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

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Risk indicators for financial market infrastructure: from high frequency transaction data to a traffic light signal*

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Abstract

This paper identifies quantitative risks in financial market infrastructures (FMIs), which are inspired by the Principles for Financial Market Infrastructures. We convert transaction level data into indicators that provide information on operational risk, changes in the network structure and interdependencies. As a proof of concept we use TARGET2 level data. The indicators are based on legislation, guidelines and their own history. Indicators that are based on their own history are corrected for cyclical patterns. We also define a method for setting the signaling threshold of relevant changes. For the signaling, we opt for a traffic light approach: a green, yellow or red light for a small, moderate or substantial change in the indicator, respectively. The indicators developed in this paper can be used by overseers and operators of FMIs and by financial stability experts.

Keywords: risk indicator, central bank, granular data, TARGET2, oversight, financial stability, forecasting.
JEL classifications: E42, E50, E58, E59.

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* Berndsen and Heijmans can be reached at r.j.berndsen@dnb.nl and ronald.heijmans@dnb.nl, respectively. Heijmans is a member of one of the user groups with access to TARGET2 data in accordance with Article 1(2) of Decision ECB/2010/9 of 29 July 2010 on access to and use of certain TARGET2 data. DNB and the PSSC have checked the paper against the rules for guaranteeing the confidentiality of transaction-level data imposed by the PSSC pursuant to Article 1(4) of the above mentioned issue. The views expressed in the paper are solely those of the authors and do not necessarily represent the views of the Eurosystem or De Nederlandsche Bank.

1 Introduction

Financial Market Infrastructures (FMIs) play a key role in the smooth functioning of the economy. They facilitate the clearing, settlement, and recording of monetary and other financial transactions. If an FMI is not properly managed, it can pose significant risks to the financial system and be a potential source of contagion, particularly in periods of market stress. Due to their important role in the economy, FMIs have to meet high standards laid down in the Principles for Financial Market Infrastructures (PFMI, CPSS (2012)). A number of these risks defined by the Principles are quantitative in nature.

The aim of this paper is to develop risk indicators using FMI transaction level data, which are inspired by the Principles for Financial Market Infrastructures (PFMIs, CPSS (2012)). In general we define a risk indicator as a pair of variables (Observation, Benchmark) where Observation is the particular value of the risk indicator at some point in time examined. The Benchmark value indicates normal value of the indicator. If the Observation deviates far enough from the Benchmark we have a signal. As a proof of concept we use TARGET2 transaction level data spanning June 2008 to December 2016. This period corresponds with approximately 750 million transactions. Analyzing such an amount of transactions is computationally demanding. In addition to viewing at the level of all transactions, we deepen our analysis by differentiating between the different payment types in order to gain a better understanding of the different network layers present in the data. Our indicators are linked to operational risks, changes in the network structure and interdependencies. Even though the focus of this paper is TARGET2, the indicators could be applied to other FMIs as well, as the risks defined by the Principles are also applicable to other FMIs. The approach of constructing our indicators is as follows: The first step is to develop indicators. Second, we correct for seasonality and trends where needed (in line with Timmermans and Heijmans (2017)). As a third step we determine the signaling threshold at which an indicator should give an alarm. These alarms help overseers, operators or financial stability experts in assessing the risk.

This paper adds to the stand of the literature on FMIs and in particular to large value payment systems. Li and Pérez-Saiz (2016) measure systemic risk in the network of financial market infrastructures (FMIs) as the probability that two or more FMIs have a large credit risk exposure to the same FMI participant. They have constructed indicators of credit risk exposures in three main Canadian FMIs during the period 2007 – 2011. They have used extreme value methods to estimate this probability. They find large differences in the contribution to systemic risk across participants. They also find that when participants are in financial distress, they tend to create large credit exposures in two or more FMIs. Their results suggest that an appropriate oversight of FMIs may benefit from an in-depth system-wide analysis, which may have useful implications for the macro prudential regulation of the financial system. Massarenti et al. (2012) study the timing of TARGET2 payments. They find that most value is transferred in the last business hour of the day. This means that a disruption at this time can have larger consequences than on other times of the settlement day since: 1) the value is large, a disruption can seriously harm liquidity flows, 2) it is the last hour of the business day, there is little time to solve the disruption and fulfill payment obligations.

Part of the literature focuses on network topology of large value payment systems, see e.g. Chapman et al. (2010), Embree and Roberts (2009), Heijmans et al. (2016) and Pröpper et al. (2013). León and Pérez (2014) assess the importance of FMIs using authority and hub centrality. These measures allow for assessing FMIs' global importance unlike standard measures like e.g. degree and eigenvector centrality. Squartini et al. (2013) show early-warning signals for topological collapse in interbank networks. They study quarterly interbank exposures amount Dutch bank between 1998 and 2008. The outcome of their research is relevant for bank regulators. One of their findings is a well-defined core-periphery structure. In contrast to our paper they use highly aggregated data instead of granular data.

Empirical work on other FMIs is more recent, due to data problems. Cruz Lopez et al. (2013) study systemic risk within a CCP. Cox et al. (2014) study the link between CCPs. These links enable participants to clear positions in any linked CCP without needing to maintain multiple CCP memberships. Mägerle and Nellen (2011) study the risk management of financial exposures resulting from links between CCPs. They find that a fragmented clearing system with multiple CCPs is inefficient. They illustrate that interoperability resolves the inefficiencies associated with fragmentation. It enables traders to multilaterally net their positions across all CCPs, which minimizes margin requirements and counterparty exposures in the clearing system. Menkveld et al. (2015) investigate the effects of central clearing on collateral demand and prices. Another often used method to investigate the potential impact of disruptions in large value payment systems is simulation. Simulations can typically ask 'what if' type questions. Most of the simulations in the literature can roughly be divided into operational risk, liquidity risk, credit risk and behavior of participants, see Heijmans and Heuver (2012) for a comprehensive overview.

This paper is organized as follows. Section 2 describes briefly the FMI TARGET2 and the data we have used in our analysis. Section 3 explains how the risk indicators are developed. Section 4 shows the risk indicators. Section 5 provides guidance in how to use the indicators and how a monitoring dashboard looks like. Section 6 summarizes and provides conclusions.

2 Data

2.1 TARGET2

TARGET2 is the real-time gross settlement (RTGS) system owned and operated by the Eurosystem.[1] Payment transactions in TARGET2 are settled one by one on a continuous basis, in central bank money with immediate finality. There is no upper or lower limit on the value of payments.

