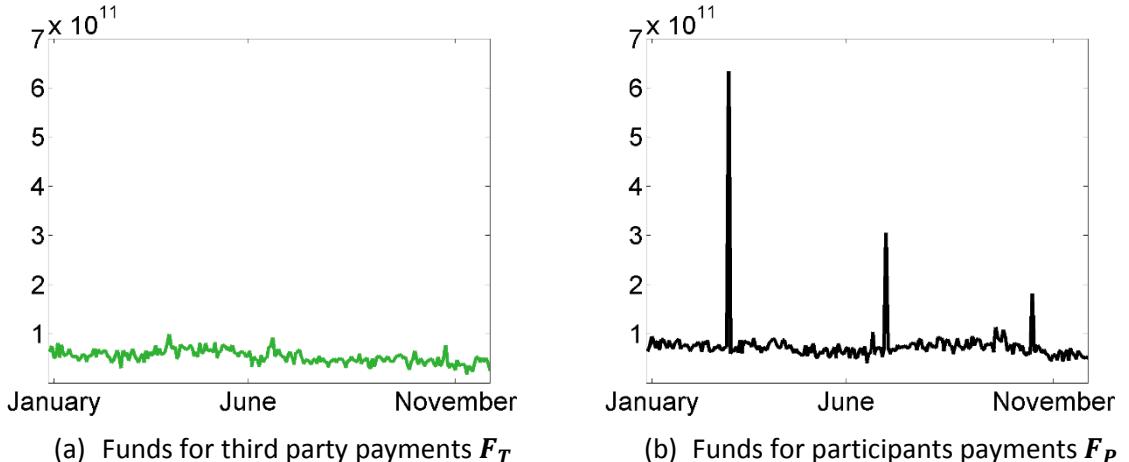


Figure 9. External Funds

#### 4 Conclusions and future research

Many financial services networks are classified as core-periphery structures (van Lelyveld and In 't Veld, 2012). In our study among the main findings we observe that both networks follow into this model. The graphs exhibit very similar dynamics in terms of value of the operations, whereas in terms of volume they have different properties. We have not found significant differences among

the topological measures of both networks, nevertheless the weighted graph created on third party payments has larger core with higher connectivity than the weighted graph created on participants' payments. This help to increase connectivity among direct participants and the overall structure of the network become more stable as liquidity has more channels to flow among institutions. Further by comparing daily volume, proportion of external funds used and value of external funds, we observe that third party payment do not create strong pressure on the use of liquidity as no remarkable jumps are presented in the studied period. These findings allow us to conclude that the contribution of the third party payments in the network dynamics is very important in terms of smooth liquidity distribution.

Nevertheless, the features of the core-periphery enclosed yet many research questions related to stability and efficiency in the system. For instance, are nodes in the core equally important, and if not what distinguish them from one another? What will be the impact on the network's dynamics if there are disruptions in the core? These questions are relevant form operational and systemic perspective and it is worth to be studied in more details in the case of SPEI.

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# Chapter 6

## Measuring free riding in large-value payment systems: the case of TARGET 2

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*Martin Diehl*

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\* This article first appeared in Journal of Financial Market Infrastructure, 27 March 2013. The publisher gratefully acknowledges the permission to reprint this article.

# Measuring free riding in large-value payment systems: the case of TARGET2

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(Received February 18, 2013; accepted February 19, 2013)

*This paper addresses the question of how free riding in large-value payment systems should be properly measured. Based on the valuable proposal by Denbee, Garratt and Zimmermann, various measures of free riding in large-value payment systems are investigated. Assessing the measures proposed in the literature against a list of rational postulates for measurement reveals their weaknesses. To overcome these weaknesses, we define three other measures, which are designed to be used for econometric studies and yield results independent of the size, composition and other special features of the payment system. Empirical results for nine important participants in TARGET2-BBK are displayed and compared. It turns out that a combination of at least two measures would be recommended for capturing the various aspects of free riding. The measures reveal some stable payment behavior for most banks over time, but also some remarkable regime shifts that yield interesting insights about single participants. The calculated levels of free riding can be judged to be rather low given the empirical results. In addition, the stable pattern over time raises the question of whether other unobserved features explain the different payment patterns such that labeling as a free rider based purely on measurement would be premature.*

## 1 INTRODUCTION

Payment economics deals with the smooth flow of liquidity as a means to settle payments. The smoother the flow, the less initial liquidity provision is needed. The available settlement liquidity<sup>1</sup> of a single participant consists of the initial opening balance, the available intraday credit and incoming payments during the business day. Therefore, a payment system as a whole benefits from participants providing early liquidity to other participants in the system and reusing incoming payments

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This paper represents the author's judgements and views and does not necessarily reflect the opinion of the Deutsche Bundesbank.

<sup>1</sup> See Bech *et al* (2012, p. 7) for the distinction between settlement, funding and market liquidity.

quickly for the settlement of their own submitted payments. Especially in a real-time gross settlement (RTGS) system, banks rely heavily on incoming funds to finance their own submitted payments. The ratio of total payments to liquidity used (the so-called liquidity efficiency) easily reaches double digit values. If the liquidity efficiency level reaches ten, the participant will pay 90% of all submitted payments by reusing incoming funds over the day.

Since liquidity is costly, a bank may attempt to reserve liquidity, for example, for the payments that would cause higher delay costs. In addition, higher uncertainty provides incentives to postpone payments until part of the uncertainty is resolved.<sup>2</sup> Thereby, banks would reduce the available level of liquidity in the system and may hamper the smooth flow of liquidity. As a possible consequence it will contribute to the risk of a gridlock situation at the end of the business day. This behavior is rational from the view of a single participant (see Alentorn *et al* (2005) for a short description of the risk–efficiency trade-off). From the view of the system operator and from the view of the whole group of participants it is more beneficial if participants do not withhold any incoming liquidity for too long. The reaction of the owners and operators of large-value payment systems (LVPSs) is twofold. Firstly, some operators introduced liquidity-saving mechanisms into their RTGSs in order to reduce the minimum level of liquidity needed and/or collateral required. Secondly, some have implemented institutional features to induce early payment (regulative requirements, such as throughput guidelines and immediate submission requirements, or incentives, for example, graduated intra-day tariffs) in their pursuance of avoiding gridlocks at the end of the business day (for an overview of liquidity-saving mechanisms, see Norman (2010)). The first approach does not aspire to change the payment behavior of the participants and simply helps the banks to deal with their liquidity needs out of the payment flow (for an estimation of the benefits of introducing liquidity-saving mechanisms see Diehl and Schollmeyer (2012)). The second approach can be seen as taking into account the possibility of a strategic component in the bank's decision about its sequence of payment submission. Both approaches can be and are used in combination.

In order to deal with the problem of low liquidity efficiency, the operators of an LVPS should first measure the degree of strategic free riding and determine the extent to which, if at all, single participants behave as free riders. At this point of the discussion, free riding can be defined as deliberate withholding of incoming liquidity. The basic measurement problem is that the time of payment is observable, but the

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<sup>2</sup> Bech *et al* (2012, p. 12), give as an example a bank acting as a correspondent for other banks with its incentive not to send payments on behalf of the client banks that may fail during the day.

time of the settlement manager's reception of the payment order is not.<sup>3</sup> Hitherto, very few papers about the concepts of measurement of free riding in LVPS have been published. A paper worth considering was presented by Denbee *et al* at the Bank of Finland 8th Simulator Seminar in 2010 and published in a revised version in 2012 (see Denbee *et al* 2012). They construct two measures and thereby provide the calculated indicators for free riding in CHAPS.<sup>4</sup> In addition, they simulate CHAPS and compare the measures of free riding after randomly rearranging the sequence of payments with the real situation and draw the following conclusion.

Therefore strategic delay and urgent payments do not appear to be a problem for liquidity at a system-wide level. However, at the level of individual settlement banks there may still be apparent inequitable distributions of liquidity usage.

This paper follows the initiative of Denbee *et al* (2012) and develops various measures of free riding in LVPS based on a list of measurement axioms to be adhered to. It is therefore a conceptional approach to improve measurement of payment pattern in LVPS. Besides serving the better understanding of the level of free riding and the necessity of operators' intervention these data shed some insights on payment behavior of the participants. They may contribute to the ongoing developments in modeling payment systems.

All developed measures are based on the concept of free riding in payment economics (Section 3) and measurement axioms (Section 4). It is shown that translation of the theoretical concept of free riding into a single numerical figure is not at all simple or unambiguous. Therefore, various measures are proposed and checked against the prior stated axioms (Section 5). Data for the various measures for participants in TARGET2-BBK<sup>5</sup> is presented. A comparison of the empirical data enables conclusions for the considerations about the construction of measures for free riding (Section 6). Finally, in Section 7 a first economic interpretation about the measured level of free riding in TARGET2-BBK is given.

## 2 CONCEPT OF FREE RIDING IN PAYMENT ECONOMICS

The concept of free riding in welfare economics was clearly spelled out by Mancur Olson in his book *The Logic of Collective Action* (1965). He defined a free rider as someone who benefits from a collective activity without participating in it. That

<sup>3</sup> This formidable measurement problem has even induced the construction of quantitative models of the participants' possible actions in order to be able to estimate the benefits of settlement liquidity. See Bech *et al* (2012, p. 10) and Atalay *et al* (2010).

<sup>4</sup> CHAPS, the Clearing House Automated Payment System, is based in London and offers same-day sterling fund transfers.

<sup>5</sup> TARGET2-BBK is the German component of TARGET2, the LVPS of the Eurosystem. The Deutsche Bundesbank is responsible for contact with all participants in TARGET2-BBK.

could mean someone consumes more than their fair share from a common good or contributes less than their fair share to the costs of providing the common good.

The transfer of the concept of free riding into payment economics is straightforward. Of course, liquidity itself cannot be called a public good, since money belongs to someone who has the right to exclude others from using it. And its use is subject to rivalry. A bank cannot pay more than one bill with the same liquidity. Nor can another bank use the same liquidity at the same time. However, a bank, having received a payment, can use it for its payments thereafter. Therefore, a high turnover of initial liquidity provided to a payment system may help to lower the overall level of liquidity required. As a consequence, liquidity is and remains a private good. However, the level of liquidity used in a payment system at an early time in the business day has positive external effects that constitute a common good.

In this sense we can call someone who pays very early as contributing positively to the common good “early liquidity”. However, someone who pays relatively late or withdraws liquidity, notwithstanding the fact of unsubmitted own payments, could, everything else constant, be considered a free rider. Two problems occur. Firstly, we have to define clearly what is meant by “relatively” late. This question will be dealt with in depth in Section 5. Secondly, as usual the condition of “all else being equal” creates some pitfalls. The need for payments occurs in a continuous flow displaying some peaks and troughs due to batch processing at some point in the payment chain and due to closure times of the various payment and settlement systems used. From the view of a liquidity manager sitting at the interface between the bank and the payment system all payments have a “natural” payment time. Given the fact that liquidity is costly (and the earlier it is needed the more costly it is) the liquidity manager may feel tempted to withhold some (large value) payments from immediate submission after their “occurrence” although he may have sufficient liquidity or available credit lines. One rationale is to stay on the safe side and to have a buffer of available liquidity for possible liquidity shocks (large time-sensitive outflows which may incur costs in case of delay). A second rationale is to limit bilateral or multilateral outstanding claims and to reduce liquidity risk in case of a failure. However, since the distribution of the “natural” payment times is, from the view of the system operator, not observable, the labeling as “free rider” may be subject to some doubts. Another feature that may not be constant in the comparison of two payment-system participants is their perceived credibility. A bank with a high credibility may not be subject to so many limit restrictions by others. Consequently, on average it may receive payments earlier. Compared with other banks, which, due to a lower credibility, try to pay as early as possible, the first bank could be perceived as a free rider, although withholding liquidity was not its intention.

Therefore, after measuring free riding the possible reasons for the outcome still have to be explored before using the label “free rider”.

### 3 AXIOMS FOR MEASURES OF FREE RIDING

Any measure serving the purpose of distinguishing free riders from non-free riders should in practice fulfill certain requirements. Three sets of axioms may be defined: first, and most importantly, axioms about the content of the measure; second, axioms about the way of measurement; and third, axioms about the output and its practicality. The axioms in perceived decreasing order of importance follow below.

(1) Axioms about the content.

- (a) *Transfer principle*: the measure should be reactive to any transfer in timing, ie, any significant shift in the timing of a specific sizable payment should lead to a change in the indicator. Shifting a payment to an earlier point in time should lower the measured extent of free riding and likewise shifting to a later point in time would raise it. For operational reasons this may in practice not hold for any shift of a payment value below a threshold to be defined over a period shorter than a time span to be defined.
- (b) *Relevance principle*: the measure should concentrate on the payments potentially under the influence of the timing decisions of the participants.

(2) Axioms about the method.

- (a) *Postulate of scale-invariance*: the measure should be scale-invariant as to the value and volume of the respective LVPS and to the value and volume of the participant in question. The measurement should not differ if the sum of transferred values or the number of submitted payments is multiplied by any constant.
- (b) *Postulate of participant-invariance*: the measure should be invariant as to the number of participants of the LVPS and the number of participants included in the measurement (note that any reasonable measure requires at least two participants).
- (c) *Postulate of institution-invariance*: the measure should be invariant as to the institutional setting of the LVPS in question. This is to enable a cross-LVPS comparison of the degree of free riding.
- (d) *Anonymity principle*: the measure should be impartial, ie, the participants in question stay anonymous for the time of measurement.
- (e) *Postulate of full coverage*: the measure should be defined for the full range of possible payment behaviors and payment-network features, ie, it should be invariant as to questions of whether the participant is a net

sender or net receiver on that day, whether the participant has many or just a few links, whether the system has many or only a few ancillary systems, etc.

(3) Axioms about the output.

- (a) *Postulate of ordinal or ratio scale*: the measure should at least result in an ordinal scale, preferably in a ratio scale such that further econometric analysis of the result are possible. An outcome on a ratio scale would enable us to define the extent of free riding for a participant or the extent of non-free riding.
- (b) *Postulate of true measurement*: the obtained measures should be free of any technically implied jumps in value.
- (c) *Postulate of operability*: finally, the measure should be operationally attractive, ie, be calculable with a reasonable amount of input.

The axioms about the content are most important. However, the interpretation of the transfer principle is nontrivial. From a theoretical point of view the principle should be followed strictly. However, given the fact that the numbers of payments for many banks reach into the tens of thousands, it is easily seen that for pragmatic reasons an operationally reasonable relaxation of the principle should be warranted. That is why somewhat vague formulations (“significant”, “sizable”) are used, instead of focusing on payments of any kind.

The axioms about the method provide for the necessary comparability of measurement across LVPS and over time. Unless a onetime measurement is intended they ought to be followed. As for the axioms about the output, they are based on practical reasoning such as enabling the usefulness of the measures for further calculations or econometric studies.

#### 4 EMPIRICAL MEASURES OF FREE RIDING

In this section we investigate five measures. Two are proposed by Denbee *et al* (2012), which constitutes the most definitive reference in the relevant literature to this point. We use the names given to them by Denbee *et al*: “cost-based measure” and “risk-based measure”. Partly in order to overcome the shortcomings of these measures, other measures have been constructed. Two are mainly based on the timing of payments. While the “time-based measure” is mainly based on average settlement time, the “early payment indicator” takes into account the higher importance of earlier time bands for the available liquidity in the system. Finally, we have a closer look into the “relative net sending indicator”, which draws on the ratio of a participant’s net sending to their total credits and a participant’s net receiving to their total debits.

The following empirical examples are taken from real data of TARGET2-BBK. The discussed measures of free riding were calculated for nine participants in the national component of TARGET2, which is governed by the Deutsche Bundesbank. They are calculated on a daily basis for the period from January 2008 through March 2012. Whenever the time of settlement is divided into slices, the relevant time band is defined as one minute. Given the total time for banks' own submission of payments from 07:00 through 18:00, a total number of 660 time bands is taken into account. The time span of one minute is evidently shorter than the time necessary for manual interference of a payment manager with the objective to manipulate the sequence of payments.

#### 4.1 Cost-based measure

The cost-based measure is defined by Denbee *et al* (2012) based on the share of total liquidity a bank provides in relation to its share of total payments.<sup>6</sup> The liquidity provision for bank  $i$  is the largest net debit position at any point during the day:

$$L_i = \max_t \left[ \sum_{s=0}^t (x_{i,s}^{\text{sent}} - x_{i,s}^{\text{rec}}) \right],$$

where  $\sum_{s=0}^t x_{i,s}^{\text{rec}}$  is the total amount received by bank  $i$  from the start of the day until time  $t$  and  $\sum_{s=0}^t x_{i,s}^{\text{sent}}$  is the respective amount sent until time  $t$ . If the bank were a net receiver on that day and never yielded a positive net provision of liquidity at any point in time during the day,  $L_i$  would be equal to zero, since the largest net debit position was at the start of the day.

According to Denbee *et al*  $L_i$  represents the cost burden of bank  $i$  for payments, since it reflects the largest net debit position equaling the maximum amount of own liquidity of bank  $i$  used for payments on that day. Consequently, they define a free rider as a bank that uses a larger share of system liquidity than it provides. They define  $\mu_i$  as the cost-based measure of free riding in the following formula:

$$\mu_i = \frac{L_i}{\sum_{i=1}^n L_i} - \frac{P_i}{\sum_{i=1}^n P_i},$$

where  $P_i$  denotes the total value of payments made by bank  $i$  on that day. The possible values range from  $-1$  (one bank made almost all the payments but provided almost no liquidity) to  $1$  (one bank provided almost all the liquidity but made almost no payments). If the share of liquidity provided by a bank equals its share of payments, then  $\mu_i = 0$ . Whenever  $\mu_i < 0$  Denbee *et al* call bank  $i$  a free rider.

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<sup>6</sup>The following paragraphs about the definition are almost directly taken from Denbee *et al* (2012, p. 58).

The cost-based measure fulfills most of the stated axioms, but clearly not all. The transfer principle is not met, since any significant transfer in timing will change the measure only if it affects the maximum net debit position. Any other payments can be shifted back and forth without changing  $\mu_i$ . The principle of full coverage could also be seen as violated, since the measure does not differentiate between different payment patterns within the group of banks that are net receivers on that day. All banks who are net receivers achieve  $L_i = 0$ . Therefore, their  $\mu_i$  differs only according to their payments, not taking into account the amount of the incoming payments already received by a specific bank. That causes a technical jump at the threshold of net sending versus net receiving. Once a bank passes the threshold and becomes a net sender, then the stream of incoming payments is again taken into account for calculating the cost-based measure.

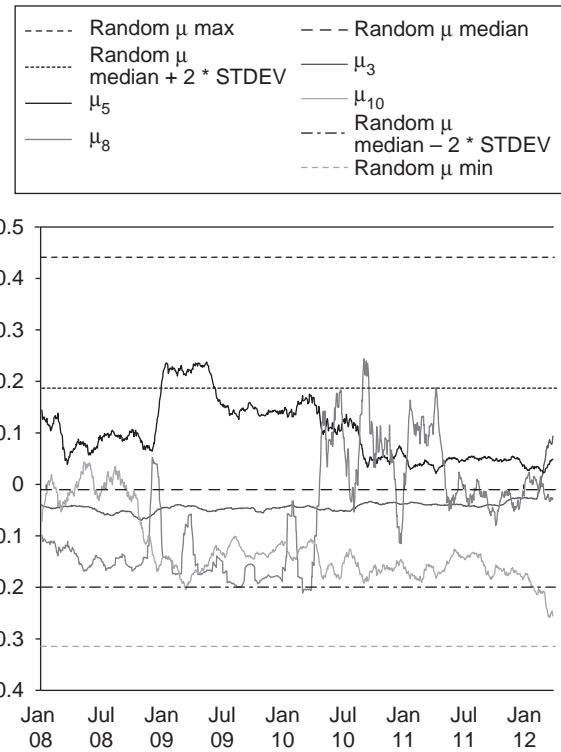
The measure implies more technical jumps if not all participants are taken into the calculation. In an LVPS with a small number of participants it may be useful to calculate  $\mu_i$  for all participants. In TARGET2, however, that would mean calculating several hundreds of participants, which is not really practical. However, if not all participants are taken into account,  $\mu_i$  will be different for the different numbers of participants examined. Therefore, the postulate of participant-invariance is also violated unless we provide full coverage of all participants.

Figure 1 on the facing page displays the twenty-two-day moving average of the cost-based measure of free riding for a selection of banks in TARGET2-BBK (the average month has twenty-two working days).

In order to get an understanding of the significance of free riding given by  $\mu_i < 0$ , the measures were additionally calculated for a random distribution of payment sequence. This random distribution yielded a median for the cost-based measure of close to zero. Figure 1 displays the median of the random calculation, the respective maximum and minimum and the median plus or minus twice the standard deviation of the randomly created distribution.

At first glance, several points should be noted.

- The twenty-two-day moving averages of  $\mu_i$  display remarkable stability for a number of banks.
- It appears that regime shifts (when a bank moves from a non-free rider towards a free rider) occur, here given by the changing behavior of bank 8.
- None of the  $\mu_i$  is significantly below the median minus twice the standard deviation and all are well short of the randomly calculated maximum or minimum.

**FIGURE 1** Cost-based measure of free riding for selected banks in TARGET2-BBK (twenty-two-day moving average).

## 4.2 Risk-based measure

According to Denbee *et al* (2010) the total risk,  $T$ , is defined as the sum of all average positions when a bank is a net sender.<sup>7</sup> For the period  $t$  the net sending position of bank  $i$  is defined as  $N_{i,t}$ , which is given by

$$N_{i,t} = \sum_{s=0}^t x_{i,s}^{\text{sent}} - \sum_{s=0}^t x_{i,s}^{\text{rec}},$$

and the average,  $N_i$ , is defined as

$$N_i = \frac{\sum_{t=0}^T N_{i,t}}{T}.$$

<sup>7</sup> The following definition draws closely on Denbee *et al* (2010, p. 5) and Denbee *et al* (2012, p. 63).

Given the above definition of total risk,  $T$ , Denbee *et al* concentrate on net senders only, which gives the formula

$$\tau = \sum_{i: N_i > 0} N_i.$$

They calculate  $\sigma_i$ , the risk-based measure for free riding of bank  $i$ , according to the share of total risk taken by a bank:

$$\sigma_i = N_i / \tau.$$

A free rider is considered to hold, on average, the liquidity of other banks in the system and will display  $\sigma_i < 0$ .

The risk-based measure as defined by Denbee *et al* (2010) does not fulfill all axioms. Most important, the transfer principle is violated, since all transfers not happening at a time when the bank is a net receiver do not affect the measure. Moreover, the postulate of scale-invariance is not met unless all participants are taken into account. If, in LPSSs with many participants, the analysis is to concentrate on systemic important participants, the degree of free riding differs according to the selection of participants. In addition, given the same relative size of the average net sending positions of two participants (in relation to the total value sent), the larger of the two will display a higher  $\sigma$ . In addition, the measure is not indifferent to the share of participants taken into account. At best, all participants should be looked at simultaneously. However, for operational reasons this may not be feasible for LPSSs with many participants. In these cases the cost-based measure will yield different results for different numbers and compositions of participants. Finally, in a smaller group, the measure may jump for technical reasons on days when the number of banks that are on average net senders declines into low figures.

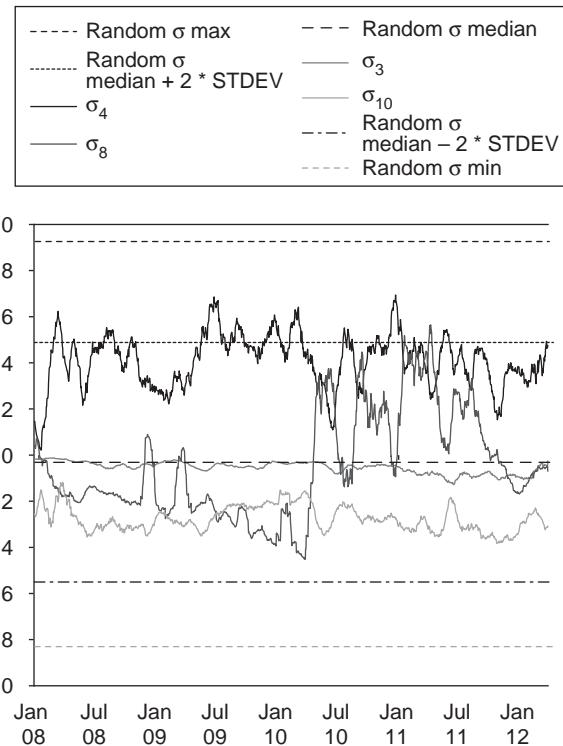
However, Denbee *et al* (2012) revised their risk-based measure and yielded significant improvements in terms of fulfilling the axioms, albeit not fully. The revised risk-based measure takes into account the time-weighted exposure of banks' net sender positions. The sum of all time-weighted exposures of a bank, ie, periods of net sending, is compared with the time-weighted share of sent payments. If the latter exceeds the former, the difference will be negative, signaling free riding according to Denbee *et al*.

This measure is a significant improvement on the cost-based measure, since the transfer principle is less violated, because the measure does not only look at one point in time. However, all times when a bank is a net receiver are excluded. The different timing of payment in these times does not change the measure unless the threshold towards becoming a net sender is passed again.

Again, the calculated risk-based measures (based on the given definition from Denbee *et al* (2010)) are compared with the measures from the random distribution.

## Measuring free riding in LVPS: the case of TARGET2

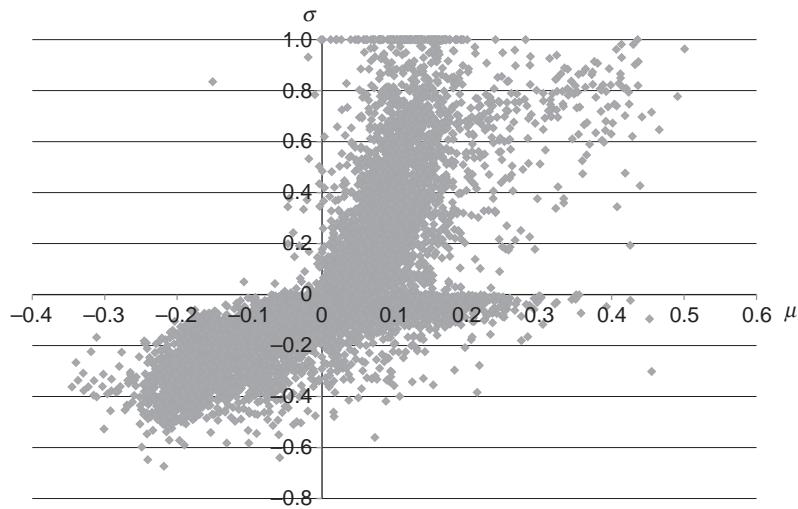
**FIGURE 2** Risk-based measure of free riding for selected banks in TARGET2-BBK (twenty-two-day moving average).



For the sake of clarity, Figure 2 displays measures for only four selected banks. However, the measures were calculated for a group of nine banks. Unlike in Denbee *et al* (2010), the sum of all measures does not add up to 1, since only a fraction of all settlement banks are taken into account. The risk-based measures display a significantly larger range of values and much more volatility than the cost-based measures. The volatility may be caused partly by the technically implied jumps due to the definition above. Again, some banks act permanently at a rather stable level of risk-based free riding and others (again, bank 8) display a significant regime shift from a non-free rider towards a free rider.

The joint distribution of cost-based and risk-based measures of free riding is displayed in Figure 3 on the next page. It clearly shows a positive correlation. However, it can also be recognized as the technically implied clustering in case of  $\sigma_i = 0$ .

**FIGURE 3** Joint distribution of cost-based and risk-based measures of free riding for nine participants of TARGET2-BBK for the period January 2008–March 2012.



#### 4.3 Time-based measure

In an extension of the above-discussed measures for free riding, a time-based measure is constructed. We intend to construct such a measure in order that the violation of the transfer principle is reduced to a minimum. The total time of active payment submission is divided into 660 slices (every minute for the total of 11 hours). The payments sent within a minute are taken together as being sent in the same time band. This is a reasonable reaction time for a payment manager trying to influence the sequence of payment submission. The division of the total settlement time into time bands is necessary in order to yield the same number of payment packages sent. The calculation of any simple average payment time based on the true settlement time of every single payment is possible. However, once the various payment times are weighted differently, it is necessary to deal with the same number of payment packages.

For those 660 payment packages an average payment time index is calculated. The payment time index yields a number between 0 and 1, meaning the share of the total settlement time elapsed when half of the values to be sent are settled. For example, a payment time index of 0.4 means that after 40% of the total settlement time half of all payments of this participant on this day are already settled (in addition to the average, any other percentile can be displayed as the payment time index). However,

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the average payment time index may not suffice to serve as a measure for free riding, since it does not take into account the incoming payments of a participant. To get an index of the timing of received payment, a reception time index is calculated accordingly. An average reception time index of 0.4 means that, after 40% of the total settlement time, half of all incoming payments of this participant on this day are already settled.

The time-based measure of free riding for a bank  $i$ ,  $\delta_i$ , is defined as

$$\delta_i = \text{average reception time index}_{\text{bank } i} - \text{average payment time index}_{\text{bank } i}.$$

The index  $\delta_i$  is negative for a free rider that needs a larger share of the business day to send half of their payments than to receive half of the incoming payments.

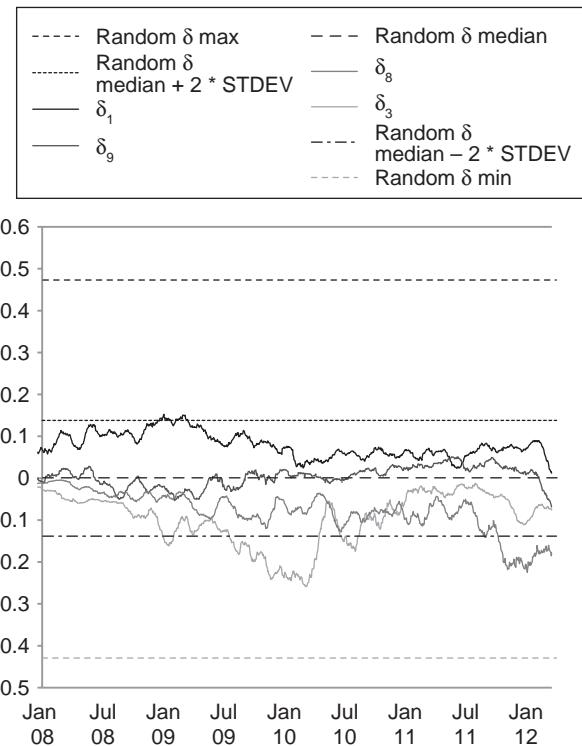
It should be noted that this measure is applicable to any number of participants, even a single participant. In addition, it fulfills the transfer principle to the extent that every transaction changing the settlement time of a certain payment such that it shifts to the next minute time band will have an effect on the measure. Given the limitation to 660 time bands the measure is still operational.

The selected data for the time-based measure of free riding is displayed in Figure 4 on the next page. It shows at first sight some similarities to the cost- and risk-based measures. Most banks follow a stable path of  $\delta$  and only a few display a significant regime shift upward (bank 8) or downward (bank 3). However, the absolute numbers are more significant in comparison with the randomly calculated distribution. Two banks are at least partially significantly below the value of the median minus twice the standard deviation of the random distribution of  $\delta$ . Three banks (only one is shown here) are permanently in the positive realm. No bank ever comes close to the maximum or minimum of the random distribution.

Therefore, the level of free riding may again be judged low according to this indicator. Moreover, the time-based measure of free riding allows some more insight. If we are to judge free riding as voluntarily withholding liquidity, we have to somehow find an indication for the motives behind the observed payment pattern. This is not really possible. However, voluntarily withholding liquidity may lead to some correlation between the reception time and the payment time, which is stable for more than just one day. This leads to the question of whether there is any stable correlation between the two timing indexes.

In Figure 5 on page 15 the correlation for consecutive periods of twenty-two days between the average payment time and the average reception time is depicted for only three banks. The picture will not change substantially if more banks are included; it will just become less clear. What can be stated is that the correlation between the two timing indexes increases and decreases in an obviously erroneous way without indicating any systemic feature. This holds for all nine banks under consideration and it is taken as another sign of overall low level of free riding.

**FIGURE 4** Time-based measure of free riding for selected banks in TARGET2-BBK (twenty-two-day moving average).



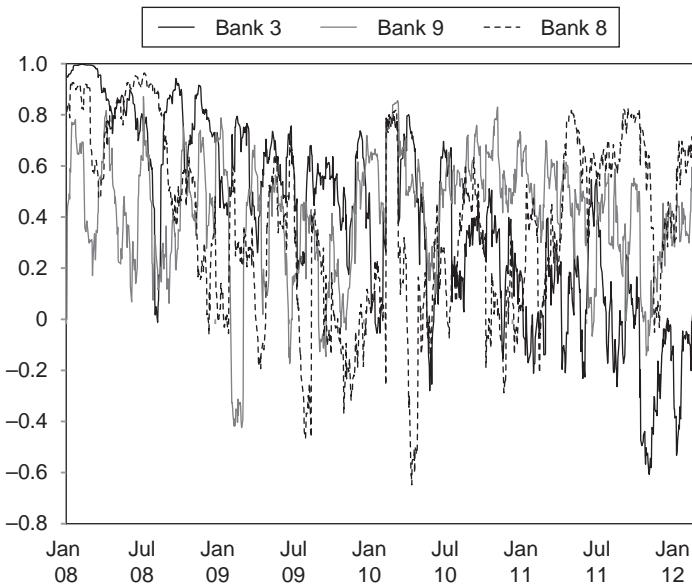
#### 4.4 Early payment indicator

The average payment time calculates a single point in time at which the average of all payments in value has been settled. All payments are taken into account at a proportionate factor. For the question of liquidity efficiency in the system, however, the payments in the early time bands play a disproportionately high role. The following example of two fictitious banks may illustrate the point (see Figure 6 on page 16).

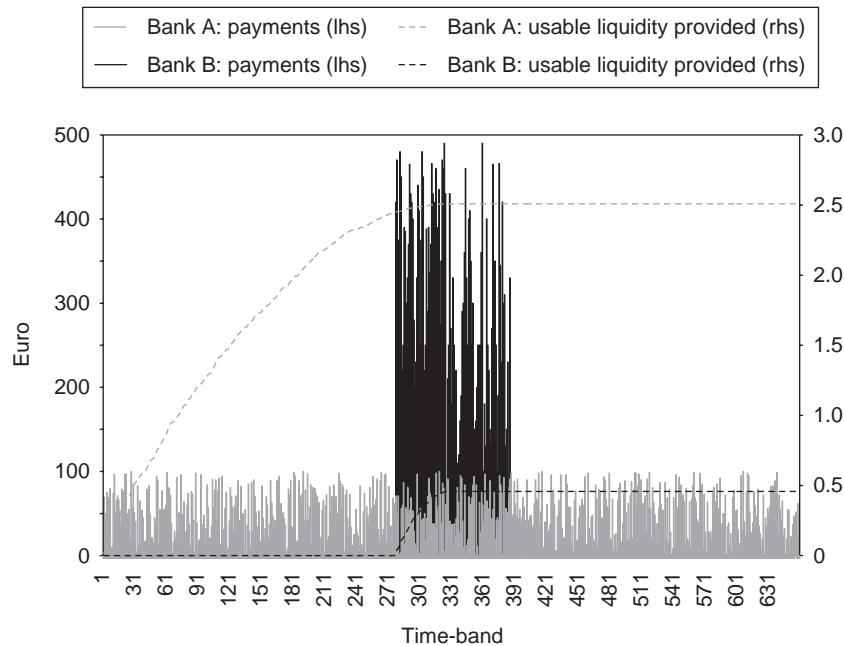
Both banks settle on a single day the total value of €33 096. Bank A uses all of the displayed 660 time bands of equal length. Bank B, however, concentrates the payments on 109 time bands around the middle of the business day. Both Banks have the same average payment time. The average payment time index is 0.49583, meaning that after 49.6% of the time of the business day they have settled half of their total payment value for the whole day. In time band terms this means that after the 328th time band both have settled half of their total settlement value.

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**FIGURE 5** Correlation of payment time index and reception time index (twenty-two day periods).



However, it can clearly be seen that the amount of liquidity early in the day provided by Bank A is much higher than for Bank B. The latter has not made a single payment until time band 277, whereas the former has at that time already settled more than 42% of its total settlement value. Given a plausible assumption about liquidity efficiency, we can calculate the overall impact of that different payment pattern on the total liquidity available. If we assume the liquidity efficiency to be 10, it will mean that initial liquidity in the morning is transferred ten times. The turnover rate may decrease in later time bands (here assumed a proportionate decrease in time) and may become zero by midday. The latter assumption is justifiable given the need for a disposition of overnight balances by banks at a sufficiently early point in time. If we multiply the liquidity provided by a bank with the turnover rate for the respective time band and sum the products, we will receive the usable liquidity provided by that bank. Figure 6 on the next page shows that this usable liquidity for Bank A reaches 2.5; more than five times higher than the figure for Bank B. The number means that two and a half other banks of equal size could settle their payments with the liquidity provided by Bank A.

**FIGURE 6** Distribution of payments on time bands for two fictitious banks.

The business day is divided into 660 time bands. The usable liquidity is calculated by the sum of the products of the liquidity sent times the time band specific turnover rate. The turnover rate is 10 for the first time band, decreases proportionately with time bands and stays at zero from time band 330 onwards.

Clearly, the average payment time does not provide this insight into the true contribution of liquidity to the payment system.

Therefore, an early payment indicator is calculated by weighing earlier time bands with a higher factor than later ones. In calculating the average payment time, all time bands are weighed with the same factor. In calculating the early payment time, the weighing factors for different time bands differ. The factor for the last time band is taken as zero. For all other time bands,  $t$ , the factor is calculated as

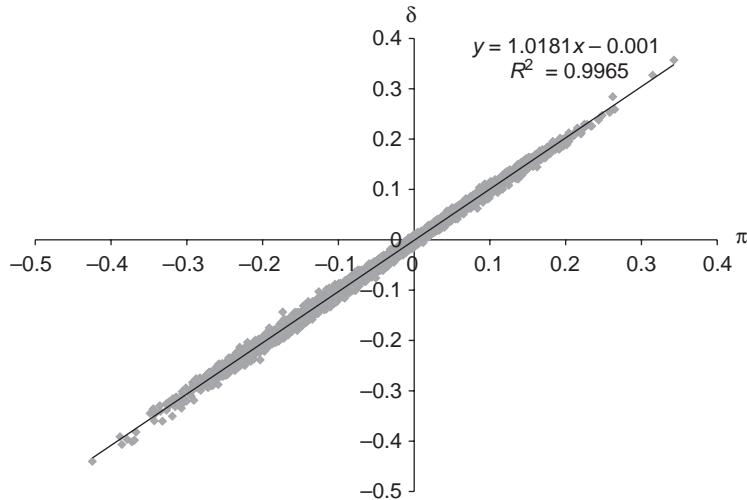
$$\text{factor}_t = (1.001^{660-t}) - 1.$$

The factor of a time band is 0.1% higher than the factor of the next time band. In the extreme case that a participant sends all of its payments in the first time band, the early payment indicator becomes 1. Consequently, the early payment indicator will be zero if all payments of a participant are sent in the last time band. Equally, an early reception indicator is calculated using the same factors for the respective time bands and the same logic.

## Measuring free riding in LVPS: the case of TARGET2

**FIGURE 7** Comparison of the time-based measure,  $\delta$ , and the early payment indicator of free riding,  $\pi$ , for nine participants in TARGET2-BBK for the period January 2008–March 2012.

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The early payment time indicator for free riding,  $\pi_i$ , is defined as the difference between early payment indicator and early reception indicator:

$$\pi_i = \text{early payment indicator} - \text{early reception indicator}.$$

A negative difference is considered to indicate free riding.

As for the axioms, the early payment indicator of free riding must be assessed in a similar way to the time-based measure of free riding. It fulfills all postulates, especially the transfer principle and the full coverage postulate.

The empirical data (see Figure 7) shows that the difference between the time-based measure of free riding (based on the average timing) and the early payment indicator of free riding (based on disproportionately large consideration of earlier time bands) yields similar results. The ranking of banks is equal and the level of indicated free riding matches very well, although not perfectly. However, it must be noted that, in extreme cases, the early payment indicator is more sensitive to single shifts in the more important early hours of a business day. In general, the overall very small difference between the two indicates the low degree of free riding, since obviously none of the banks tries to economize significantly on the early liquidity.

#### 4.5 Relative net sending indicator

The time-based measure and the early payment indicator of free riding are superior to the cost-based and risk-based measures in terms of not violating the measurement postulates. However, the cost-based measure of Denbee *et al* does have a special focus on extreme situations (maximum of net positions). The other measures are lacking that focus. Therefore, concentrating solely on the latter would mean possibly not capturing some aspects of free riding.

Therefore, as a complement to the measures of Denbee *et al*, another index focussing on the net sending of a bank shall be calculated. To overcome some weaknesses the outgoing and incoming payments are taken into account at the same time. Thereby, the restriction to deal with net senders or net receivers only is overcome.

Firstly, the largest accumulated amount of net sending in a time band is calculated and divided by the sum of all incoming payments. The rationale for this is that a bank may very well be a net sender if it expects a lot of incoming payments. Secondly, the largest accumulated amount of net reception in a time band is divided by the sum of all outgoing payments on that day. The second part is intuitively seen as the critical one, since a bank displaying a large surplus of net received payments is obviously a bank hoarding a lot of liquidity. However, the value has to be related to the total amount of outgoing payments on that day. In addition, the bank may display a large surplus of net sent payments on the same day at another time band and can thus claim that it has provided a lot of net liquidity to the system. Therefore, both aspects have to be considered together. The relative net sending indicator of free riding,  $v_i$ , is the difference between the two:

$$v_i = \frac{\max_t N_{i,t}}{\sum_{t=0}^T x_t^{\text{rec}}} - \frac{\text{Abs}(\min_t N_{i,t})}{\sum_{t=0}^T x_t^{\text{sent}}},$$

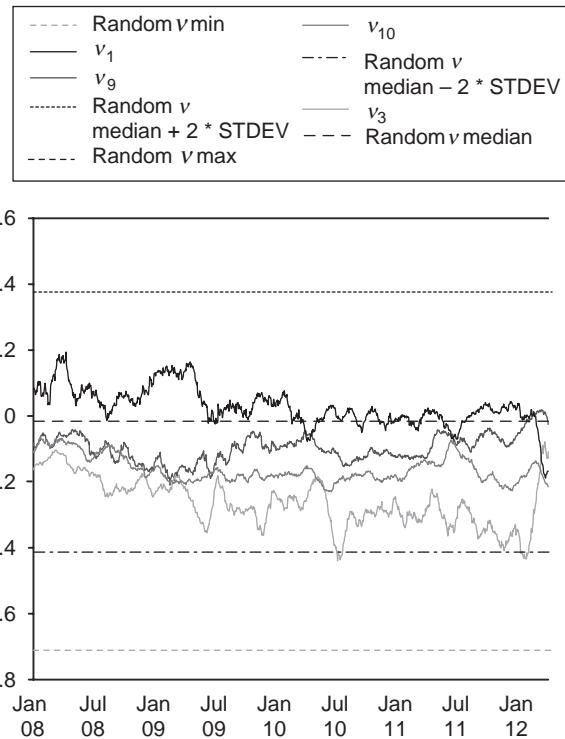
where

$$N_{i,t} = \sum_{s=0}^t x_{i,s}^{\text{sent}} - \sum_{s=0}^t x_{i,s}^{\text{rec}}.$$

This definition of a measure of free riding also violates the transfer principle, although to a lesser extent, since it involves possibly two time bands. However, it meets the full coverage postulate and the postulate of true measurement, since it implies no jumps in value for technical reasons. In addition, it is indeed independent of the group size. One obvious weakness of the measure is the nonconsideration of the respective time bands. If the maximum of net sending is held at a very late time band and the minimum of net sending (which is the maximum of net reception) is held at a very early time band, the bank may nevertheless be considered a free rider, even if  $v_i$  is zero or slightly positive. Therefore, this measure cannot be used as a sole indicator and has to be counterchecked by other measures taking into account the timing of payments.

## Measuring free riding in LVPS: the case of TARGET2

**FIGURE 8** Relative net sending indicator of free riding for selected banks in TARGET2-BBK (twenty-two-day moving average).

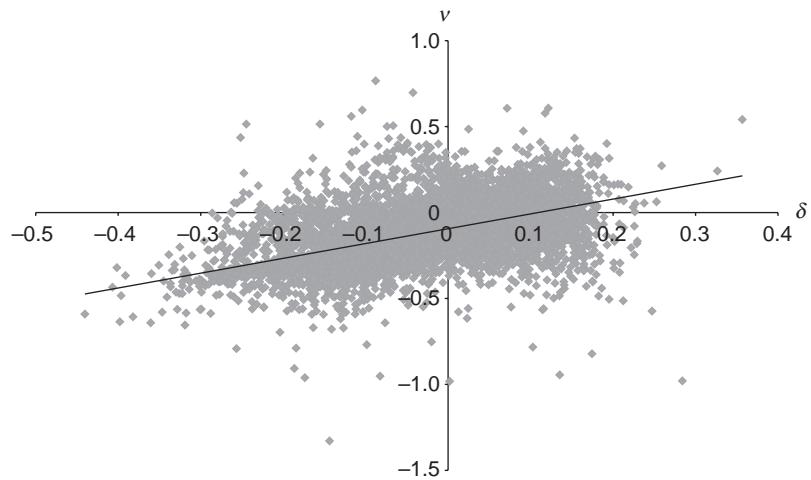


The results for the relative net sending indicator of free riding (see Figure 8) are, to some extent, different from the time-based measure and the early payment time indicator.

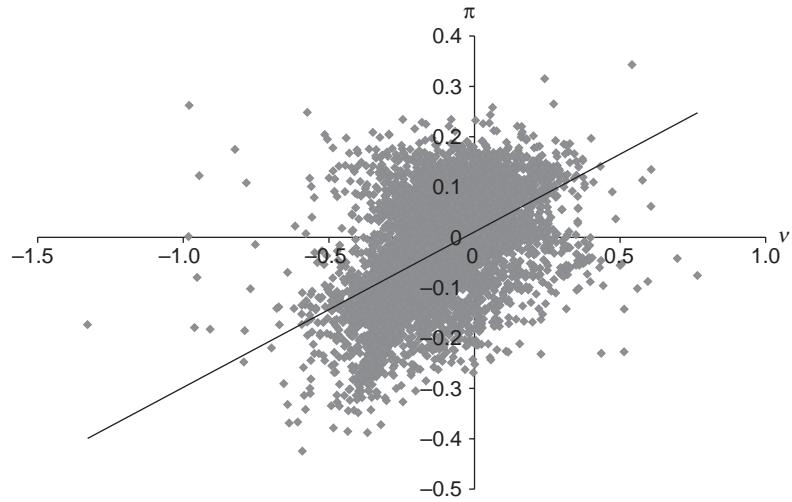
The relative net sending indicator of free riding displays more negative values than the other indicators. This clearly points to some aspects not yet covered by the other measures. However, similarly to the other measures, the level of the median of the random distribution minus twice the standard deviation is hardly reached. However, the banks again follow a certain regime displaying more volatile movements over the course of months.

The comparison of the relative net sending indicator of free riding with the time-based measure and the early payment indicator of free riding reveals a positive, albeit far from perfect, correlation, as can be seen in Figure 9 on the next page and Figure 10 on the next page.

**FIGURE 9** Comparison of the time-based measure,  $\delta$ , and the relative net sending indicator of free riding,  $v$ , for nine participants in TARGET2-BBK for the period January 2008–March 2012.



**FIGURE 10** Comparison of the relative net sending indicator of free riding and the early payment indicator of free riding for nine participants in TARGET2-BBK for the period January 2008–March 2012.



## 5 COMPARING THE FREE RIDING MEASURES

Starting with the empirical comparison, Figure 11 on the next page displays the various rank distributions of the nine banks under consideration according to the following five measures of free riding.

- $\mu$ : cost-based measure of free riding.
- $\sigma$ : risk-based measure of free riding.
- $\delta$ : time-based measure of free riding.
- $\pi$ : early payment indicator of free riding.
- $\nu$ : relative net sending indicator of free riding.

The ranks of the banks (the higher the rank, the more a bank must be judged as a free rider) are assigned according to the average value of the respective measures from January 2008 through March 2012.