TARGET2 settles payments related to monetary policy operations, interbank and customer payments, and payments related to the operations of all large-value net settlement systems and other FMIs handling the euro (such as securities settlement systems or central counterparties). Most of the 1,007 direct participants are euro area credit institutions, several large non-euro area banks (notably UK and US) and euro area central banks. Besides the euro area central banks, several other central banks in the European Union have access to TARGET2.[2]

TARGET2 is operated on a single technical platform. Business relationships are established

[1] TARGET2 stands for Trans-European Automated Real-time Gross settlement Express Transfer system.

[2] The non-euro area countries with access to TARGET2 are: Bulgaria, Croatia, Denmark, Poland and Romania (status July 2016). At the start of our data set there have been a few countries in the European Union that did not have the euro yet: Estonia, Latvia, Lithuania, Slovakia.

between the TARGET2 users and the respective central bank. In terms of the value processed, it is one of the largest payment systems in the world. Table 1 provides some general statistics on TARGET2 for the year 2014. It processes on average more than 350,000 transactions daily with a corresponding turnover of 1,900 billion euros. The average transactions value is EUR 5.5 million.

Table 1: TARGET2 facts in 2014.

Number of participants	TARGET2 had 1,007 direct participants, 837 indirect participants and 5,037 correspondents
Number of ancillary systems	TARGET2 settled the cash positions of 84 ancillary systems
Daily averages	TARGET2 processed a daily average of 354,263 payments, representing a daily average value of EUR 1.9 trillion
Average transaction value	EUR 5.5 million
Payment values	more than two-thirds of all TARGET2 payments had a value of less than EUR 50,000 each: 13% of all payments had value of over EUR 1 million
Peaks	the peak in volume turnover was 30 June 2014 with 568,060 transactions and peak value turnover was on 30 April 2014 with EUR 3,155 billion
Large-value payment system traffic	TARGET2's share in total large-value payment system traffic in euro was 91% in value terms and 61% in volume terms
SSP technical availability	100%

source: ECB, `https://www.ecb.europa.eu/paym/t2/html/index.en.html`

2.2 Evolution of TARGET2

TARGET2 has been introduced in November 2007. The countries participating in TARGET2 migrated to TARGET2 in three waves, from November 2007 to May 2008. Most euro area central banks have migrated completely from their national predecessor fully to TARGET2. However, several central banks choose to maintain their national transactions in their TARGET2 predecessor, conform the legal documentation, in the so-called proprietary home accounting (PHA) module. Since the fall of 2013 all countries migrated completely to TARGET2 for all their transactions. This means that we have a fully representative transaction data set since then.

2.3 TARGET2 transaction data

Our data set contains all individual transactions settled in TARGET2 from June 2008 until 2016. This corresponds with approximately 750 million transactions. Truncating the first five months of 2008 removes possibly atypical behavior during the bedding period. In case it is to be expected that the domestic transactions settled in the PHAs influences the indicator, we start our data set in January 2014.

TARGET2 distinguishes between several payment types. (Table 2). The payments are divided into four different groups: 1) main transactions, 2) payments with a central bank involved, 3) payments from and to ancillary systems (AS) and 4) liquidity transfers.

There are many banks, especially the larger ones, which have more than one account in TARGET2. This is most likely due to that bank's internal administrative reasons. Transfers between the accounts of the same bank (category 4.4), is not seen as an actual payment, but just an administrative shift of liquidity between two accounts of the same legal entity. Therefore, category 4.4 is often omitted from the official published ECB TARGET2 statistics as these transactions do not reflect an economic process. For this reason we also exclude the 4.4. category, when we look at all transactions which should reflect an economic process. Category 4.6 and 4.7 have been introduced at the start of TARGET2 securities (T2S) in 2015. The migration of T2S is also done in migration waves. This payment category will therefore increase over time.

The daytime opening of TARGET2 is between 7.00 and 18.00. Category 1.1 can only be processed by TARGET2 until 17.00. Besides the daytime opening, TARGET2 also allows some ancillary systems to settle during the night (between 19.30 and 7.00). However, as these payments are limited in number and amount and only reflect a small part of the transaction types settled in TARGET2 we omit them from the scope of our analysis.

2.4 Critical participants in TARGET2

The Eurosystem has set extra technical requirements for participants which are considered critical. These extra requirements should reduce the probability that these banks are not able to pay (for some time) due to technical problems.

The 'Information guide for TARGET2 users' provides a general guideline for participants

Table 2: Description of the different payment types in TARGET2.

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

source: ECB

which are considered critical (ECB, 2014). The Eurosystem considers a credit institution (commercial bank) as critical in TARGET2 if it consistently settles at least 1% in terms of value of the TARGET2 turnover on a daily average (excluding transactions submitted by third parties, e.g. ancillary systems). Besides credit institutions there are several ancillary systems which are considered critical. However, the turnover related to ASs are relatively small compared to turnover of critical credit institutions.

3 Constructing risk indicators

3.1 General principle

TARGET2 transactions will be converted into risk indicators. We define a risk indicator as a pair of variables (Observation, Benchmark) where Observation is the particular value of the risk indicator at some point in time examined. The Benchmark value indicates normal value of the indicator. If the Observation deviates far enough from the Benchmark we have a signal.

The signaling of the risk indicators are based on one of the three following quantitative measures:

1. Regulatory quantitative measure;

2. Quantitative (external) guideline;

3. Its own history (absolute and/or relative change).

The regulatory measure provides the most straightforward indicators.[3] In case an FMI has to follow a certain rule that can be quantitatively tested; it is easy to establish the Benchmark. An external guideline, that is not legally binding but nonetheless common practice, may also serve as an adequate Benchmark. The measure is known and can be easily calculated, similar to the regulatory measure. However, in most cases it will not be possible to define a quantitative legal obligation or guideline. In these cases it will be necessary to develop a Benchmark that is based on its own history.

The risk indicators we develop have to follow two general requirements. The indicators should be: 1) easy to explain to an end-user and 2) relevant and scientifically correct. The reason why they have to be easy to explain is that end-users, e.g. managers, regulators or policy advisors, are the intended recipients of this type of information. Otherwise, they are likely to stay unused. Besides, there will be many risk indicators, which have to be understood. The second requirement is rather obvious as the indicator has to be based on a good foundation. However, these two requirements may contradict each other. Therefore, we will opt for the so called 'traffic light' approach (green, yellow, red). In case of green light,

[3]An example of a strong rule laid down in the PFMIs is the 2 hour recovery time.

there does not seem to be a problem with a certain indicator relative to the Benchmark. A yellow light shows a moderate change and a red light shows a substantial change in the indicator relative to the Benchmark.

3.2 Deseasonalize indicator time series

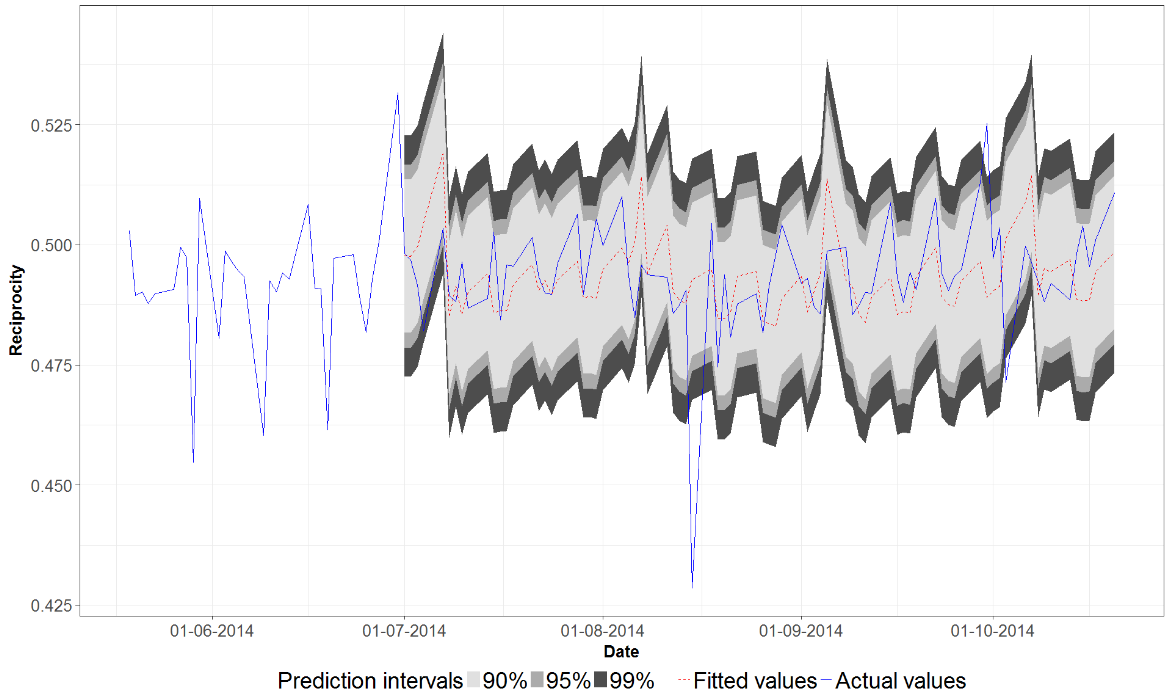
The indicators that need to be based on their own history, have to be corrected for cyclical patterns as we want to differentiate between normal and deviating patterns. There are cyclical patterns in TARGET2 and indicators based on TARGET2 transaction data (see Timmermans and Heijmans (2017) and Van Ark and Heijmans (2016)). Timmermans and Heijmans (2017) investigate cyclical patterns on TARGET2 risk indicators and network properties. They have tested the performance of several models to correct for these patterns, such as weeks, months and days around reserve maintenance requirements. They find that a simple ARIMA model with dummies performs best for this type of time series. We will filter our indicator time series with that model before applying the 'traffic light' approach to it. The time series they investigate consists of many network properties, operational aspects and links to other FMIs. Especially for the Herfindahl Hirshman Index (HHI) based indicators, which will be thoroughly discussed in section 4.2, they have found clear and strong cyclical month patterns. See Appendix A for a brief description of their model setup.

Van Ark and Heijmans (2016) focus their analysis on the number of transactions and the turnover in the Dutch of TARGET2 at aggregation levels of 10 minutes and one hour interval. This in contrast to Timmermans and Heijmans (2017) who use daily aggregates.

3.3 Forecast indicator time series

After the time series of risk indicators that are based on their own history have been corrected for seasonality we can define the thresholds for signaling (red and yellow light of the traffic light). We use the forecasting method described by Timmermans and Heijmans (2017) to forecast the next month. Figure 1 graphically presents an example of how the forecasting will appear. The blue line shows the actual value of the time series. The red line is the forecasted value for the next month (in this case August 2015). The gray shaded areas show the 90%, 95% and 99% interval of the forecasted values based on the years before.

Figure 1: Forecasting example.



source: Timmermans and Heijmans (2017)

The figure shows that the time series are relatively volatile and can therefore reach beyond the 99% interval of the forecasted value. These forecasted (or fitted) values will be compared to the actual (or real) values of the indicator. In case the actual values exceed a certain interval (95% respectively 99%) of the forecasted values several times, we set the traffic light to yellow respectively red. The 95% respectively 99% interval corresponds with a 2.0 respectively 2.6 standard deviations in case of a normal distribution. However, the distribution of the actual values of the indicators is not a perfect normal distribution. These distributions contain fat tails. As a consequence we chose for the signaling that the number of times the actual value of the indicator lies outside the forecasted interval more than once.

4 Risk indicators

In this section we construct risk indicators based on TARGET2 transactions. Depending on the indicator all or a subset of these transactions will be included. For the indicators described in section 4 we differentiate between the following groups:

- all transactions;
- 1.1 transactions;
- 1.2 transactions;
- 1.1 and 1.2 transactions;
- 3.1 to 3.5 transactions (also named 3.x).

All transactions obviously include all transactions listed in Table 2, which provides on overview at system level. The 1.1 and 1.2 transactions focus on the transactions between banks (on behalf of their customer or their own business). The 3.1 to 3.5 transactions comprise the transactions from TARGET2 to the Ancillary Systems and vice versa. We focus our analysis to the aforementioned groups as we deem these transactions the most important from an economic point of view. However, other payment categories may also include relevant information.