A high rank means that the bank is more prone to being judged a “free rider”. The time-based measure,  $\delta$ , can hardly be seen, since the rank distribution is almost precisely the same as for the early payment indicator of free riding,  $\pi$ .

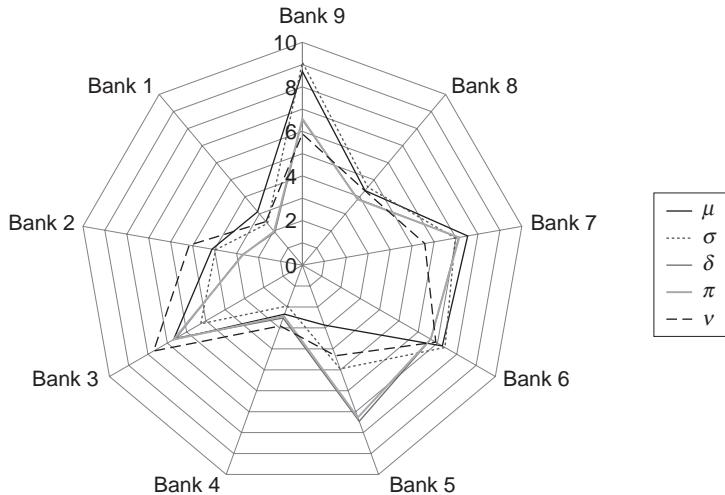
The various measures, aside from the time-based measure and the early payment indicator of free riding, lead to different ranks for the respective banks. Whereas bank 6 and bank 8 are assigned average ranks within a range of less than two, bank 9 and bank 5 are assigned ranks differing by more than three from each other. It appears that it is worth judging the question of free riding with consideration of more than one measure since they capture different aspects.

Since the cost-based and risk-based measures violate quite a number of reasonable axioms, the use of other measures is proposed. The violation of axioms constitutes a conceptual weakness which will weigh even more if the measures are further used for econometric studies and analyses.

The time-based measure and the early payment indicator of free riding yield such similar results that only one should be used. The one more sensitive to early liquidity (the subject in question) is clearly the latter.

The relative net sending indicator of free riding also violates the transfer principle, but by less than the cost-based measure does. In addition, the other axioms are met. In particular, the postulate of true measurement (no technically caused jumps) is fulfilled. Therefore, the measure is worth using as an additional indicator capturing aspects which are overlooked by just observing the early payment indicator of free riding. However, since it does not consider the respective timing of the phenomena observed, it should be used only complementarily.

**FIGURE 11** Rank distribution of nine participants in TARGET2-BBK according to the average of the various measures for the period January 2008–March 2012.



The numbering of the banks is not consistent with the previous figures.

## 6 ECONOMIC INTERPRETATION

We do not yet have an answer to the question of the real level of free riding, what can we conclude for the level of free riding in TARGET2-BBK?

Most indicators are pretty stable over time and in a narrow range around a neutral level. Therefore, bank-specific regimes in payment time, etc, are clearly identifiable. However, the overall level of free riding seems to be rather low given the comparison with the results of a random distribution of payments, since all participants display a very high correlation between their early payment indicator and their time-based measure. Consequently, no participant can be judged as overactively avoiding large-value payments in the morning. No systematic correlation of the payment time with the reception time has been discovered, giving a strong hint that voluntarily withholding liquidity is of rather low importance. In general, peer pressure seems to work and to limit free riding to a considerably low level.

But still, how could the recognizably stable regimes for most measures, albeit at a low level, be explained? Firstly, the overall high volatility of daily data – remember the regimes depicted twenty-two-days moving averages – and the regime shifts affect the observability. Secondly, banks only observe bilateral exchanges (and may only watch

absolute net transfers). Finally, the timing is mainly interesting for rare time-sensitive payments and big transfers.

Therefore, the rather stable and low levels of most free riding measures for most participants give rise to the assumption that a sizeable proportion of the small differences can be explained by chance and possibly by diverse creditworthiness. Some banks may actively seek to be perceived as early payers, and thereby accept some others paying relatively later. These issues leave plenty of room for further investigation of the payment pattern of banks in LVPSs.

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# Chapter 7

## Central bank intervention in large-value payment systems: an experimental approach

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*Peter Heemeijer – Ronald Heijmans*

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\* This article first appeared in Journal of Financial Market Infrastructures, 24 April 2015. The publisher gratefully acknowledges the permission to reprint this article.



**Research Paper**

## **Central bank intervention in large-value payment systems: an experimental approach**

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(Received February 5, 2015; revised April 13, 2015; accepted April 14, 2015)

### **ABSTRACT**

This experimental study investigates the behavior of banks in a large-value payment system. More specifically, we look at the reactions of banks to disruptions in the payment system and the way incentives of the central bank can change banks' behavior. The game used in this experiment is a stylized version of a 2006 model of Bech and Garratt in which each bank can choose between paying in the morning (efficient) or in the afternoon (inefficient) and builds on the 2010 game by Abbink *et al.* The results show that a positive (negative) incentive to pay late steers payments to the inefficient (efficient) equilibrium. In contrast to our expectations, providing detailed information on disruptions steers payments toward the inefficient equilibrium.

**Keywords:** payment systems; financial stability; experiment; decision making; central bank intervention.

### **1 INTRODUCTION**

Payment systems play a crucial role in the economy, as they facilitate the settlement of financial obligations of two or more economic actors. Most payment obligations,

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Print ISSN 2049-5404 | Online ISSN 2049-5412  
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particularly very large payments, are settled in these systems. Therefore, such systems must be of a high standard (Committee on Payment and Settlement Systems 2012). During the financial crisis, payment systems functioned well in a technical sense, meaning that there were no serious disruptions. The best known example of a large-scale disruption happened after the terrorist attacks on the World Trade Center in 2001. The damage to property and communication systems made it difficult or even impossible for some banks to execute their payments. The impact of the disruption was not limited to the banks that were directly affected. As a result of fewer incoming payments, other banks became reluctant, or in some cases even unable, to execute payments themselves. The Federal Reserve responded by providing liquidity through the discount window and open market operations.

The fact that banks can pay on time does not necessarily mean they do. Banks can use payment systems differently. If banks start to delay payments, this can seriously hamper payment flows, and in extreme cases cause a gridlock in which every participant in the payment system waits for other participants to make the first payment.<sup>1</sup> As the behavior of banks in a payment system can have serious effects on the liquidity provision between banks, it is important that they behave “appropriately” in these systems. A central bank needs to know how to incentivize such appropriate behavior. Having the right incentives built into payment systems may help to let banks behave in a way that is most suitable for an efficient functioning payment system. Aside from technical problems in these payment systems there are two major reasons why banks do not pay on time.

- (1) An individual bank may have technical problems in its internal system, which makes it unable to execute payments.
- (2) A bank delays its payments intentionally; however, this intention is usually unknown by its counterparties.

The fact that it pays later on the due date does not mean it delays intentionally, as we do not know when the payment obligation was due.<sup>2</sup> Massarenti *et al* (2012) study the timing of TARGET2 payments. They find that most value is transferred in the last

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<sup>1</sup> Even the delay by a very large bank in the system can cause liquidity problems beyond its direct counterparties. Very large banks are called critical participants in TARGET2 and have to implement some additional measures (see European Central Bank 2010). TARGET2 (Trans European Real Time Gross Settlement Express Transfer) is the real-time gross settlement (RTGS) system owned and operated by the Eurosystem.

<sup>2</sup> Diehl (2013) looks at measures to identify free-riding behavior (in other words, delay) of banks in the German part of the European large-value payment system.

business hour of the day. This means that a disruption at this time can have serious consequences:

- as the value is large, a disruption can seriously harm liquidity flows;
- as it is the last hour of the business day, there is little time to solve the disruption and fulfill payment obligations.<sup>3</sup>

Heijmans and Heuver (2014) look at early warning indicators in a large-value payment system (LVPS). They also find that the timing of payments is a crucial indicator for stress.

Timely execution of payments by participants results in reusability of liquidity. The liquidity received from a counterparty can be used to make a bank's own payments. In particular, LVPSs such as TARGET2, which settles each payment immediately (in real time) and individually (gross) demand high liquidity. For central banks it is therefore important that such systems have the right incentives (following from the setup of the payment system) and transparency, or at least no disincentives to pay on time (or early). Bech *et al* (2012) show that the monetary policy by the Federal Reserve during the global financial crisis had the unintended side effect that banks started to pay earlier as there was more (cheap) liquidity available by banks in the American LVPS, Fedwire.

Our study is closely related to the experimental literature on coordination games (see also Abbink *et al* 2010). Pure coordination games involve multiple equilibria with the same payoff consequences, provided all players choose the same action. The players' task is to take cues from the environment to identify focal points (Mehta *et al* 1994; Schelling 1960). More akin to our problem are studies on games with Pareto-ranked equilibria. In these games one equilibrium yields higher payoffs to all players than other equilibria, such that rational players should select it (Harsanyi and Selten 1989). However, experimental subjects often coordinate on inferior equilibria. This happens in particular when the Pareto-dominant equilibrium is risky (Van Huyck *et al* 1990, 1991) as is the case in our research, or other equilibria are more salient (Abbink and Brandts 2008). For an overview of coordination game experiments we refer the reader to Devetag and Ortmann (2007). With the exception of Abbink *et al* (2010), no existing studies tackle the problem of random disruptions.

How can behavior in a payment system that is affected by disruptions be influenced by an authority? A disruption in our experiment is a situation in which one or more players are unable to execute their payments on time. Such a disruption could be due to technical problems or (temporary) financial problems. The influence of the authority

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<sup>3</sup> Although there is the option to postpone the closing time of the system as long as required, it is not likely that the closing time of the system will be postponed because of the technical problems of a few participants.

can be a negative or positive incentive when all players choose the undesired option (ie, delaying payments) or provide information on the disruption. The players are all equal in size, ie, the impact of any player's choices on any other player is constant. The setup of our game is similar to the homogeneous market case of Abbink *et al* (2010), although they also investigate the situation in which not all market participants are equally sized (which they call a heterogeneous market). Our paper builds on this paper by looking at elements that (may) steer the outcome of the game other than the disruption probability.

The outline of this chapter is as follows. Section 2 describes the experimental design (including the game-theoretical model) and the procedures used. Section 3 discusses the results, while Section 4 provides an analysis to explain the observed experimental data. Section 5 provides conclusions.

## 2 EXPERIMENTAL DESIGN AND PROCEDURES

### 2.1 Design

Our design is based on a model by Bech and Garratt (2006), which is an  $n$ -player liquidity management game similar to the setup of Abbink *et al* (2010). The game envisions an economy with  $n$  identical banks which use a real-time gross settlement system operated by the central bank to settle payments and securities. Banks intend to minimize settlement cost. In this game, the business day consists of two periods in which banks can make payments: morning and afternoon. At the beginning of the day banks have a zero balance on their accounts at the central bank. At the start of each business day each bank has a request from customers to pay a customer of each of the other ( $n - 1$ ) banks an amount  $Q$  as soon as possible. To simplify the model, the bank processes all  $n - 1$  payments either in the morning or in the afternoon. If a bank does not have sufficient funds to execute a payment, it can obtain intraday credit, which is costly and reflected by a fee,  $F$ . This fee can be avoided by banks by delaying their payments to the afternoon. With this delay, however, there are some social and private costs involved, indicated by  $D$ . For example, a delay may displease customers or counterparties, which leads to costs in terms of potential claims and reputation risk. Also, in the case of operational disruptions, payments might not be settled by the end of the business day. This disruption can be either a failure of the payment system to operate appropriately or a failure at the bank itself. The costs in this case can, for example, be claims as a result of unsettled obligations or loss of reputation. The trade-off between the cost  $F$  in the case of paying in the morning and cost  $D$  of paying in the afternoon is made by each bank individually. Bech and Garratt (2006) investigate the strategic adjustment banks make in response to temporary disruptions. In particular, they focus on equilibrium selection after the disruption is over.

**TABLE 1** Overview of experimental treatments.

Treatment number	Treatment name	Disruption probability	Forced $Y$ known to others?	Number of groups
1	Baseline	25	No	15
2	Bailout	25	No	14
3	Punishment	25	No	17
4	Information	25	Yes	15

In line with the experiment of Abbink *et al* (2010) we use a simple version of the theoretical model by Bech and Garratt (2006). Because  $F \geq D$  there are two equilibria in pure strategies, assuming each bank maximizes its own earnings. Either all banks pay in the morning or all banks pay in the afternoon. The morning equilibrium is the efficient equilibrium (see Bech and Garratt 2006, Proposition 1). In each of the several rounds of the experiment the banks have to make a choice between paying in the morning (choice  $X$ ) and in the afternoon (choice  $Y$ ). Furthermore, in each round there is a probability of 25% that a bank is forced to pay in the afternoon. This means that the bank cannot pay in the morning, but is forced to delay payment. Before a bank knows it is forced to choose  $Y$ , it has to make a choice (either  $X$  or  $Y$ ). In Abbink *et al* (2010) banks knew directly that they were forced. Letting the participants choose first allows us to analyze the free choice of each participant given the outcome of the previous rounds. The other banks observe that there was a delay at this bank and, depending on the treatment, they either do or do not know whether it was caused by a disruption (a forced  $Y$ ) or a deliberate decision.

Abbink *et al* (2010) investigate the impact of changing disruption probabilities over time, looking at disruption probabilities of 15%, 30% and 45%. They also investigate two different market types: a homogeneous market, in which each player has the same size and therefore the same impact, and a heterogeneous market, in which there is one large player and several smaller ones. Our experiment uses only one disruption probability. Based on the experiences of Abbink *et al*, we chose a probability of 25%, which is large enough to have sufficient disruption events but not so large that it will steer the outcome of the experiment too much toward the inefficient equilibrium.

The ability of an authority, such as a central bank, to steer the outcome of the experiment is the core parameter of the experiment. We implemented the steering of the central bank in three different ways.

- (1) It can give a positive incentive by “rewarding” the participants if they all choose  $Y$ . This is illustrated by the situation of the 9/11 terrorist attacks, when the Federal Reserve injected large sums of liquidity into the system.

- (2) It can give a negative incentive by “punishing” the participants if they all choose  $Y$ . A negative incentive could be an increasing price scheme. If a participant in the payment system pays early (ie, in the morning), the price for the payment is lower than when it pays late (ie, in the afternoon). Similarly, the central bank could introduce a throughput guideline in which a bank has to pay a certain percentage of the payment before, say, 13:00, as is the case in the UK large-value payment system, CHAPS (Clearing House Automated Payment System (see Becher *et al* 2008)). Even though in both examples the incentive would be at individual bank level, the incentive is similar when the whole market chooses to pay late.
- (3) It can provide information to all participants about the disruptions (forced  $Y$ ) of all participants.

Table 1 on the preceding page provides an overview of the different treatments investigated in the experiment. Instructions are presented in Appendix A. After each round, all banks see the choices of the other banks. In treatments (1)–(3) it is not known by the other banks if a bank was forced to pay in the afternoon or chose to do so intentionally. In our experiments, when all participants in treatments (2) and (3) chose  $Y$ , or were forced to, the following message was shown on screen (see Appendix A): “All participants chose  $Y$ . Therefore, the payoff is not 2 but 3 in the bailout and 1 in the punishment treatment”. The experiment consists of fifty-two rounds. The forced  $Y$  are predefined and pseudorandom with a probability of 25%. Each participant faces the same number of forced  $Y$ s.

Table 2 on the facing page shows the earnings of the four different treatments of Table 1 on the preceding page, where  $X$  stands for paying in the morning and  $Y$  for paying in the afternoon. Earnings are determined by a maximum payoff of 5, while  $F = 2$  and  $D = \frac{3}{4}$ . If all participants choose  $Y$ , the  $D$ -value changes to  $\frac{1}{2}$  for the positive incentive treatment and to 1 for the negative incentive treatment.<sup>4</sup> As  $F > D$  for all treatment, the only two Nash equilibria are either all participants pay in the morning (choose  $X$ ) or all participants pay in the afternoon (choose  $Y$ ) (see Bech and Garratt (2006, Proposition 1) for more details).

## 2.2 Procedures

The experiment was run with undergraduate students at the University of Amsterdam using their Center for Research in Experimental Economics and Political Decision Making (CREED) laboratory. Upon arrival, participants were randomly seated in the

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<sup>4</sup> Earnings in the case of paying in the afternoon equal  $-(n - 1)D + 5$ , with  $n$  being the total number of banks. Earnings if the bank instead chooses to pay in the morning equal  $-(n - 1 - |S|)F + 5$ , where  $|S|$  denotes the number of other banks paying in the morning.

**TABLE 2** Pay-off structure of the experimental treatments.

Number of other players choosing <i>X</i>	Number of other players choosing <i>Y</i>	Baseline		Bailout	
		Your earnings from choosing <i>X</i>	Your earnings from choosing <i>Y</i>	Your earnings from choosing <i>X</i>	Your earnings from choosing <i>Y</i>
4	0	5	2	5	2
3	1	3	2	3	2
2	2	1	2	1	2
1	3	-1	2	-1	2
0	4	-3	2	-3	3

Number of other players choosing <i>X</i>	Number of other players choosing <i>Y</i>	Punishment		Information	
		Your earnings from choosing <i>X</i>	Your earnings from choosing <i>Y</i>	Your earnings from choosing <i>X</i>	Your earnings from choosing <i>Y</i>
4	0	5	2	5	2
3	1	3	2	3	2
2	2	1	2	1	2
1	3	-1	2	-1	2
0	4	-3	1	-3	2

laboratory and then the instructions for the experiment were given out. Students could only participate in the experiment once.

The computerized experiment was set up in an abstract way, avoiding suggestive terms such as “banks”. Choices were simply labeled  $X$  and  $Y$ , and forced choices were indicated by  $Y_f$  on the participants’ computer screen. Participants were randomly divided into groups of five students (labeled P1 to P5), whose composition did not change during the experiment. All payoffs were in experimental Talers, which were converted into euro at a fixed exchange rate made known to the participants at the end of the experiment. Each experiment took approximately one hour and the average earnings were €22.97, which included a show-up fee of €5. In total, 305 students participated in the experiment.

### 3 RESULTS

This section describes the results of the four experimental treatments of Table 1 on page 21. We look at choice frequencies and a measure to capture the degree of coordination. “Full coordination” is the situation where all participants make the same choice (either  $X$  or  $Y$ ). Sections 3.1 and 3.2 describe the choice frequencies and the degree of coordination of the treatments, respectively. Section 3.3 gives an insight in the reaction patterns of participants, given the outcome of the previous round.

#### 3.1 Choice frequency

We take a first look at the data by looking at the choice frequencies of the four different treatments, as depicted in parts (a)–(d) of Figure 1 on the facing page. The choices in the figure are represented by four options: the participant can

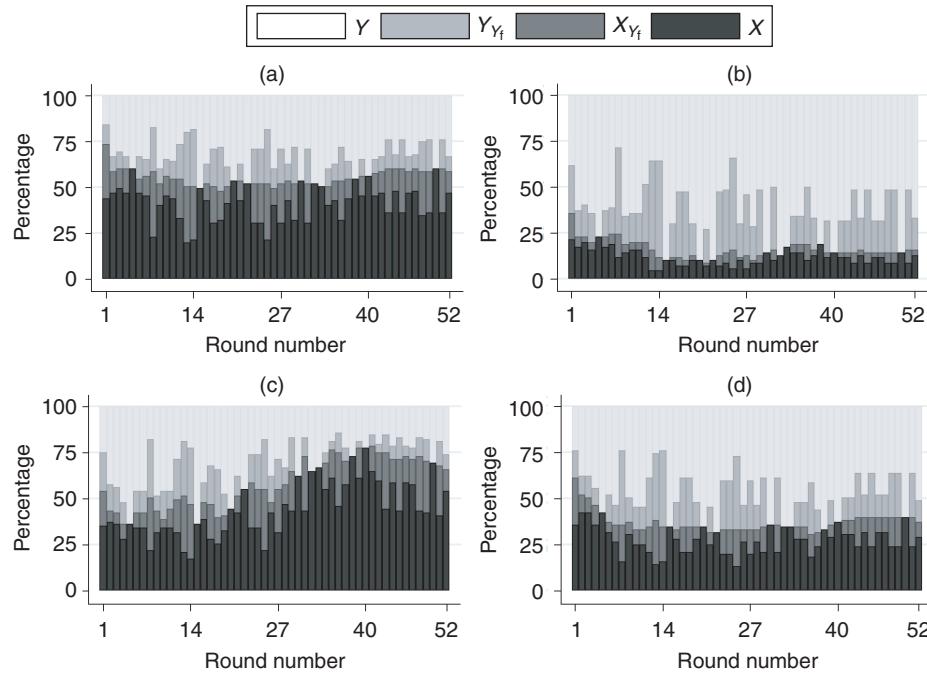
- (1) “choose”  $Y$  initially, but is not forced to choose  $Y$  (baseline,  $Y$ ),
- (2) “choose”  $Y$  initially but is also forced to choose  $Y$  (positive incentive,  $Y_{Y_f}$ ),
- (3) “choose”  $X$  initially but is forced to choose  $Y$  (negative incentive,  $X_{Y_f}$ ) or
- (4) “choose”  $X$  initially but is not forced to choose  $Y$  (information,  $X$ ).

This representation allows for analysis of both the participants’ actual or initial responses (called  $X_{\text{ini}}$  or  $Y_{\text{ini}}$ ) and the final outcome (including disruption) of previous rounds (called  $X_{\text{fin}}$  or  $Y_{\text{fin}}$ ).<sup>5</sup>

Table 3 on page 26 and Figure 1 on the facing page show that for the baseline treatment (part (a)) the participants choose  $X_{\text{ini}}$  55% of the time. This choice stays

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<sup>5</sup> Final outcome is defined by  $Y_{\text{fin}} = X_{Y_f} + Y_{Y_f} + Y$  and  $X_{\text{fin}} = X$ ; initial choice is defined by  $Y_{\text{ini}} = Y + Y_{Y_f}$  and  $X_{\text{ini}} = X + X_{Y_f}$ .

**FIGURE 1** Frequency plots for choosing  $X$  or  $Y$  for the four treatments.

(a) Baseline. (b) Positive incentive. (c) Negative incentive. (d) Information.

constant over the whole experiment (there is no significant difference between the first and second half of the experiment). Due to the disruption probability of 25%,  $X_{\text{fin}}$  is 42%. The bailout treatment (part (b) of Figure 1) shows that the number of participants choosing  $X_{\text{ini}}$  drops to 16% compared with the baseline. A drop is not surprising, as it becomes more profitable for banks if they all coordinate on  $Y$ . The punishment treatment (part (c) of Figure 1), on the other hand, shows an increase of the  $X_{\text{ini}}$  to on average 58%. An increase was expected as it becomes less profitable for banks to all choose  $Y$  under this treatment. Although the average  $X_{\text{ini}}$  of the punishment treatment is above the baseline, there are clear differences between rounds. In contrast to the baseline treatment, the punishment treatment shows a significant increase between the first and second twenty-six rounds, from 46% to 70%, respectively ( $p < 0.01$ , binomial test). The first half of the experiment is lower and the second half has a higher choice frequency than the Baseline treatment. This could be seen as a learning effect. This suggests that the participants realize that if they coordinate on  $Y$ , this is less profitable for everyone. In other words, the results suggest that it is possible

**TABLE 3** Average choices of  $X$  per treatment.

Treatment	$X_{\text{ini}}$			$X_{\text{fin}}$		
	Rounds 1–26	Rounds 27–52	All rounds	Rounds 1–26	Rounds 27–52	All rounds
Baseline	54	56	55	40	43	42
Bailout	17	15	16	12	12	12
Punishment	46	70	58	34	55	45
information	38	37	38	27	28	28

All values are percentages.

to steer the equilibrium by setting a negative incentive (punishment) for collective undesired behavior (coordinating on  $Y$ ).

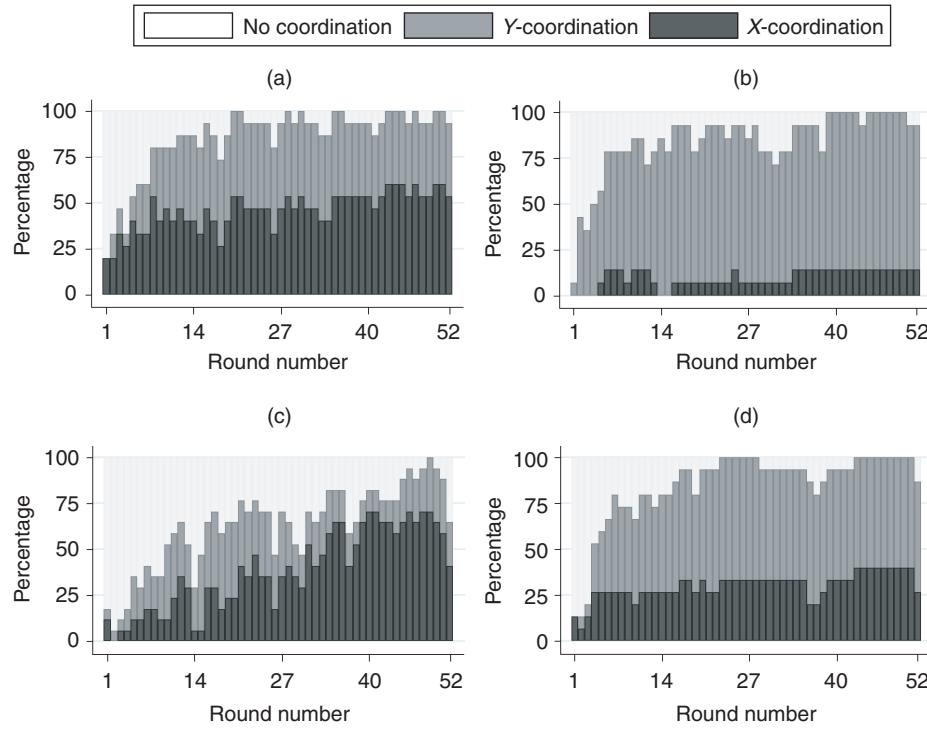
The information treatment (part (d) of Figure 1 on the preceding page) shows, in contrast to our expectation, that participants choose  $X_{\text{ini}}$  less often than the baseline case (28% versus 54%). This may be explained as follows. In contrast to the other treatments, participants are now aware of the deliberate or disrupted  $Y$ . If they see a deliberate  $Y$  among forced  $Y$ s, they are more in favor of also choosing  $Y$  in the next round, while in the baseline treatment they still may expect that some of the intentional  $Y$ s are forced and therefore be more in favor of choosing  $X$  in the next round. The question is, however, whether this principle is also true if disruptions only occur occasionally, as is the case for LPSSs. In LPSSs, participants might be reluctant to believe it was a disruption, unlike the experiment.

### 3.2 Frequencies of full coordination

Figure 2 on the facing page depicts the frequency with which full coordination on either  $X$  or  $Y$  is achieved. Full coordination means that all participants in a group choose either  $X_{\text{ini}}$  or  $Y_{\text{ini}}$  (the choice of the participants before the disruption). A general observation on the coordination of the four different treatments is that each treatment moves to (almost) 100% coordination either on  $X$  or  $Y$ . In most cases an individual group moves to full coordination on either  $X$  or  $Y$ . For the baseline, bailout and information treatments this coordination starts in the first half of the experiment, while for the punishment treatment this only seems to begin in the later rounds of the experiment. Besides, it is not as persistent in this treatment as in the other treatments.

The baseline treatment (part (a) of Figure 2 on the facing page) shows that coordination on  $X$  increases from roughly 25% to 50%. The coordination on either  $X$  or  $Y$  increases in the first twenty rounds to (almost) 100% and remains close to 100% coordination.

**FIGURE 2** Frequency plots of full coordination for coordination on  $X$  or  $Y$  (before disruptions) for the four treatments.



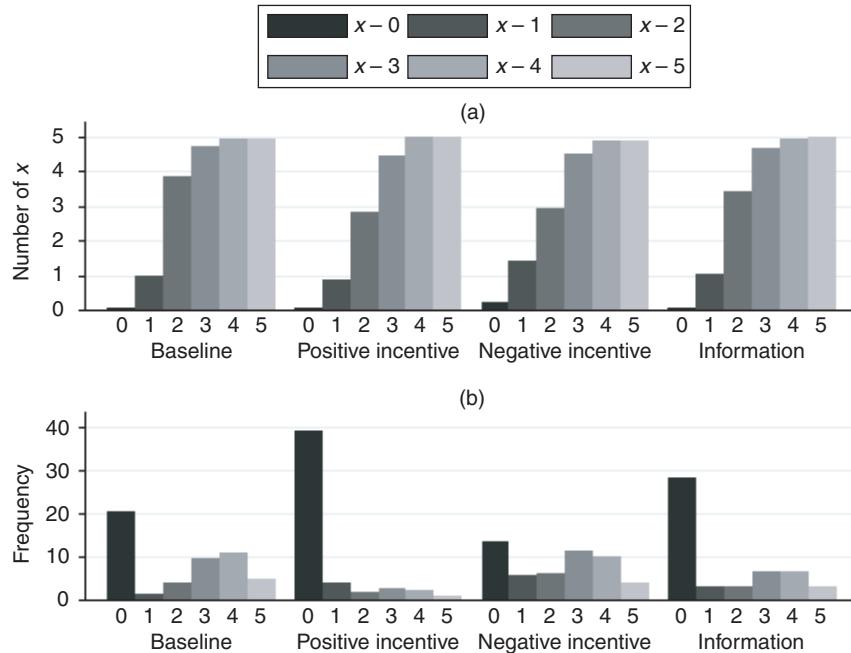
(a) Baseline. (b) Positive incentive. (c) Negative incentive. (d) Information.

The bailout treatment (part (b) of Figure 2), on the other hand, shows only little coordination on  $X$ . The positive incentive if everyone chooses  $Y$  steers choices toward the inefficient equilibrium.

The punishment treatment (part (c) of Figure 2) clearly shows an increasing trend of coordination on  $X$ , which is in line with the increase in frequency of choice  $X$  (see part (c) of Figure 1 on page 25). This again suggests that steering the equilibrium in the payment system is possible by having a negative incentive (lower reward) for collective undesired behavior. The trend of moving toward (almost) 100% coordination is much slower than for the other treatments.

The information treatment (part (d) of Figure 2) shows less coordination on  $X$  but similar trends in moving to 100% coordination on either  $X$  or  $Y$  than the baseline treatment.

**FIGURE 3** (a) The average number of participants choosing  $X$  in round  $n$  if the outcome in round  $n - 1$  was 0, 1 $X$ , 3 $X$ , 4 $X$  or 5 $X$  and (b) the number of times that the number of  $X$  choices was 0, 1, 2, 3, 4 or 5 for each of the four treatments.



### 3.3 Reaction patterns

Part (a) of Figure 3 shows the average number of participants choosing  $X$  in round  $n$ , given the number of participants that chose  $X$  and were able to choose  $X$  in round  $n - 1$ . The choice of a participant who was forced to choose  $Y$  is set to  $Y$  no matter the actual choice. This graph shows that if four or five of the five participants have chosen  $X$  and are not forced to choose  $Y$  in the previous round (round  $n - 1$ ), (almost) all five will choose  $X$  in the current round (round  $n$ ) in each of the four treatments. When three out of five participants have chosen  $X$  and are not forced to choose  $Y$  in the previous round, on average 4.5 participants will choose  $X$  in the current round. The differences between the four treatments are small. The largest difference between the four treatments occurs when two out of five participants choose  $X$  in the previous round. In the current round 4, 3, 3 and 3.5 participants will choose  $X$  for treatments (1), (2), (3) and (4), respectively. In the situation where all participants have chosen (or were forced to choose)  $Y$ , participants will keep on choosing  $Y$  in the next round.

This means that once the participants coordinate on  $Y$  it is not likely that they will move away from that equilibrium.

Part (b) of Figure 3 on the facing page shows the number of times a round consisted of, on average, 0, 1 $X$ , 2 $X$ , 3 $X$ , 4 $X$  or 5 $X$ . In other words, it shows the likelihood of the combination of the  $X$  and  $Y$  choices per round in the different treatments. The outcome is in line with the choice frequencies presented by Figure 1 on page 25. The baseline treatment shows that all participants in the group choose  $Y$  in twenty out of the fifty-two rounds. In the bailout treatment this is almost forty out of fifty-two rounds (or close to 75%); in the punishment treatment this is thirteen out of fifty-two and in the information treatment this is almost thirty out of fifty-two.

Combining the information from the two graphs in Figure 3 on the facing page, we learn that a group that coordinates on the inefficient equilibrium (all  $Y$ ) will not return easily to the desired equilibrium, which is in line with the findings of Abbink *et al* (2010). This is equal for all treatments. But the likelihood of reaching the inefficient equilibrium varies greatly between the different treatments. In other words, we might not be able to move them away from the inefficient equilibrium with the incentives, but we can partly prevent the participants from reaching this equilibrium.

#### 4 DYNAMICS

The results show that positive (bailout treatment) steers the equilibrium more to the undesired ( $Y$ ) equilibrium. The negative incentive (punishment treatment) steers it more to the desired ( $X$ ) one. The information treatment unexpectedly leads to more coordination on the undesired equilibrium. This section studies some possible simple dynamics.

We follow the reasoning of Abbink *et al* (2010), who study simple dynamics that may explain the patterns of behavior we have observed. They use an agent-based model to analyze possible adaptation heuristics.<sup>6</sup> The primary goal is to study the behavior of decentralized decision making of complex systems. The simulated agents adapt their behavior as a response to feedback they receive from the simulated strategic interaction (such as financial markets) about the success of their previous choices. In general, successful choices are more likely to be reinforced.

The literature on the use of agent-based modeling in the behavior of payment systems is still limited. Alexandrova-Kabadjova *et al* (2007) developed an agent-based model of the competition between payment cards by focusing on the interactions between consumers and merchants, which determine the subscription and usage of cards. In the realm of LVPSs, Galbiati and Soramäki (2011) implemented a model

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<sup>6</sup> Agent-based modeling is a rapidly developing field grounded in biological, social and other sciences (see, for example, Cristelli 2013; LeBaron 2006; Miller and Page 2007).

of a real-time gross settlement system and analyze its response to payment delays, but they do not look at disruptive shocks. Arciero *et al* (2009) introduced a model to simulate the response of large-value payment systems to disruptive events.

We start this section with a behavioral rule which has limited rationality (see Section 4.1). Sections 4.2–4.4 show more advanced heuristics.

#### 4.1 Stick to your choice

The first “heuristic” we look at is a relatively simple one. Each player makes the same choice as in the last round; in other words, they stick to their previous choice. With a probability  $\beta$  the player experiments and chooses the other option. The “stick to your choice” heuristic only contains very limited rationality, and is slightly more advanced than random choices.

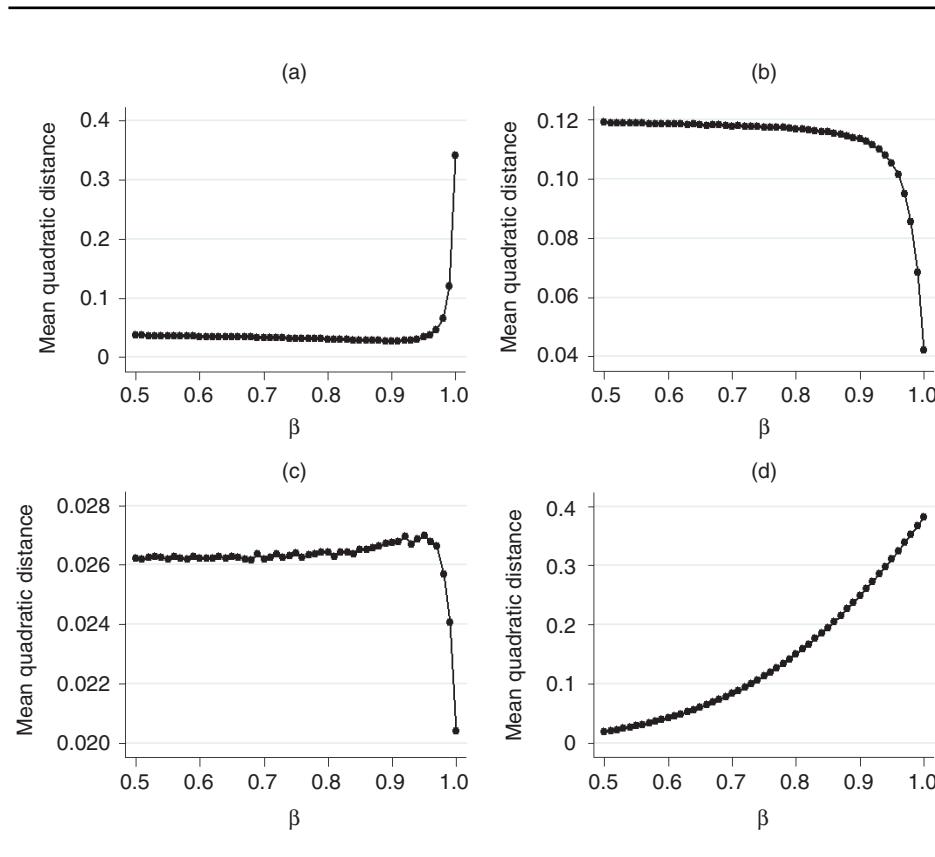
The behavior of the players can be summarized as follows.

- (1) In period 1, each player chooses  $X$  with the exogenous initial propensity  $\alpha$ ,  $Y$  with probability  $1 - \alpha$ .
- (2) In every following period  $t$ ,
  - (a) with probability  $\beta$  each player chooses the option that has been most successful in period  $t - 1$ ,
  - (b) with probability  $1 - \beta$ , the player chooses the other option.

The basic principle of this behavior is valid for all heuristics mentioned in this section.

In contrast to Abbink *et al* (2010) we do not show the result for just a few  $\beta$ . Figure 6 on page 33 shows, for  $\beta = 0.5, \dots, 1$  the quadratic difference between the imitation heuristic and the actual outcome of the experiment for each of the four treatments. We intentionally start from 0.5 instead of 0, because values lower than 0.5 suggest that players experiment more often than they follow the rule, which we do not deem plausible.

Figure 4 on the facing page shows the results for the “stick to your choice” heuristic. The  $\beta$  values for treatments (1) and (4) are 0.89 and 0.61, respectively. The  $\beta$  values for treatments (2) and (3) are both 1. This means that the players in these two treatments always follow the heuristic and never experiment. Figure 5 on page 32 shows for the best possible  $\beta$  of Figure 4 the fraction of  $X$  according to the “stick to your choice” heuristic and the actual experiment. The heuristic follows the actual experiment quite well for treatment (1). For treatments (2) and (4) the heuristic overestimates the choices of  $X$ . For treatment (3) the heuristic slightly overestimates in the first half of the experiment, while it underestimates in the second half. We can conclude that this heuristic only gives reliable results for treatment (1).

**FIGURE 4** Results for the “stick to your choice” heuristic: sum of squares.

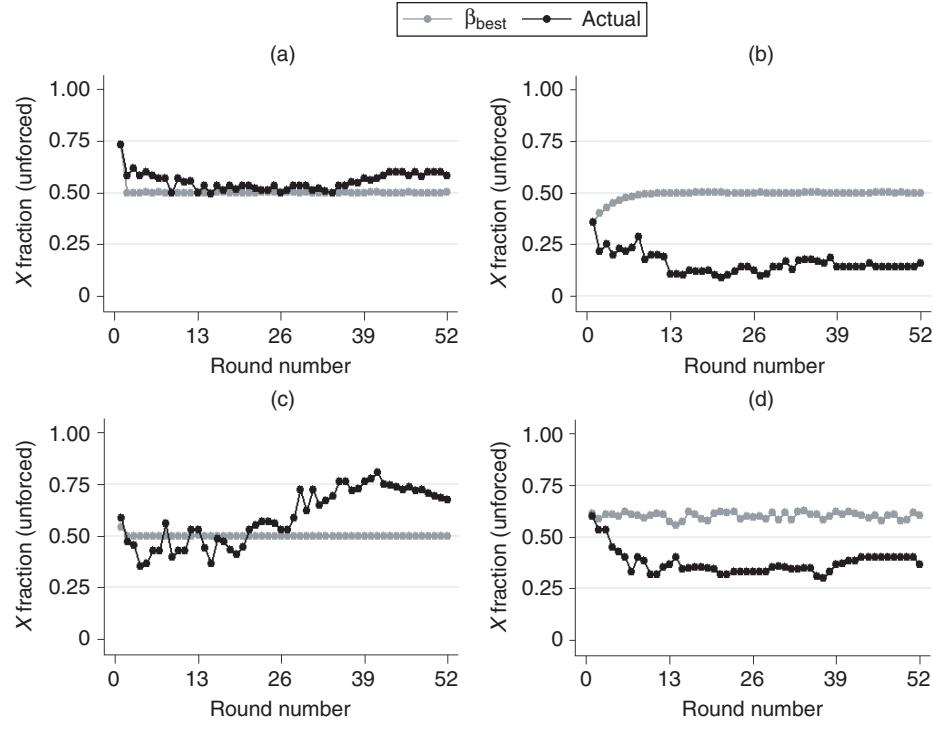
(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

## 4.2 Imitation

Imitation can be seen as a simple heuristic. It ignores higher level strategic behavior. It was successful in explaining the observed behavior in Crawford (1995) and Abbink and Brandts (2008). A player following this strategy simply compares the payoffs all players gained in the previous period and copies the behavior of whoever was most successful.

We now study the predictions of a dynamic model based on the imitation heuristic. The players in such a model primarily follow the pattern of imitation. However, the model has to be complemented with some experimentation. Otherwise the game would be locked after the second round and nothing would change. In other words, with some probability  $\beta$  the player will follow the imitation pattern and with probability  $1 - \beta$

**FIGURE 5** Results for the “stick to your choice” heuristic: fraction.

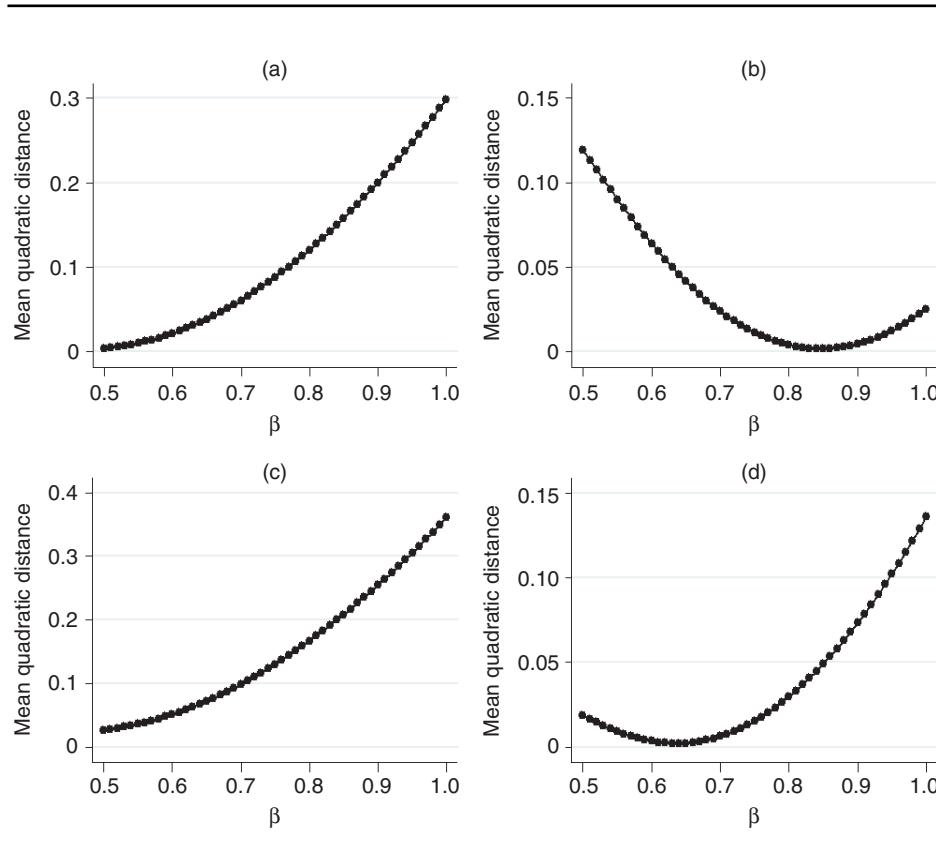


(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

the player will randomly choose one of the other strategies. As in this case we only have one other strategy, they will choose the opposite strategy.

The best possible  $\beta$  value for treatments (1) and (3) is 0.5. This means that in 50% of the cases the player chooses to follow the rule and in 50% they experiment. The  $\beta$  values for treatments (2) and (4) are 0.85 and 0.64, respectively.

Figure 7 on page 34 shows, for the best possible  $\beta$  from Figure 6 on the facing page, the fraction of  $X$  according to the actual experiment and the imitation heuristics with this  $\beta$ . We can see that the heuristic follows the actual experiment quite closely for treatments (1), (2) and (4). However, for treatment (3) it does not. This suggests that for treatment (3) there is no plausible  $\beta$  for the imitation heuristic that follows the actual outcome of the experiment. The closer the mean quadratic distance is to zero, the better the heuristics fits the real experiment. However, the mean quadratic distance is not constant over the whole experiment. This means that the heuristic model does

**FIGURE 6** Results for imitation heuristic: sum of squares.

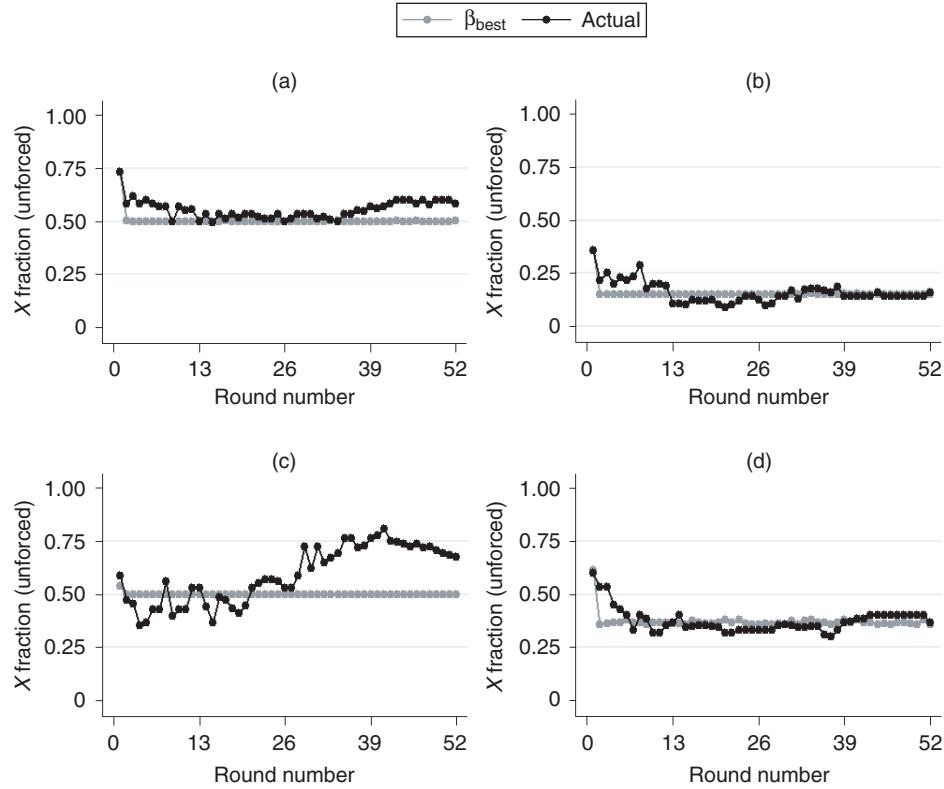
(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

not fit the outcome of the experiment as well for each round. This is especially clear for treatment (3), where the deviation varies substantially.

### 4.3 Myopic best response

The second simple heuristic we study is the myopic best response, which is similar to imitation. However, myopic best response follows a very different reasoning than imitation, since it compares hypothetical instead of observed choices. A player looks at all the other players' choices in the preceding round and chooses the option that would have been optimal in the light of this combination of choices. Again, an experiment parameter ensures that behavior does not get locked in to a pattern after the first round.

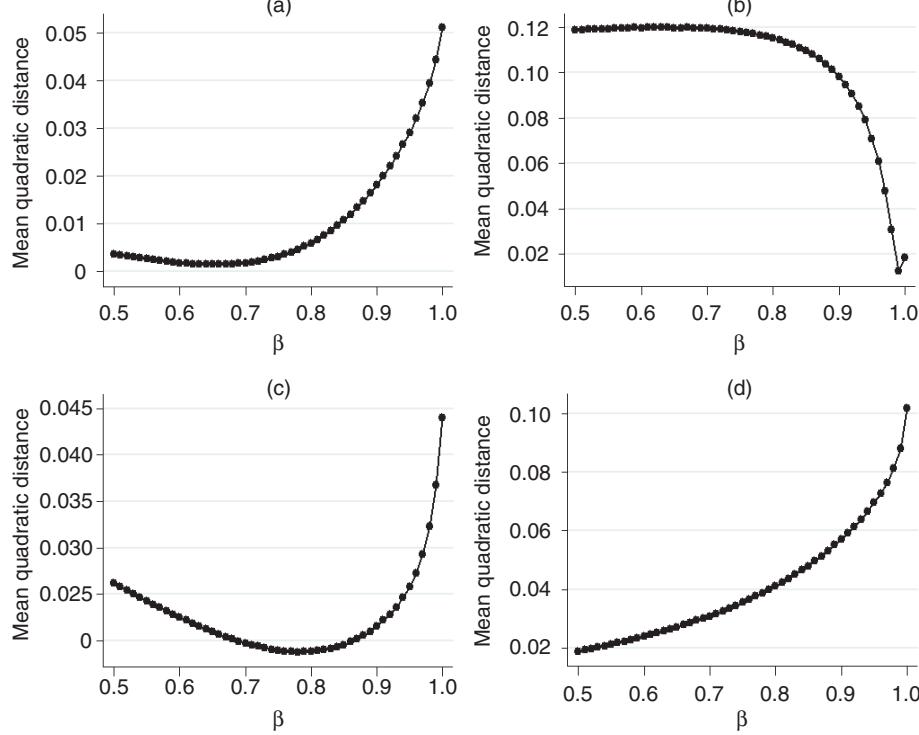
**FIGURE 7** Results for imitation heuristic: fraction.



(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

Figure 8 on the facing page shows, for  $\beta = 0.5, \dots, 1$ , the quadratic difference between the myopic best response heuristic and the actual outcome of the experiment for each of the four treatments. The best possible  $\beta$  values for treatments (1)–(4) are 0.66, 0.99, 0.76 and 0.50, respectively. The closer the mean quadratic distance is to zero, the better the heuristics fit the real experiment.

Figure 9 on page 36 shows for the best possible  $\beta$  from Figure 8 on the facing page, the fraction of  $X$  according to the actual experiment and the imitation heuristics with this  $\beta$ . The best fit of this heuristic is for treatment (1), as the two lines follow each other quite closely. For treatments (2) and (3) the lines do not follow each other closely and fluctuate over the course of the experiment. This suggests that this heuristic is not such a good predictor. For treatment (4) the best  $\beta$  overestimates the actual values for almost all rounds.

**FIGURE 8** Results for myopic best response heuristic: sum of squares.

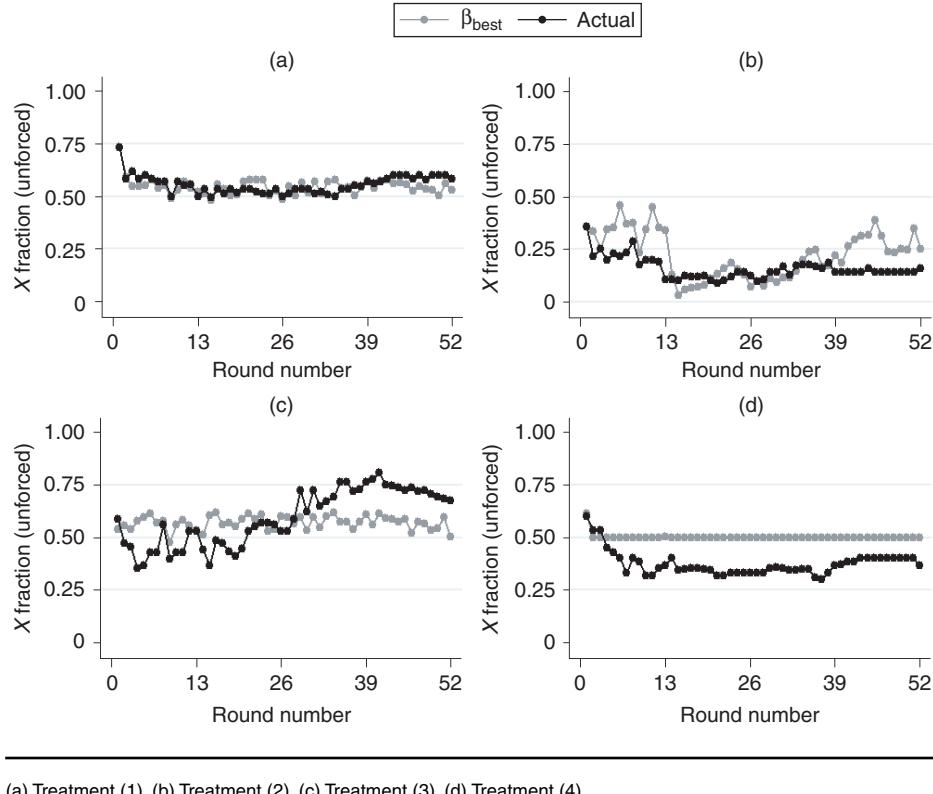
(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

#### 4.4 “Choose $X$ when profitable”

In line with Abbink *et al* (2010) we also look at the heuristic “choose  $X$  when profitable”. The failure of the previous models to predict our data can be ascribed to their high sensitivity to  $Y$  choices observed. As soon as players observe more than one  $Y$ , they switch to the inefficient equilibrium and are unlikely to get out of it again. It is noteworthy that, with two  $Y$  choices, those who chose  $X$  still made a profit of 1, though it is no longer the best response to choose  $X$ .

Figure 10 on page 37 shows, for  $\beta = 0.5, \dots, 1$ , the quadratic difference between the “choose  $X$  when profitable” heuristic and the actual outcome of the experiment for each of the four treatments. The best possible  $\beta$  values for treatments (1)–(4) are 0.57, 0.50, 0.62 and 0.50, respectively. The closer the mean quadratic distance is to zero, the better the heuristics fits the real experiment.

**FIGURE 9** Results for myopic best response heuristic: fraction.



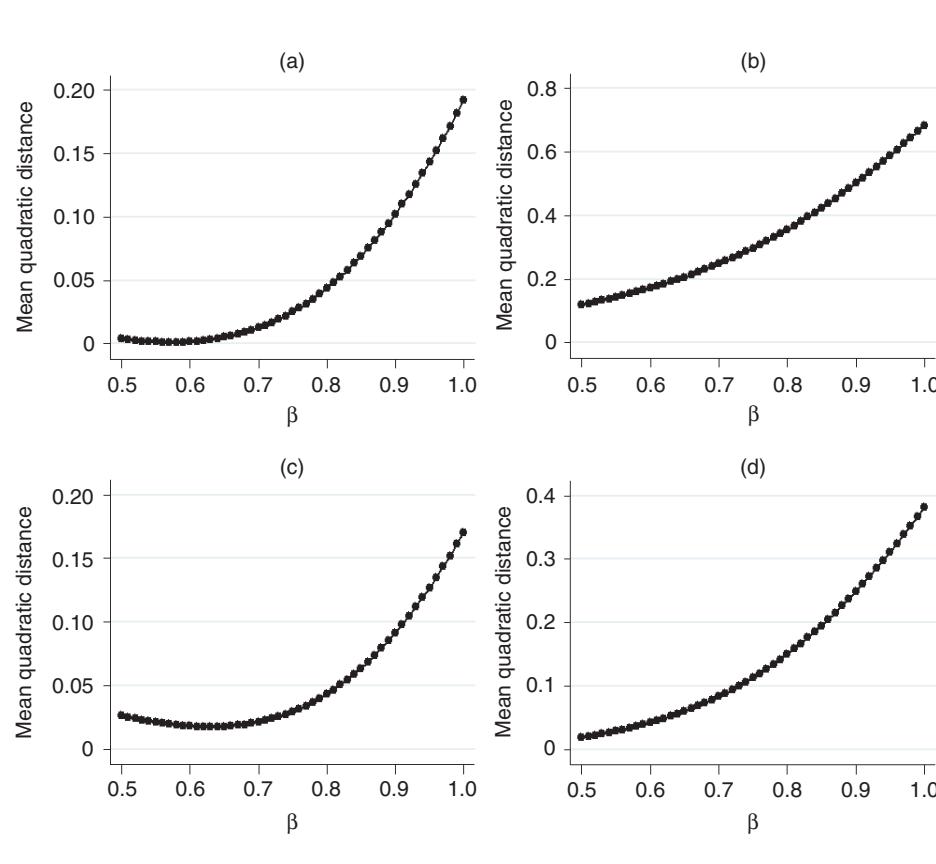
(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

Figure 11 on page 38 shows, for the best possible  $\beta$  from Figure 10 on the facing page, the fraction of  $X$  according to the actual experiment and the “choose  $X$  when profitable” heuristics with this  $\beta$ .

## 5 CONCLUSIONS

In this paper we used a stylized coordination game of Bech and Garratt (2006) to experimentally study bank behavior in a large-value payment system that is hindered by disruptions. The game builds on that of Abbink *et al* (2010). We draw the following conclusions.

First, once player behavior moves in the direction of coordination on the inefficient equilibrium, it is not likely that it returns to the efficient equilibrium. This is in line with the outcome of Abbink *et al* (2010). The reason for this is that one player has to

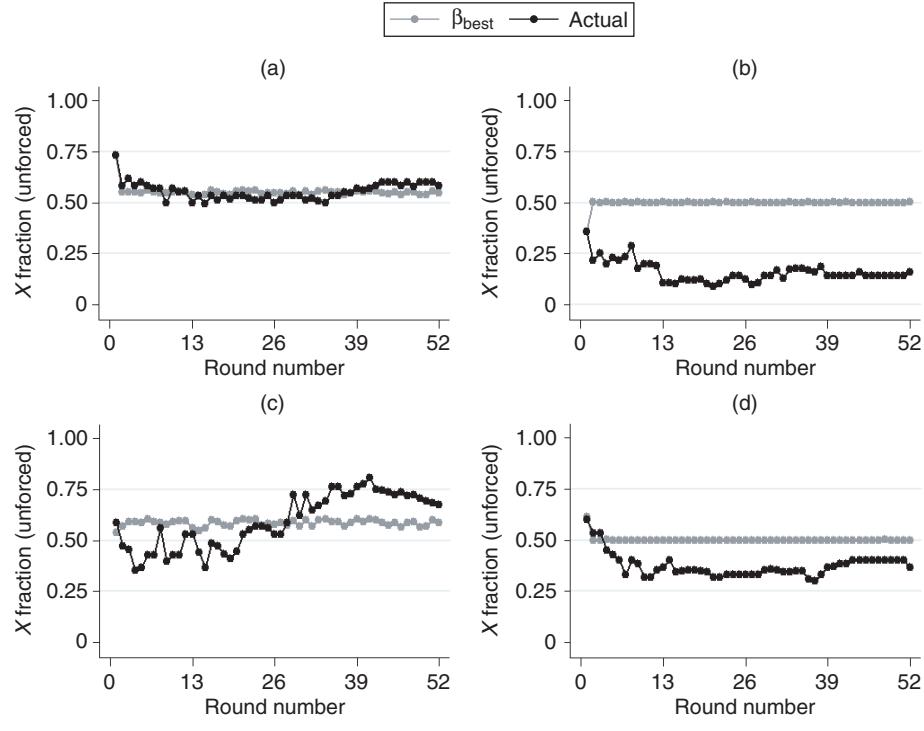
**FIGURE 10** Results for “choose  $X$  when profitable” heuristic: sum of squares.


(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

take the lead in going for the efficient equilibrium, but this is costly if other players do not follow.

Analysis of different types of heuristics shows that the heuristic that fits our data best differs between treatments. This means that there is no single heuristic that best fits all treatments. For the baseline treatment the “stick to your choice” and “choose  $X$  when profitable” heuristics fit the data best. The baseline treatment is similar to the homogeneous case of Abbink *et al* (2010) (the disruption percentage is different, however). For the bailout treatment the imitation heuristic performs best. The “choose  $X$  when profitable” heuristic performs the worst. For the punishment treatment none of the heuristics performs well. For the information treatment imitation performs the best.

**FIGURE 11** Results for “choose  $X$  when profitable” heuristic: fraction.



(a) Treatment (1). (b) Treatment (2). (c) Treatment (3). (d) Treatment (4).

An intervention or action from the central bank affects the average choice of  $X$ . If participants know that they will be “punished” for collective undesired behavior (ie, all participants choose  $Y$ ), they will more likely choose  $X$ . A bailout, on the other hand, will make participants choose  $Y$  more often. The outcome of the punishment and bailout treatment is in line with the expectation. Surprisingly, in the punishment treatment, the average  $X$  in the second half of the experiment is significantly larger than in the first half (46% versus 70%). However, as for the other treatments, as soon as all banks choose  $Y$ , the participants will keep on choosing  $Y$ . This suggests that a negative incentive for collective undesired behavior keeps participants from moving to the undesired equilibrium (ie, all  $Y$ ), but as soon as the undesired equilibrium has been reached they will stay there. In other words, an authority can build incentives into their payment system to partly prevent participants collectively making undesired choices, but it still needs an additional mechanism to move participants back to desired behavior as soon as all participants make the undesired choices simultaneously.

Contrary our expectation, providing information on the forced  $Y$ s leads to more coordination on the undesired equilibrium. This suggests that an authority must be careful when or how to provide information on (short-term) disruptions, as it may lead to an undesired effect.

## APPENDIX A. INSTRUCTIONS TO PARTICIPANTS

### A.1 Baseline treatment

#### A.1.1 *Introduction*

Welcome to the experiment. In the experiment you will make decisions. You can earn money by participating in the experiment. How much you earn depends on your own decisions and on the decisions of other participants in the experiment. At the end of the experiment, a show-up fee of €5 plus your total earnings during the experiment will be paid to you in cash. Payments are confidential: we will not inform participants of the earnings of other participants. In the experiment, all earnings will be expressed in Talers, which will be converted into euro according to the exchange rate

$$1 \text{ Taler} = 16\text{¢}.$$

In this experiment you can avoid making any loss (negative earnings). However, note that if you end up with a loss, it will be charged against your show-up fee. At the end of the experiment, your cash reward is always either 0 or a positive amount in euro. It is not possible that you end up with a negative cash reward.

It is not permitted to talk or communicate with others during the experiment. If you have a question, please raise your hand and we will come to your desk to answer you.

#### A.1.2 *Groups*

During the experiment you will participate in a group of five players. You will be matched with the same players throughout the experiment. In the experiment, you will be identified as “P1”. The other players in your group will be labeled “P2”, “P3”, “P4” and “P5”. You will not be informed who the other players are, nor will they be informed of who you are.

#### A.1.3 *Rounds*

The experiment consists of fifty-two rounds. In each round you and the other four players in your group choose one of two options:  $X$  or  $Y$ .

**TABLE A.1**

Number of other players choosing $Y$	Your earnings from choosing $X$	Your earnings from choosing $Y$
0	5	2
1	3	2
2	1	2
3	-1	2
4	-3	2

#### A.1.4 Earnings

Your earnings in a round depend on your choice and on the choices of the other four players, in the following way:

- if you choose  $Y$ , your earnings are 2 Talers regardless of the choices of the others;
- if you choose  $X$ , your earnings depend on how many of the other players choose  $Y$ .

Your exact earnings in Talers from choosing  $X$  or  $Y$ , for a given number of other players choosing  $Y$ , are listed in Table A.1. This earnings table is the same for all players.

For example, if two other players choose  $Y$ , then your earnings from choosing  $X$  will be 1, while your earnings from choosing  $Y$  would be 2.

#### A.1.5 Forced $Y$

Note, however, that your preferred option may not be possible. In each round, each of you will face a 25% chance that you are forced to choose option  $Y$ . We will call this a “forced  $Y$ ”. After you have made your preferred choice, you will see whether your option is possible or not.

Whether or not a player is forced to choose  $Y$  is randomly determined by the computer for each player separately and independently from the other players. Further, a forced  $Y$  does not depend on what happened in previous rounds.

For your convenience, on the computer screen where you make your decision you will be reminded of the chance of playing a forced  $Y$ . Furthermore, in the table at the bottom of that screen (showing past decisions and earnings) your forced  $Y$  are indicated by an ‘F’ in the column showing your choices. Note that you will not be informed of other players’ forced  $Y$  choices.

### A.1.6 Exercises

You are now kindly requested to do a few exercises on the computer to make yourself fully familiar with the earnings table. In these exercises you cannot earn any money. The exercises are not part of the fifty-two rounds of the experiment.

### A.1.7 Start of the experiment

After the exercises, we will start the experiment.

If you have a question, please raise your hand and we will come to your desk to answer you.

## A.2 Bailout treatment

### A.2.1 Introduction

Welcome to the experiment. In the experiment you will make decisions. You can earn money by participating in the experiment. How much you earn depends on your own decisions and on the decisions of other participants in the experiment. At the end of the experiment, a show-up fee of €5 plus your total earnings during the experiment will be paid to you in cash. Payments are confidential: we will not inform participants of the earnings of other participants. In the experiment, all earnings will be expressed in Talers, which will be converted into euro according to the exchange rate

$$1 \text{ Taler} = 16\text{¢}$$

In this experiment you can avoid making any loss (negative earnings). However, note that if you end up with a loss, it will be charged against your show-up fee. At the end of the experiment, your cash reward is always either 0 or a positive amount in euro. It is not possible that you end up with a negative cash reward.

It is not permitted to talk or communicate with others during the experiment. If you have a question, please raise your hand and we will come to your desk to answer you.

### A.2.2 Groups

During the experiment you will participate in a group of five players. You will be matched with the same players throughout the experiment. In the experiment, you will be identified as “P1”. The other players in your group will be labeled “P2”, “P3”, “P4” and “P5”. You will not be informed who the other players are, nor will they be informed of who you are.

### A.2.3 Rounds

The experiment consists of fifty-two rounds. In each round you and the other four players in your group choose one of two options: *X* or *Y*.

**TABLE A.2**

Number of other players choosing $Y$	Your earnings from choosing $X$	Your earnings from choosing $Y$
0	5	2
1	3	2
2	1	2
3	-1	2
4	-3	2

#### A.2.4 Earnings

Your earnings in a round depend on your choice and on the choices of the other four players, in the following way:

- if you choose  $Y$ , your earnings are 2 Talers regardless of the choices of the others;
- if you choose  $X$ , your earnings depend on how many of the other players choose  $Y$ .

Your exact earnings in Talers from choosing  $X$  or  $Y$ , for a given number of other players choosing  $Y$ , are listed in Table A.2. This earnings table is the same for all players.

For example, if two other players choose  $Y$ , then your earnings from choosing  $X$  will be 1, while your earnings from choosing  $Y$  would be 2.

#### A.2.5 Forced $Y$

Note, however, that your preferred option may not be possible. In each round, each of you will face a 25% chance that you are forced to choose option  $Y$ . We will call this a “forced  $Y$ ”. After you have made your preferred choice, you will see whether your option is possible or not.

Whether or not a player is forced to choose  $Y$  is randomly determined by the computer for each player separately and independently from the other players. Further, a forced  $Y$  does not depend on what happened in previous rounds.

For your convenience, on the computer screen where you take your decision you will be reminded of the chance of playing a forced  $Y$ . Furthermore, in the table at the bottom of that screen (showing past decisions and earnings) your forced  $Y$  are indicated in the column showing your choices with an “F”. Note that you will not be informed of other players’ forced  $Y$  choices.

#### A.2.6 Intervention

If in a round of the experiment all players choose  $Y$  or are forced to choose  $Y$ , there will be an intervention. In this round, all player's choices will be reset to  $X$ . According to the payoff table, your payoff in this round will be 3. The intervention lasts only one round, but could happen multiple times during the experiment.

#### A.2.7 Exercises

You are now kindly requested to do a few exercises on the computer to make you fully familiar with the earnings table. In these exercises you cannot earn any money. The exercises are not part of the fifty-two rounds of the experiment.

#### A.2.8 Start of the experiment

After the exercises, we will start the experiment.

If you have a question, please raise your hand and we will come to your desk to answer you.

### A.3 Punishment treatment

#### A.3.1 Introduction

Welcome to the experiment. In the experiment you will make decisions. You can earn money by participating in the experiment. How much you earn depends on your own decisions and on the decisions of other participants in the experiment. At the end of the experiment, a show-up fee of €5 plus your total earnings during the experiment will be paid to you in cash. Payments are confidential: we will not inform participants of the earnings of other participants. In the experiment, all earnings will be expressed in Talers, which will be converted into euro according to the exchange rate

$$1 \text{ Taler} = 16\text{¢}$$

In this experiment you can avoid making any loss (negative earnings). However, note that in case you end up with a loss, it will be charged against your show-up fee. At the end of the experiment, your cash reward is always either 0 or a positive amount in euro. It is not possible that you end up with a negative cash reward.

It is not permitted to talk or communicate with others during the experiment. If you have a question, please raise your hand and we will come to your desk to answer you.

#### A.3.2 Groups

During the experiment you will participate in a group of five players. You will be matched with the same players throughout the experiment. In the experiment, you

**TABLE A.3**

Number of other players choosing $Y$	Your earnings from choosing $X$	Your earnings from choosing $Y$
0	5	2
1	3	2
2	1	2
3	-1	2
4	-3	2

will be identified as “P1”. The other players in your group will be labeled “P2”, “P3”, “P4” and “P5”. You will not be informed who the other players are, nor will they be informed of who you are.

### A.3.3 Rounds

The experiment consists of fifty-two rounds. In each round you and the other four players in your group choose one of two options:  $X$  or  $Y$ .

### A.3.4 Earnings

Your earnings in a round depend on your choice and on the choices of the other four players, in the following way:

- if you choose  $Y$ , your earnings are 2 Talers regardless of the choices of the others;
- if you choose  $X$ , your earnings depend on how many of the other players choose  $Y$ .

Your exact earnings in Talers from choosing  $X$  or  $Y$ , for a given number of other players choosing  $Y$ , are listed in Table A.3. This earnings table is the same for all players.

For example, if two other players choose  $Y$ , then your earnings from choosing  $X$  will be 1, while your earnings from choosing  $Y$  would be 2.

### A.3.5 Forced $Y$

Note, however, that your preferred option may not be possible. In each round, each of you will face a 25% chance that you are forced to choose option  $Y$ . We will call this a “forced  $Y$ ”. After you have made your preferred choice, you will see whether your option is possible or not.

Whether or not a player is forced to choose  $Y$  is randomly determined by the computer for each player separately and independently from the other players. Further, a forced  $Y$  does not depend on what happened in previous rounds.

For your convenience, on the computer screen where you take your decision you will be reminded of the chance of playing a forced  $Y$ . Furthermore, in the table at the bottom of that screen (showing past decisions and earnings) your forced  $Y$  are indicated by an “F” in the column showing your choices. Note that you will not be informed of other players’ forced  $Y$  choices.

#### *A.3.6 Intervention*

If in a round of the experiment all players choose  $Y$  or are forced to choose  $Y$ , there will be an intervention. In this round, all player’s choices will be reset to  $X$ . According to the payoff table, your payoff in this round will be 1. The intervention lasts only one round, but could happen multiple times during the experiment.

#### *A.3.7 Exercises*

You are now kindly requested to do a few exercises on the computer to make you fully familiar with the earnings table. In these exercises you cannot earn any money. The exercises are not part of the fifty-two rounds of the experiment.

#### *A.3.8 Start of the experiment*

After the exercises, we will start the experiment.

If you have a question, please raise your hand and we will come to your desk to answer you.

### **A.4 Information treatment**

#### *A.4.1 Introduction*

Welcome to the experiment. In the experiment you will make decisions. You can earn money by participating in the experiment. How much you earn depends on your own decisions and on the decisions of other participants in the experiment. At the end of the experiment, a show-up fee of €5 plus your total earnings during the experiment will be paid to you in cash. Payments are confidential: we will not inform participants of the earnings of other participants. In the experiment, all earnings will be expressed in Talers, which will be converted into euro according to the exchange rate

$$1 \text{ Taler} = 16\text{¢}$$

In this experiment you can avoid making any loss (negative earnings). However, note that in case you end up with a loss, it will be charged against your show-up fee.

At the end of the experiment, your cash reward is always either 0 or a positive amount in euro. It is not possible that you end up with a negative cash reward.

It is not permitted to talk or communicate with others during the experiment. If you have a question, please raise your hand and we will come to your desk to answer you.

#### A.4.2 Groups

During the experiment you will participate in a group of five players. You will be matched with the same players throughout the experiment. In the experiment, you will be identified as “P1”. The other players in your group will be labeled “P2”, “P3”, “P4” and “P5”. You will not be informed who the other players are, nor will they be informed of who you are.

#### A.4.3 Rounds

The experiment consists of fifty-two rounds. In each round you and the other four players in your group choose one of two options: *X* or *Y*.

#### A.4.4 Earnings

Your earnings in a round depend on your choice and on the choices of the other four players, in the following way:

- if you choose *Y*, your earnings are 2 Talers regardless of the choices of the others;
- if you choose *X*, your earnings depend on how many of the other players choose *Y*.

Your exact earnings in Talers from choosing *X* or *Y*, for a given number of other players choosing *Y*, are listed in Table A.4 on the facing page. This earnings table is the same for all players.

For example, if two other players choose *Y*, then your earnings from choosing *X* will be 1, while your earnings from choosing *Y* would be 2.

#### A.4.5 Forced *Y*

Note, however, that your preferred option may not be possible. In each round, each of you will face a 25% chance that you are forced to choose option *Y*. We will call this a “forced *Y*”. After you have made your preferred choice, you will see whether your option is possible or not.

Whether or not a player is forced to choose *Y* is randomly determined by the computer for each player separately and independently from the other players. Further, a forced *Y* does not depend on what happened in previous rounds.

**TABLE A.4**

<b>Number of other players choosing <math>Y</math></b>	<b>Your earnings from choosing <math>X</math></b>	<b>Your earnings from choosing <math>Y</math></b>
0	5	2
1	3	2
2	1	2
3	-1	2
4	-3	2

For your convenience, on the computer screen where you take your decision you will be reminded of the chance of playing a forced  $Y$ . Furthermore, in the table at the bottom of that screen (showing past decisions and earnings) your forced  $Y$  are indicated in the column showing your choices with an “F”. In the same way, you will be informed of other players’ forced  $Y$  choices.

#### A.4.6 Exercises

You are now kindly requested to do a few exercises on the computer to make you fully familiar with the earnings table. In these exercises you cannot earn any money. The exercises are not part of the fifty-two rounds of the experiment.

#### A.4.7 Start of the experiment

After the exercises, we will start the experiment.

If you have a question, please raise your hand and we will come to your desk to answer you.

### **DECLARATION OF INTEREST**

The views expressed are those of the authors and do not necessarily represent the views of De Nederlandsche Bank.

### **ACKNOWLEDGEMENTS**

We thank Ron Berndsen, the anonymous referees and the participants of the Bank of Finland Payment and Settlement System Simulation Seminar for providing useful comments.

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# Chapter 8

## Intraday liquidity management and systemic risk in the Danish interbank market

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*Søren Truels Nielsen*

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# Intraday Liquidity Management and Systemic Risk in the Danish Interbank Market

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## Abstract

In high value real time gross settlement systems as those employed in almost all developed economies, banks rely to some degree on incoming funds during the day to finance outgoing payments. This mutual reliance across the banks is necessary in order to facilitate a smooth payment settlement and to limit the need for liquidity reserves, but it requires a high degree of coordination among the participants, and it also poses a potential systemic risk because an incident one place in the system may spread to the rest of the system. This paper presents an analysis of the Danish interbank market simulating various shocks to the system, and allowing the participants to react dynamically to these via a binary reaction function. We find that the systemic risk is generally low at the moment owing to the fact that the participants are holding ample liquidity reserves.

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## 1 Introduction

In high value real-time gross settlement (RTGS) systems as those employed in most developed economies participants are typically to some degree dependent on incoming payments to fund their own outgoing payments. This mutual reliance across the participants is necessary in order to facilitate smooth payment settlement and limit the need for liquidity reserves, but it requires a degree of coordination among participants, and also introduces a potential systemic risk because an incident one place in the system may spread and have adverse effects on other parts of the system.

The reliance on incoming payments to fund outgoing payments also introduces a strategic element to the intraday settlement of payments in the form of moral hazard. For any participant it may be tempting to postpone outgoing payments in order to reduce the use of liquidity and intraday credit facilities, but if all participants do this the advantage is eroded and everybody may potentially be worse off.

In the Danish RTGS system, Kronos, a high degree of coordination is observed with the bulk of payments being resolved before noon. Such a coordinated behavior is beneficial to the participants and the system as a whole, as it conserves the use of liquidity and intraday credit facilities, but will inherently be delicate and can have adverse effects if disturbed. This is especially a concern in times of financial turmoil or distress as a lower degree of coordination and consequently a higher need for liquidity reserves or costly credit may accentuate the participants' difficulties.

In this paper we simulate the Danish interbank market adopting a binary reaction function by which participants are allowed to change the profile or timing of their payments during the day as a response to changed market conditions following from extreme but plausible events such as the default of a large participant.

This study is limited to three particular scenarios. These three cover the default of a large participant, an inflow dry-up also for a large participant and, finally, a scenario in which a group of participants become cautious of the rest of the market and hold back payments. Each scenario is simulated each day over a month-long period with and without the endogenous reaction function and also in a scenario where liquidity reserves for all participants are reduced. We will also take a look at particular days for each of the three setups.

The paper is organized as follows. Section 2 presents the background for the intraday liquidity management and incentives of the participants. Section 3 introduces the endogenous reaction function allowing participants to respond to changed market conditions, and motivates its particularities. A quick overview of the data involved in the simulation is presented in section 4. In section 5 the results of the various simulations are presented, and finally section 6 offers some concluding remarks.

## 2 Intraday liquidity management

Managing liquidity for payment purposes during the day is a non-trivial task. On one hand there is an incentive to postpone payments in order to reuse liquidity from incoming payments and thus limit the use of costly credit. However, if all participants do this no one gains anything and payments are just pushed further and further up the day which may not be favorable from a social standpoint. On the other hand, there may be an incentive to pay early (or at least in a timely manner) as this signals to other participants that the institution is sound and reliable. Bech & Garratt (2003) develop a game theoretical model in which two participants are faced with costly credit but also a cost related to delaying payments. In this framework they find that under certain circumstances the intraday liquidity management game bears resemblance to the classic prisoner's dilemma in which the participants may not cooperate (e.g. coordinate payments) even though it is in their common best interest. In a repeated setup, however, cooperation is easier to establish as it is enforceable through a sanctioning system<sup>2</sup> which would also explain the high degree of coordination observed in the Danish interbank market as is shown in detail in section 4.

Another incentive for participants to postpone payments within the day is the exposure they face. If one participant completes all their outgoing payments early and before receiving any payments themselves they will face the risk of other participants defaulting and not completing their payments, and thus putting a strain on the first participant's liquidity reserves. Note that this is not a credit risk as all transactions are processed on a real-time basis, but rather, it is a question of liquidity management, and all participants have an incentive to manage both their bilateral and multilateral exposures within the day. In an empirical study of the liquidity effects from the September 11, 2001 terrorist attack on World Trade Center McAndrews & Potter (2001) find that in the American FedWire system the

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<sup>2</sup>For instance a *grim trigger* strategy, where the participant pays early so long as the same behavior is observed from the counterpart. If the counterpart pays late just once the participant subsequently pays late.

participants on an average day pay out about 80 pct. of what they receive, but that this figure drops sharply to around 20 pct. in the days immediately following the attack. After the attack many participants had operational issues caused by damage from power outages and flooding, and this combined with the general turmoil following the attack caused many participants to take a hesitant or cautious stance in the payment system holding back payments waiting to see if liquidity was flowing from the other end. These findings corroborate the hypothesis that participants in RTGS systems actively manage their liquidity during the day, and that these changed patterns of payments may be especially evident during stressful periods, be they operational or financial in nature.

Several others have observed and studied the incentives and strategic behavior of participants in a payments context. Angelini (2000) studies the participants' intraday incentives in the short term money market, while Martin & McAndrews (2008) employ a game theoretical approach and show how liquidity saving mechanisms can be optimizing under certain circumstances. Heijmans & Heuver (2011) discuss behavioral patterns for participants in RTGS systems in both normal and stressful times based on observations from the Netherlands. They cover many areas such as changed timing of payments, money market dry-up, bilateral limits among others.

Active intraday liquidity management is well established as a field of theoretical and observational interest, but channeling these insights into a practical model or framework that allows for more realistic simulations of the interbank market is no trivial matter and has only been tried few times. In the following section we will briefly recap one such attempt and present an adaption of it in order to apply it to Kronos data.

### **3 Endogenous reactions**

Traditionally, when simulating payment flows there has been little or no focus on participant reactions. Probably the most common simulation experiment is the default of a large or important participant. Every payment to and from the particular participant is cancelled and all other payments are settled as normal granted that the sending participant has enough liquidity (or credit) to carry out the payment. This exercise usually yields a lot of interesting insights about the general state of the payment system, the participants, and their interconnectedness, but it is not a particularly realistic approach because, as already discussed, there is really no reason to believe that participants would behave as if nothing had happened when for instance a large participant defaults. On the contrary the uncertainty that such an

event gives rise to will likely have participants act more cautiously than they otherwise would. This could consequently have a detrimental effect on the system as a whole, as the distribution of liquidity is hampered.

One notable exception to the static simulations is Afonso & Shin (2010) who construct a reaction function inspired by the findings of McAndrews & Potter (2001). They derive a binary framework in which participants can switch between two regimes, where their behavior is either characterized as "normal" or "cautious". With this function they simulate various shocks in a system of generated payments data modeled after FedWire and find that allowing for endogenous responses may potentially make bad situations worse.

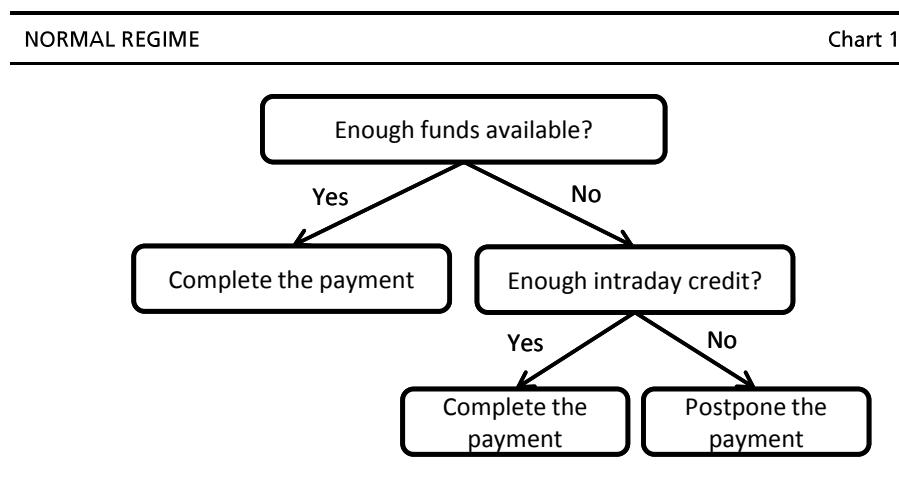
The approach employed here is similar in the sense that we also model a binary framework for the participants, but it differs on some of the specifics and more notably we apply the model on actual payments data. In the following we will present this adaption of the model.

### **3.1 A binary reaction function**

When there is an unexpected shock to the system the hypothesis is that participants will be more observant, and suspicious, of the system as a whole and the participants' own liquidity situation in particular. The participants know that a shock in one place may propagate to other participants and have adverse consequences for the entire system. However, because participants only observe their own balance and payment queue they will have to rely on what signals are available to infer the general state of the system. In a nutshell, receiving a payment from a participant is a good sign, as it signals that the participant is willing and able to make payments. If a participant is not receiving any payments and liquidity is tight, it may be perfectly sensible for the participant to take a cautious stance and wait for incoming payments.

Liquidity and positions towards other participants are good candidates for a reaction function, and this is indeed what the function is based on. The participants' own balances are used to decide when a participant is "normal" and when it is "cautious", and the participants' multilateral positions are used to make sure that cautious participants are strengthening their balances.

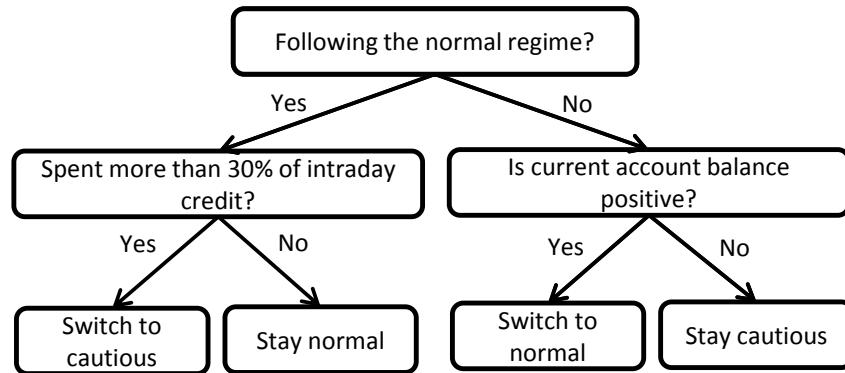
Every participant starts the day following the normal regime completing payments as if nothing had happened.<sup>3</sup> As such, when using actual payments data, there is no need to model this regime because we assume that the observed payments pattern is “normal”. There may be exceptions to this rule, for instance, when simulating the default of a participant, all payments to and from that participant are cancelled, and thus deviating from the actual payment pattern even if following the normal regime, though not introducing any behavioral elements. Another binding constraint for participants following the normal regime is, of course, their liquidity. If some participant has exhausted all liquidity and intraday credit, the participant cannot complete payments. This situation will, however, never arise in the normal regime as participants will always shift to the cautious regime before exhausting all their credit as described below. The normal regime is depicted in chart 1.



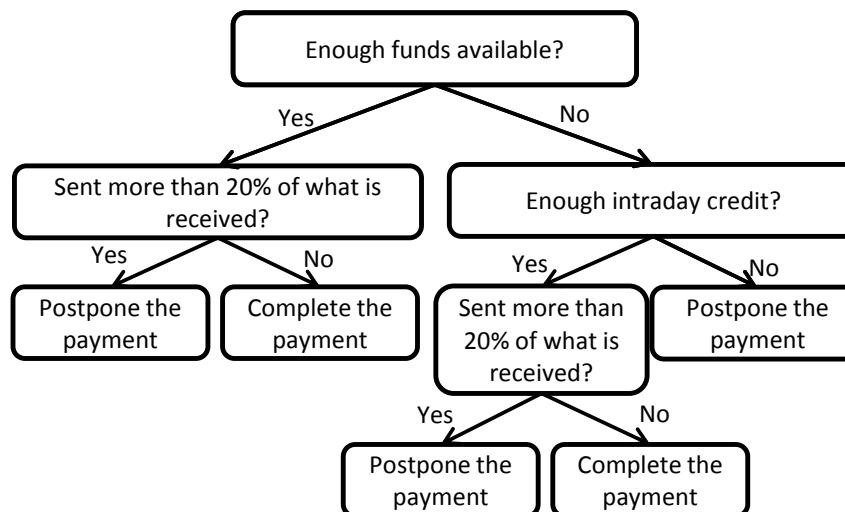
When a participant has used up a certain portion of their maximum intraday credit it is assumed that they will begin to get worried about the market. More specifically, whenever a participant has used up 30 pct. of their intraday credit they will switch to the cautious regime. The limit is set, because on average very few participants ever use more than 30 pct. of their intraday credit as is shown in section 4 below. The participant will remain cautious until the credit position is closed and the participant again has a positive balance on their current account. If the participant is able to build enough liquidity to close their intraday overdraft, it is assumed that the participant is again confident that payments are flowing and the participant will thus switch back to the normal regime. The switch rule is depicted in chart 2.

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<sup>3</sup> This holds true unless something else is specifically indicated.



When participants follow the cautious regime they will be hesitant to complete outgoing payments. In practice they will observe the rule that no payments are made so long as they, in value, have sent more than 20 pct. of what they have received. With this rule a “cautious” participant is bound to improve their balance granted that they receive any payments at all. As already discussed, this rule is designed to capture the more hesitant stance of the cautious participant. The cautious regime is depicted in chart 3.

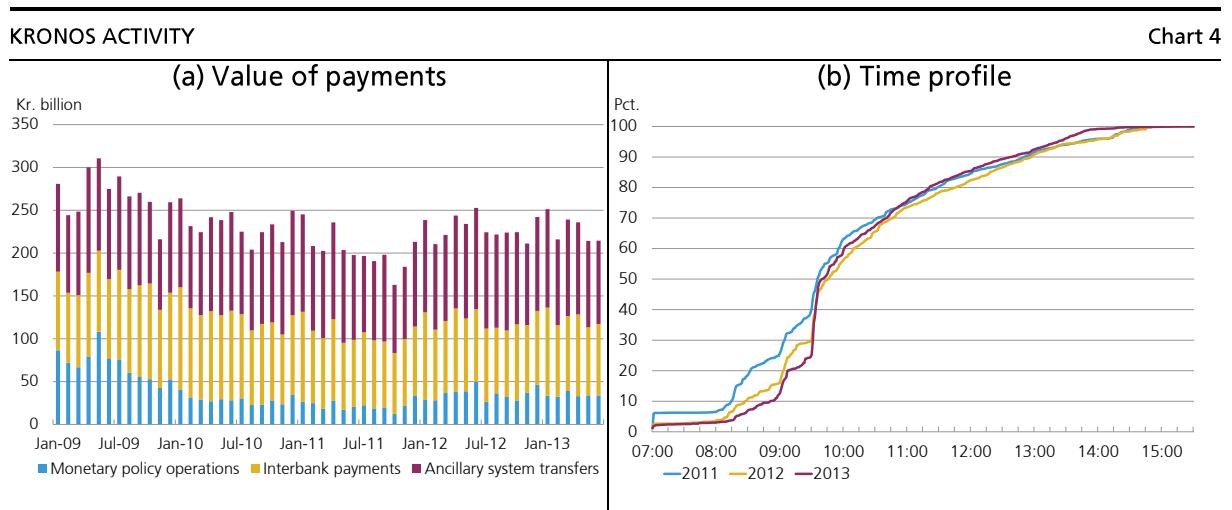


Participants who are observing the cautious regime will do so until they are sufficiently satisfied that market conditions have improved. Specifically, we define that participants remain cautious until they have closed their intraday overdraft, and thus, again have a positive balance on their current account.

## 4 Data

This study is based on transactions data from the Danish RTGS system, Kronos, from June 2013. In the following we will present some basic figures from Kronos in order to set the stage for the simulations in the following section. These cover the value and volume of payments, time profile of payments during the day, concentration of the market, liquidity reserves, and the use of intraday credit facilities.

In Kronos, the daily turnover averages 217 billion Danish kroner spread over approximately 4,300 individual payments in June 2013, corresponding to roughly 10 pct. of Denmark's annual GDP. 45 pct. of the value can be attributed to interbank payments (including client payments), transfers to ancillary systems constitute around 40 pct. of the total value, leaving around 15 pct. for monetary policy operations.<sup>4</sup> The overall development in the activity in Kronos is depicted in chart 4(a).



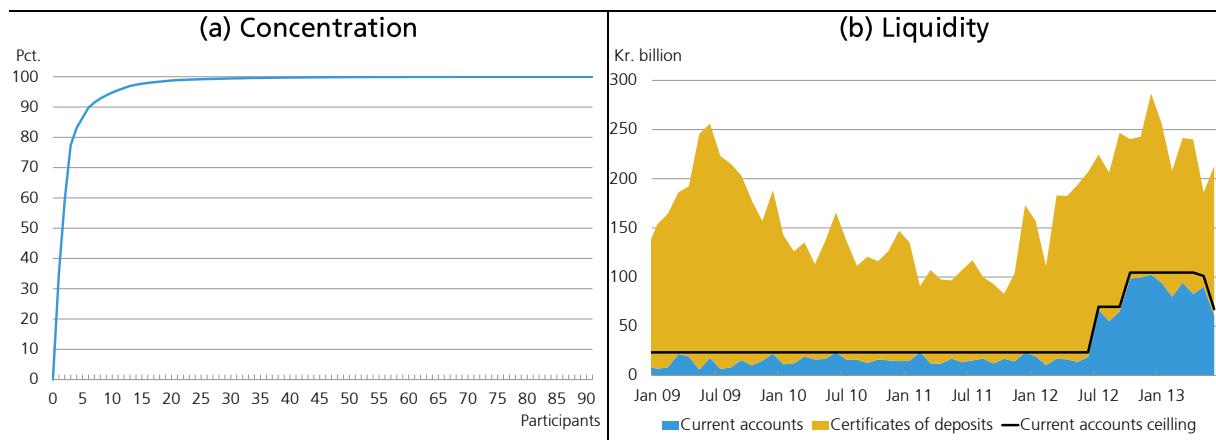
As already mentioned above, the profile of payments in Kronos during the day is characterized by a high concentration before noon with a remarkable jump at 9:30, cf. chart 4(b). There is not much activity before 8:00 am, and more than 80 pct. of the daily turnover is settled before noon. There is little change in this pattern over time.

The Danish banking sector is highly concentrated with a few very large actors, and many smaller institutions. As such the five largest banks constitute approximately 90 pct. of all the activity in Kronos, cf. chart 5(a). The remaining 10 pct. is divided among around 100 smaller (some very small) banks and other financial institutions.

<sup>4</sup> Note that monetary policy operations under normal circumstances only are conducted on Fridays.

CONCENTRATION AND LIQUIDITY

Chart 5



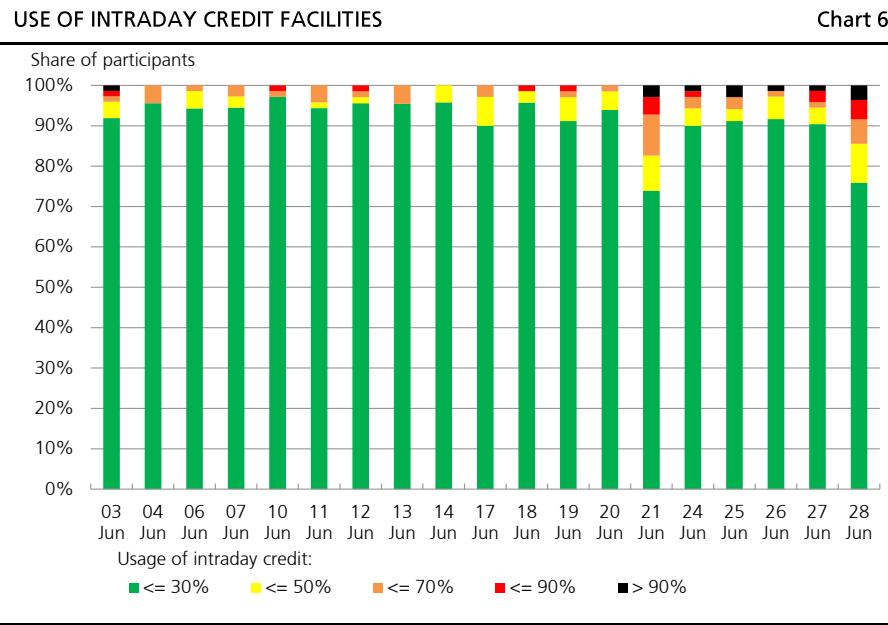
Note: Chart (a) depicts the cumulated total value of payments starting from the largest participant. Chart (b) depicts the participants' gross claim on Denmark's Nationalbank.

Under the present market conditions the banks are generally holding ample liquidity reserves, cf. chart 2(b). Currently (June 2013) banks are holding some 60 billion Danish kroner on their current accounts and another 150 billion Danish kroner in monetary policy deposits.<sup>5</sup> Because of the current conditions in the market with negative interest rates the banks are holding close to the current accounts ceiling at all times as is also evident in chart 5(b).<sup>6</sup>

As a consequence of the relatively high liquidity reserves held by the banks, the use of intraday credit facilities is fairly limited as is shown in chart 6 ("bushfire diagram"). On almost all business days in June 2013 more than 90 pct. of all banks use less than 30 pct. of their maximum intraday credit.

<sup>5</sup> The monetary policy deposits, called certificates of deposit, are traded every Friday with a one week term.

<sup>6</sup> The current account ceiling is a monetary policy mechanism that limits the amount of liquidity available to the market as a whole. Any excess liquidity is automatically transformed into monetary policy deposits. Currently the interest rate on monetary policy deposits is lower than on the current account deposits giving the participants an incentive to hold as much liquidity on their current accounts as possible.