4.1 Operational indicators

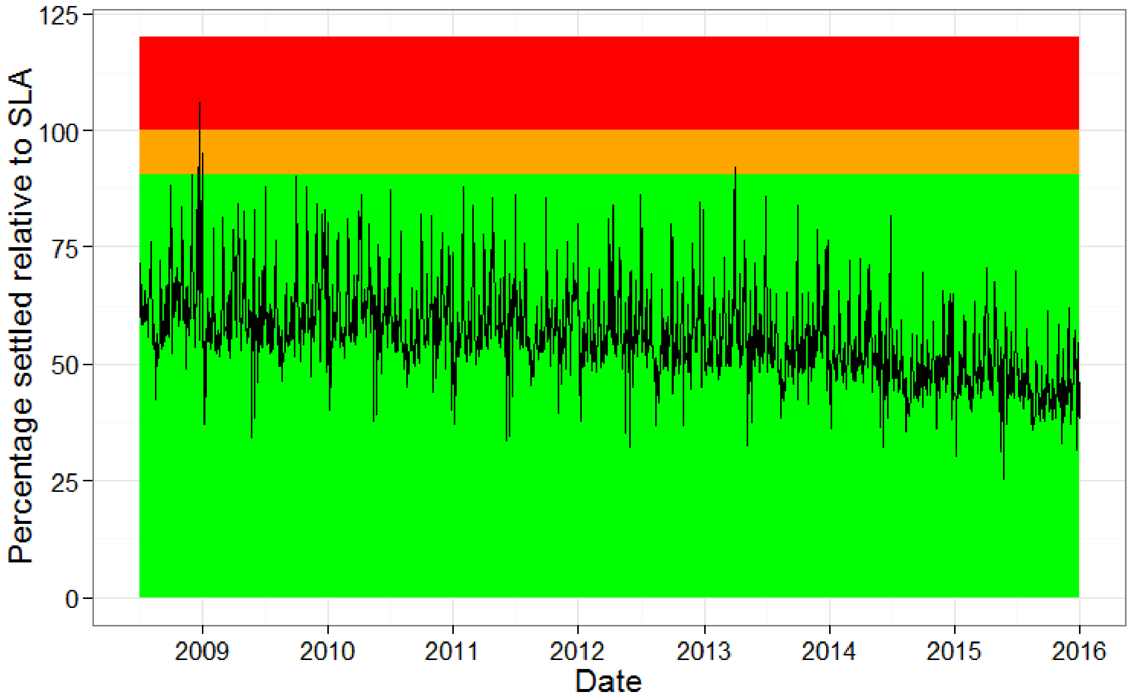
4.1.1 Relative use of the system

Just looking at the number of transactions does not provide much information on the operational performance of the system. Figure 2 presents the number of transactions per day relative to the maximum number of transactions that TARGET2 guarantees to settle according to the service level agreement.[4] In this graph all transactions have been used, including payment category 4.4, as these transactions also have to be settled.[5] This figure

[4]For illustration purposes we have set the maximum to an indicative number of transactions guaranteed to 525,000 with an increase of 3%. However, the principle of the indicator does not change if these values are set to the actual values used in a large value payment system.

[5]A correction for seasonal patterns is not necessary for this indicator as we do not look at trend changes.

Figure 2: Number of transactions per day.



allows us to see how heavily the system is used and what the trend developments are in terms of the use and adequacy of the capacity.[6]

The question is, when should this indicator trigger an alarm? A red light should be given when the daily number of transactions in a calendar month (X) exceeds the maximum level (X_{max}) agreed in the service level agreement (SLA):

$$\frac{X_{max}}{X} >= 1 \quad for \quad X > 0 \tag{1}$$

And a yellow light should be given in case the daily number of transactions in a calendar month exceeds a level lower than this maximum ($X_{max-\delta}$):

$$X_{max-\delta} >= 1 \tag{2}$$

We choose for δ one standard deviation of the fluctuation of the daily number of transactions. However, this value can be any preferred value depending on the calibration for this

[6]This can be done in the same way for e.g. hourly basis.

specific alarm.

Table 3 shows the "traffic light" information provided to the overseer for three selected months in our data sample. Besides the information on the last months, the traffic lights of the months (e.g. 6 to 12 months) prior to the last months could be given or the number of red, yellow and green traffic lights.

Table 3: Operational capacity risk indicator.

	June 2008	March 2013	October 2015
Above max	1	0	0
Above max-δ	2	1	0
Traffic light	Red	Yellow	Green

In case the system is too heavily used, it may lead to delays in payments. Too heavily means in this case that the system has to settle more obligations than it is technically able to, not contractually. The ECB publishes the transit times of payments sent in by its participants.[7]

4.1.2 Throughput risk indicator

The previous indicator looked at the number of transactions settled in a day (or intraday). The throughput guidelines look at the cumulative value settled over the day. These guidelines are intraday deadlines by which individual banks are required to send a predefined proportion of the average value of their daily payments. CHAPS, the British large value payment system, enforces these guidelines, see Ball et al. (2011). Enforcement of the throughput guidelines relies on peer pressure rather that financial or regulatory enforcement (see Becher and Tudela, 2008).[8]

In contrast to the indicator showing the number of transactions settled relative to the TARGET2 service level agreement, the throughput guidelines do not have such a strict reference. However, the throughput guidelines can be calculated easily and are very straightforward.

[7] https://www.ecb.europa.eu/paym/t2/professional/indicators/html/index.en.html

[8] see e.g. $http://www.bankofengland.co.uk/publications/Documents/quarterlybulletin/2014/qb14q207.pdf$

The throughput guidelines set up by CHAPS for each participants are as follows:

$$\text{Transferred value before 12.00} <= 50\% \tag{3}$$

$$\text{Transferred value before 14.30} <= 75\% \tag{4}$$

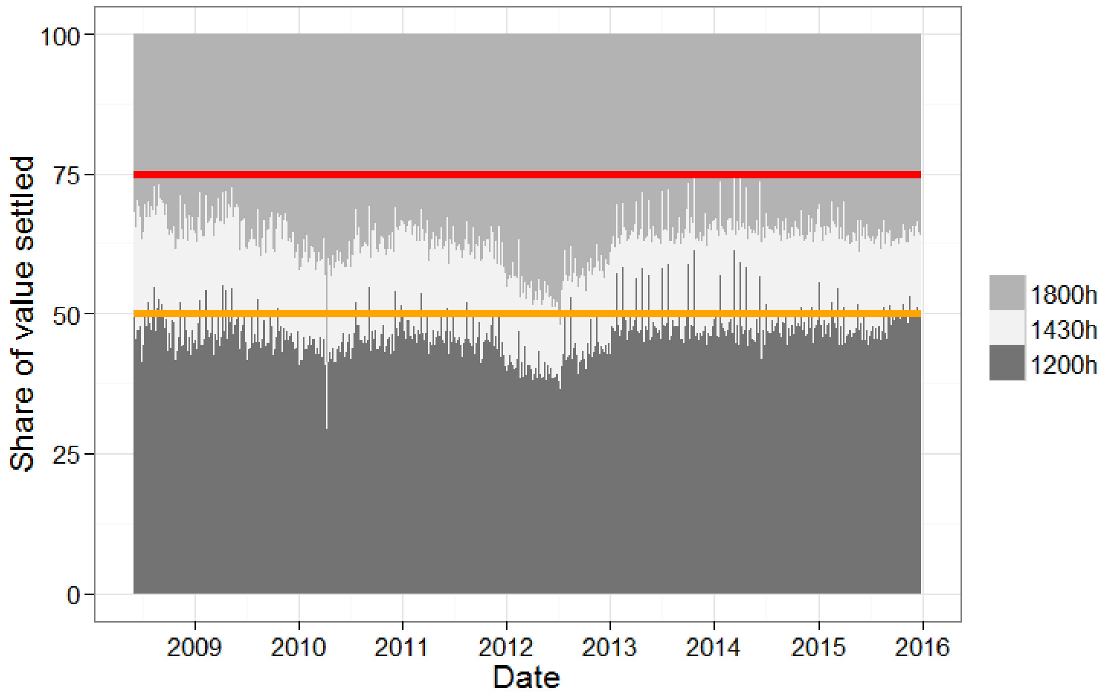
We use these individual bank throughput guidelines to define a system-wide guideline for potential liquidity stress. This means we look at all the liquidity settled by all banks before 12.00 and 14.30. The later banks settle their obligations (intentionally) within the settlement day, the more vulnerable the system is to operational problems. There is less time to solve a problem if it occurs close to the end of the settlement day. Besides this, a grid lock becomes more likely when banks delay payments. Again, the number of times the system is above the throughput threshold will be counted.