Note: For each participant the maximum use of intraday credit is selected each day.

For the simulations we use data from June 2013. We simulate each of the chosen scenarios for every day during the month and present the overall outcome as well as more details on a specific day. We analyze a closed system consisting of the 20 largest participants, but as is evident in chart 5(a) this accounts for almost all payments in the system. Endogenous reactions are only allowed in interbank and client payments meaning that everything else is treated as exogenous. Thus, the liquidity effect of, for instance, transfers to ancillary systems is accounted for, but the participants have no way to influence them. Likewise the liquidity effect of payments to and from participants beyond the 20 largest is accounted for, but the payments are not modeled explicitly.

## 5 Results

This study consists of three distinct scenarios covering the default of the largest participant, the liquidity dry-out of the same participant, and a scenario where a group of participants become anxious of the market and follow the cautious regime the entire day. For every scenario three distinct simulations are conducted: A static scenario with no endogenous response, a scenario with the above described endogenous response, and finally a scenario with endogenous response and where every participant's access to intraday credit facilities is reduced by 25 pct.

The simulator itself is relatively simple, processing the payments of the day chronologically as they are introduced into the system. If a payment is postponed for one reason or the other it

is pushed 30 minutes up the day at which point it is processed again. Contrary to Kronos there is no algorithm for solving gridlocks in the simulator, and neither is there a queuing facility apart from what the actual data reflects.<sup>7</sup>

Somewhat related to this it is also important to note, that all payments are treated equally. Some payments are obviously more urgent than others and their completion has a higher priority, but this is not modeled explicitly in the simulator. This is a limitation of the model, but also very hard to model in practice as it is hard to identify which payments are more important, and would require a number of non-trivial assumptions.

### **5.1 Default of largest participant**

This first scenario is inspired by Bank for International Settlement's Principles for Financial Markets Infrastructure in which it is recommended that an RTGS system should be able to withstand the default of the participant who generates the largest net liability on any day.<sup>8</sup> It is not specified exactly how this is to be interpreted, but it is usually tested in a static simulation setup. Here we shall examine both the static and the dynamic setup, in which the participants are allowed to respond to the changed conditions, and compare the results.

When the largest net debtor is removed from the system we expect the liquidity to become strained for the remaining participants to some degree. The severity depends on the distribution of payments and also the total amount of liquidity available in the market. Recalling chart 5(b) above there is currently a substantial amount of liquidity in the market, and thus the systemic risk is not perceived to be very high. Introducing endogenous reactions allowing the participants to be more hesitant is expected to worsen the situation.

Looking first at some statistics for the entire month it is evident that there is no sign of major systemic impact from the default of the largest participant, cf. chart 7. A lot of payments are cancelled every day as a natural consequence of the largest participant defaulting, however, allowing for endogenous reactions hardly changes the picture, and even more astounding reducing all participants' intraday credit lines by 25 pct. neither has any noteworthy impact. This is a consequence of the ample liquidity reserves the participants currently hold. Looking at chart 7(b) we see the maximum end of day intraday credit positions among the largest participants. These are generally not critical, and typically very low. These positions are of

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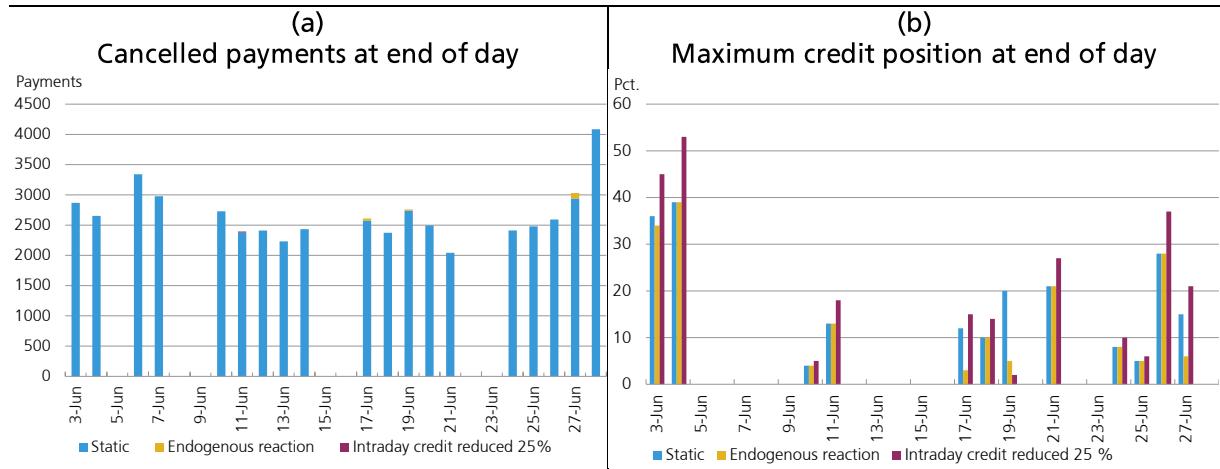
<sup>7</sup> The gridlock algorithm, however, has never been invoked in practice.

<sup>8</sup>BIS (2012).

course not allowed and should be closed, but in a situation where a large participant defaults it is not unreasonable to assume that the central bank would start buying certificates of deposit to loosen the liquidity. Also notable, is that introducing endogenous reactions will sometimes lower the maximum end of day credit position. This is because participants turn cautious and postpone payments.

DEFAULT OF LARGEST PARTICIPANT – OVERVIEW

Chart 7



Note: Chart (a) depicts the total number of cancelled payments as a consequence of the shock. Chart (b) depicts the largest relative maximum credit position at the end of the day.

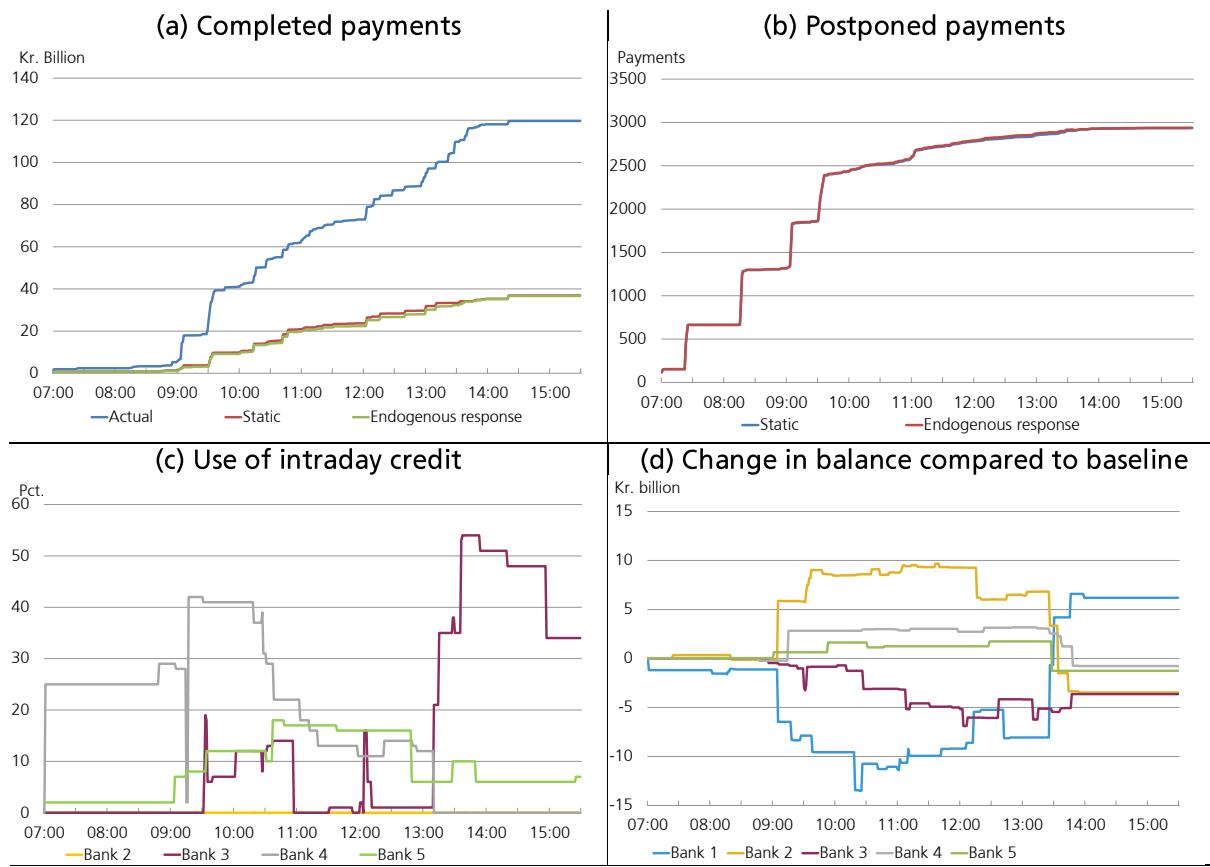
Next, we pick out one specific day during the period and have a closer look at the development during the day. We choose a day where there is a notable impact on the system from the default. The development during the day is summed up in chart 5. On this particular day the default causes only one third of the actual value to be settled at the end of the day corresponding to almost 3,000 cancelled payments, cf. chart 8(a) and 8(b). In this scenario there is very little difference in cancelled payments when comparing the static setup with the setup allowing endogenous reactions signifying that not many participants use up more than 30 pct. their maximum intraday credit.

This is evident from chart 8(c) showing the largest participants' credit use during the day. Bank 4 crosses the 30 pct. limit around nine in the morning, and starts to postpone payments and manages to close the credit position in the afternoon. At this time Bank 3 starts using a lot of credit and only manages to bring it down to around 30 pct. at the close of business. Looking at the change in the participants' balances compared to the actual levels, we see that Bank 1 (the defaulted participant) ends the day being better off liquidity-wise because of the large net obligation. All other participants are worse off, especially Bank 2 and Bank 3.

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DEFAULT OF LARGEST PARTICIPANT - DETAILED

Chart 8



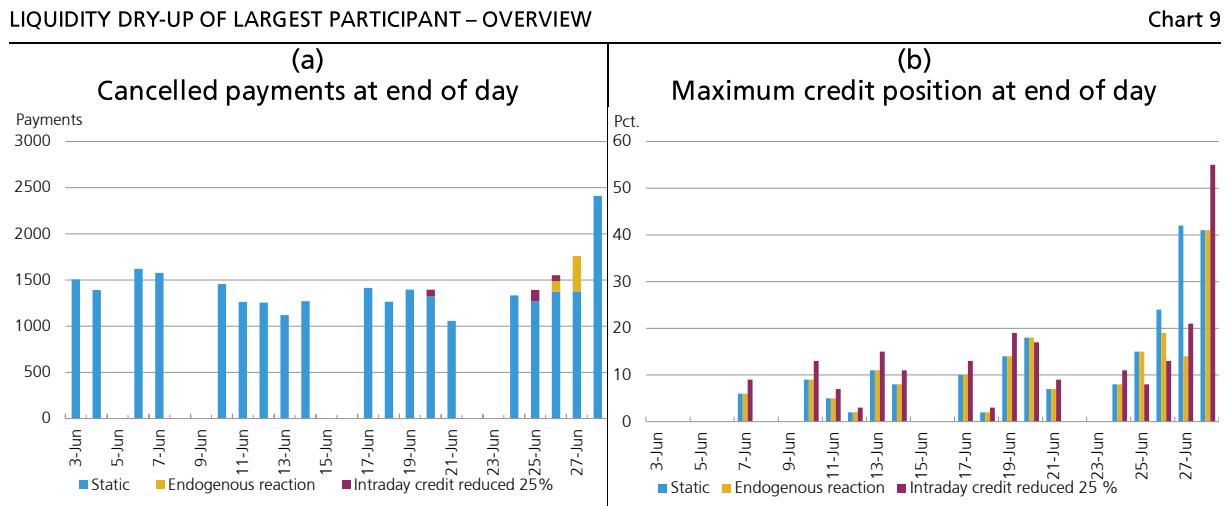
Note: Chart (d) depicts the change in balances compared to the baseline in which there is no shock.

## 5.2 Liquidity dry-up of largest participant

The second scenario is inspired by Afonso & Shin (2010) who simulate a scenario in which the largest participant experiences a complete inflow dry-up in the sense that the participant does not receive a single payment the entire day. This is obviously an extreme scenario and is designed to capture the situation where the market suddenly becomes very suspicious of a certain participant. In this scenario it is unclear what the consequences are. Certainly, the participant not receiving any payments will be strained, but whether this will spill over to other participants depends on the liquidity situation in the market and the distribution of payments to and from the exposed participant.

Again, we first have a look at the statistics for the entire month, and looking at chart 9(a) the results are not alarming. A large number of payments are cancelled, which is to be expected when a large participant does not receive any payments the entire day. Again, we also do not see a large impact on the number of cancelled payments from introducing the endogenous response. On the credit side the results are also reasonable at the close of business, cf. chart

9(b). On the final day of the month one participant has spent 40 pct. of the intraday credit, but otherwise the maximum usage of intraday credit is below 20 pct. at the end of the day.



Note: Chart (a) depicts the total number of cancelled payments as a consequence of the shock. Chart (b) depicts the largest relative maximum credit position at the end of the day.

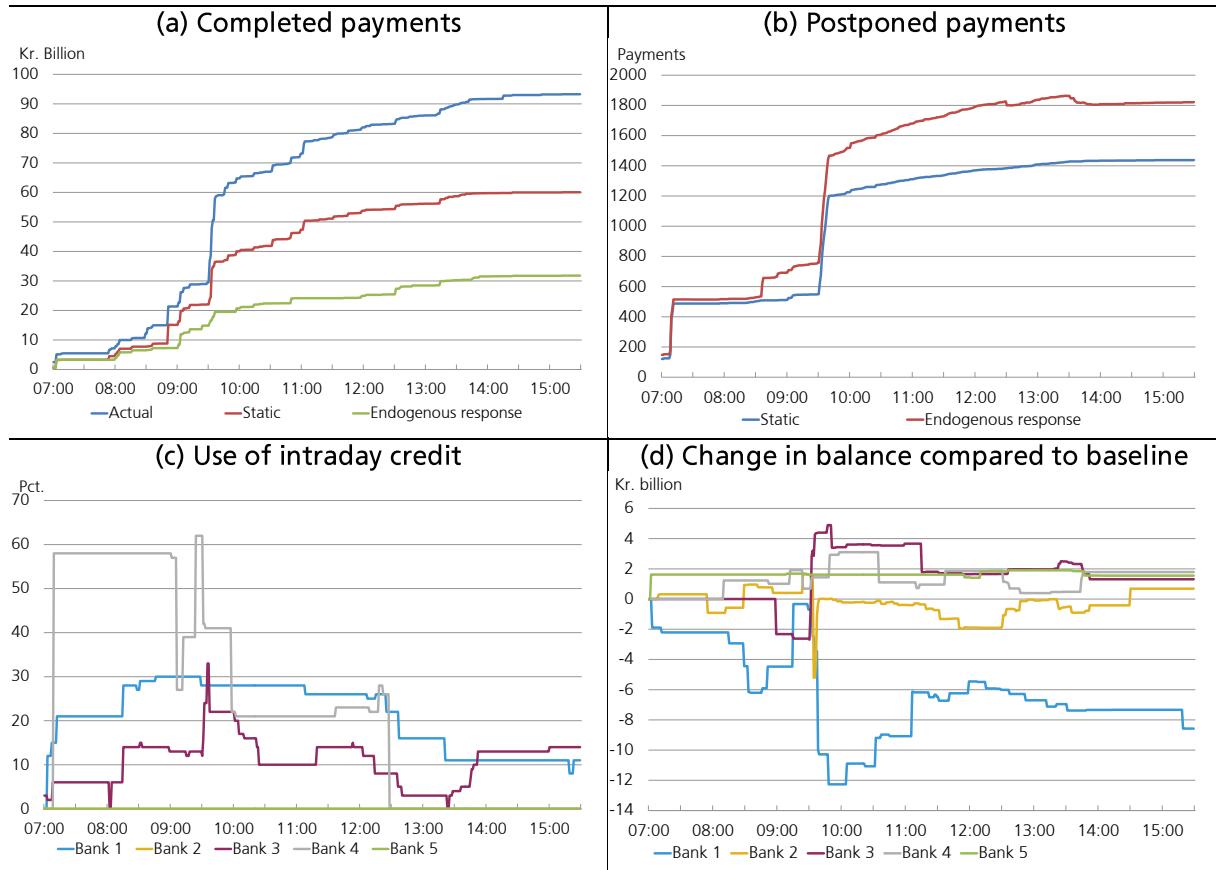
Looking closer at a particular day in the period, again we choose a day where the dry-up causes a certain impact. The value settled this day is two thirds of the actual value in the static setup, and only one third in the setup allowing for endogenous reactions, cf. chart 10(a). This implies that the first order effect causes one or more banks to break the 30 pct. limit on intraday credit. At the end of the day 1,800 payments are cancelled when allowing for endogenous responses, cf. chart 10(b).

In chart 10(c) the credit use is depicted, showing that Bank 1 (who is the exposed participant), not surprisingly, hits the 30 pct. limit before noon and start postponing payments to improve the balance. At the end of the day the exposed participant is still using about 10 pct. of the intraday credit.<sup>9</sup> Also Bank 3 and Bank 4 hit the limit and start postponing payments. They both manage to close the positions, but then Bank 3 starts using credit again and end the day with a deficit. Chart 10(d) depicting the change in the participants balances compared to the actual levels shows that the exposed bank's balance is notably worsened while the other participants are a better off.

<sup>9</sup> The participant is obviously not receiving any interbank payments – the balance has been improved by exogenous factors such as payouts from ancillary systems or other payments not explicitly modeled.

### Liquidity dry-up of largest participant - detailed

Chart 10



Note: Chart (d) depicts the change in balances compared to the baseline in which there is no shock.

### 5.3 Precautionary demand

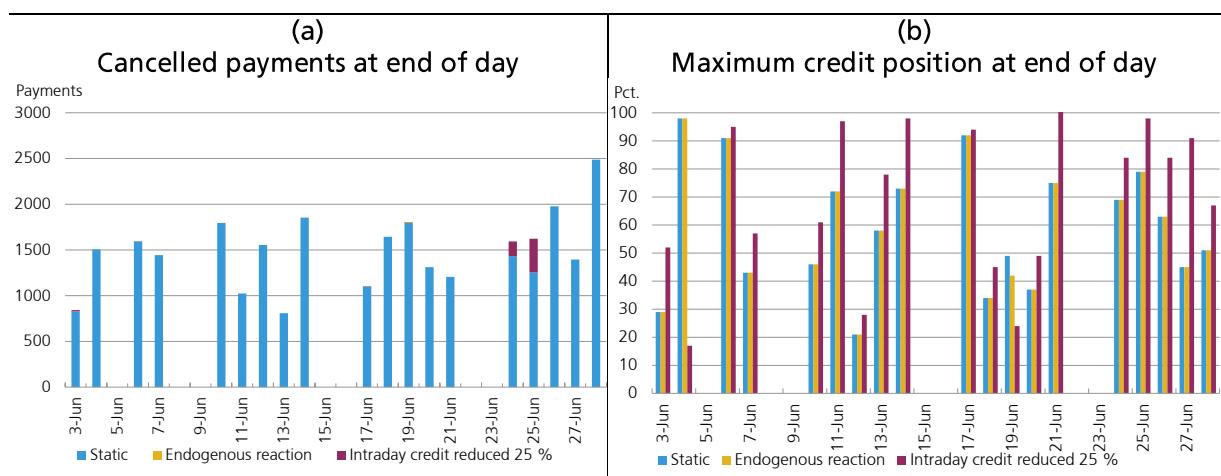
The final scenario we consider is specifically designed to explore the effect of the response function. In this scenario a group of five participants become anxious of the market and follow the cautious regime the entire day. This is a non-incident scenario in the sense that, opposed to the other two scenarios, there is no actual shock introduced in the system, apart from the sudden shift in behavior of a group of participants. Again the impact is hard to predict as it depends on a number of intertwining factors, but when a group of larger participants are hoarding liquidity it will put a strain on the remaining participants' liquidity.

The number of cancelled payments in the precautionary demand scenario is generally in line with that of the dry-up scenario but somewhat lower than the default scenario, cf. chart 11(a). As with the other two scenarios, allowing for the endogenous reaction does not change the picture, and even when reducing intraday credit 25 pct. the impact is limited. Turning to chart 11(b), the maximum use of intraday credit at the end of the day is remarkably high on almost

every day of the period. This is due to the fact, that when a group of banks are hoarding liquidity it hits every participant they are connected to. Among these are bound to be some smaller participants who do not have many payments during the day, and if they are expecting a large payment in the afternoon and do not get it they may not have the possibility to improve their situation by postponing outgoing payments even if endogenous reactions are allowed. This is also reflected in the chart by the fact that the maximum credit positions are equally high in the static and endogenous response setup, where the endogenous response setup typically warrants lower credit use at the end of the day in the other two scenarios.

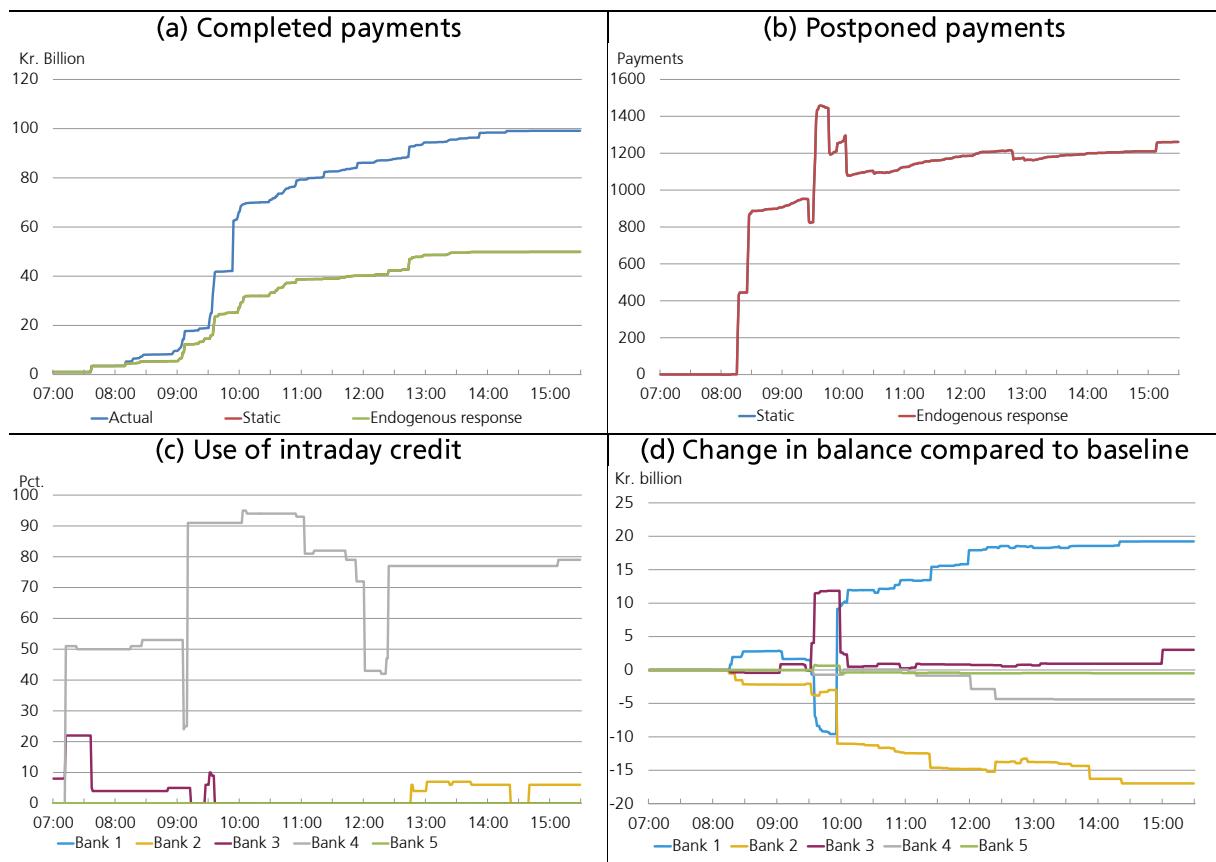
PRECAUTIONARY DEMAND – OVERVIEW

Chart 11



Note: Chart (a) depicts the total number of cancelled payments as a consequence of the shock. Chart (b) depicts the largest relative maximum credit position at the end of the day.

Looking again at a single day during the period we see that on this particular day only half of the actual value is settled when a group of banks are acting cautious, cf. chart 12(a). Allowing the rest of the banks to also react endogenously, hardly changes the picture. At the end of the day some 1,200 payments were cancelled as is evident in chart 12(b). In this scenario the cautious banks are Bank 1, 3, 5, 7, and 9. So when we observe in chart 12(c) that Bank 2 and bank 4 ends the day with deficits this is no surprise. Looking at chart 12(d) it is even clearer. Here Bank 1, 3, and 5 are better off while Bank 2 and 4 are worse off. Note that even though Bank 2 seems to take a larger hit than Bank 4, it is Bank 4 that is in most trouble having used up 80 pct. of his intraday credit at the close of business.



Note: Chart (d) depicts the change in balances compared to the baseline in which there is no shock.

## 6 Conclusions

In this study we have simulated the Danish interbank market introducing a number of shocks under various conditions. The overall impression from the results is that the Danish interbank market is relatively robust owing to the fact that the banks currently are holding ample liquidity reserves. Even though some participants may end in an unfavorable situation the consequences do not seem systemic in nature in the sense that they do not spread to the rest of the system.

Apart from investigating the robustness of the interbank market this study has also been an attempt at modeling the participants' reactions to shocks and stress. This was achieved through a simple binary reaction function allowing the participants to act more cautiously under certain conditions, postponing payments in order to improve their liquidity situation. Although this endogenous reaction did allow for some change during the day the impact was not dominating. Under conditions where liquidity is tighter this may change, as was also indicated by the setups where credit lines were decreased.

The use of such endogenous reactions is not widespread in the literature and for good reason too. There are many non-trivial assumptions made when introducing these reaction functions and more empirical foundation for these is definitely needed. Modeling banks liquidity management within the day is a very complex task, because the banks have different types of payments, some of which are more urgent or important than others, and the banks themselves may follow differing strategies altogether. In this particular setup we opted for a fairly simple reaction function ignoring the heterogeneity of both payments and the participants themselves in order not to assume too much about factors that are essentially unknown. The simplicity of this approach is also the strength, in that it may be reasonable to assume that liquidity managers in a stressful periods stick to a simple rule-of-thumb when deciding on when to release payments.

In deciding between doing static and dynamic simulations one must, however, remember that static simulations are based on the implicit assumption that banks do not react to sudden changes in market conditions which is unrealistic. For that reason it is reasonable to believe that the dynamic simulations do have some merit, and that work on improving the credibility of these may prove to be a fruitful endeavor. Especially, more empirical work to map the actual behavior of the banks will help render dynamic simulations more credible.

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# Chapter 9

## Examining full collateral coverage in Canada's large value transfer system

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*Lana Embree – Varya Taylor*

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\* This article first appeared in Bank of Canada Working Paper series, 29 July 2015. The publisher gratefully acknowledges the permission to reprint this article.



BANK OF CANADA  
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Working Paper/Document de travail  
2015-29

# **Examining Full Collateral Coverage in Canada's Large Value Transfer System**

by Lana Embree and Varya Taylor

Bank of Canada Working Paper 2015-29

July 2015

# **Examining Full Collateral Coverage in Canada's Large Value Transfer System**

**by**

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## **Acknowledgements**

We would like to thank Joey Murray and Gabriel Xerri for their instrumental research assistance. This paper also benefited from the valuable comments and suggestions provided by Nellie Zhang, Paul Miller, Miguel Molico, James Chapman, Hector Perez Saiz, Sean O'Connor, Neville Arjani, Matti Hellqvist and attendees of the 2014 Bank of Finland Simulator Seminar and 2014 Queens University-Bank of Canada Workshop on the Future of Payments.

## Abstract

The Large Value Transfer System (LVTS) is Canada's main electronic interbank funds transfer system that financial institutions use daily to transmit thousands of payments worth several billions of dollars. The LVTS is different than real-time gross settlement (RTGS) systems because, while each payment is final and irrevocable, settlement occurs on a multilateral net basis at the end of the day. Furthermore, LVTS payments are secured by a collateral pool that mutualizes losses across participants in the event of a default.

In this paper, we use the Bank of Finland Simulator to examine the implications of fully collateralizing LVTS payments, similar to an RTGS. An important caveat to consider, however, is that the simulations do not take into account the anticipated change in payment behaviour in response to a change in collateral requirements. In this regard, we include a queuing mechanism to at least reflect more efficient use of liquidity. The results indicate that collateral requirements vary by participant and some participants actually require less collateral in the simulation than what is required under the current LVTS design.

*JEL classification:* E, E4, E47, G, G2, G21

*Bank classification:* Financial institutions; Payment clearing and settlement systems

## Résumé

Le Système de transfert de paiements de grande valeur (STPGV) est le principal système interbancaire de virement électronique de fonds du Canada. Il est utilisé quotidiennement par les institutions financières pour transmettre des milliers de paiements dont la valeur s'élève à plusieurs milliards de dollars. Le STPGV diffère des systèmes à règlement brut en temps réel, car, bien que chaque paiement soit final et irrévocable, le règlement se fait à la fin de la journée par l'inscription des positions nettes multilatérales. De plus, les paiements effectués sont garantis par un portefeuille de sûretés, ce qui permet de répartir les pertes entre les participants en cas de défaillance.

À l'aide du simulateur de la Banque de Finlande, nous étudions les effets qu'entraînerait pour les participants au STPGV le nantissement de la totalité des paiements, une exigence similaire à celle qu'on trouve dans le cas des systèmes à règlement brut en temps réel. Il convient toutefois de souligner que les simulations ne tiennent pas compte du changement anticipé des habitudes de paiement qu'induirait une modification des exigences en matière de sûretés. C'est pourquoi nous intégrons un mécanisme de mise en attente, qui permet de simuler partiellement une utilisation plus efficiente des liquidités. Les résultats montrent que les exigences varient selon les participants et que, pour certains d'entre eux, le montant qui leur est imposé par le simulateur est, en fait, inférieur

à celui qu'ils sont tenus d'acquitter dans le cadre du STPGV tel qu'il est conçu actuellement.

*Classification JEL : E, E4, E47, G, G2, G21*

*Classification de la Banque : Institutions financières; Systèmes de compensation et de règlement des paiements*

## Non-Technical Summary

Many large-value payment systems in the world use real-time gross settlement (RTGS) systems, where each payment is fully collateralized and settled on a payment-by-payment basis. The Large Value Transfer System (LVTS), owned and operated by the Canadian Payments Association, is not an RTGS, because it settles on a multilateral net basis at the end of the day and participants only partially collateralize their credit risk. However, because payments are final and irrevocable in real time, the LVTS is RTGS-equivalent.

In our paper, we examine the implications of fully collateralizing LVTS payments using the Bank of Finland Simulator. We then compare the simulation results to the collateral requirements participants actually face in the LVTS. We find that collateral requirements at a system-wide level increase; however, some participants, typically smaller participants, actually see a decrease in collateral requirements. We also find that the introduction of a bypass queue results in collateral savings at a system-wide level. The results indicate that further work could be done to explore the liquidity efficiencies of the current LVTS design at a participant level.

Indeed, the Canadian Payments Association, owner and operator of the LVTS, is undertaking a multi-year project to review and modernize its payment systems. The results from this paper could provide some insight into the implications of adopting a fully collateralized system, similar to an RTGS. If the LVTS were fully collateralized, those participants that face an increase in collateral requirements may delay their payments to rely on incoming funds rather than collateral. There are several approaches that could be used to reduce payment delay, however, including liquidity-saving mechanisms such as queuing, throughput rules and fee structures.

## 1. Introduction

The Large Value Transfer System (LVTS) is owned and operated by the Canadian Payments Association (CPA) and is Canada's main interbank system for large-value payments.<sup>1</sup> Financial institutions use the LVTS to process around 30 thousand payments per day, worth \$150 billion.<sup>2</sup> Given its critical importance to the Canadian financial system, the LVTS is designated as systemically important under the Payment Clearing and Settlement Act and subject to oversight by the Bank of Canada. The Bank's oversight objective is to ensure that the LVTS has adequate risk controls to operate safely and efficiently.

Most large-value payment systems are real-time gross settlement (RTGS) systems that are settled on a fully collateralized, payment-by-payment basis.<sup>3</sup> The LVTS is different than RTGS for two reasons. First, the LVTS settles at the end of the day on a multilateral net basis; however, each payment is final and irrevocable in real time. For that reason, the LVTS is often described as a "hybrid" between a deferred net settlement system and an RTGS. Second, the LVTS has two payment streams available to participants: Tranche 1 (T1) and Tranche 2 (T2). As described later, participants fully secure intraday credit in T1 by pledging collateral to the Bank. However, in T2, intraday credit is secured by a collateral pool also pledged by participants to the Bank.

In this paper, we use the Bank of Finland Simulator to examine the potential implications of fully collateralizing LVTS payments, similar to an RTGS. Our results indicate that the increase in collateral requirements at a system level is not unreasonable given the total collateral currently available in the system. However, at a participant level, the results indicate that some participants face a greater impact than others, and some even see lower collateral requirements relative to what they currently pledge for the LVTS.

## 2. Motivation

In April 2012, the Committee on Payment and Settlement Systems<sup>4</sup> and the International Organization of Securities Commissions (CPSS-IOSCO) released a set of risk-management principles that apply to financial market infrastructures, including systemically important payment systems such as the LVTS (CPSS-IOSCO 2012). The principle on credit risk requires a payments system to cover its current and future exposures to each participant fully using collateral and other equivalent financial resources. The LVTS meets the credit-risk principle because:

- the total value of collateral pledged by participants to the Bank is sufficient to cover the single largest potential default, and

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<sup>1</sup> For a thorough review of the LVTS, see Arjani and McVanel (2006).

<sup>2</sup> Source: Canadian Payments Association.

<sup>3</sup> An RTGS is a fully collateralized system that facilitates the "continuous (real-time) settlement of funds or securities transfers individually on an order by order basis (without netting)" (CPSS 2003).

<sup>4</sup> This committee was renamed the Committee on Payments and Market Infrastructures (CPMI) in September 2014.

- the Bank provides an explicit guarantee to settle the system if there were multiple defaults on the same day and insufficient collateral.

The Bank's explicit guarantee of settlement, which is enshrined in legislation, constitutes equivalent financial resources under the principles and ensures that intraday credit risk is always fully covered.

Nonetheless, the principle also suggests that a payment system achieve settlement finality by employing an RTGS system.<sup>5</sup> Whether or not an RTGS should be adopted in Canada, a review of the LVTS design and risk controls is warranted because the LVTS was introduced more than 15 years ago. Since then, significant advances in payments technology and liquidity-saving mechanisms have been made. With that in mind, the CPA is currently undertaking a multi-year project to review and modernize its clearing and settlement systems (for both its retail and large-value payment systems). This review will involve extensive research on the options available for increasing safety and efficiency. The results from this paper could provide some insight into the implications of adopting an RTGS from a collateral perspective. Further, this paper allows us to consider the implications of removing the Bank's guarantee, since participants in an RTGS system fully cover their own credit exposure.

### **3. LVTS Collateral Requirements**

The T1 and T2 payment streams each have their own collateral requirements and loss-sharing arrangements in case of a default. In the T1 payment stream, the Bank provides participants an intraday line of credit that is fully secured by collateral pledged to the Bank at the start of the payments cycle.<sup>6</sup> The value of collateral that a participant apportions to T1 determines their T1 Net Debit Cap (T1NDC), which provides participants with a set value of intraday credit.<sup>7</sup> If a participant requires additional credit, it can simply pledge more collateral to the Bank.<sup>8</sup> As such, the T1 payment stream is similar to an RTGS system because it is fully collateralized by the sending participant.

In T2, participants grant bilateral credit limits (BCLs) to each other, which determine the maximum negative position that a participant can have vis-à-vis the grantor of the BCL. Each participant determines the value of BCLs to grant to other participants, but in practice BCL

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<sup>5</sup> The "Principles for Financial Market Infrastructures" encourage an RTGS design, both in the explanatory notes for the credit-risk principle and in the key considerations of the settlement finality principle (CPSS-IOSCO 2012).

<sup>6</sup> The assets eligible for collateral, as well as corresponding haircuts and other terms and conditions, are determined by the Bank. See <http://www.bankofcanada.ca/wp-content/uploads/2014/03/SLF-Policy.pdf>.

<sup>7</sup> The T1NDC represents the maximum negative multilateral net position a participant can have in T1. A negative multilateral position means that the total value of payments sent by a participant is greater than the total value of payments received.

<sup>8</sup> While a participant can increase its T1NDC during the payments cycle by apportioning additional collateral, a participant can also reduce its T1NDC, but only to the extent that its multilateral net position is fully covered at the time of reduction.

values tend to be reciprocal.<sup>9</sup> The BCLs also determine a participant's multilateral T2 Net Debit Cap (T2NDC), which limits the total negative position a participant can have vis-à-vis all participants.<sup>10</sup> The T2NDC for each participant is calculated as the sum of BCLs that a participant is granted multiplied by the system-wide percentage.<sup>11</sup>

To secure T2 intraday credit, participants are required to pledge collateral to the Bank equal to the largest BCL it has granted, multiplied by the system-wide percentage. In that sense, the pledged collateral allows participants to more readily receive payments, which in turn provides it with a source of intraday liquidity through incoming funds.

Because participants only partially collateralize their T2 credit-risk exposure, T2 payments are less costly than T1 payments in terms of collateral requirements.<sup>12</sup> Table 1 compares the daily value of payments sent in each payment stream to the value of collateral pledged. On average, 32 cents worth of collateral is pledged for every dollar of T1 payment sent. This is 28 cents more, on average, than a T2 payment. It is not surprising, then, that the vast majority of payments are sent through T2. Indeed, payments sent through T1 are typically those sent to the Bank to settle payment obligations arising from other systems. In such cases, participants are often obliged to use T1 because the Bank provides only a relatively small amount of bilateral credit in T2 to each participant. T1 can also be used when insufficient collateral is available in T2 and the payment is time critical.

**Table 1: Average daily payments sent and collateral pledged**

	<b>T1</b>	<b>T2</b>	<b>Total</b>
Value of payments sent	\$39b	\$115b	\$154b
Volume of payments sent	403	32,797	33,200
Value of collateral pledged	\$12b	\$5b	\$17b
Value of collateral pledged per dollar of payment sent	\$0.32	\$0.04	\$0.11

Sources: Bank of Canada and CPA data for April 2014

In addition to pledging collateral for T1 and T2, participants may, at their discretion, pledge “excess collateral.” Excess collateral serves as a buffer when additional collateral is needed on short notice. For example, a participant may need to increase its T1 credit or increase its largest BCL during the payments cycle. Excess collateral may also be used at the end of the day to collateralize an advance from the Bank to settle a final obligation.<sup>13</sup>

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<sup>9</sup> The Bank also grants a relatively small BCL to each participant equal to 5 per cent of the sum of all BCLs granted to that participant by other participants.

<sup>10</sup> The T2NDC represents the maximum negative multilateral net position a participant can have in T2. A participant can adjust BCLs during the payments cycle so long as the collateral requirement is met. If a participant increases its largest BCL, it is required to apportion additional collateral. However, if a participant decreases its largest BCL intraday, its collateral requirement does not change.

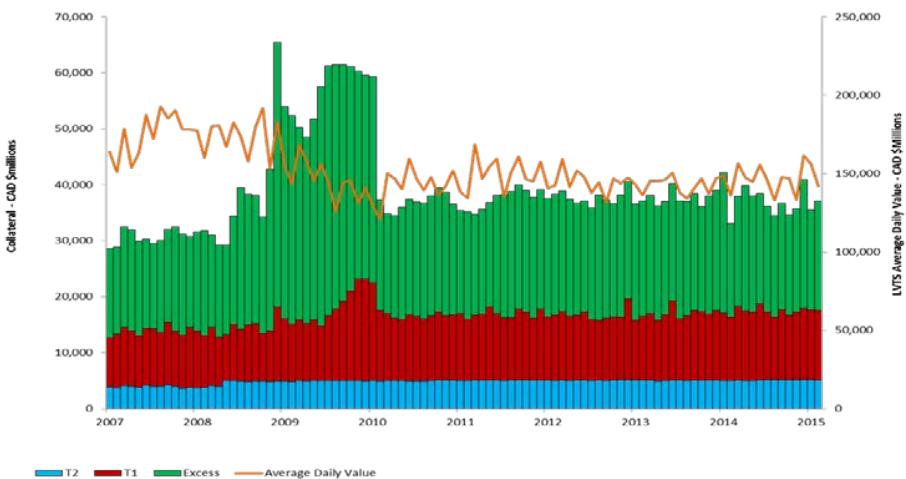
<sup>11</sup> The system-wide percentage is currently set at 30 per cent.

<sup>12</sup> In aggregate, the collateral pledged by all participants is always sufficient to cover the single largest default. This is demonstrated by Engert (1993).

<sup>13</sup> McPhail and Vakos (2003) discuss the motivations for maintaining excess collateral, as well as the factors that influence how much excess collateral a participant chooses to maintain.

During the financial crisis, the Bank temporarily broadened the types of assets eligible as collateral. Figure 1 shows a spike in excess collateral during that period, which reflects its use as a precautionary buffer during a period of financial instability and the greater ease of pledging additional collateral types. The Bank maintained the eligibility of some of the broadened collateral, and since 2010, excess collateral remains fairly stable as is the value of payments sent.

**Figure 1: Average Value of Collateral and Daily Payments**



In the event a participant defaults on its final LVTS settlement obligation at the end of the day, the Bank will provide the necessary liquidity to settle the system. To secure this advance, the Bank will immediately seize the defaulter's T1 and T2 collateral and call upon other participants (survivors) to pay an additional settlement obligation (ASO) to cover any remaining shortfall. Hence, T2 is a “survivors pay” arrangement where ASOs are determined on a pro rata basis according to the largest credit limit each survivor granted to the defaulter during the payments cycle:<sup>14</sup>

$$ASO_i = Shortfall \cdot \frac{BCL_{ix}}{\sum_{n=1}^N BCL_{nx}}, n \neq x,$$

where

- shortfall is the defaulter's remaining settlement obligation following seizure of its collateral,
- $BCL_{ix}$  is the largest BCL granted by participant ( $i$ ) to defaulter ( $x$ ) during the cycle, and
- $N$  is the number of LVTS participants.

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<sup>14</sup> Since the T2 loss-allocation formula is based on the relative value of BCLs granted to the defaulter, participants have incentive to monitor other participants' creditworthiness. A participant may lower a BCL to minimize credit-risk exposure (by reducing the negative position the counterparty can incur); however, a participant is still liable for the largest BCL granted to the defaulter at any time during the payments cycle.

The maximum ASO a participant would be required to pay is equal to the T2 collateral it is already required to pledge. This is also known as a participant's MaxASO.

In the event that more than one participant defaults and the collateral pool is insufficient to cover the final net debit positions of the defaulters, the Bank will advance funds to guarantee settlement. In providing this residual guarantee, the Bank becomes an unsecured creditor for the residual amount.

Several research papers by the Bank demonstrate that a defaulter's own collateral is generally sufficient to settle the LVTS and ASOs are typically small if needed. Further, in simulated multiple-default scenarios, the Bank's residual guarantee is not frequently invoked.<sup>15</sup>

## 4. LVTS Payment Queues

The LVTS has separate queues for T1 and T2 payments. A payment will enter the T1 or T2 queue if it does not pass the applicable risk control tests (i.e., if the payment results in a net debit position that exceeds the participant's credit limit within the payment tranche) *and* the payment is above a minimum threshold value of \$100 million.<sup>16</sup> Queued payments are resubmitted on a first-in-first-out basis when a participant's available credit increases or when they can be netted against other payments in batches as part of an algorithm that runs every 15 minutes. Unsettled payments remaining in the queue for more than 35 minutes expire and must be resent by the sending participant.

Under CPA rules, participants are encouraged to manage their liquidity and discouraged from excessive use of the payment queues. The queues are therefore used infrequently. Nonetheless, these queues are collateral savings mechanisms that serve to mitigate potential gridlock for relatively large payments.

## 5. Methodology

We use the Bank of Finland Simulator (modified to replicate the unique design of the LVTS) to estimate the additional collateral requirements participants could face if they were to fully collateralize all LVTS payments, similar to an RTGS. Using historical data as our base case, we estimate the collateral required for each participant by simulating T2 payments as if they were fully collateralized T1 payments. The data used in the simulations include LVTS payments and pledged collateral for each participant over the period July to December 2013 (a total of 125 business days). As shown in Figure 1, the sample period, while only six months, is fairly representative of a stable period since 2010.

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<sup>15</sup> See Ball and Engert (2007) and Zhang and Hossfeld (2010).

<sup>16</sup> The threshold value is determined by each participant, but must be equal to or greater than \$100 million – so-called “jumbo payments.” Participants can also set the threshold to zero, which means no payments will be sent through the queue.

We examine two different simulation cases and compare them to the actual collateral requirements (the base case):<sup>17</sup>

#### ***Case 1: Full collateral coverage with unlimited credit***

In Case 1, we simulate all T1 and T2 payments through the fully collateralized T1 payment stream and assume unlimited credit for each participant. Since no payments are rejected or queued, this allows us to observe the collateral that would be required to send all payments at the exact time they were actually submitted in the base case.

For each participant, we then calculate the difference between the value of collateral required in the base case (determined by a participant's maximum intraday net debit position in T1 plus its MaxASO) and the value of collateral required to cover the largest net debit position the participant experiences in the simulation.

#### ***Case 2: Full collateral coverage with credit limits and queuing***

In Case 2, we simulate all T1 and T2 payments sent through the T1 payment stream, but we set credit limits for each participant. In this case, credit limits, which must be fully collateralized, are assumed to be equal to the value of T1 and T2 collateral a participant is required to pledge in the base case.

In this scenario, payments may initially be rejected because they fail to pass the risk control test (i.e., the payment causes the participant's net debit position to exceed its limit). Payments initially rejected are sent to a centralized queue. Unlike the current LVTS queue, the queue in the simulation does not require payments to be greater than a threshold value. It also incorporates a first-in-first-out bypass algorithm that will resubmit queued payments once a participant's credit increases through incoming payments or additional collateral that was pledged in the base case.<sup>18</sup> If the first payment in the queue is too large to be resubmitted, the algorithm will attempt to resubmit the next payment in the queue, and so on.<sup>19</sup> However, if a payment stays in the queue for more than 30 minutes, it will expire and finally be rejected. The queue can be considered as a centralized liquidity-saving mechanism and the likely desire by participants to reorder their payments to make better use of liquidity.

In Case 2, we account for the collateral required to cover the largest negative position the participant incurred (which is less than or equal to the credit limit) and the payments that were ultimately rejected by the queue.<sup>20</sup> To estimate the collateral required to cover these rejected payments, we examine the credit the participant has available at the end of the day (EOD). EOD credit is simply a participant's credit limit net its EOD position, which may be positive or negative. If the total value of rejected payments exceeds EOD credit, the participant would have to pledge additional collateral to cover the remaining rejected payments. However, if the value of

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<sup>17</sup> The base case consists of the actual payment flows made through T1 and T2 and the associated collateral requirements.

<sup>18</sup> The simulation includes additional collateral a participant may have pledged intraday in the base case.

<sup>19</sup> The existing LVTS queue does not have a bypass feature, so if a queued payment cannot settle upon retesting, no further payments are retested.

<sup>20</sup> By accounting for the collateral required to cover rejected payments in Case 2, we can compare the results to Case 1, since the same number of payments are settled in both cases.

rejected payments could be covered by the EOD credit available, no additional collateral is required.<sup>21</sup>

## 6. Change in Payment Behaviour

The simulations are based on historical data and do not take into account the change in payment behaviour that would be expected if new collateral requirements were introduced. Presumably, participants would manage their liquidity differently and may, for example, wait to receive payments before sending them. As such, the results only serve to provide some insight into the potential implications of fully collateralizing existing LVTS payments. To a limited extent, however, the use of a first-in-first-out bypass queue in the simulations partially reflects a participant's decision to reorder payments according to available liquidity.

## 7. Simulation Results

Simulation results are provided for the system as a whole, and for large (6) and small participants (9), as determined by payments value.