Figure 3a shows the throughput guidelines of TARGET2 as defined by Ball et al. (2011). The yellow and red lines show the 50% and 75% Benchmark of the value settled, before 12.00 and 14.30 respectively. In case the dark gray area is above the yellow line, TARGET2 does not obey the first guideline (50% settled before 12.00) and similar if the white area is above the red line it does not obey the second guideline (75% settled before 14.30). In TARGET2 the first guideline has not been met several times since the start of TARGET2. The second guideline, however, has only been violated twice. In order to prevent continuous alarms, we suggest that the guideline has to be violated three or more times in the same months to trigger an alarm. We observe a decrease in the timing of the payments from the end of 2011 to the beginning of 2012. This may be due to the introduction of the 3-years long term refinancing operation (3Y-LTRO) of the Eurosystem. Banks in the Eurosystem have heavily used these 3Y-LTROs leading to excess liquidity. Bech et al. (2012) explain the link between monetary policy implementation and settlement liquidity. They find that the large amounts of Federal reserves led to a decrease in the timing of payments.

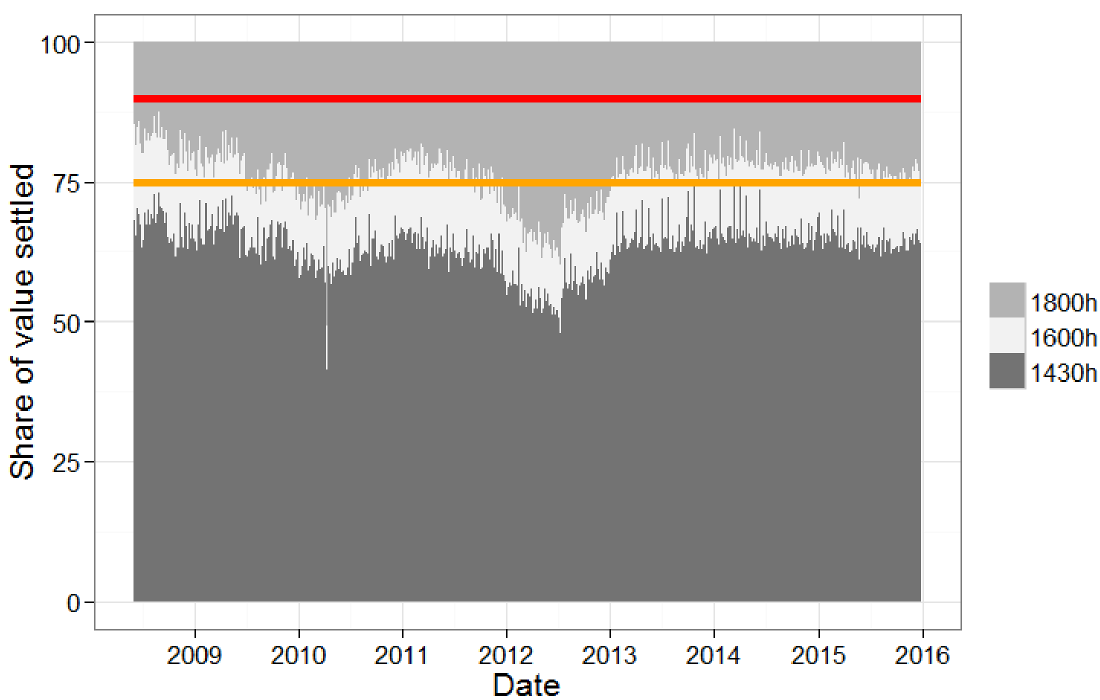
Figure 3b shows an alternative way of defining the throughput guidelines. This figures uses throughput guidelines of 14.30 (yellow light, 75%) and 16.00 (red light, 90%). A problem later on the day has less time to be solved to the closing time of the payment system.

Figure 3: Throughput guidelines.

(a) Throughput of value before 12.00 and 14.30 with the 50% 75% throughput guidelines.



(b) Throughput of value before 14.30 and 16.00 with the 75% 90% throughput guidelines.



Besides looking at the throughput guidelines of all transactions of TARGET2, it is also possible to concentrate on transactions only related to e.g. payments between banks (category 1.1 and 1.2 of Table 2). Participants do not always have control over the timing of payments, e.g. CLS payments are made at specific times. It is also possible to focus on the flows of the critical participants only, as defined by section 2.4.

4.2 Herfindahl-Hirschman Index

The Herfindahl-Hirschman Index (HHI) is in general terms a measure of the size of firms (in our case banks) in relation to the industry and an indicator of the amount of competition among them. The HHI is calculated by the following formula:

$$HHI = \sum_{i=1}^{N} {M_i}^2 \tag{5}$$

where M_i is the market share of participant i relative to the market total and N the number of participants in the system.

The normalized HHI can be calculated by:

$$HHI_{norm} = \frac{HHI - 1/N}{1 - 1/N} \tag{6}$$

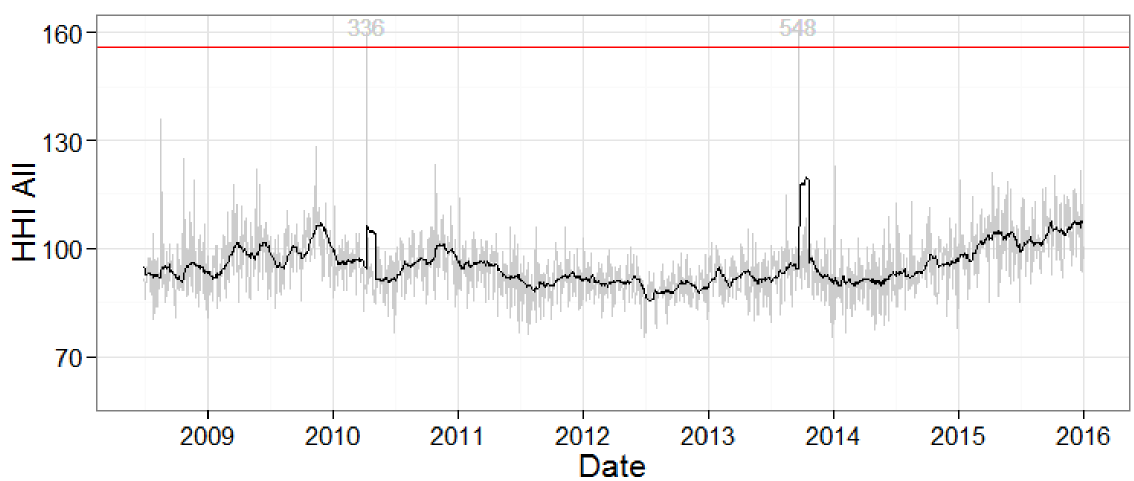
The $\mathrm{HHI}_{\mathrm{norm}}$ gives insight into the distribution of the relative turnover of participants. It varies between zero (all participants have the same share in turnover) and one (only participant has transactions). In the HHI the distribution remains visible in just one number. However, the largest participants contribute the most to the HHI. In a measure like the average turnover the distribution is lost unless the standard deviation or the quantiles are indicated.

4.2.1 HHI turnover

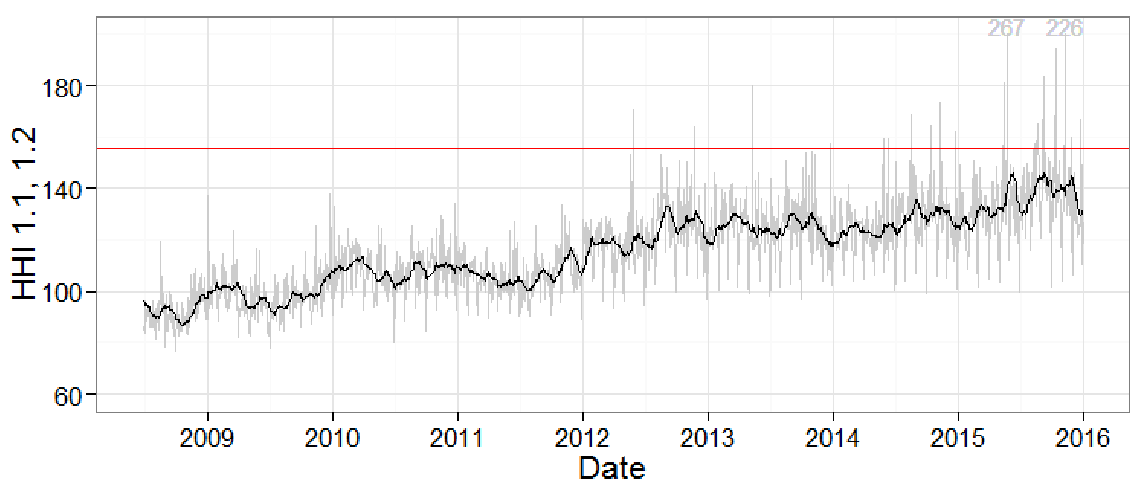
Figure 4a shows the normalized index for all participants in TARGET2. The M_i of equation 5 is in this case the value of all outgoing payments of participant i divided by the total turnover of TARGET2. The HHI is indexed with a value of 100 for the first observation to make the figure easier to read. Figure 4b provides the same normalized index but than for transaction type 1.1 and 1.2 only. This provides a better understanding of the value of the payment flows between commercial banks and how they are distributed. These payment types only include commercial banks on both the sending and receiving side. An advantage of considering only these transaction types is that the participants (banks) are similar in nature. This makes interpretation of an indicator easier. A banking view would be relevant from e.g. a financial stability point of view.

Figure 4: Herfindahl-Hirschman Index of the outgoing turnover. The initial value has been set to 100. The thick black line shows the 20-day moving average.

(a) All transactions.



(b) 1.1 and 1.2 transactions.



Both graphs clearly show a volatile pattern (light gray line), with occasional very large spikes. Therefore, we smooth (20 day moving average) the HHI time series to get a better understanding of the underlying trend (thick black line). When one or more of the largest market participants have a significant increase of their outgoing payment flows, this will lead to an increase of the HHI. On the other hand, when the market participants become more homogeneous this will lead to a decrease of the HHI. The size of a participant (often a bank) and its corresponding turnover does not usually change overnight but over the course of months or even years. However, a sudden increase could be the result of mergers of banks. Also, the introduction of a new ancillary system could cause serious changes in the turnover. Even though such an increase is sudden, they are known in the market and could easily be linked to such an event.

To convert the time series into an indicator we compare the forecasted with the actual HHI of the current month. We count the number of times the actual HHI lies above the 99% and 95% interval of the forecasted value for a red and yellow light, respectively (see section 3.3 for the forecasting procedure. We are only interested in the cases that the actual HHI lies outside the 99% and 95% interval at the top and not at the bottom side as we perceive an increase of the HHI as higher (concentration) risk.

Due to the random and large fluctuation of the data we observe that the actual value lies outside the 99% and 95% confidence interval on a regular basis. Therefore, we set the number of times in a month the actual value has to lie above the forecasted (99%) value to 3 for a red light (equation 7a) and above the forecasted (95%) value to 3 for a yellow light (equation 8a). Also, a red light will be created if the smoothed HHI index lies above 156 (Equation 7b) at least once during the month, see Appendix B for an explanation of this number. This threshold is required because the system could increase slowly over time without giving any yellow or red lights.