### *Case 1*

Recall that in Case 1, all payments are sent through T1 at the same time they were submitted in the base case and participants have unlimited credit. This provides a simulation of the amount of collateral participants would need to send all payments through T1 at the original submission times. Compared to the base case, the results indicate that the average daily value of collateral increased by \$396 million for the system as a whole (Table 2).

**Table 2: Change in daily collateral requirements**

	Average daily (\$ million)	Minimum (\$ billion)	Maximum (\$ billion)	St. dev. (\$)
System-wide	+ 396.2	- 7.6	+ 4.1	+ 893.3m
Large (6)	+ 758.5	- 7.6	+ 4.1	+ 1.2b
Small (9)	+ 154.8	- 1.3	+ 2.2	+ 503.1m

The results in Table 2 also show that, on certain days, some participants actually see a decrease in the amount of collateral required. While this may seem counterintuitive, a reduction in collateral can occur if there is increased netting when the T1 and T2 payment streams are

<sup>21</sup> This approach leads to an overestimation of collateral because it does not account for the fact that if a participant pledges additional collateral to cover their rejected payments, the recipients of those payments would benefit from an increase in their own net position. These recipients would therefore require less collateral if they needed to cover any of their own rejected payments.

combined and/or when a participant pledges collateral in the base case that is higher than what the actual payment flows would demand. Recall that in T2, participants essentially collateralize the credit they extend to other participants, which in turn can be a source of liquidity through incoming payments.<sup>22</sup> The simulation, however, reveals that for some participants, providing this credit to other participants is less optimal than collateralizing their own individual payments. In other words, providing credit in the base case can be more of a cost than benefit for some participants.

On average, large participants experience an increase in collateral on 82 per cent of the days in the sample, while small participants do so on 46 per cent of the days (Table 3). The average value of an increase (given an increase has occurred) is higher for large participants (\$1.1 billion) compared to small participants (\$478 million). This result indicates that the large participants are making more efficient use of the current LVTS collateral design by sending a greater value on credit.

**Table 3: Increases in collateral requirements**

	% of days increased	Average daily Increase (\$)	Median daily increase (\$)	Minimum Increase (\$)	Maximum Increase (\$)	St. dev. (\$)
Large (6)	82	1.1b	1.0b	7.1m	4.1b	733.7m
Small (9)	46	478.3m	159.3m	300.8k	2.2b	559.3m

The results indicate a fair amount of variation between participants in the sample, reflecting differences in their liquidity management. Similarly, some participants experience high daily variation, reflecting variation in their own daily liquidity management.

To gauge whether participants could manage the simulated collateral requirements, we compare Case 1 results to the collateral pledged in the base case (Table 4). For small participants, Case 1 collateral required represents, on average, 93 per cent of the collateral pledged to T1 and T2 in the base case and is sufficient on 72 per cent of the days in the sample. However, for large participants, the amount of collateral required in Case 1 represents, on average, 152 per cent of the collateral pledged to T1 and T2 in the base case and is sufficient on only 35 per cent of the days. When Case 1 collateral requirements are compared to total collateral pledged in the base case including excess collateral, both large and small participants can meet the Case 1 collateral requirements for the majority of the days in the sample (84 per cent and 86 per cent of the days, respectively).

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<sup>22</sup> The decision to grant a BCL is not only influenced by expected payment flows but also other factors including the creditworthiness of the counterparty. In addition, participants pledge collateral to T1 at the beginning of the payments cycle according to how much T1 credit they *expect* to use during the day. It is possible that not all of this credit is always fully utilized.

**Table 4: Case 1 collateral requirements relative to the base case**

	% of base case collateral	% of days base case collateral sufficient	% of base case collateral including excess	% of days base case collateral including excess sufficient
Large (6)	152	35	60	84
Small (9)	93	72	45	86

Another way to observe the effect of full collateralization across participants is to examine the collateral required for every dollar of payment sent. When compared to the base case, some participants face a relatively large increase (Table 5). For example, Participants A, B and C pay approximately 20 cents more per dollar than in the base case. On the other hand, participant N saves 45 cents for every dollar sent and participants G and H face no change, on average. Indeed, most of the large participants (denoted in blue) face an increase, while most of the small banks actually see a decrease. We note, however, that the results are not perfectly correlated with participant size, since participants can vary by how efficiently they manage their liquidity in the base case. For the system as a whole, there is an overall increase of 5 cents for every dollar sent.

**Table 5: Collateral required per dollar of payment sent**

Participant*	Case 1	Base case	Case 1 – Base case
A	\$0.34	\$0.12	\$0.22
B	\$0.33	\$0.13	\$0.20
C	\$0.38	\$0.20	\$0.18
D	\$0.15	\$0.08	\$0.08
E	\$0.12	\$0.07	\$0.04
F	\$0.09	\$0.06	\$0.03
G	\$0.20	\$0.21	\$0.00
H	\$0.08	\$0.08	\$0.00
I	\$0.19	\$0.21	-\$0.02
J	\$0.16	\$0.17	-\$0.01
K	\$0.11	\$0.19	-\$0.09
L	\$0.20	\$0.30	-\$0.10
M	\$0.20	\$0.36	-\$0.17
N	\$0.08	\$0.53	-\$0.45
System-wide	\$0.13	\$0.08	+\$0.05

\*Large participants are denoted in blue.

### **Case 2**

In Case 2, participants are assigned a credit limit equal to the T1 and T2 collateral they were required to pledge in the base case. If a payment is submitted when there is insufficient credit available, it will enter the queue. A queued payment will either pass the risk control when more credit is available, or it will be rejected if it cannot pass within 30 minutes.

In general, large participants have a higher value of rejected payments than small participants (Table 6), which is understandable since large participants tend to send more payments and may require more credit. The value of rejected payments for each participant is compared to the credit they have at the EOD. When EOD credit is sufficient to cover rejected payments, we assume a participant would reorder their payments and send them later in the day. If EOD credit is insufficient, we assume additional collateral would be pledged in order to resend the rejected payments. When comparing the value of rejected payments to EOD credit, we find that the vast majority of rejected payments can be settled without additional collateral.<sup>23</sup>

**Table 6: Rejected payments**

	Average daily value of rejected payments* (\$ million)
System	10.0
Large (6)	21.6
Small (9)	2.2

\*Including zeros

In Table 7, the average daily collateral required in Case 2 is compared to the base case. In this scenario, the system as a whole sees a decrease in collateral requirements (-\$4.6 million). Large participants, however, face an increase in daily collateral requirements, on average (\$55.3 million), but the increase is much smaller than in Case 1 (\$758.5 million). Small participants tend to see a reduction in daily collateral requirements (-\$44.5 million) compared to the base case. This is in contrast to Case 1, where smaller participants actually face an average increase (\$154.8 million).

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<sup>23</sup> In fact, only one participant on one day in the sample required additional collateral to cover rejected payments.

**Table 7: Change in daily collateral requirements**

	Average daily (\$ million)	Minimum (\$ billion)	Maximum (\$ billion)	St. dev. (\$ million)
System	-4.6	- 6.8	+ 1.7	526.8
Large (6)	+ 55.3	- 6.8	+ 1.7	802.0
Small (9)	- 44.5	- 1.1	+ 0.9	173.1

Relative to Case 1, both large and small participants face an increase in collateral requirements less often, and face much smaller average increases (Table 8). This suggests that queuing is effective for reducing the collateral requirements for both small and large participants.

**Table 8: Increases in collateral requirements**

	% of days increased	Average daily Increase	Median daily increase	Minimum increase	Maximum increase	St. dev.
Large (6)	66	\$396.3m	\$334.5m	\$330.4	\$1.7b	\$138.5m
Small (9)	33	\$80.7m	\$23.1m	\$70.4k	\$858.0m	\$1825k

In Case 2, both small and large participants are almost always able to meet the collateral requirements when compared to collateral that is currently pledged in the base case, with or without excess collateral (Table 9). For large participants, this is an improvement from Case 1, where base case collateral was more often insufficient to meet the increase in collateral requirements.

**Table 9: Case 2 collateral requirements relative to the base case**

	% of base case collateral	% days base case collateral sufficient	% base case collateral including excess	% days base case collateral including excess sufficient
Large (6)	81	98	35	100
Small (9)	58	100	29	100

Again, we can examine the collateral needed for each dollar of payment sent and compare it to the base case and Case 1 (Table 10). Most participants are better off in Case 2 than in Case 1, particularly participants A and B. Participant M also stands out because it sees even greater savings in Case 2 than in Case 1. For the system as a whole, the net effect of Case 2 is zero.

**Table 10: Collateral required per dollar of payment sent**

Participant*	Case 2	Base case	Case 2 – Base case	Case 1 – Base case
A	\$0.12	\$0.12	\$0.01	\$0.22
B	\$0.09	\$0.13	-\$0.04	\$0.20
C	\$0.37	\$0.20	\$0.17	\$0.18
D	\$0.11	\$0.08	\$0.04	\$0.08
E	\$0.06	\$0.07	-\$0.01	\$0.04
F	\$0.06	\$0.06	\$0.00	\$0.03
G	\$0.22	\$0.21	\$0.01	\$0.00
H	\$0.07	\$0.08	-\$0.01	\$0.00
I	\$0.13	\$0.21	-\$0.08	-\$0.02
J	\$0.17	\$0.17	\$0.00	-\$0.01
K	\$0.09	\$0.19	-\$0.11	-\$0.09
L	\$0.20	\$0.30	-\$0.10	-\$0.10
M	\$0.10	\$0.36	-\$0.27	-\$0.17
N	\$0.08	\$0.53	-\$0.45	-\$0.45
System-wide	\$0.08	\$0.08	\$0.00	+\$0.05

\*Large participants are denoted in blue.

## 8. Policy Considerations

Under the current LVTS design, participants pledge collateral in order to extend credit to other participants in the system. This allows participants to more readily receive payments earlier in the day, which becomes a source of liquidity to fund their own payments. If LVTS participants were to collateralize their own credit at a greater cost, they may delay payments and wait for the additional liquidity from incoming funds. Delaying payments could potentially lead to gridlock if other participants also delay their payments. Perlin and Schanz (2011) explore how a “receipt-reactive” payments strategy, where a participant sends payments only after receiving payments so as to never need to draw on credit, can impact the liquidity of other participants in the United Kingdom’s large-value payment system. Perlin and Schanz find that unless other participants revise their payment behaviour, at least one participant will become illiquid within one hour. The impact is greater the larger the participant withholding payments. Since our simulations show that large participants face higher collateral costs, we expect that if the LVTS were fully collateralized, large participants would be more likely to delay their payments.

If the LVTS were fully collateralized, however, various liquidity-saving mechanisms could be considered, including more advanced queuing algorithms.<sup>24</sup> The large-value payment system in the United Kingdom, for example, uses batch matching cycles, which allows for the offsetting of the majority of queued payments (Bank of England 2012). Further, to mitigate the potential for payment delay and gridlock, other measures could be considered, including throughput rules and a fee structure that encourages payments to be sent earlier in the day. The simulations presented in this paper demonstrate that queuing can reduce the increase in collateral requirements associated with full collateralization.

Further analysis could be performed to compare the effects of different liquidity-saving mechanisms. Consideration of more advanced queuing and other liquidity-saving mechanisms is important because participants may also face increases in collateral demands outside the LVTS. However, those participants that, in the simulation, see a decrease in collateral requirements could find themselves in a position to move the collateral they had been pledging to the LVTS to other purposes.

Another interesting policy consideration is the need for the Bank of Canada's residual guarantee. The Bank's guarantee is integral to the LVTS because it provides assurance that credit risk is fully covered while allowing for liquidity efficiency. However, our results show that LVTS may not necessarily be more efficient for all participants. Indeed, if LVTS participants were to fully collateralize their own credit exposure, the Bank's guarantee would no longer be needed. Further analysis must therefore consider whether the Bank's guarantee is still required under a new system design.

## 9. Conclusion

Our results indicate that if the LVTS were fully collateralized, some participants could face increases in collateral costs while others could see collateral savings. We also find that the introduction of a queuing mechanism with a bypass function allows for greater collateral savings at a system-wide level. In some ways, queuing can be seen as reflecting a slight change in participants' behaviour in terms of the time at which they submit payments as a means to optimize available liquidity or a centralized liquidity-saving mechanism.

Given that some participants could be better off in a fully collateralized system than the current LVTS design, these results serve as a starting point for further analysis. There are additional policy considerations the Bank and the CPA would need to review when considering a change to LVTS collateralization, particularly as it relates to the Bank's residual guarantee and other policies that could reduce the incentive to delay and offer liquidity-saving mechanisms under a fully collateralized design.

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<sup>24</sup> Atalay et al. (2010) and Martin and McAndrews (2008) analyze several liquidity-saving mechanisms.

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# Chapter 10

## Increasing the time span in payment systems stress testing simulations

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*Richard Heuver – Ronald Heijmans*

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# Increasing the time span in Payment Systems Stress Testing Simulations

Richard Heuver and Ronald Heijmans

Monday 29<sup>th</sup> June, 2015

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Simulating stress scenarios in large value payment systems usually involves measuring the liquidity positions of participants for several consecutive days. The desired time span of a simulation can vary from a single day up to several months, depending on the type of scenario that the researcher has in mind. It is not always possible to choose the ideal time span, due to the lack of available computer performance. In this paper we offer a solution to this problem by aggregating the lower value transactions, without compromising the reliability of the analysis. Depending on the level of liquidity in simulations the processing time can be reduced to less than a percent of the original.

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**Keywords:** Payment systems simulations stress testing

**JEL Codes:** D23, E42, E44, E52, E58, G1, G2.

# 1 Introduction

Large value payment systems belong to the core of the financial market infrastructures (FMIs) in the world. Issued in April 2012 by the Bank for International Settlement (BIS) and the International Organization of Securities Commissions (IOSCO), the Principles for financial market infrastructures [CPSS \(2012\)](#) have set the standards that the FMIs have to meet to ensure their robustness to withstand financial shocks. An important aspect of large value payment systems is final settlement. The most preferable situation is direct (also called real-time) settlement of payments. This means that payment become irrevocable and therefore the receiving participants can directly use the received funds. Nowadays most large value payment systems already offer this "real time gross settlement" (RTGS).

RTGS systems are usually operated by central banks. In order to generate successful payments, participants firstly have to possess a positive account balance. As central banks will not accept unsecured overdrafts, participants are obliged to deposit collateral in order to increase their payment cover.

## 1.1 What influences the participants' liquidity in a payment system?

A participant uses its account balance to generate payments, which will then flow to other balances, enabling these participants in turn to generate payments. Therefore the total of the account balances can be seen as the "payment liquidity" in a payment system. Figure 1 gives a bird eye's view on all of the elements that influence the liquidity in a payment system. Top of the figure shows the payment system containing the participants' current account balance.

Below the payment system we see three groups of liquidity influencing elements; payments (left side, light grey), money markets (center, medium grey) and the central bank facilities (right side, dark grey). At the bottom of the figure we see the participants' amount of collateral, either in the own books or deposited at the central bank. The first and most direct influence comes from payments (left side, light grey). Incoming and outgoing payments directly lead to an increase or decrease of the account balance, respectively. The outgoing payment flows can be steered by postponing or canceling of payments. It is however obvious that eventually payment obligations will have to be fulfilled, either because of the participants' own obligations, or because of the obligations of its clients. Whenever a participants' amount of liquidity reaches its utmost bottom, no more outgoing payments can be processed. Incoming payments are generated by the other participants and can therefore not be influenced. As most

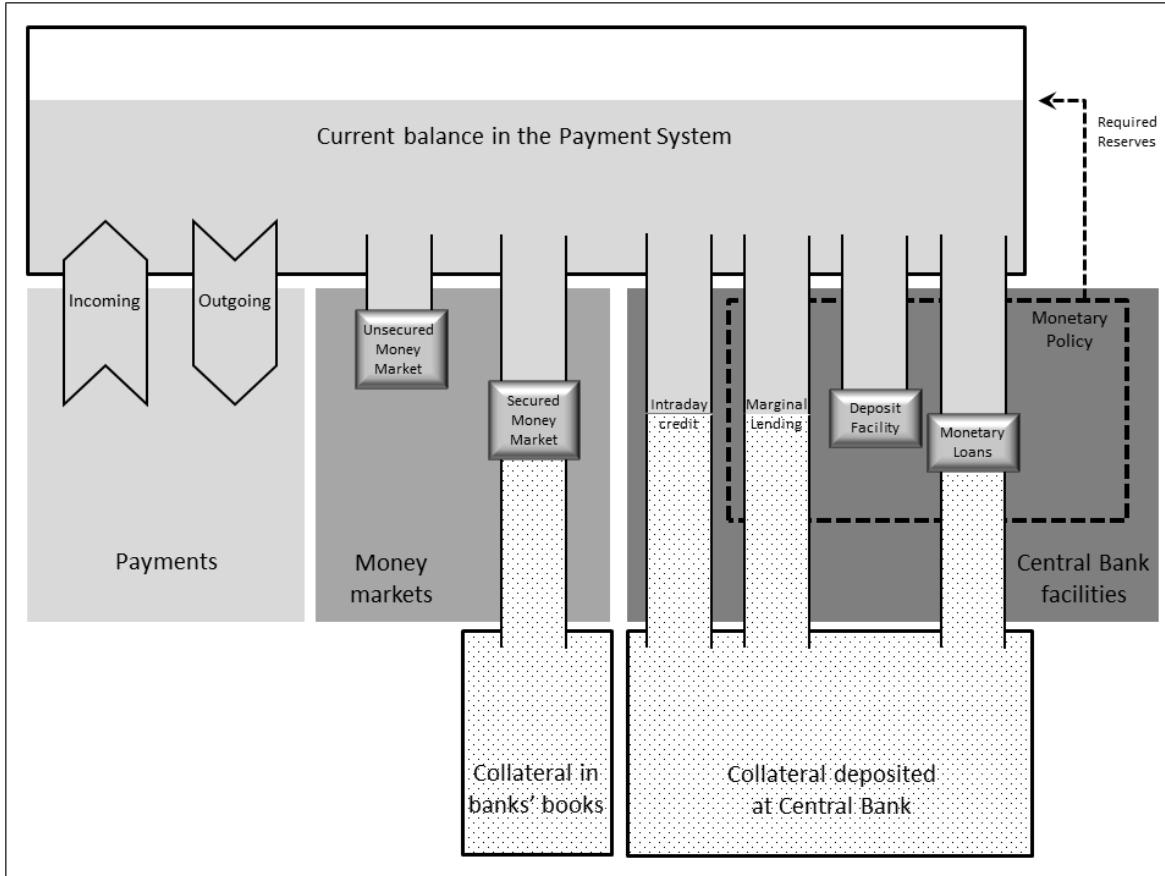


Figure 1: Elements that influence the liquidity in the payment system.

participants monitor their payment flows, it would sooner or later become apparent that a participant stopped paying, causing them to set a maximum limit to the position vis-a-vis this participant. A possible shortage or surplus of liquidity would usually trigger the participant to turn to the money market (center, medium grey). When, for instance, a shortage is foreseen the money market will be entered in order to obtain a short term loan. After the deal is agreed, the participants' counterparty will transfer the loan amount through the payment system and the account balance increases. When the money market loan expires (which is most often the next day), the refund payment is generated, leading to the same decrease of the balance. In case there is a high level of trust between participants the majority of trades will be unsecured, meaning that loans are not guaranteed by collateral. If, however, the participants' counterparties lack trust and ask a higher loan rate it might become necessary to agree on a secured trade, therefore leading to the requirement to deposit collateral from its own books. In this case collateral is transferred from the borrower to the lender, and at the same time the loan amount is transferred to the borrowers' account balance in the form of the money market loan. These actions are reversed the day the loan expires.

A volume control slider is drawn on top of both of these liquidity influencing elements as the participant is able to actively steer its use. Lastly, at the right side we see the central bank (dark grey) that offers four liquidity elements. Going from left to right we first see the intraday credit facility. As continuous flows of incoming and outgoing payments make the account balance fluctuate, it is possible that the balance drops beneath zero. As a central bank requires that any form of debt is covered by collateral, the moment the account balance becomes negative, the same amount of collateral will be blocked. If at the end of the day the account balance is still beneath zero, intraday credit automatically becomes overnight credit, which is marginal lending. The use of these two facilities is not directly steered by a participant.

Whenever there is a liquidity surplus and the participant does not want to enter the money market, there's the possibility to use the central banks' deposit facility and receive the overnight deposit rate. The marginal lending and deposit facility together are called the standing facilities.

The third liquidity influencing element within the central bank is formed by the long-term monetary loans offered that are offered by the central bank. In this case, again collateral is necessary. When a monetary loan has been granted, collateral will be transferred into the books of the central bank and the loan amount will be transferred to the account of the participant, therefore increasing its liquidity.

Standing facility, monetary lending and reserve requirement form the monetary policy of a central bank. The reserve requirement in itself is not a direct influencing element. Each maintenance period the average account balance is measured and compared to the minimum requirement set by the central bank. As falling below the requirement will lead to a penalty rate, the participant will have to take care of steering its end-of-day balance using any of the possible elements.

The outline of this paper is as follows. Section 2 describes the research question, section 4 describes the Bank of Finland Payment and Settlement Simulator that was used in this paper, section 5 describes the simulations that were performed to answer the research question, while section 6 describes the conclusions.

## 2 Research Question

Performing simulations usually takes a fair amount of time. After a plan has been made, data must be entered and, once simulations have been executed, the output must be analyzed. This is an iterative process; only after a couple of try runs, it becomes clear what the definitive set of simulations will look like and which parts will have to be analyzed. Every simulation run takes time, therefore one can win time by keeping the amount of data as small as possible.

### 2.1 What was the time span used in past simulations?

In order to investigate the most used time span in simulations, table 1 shows a list of all publications on simulations in which the Bank of Finland Payment and Settlement Simulator (in short BoF-PSS2 Simulator) has been used.

Table 1: Number of days used in past simulations using the BoF-PSS2 Simulator.

Author(s)	Nr.of days	Nr.trans- actions (* 1,000)	Title
Hellqvist (2009)	22	63,5	A quantitative assessment of international best practice for..
Arciero (2010)	28	3605	Evaluating the impact of shocks to the supply of overnight u..
Arculus et al. (2010)	21	623,86	The impact of payment system design on tiering incentives..
Arjani (2007)	64	1050	Examining the tradeoff between settlement delay and intraday..
Bech and Soramäki (2005b)	21	10314	Systemic Risk in a Netting System Revisited..
Bech and Soramäki (2005a)	64	59,2	Gridlock Resolution and Bank Failures in Interbank Payment ..
Bedford et al. (2005)	21	2100	Analysing the Impact of Operational Incidents in Large-Value..
Clarke and Hancock (2010)	10	310	Participant operational disruptions: the impact of system de..
Denbee et al. (2010)	102	12750	Methods for evaluating liquidity provision in real-time gros..
Hellqvist (2009)	18	2950	Liquidity effects of a participant-level operational disrupt..
Hellqvist (2009)	22	404,8	Simulations in the Dutch interbank payment system: A sensit..
Hellqvist and Koskinen (2005)	22	2,13	Stress testing securities clearing and settlement systems us..
Hellqvist and Snellman (2007)	19	906	Simulation of operational failures in equities settlement..
Imakubo and McAndrews (2007)	10	1200	Funding levels for the new accounts in the BOJ-NET..
Johnson et al. (2005)	10	4031	Economising liquidity with deferred settlement mechanisms..
Koponen and Soramäki (2005)	4	2500	Intraday Liquidity Needs in a Modern Interbank Payment Syst..
Lasaosa and Tudela (2007)	21	2500	Risks and efficiency gains of a tiered structure in large-va..
León et al. (2010)	22	162,3	Systemic risk in large value payments systems in Colombia: a..
Ledrut (2007)	22	537	How can banks control their exposure to a failing participan..
Leinonen and Soramäki (2005)	100	179	Optimising Liquidity Usage and Settlement Speed in Payment S..
Lovin (2010)	106	1092	Systemically important participants in the ReGIS payment sys..
McVanel (2007)	170	2900	The impact of unanticipated defaults in Canadas Large Value..
Oleschak and Nellen (2010)	15	1800	Does SIC need a heart pacemaker?..
Petterson (2005)	1	5,1	Simulation of liquidity levels and delays in the Swedish RIX..
Renault and Pecceu (2007)	23	621	From PNS to TARGET2: the cost of FIFO in RTGS payment system..
Schmitz and Puhr (2007)	22	335	Risk concentration, network structure and contagion in the A..
Lovin and Pineta (2010)	85	850	Operational risk in ReGIS a systemically important payment..
Hellqvist (2009)	41	140,589	Operational disruption and the Hungarian real time gross set..
Average	22	878	

## **2.2 The desire to keep the time span short**

There are several reasons why time spans have been kept rather short in past simulations.

Firstly there's the shortage of computer processing power and in a way also human processing power. The longer the simulator takes to process the transactions, the longer the researcher has to wait to get on with the research.

There's also the related problem of the increasing complexity of payment systems. In the early days, payment systems were straightforwardly simple. Nowadays almost every RTGS system contains additional functionality, like sorting within waiting queues, re-entry of rejected payments, bilateral limits and so on, which have to be built into the simulated system in order to fully mimic it. During simulations this will require processing power, leading to longer lasting simulations, thus forcing the researcher to keep the time span short.

## **2.3 The desire to increase the time span**

When the researcher uses historical transaction data from the payment system, a period is desired which is a good representation of the total period. An example of searching for a specific period and whether this can be used as a simulation source, can be found in the amount of intraday credit used in TARGET2. Figure 2 shows box-plots for each month spanning February 2008 to July 2012. Both on the level of the extremes, as well as in the 25-75 percentiles, it is clear that there remain huge differences between months and that neither month can act as a good representation for the whole period. In order to ensure that a simulation is performed on a representative time span, one would ideally use about a half a year's transaction data. At the moment this is not possible due to the limited performance of the computers at hand.

Another reason for the desire to increase the time span of simulations arises from types of scenario analyzes. Testing of payment systems' characteristics doesn't require the need to feed long periods of transaction data. The same goes for scenarios in which the failure of one or more participants is simulated and the resilience of others is tested. However, scenarios in which the ability of participants to withstand shocks of any kind is often a matter of several days, sometimes weeks, and in some cases even months before liquidity drains start to show. In these cases the researcher probably desires to increase the time span of simulations in order to find out what happens in the longer run.

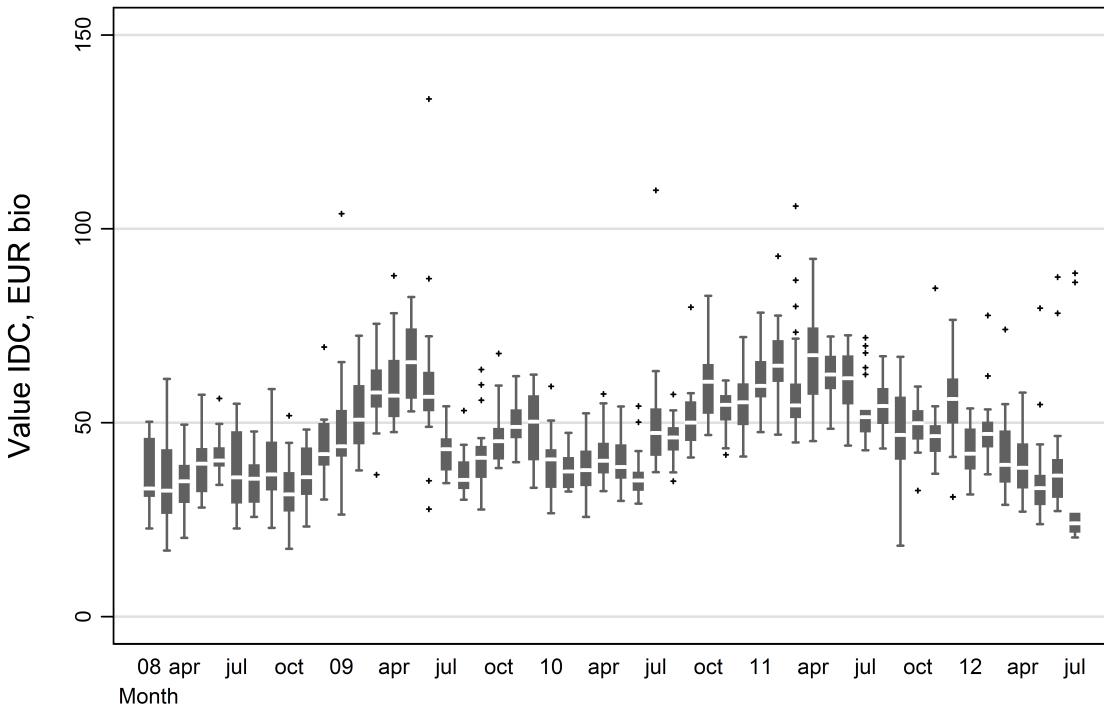


Figure 2: Daily amount of intraday credit used in the TARGET2 payment system, per month.

During the recent years longer-term scenarios are becoming more and more wanted. When, for instance, using the BoF-PSS2 Simulator, the scope of analysis is the functioning of the money market, it will become interesting how the liquidity needs within the payment system change in the course of several months instead of weeks. As the BoF-PSS2 Simulator software enables the user to add new functionality, it could be made possible to simulate a money market that (again) enables participants to steer their end-of-day balances and stop their dependence on monetary loans. These kind of analysis ask for a time span of several months.

## 2.4 Could we compress the amount of transactions in a simulation?

When sorting all TARGET2 transactions according to their size, usually the smallest payments are most frequent. Figure 3 below shows the cumulative share in number and value of payments (like the Lorenz curve). The lower value payment on the left hand side contain a huge share in the number of transactions while the high value payments at the right hand side make only a small share of the number, but a huge share on the

value of payments.

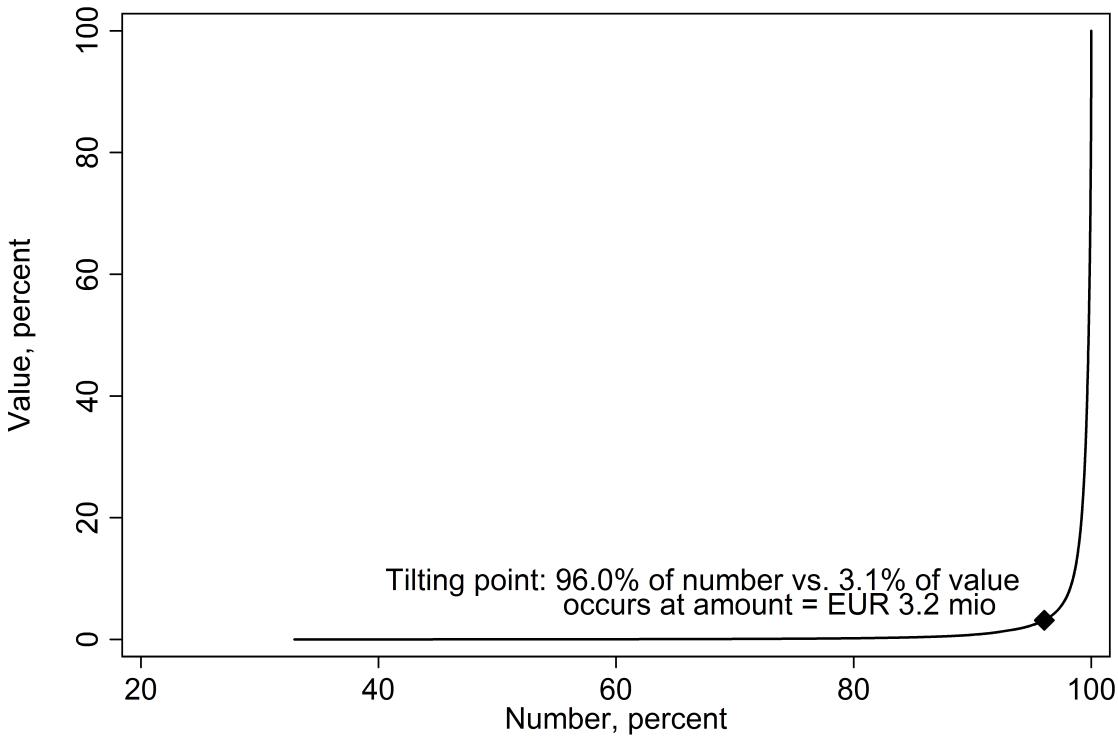


Figure 3: Cumulated share of value and number of transactions in TARGET2-NL. Based on the transactions of five representative days used in the simulations.

Although the low value payments have the largest impact on the performance of simulations, the influence on liquidity is clearly negligible. It is therefore to be expected that the number of transactions to be used in simulations can be reduced by aggregation, without significantly altering the outcome. Aggregation of transactions can be achieved by summing all transactions between two participants below a ceiling value. No netting of transactions should be performed, therefore leaving the characteristic of the payment system untouched; it will still handle the gross amount of payments. The simulation outcome would have to be compared to the original and show no significant increase in the use of liquidity.

We therefore come to the following research question:

**Is it possible to increase the time span in payment systems simulations by aggregating transactions between participants below a certain value, without disturbing the outcome of simulations compared to the original simulation?**

### 3 Methodology

The BoF-PSS2 Simulator uses three input sources:

$$SI = \{P, L, T\} \quad , \text{ where} \quad (1)$$

$SI$  = Simulation Input,  $P$  = Participants,  
 $L$  = Liquidity at startup,  $T$  = Transactions

The liquidity that is available to the participants at the startup consists of two evenly divided parts:

$$L = AB + CL \quad , \text{ where}$$

$AB$  = Liquidity at Accounts Balances,  $CL$  = Liquidity in Credit limits

During execution of the simulations, the outcome is stored at the desired level of granularity. We will use measures stored at account level; percentage settled, liquidity lower bound, balance drop and average queue value. These statistics will be described in more detail; see section [5.2](#).

Each simulation outcome containing the original transactions is then compared to the simulations containing aggregated transactions:

$$BS \approx AS \quad , \text{ where} \quad (2)$$

$BS$  = Benchmark Simulation using original transactions,  
 $AS$  = Aggregation Simulation using aggregated transactions

Aggregation of transactions is executed at ten levels. It starts at zero, which is the the benchmark simulation (no aggregation performed), and is increased up to the desired "aggregation ceiling" value (chosen at EUR 3.6 million).

$$BS = \{P, L, T_{agg}\} \quad , \text{ where} \quad (3)$$

$$agg = \{0\}$$

$$AS = \{P, L, T_{agg}\} \quad , \text{ where} \quad (4)$$

$$agg = \left\{ \frac{1}{9}, \frac{2}{9}, \dots, \frac{9}{9} \right\}$$

The following steps are taken when aggregating the transactions:

- for each set of transactions from the one participant to the other, below the ceiling amount
- totalize the value of these transactions
- calculate the average settlement time, weighted by the value of transactions
- remove this set of selected transactions and use the calculated single transaction
- merge this set with the non-selected transactions (above the ceiling value) and use this as input for the BoF-PSS2 Simulator.

Performing a comparison of the benchmark to the aggregated versions must be repeated for a range of liquidity levels. A situation in which there is full liquidity will lead to immediate settlement of all transactions. The opposite is the absence of liquidity in which none of the payments can be settled. The BoF-PSS2 Simulator will be most useful in situations somewhere in between these two extremes, therefore the set of aggregation level comparisons will be repeated at ten levels of liquidity.

$$BS, AS = \{P, L_{liq}, T\} \quad , \text{ where} \quad (5)$$

$$liq = \left\{ \frac{9}{9}, \frac{8}{9}, \dots, 0 \right\}$$

Maximum liquidity is defined as the total of all debits within that day.

The result is a set of hundred simulations:

- comparison of the benchmark simulation to nine aggregation simulations
- repetition of this comparison at ten levels of liquidity.

## 4 The BoF-PSS2 Simulator

Running a simulation requires the following steps (see also figure 4):

- Defining the payment system
- Loading participants, transactions, opening balances and (optionally) bilateral limits
- Defining simulations
- Running simulations
- Exporting the generated statistics for further analysis.

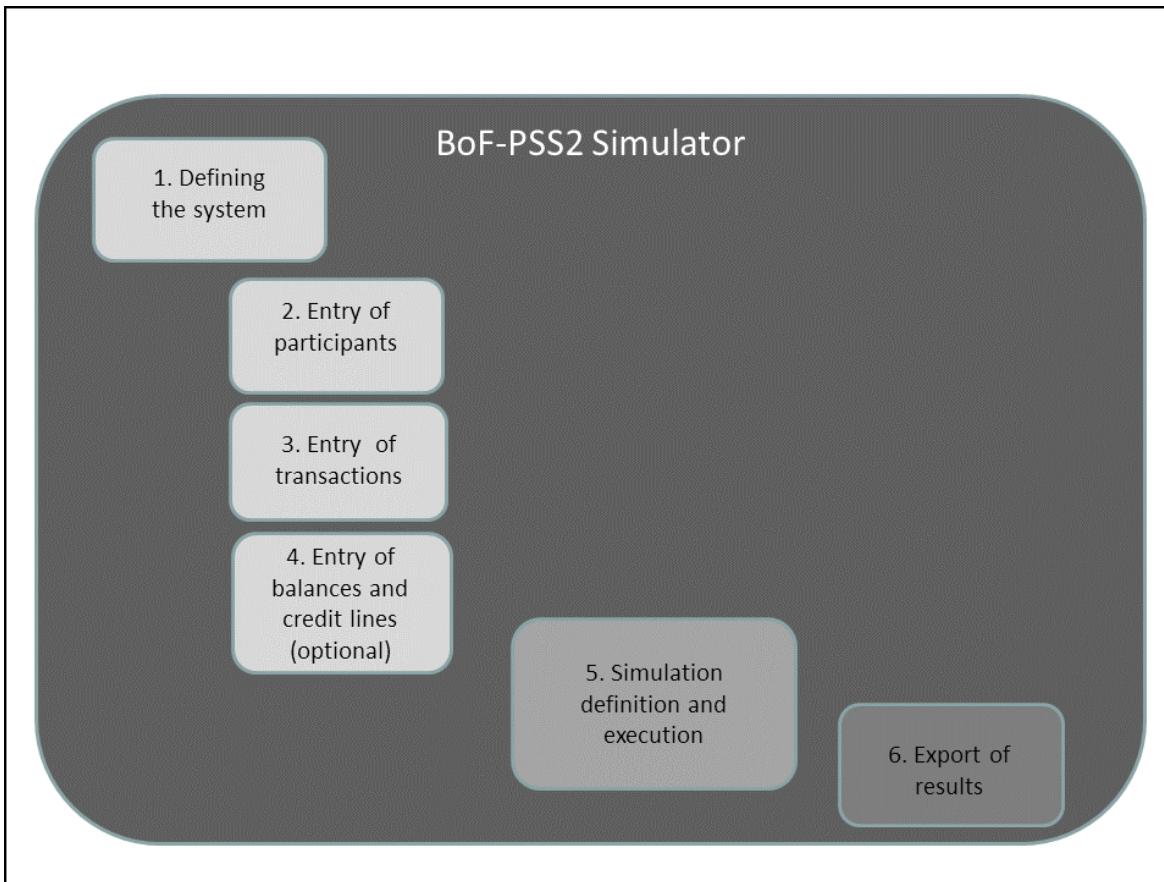


Figure 4: Actions and components using the BoF-PSS2 Simulator.

The main use for the BoF-PSS2 Simulator is the usage and throughput of liquidity in the system, for which several detailed statistics can be generated. An example of typical use would be the addition of a new liquidity saving feature to an existing payment system and testing how much the liquidity needs decreases for the participants. In such case the payment system itself is the focus of the research. Another focus in

which the BoF-PSS2 simulator is often used is the robustness of testing individual participants to withstand an occurring liquidity shock.

When keeping in mind the liquidity elements in figure 1, one can think of a wide variety of other simulation scenarios:

- The central bank will start an exit strategy by decreasing the amount of monetary loans. If participants are not able to use money markets for their liquidity needs, which participants will face problems meeting their reserve requirements?
- A crisis will trigger collateral deterioration. Depending on the type of collateral impacted, which participants will face problems?
- Given that money markets would grow to a point similar to before the crisis, could it be possible that the use of standing facilities will come to a halt?
- If a participant faces a nascent bank run (e.g. increasing the outgoing payments to a 140%), how long will it take before severe liquidity problems occur?

Although the BoF-PSS2 Simulator was not originally designed for these kind of analyzes, the openness of the simulator software enables the user to alter the scope by e.g. adding new transactions in between days or adding behavior through the use of user-defined modules.

Often the researcher starts a large group of simulations in sequence. As this is quite time-consuming, the BoF-PSS2 Simulator has recently been enhanced with a command line interface (CLI). This feature enables the user to automatically start the most important functions using either operating system commands, a script-file or directly from within other software. We used Stata to prepare data, start CLI-commands (in order to input data, define and start simulations and export the results) and afterward analyze the results.

Figure 5 shows how the series of simulations have been executed:

- 0 - Selection and altering of data from the payment system using Stata
- 1 - Defining the payment system (one-time effort)
- 2 - Entry of participants
- 3 - Entry of transaction data
- 4 - Entry of start-of-day balances and credit lines
- 5 - Defining and execution of a simulation batch
- 6 - Export of statistics

7 - Automatically repeating parts 2-7 using the command line interface

8 - Analysis of exported statistics using Stata.

Once a payment system is defined, all other commands (2-7) can be executed through the command line interface (dark area) which enables the possibility of using the looping facility in Stata to generate series of simulations.

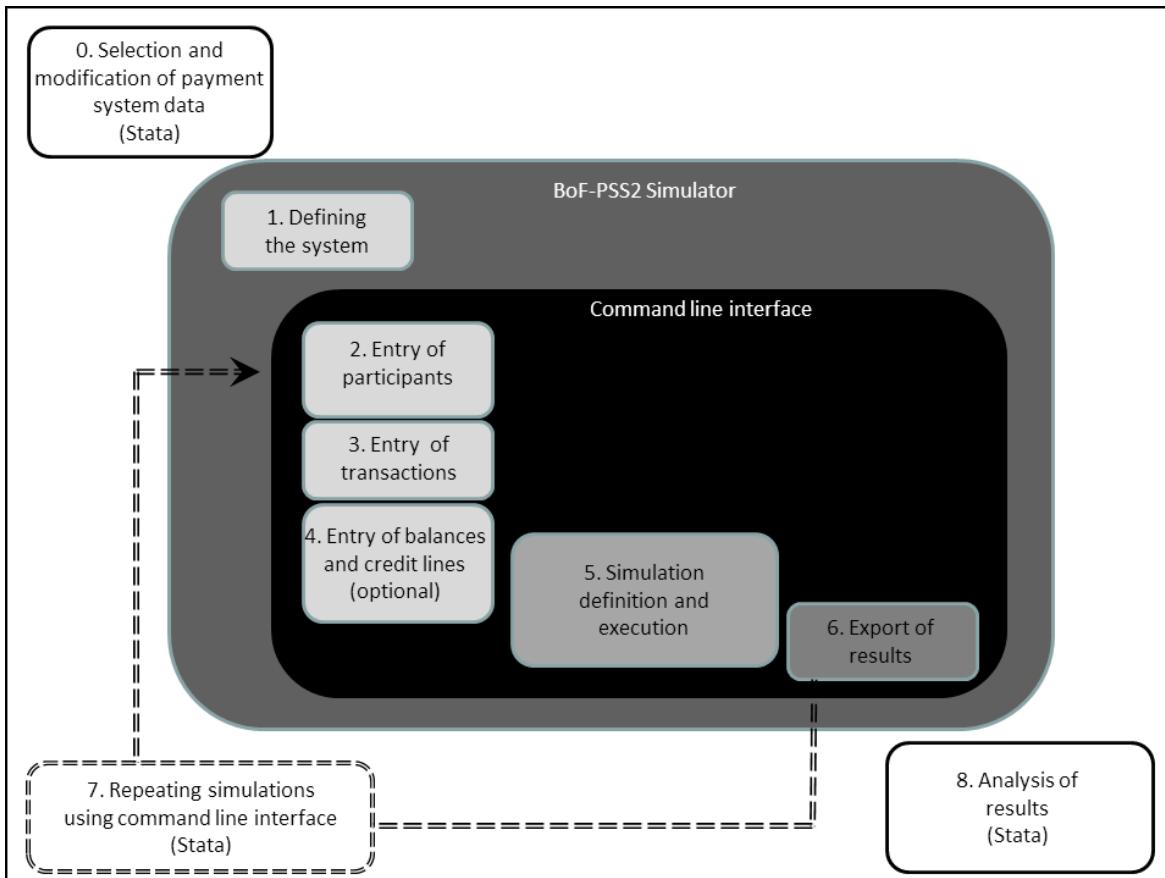


Figure 5: Automating simulation runs using the command line interface.

## 5 Performed simulations

### 5.1 Data used

From the period spanning February 18, 2008 to June 13, 2014, five days were chosen from the Dutch part of TARGET2, according to the increasing number of transactions settled:

- lowest number (June 9, 2014, containing 25,408 transactions)
- first quartile (November 12, 2012, containing 39,886 transactions)
- medium (May 11, 2010, containing 43,125 transactions)
- third quartile (July 18, 2008, containing 47,601 transactions)
- highest number of transactions (December 22, 2008, containing 96,898 transactions).

This ensured us that the series of hundred simulations were based on a representative set of days.

### 5.2 Statistics used

In order to assess the liquidity flows within the system, we used four available statistics at account level; percentage settled, lower bound, balance drop and average queue value.

#### Percentage settled

The value of payments settled as a percentage of the value submitted gives a good view of the throughput of payments.

#### Lower bound

This well known statistic is the minimum amount of liquidity needs for all of the payments to be settled at the end of the day ([BoF, 2013](#)). It consists of the difference between outgoing and incoming transactions and is not affected by the waiting queue.

$$LB_i = \max \left( 0, \sum_{k=1}^{d_i} a_{i,k} - \sum_{j=1}^n \sum_{k=1}^{d_j} a_{j,k} \middle| (r_{j,k} = i) \right) \quad (6)$$

where

$a_{j,k} \in \mathbb{R}_+$  = the value of payment  $k$  of participant  $j$

$r_{j,k} \in \{1, \dots, j-1, j+1, \dots, n\}$  = the receiver of the payment.

### Balance drop

This statistic is the difference between the start-of-day balance and the minimum balance within the day and forms a good measure for the amount of liquidity that a participant contributed to the throughput of payments. The balance will only drop when the cumulated amount of outgoing payments is higher than the amount of incoming payments at a certain point in time. In such a case the participant has actively contributed to the throughput of liquidity in the system.

### Average queue value

This gives the average value of queued payments within the day, weighted by the time that the payments were in the waiting queue, and forms a good measure for liquidity problems. As liquidity decreases, it can be expected that waiting queues arise, therefore the average queue value will increase.

## 5.3 Outcome of simulations

After running the simulations, the following output is available for analysis:

- for all of the five days
- at ten levels of liquidity
- one benchmark simulation (without aggregation)
- can be compared to nine aggregation simulations
- using four different statistics.

This totalizes to 500 simulations, of which 50 benchmark simulations (10 levels of liquidity for 5 days) that will all be compared to 9 aggregation simulations. The deviation from the benchmark value will be computed as a percentage difference, with the benchmark set at 100%.

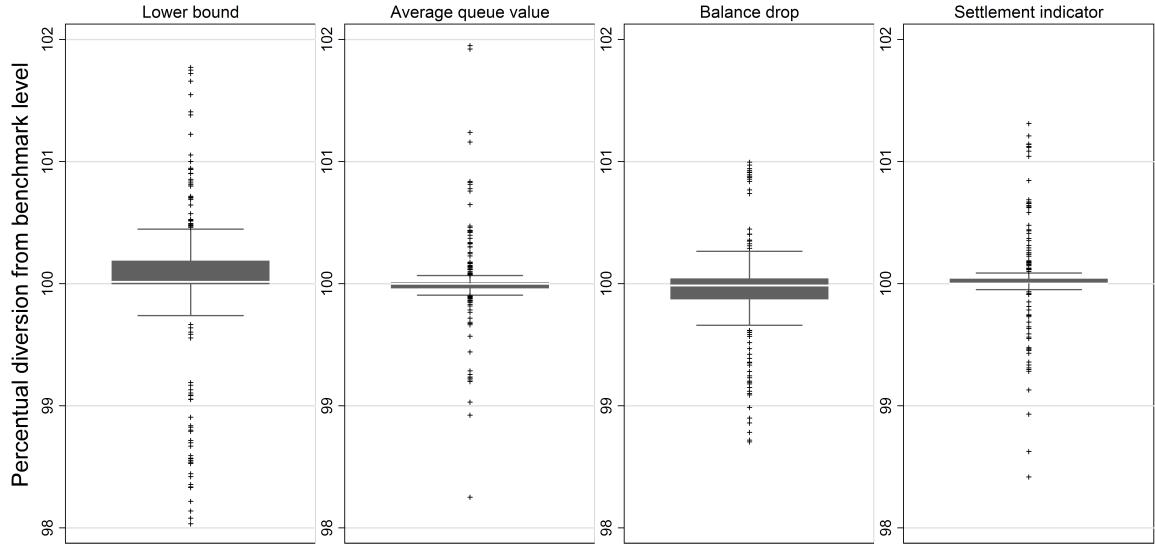


Figure 6: Outcome of simulation runs. For each statistic the percent diversion from the benchmark simulation (i.e. 100) was calculated. For five days, ten benchmark simulations (at different liquidity levels) have each been compared to 9 simulations at different aggregation levels.