A red light is given if one of the following two equations is met:

$$HHI_{t_0}(fc99) \geq 3 \tag{7a}$$

$$(\text{HHI MA})_{(t_0)}(max) > 156 \tag{7b}$$

And a yellow light when:

$$HHI_{t_0}(fc95) \geq 3 \tag{8a}$$

where $HHI_{t_0}(fc99)$ and $HHI_{t_0}(fc95)$ are the number of days in month t_0 that the actual value lies above the forecasted 99% and 95% confidence interval, respectively, and $(\text{HHI MA})_{(t_0)}(max)$ the maximum value of the 20 day moving average of the HHI in month t_0

4.2.2 HHI degree

The HHI of section 4.2.1 showed a measure of the size of each participant or bank in terms of their turnover. This does not indicate much about how connected each bank is in the network. To get a better understanding of the distribution of the links in the network we zoom in to the local structure of the network. We first look at degree, which is a simple network measure that gives information on the direct surrounding of each node (participant). Degree is the number of links of each node per day. The total number of in- and out-going links is calculated for each node per day. We weight this link by its value as we deem a link with a high value to be more important than a link with a small value. The degree is calculated by the following formula:

$$k_i = \sum_{j=1}^{N} A_{ij} \tag{9}$$

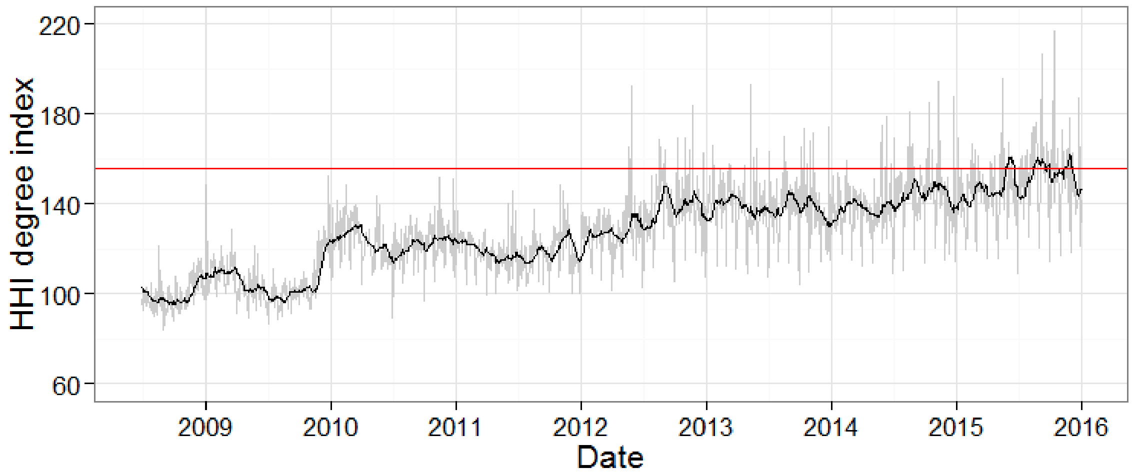
where A_{ij} is adjacency matrix and N the number of participants.

Figure 5 shows the normalized HHI for degree for categories 1.1 and 1.2 (with the first value set to 100) for the whole data set (5a) and a subset (5b). The M_i of equation 5 corresponds in this case with the value weighted degree of participant i divided by the total degree of the system. Similar to the HHI for outgoing payment values the bank which has the highest value weighted degree contributes the most to the HHI.

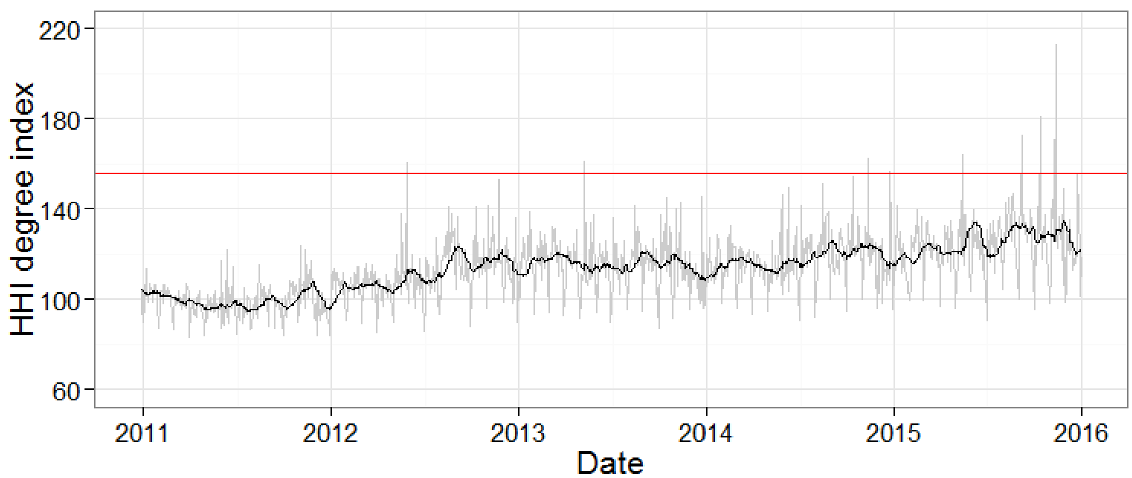
The signaling method is equal to the HHI based on value. Figure 5a shows that the threshold of equation 7b would have triggered a red light. Also in the months that follow, this threshold is reached several times. In case the overseer/operator or financial stability expert is aware of the underlying changes that causes the indicator to reach this threshold, it can choose to ‘reset’ the index and shorten the period to look at as is depicted by Figure 5b. Similarly, the expert in charge could decide to increase the threshold to e.g. 200.

Figure 5: Herfindahl-Hirschman Index for degree: 1.1 and 1.2 transactions.

(a) Degree June 2008 to 2015



(b) Degree 2011 to 2015



4.2.3 HHI centrality measures

The degree provides information on the direct surrounding of each participant. Eigenvector centrality is a more advanced network property and captures the importance of connected nodes in the network. Besides looking at the (value weighted) amount of links of each participant, the eigenvector centrality also captures how important each connected node is. This means that a node can have links to many other nodes (high degree), but in order to also have a high eigenvector centrality, the connected nodes must also have many connections to other nodes.

The eigenvector centrality of node v_i can be written as a function of the eigenvector centrality of its neighbors ($c_e(v_j)$) in the following way, see **?**.

$$c_e(v_i) = \frac{1}{\lambda}\sum_{j=1}^{n} A_{j,i} c_e(v_j) \tag{10}$$

where $A_{j,i}$ denotes the transpose of adjacency matrix A and λ corresponds to an eigenvalue of $A_{j,i}$.