Figure 6 visualizes this outcome using boxplots. The boxes span the inter quartile range (IQR) from 25% till 75%, taking 50% of the population. Together with the whiskers, which are placed at 1.5 times IQR, the plotted range comes to 99.73% of the group, under the condition of normal distribution. The plus-signs show the remaining individual values. For a clear visibility of the boxes and whiskers, not all outer values are shown. The figures makes clear that, for all four statistics, the huge majority of simulations fall within the 99-101 range and are there fully comparable to the benchmark simulations.

Figure 7 shows the same comparison to the benchmark simulations at four statistics broken down into the ten liquidity levels. The vertical axes all show the 97, 100 and 103 level of comparison. Showing all outer values containing the extreme diversions from the benchmark causes the IQR boxes and whiskers to be compressed. It can be concluded that the majority of simulations fall within very acceptable ranges, but at the same time few simulations show large diversions. These diversions occur mainly at the lowest liquidity levels 1 to 3. These are the liquidity levels where all participants are suffering from huge liquidity shortages, waiting queues are huge, and many transactions remain unsettled.

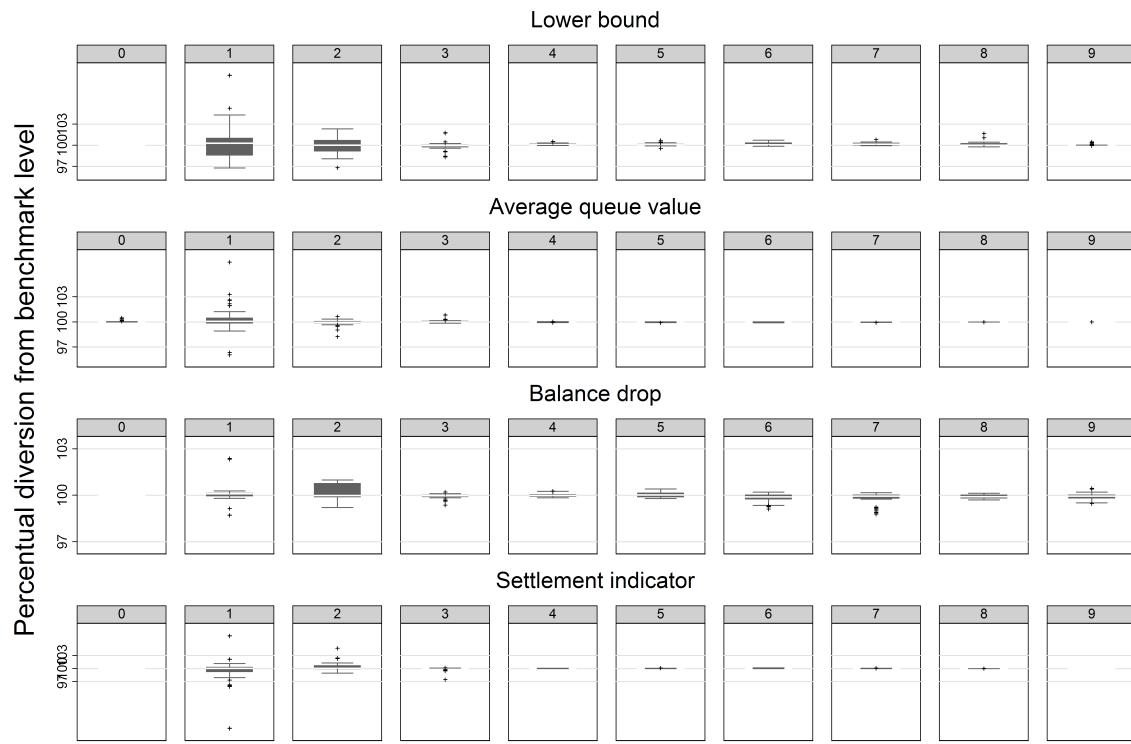


Figure 7: Outcome of simulation runs, by liquidity levels.

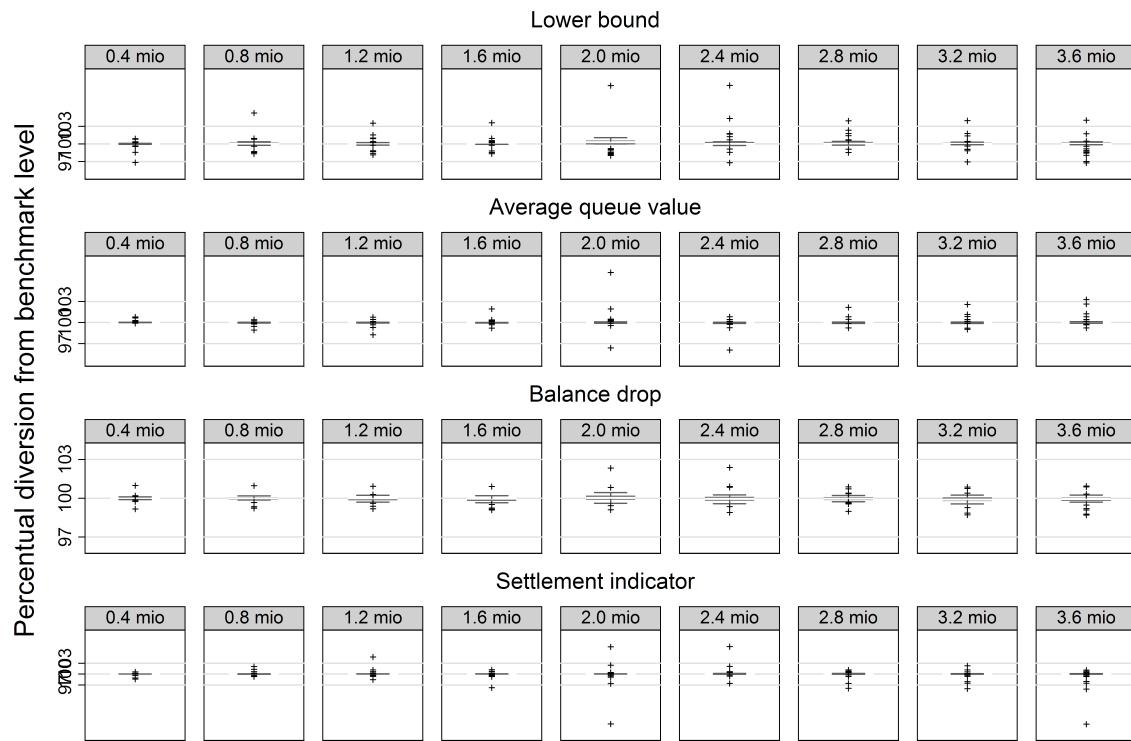


Figure 8: Outcome of simulation runs, by aggregation levels.

Figure 8) shows us the same data, now ordered by aggregation level. There appears to be no increasing level of diversions visible at increasing aggregation level. The conclusion then must be drawn that even up to the highest level of aggregation, i.e. EUR 3.6 million, the percent share in the value of transactions is small enough for aggregation simulations to be fully comparable to the benchmark simulations.

## 5.4 Gain in speed

The aim of the simulation batches was to reduce the number of transactions by aggregating below the aggregation ceiling. As the BoF-PSS2 Simulator also saves performance statistics about each simulation run, these statistics were used to analyze the duration of simulations. The outcome is presented in figure 9.

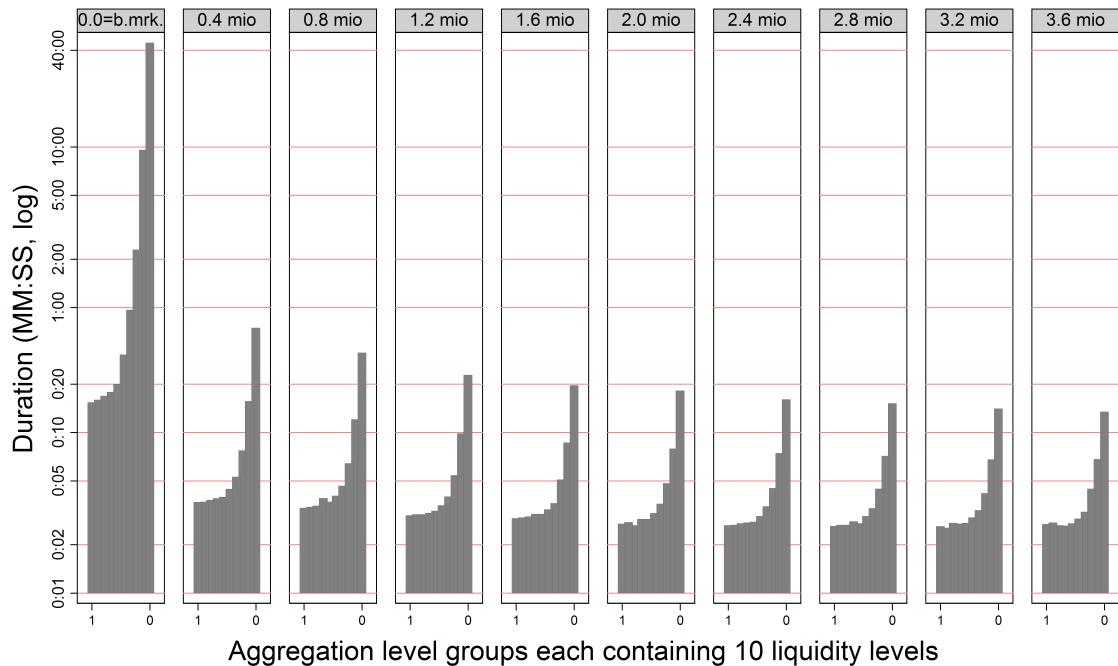


Figure 9: Speed of simulation runs. Most left graph - no aggregation; most right graph - highest level of aggregation (i.e. 3.6 million). Within each graph: most left - full liquidity; most right - none. Simulation dataset 22dec2008.

The figure shows all hundred simulations that were executed using day December 22nd, 2008, containing the largest number of transactions. Each aggregation level is gathered in one group, starting at no aggregation on the left, to the highest aggregation on the right. Within each group, a simulation duration is present for each liquidity level, starting at full liquidity on the left, to no liquidity on the right. The most left

simulation on acts as the starting point, showing the full liquidity benchmark simulation duration of 15 seconds, followed by the other nine benchmark simulations, and ending at the benchmark simulation with no liquidity that took 44 minutes and 32 seconds. It becomes clear that there is gain of speed both at level of aggregation as well as at level of liquidity. This will be more explicitly analyzed hereafter.

## 5.5 Speed of simulations influenced by aggregation and liquidity levels

Both aggregation as well as liquidity level influence the speed of simulations. Figure 10 shows the relation between the compression level (x-axis, left side means maximum compression) and the resulting duration of simulations. The declining number of transactions linearly decrease the duration of simulations.

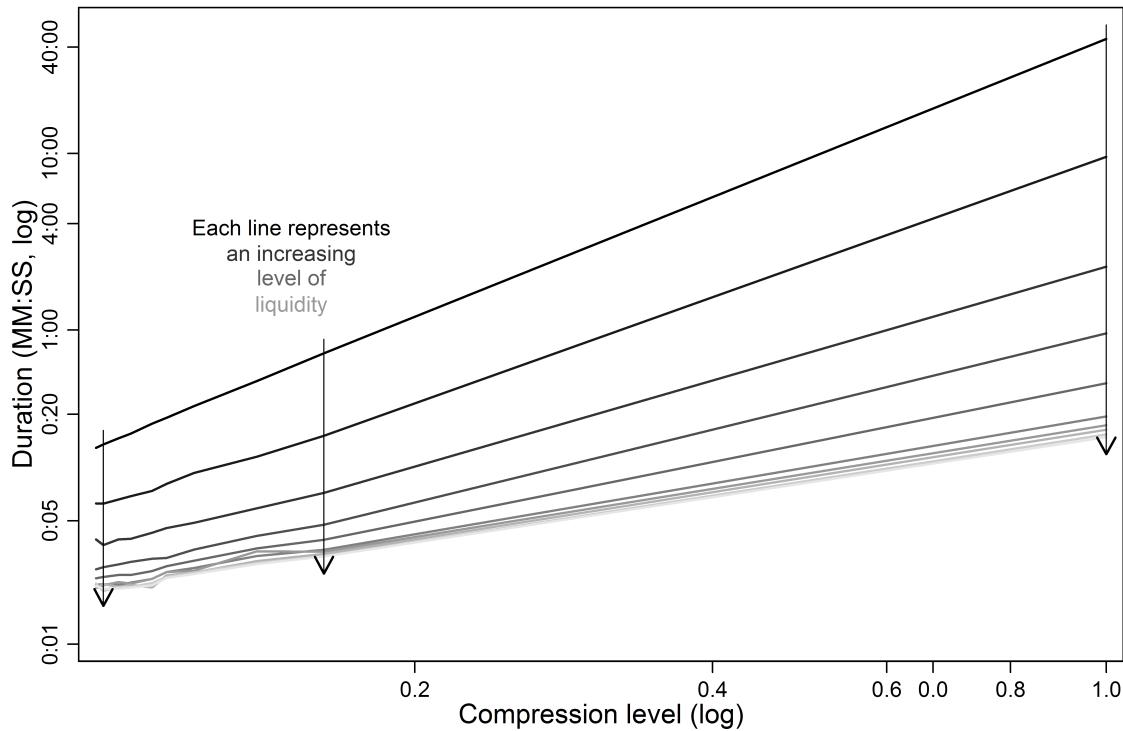


Figure 10: Speed of simulations influenced by compression level. For each observed level of liquidity one line is drawn, showing the relation between compression and duration of simulation runs. Simulation dataset containing date 22dec2008.

In figure 11 the liquidity level is shown on the x-axis, starting on the left side with full liquidity. Looking towards the right, it becomes evident that there is a more than logarithmic growth in the duration of simulations caused by the decreasing level of liquidity. The growth of the duration starts booming at liquidity levels 0.3. The top

(dark) line stands for the benchmark simulations, below which the aggregation simulations can be found.

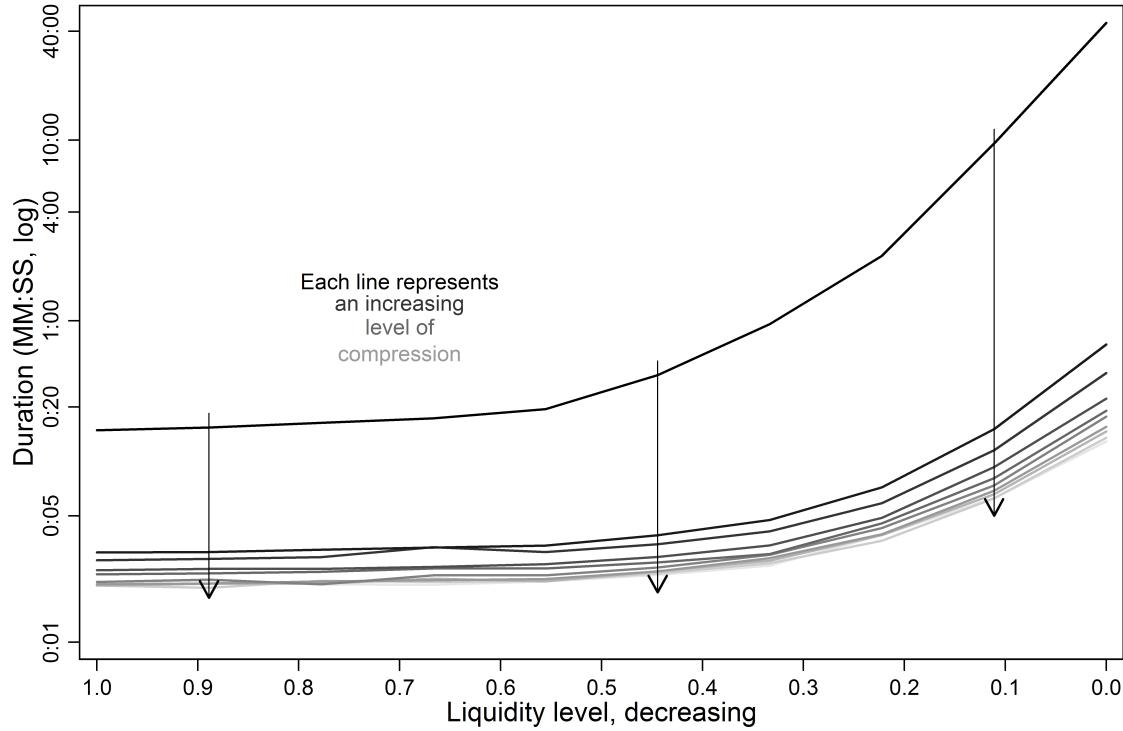


Figure 11: Speed of simulations influenced by liquidity level. For each observed level of compression one line is drawn, showing the relation between liquidity and duration of simulation runs. Simulation dataset containing date 22dec2008.

## 6 Conclusions

Researchers usually take historical transactions from payment systems to be used in simulations. The desired time span of simulations can vary from a few days up to several months, depending on the type of scenario that the researcher has in mind. It is not always possible to choose the ideal length of the time span, due to the lack of available computer performance. It is because of the typical distribution of the value of payments, that this problem can be solved by aggregating the low value transactions, without compromising the reliability of the analysis.

This was made possible by setting up one benchmark simulation and nine simulations at different levels of aggregation and comparing the outcome. This set of simulations was then carried out at ten different levels of liquidity in order to cover all possible liquidity scenarios.

The results have shown us that at all levels of aggregation and liquidity the outcome of the simulations are fully comparable. Further more it appears that the decreasing level of liquidity brings the highest contribution to the increasing duration of simulations.

We conclude that aggregation of transactions below a certain value is a reliable approach towards increasing the speed of simulations and as such the possible time span to be used in simulations. The increase in the duration of simulations is the highest at the level of severe liquidity problems for all participants. The researcher must realize that diversions from the original simulation can become larger and therefore the nature of diversions must first be analyzed.

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# Chapter 11

## Signalling analysis tests for early warning indicators from large-value payment systems

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*Matti Hellqvist – Jussi Leinonen – Girts Maslinarskis*

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# **Signalling analysis tests for early warning indicators from large-value payment systems**

**Matti Hellqvist, European Central Bank,  
Jussi Leinonen, Bank of Finland and  
Girts Maslinarskis, Latvijas Banka\***

## **Abstract**

We present an idea and implementation of a testing framework for early warning indicators (EWI) which are derived from LVPS data. Such indicators could warn in advance of adverse changes in the behaviour of separate LVPS participants or crystallization of risks in the financial market. The implementation is based on signalling analysis approach introduced in Sarlin (2013) and Alessi & Detken (2011). In addition, the paper provides discussion on use of signalling analysis on LVPS data and elaborates the adaptations and modifications on the method, which can be necessary due to the frequency and nature of this data. Beyond theoretical fundamentals, this paper also illustrates the practical side of the testing process.

## **1 Introduction**

Large value payment systems (LVPS) provide the core infrastructure which is needed for settlement of transactions from the real economy or from financial markets. As such they concentrate a lot of information about the activities and functioning of the economy or the financial markets and the participants acting in these markets. The data from LVPS contains granular information on timing, values and participants of payments as well as information on the liquidity positions and liquidity management of the participants.

There is a growing number of studies, where the data and information from LVPS is utilised<sup>1</sup>. This data can potentially be beneficial and support many responsibilities of regulators ranging from oversight of financial market infrastructures, supervision of banks, macro-prudential analysis to even monetary policy analysis. Idea has been presented that early

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\* The views expressed are those of the authors and do not necessarily represent the views of the European Central Bank, Bank of Finland or the Latvian Banka.

<sup>1</sup> E.g.: Heijmans, R., Heuver, R. (2011). Is this bank ill? The diagnosis of doctor TARGET2; Furfine, C. (1999). The microstructure of the federal funds market; Arciero, L. & al (2013). How to measure the unsecured money market ? The Eurosystem's implementation and validation using TARGET2 data; Tölö, E. & al (2014). Do private signals of a bank's creditworthiness predict the bank's CDS price ? Evidence from the Eurosystem's overnight loan rates.

warning indicators (EWI) could be derived from the LVPS data<sup>2</sup>. These could identify and flag changes in the behaviour of individual LVPS participants or overall market practices, which precede or lead to collapses or crystallisation of risks - or increased level of risk of such extreme events.

The focus of this paper is to find structured tests, which could be used to assess objectively the quality of potential EWIs based on LVPS data. Such test should show if an EWI can provide reliable signals and whether these signals can be detected early enough to be valid for timely warning purposes. The paper presents one implementation of testing framework with signalling analysis method. Additionally we discuss the required adaptations and modifications on the signalling analysis which we considered to be necessary in this context.

As main conclusions from the presented study, we consider that signalling analysis can be used to test also EWIs based on LVPS data, but the high frequency of the data requires modifications in the approach such as allowing some flexibility in the time lag between a signal from an indicator and expected occurrence of a crisis.

One essential benefit of the use of signalling analysis approach is that it allows taking into account the policy maker's preferences. Both in- and out-sample datasets should be utilized in the testing of EWIs. However, we found it challenging to find such control data sets, which would have sufficiently high frequency and repeated occurrences of relevant crises events. It is emphasized that all the data shown up in the paper are fictional and displayed only for illustration purposes. The actual analysis was based on data from TARGET2 system, but due to confidentiality reasons these results are not included in the current paper.

The remainder of the paper is structured as follows. The second section introduces two alternative testing approaches and explains the motivation behind the decision to use signalling analysis. The third section provides the description on the theory of the signalling analysis approach and practical aspects of the analysis approach. The fourth section illustrates our implementation of the signalling approach in practice, by showing the steps how realisation is achieved and also provides insight into the testing framework in general. Section four also describes the specific issues which were faced related to use of signalling analysis on LVPS data. The last section concludes the work.

## 1.1 Choice of the model

Our task for the current study was to implement a testing framework which could be used to objectively assess and compare proposed early warning indicators based on LVPS data. The question which arises here is 'On what model should the testing framework be based?'

Early warning indicators are typically, if not always, imperfect so that their predictions contain correct warnings or signals as well as incorrect predictions or noise. An indicator can be incorrect either by not predicting a crisis or by predicting a crisis which did not materialise. Traditionally the goodness of an indicator has been measured with a ratio between the frequency of the signal and noise. According to Alessi & Detken (2011), in order to decide the acceptable performance of indicators, one must proceed beyond the signal-noise-ratio method and also consider the preferences of policy makers regarding missed cases and false alarms. This requires an indicator to provide positive utility compared to a benchmark case in which indicator is ignored, and thus results in much tougher criterion to evaluate indicators' usefulness.

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<sup>2</sup> Laine, T., Nummelin T., Snellman H., (23/2011). Combining liquidity usage and interest rates on overnight loans: an oversight indicator

The first option here is to use the so-called signalling approach, which is one of the two threshold approaches using a binary dependent variable. The second approach is the discrete-choice (probit/logit) model.

According to Alessi & Detken (2011), the choice between both models mainly depends on the degree of expected non-linearity between the indicator and the event variable. In the signalling approach a warning signal is issued when an indicator exceeds a threshold, here defined by a particular percentile of an indicator's own distribution. This approach assumes an extreme non-linear relationship between the indicator and the event to be predicted. As there might be a need to test a large variety of potential indicator variables, conclusions drawn from regression based analysis might be easily misleading. Therefore the signalling approach should be considered the most appropriate.

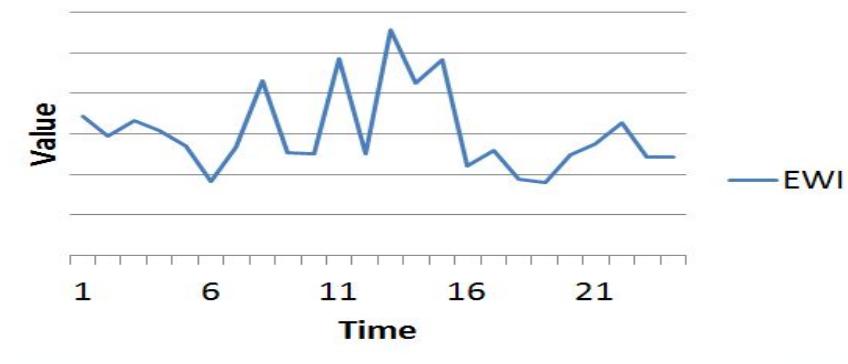
A useful feature of the signalling approach is that it allows the policy maker's preferences to be taken into consideration, when the threshold or trigger value for the EWI is defined. In case the policy maker considers that the priority is to capture all the possible crises while tolerating some false alarm errors, the threshold will be set fairly low. However, if policy maker's preference is to avoid false alarm errors, the threshold will be set rather high.

## 2 Signalling analysis

### 2.1 Practical application of signalling analysis

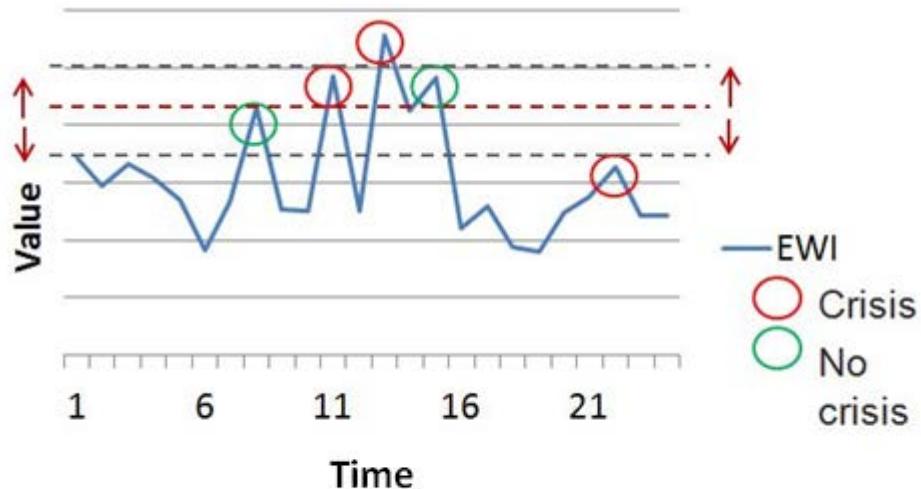
The following is a simplified example of a practical calculation of signalling analysis. First, consider an artificial time series of historical early warning indicator values. This is illustrated in the figure 1. As a prerequisite, the indicator must be able to show variations in the signal level and optimally it should reach peak values before the crises.

**Figure 1.** Example time series of early warning indicator.



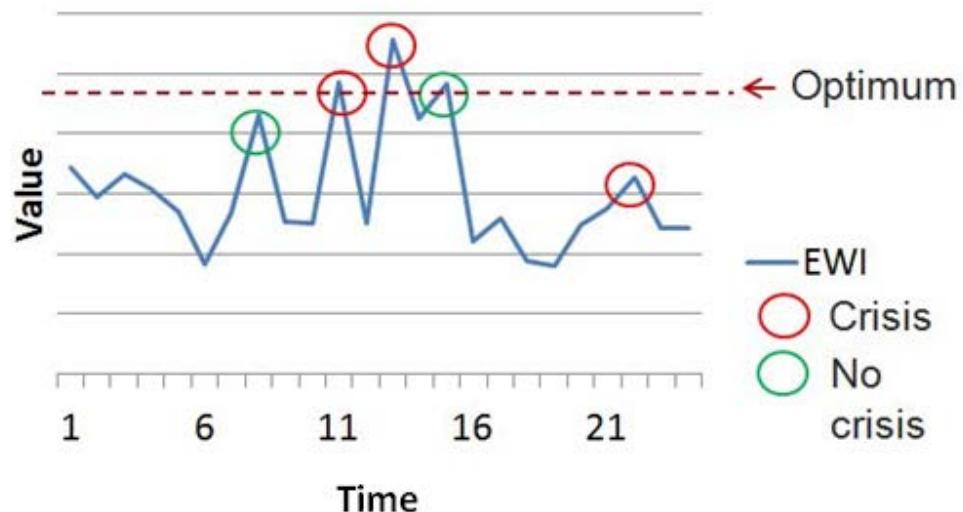
When the crisis moments related to the studied time period are known, these can be reflected on the time series of the indicator. Not all peak values are likely related to an actual crisis situation. For simplicity, only the peaks of the EWI are labelled below in figure 2 either as a crisis situations with red or as tranquil periods with green. The threshold value is illustrated as the dotted horizontal lines. To establish the optimal threshold value it is necessary to compromise between missed crisis identifications and false alarms.

**Figure 2.** Choice of optimal threshold by compromising between missed crisis identifications and false alarms.



Signalling analysis can be utilized to calculate the optimal threshold, when the preference between error types is established. For example, in figure 3 both error types are weighed equally which sets the threshold here at the red dotted line.

**Figure 3.** Selection of optimal threshold by the means of signalling analysis.



## 2.2 Theoretical Considerations

After a certain threshold value for an EWI is selected, each point of the evaluation sample, the time series provided by each indicator, falls into one of the following quadrants of the following matrix:

	Crisis occurred	No crisis occurred
Signal issued	A	B
No signal issued	C	D

In the matrix above, A is the number of observations in which an indicator provides a correct signal and B the number of observations in which a wrong signal is issued. Furthermore, C is the number of observations in which the indicator failed to provide a signal even though crisis would follow and D the number of observations in which no signal was issued and no crisis followed. The question is then what should be the time frame between the signal and the crisis? In other words, how quickly is the crisis expected to occur after the indicator has signalled it?

To determine the effectiveness of an indicator to signal an upcoming crisis event, a lag or forecasting horizon should be defined. This shows the time difference between the warning signal and the commencement of the crisis event. In the case of LVPS data the indicators are typically calculated on daily level and thus the lag is presented in business days.

According to Alessi & Detken (2011), the equation for calculation of the loss function in proposed signalling approach is as follows:

$$(1) \quad L = \theta \frac{C}{A+C} + (1-\theta) \frac{B}{B+D}$$

Where,

$\frac{C}{A+C}$  = ratio of missed cases error (the crisis occurred);

$\frac{B}{B+D}$  = ratio of false alarm error (the crisis has not occurred);

$\theta$  = preference parameter which shows the relative importance of missed cases errors with respect to false alarm error

The next step after having calculated the loss function is to calculate usefulness of the indicator.

Usefulness ratio of an indicator is then as follows (Alessi & Detken, 2011):

$$(2) \quad U_a = \min[\theta; 1 - \theta] - L$$

If the usefulness is positive, the indicator in question can be considered as useful. If it is negative, the indicator provides more losses than gains as an early warning indicator, suggesting that the indicator is not useful for early warning purposes. However if it is equal to zero, there are neither losses nor gains from the use it.

In order to analyze the forecasting performance of the indicators in question, the optimal thresholds for each indicator need to be calculated by minimizing the loss function L.

After that the quadrants of the matrix above are computed. The optimal threshold of the indicator is the one which provides the highest usefulness ratio through minimizing the loss function.

According to Sarlin (2013) the new loss function (3) and Usefulness measure (4) were introduced for assessing early warning indicators which accounts for unconditional probabilities of the crises P1 ( $P1 = (A+C)/(A+B+C+D)$ ) and tranquil periods - P2 ( $P2 = (B+D)/(A+B+C+D)$ ). This adaptation takes into account the known low a priori frequency of the crises in our daily data set. In datasets where crises are very rare, the correct no alarm signals might otherwise dominate the results of matrix, which can lead to the situation when the value of loss function might be very low and ultimately lead to positive usefulness of indicator which is not to a lesser extent useful.

$$(3) \quad L = \theta \frac{C}{A+C} P1 + (1-\theta) \frac{B}{B+D} P2$$

$$(4) \quad U_a = \min[\theta P1, P2(1-\theta)] - L$$

Sarlin (2013) and Behn et al. (2013) expand the calculation of Usefulness by modifying it further to calculate Relative Usefulness (5) which is a percentage of the Usefulness that a policymaker would gain with a perfectly performing model (a perfectly performing indicator would achieve Type I error (missed cases errors) = Type II error (false alarm errors) = 0, implying Loss function = 0). In their view, relative Usefulness provides better means for representing the information rather than only reporting a single number as in case of Absolute Usefulness (above in (2)). In particular, relative Usefulness facilitates comparisons of models for policy-makers with different preferences. Relative Usefulness would be calculated as follows:

$$(5) \quad U_r = \frac{U_a}{\min[\theta P1, P2(1-\theta)]}$$

### 3 Testing framework

#### 3.1 Practical approach

In order to illustrate how the above discussions on theoretical considerations and practical applications of testing could be implemented in practice, this section shows the steps how realization is achieved and provides insight into testing framework in general.

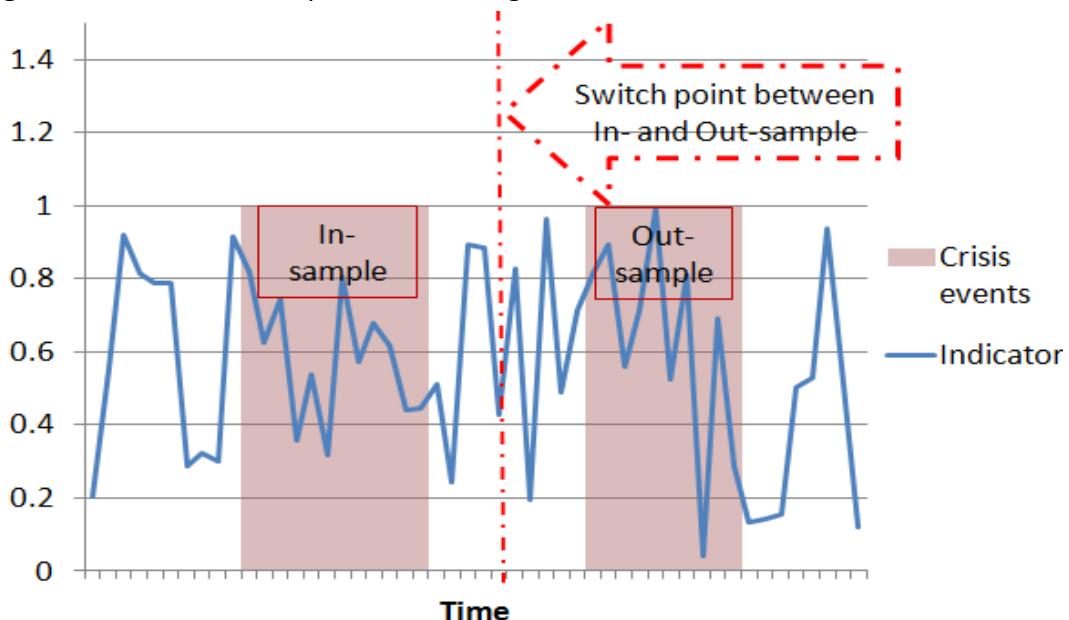
To be able to test any indicator, the following data are necessary: both a time series of early warning indicator observations and a corresponding control dataset illustrating the presence of a crisis. The control dataset is composed of a binary variable time series, taking value 1 for crisis observations and zero otherwise.

This list also includes the date on which crisis commenced, thus indicating the date before which the indicator is expected to provide some warning signals. The caveat is that banks' financial troubles logically initiated prior to any observed crisis or failure and the exact date of observed failure may well be into the crisis; in other words, some signals identified prior to the crisis might, in fact, occur during the formulation of the crisis. Without more perfect data, an approximation is needed to choose only signal well in advance of crises so as to avoid using signals from a pre-crisis period.

There is not just one control dataset for all the possible cases. There can be several of them to highlight each possible type of crisis phenomena of focus. They can be constructed on the system level, country level or bank level depending on the occasion. In essence, if the early warning time series consist of values calculated for single bank, then obviously the control dataset illustrates the crisis occurrence for that single bank.

To be able to do testing, two separate datasets needed (in-sample and out-sample datasets, see figure 4) where there are separate crisis occurrences. In-sample data run is necessary to be able to calibrate the threshold or trigger of indicator above which the warning signals are detected, whereas the out-sample data run is needed to test this trigger in terms of usefulness.

**Figure 4.** In- and out-sample data sets together with indicator X time series



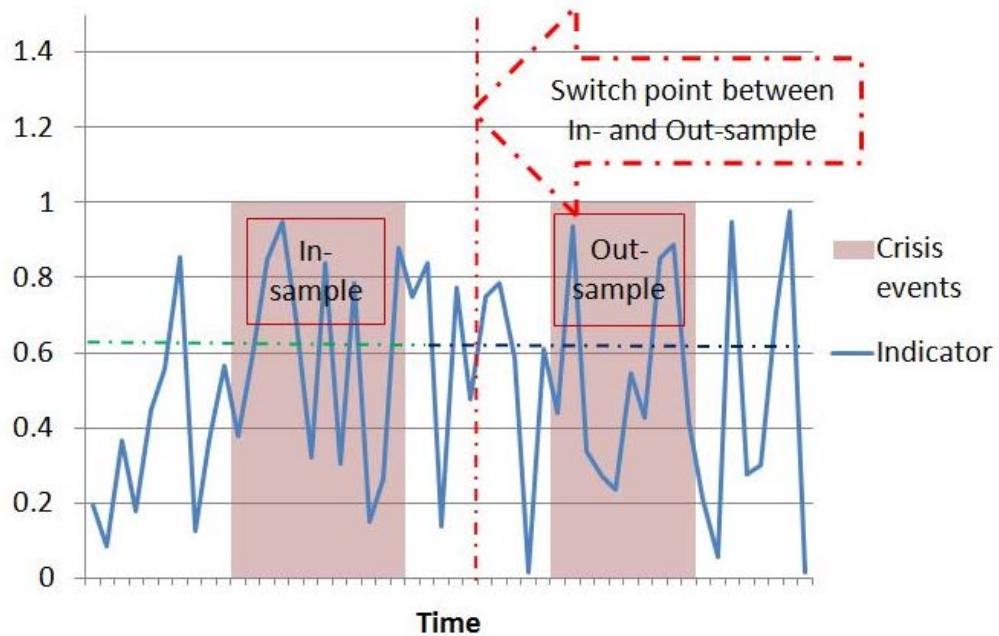
The next step is to limit the errors in the data by omitting from the data set signal points immediately prior to, during and after crisis. This is vital to eliminate so-called crisis and post-crisis bias. Logically, including data from crisis and post-crisis bias creates a false view of an indicator's performance. Because different banks/countries experience crises on different dates, clearing the crisis dates needs to be done individually for each bank/country. When evaluating myriad banks/countries, scrubbing the data can be a dreadful task.

The next step is the optimization phase. The optimization task is to find which threshold of indicator (see figure 5) minimizes the loss function at in-sample data run.

The following step is to calculate the relative usefulness for that threshold value of indicator which was found at optimization phase, assuring that the performance of an indicator's threshold chosen in in-sample data run is as good at prediction of crisis events in out-sample as it was in in-sample data run (see figure 5). The calculated usefulness may have three different types of response: positive, negative or at level of zero.

If it provides positive usefulness, it provides more gains than losses as early warning indicator, which means the indicator is suitable for early warning purposes. However if it provides negative usefulness, the losses from its utilization outweigh the gains, which means this indicator is not appropriate to serve as early warning indicator. Whereas the indicator provides usefulness being zero, it suggests that there are neither losses nor gains from the use of this indicator, which actually means there is no sense of use of such an indicator for early warning purposes.

**Figure 5.** In- and out-sample data sets together with indicator X time series (horizontal green dotted line showing the optimal threshold/trigger and horizontal dark blue dotted line – the level of threshold/trigger for which usefulness is calculated in out-sample data run)



### 3.2 Applying Signalling analysis on LVPS data

While applying signalling analysis on LVPS data some challenges or adaptations of the method were found to be necessary. The way how we tried to overcome these issues, or how they could possibly be addressed, are discussed here.

Signalling analysis assumes the availability of a control data set, which optimally would contain repeated occurrences of similar crisis events. This is needed to be able to define separated in-sample and out-sample data sets for the estimation and testing of an early warning indicator. Related to oversight of LVPS, which was the main focus of our analysis, we found it very difficult to find such crises data sets. Focus of oversight is in safety and efficiency of financial market infrastructures. Events such as operational incidents are not feasible as crises since they are by definition unexpected. Definition of increased inefficiency of the system e.g. via high level of settlement delays as a crisis would build a circular reference to the typical indicators derived from LVPS data.

Our solution was to use external data on country level bank crises or participant level crises incidents. These can be more relevant crisis categories for supervisory view or macro-prudential analysis, but do still also carry potential for disturbances in payment systems. Moreover the possibility to find leading indicators for such events from the LVPS data could be helpful. Additionally we built the testing framework so that usage of out-sample run was possible to be switched on and off as a parameter depending on data availability.

Alternative idea, which is left for future studies, would be to set up and simulate artificial crisis situations. In these cases the timing of the crisis could be completely controlled, but the challenge would remain in how realistic data could be created on the actual reactions of the participants, especially when the focus is on early warnings and signals preceding a crisis. The implementation of signalling analysis took into account as a variable the time difference between the indicator and control data time series in days. We call this variable the lag. In the testing it was allowed to vary between one day and a maximum value, which was defined in a parameter. Different levels for the maximum lag were tested. With this approach, the result of the tests also deliver information about how much in advance the given tested indicator would deliver the best usefulness value as an early warning signal.

It should be noted that the selection of the lag was defined in the tests in a rigid way. The test assumes and requires that the signal is always received the same amount of days in advance. Thus if, as an example, the lag of 20 was selected, signal of the crisis occurring 22 days before would be counted as a false alarm. The current implementation can thus be considered to be very cautious and strict.

In our experience, positive usefulness figures seem to be found more commonly with smaller values of the lag variable. If maximum lag is set far beyond one month, no useful or stable signals with higher lag values were usually found. This seems to suggest that there could be at most 1 month lead time with some changes in the LVPS data but not more. However, this is naturally dependent on the type and quality of the tested indicators and data.

Another specificity which we experienced with the LVPS data was that seemingly random individual outlier observations could interfere in the selection of the threshold and outcome of the signalling analysis. This can be caused by two issues. First obvious cause is that the high frequency of the daily observations from LVPS data may provide noisy data values. The second reason is that the crises events are typically rare compared to the number of observations in the daily time series. Thus the periods when no signal is expected provide lot of possibilities for outliers to emerge.

This issue could possibly be mitigated by smoothening, aggregation or down sampling of the data. We implemented an approach for this purpose, which we called warning radius. It is defined as the number of days of inaccuracy in the lag, which is allowed for the EWI predictions. Thus as an example, with a lag of 20 days and warning radius of 2 days, signal which is issued for a crisis is classified as correct indication if the control data has crisis event indicated anywhere in the time range  $20 \pm 2$  days after the date of the indicator. If the same time range of  $20 \pm 2$  days contains also non crisis days in the control data, also "no signal" would be counted as correct no warning. Without the warning radius, the signalling test would count only those signals which are issued exactly at the given lag. Nonzero value in the warning radius parameter will thus by definitions improve the usefulness if all other values are kept equal. It will smoothen down the noise from the data and favour indicators which deliver stronger consistent signals. This measure should be utilized cautiously, and only allow small values of the radius compared to the used lag. Otherwise the information of the signal becomes too much blurred and also warning signals generated very shortly before the start of crisis event could be considered as good signals, even though in reality they are outside of the acceptable range and therefore invalid.

Sensitivity analysis of the warning radius and maximum lag parameters confirmed that, usefulness values generally improved when the radius was increased. However, this worked better for shorter maximum lag values. In cases where longer maximum lags were allowed, the effect was not visible so clearly. This could be because of too noisy data or simply lack of reliable signals in the first place.

## 4 Conclusions

Signalling analysis can be used as a tool for objective assessment of quality and information value provided by a proposed early warning indicator. There is a trade-off between missed cases errors and false alarm errors. This approach allows taking into account the actual policy maker's preference related to this trade-off and the sensitivity of the warning indicator.

For the analysis of granular daily time series of LVPS data we found that the signalling analysis approach is also usable, but it was necessary to include two additional parameters to the standard approach. First, the time lag between the crisis and the preceding EWI signal was made a free parameter in the threshold optimisation. This allows us to test freely how early any given indicator was able to provide signal or with which lag the indicators perform best. It can be necessary to define still the minimum or maximum time lag to make the indicators useful for practical purposes.

Second, it was beneficial to level down the noisy indicator signals. For this we chose to allow a variation in the time lag, which we called the warning radius. It could be utilized in the testing framework to prevent the signalling analysis to be too strict towards indicators which might be potentially useful.

For proper testing of indicators derived from the LVPS data the main challenge is in definition of credible control data sets. It would be necessary to have repeated crisis events to be able to have separated data sets for training and testing of the indicators. As related possible future work, generation of controlled artificial test data sets could be beneficial. Also there is a need to set up multi variable approach for the indicators as well as the tests for the EWI performance.

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# Chapter 12

## Forecasting intraday throughput of large value payment system participants using neural networks: a preliminary approach

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*Patrick Joseph M. Sadornas*

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# **Forecasting Intraday Throughput of Large Value Payment System Participants Using Neural Networks: A Preliminary Approach\***

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## **Abstract**

This paper presents a preliminary work on the exploration of artificial neural networks (ANN) in forecasting the time series of intraday throughput (hourly cumulative outgoing payments) of selected participants in the Philippine large value payment system (LVPS). One month of transaction data from the LVPS was obtained and pre-processed to come up with the hourly time series for the Top 5 participants. The data set was split into 80% training data set and 20% test data set.

The best average prediction performance obtained for forecast horizons of one (1), two (2), three (3) and four (4) days resulted in average mean absolute scaled error (MASE) of 0.50, 0.60, 0.67, and 0.69, respectively. However, ANN performance vary between participants owing to possible differences in services, client base, and transaction volume. While the resulting ANN model approximates the general trend and seasonality of the throughput data, the accuracy of the model still needs further improvement for real-world regulatory monitoring. Future work will involve determining the effect of additional training data, use of pre-defined rules and indirect prediction, as well as general refinement of the ANN model.

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\*This paper is very preliminary in nature and presents an initial exploration of using and configuring an artificial neural network for the task of forecasting LVPS time series.

\*\*The author is grateful for the assistance provided by colleagues from the BSP Payments and Settlements Office, Office of Supervisory Policy Development, and the Core IT Specialist Group as well as for the comments/inputs of Dr. Remedios Bulos and Dr. Nelson Marcos of DLSU. The views expressed are those of the author and do not necessarily represent the views of BSP or DLSU.

## **1 Introduction**

The Basel Committee on Banking Supervision (BCBS) characterizes banks as essentially being in the business of converting short-term deposits into long-term loans, making them inherently vulnerable to problems related to liquidity. Liquidity, as defined by BCBS, is the ability of a bank to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses. The effective management of liquidity risk helps ensure a bank's ability to meet its obligations amidst uncertainties arising from external events and behavior of other entities. Further, a shortfall in liquidity at a single institution can have an impact to the whole financial system. (BIS, 2008)

The global financial crisis that ensued after the collapse of Lehman Brothers investment bank in 2007 lead to the formulation of new regulatory standards aimed at promoting increased stability in the global financial system. One of which is the "Principles for Sound Liquidity Risk Management and Supervision" issued by the BCBS in 2008 which set out the qualitative guidance for managing and supervising liquidity risk (BIS, 2008). To complement these qualitative principles, the BCBS subsequently issued "Monitoring Tools for Intraday Liquidity Management" in 2013 setting out a framework for quantitative monitoring of intraday liquidity risk of banks. The said monitoring framework noted that the management of intraday liquidity risk forms a key element of a bank's overall liquidity risk management framework (BIS, 2013).

Among the key aspect proposed to be monitored is intraday throughput, which is the percentage of a bank's outgoing payments (relative to total payments) by value within each hour of the business day (BIS, 2013). The data is divided into hourly buckets to facilitate meaningful analysis.

This study explores ways of deriving this information from the transaction records of the Philippine large value payment system (LVPS) and forecasting this data using artificial neural networks (ANN) for possible use in regulatory monitoring. The Philippine Payments and Settlement System (PhilPaSS), which is the name of the Philippine LVPS, processes and settles large-value payments instructions from over 100 participants, composed of banks and other financial institutions (BSP, 2013). From the sample PhilPaSS data, an hourly time series of the cumulative payments is derived and considered for forecasting. This information will aid regulators in monitoring the payments pattern or liquidity requirements of individual banks. If successfully refined, this method may be applied across all participants in the LVPS and facilitate the prediction of the liquidity requirement of the entire system.

## **2 Related Literature**

According to Ahmed et al. (2010), machine learning models have been gaining acceptance as an alternative to classical statistical models. They conducted a large scale comparison study of various machine learning models for time series forecasting. Their study considered multilayer perceptron (MLP) (simple ANN), Bayesian neural networks, radial basis functions, generalized regression neural networks (kernel regression), K-nearest neighbor regression, CART regression trees, support vector regression, and Gaussian processes (GP). By comparing the performance of these models in their basic forms, they found that the MLP and GP yielded the best results. In the area of financial time series forecasting, Krollner et al. (2010) surveyed literature on machine learning and artificial intelligence used to forecast stock market movements and found ANNs to be the dominant technique used in this area.

Josef (1996) describe ANNs as processing devices or algorithms that are modeled after the operation of biological neurons but on a smaller scale and are typically organized in layers that are made up on interconnected nodes containing an activation function. ANNs have an *input layer* where patterns are presented, one or more *hidden layers* where actual processing is done via the weighted links between nodes, and an *output layer* that produces that result of a specific task. This form of ANN implementation is also referred to as an MLP.

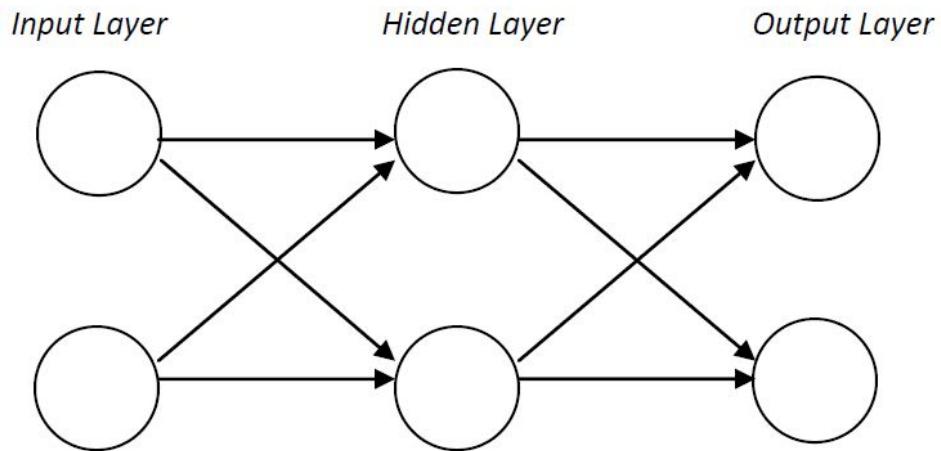


Figure 1. Typical ANN Architecture

Given an input, ANNs modify the weight of the links between nodes through some form of learning rule. The most commonly used learning rule is called the delta rule or *backpropagation*. This is a supervised learning process where the network ‘learns’ every time it is presented with new input through forward activation flow of outputs and weight adjustments through backward error propagation. (Josef, 1996)

### 3 Data Set and Neural Network Implementation Used

Using one month of transaction data from PhilPaSS, the cumulative outflow of funds from the financial institutions with the highest total transaction value were derived and cast as an hourly time series. PhilPaSS starts business operations from 9:00 AM and closes at 6:00 PM, thus the transactions can be divided into 9 hourly buckets. The data included transactions for 21 business days and the resulting time series for a single participant is composed of 189 data points. The time series was divided into 80% (21 days) training set and 20% (4 days) test set. The training set is used by the ANN model to learn the pattern of the throughput data while the test set is used to determine the ability of the model to generalize the pattern and predict future throughput. As this is only an initial approach, only the five (5) participants with the highest value of total outgoing payments for the month were selected for the forecasting task.

Figure 2 shows the steps taken to prepare the input to the forecasting model. The raw transaction data consisting of 77,215 records was filtered to limit the data to transactions initiated by the five (5) participants, eventually arriving at 16,013 records. The resulting data set contains a timestamp, source, destination, and payment amount. A program was developed to generate the cumulative hourly data for each of the selected participants based on the filtered transaction data. The resulting time series served as the input into the forecasting model.

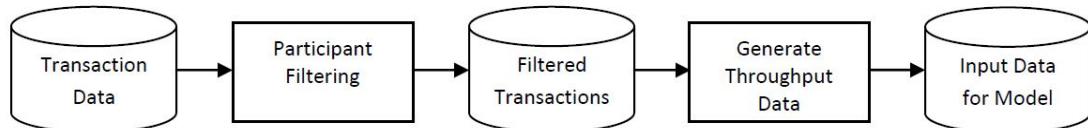


Figure 2. Data Preparation Steps

The neural network training and evaluation was performed using R Statistical Data Analysis environment. The *nnetar* method within R's *forecast* package generates a feed-forward neural network with a single hidden layer and lagged inputs (previous period's values) for forecasting single-variable time series (Hyndman, 2014).

The two primary parameters of the *nnetar* method is the number of hidden units (*size*) of the ANN and the number of lagged inputs (*p*) to consider as input to model. There is no hard-and-fast rule in determining the appropriate number of hidden units that must be used in a particular neural network. The number of hidden units as well and the number of lagged variables were varied to determine the best performing configuration.

## 4 Forecast Evaluation

Mean Absolute Scaled Error (MASE) as defined by Hyndman and Koehler (2005) was used to evaluate the performance of the forecasting model. This measure scales the absolute error based on the in-sample (training set) mean absolute error (MAE) from a benchmark forecast method. Assuming that the benchmark forecast method is the naïve method (i.e. taking the immediately preceding period's value to be the forecasted value), the scaled error is computed using the following formula:

$$q_t = \frac{e_t}{\frac{1}{n-1} \sum_{i=2}^n |Y_i - Y_{i-1}|} \quad (1)$$

The numerator is the absolute error of the forecast and the denominator is the MAE from the one-step naïve forecast. Hyndman and Koehler (2005) indicated that the scaled error is less than one if it arises from a better forecast than the average one-step benchmark forecast computed in-sample. Conversely, it is greater than one if the forecast is worse than the average one-step benchmark forecast computed in-sample.

From this, the MASE is computed simple as

$$MASE = \text{mean}(q_t) \quad (2)$$

When MASE is less than 1, the proposed method gives, on average, smaller errors than the one-step errors from the benchmark method (Hyndman and Koehler, 2005).

## 5 Result of Experiments

Initially, the number of hidden units of the neural network, the *size* parameter, was varied as a proportion of the number of total number of lagged inputs (rounded to the nearest whole number) as follows:

Table 1. Initial Size Parameters

No. of lagged inputs	Proportion of Size Parameter to No. of Lagged Inputs						
	1/7	2/7	3/7	4/7	5/7	6/7	7/7
9 (1 day)	1	3	4	5	6	8	9
18 (2 days)	3	5	8	10	13	15	18
27 (3 days)	4	8	12	15	19	23	27
36 (4 days)	5	10	15	21	26	*	*

\*The current implementation of *nnetar* limits the total number neural network weights resulting from the combination of the *size* and *p* parameters. Thus, these combinations were not tested.

The numbers indicated in each cell of Table 1 were used to build and train a neural network. In each case, the resulting error metric, MASE, is computed.

The implementation of most neural networks, such as those generated by *nnetar*, randomly initializes the weights of a neural network thereby generating a slightly different neural network in each run (Hyndman, 2012). Thus, the ANN model training and forecasting process is executed five (5) times for each parameter combination and the average MASE value is noted.

The best configuration for each participant based on parameters indicated initially tested are summarized in Table 2. Detailed MASE values of the individual participants for the initial run are included in the Appendix as Tables A1 to A5.

Table 2. Best ANN Configurations after Initial Run

Participant	No. of Lagged Inputs	No. of Hidden Units	MASE
A	27	4	0.91
B	18	3	0.45
C	36	10	0.89
D	36	26	0.78
E	18	3	0.50

While the configurations for Participants B and E resulted in reasonable MASE values, those of Participants A, C, and D are still relatively close to 1. Thus, another set of ANN configurations were explored using smaller number of hidden units but higher number of

lagged inputs. Detailed MASE values of the individual participants for the second run are included in the Appendix as Tables A6 to A10.

The best ANN configuration for each participant is updated after the second run and summarized in Table 3. The updated values are set in **bold**.

Table 3. Best ANN Configurations after Second Run

Participant	No. of Lagged Inputs	No. of Hidden Units	MASE
A	27	<b>1</b>	<b>0.44</b>
B	<b>36</b>	3	<b>0.44</b>
C	36	<b>7</b>	<b>0.82</b>
D	<b>45</b>	<b>1</b>	<b>0.40</b>
E	<b>27</b>	<b>1</b>	<b>0.42</b>

As the MASE of Participant C remained relatively close to 1, a special run is performed to explore possible performance improvement. Noting a gap in testing between 8 and 9 hidden units for 36 lagged inputs, the performance of these configurations were tested and summarized in Table 4.

Table 4. Average MASE for Third 1-Day Forecast

Participant	No. of lagged inputs	No. of Hidden Units	
		8	9
A	36 (4 days)	1.46	<b>1.42</b>
B	36 (4 days)	<b>0.77</b>	0.86
C	36 (4 days)	0.84	<b>0.79</b>
D	36 (4 days)	0.86	<b>0.82</b>
E	36 (4 days)	<b>1.28</b>	1.44

The performance of the model for Participant C slightly improved but it remained the lowest among the participants. Based on the configurations explored, the final ANN configurations are summarized in Table 5.

Table 5. Best ANN Configurations after Third (Final) Run

Participant	No. of Lagged Inputs	No. of Hidden Units	MASE
A	27	1	0.44
B	36	3	0.44
C	36	<b>9</b>	<b>0.79</b>
D	45	1	0.40
E	27	1	0.42

The ANN parameters in Table 5 were used in generating 2-, 3-, and 4-day forecasts. The resulting MASE for the forecasts are shown in Table 6. The results show that some participants are easier to model than others. For instance, MASE for Participant E remains relatively low (i.e. good performance) across all forecast horizons while the MASE for Participant A and C fluctuate. The MASE for Participant B and D exhibit an increasing trend (i.e. lower performance) as the forecast window increases. The instability of the model performance across forecast horizon may be influenced by various factors such as variety of

products/services offered, diversity of customer base, and variability of the volume of transaction.

Table 6. MASE for 1- to 4-Day Forecasts

Participant	Forecast			
	1-Day	2-Day	3-Day	4-Day
A	0.44	0.83	0.75	0.73
B	0.44	0.52	0.62	0.69
C	0.79	0.61	0.90	0.79
D	0.40	0.63	0.63	0.70
E	0.42	0.43	0.47	0.56
<b>Average</b>	<b>0.50</b>	<b>0.60</b>	<b>0.67</b>	<b>0.69</b>

A visual representation of a 4-day forecast is shown in Figure 3. The horizontal axis represents the hours of operation of the LVPS and each “cycle” is composed of nine (9) hours. The vertical axis represents the cumulative peso value spent as of a given hour. The plot shows the 17 days of training data and four (4) days of forecast. For the graphical plots, the **black line** represents the training data while the **thin red line** represents the test data. The **thick blue line** represents the forecast generated by the neural network.

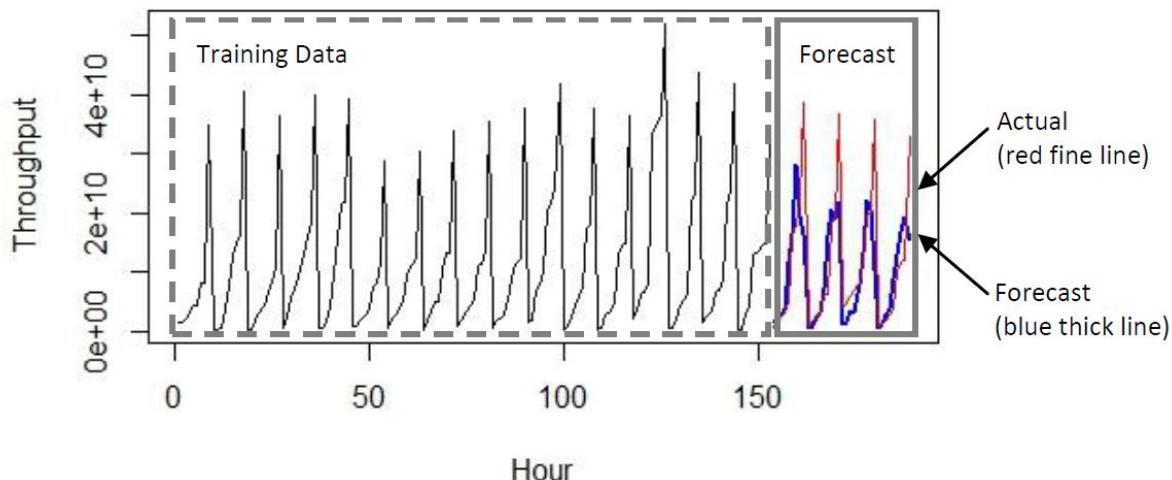


Figure 3. Illustration of a 4-day Forecast

Figures 4 to 8 show the graphical plot for each participant, zooming in on the test set to clearly show the artifacts that accompany the forecasts generated by the ANN models. The 4-day forecasts are shown to better illustrate the overall performance of a given ANN model.

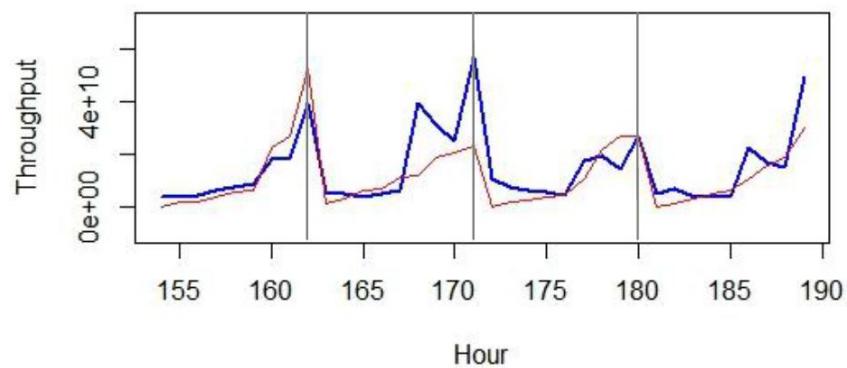


Figure 4. Actual Throughput vs. Forecast – Participant A

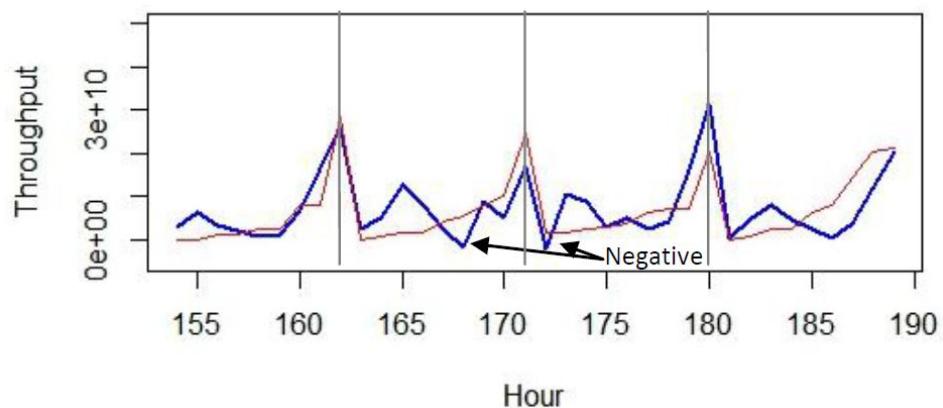


Figure 5. Actual Throughput vs. Forecast – Participant B

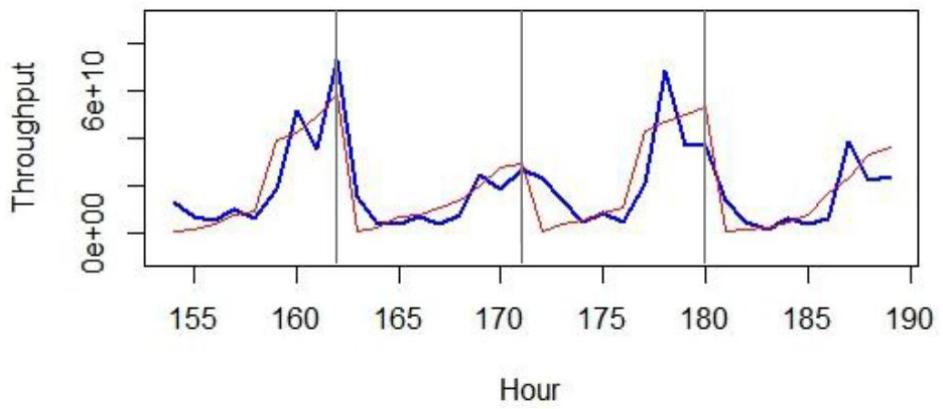


Figure 6. Actual Throughput vs. Forecast - Participant C

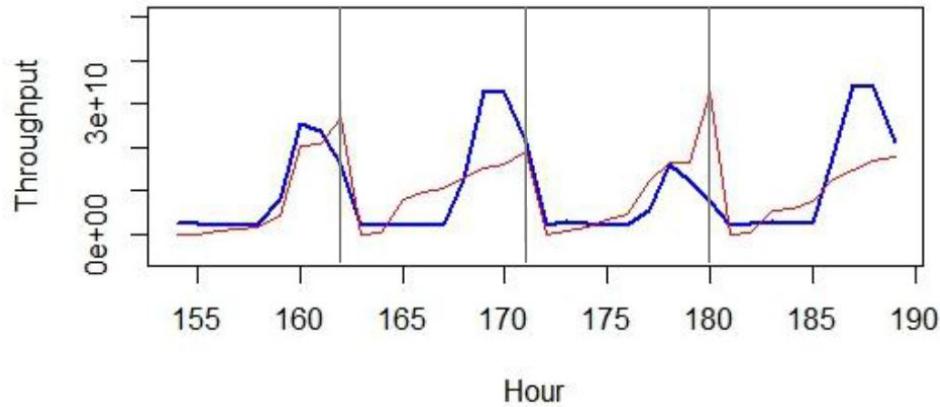


Figure 7. Actual Throughput vs. Forecast – Participant D

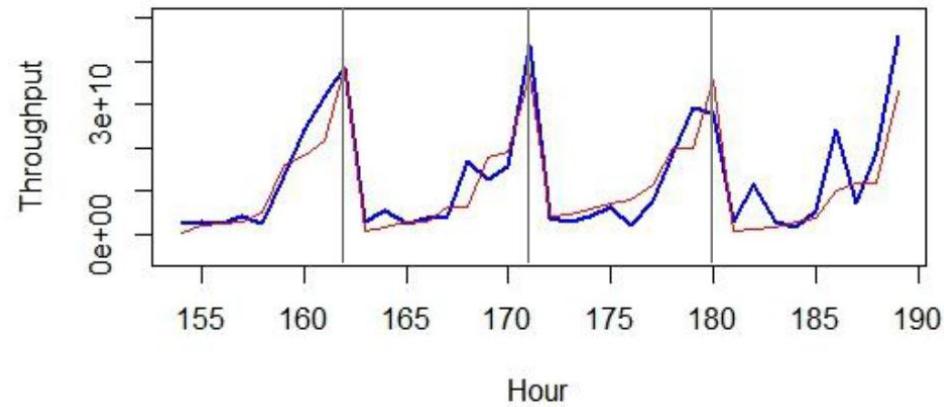


Figure 8. Actual Throughput vs. Forecast – Participant E

While the trend and seasonality are broadly matched for each of the five participants, the forecasted throughput occasionally results in a reduction in value within the day. There are also instances when the predicted throughput for a given hour is negative (Participant B). These are undesirable patterns as the data is supposed to represent the cumulative outgoing payments as of a given hour. Future work will explore possible solutions to eliminate these patterns using rules or indirect prediction (i.e. predicting the hourly outflows instead of directly forecasting the cumulative throughput).

## **6 Conclusion and future work**

This preliminary work shows the potential of ANNs in forecasting the throughput of individual participants in a large value payment system. The throughputs of some participants are easier to model than others. There are many factors that may contribute to this including variety of services offered, diversity of client base, and transaction volume. While the ANN models generally approximate the trend and seasonality of the throughput data of the selected participants, the forecast errors remain significant.

It should also be noted that the available data was split in two (i.e. train and test) for the purpose of selecting the combination of ANN parameters that yield the least error. A more ideal evaluation process would be to use a third data set composed of data points not in either of the two data sets. However, such setup was limited by the amount of available data.

Further work will be focused on improving the design of the ANN model and gathering additional input variables to facilitate eventual use for real-world regulatory monitoring.

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## Appendix

The following tables show the MASE values obtained from the initial batch (A1 to A5) and second batch (A6 to A10) of 1-day forecasts for the different participants. The MASE of the best performing configuration for a given number of lagged inputs is set in **bold** while the MASE of the best performing configuration for the participant is underlined.

Table A1. Average MASE for Initial 1-Day Forecast – Participant A

No. of lagged inputs	Proportion of Size Parameter to No. of Lagged Inputs						
	1/7	2/7	3/7	4/7	5/7	6/7	7/7
9 (1 day)	<b>1.04</b>	1.25	1.36	1.45	1.32	1.22	1.28
18 (2 days)	<b>2.64</b>	3.24	3.38	3.46	3.51	3.58	3.15
27 (3 days)	<u>0.91</u>	1.23	1.21	1.47	1.66	1.63	1.69
36 (4 days)	<b>1.21</b>	1.45	1.52	1.65	1.66	-	-

Table A2. Average MASE for Initial 1-Day Forecast – Participant B

No. of lagged inputs	Proportion of Size Parameter to No. of Lagged Inputs						
	1/7	2/7	3/7	4/7	5/7	6/7	7/7
9 (1 day)	<b>0.80</b>	0.94	1.15	1.73	1.97	2.80	2.94
18 (2 days)	<u>0.45</u>	0.65	0.87	1.10	1.16	1.09	1.09
27 (3 days)	<b>0.85</b>	1.08	1.11	1.10	1.13	1.17	1.14
36 (4 days)	<b>0.55</b>	0.91	1.09	1.13	1.15	-	-

Table A3. Average MASE for Initial 1-Day Forecast – Participant C

No. of lagged inputs	Proportion of Size Parameter to No. of Lagged Inputs						
	1/7	2/7	3/7	4/7	5/7	6/7	7/7
9 (1 day)	1.36	1.11	1.08	<b>1.04</b>	1.09	1.14	1.17
18 (2 days)	<b>1.44</b>	1.48	1.61	1.55	1.55	1.56	1.56
27 (3 days)	1.24	<b>1.16</b>	1.19	1.28	1.37	1.33	1.35
36 (4 days)	0.92	<u>0.89</u>	0.93	1.05	1.06	-	-

Table A4. Average MASE for Initial 1-Day Forecast – Participant D

No. of lagged inputs	Proportion of Size Parameter to No. of Lagged Inputs						
	1/7	2/7	3/7	4/7	5/7	6/7	7/7
9 (1 day)	1.15	0.97	<b>0.94</b>	0.96	0.96	1.06	1.03
18 (2 days)	<b>1.05</b>	1.08	1.21	1.26	1.24	1.26	1.26
27 (3 days)	<b>0.98</b>	1.10	1.02	1.09	1.15	1.14	1.16
36 (4 days)	0.81	0.83	0.80	0.80	<b>0.78</b>	-	-

Table A5. Average MASE for Initial 1-Day Forecast – Participant E

No. of lagged inputs	Proportion of Size Parameter to No. of Lagged Inputs						
	1/7	2/7	3/7	4/7	5/7	6/7	7/7
9 (1 day)	<b>1.08</b>	1.09	1.16	1.18	1.17	1.29	1.22
18 (2 days)	<b>0.50</b>	0.68	0.81	0.79	0.77	0.88	0.92
27 (3 days)	<b>0.95</b>	1.76	2.01	2.48	2.78	2.57	2.79
36 (4 days)	<b>1.33</b>	1.44	1.56	1.52	1.50	-	-

Table A6. Average MASE for Second 1-Day Forecast – Participant A

No. of lagged inputs	Number of Hidden Units						
	1	2	3	4	5	6	7
27 (3 days)	<b>0.44</b>	0.77	0.90	0.91	1.00	1.06	1.10
36 (4 days)	<b>0.74</b>	1.25	1.38	1.40	1.21	1.32	1.30
45 (5 days)	0.96	0.96	0.89	0.90	0.88	<b>0.85</b>	0.91
54 (6 days)	1.21	1.10	1.18	1.08	<b>1.06</b>	1.13	1.08
63 (7 days)	<b>0.54</b>	0.61	0.68	0.76	0.79	0.81	0.79

Table A7. Average MASE for Second 1-Day Forecast – Participant B

No. of lagged inputs	Number of Hidden Units						
	1	2	3	4	5	6	7
27 (3 days)	0.56	<b>0.54</b>	0.81	0.85	0.98	1.00	1.03
36 (4 days)	0.52	0.53	<b>0.44</b>	0.54	0.55	0.58	0.60
45 (5 days)	0.72	0.92	0.76	0.70	0.63	<b>0.62</b>	0.64
54 (6 days)	<b>0.49</b>	0.73	0.67	0.54	0.69	0.75	1.01
63 (7 days)	1.53	1.26	1.06	0.77	0.75	0.72	<b>0.68</b>

Table A8. Average MASE for Second 1-Day Forecast – Participant C

No. of lagged inputs	Number of Hidden Units						
	1	2	3	4	5	6	7
27 (3 days)	1.25	1.32	1.21	1.24	<b>1.19</b>	1.20	1.21
36 (4 days)	0.88	1.10	1.04	0.96	0.92	0.91	<b>0.82</b>
45 (5 days)	1.17	1.35	1.31	1.24	<b>1.108</b>	1.15	1.112
54 (6 days)	0.88	1.00	0.93	0.93	0.93	0.87	<b>0.87</b>
63 (7 days)	1.70	1.40	1.15	1.10	0.99	0.93	<b>0.90</b>

Table A9. Average MASE for Second 1-Day Forecast – Participant D

No. of lagged inputs	Number of Hidden Units						
	1	2	3	4	5	6	7
27 (3 days)	<b>0.72</b>	0.77	0.99	0.98	0.99	1.03	1.08
36 (4 days)	<b>0.76</b>	0.80	0.78	0.76	0.81	0.80	0.79
45 (5 days)	<b>0.40</b>	0.48	0.56	0.59	0.64	0.65	0.73
54 (6 days)	<b>0.54</b>	0.61	0.66	0.69	0.72	0.76	0.79
63 (7 days)	<b>0.73</b>	0.84	0.87	0.87	0.91	0.88	0.89

Table A10. Average MASE for Second 1-Day Forecast – Participant E

No. of lagged inputs	Number of Hidden Units						
	1	2	3	4	5	6	7
27 (3 days)	<b>0.42</b>	0.79	0.85	0.95	0.98	1.33	1.69
36 (4 days)	<b>0.73</b>	1.17	1.27	1.39	1.33	1.29	1.36
45 (5 days)	<b>0.53</b>	0.53	0.56	0.62	0.59	0.63	0.68
54 (6 days)	0.81	0.80	0.73	<b>0.72</b>	0.74	0.73	0.84
63 (7 days)	0.74	0.66	0.53	<b>0.52</b>	0.58	0.63	0.67

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# Chapter 13

## Estimating the intraday liquidity risk of financial institutions: a Monte Carlo simulation approach

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*Carlos León\**

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\* This article first appeared in Journal of Financial Market Infrastructures, 27 September 2012. The publisher gratefully acknowledges the permission to reprint this article.

## Estimating the intraday liquidity risk of financial institutions: a Monte Carlo simulation approach

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*The recent financial crisis has shown that liquidity risk is far more important and intricate than regulators had previously acknowledged. The shift from bank-based to market-based financial systems and from deferred net settlement systems to liquidity-demanding real-time gross settlement of payments explains some of the shortcomings of traditional liquidity risk management. Although liquidity regulations do exist, they are still in an early stage of development and discussion. Moreover, not all connotations of liquidity are being equally addressed. Unlike market and funding liquidity, intraday liquidity has been absent from financial regulation, and has appeared only recently, after the crisis. This paper addresses the measurement of large-value payment system intraday liquidity risk. Based on the generation of bivariate Poisson random numbers for simulating the minute-by-minute arrival of received and executed payments, each financial institution's intraday payments' time-varying volume and degree of synchrony (ie, timing) is modeled. Modeling the uncertainty of intraday payments allows us to oversee participants' intraday behavior, to assess their ability to fulfill intraday payments at a certain confidence level, to identify participants that are nonresilient to changes in payment timing mismatches, and to estimate intraday liquidity buffers. These results are useful for financial authorities and institutions given the increased importance of liquidity risk as a source of systemic risk, and the recent regulatory amendments.*

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The opinions and statements in this paper are the sole responsibility of the author and do not necessarily represent those of Banco de la República or its Board of Directors. Results are illustrative; they may not be used to infer credit quality or to make any type of assessment for any financial institution. The author is indebted to Clara Machado for the numerous and vital discussions that supported the design of the model and the final version of the paper. Comments and suggestions were provided by Fernando Tenjo, Joaquín Bernal, Freddy Cepeda and Fabio Ortega. Valuable comments and suggestions from an anonymous referee significantly enhanced the original version of this paper. Large-value payment system data was processed with assistance from Freddy Cepeda and Fabio Ortega. Any remaining errors are the author's own.

## 1 INTRODUCTION

It is widely accepted that liquidity risk mismanagement played a key role in the recent global financial crisis. The literature recommends improving liquidity risk management by imposing and monitoring liquidity requirements on systemically important banks and broker dealers (French *et al* (2010)), or designing liquidity buffers in order to mitigate systemic risk (Capel (2011); International Monetary Fund (2010b); Borio (2009); and Tirole (2008)).

Although liquidity regulations and tools do exist, they are still in an early stage of development and discussion (International Monetary Fund (2010a) and Tucker (2009)). Moreover, not all connotations of liquidity are equally addressed by risk literature or regulation. Liquidity has focused on market and funding liquidity, where both correspond to the ability to generate cash from balance sheet liabilities and asset positions, respectively, whereas liquidity risk has traditionally focused on measuring mismatches between them (eg, short-term liabilities and liquid assets).<sup>1</sup>

As acknowledged by Ball *et al* (2011), prior to the recent financial crisis regulators did not focus on intraday liquidity risk and there were no standard monitoring or liquidity management measures in place. Authorities have only begun to focus on intraday liquidity since the crisis. Two main structural shifts may explain the new emphasis on intraday liquidity:

- (1) the shift from bank-based to market-based financial systems;
- (2) the evolution of payment systems from deferred net settlement systems to liquidity-demanding real-time gross settlement (RTGS) systems.

It is important to acknowledge that these structural shifts have not resulted from shocks. They are the result of a continuous and protracted evolution of financial markets. However, because prudential regulation has ignored these structural shifts for decades, the regulatory challenge is substantial: an intraday liquidity risk management framework must be designed.

Among the four typical stages of risk management (ie, identifying, assessing, monitoring and mitigating risk) this paper focuses on the second stage. The approach presented in this paper for assessing the intraday liquidity risk of large-value payment systems (LVPSs) is based on the generation of bivariate Poisson random numbers for simulating the minute-by-minute arrival of received (incoming) and executed (outgoing) payments. In this sense, following Ball *et al* (2011), the identified source of

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<sup>1</sup> For instance, Tirole (2008) refers to funding liquidity as how much can be raised on the liability side of the balance sheet, while market liquidity refers to the asset side, with prudential measurements of liquidity usually consisting of measuring some mismatch between short-term liabilities and liquid assets.

intraday liquidity risk modeled here is the timing mismatch between incoming and outgoing payments, which may lead to significant intraday liquidity needs.

This Monte Carlo simulation procedure is capable of modeling the intraday-dependency governing the joint arrival of both types of payments, along with their value. Thus, the simulation procedure is able to capture the degree of synchrony (ie, the timing) attained by each financial institution when receiving and executing payments (ie, the virtuous circle of coordinated actions by settlement agents), where such synchrony and the volume of payments varies throughout the day.

The main outcome of the proposed procedure is estimating a risk measure or metric such as an intraday liquidity value-at-risk (VaR) that is able to answer a rather specific question: what are an institution's maximum intraday liquidity needs at a defined confidence level? An answer to this question may be suitable for:

- (1) overseeing participants' intraday behavior;
- (2) assessing their ability to fulfill intraday payments at a certain confidence level;
- (3) identifying participants who are nonresilient to changes in timing mismatches of payments;
- (4) estimating intraday liquidity buffers.

Regarding the most recent amendments to financial regulation and the increasing importance of liquidity risk as a source of systemic risk, results are useful for financial authorities, institutions and market infrastructures tackling the challenge of managing intraday liquidity risk.

This paper is structured as follows. Section 2 briefly addresses the increasing relevance of intraday liquidity risk management. Section 3 describes the intuition and procedure behind the proposed approach to simulating the minute-by-minute liquidity (Appendix A contains a comprehensive technical explanation of the Monte Carlo simulation algorithm). Section 4 presents preliminary results and analysis for a set of institutions participating in Colombia's LVPS. Section 5 presents some final comments on the approach, its usefulness and the challenges ahead.

## **2 THE INCREASING RELEVANCE OF LIQUIDITY AND INTRADAY LIQUIDITY RISK MANAGEMENT**

The recent financial crisis has highlighted the need to improve liquidity risk management, including the management of intraday liquidity risk (Ball *et al* (2011)). Liquidity is by no means a new concept. It is, however, still an elusive one. It comprises several dissimilar connotations, such as market, funding or intraday liquidity. Although these connotations of liquidity allow for a fairly clear theoretical distinction,

in practice they are entangled, particularly under stress scenarios. In this sense, all connotations of liquidity should be equally addressed by prudential regulation.

Notwithstanding the importance of properly addressing liquidity risk and its connotations, related regulation is scarce when compared with solvency regulation. The contemporary momentum of liquidity and intraday liquidity regulation has arisen from the recent global financial crisis, which exposed structural shifts in financial markets that have increased the relevance of designing a proper prudential regulatory framework.

Two such structural shifts are commonly acknowledged in the literature. First, the shift from bank-based to market-based financial systems, and second, the shift from deferred net settlement systems to liquidity-demanding RTGS of payments. As explained below, the former has increased the importance of all connotations of liquidity risk, whereas the latter has emphasized the relevance of intraday liquidity risk.

## **2.1 The relevance of liquidity risk in market-based financial systems**

The underdevelopment of liquidity regulation is due to the traditional focus on solvency, which is the legacy of banking runs dominating systemic risk origins since the outbreak of the Great Depression. Consequently, liquidity risk has evaded prudential regulation.

The best example of the absence of liquidity risk management is the regulatory approach by the Basel Committee on Banking Supervision. As documented by Goodhart (2008), the Basel Committee on Banking Supervision's original goal was to reverse the downward trend in capital and liquidity for the main international commercial banks. However, for reasons yet to be discovered, this downward trend was reversed for capital, not for liquidity. Thus, according to Eichengreen (2008), some of the Basel Accord's critics argue that its focus on capital adequacy (ie, lack of liquidity requirements) encouraged regulators to neglect the importance of liquidity in their supervisory activities.

Additionally, not only does the Basel Committee's regulation disregard liquidity risk management, but it is dedicated to banks only, for which it measures mismatches between short-term liabilities (eg, deposits) and liquid assets (eg, loans and investment portfolios). In today's financial markets, with many functions that previously defined banks' traditional domain increasingly being performed by securities markets and nonbank market participants (Kambhu *et al* (2007)),<sup>2</sup> focusing on solvency and

---

<sup>2</sup> This scheme, in which markets and nonbank participants involve in credit intermediation activities traditionally performed (and regulated to be performed) by banks, is commonly referred to as the "parallel banking system" or "shadow banking system" (Krugman (2009) and Acharya *et al* (2009)).

ignoring liquidity is highly unsafe from a prudential point of view. Therefore, the structural shift from bank-based to market-based systems and the evolution of financial infrastructures, where market and asset liquidity has become as important as the solvency of banks, explains to some extent the increasing relevance of liquidity risk management.

Hence, as a consequence of the nature of the global financial crisis, Ackermann (2008) draws two key conclusions. First, in our capital-based financial system, which has developed as a result of disintermediation and credit risk transfer, liquidity is far more important than in a purely bank-based financial system. Second, better liquidity management, rather than higher capital buffers, is likely to provide the right answer.<sup>3</sup>

## **2.2 The relevance of intraday liquidity risk in RTGS payment systems**

A second structural change that has brought about the increasing relevance of liquidity risk is the evolution of financial markets from deferred net settlement systems to liquidity-demanding RTGS of payments.<sup>4</sup> As recognized by the Committee on Payment and Settlement Systems (1997), this structural shift was encouraged by banking authorities in an attempt to limit settlement and systemic risk in the interbank settlement process, and to contribute to the reduction of the settlement risk in securities and foreign exchange transactions. However, as pointed out by Bernal (2009) and Bech and Soramäki (2002), in RTGS systems the reduction in settlement risk is traded off against increased liquidity requirements so that the payment system becomes more reliant on the virtuous circle of coordinated actions by participating settlement agents and, therefore, increased liquidity risk.<sup>5</sup> Following Ball *et al* (2011), this means that, whereas RTGS systems financial institutions can reuse liquidity from incoming payments to fund outgoing payments, timing mismatches between incoming and outgoing payments can lead to significant (intraday) liquidity needs.

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<sup>3</sup> Ackerman (2008) goes further, stating that higher capital requirements may have an adverse effect: if they are too onerous, more activities will be pushed to unregulated parts of the financial system.

<sup>4</sup> A deferred net settlement system effects the settlement of obligations or transfers between or among counterparties on a net basis at some later time. An RTGS system consists of the continuous (real-time) settlement of funds or securities transfers individually on an order-by-order basis (without netting); the processing of instructions is carried out on an individual basis at the time they are received rather than at some later time (Committee on Payment and Settlement Systems (2003)). Bech (2008) documents that the number of central banks that implemented RGTS systems increased from 3 in 1985 to 93 at the end of 2006. According to World Bank (2011), from a total of 142 countries surveyed as of December 2010, 116 (83%) have an RTGS system for their LVPSs.

<sup>5</sup> Such increasing demand for intraday liquidity is also documented by Bech (2008), Rochet (2008) and Committee on Payment and Settlement Systems (1997).

Consequently, as documented by Leinonen and Soramäki (2004), interest in intraday liquidity results from payment system development and shrinking delivery times. Before the 1990s, operations were strictly on the daily level and intraday liquidity had no significance. As the speed of processing payments has been increased and central banks have converted to RTGS, intraday liquidity has received increasing emphasis.

For instance, the emergence of intraday liquidity risk is rather clear in the evolution of Basel Committee on Banking Supervision's approach to liquidity risk. What the Basel Committee on Banking Supervision (2000) regarded as the "Principles for the Assessment of Liquidity Management in Banking Organizations" referred to short-term liquidity management in a day-to-day basis for banks reliant on short-term funding, and in a one-to-three-months-ahead basis for other banks that are not reliant on short-term funding. Intraday liquidity risk was mentioned but was not regarded as being decisive.

More recently, the Basel Committee on Banking Supervision (2008) explicitly included the management of intraday liquidity risk as a principle on its own (Principle 8), where its purpose is meeting payment and settlement obligations on a timely basis under both normal and stressed conditions in order to contribute to the smooth functioning of payment and settlement systems.<sup>6</sup> Furthermore, even more recently, the document entitled Basel III (Basel Committee on Banking Supervision (2010)) acknowledges that intraday liquidity needs may not be covered by Basel III's new liquidity coverage ratio,<sup>7</sup> and states that the Basel Committee on Banking Supervision is reviewing if (and how) intraday liquidity should be addressed.

In the report "Principles for financial market infrastructures" (Committee on Payment and Settlement Systems and the International Organization of Securities Commissions (2012)), Principle 7 is dedicated to liquidity risk management by financial market infrastructures, where the main objective is that such infrastructures maintain sufficient liquid resources to effectuate same-day and, where appropriate, intraday and multiday settlement of payment obligations with a high degree of confidence (Committee on Payment and Settlement Systems and International Organization of Securities Commissions (2012)).

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<sup>6</sup>The Basel Committee on Banking Supervision (2000) document only referred to intraday liquidity four times, with only one mention related to liquidity management (Principle 5). The Basel Committee on Banking Supervision (2008) document makes about sixty references to intraday liquidity (Principles 3, 5, 9 and 10), and devotes Principle 8 to recognizing its importance within a bank's broader liquidity management strategy and its contribution to systemic risk via the smooth functioning of the payment system.

<sup>7</sup>The liquidity coverage ratio is a standard measure that aims to ensure that a bank maintains an adequate level of unencumbered, high-quality liquid assets that can be converted into cash to meet its liquidity needs for a thirty calendar day time horizon under a significantly severe liquidity stress scenario specified by supervisors (Basel Committee on Banking Supervision (2010)).

Another example of the increasing focus of regulation on intraday liquidity risk is the UK Financial Services Authority's (FSA's) novel liquidity adequacy regulation (FSA (2012)), which considers intraday liquidity to be a key risk driver in its new liquidity regime. As in the principles of Basel Committee on Banking Supervision (2008), the FSA's aim is to ensure that firms are able to meet their payment and settlement obligations on a timely basis in both normal and stressed conditions, emphasizing that this is important for the firm, the firm's counterparties and the smooth functioning of payment and settlement systems as a whole. It is worth noting that, unlike the Basel Committee on Banking Supervision, the FSA's liquidity regulation is not intended for banks only, and refers to "firms", with this term comprising banks, building societies and some types of investment firms. According to JP Morgan (2010), this new regulatory regime includes for the first time all FSA-regulated broker-dealer firms under formal liquidity resource supervision.

In the author's view, concurring with Hervo (2008), structural developments in the financial industry have led to a clear trend in shortening time horizon of liquidity risk and liquidity management. As Hervo (2008) quotes regarding contemporary financial markets, "my short-term is intraday, my medium-term is overnight and my long-term is one week".

Although payment and settlement systems have received relatively little attention from financial market researchers (Leionen and Soramäki (2004)), intraday liquidity literature has gained momentum, especially with works by Bech (2008), Leionen (2007) and Koponen and Soramäki (1998). In the Colombian case, LVPS intraday liquidity has been addressed by Bernal *et al* (2011), Bernal (2009) and Bernal and Merlano (2005), while some models based on LVPS payments data for payments simulation, connectedness assessment and the identification of systemic importance have been developed recently (Cepeda (2008); Machado *et al* (2009); León *et al* (2011); and León and Machado (2011)).

However, the available literature does not address intraday liquidity risk explicitly, and lacks risk measures or metrics (such as an intraday liquidity VaR or expected shortfall) that are able to answer a rather specific question: what are an institution's maximum intraday liquidity needs at a defined confidence level? The next two sections deal with how to address this type of question.

### 3 MONTE CARLO INTRADAY LIQUIDITY SIMULATION

Monte Carlo simulation methods are suitable for addressing problems of almost any degree of complexity, and can easily address factors that most other approaches have difficulty with. They become more useful as the complexity and/or dimensionality of the problem increases (Dowd (2005)). Therefore, as the case in hand comprises several factors to be simultaneously modeled in order to deal with a financial institution's

intraday liquidity uncertainty, Monte Carlo provides a compelling approach. The next two subsections contain an explanation of the intuition behind using the Monte Carlo simulation approach to deal with intraday liquidity uncertainty and on the designed procedure, respectively.

### **3.1 Dealing with intraday liquidity uncertainty**

According to Principle 8 of Basel Committee on Banking Supervision (2008), a strategy for achieving intraday liquidity management objectives involves six elements. Elements 1, 2 and 6 are as follows.<sup>8</sup>

- Financial institutions should have the capacity to measure expected daily gross liquidity inflows and outflows, anticipate the intraday timing of these flows where possible, and *forecast the range of potential net funding shortfalls that might arise at different points during the day.*
- Financial institutions should have the capacity to *monitor intraday liquidity positions against expected activities* and available resources.
- Financial institutions should be *prepared to deal with unexpected disruptions to their intraday liquidity flows.*

Additionally, according to Basel Committee on Banking Supervision (2008, Principles 10 and 11), liquidity stress tests and contingency plans should observe the following elements.

- Stress tests should consider the implication of the scenarios across different time horizons, including on an intraday basis.
- Financial institutions' stress tests should consider how the behavior of counterparties would affect the *timing of cash flows, including on an intraday basis.*
- The size of *financial institutions' liquidity cushions should also reflect the potential for intraday liquidity risks.*

Likewise, Committee on Payment and Settlement Systems and International Organization of Securities Commissions (2012) regards intraday liquidity as key for overall liquidity risk management by financial market infrastructures. For instance, these principles encompass the following considerations.

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<sup>8</sup> The reader should be aware that these principles from Basel Committee on Banking Supervision (2008) are limited to banks. Taking into account the importance of the nonbanking institutions in financial markets, the author avoids limiting the application of these principles to banks; the author refers to "financial institutions" instead of banks. Please note that all emphasis is the author's.

- A financial market infrastructure should *maintain sufficient liquid resources ... to effect same-day and, where appropriate, intraday and multiday settlement of payment obligations with a high degree of confidence* under a wide range of potential stress scenarios.
- A financial market infrastructure should have *effective operational and analytical tools to identify, measure, and monitor its settlement and funding flows on an ongoing and timely basis, including its use of intraday liquidity.*

A common approach suitable for tackling the quantitative demands imposed by these elements is Monte Carlo simulation. All elements, particularly the italicized parts, converge to modeling financial institutions' intraday payments uncertainty (ie, expected liquidity, potential shortfalls, liquidity scenarios, etc), whereas dealing with uncertainty is the whole point of building a Monte Carlo model (Hubbard (2009)).<sup>9</sup>

Traditional Monte Carlo methods in finance are aimed at repeatedly simulating the random process governing the returns of an asset or instrument, where the governing process is the geometric Brownian motion, along with some other variations to this customary process.<sup>10</sup> Such typical application of Monte Carlo is rather straightforward and flexible since the random process is easily simulated (ie, there is only one stochastic process for each asset), even when considering the dependence across different assets.

However, simulating intraday liquidity is more intricate. In order to measure expected intraday liquidity inflows and outflows (Basel Committee on Banking Supervision (2008, Principle 8)), two different stochastic processes are to be simulated: one governing the inflows (arrival of received payments), and the other governing the outflows (arrival of executed payments). Because of the type of behavior to be modeled (arrival of payments), geometric Brownian motion is unsuitable, and an arrival-type process has to be used. Each process has to be generated with a Poisson process.

Furthermore, since the degree of synchrony between the arrival of received and executed payments is critical for modeling the virtuous circle of coordinated actions by agents typical of RTGS systems (Bernal (2009)), the simulation of the random processes has to capture executed and received payments' dependence: each process has to be generated from a bivariate Poisson process. Paraphrasing Ball *et al* (2011), this would allow for modeling the timing mismatches between incoming and outgoing

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<sup>9</sup> Note that the term "uncertainty" is not used in the Knightian sense (Knight (1921)), where uncertainty is related to cases in which quantifying probabilities is not possible. In this paper the term "uncertainty" is as in Hubbard (2009), where it corresponds to the lack of complete certainty about the true outcome, with uncertainty being measurable (contrary to Knight's use of the term) by the assignment of probabilities to various outcomes.

<sup>10</sup> Some of the most popular variations are jump-diffusion models (Merton (1976) and León (2009)) and fractional Brownian motion (Mandelbrot and Van Ness (1968) and León and Reveiz (2011)).

payments that lead to an increase in the amount of intraday liquidity required to continue making payments in a timely fashion.

Additionally, the size (ie, monetary value) of the payments has to be modeled along with the frequency of arrival, where the size of payments may not be distributed as a normal variable and where samples may not be large enough to make (parametric) distributional assumptions. Finally, since the behavior of the arrivals, their dependence and their monetary value are not constant throughout the day, the simulation's factors or parameters have to be time-dependent.

Altogether, these considerations demand a Monte Carlo simulation model that is significantly different from its standard implementation in finance. The next subsection addresses the procedure behind an implementation of the Monte Carlo model that is suitable for this paper's purposes. Appendix A contains a comprehensive technical explanation on the Monte Carlo simulation algorithm, with an emphasis on the simulation of bivariate Poisson random variables for the intraday arrival of executed and received payments.

### 3.2 Implementation

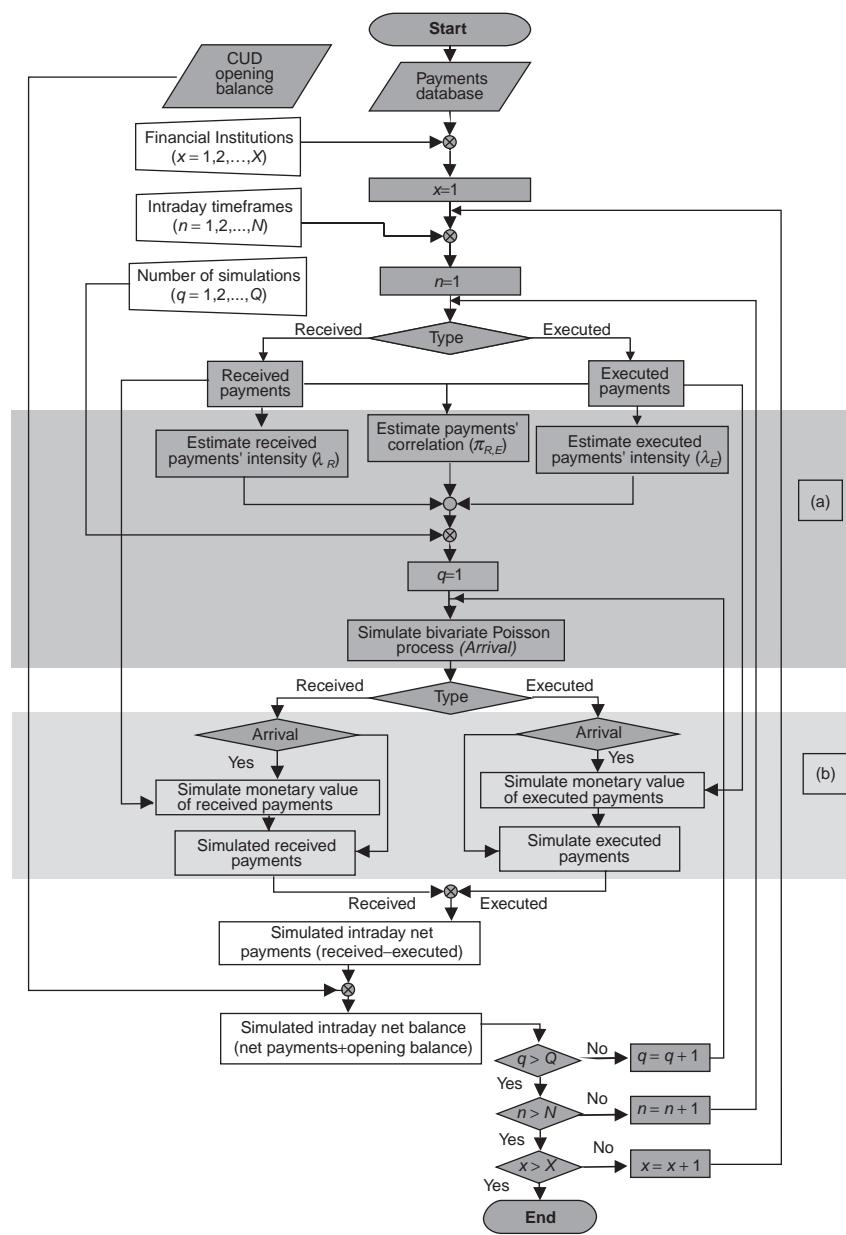
The model could be concisely described as the joint and time-dependent simulation of a bivariate Poisson processes for intraday executed and received payments, and their monetary value. The core of the model is the Monte Carlo simulation of bivariate Poisson random variables for the intraday arrival of executed and received payments, while the simulation of their monetary value using bootstrap historical simulation is subordinated to their arrival. The implementation of the model proposed here is done in MATLAB. It consists of an algorithm executing the procedure depicted in Figure 1 on the facing page.

The algorithm consists of five main inputs: two databases, for LVPS payments and opening balances, which contain information for all participating financial institutions during one day; and three manual inputs, which select the financial institutions to analyze, define the intraday time frames to use, and the number of simulations to generate.

After reading the inputs, the algorithm selects the first financial institution (eg, bank A) and the first time frame to use (eg, from 07:00 to 08:00). According to this selection, the LVPS orders and opening balances databases are filtered. Afterward, the algorithm classifies both types of payments (ie, executed and received) for the selected institution and time frame.

Afterward (part (a) of Figure 1 on the facing page), the Monte Carlo simulation of the payments' arrival starts by estimating the intensity of the executed and received processes ( $\lambda_E$  and  $\lambda_R$ ), along with their correlation ( $\pi_{(E,R)}$ ). After estimating the parameters required for the simulation of the bivariate Poisson process for the intraday

**FIGURE 1** Algorithm's procedure (flow chart).



(a) Monte Carlo simulation of bivariate Poisson processes for the intraday arrival of payments. (b) Bootstrapped historical simulation of received and executed payments' monetary value. Source: author's own design.

arrival of payments, the algorithm generates the first of the simulations to make for this financial institution, for the selected time frame. Based on the algorithm designed by Yahav and Shmueli (2011) for simulating bivariate Poisson processes, the algorithm yields a minute-by-minute two-dimensional vector where the simulated joint-occurrence of executed and received payments is registered.<sup>11</sup>

Subsequently, after simulating the first path of arrivals for the selected financial institution and time frame, the algorithm employs the bootstrapped historical simulation method for generating the monetary value of each of the arrivals previously simulated (part (b) of Figure 1 on the preceding page). Thus, each time the algorithm generates the arrival of an executed (received) order, the algorithm employs a uniform random number generator to resample – with replacement – from the historical record of monetary values of executed (received) payments that the selected financial institution made during the selected time frame. This process yields a minute-by-minute two-dimensional vector where the simulated value of executed and received orders is registered.

Next, the monetary value of received and executed payment orders is subtracted. The result is the simulated intraday net payments. If the opening balance is added, the result is the simulated intraday net balance for the selected financial institution and time frame. Both results are the main building blocks of the model: a single simulation of the minute-by-minute liquidity balance (with and without opening balance) for a selected financial institution and time frame. In order to make all the simulations defined by the user, and to cover all financial institutions and time frames, the algorithm performs three loops.<sup>12</sup>

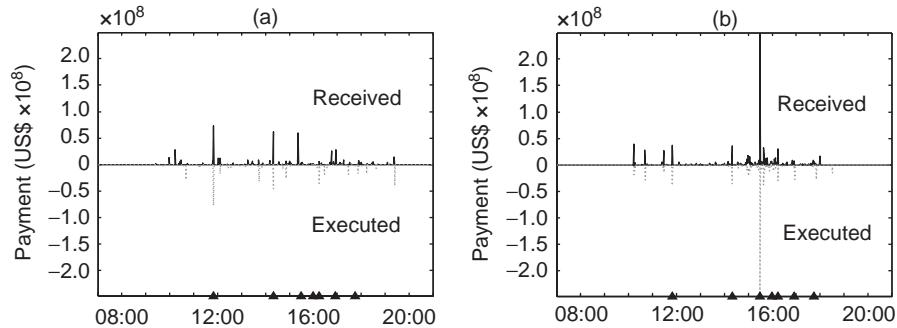
#### 4 PRELIMINARY RESULTS

Based on a day of transactions from the February 2012 LVPS database, this section applies the proposed model to simulate the intraday liquidity of two selected financial institutions.<sup>13</sup> The financial institutions selected belong to the top-ten systemically important institutions according to León and Machado (2011), and they correspond

<sup>11</sup> Note that the occurrence of executed or received payments per minute is not limited to a binary outcome (ie, 0 or 1 payments). During a minute several occurrences may take place, with each minute potentially containing several payments. Appendix A contains a comprehensive technical explanation of the Monte Carlo simulation algorithm.

<sup>12</sup> This is a technical drawback of the proposed model. In the case of Colombia's LVPS, where more than 100 financial institutions participate directly in the LVPS, with thirteen time frames (ie, hourly, from 07:00 to 20:00), with 1000 simulations, the whole procedure for a single day consists of about 2 million registers.

<sup>13</sup> Due to disclosure issues, the opening balance and payments data in this section was multiplied by a factor of  $1 \pm 0.1$  in order to ensure financial institutions' anonymity without sacrificing congruence and comparability.

**FIGURE 2** Hourly intraday payments for selected institutions CBF1 and BDF1.

(a) CBF1 opening balance: US\$750.0 million. Total executed/received: US\$498.7/538.1 million. (b) BDF1 opening balance: US\$0.3 million. Total executed/received: US\$872.8/871.3 million. Received and executed payments have positive and negative signs, respectively. Triangles along the  $x$ -axis identify the presence of CSD and LVPS liquidity saving mechanisms. Source: author's calculations, data from the LVPS.

to a commercial banking firm (henceforth referred to as CBF1) and a broker-dealer firm (BDF1). The selected time frame corresponds to an hour-by-hour<sup>14</sup> breakdown of the Colombian LVPS working hours (ie, 07:00–20:00). The selected number of simulations for all calculations is 1000, but figures display 100 simulations for comprehensibility purposes.

Figure 2 displays the observed minute-by-minute intraday payments for selected institutions CBF1 and BDF1. Executed and received payments appear with negative and positive signs, respectively. It is clear that modeling the intraday liquidity as a non-time-varying process would be inconvenient. The intraday liquidity of financial institutions is heavily dependent on the schedule or timeline designed by the administrator of the LVPS and by all other infrastructures that use the LVPS as their settlement system, and on the design of the LVPS, which may be deferred net settlement systems or RTGS, and may also include liquidity saving mechanisms and other types of rules that affect decision-making by the system's participants.

<sup>14</sup>An hourly division of the intraday was used in order to attain data-abundant time frames for a representative number of institutions for the whole intraday. Given that highly active institutions along the whole intraday are scarce, using “long” windows reduces the estimation error of the parameters and maximizes the number of institutions to work with. Although the chosen length of time frames is convenient, its soundness is worth examining, as pinpointed by the anonymous referee. Appendix C displays three different assumptions for the length of the windows that divide the intraday time frame (ie, one hour, thirty minutes, fifteen minutes), where there is evidence of a nonnegligible difference between the assumptions, but where it is evident that the cross-section analysis and the conclusions remain.

Figure 2 on the preceding page confirms that the pattern of intraday payments is determined in most part by the liquidity saving mechanisms of the Central Bank's Central Securities Depository (CSD) and the LVPS (triangles along the  $x$ -axis); the former consists of optimization algorithms running at 11:50, 14:20, 15:30, 16:15, 16:55 and 17:45, while the latter runs at 16:00.<sup>15</sup> The CSD's optimization algorithms are key to the intraday liquidity of financial institutions since the central government local bond market (ie, the TES market) is the most active and liquid in the Colombian financial system, where CSD TES-related payments account for about 50% of LVPS total payments (Banco de la República (2011)).

It is also clear that, for the selected date, both institutions display a distinctive pattern of intraday liquidity. Beyond any particularity arising from the choice of the date, these results arise from their characteristic business and regulatory framework. For instance, commercial banks have to comply with reserve requirements, whereas broker-dealer firms do not have to. Commercial banks trade bonds and foreign exchange on their own account only, whereas broker-dealer firms trade on their own account and on behalf of clients, profiting from brokerage via commissions; broker-dealer firms are allowed to trade stocks, whereas commercial banks are not.

It is important to stress that such characteristics may explain two distinctive features of the selected financial institutions. First, the intraday liquidity pattern is more concentrated at the end of the day for BDF1. This pattern results from

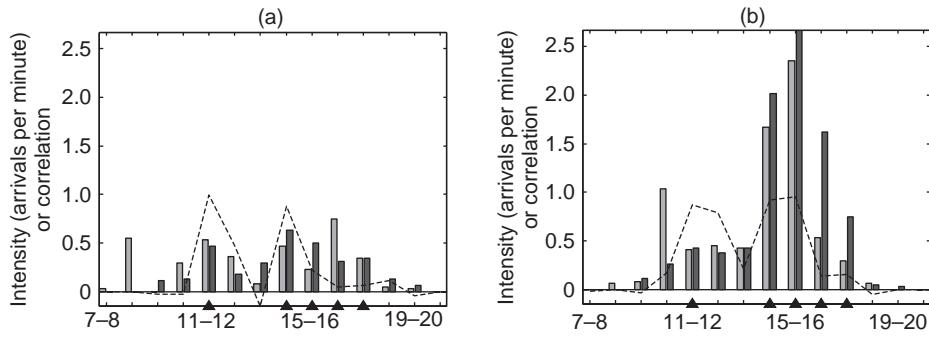
- the lack of reserve requirement and the corresponding low level of opening balance,
- its reliance on the liquidity arriving from the virtuous circle of coordinated actions by other settlement agents,
- the prominence of liquidity saving mechanisms provided by the CDS for TES-related transactions.

On the other hand, CBF1, which holds high levels of opening balance (ie, around 2700 times that of BDF1) due to reserve requirements, may execute payments earlier.<sup>16</sup>

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<sup>15</sup> For an introduction to the design and functioning of the Colombian RTGS payment system and its timeline, please refer to Bernal *et al* (2011), Banco de la República (2011) and Bernal and Merlano (2005).

<sup>16</sup> As in 52% of the countries using an RTGS system (World Bank (2011)), local participants may use all their reserve requirements balance for intraday settlement purposes. Reserve requirements in Colombia are based on the daily averaging of reserve requirements within a two-week reserve maintenance period. According to Gray (2011), averaging reserve requirements is an effective way of enhancing liquidity management, but the reserve maintenance period needs to be at least two weeks long.

**FIGURE 3** Estimated intensities ( $\lambda_E$  and  $\lambda_R$ ) and correlation ( $\pi_{(E,R)}$ ) parameters.

(a) CBF1. (b) BDF1. Light gray bars: intensity of executed. Dark gray bars: intensity of received. Dashed line: correlation. Triangles along the  $x$ -axis identify the presence of CSD and LVPS liquidity saving mechanisms. Source: author's calculations and data from the LVPS.

Second, the size of payments is also distinctive, with payments executed and received by the BDF being about 1.8 times those of the CBF.

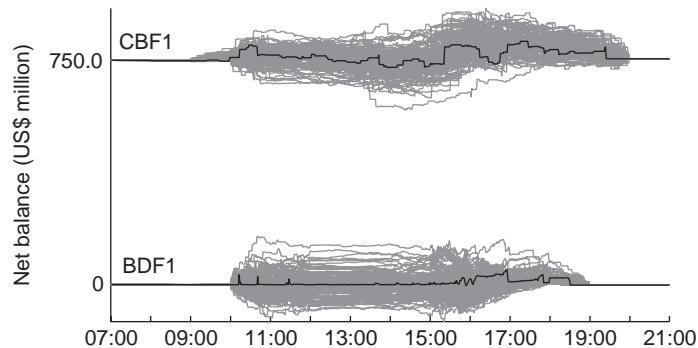
The estimated parameters for the Monte Carlo simulation of bivariate Poisson process for the intraday arrival of payments for both selected financial institutions are displayed in Figure 3.<sup>17</sup>

Based on the estimated parameters, Figure 4 on the next page exhibits 100 extracts from simulating 1000 times the minute-by-minute intraday liquidity of the two selected financial institutions with hourly time frames.<sup>18</sup> This figure corresponds to the simulated intraday net balance; that is, it considers the opening balance of each institution.<sup>19</sup>

<sup>17</sup> The intensities ( $\lambda_E$  and  $\lambda_R$ ) were estimated using the standard maximum likelihood estimate for a Poisson distribution, whereas the correlation ( $\pi_{(E,R)}$ ) was estimated as a standard correlation coefficient; as previously explained, each parameter was estimated for its corresponding time frame.

<sup>18</sup> To achieve a fair approximation of the correlation of the simulated bivariate Poisson series to the target correlation is the mainstay of the bivariate Poisson process and the model. As presented in Appendix B, the mean of the correlation of the simulated bivariate Poisson series replicates the target correlation, whereas the simulated correlation of each series disperses around the target correlation as expected.

<sup>19</sup> Under certain circumstances it would be useful not to consider the opening balance. For example, to analyze the ability of an institution to face executed payments with received payments (ie, the virtuous circle of liquidity). Other analysis may be available by excluding some intraday funding sources, for example. This would allow for an analysis of the reliance of an institution on Central Bank or on the monetary market's intraday liquidity. In forthcoming papers the author expects to implement such variations to the model.

**FIGURE 4** Observed and simulated intraday net balance paths for CBF1 and BDF1.

CBF1 opening balance: US\$750.0 million. BDF1 opening balance: US\$0.3 million. Gray lines: simulated. Black lines: observed. Source: author's calculations.

Taking into account the fact that the Colombian LVPS is an RTGS system where no intraday overdraft is allowed, it is interesting to discover that intraday liquidity paths simulated for the CBF1 remain positive for any scenario. Thus, under the model and assumptions proposed here, the CBF would not exhaust its liquidity, and would be able to fulfill its intraday payments without delays or queuing. The rationale behind this finding is the existence of the reserve requirement for commercial banks, which serves as an important source of liquidity for this type of financial institution, as in Bernal *et al* (2011).

Meanwhile, because the opening balance of BDF1 is significantly lower than that for CBF1 (about 0.04% of CBF1's), BDF1's simulated paths where its liquidity is exhausted are representative. This also corresponds with findings by Bernal *et al* (2011) regarding the reliance of nonbanking institutions (ie, with no reserve requirements) on the virtuous circle of intraday liquidity, along with the presence of significantly higher turnover ratios for BDFs when compared with CBFs; for the two selected financial institutions, the turnover ratio (ie, the ratio of payments and opening balance) reached 0.7 and 3181.2 for CBF1 and BDF1, respectively.

Since the simulated minute-by-minute balance of received and executed orders is available, it is possible to estimate a VaR type of measure of intraday liquidity risk.<sup>20</sup> This measure would answer the following question: what are an institution's maximum intraday liquidity needs at a defined confidence level? The answer to this

<sup>20</sup> Estimating other risk measures (eg, expected shortfall) is straightforward under the model proposed here.

**TABLE 1** CBF1 and BDF1: intraday liquidity VaR (US\$, millions).

Institution	Opening balance	Executed payments	Turnover ratio	Net balance	Scenarios (99% VaR)			
					Intraday (upper bound)		15:30	
					Opening balance	utilization (%)	Net balance	utilization (%)
CBF1	750.0	498.7	0.7	570.6	23.9	606.3	19.2	678.5
BDF1	0.3	872.8	3181	-126.7	46 294	-94.1	34 389	-34.8
								12 782

Source: author's calculations.

question is displayed in Table 1 on the preceding page for three different intraday scenarios:<sup>21</sup> the maximum intraday liquidity needs within the day, by the end of the day (ie, 17:00), and at a significant moment within the day (here, for example, 15:30). A 99% confidence level and 1000 simulations are used for all calculations.

The first scenario (ie, within the day) corresponds to the “upper bound”. Bech and Soramäki (2002) define the upper bound as the amount of liquidity required to settle all payments immediately. Under this bound the liquidity need is maximized, as in an RTGS payment system. This is the most conservative (ie, liquidity demanding) intraday scenario.

The second scenario (ie, by the end of the day) corresponds to the “lower bound”. Bech and Soramäki (2002) define the lower bound as the liquidity required by the system if all payments are to be settled collectively at the close of the day, as in a deferred net settlement system. The author’s choice of the “by the end of the day” minute for the Colombian case corresponds to the time where the settlement of securities and cash has reached about 95–98% and 85–90%, respectively.

Finally, the choice of 15:30 as a significant moment within the day for the Colombian LVPS corresponds to the middle of both institutions’ executed payments most active time frame (ie, 15:00–16:00). During this hour the payments executed by both institutions correspond to 37.5% of their executed payments, the highest of the intraday, where the accumulated executed payments reach 67.8% and 79.8% of each institutions’ total, for CBF1 and BDF1, respectively. Furthermore, the 15:30 time is half an hour before the closing of the access to the monetary (Lombard) liquidity window of the Central Bank.

However, as previously mentioned, because the Colombian LVPS relies on an RTGS system where overdrafts are not allowed, all paths below the zero net balance level (ie, negative net balances) are simply unfeasible. Yet simulating those paths allows the resilience of a financial institution facing an unexpected and extreme change in its intraday liquidity patterns to be estimated. The results from the simulation may help to identify nonresilient institutions, since institutions that are heavily reliant on incoming payments may be vulnerable to a liquidity stress should their counterparties decide to delay or stop making payments to it (Ball *et al* (2011)).

A financial institution displaying net balance paths significantly below zero could be considered as nonresilient and a potential source of delays and interruptions for the functioning of the LVPS under extreme but plausible circumstances. The overall resilience of such an institution would depend, for instance, on its stock of eligible and unencumbered collateral for accessing central bank liquidity facilities, or for accessing the monetary market.

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<sup>21</sup> Please note that these scenarios correspond to the time horizon in a typical VaR model.

The previously presented VaR-type measure of intraday liquidity risk is replicated for a wider set of CBFs and BDFs.<sup>22</sup> Based on the same database and assumptions (eg, 99% confidence interval, 1000 simulations, three different intraday scenarios) Table 2 on the next page exhibits the 99% net balance VaR and the percentage of opening balance that would have been used to surmount such scenario for an average CBF and BDF.<sup>23</sup>

The mean VaR by type of institution confirms the findings for CBF1 and BDF1. The average CBF holds a significant amount of funds at the beginning of the day (about 49.5% of the average executed payments), which allows it to withstand a 99% confidence level adverse setting at any moment within the day. Even at the most severe scenario (ie, the upper bound) the average CBF holds a positive net balance, and requires a fraction of its opening balance (94.1%). As before, such a significant amount of funding at the beginning of the day results from reserve requirements for CBFs.

On the other hand, the average BDF, which is not covered by reserve requirements, holds a significantly lower opening balance at about 0.04% of the opening balance of the average CBF, and equivalent to 0.5% of the average executed payments. Because of this low level of funds at the beginning of the day, the average BDF would be unable to fulfill its intraday payments at a 99% confidence level adverse setting, not even at the less adverse scenario (ie, the lower bound).<sup>24</sup> The resilience of the average BDF would depend mainly on its stock of eligible and unencumbered collateral for accessing central bank's liquidity facilities or for accessing the monetary market.

Results for the selected individual institutions (ie, CBF1 and BDF1) and for an average CBF and BDF concur with results obtained by Bernal and Merlano (2005), Machado *et al* (2009) and León *et al* (2011). For instance, based on the comparison of the upper bound and the available balances of financial institutions, Bernal and Merlano (2005) found that liquidity shortages existed for BDFs, even at the aggregated level, whereas CBFs' required reserve balance held at the central bank was enough to settle the totality of obligations in the payments system. Likewise, based on a mix of network theory and simulation of payments, Machado *et al* (2009) and León *et al* (2011) found that BDFs are prone to exhausting their liquidity and queuing payments

<sup>22</sup> The LVPS database for the selected date comprised nineteen CBFs and twenty-six BDFs, among other types of financial institutions. The institutions included in the set used in this exercise were eleven CBFs and eight BDFs (see Table 2 on the next page); the criterion for inclusion was a threshold of at least ten payments per hour on average within the day.

<sup>23</sup> The results of Table 2 on the next page correspond to nonweighted averages. When using weighted averages the intraday liquidity requirements increase for both types of financial institutions, but the analysis remains.

<sup>24</sup> A similar conclusion is obtained by Bernal and Merlano (2005) regarding delays due to insufficient intraday funds by BDFs and other nonbanking firms in the Colombian market.

**TABLE 2** Average CBF and BDF: intraday liquidity VaR (US\$, millions).

Type of institution	Average opening balance	Average executed payments	Average turnover ratio	Scenarios (average 99% VaR)					
				Intraday (upper bound)		15:30		17:00 (lower bound)	
				Net balance	Opening balance utilization (%)	Net balance	Opening balance utilization (%)	Net balance	Opening balance utilization (%)
CBFs	305.8	618.3	2.0	18.1	94.1	59.2	80.6	92.4	69.8
BDFs	1.3	257.2	199.6	-58.9	4671.3	-43.3	3462.3	-23.8	1945.6

Nonweighted averages for eleven CBFs and eight BDFs. Source: author's calculations.

when the LVPS network faces an attack (ie, failure to pay by an overly connected selected institution).

However, as previously mentioned, the approach presented here improves the measurement of intraday liquidity risk by allowing for estimating standard metrics such as VaR or expected shortfall. This is an important contribution since it provides a known framework (eg, VaR) for designing high degree of confidence stress scenarios such as those suggested by Committee on Payment and Settlement Systems and International Organization of Securities Commissions (2012) for financial market infrastructures.<sup>25</sup>

The results of the model are important for financial authorities. Authorities in charge of prudential regulation, supervision and oversight may use this type of intraday liquidity VaR in order to assess the resilience of financial institutions or financial market infrastructures when confronting intraday liquidity shocks. This information is key for authorities since, as emphasized by Kodres (2009), failure or insolvency are not the only sources of systemic shocks, but mere failure-to-pay or nonpayment of transactions can gridlock the entire financial system.

Furthermore, as acknowledged by Committee on Payment and Settlement Systems (2005), a higher-than-optimal degree of systemic risk in key payment and settlement systems may result from negative externalities, with RTGS-related negative externalities coming in the form of insufficient incentives to consider the full impact on others of delaying outgoing payments. In this sense, the model's results are an approximation to

- the impact of changing timing mismatches on an institution's intraday liquidity,
- its ability to avoid delaying outgoing payments,
- its share of systemic risk in the LVPS.

Additionally, taking into account recent amendments to financial regulation (eg, from the Committee on Payment and Settlement Systems and International Organization of Securities Commissions, Basel Committee on Banking Supervision and the FSA), this model may be a starting point for assessing financial institutions' liquidity and intraday liquidity adequacy. Accordingly, being able to contrast financial institutions' real-time observed intraday liquidity with the model's resulting intraday liquidity uncertainty may be valuable input for an overseer trying to identify abnormal intraday liquidity stances.

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<sup>25</sup> The principles issued by Committee on Payment and Settlement Systems and International Organization of Securities Commissions suggest using a high degree of confidence for determining adequate levels of liquidity for financial infrastructures, where the default of the participant and its affiliates that would generate the largest aggregate liquidity obligation is the suggested metric for such stress scenarios. However, it is difficult to assess the degree of confidence of such an event happening. In this sense, the approach proposed here may provide an intraday liquidity risk metric that works under well-known parameters, such as a VaR with a high degree of confidence.

## 5 FINAL REMARKS

As the most recent financial crisis has revealed, nonbanking institutions are as important as banking institutions nowadays, and liquidity is as important as solvency, where financial infrastructures such as the LVPS play a key role for financial stability. This evolution of financial systems, resulting from the shift to market-based financial systems and to RTGS of payments, has been protracted but ignored to some extent, especially by prudential regulation.

As mentioned, prior to the recent financial crisis, regulators did not focus on intraday liquidity risk and there were no standard monitoring or liquidity management measures in place (Ball *et al* (2011)). Regulation is working hard in order to catch up with risks arising from increasingly important nonbanking institutions, financial infrastructures and liquidity. Regarding the latter, it is clear that regulators (for example, the Committee on Payment and Settlement Systems and International Organization of Securities Commissions, Basel Committee on Banking Supervision and the FSA) are updating their regulatory framework in order to enhance liquidity risk management for financial institutions and infrastructures, where intraday liquidity is one of the major concerns and challenges. These efforts parallel the documented trend in shortening time horizons of liquidity risk and liquidity management, with intraday liquidity as the new standard for what is considered to be short term.

The proposed model addresses a key question for intraday liquidity risk management: what are an institution's maximum intraday liquidity needs at a defined confidence level? The chosen approach allows the minute-by-minute liquidity of any financial institution to be modeled, where the main risk factors to be modeled are the arrival of executed and received payments (ie, their intensity), their synchrony (ie, their timing or correlation) and their size (ie, their monetary value). As mentioned, following Ball *et al* (2011), the identified source of intraday liquidity risk modeled here is the timing mismatch between incoming and outgoing payments, which may lead to significant intraday liquidity needs.

Besides answering that key question, the model may be suitable for quantitatively supporting analysis regarding four main issues:

- overseeing participants' intraday behavior;
- assessing their ability to fulfill intraday payments at a certain confidence level;
- identifying participants who are nonresilient to changes in timing mismatches of payments;
- estimating intraday liquidity buffers.<sup>26</sup>

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<sup>26</sup> As documented and discussed by Ball *et al* (2011), introducing intraday liquidity buffers should make institutions more resilient to any potential liquidity stress. However, their introduction also makes intraday liquidity more costly, and may result in incentives to delay payments.

These four issues, as demonstrated by the most recent financial crisis, are critical for mitigating liquidity and systemic risk, for financial institutions and financial market infrastructures.

Finally, as previously stated, the model's results are an approximation to the main negative externality arising from a financial institution within an RTGS-based LVPS: an institution's insufficient regard for the potential costs or losses that others would incur in the event of its failure to fulfill its payments in a timely manner. In this sense the model assesses the impact of varying timing mismatches on an institution's intraday liquidity, its ability to avoid delaying outgoing payments and its contribution to systemic risk.

While the advantages of the model are rather apparent, some drawbacks are worth mentioning. First, as with any other model, its outcomes should be analyzed and used with care; they intend to provide a fair explanation of reality based on their assumptions, and they are by no means a substitute for sound judgment, or the sole metric to use to measure intraday liquidity risk. Second, the author considers this model a novel approximation to a long-ignored problem, but recognizes that its usefulness depends on the ability of financial authorities to articulate the measurement of intraday liquidity risk with the other stages of risk management (ie, monitoring and mitigating risk), and to understand the business line of each type of institution. Third, the methodology is demanding in terms of computational resources.

The author also recognizes several challenges ahead.

The first is to develop an appropriate backtesting method.

The second is to run the model for a long period (eg, a month), which may discard any particularities and biases in the selection of a specific date and would allow for a comprehensive characterization of the intraday patterns of financial institutions. Despite the fact that results concur with other related models and papers that use longer periods, it is a well-known fact that the daily averaging of reserve requirements within the two-week reserve maintenance period results in cyclic patterns of opening balances for credit institutions under local regulation.

The third refers to analyzing the effects of excluding some major liquidity sources from the estimation of the model's parameters. The author's first choice would be to exclude the systemically most important financial institution, or each institution's highest-liquidity-contributing counterparty. This variant would permit the estimation of the change in intraday payment synchrony and uncertainty due to the absence or failure to pay by a relevant counterparty.

The fourth challenge consists of some technical enhancements to the algorithm:

- implementing a time-dependent Poisson process, where the progressive one-hour-window execution of the algorithm proposed here is replaced by time-dependent intensity rates and correlations;

- allowing for further intraday liquidity uncertainty from monetary value varying payments, where the bootstrap procedure is replaced by a time-varying parametrical assumption of the size of the payments;
- capturing and modeling the dependence between received and executed payments across all participants, and not only the dependence between received and executed payments for a single institution.<sup>27</sup>

The author expects to address these challenges in forthcoming extensions of this paper, especially those corresponding to the algorithm's technical enhancements.

## **APPENDIX A. MONTE CARLO SIMULATION OF INTRADAY PAYMENTS BASED ON BIVARIATE POISSON PROCESSES AND BOOTSTRAP HISTORICAL SIMULATION**

The model could be described as the joint and time-dependent simulation of a bivariate Poisson processes for intraday executed and received payments, and their monetary value. The core of the model is the Monte Carlo simulation of bivariate Poisson random variables for the intraday arrival of executed and received payments, while simulations of their monetary value using bootstrap historical simulation is subordinated to their arrival. Both simulation procedures are addressed below.

### **A.1 Monte Carlo simulation of bivariate Poisson processes for the intraday arrival of payments**

The bivariate Poisson generation is based on the algorithm proposed by Yahav and Shmueli (2011).<sup>28</sup> Their algorithm is based on the NORTA (NORMal To Anything) procedure for generating multivariate Poisson (labeled "P") data with a target correlation structure ( $\Pi_P$ ) and arrival rates ( $\lambda_1, \lambda_2, \dots, \lambda_x$ ), which is based on simulating data from a multivariate normal ( $N$ ) distribution and converting it into an arbitrary continuous distribution with specific correlation matrix. Letting  $\Phi(x)$  be the normal

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<sup>27</sup> The fourth challenge is particularly demanding. It requires shifting from bivariate to multivariate Poisson processes, where the dimension of the problem would escalate from independently generating two joint series of length  $q$  for each participant (ie, received and executed payments) to jointly generating  $N \times 2$  series of length  $q$  for the whole system, where  $N$  and  $q$  stand for the number of participants and the number of simulations, respectively. The most appealing feature of such a shift is its ability to explicitly model institutions' connectedness (via the dependence between received and executed payments across institutions), whereas the model proposed here does it implicitly.

<sup>28</sup> This section is based on Yahav and Shmueli (2011). Several references were omitted in order to preserve readability.

cumulative distribution function and letting  $\Omega(x)$  be any target cumulative distribution function, the generalized NORTA procedure is as follows.

- (a) Generate a  $q$ -dimensional normal vector  $X_N$  with mean  $\mu = 0$ , variance  $\sigma = 1$ , and a correlation matrix  $\Pi_N$ .<sup>29</sup>
- (b) For each value  $X_N, i \in 1, 2, \dots, q$ , calculate the normal cumulative distribution function (CDF) ( $\Phi(x)$ ):

$$\Phi(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\sigma^2}} e^{-u^2/2} du \quad (\text{A.1})$$

- (c) For each  $\Phi(x)$ , calculate the target cumulative distribution function ( $\Omega(x)$ ):

$$X_{y_i} = \Omega^{-1}(\Phi(X_{N_i})) \quad (\text{A.2})$$

- (d) The resulting vector  $X_Y$  is then a  $q$ -dimensional vector, distributed according to the target cumulative distribution function ( $\Omega(x)$ ), with correlation  $\Pi_N$ .

Despite the simplicity of the NORTA procedure, generating bivariate or multivariate probability distributions when the target distribution is a discrete probability distribution (ie, a random variable can assume only a certain clearly separated values) is more complicated. Such is the case for the Poisson distribution.

The Poisson distribution describes the number of times an event occurs during a specified time, space, area or volume interval. It is a discrete probability distribution since it is formed by counting (Lind *et al* (2006)), and is based on two assumptions:

- (1) the probability of an event occurring is proportional to the length of the interval;
- (2) the probability of an event occurring in an interval is independent of its occurrence in other intervals.

The Poisson distribution is defined by a single parameter ( $\lambda$ ) that expresses the probability of a number of events occurring in a fixed interval of time (ie, the mean number of occurrences in a particular interval), where  $\lambda$  is commonly referred to as the intensity of the process. The Poisson cumulative distribution function ( $\Xi(x)$ ) corresponds to:

$$\Xi(x) = \sum_{i=0}^x \frac{e^{-\lambda} \lambda^i}{i!} \quad (\text{A.3})$$

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<sup>29</sup> Generating normal multivariate random numbers (ie, with correlation matrix  $\Pi_N$ ) is straightforward by means of the Cholesky decomposition. The interested reader is referred to Cuthbertson and Nitzsche (2004) and León and Reveiz (2011).

With sufficiently large  $\lambda$ , the normal distribution is a fair approximation to the Poisson distribution, where  $\lambda$  is its mean and variance. Conveniently, as the Poisson distribution converges asymptotically to a normal distribution, attaining multivariate Poisson distributed random variables with correlation  $\Pi_P$  is straightforward since the dependence between both distributions would also converge asymptotically ( $\Pi_N \approx \Pi_P$ ).

However, as pointed out by Yahav and Shmueli (2011), when the normal distribution is not a fair approximation to the Poisson distribution (ie, when  $\lambda$  is small), the convergence in correlation ceases to exist ( $\Pi_N \neq \Pi_P$ ). The main consequence of such lack of convergence in distribution is that the feasible correlation between two random Poisson variables is no longer in the traditional range  $[-1, 1]$ , but in a narrower range  $[\underline{\pi}_P \geq -1, \bar{\pi}_P \leq 1]$ .

Furthermore, the smaller the intensity of any of the Poisson processes, the narrower the correlation range, and the more difficult it is to obtain a target correlation. As demonstrated by Shin and Pasupathy (2010), as any intensity rates  $\lambda_1$  and  $\lambda_2$  approximate to zero ( $\lambda_1, \lambda_2 \rightarrow 0$ ), the minimum feasible correlation approximates to zero ( $\underline{\pi}_P \rightarrow 0$ ). As exhibited in Figure 2 on page 87 and Figure 3 on page 89, this is the case at the beginning and the end of the day, when payments are rather scarce.<sup>30</sup>

Therefore, in order to attain bivariate Poisson random variables with intensity rates  $\lambda_1$  and  $\lambda_2$ , this paper follows the functional approximation developed by Yahav and Shmueli (2011) to estimate the relationship between the desired Poisson correlation ( $\pi_P$ ) and the actual (normal) correlation ( $\pi_N$ ). The procedure is as follows.

- Let  $U$  be a vector of uniform randomly distributed variables and compute the correlation mapping  $[\underline{\pi}_P \geq -1, \bar{\pi}_P \leq 1]$ , where:

$$\left. \begin{aligned} \underline{\pi}_P &= \text{corr}(\mathcal{E}_{\lambda_1}^{-1}(U), \mathcal{E}_{\lambda_2}^{-1}(1-U)) \\ \bar{\pi}_P &= \text{corr}(\mathcal{E}_{\lambda_1}^{-1}(U), \mathcal{E}_{\lambda_2}^{-1}(U)) \end{aligned} \right\} \quad (\text{A.4})$$

- Compute the coefficients of the exponential function estimated by Yahav and Shmueli (2011):<sup>31</sup>

$$\left. \begin{aligned} a &= -\frac{\bar{\pi}_P \times \underline{\pi}_P}{\bar{\pi}_P - \underline{\pi}_P} \\ b &= \log\left(\frac{\bar{\pi}_P + a}{a}\right) \end{aligned} \right\} \quad (\text{A.5})$$

<sup>30</sup> Since the minimum feasible correlation approximates to zero ( $\underline{\pi}_P \rightarrow 0$ ) when intensity rates approximate to zero ( $\lambda_1, \lambda_2 \rightarrow 0$ ), the implemented algorithm includes an instruction to round any intensity below 0.0167 (ie, one arrival per hour) to zero, and to simulate the two Poisson processes as noncorrelated ( $\underline{\pi}_P = 0$ ).

<sup>31</sup> Based on simulations, Yahav and Shmueli (2011) find that the relationship between the desired correlation ( $\pi_P$ ) and the actual correlation ( $\pi_N$ ) is best approximated by an exponential function  $\pi_P = a \times e^{b \times \pi_N} - a$

- (c) Based on the previously computed coefficients, compute the correlation required to generate bivariate normal random variables ( $\pi_N$ ) that approximate the target correlation ( $\pi_P$ ):

$$\pi_N = \frac{1}{b} \log \left( \frac{\pi_P + a}{a} \right) \quad (\text{A.6})$$

- (d) Generate bivariate normal random variables with  $\mu_1 = \mu_2 = 0, \sigma_1 = \sigma_2 = 1$  and correlation  $\pi_N$ .
- (e) Based on the bivariate normal random variables ( $X_N \sim N(0, \pi_N)$ ), follow the NORTA procedure with the Poisson distribution as the target CDF, with intensity rates  $\lambda_1$  and  $\lambda_2$ .

$$X_{P_i} = \mathcal{E}^{-1}(\Phi(X_{N_i})) \quad (\text{A.7})$$

The resulting vector  $X_P$  is then a two-dimensional vector, distributed according to the Poisson cumulative distribution function ( $\mathcal{E}(x)$ ), with intensity rates  $\lambda_1$  and  $\lambda_2$ , and correlation  $\pi_P$ . For the problem at hand, this procedure yields two vectors:

- (1) a minute-by-minute vector of executed payments;
- (2) a minute-by-minute vector of received payments, where several executed or received payments per minute may occur; that is, according to the intensity rates there may be more than one arrival per minute.

Both vectors contain the minute-by-minute arrival of payments (their occurrence, not their value), where both vectors approximate the target correlation corresponding to the estimated synchrony between received and executed payments.<sup>32</sup>

Due to the time-variant characteristics of the LVPS intraday payments, which display time frames with distinctive intensity rates and correlations, the aforementioned procedure is not applied to the whole day; instead, it is applied to one-hour windows, which allows for capturing the intraday seasonality of executed and received payments.

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<sup>32</sup> In order to attain comparability between simulations, the algorithm is instructed to always obtain the same monetary value of received (respectively, executed) payments as in the observed data. Such a restriction excludes the effect of payments size, and permits focusing on the analysis of changes in payments' synchrony. This does not mean that the same monetary values are used from simulation to simulation, but that the same nonparametrical distribution (ie, the observed payments) was used to generate different monetary values from simulation to simulation. Despite the convenience of the chosen approach to simulating the value of the payments, it may be useful to allow for further intraday liquidity uncertainty arising from value varying payments. This additional source of risk may be modeled by making a time-varying parametrical assumption of the size of the payments.

An alternative to this progressive one-hour-window execution of the algorithm is to design a time-dependent Poisson process, where intensity rates and correlations are functions of time.<sup>33</sup> Despite being a more elegant alternative, two main issues stand against it. First, such a procedure may further complicate the algorithm, which is already burdensome and time-consuming. Second, the design of the time-dependent parameters is by no means trivial, and may further introduce model risk into the approach.

## A.2 Bootstrapped historical simulation of received and executed payment value

The previous subsection presented the method for simulating the occurrence or arrival of both received and executed payments, but not their monetary value. The author's choice for simulating the monetary value of payments is based on bootstrapped historical simulation.

Based on Dowd (2005), the author designs a bootstrap procedure (resampling with replacement)<sup>34</sup> to simulate the monetary value of received and executed payments once they occur as a result of the arrival simulation method previously described. Each time a received (respectively, executed) payment arrives the model draws a sample from the received (respectively, executed) historical records, and takes its monetary value as the received (respectively, executed) payment's value for that occurrence.

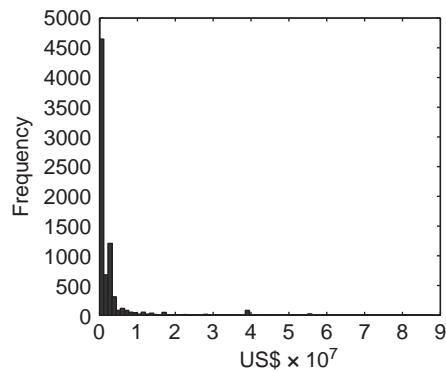
Compared with other methods available for simulating the monetary value of the payments, the bootstrap avoids unreliable assumptions such as normality of the data set or the existence of large samples (Dowd (2005)). Regarding the normality of payments, it is clear that they do not converge to a Gaussian distribution (Figure A.1 on the facing page), while it is also common to find intraday periods characterized by small samples to work with (Figure 2 on page 87 and Figure 3 on page 89).<sup>35</sup>

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<sup>33</sup> The anonymous referee suggested this clever and elegant alternative. Despite being somewhat impractical for the moment (ie, the current algorithm is already time-consuming and computationally demanding), this enhancement is being considered for a newer and more efficient version of the algorithm.

<sup>34</sup> The bootstrap procedure consists of sampling from a data set of size  $n$ . Each sampling requires the generation of uniform random numbers between 1 and  $n$  to randomly draw observations from the data set; drawn observations are returned to the data set (ie, observations are replaced into the data set). Since Monte Carlo may be broadly defined as a method that provides approximate solutions by performing statistical sampling experiments on a computer (Fishman (1995)) or a random number generator that is useful for forecasting, estimation, and risk analysis (Mun (2006)), the bootstrap procedure may be considered as involving a Monte Carlo procedure within. Therefore, the author regards the whole method presented here as an implementation of a Monte Carlo simulation.

<sup>35</sup> Small samples of payment orders are a significant problem for fairly inactive financial institutions, which tend to make payments infrequently.

**FIGURE A.1** Distribution of LVPS payments (selected day).

Source: author's calculations, data from the LVPS.

## APPENDIX B

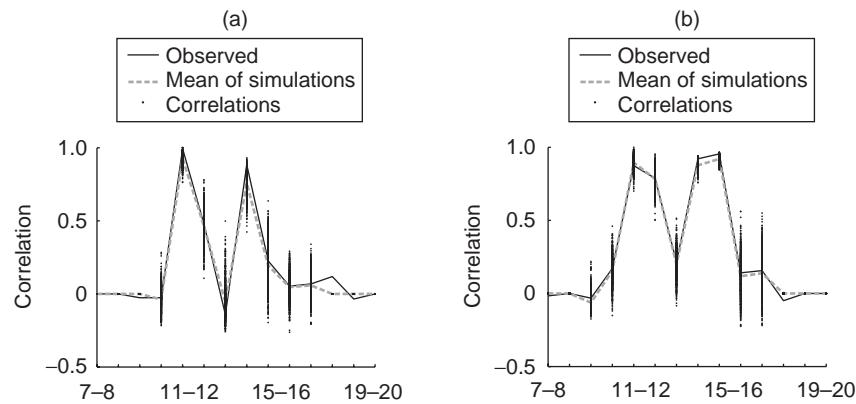
Achieving a fair approximation of the correlation of the simulated bivariate Poisson series to the target correlation is the main goal of the bivariate Poisson process and the model. Figure B.1 on the next page demonstrates that the mean of the correlation of the simulated bivariate Poisson series replicates the target correlation, while the simulated correlation of each series disperses around the target correlation.

It is worth mentioning that, since the minimum feasible correlation approximates to zero ( $\underline{\pi}_P \rightarrow 0$ ) when intensity rates approximate to zero ( $\lambda_1, \lambda_2 \rightarrow 0$ ), the implemented algorithm includes an instruction to round any intensity below 0.0167 (ie, one arrival per hour) to zero, and to simulate the two Poisson processes as noncorrelated ( $\underline{\pi}_P = 0$ ). The author regards this as a safe practice because of the theoretical support behind such an assumption (Yahav and Shmueli (2011) and Shin and Pasupathy (2010)), and because, during low-intensity periods (eg, 07:00–09:00, 19:00–20:00), the frequency of the payments is nonsignificant relative to the rest of the intervals.

## APPENDIX C

In order to assess the soundness of the selected length of the windows that divide the intraday time frame, Table C.1 on the next page displays the VaR for each institution (ie, CBF1 and BDF1) and type of institution (ie, CBFs and BFDs), where the metric corresponds to the 99% confidence VaR as a percentage of total executed payments.

It is rather apparent that the cross-section analysis is the same for any of the three assumptions considered, with the sole exception of the 15:30 scenario when

**FIGURE B.1** Algorithm's correlation fit.

(a) CBF1. (b) BDF1. Source: author's calculations.

**TABLE C.1** CBF1, BDF1, CBFs and BDFs: intraday liquidity risk (99% VaR, as percentage of total executed payments).

	One-hour window (default)	Thirty- minute windows	Fifteen- minute windows	Average
<i>Intraday (upper bound)</i>				
CBF1	35.6	35.4	42.4	37.8
BDF1	15.3	21.0	20.5	18.9
CBFs	44.6	41.3	48.3	44.8
BDFs	33.1	33.0	20.5	28.9
<i>15:30</i>				
CBF1	28.3	22.1	14.1	21.5
BDF1	12.0	17.8	19.1	16.3
CBFs	36.2	30.1	35.9	34.0
BDFs	21.8	20.7	20.0	20.8
<i>17:00 (lower bound)</i>				
CBF1	15.5	15.0	12.1	14.2
BDF1	4.5	7.0	8.2	6.5
CBFs	29.2	20.7	28.6	26.1
BDFs	10.4	8.0	7.4	8.6

Nonweighted averages for eleven CBFs and eight BDFs. Source: author's calculations.

comparing CBF1 and BDF1. However, since the monetary value of the payments made by BDF1 is significantly higher than the value of the payments made by CBF1 (ie, 1.8 times), and the opening balance is significantly higher for CBF1 (ie, 2700 times the BDF1s), the analysis and conclusions of the paper are valid regardless of the chosen assumption.

Nevertheless, any implementation and analysis resulting from the proposed approach should be aware of the trade-off between a more precise characterization of the intraday process by a more granular breakdown of the time frame, and the availability of abundant observed arrivals to estimate the parameters of the simulation for a meaningful and diverse sample of institutions.

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