Hub and authority centrality show whether the in- and outgoing links of nodes are going to or coming from important nodes, respectively. Every node in the network has both a hub score and an authority score. A node with a high hub score point to nodes with a high authority score and vice versa. The authority score is calculated as the sum of the hub scores of all nodes that point towards node i and the hub score is calculated as the sum of the authority scores of all nodes that are being pointed to by node i, as shown in the following formula (see Leskovec et al. (2014)):

$$h_i = \sum_{i \to j} a_j = \sum_j A_{ij} * a_j = A * a \tag{11}$$

$$a_i = \sum_{j \to i} h_j = \sum_j A_{ji} * h_j = A^T h \tag{12}$$

where a and h denote the vector of the authority and hub scores of all nodes, A_{ij} denotes the adjacency matrix and A_{ji} the transpose of the adjacency matrix. Equations (11) and (12) show that nodes with high hub scores (h_i) are nodes that point to nodes with high authority scores (a_i) and vice versa.

Figure 6 shows the graphs for the eigenvector centrality (6a), hub centrality (6b) and authority centrality (6c). The M_i of equation 5 corresponds with the value weighted eigenvector, hub or authority centrality of participant i divided by the total degree of the system. The higher relative volatility of the hub centrality may be caused by the lower absolute value of this centrality relative to the eigenvector and authority centrality.

4.3 FMI interdependencies

TARGET2 settles many transactions going from and to other FMIs (also called ancillary systems in the context of TARGET2). These transactions are classified as 'transactions with ancillary systems', category 3.1 to 3.5 of Table 2. Therefore, there is a liquidity interdependency between TARGET2 and these Ancillary systems (ASs). In case an AS does not receive the liquidity it cannot process its payments.[9] At the same time, if liquidity stays on the account of an AS the participants (mainly banks) do not receive their liquidity, which may lead to (temporary) liquidity shortage for these participants.

Figure 7 shows the turnover to and from all ASs in TARGET2 (dark gray area) and other transactions in TARGET2 (light gray area). The black line (right hand scale) shows the percentage of payments in value related to payment categories 3.1 to 3.5 and represented by the following equation:

$$\text{(AS share MA (\%))} = \frac{\text{AS turnover}}{\text{total TARGET2 turnover}} * 100 \tag{13}$$

Just by looking at the figure we learn that the TARGET2 total turnover (sum of both the dark and light gray area) shows quite some variation over time. Also the turnover to ASs (dark gray area) also shows some jumps and spikes. It is clear from equation 13 that the variation in this ratio can be caused by two aspects: 1) a change in the TARGET2 turnover(denominator) and 2) AS related turnover (numerator). Therefore, the indicator reflecting the interdependency between TARGET2 and ASs includes both the absolute development and the relative development. Similar to the HHI index for value related indicators we use the forecasting values and count the number of times the actual value is outside the 99% or 95% interval. However, for this indicator we look at both the top and bottom side. An increase of the relative and absolute share leads to a stronger liquidity dependency between TARGET2 and the ASs. On the other hand, a decrease could be a sign of less liquidity settled in central bank money, which is not preferred from a financial stability point of view. PFMI 9 (money settlements) encourages the usage of central bank

[9] The reason why the AS would not receive liquidity could either be due to 1) an outage of TARGET2 or 2) one or more participants have insufficient liquidity available on their TARGET2 account to make the payment to the AS.

money as it carries a lower settlement bank risk. We suggest the following for a 'red light'

$$AS_{t_0}(fc99) \geq 3 \tag{14a}$$

$$(\text{AS share})_{t_0}(fc99) \geq 3 \tag{14b}$$

$$(\text{AS share MA})_{t_0}(max) > 50\% \tag{14c}$$

We define a 'yellow light' by

$$AS_{t_0}(fc95) \geq 3 \tag{15a}$$

$$(\text{AS share})_{t_0}(fc95) \geq 3 \tag{15b}$$

where $AS_{t_0}(fc99)$, and $AS_{t_0}(fc95)$ are the number of days in month t_0 that the actual value of the ancillary system turnover lies above the forecasted 99% and 95% confidence interval, respectively. $(\text{AS share})_{t_0}(fc99)$ and $(\text{AS share})_{t_0}(fc95)$ are the number of days in month t_0 that the actual share of the value of the ancillary system turnover relative to the total TARGET2 turnover lies above the forecasted 99% and 95% confidence interval, respectively. $(\text{AS share MA})_{t_0}(max)$ the maximum value of the 20 day moving average of of this relative turnover in month t_0.

A red light will be given if Equation 14a and Equation 14b show that the Observation is at least three times a month higher than the Benchmark (99% interval). Equation 14c is an absolute threshold for the AS share. In case this threshold has been met, a red light will also be given. The reason for introducing this threshold is the same as for the HHI index indicators. In theory all transactions in TARGET2 could be related to AS but not picked up as a signal. The value of this threshold has been set to 50% as this value has only been reached once in 2009 and has substantially decreased since then.

Figure 7 gives an overview of liquidity flows between TARGET2 and all other ASs. It is also possible to create the same indicator for each (independent) ancillary system. E.g. the flows between TARGET2 and CLS (category 3.5 of Table 2) or trade by trade settlement of SSS (3.1). However, due to the sensitivity of the data we are not allowed to present graphical representations of such an indicator.

4.4 Bilateral net flows

Besides the dependency between TARGET2 and ancillary systems, banks also depend heavily on each other's liquidity. We measure this by looking at the remaining net bilateral flows of payments between banks in the system. To illustrate the cyclical flow Figure 8 shows two schematic examples of how net bilateral flows appear for three banks. In Figure 8 in the top matrix each bank pays the other bank the same amount as it receives from that bank. In such a case the net bilateral flow is 0. In Figure 8 in the bottom matrix the bilateral positions between two banks are not equal to zero. In this schematic example there is a net flow from bank B to A of EUR 90, from B to C of EUR 50 and from C to A of EUR 120. The total net flow in this example would be EUR 260.

The larger the positive value of the net bilateral flows the more difficult is for the banking community to absorb technical problems of a single bank. In case of high net bilateral flows from the problem bank to some of the receiving banks, these receiving banks should get much more liquidity than they have to pay this problem bank. In other words, the receiving banks miss a part of their incoming liquidity which they need to make their own payments to other banks. The closer the net bilateral flows are to zero, the better a technical problem (or a failure) of a bank can be solved by the receiving banks by a stop sending rule. A stop sending rule means that all banks stop sending payments to the failing participant until the problems have been solved.

The net bilateral flows can also be calculated at individual bank level. A large net bilateral flow means that on average it receives liquidity from some banks and pay to others. A stop sending rule to the problem bank might therefore not work effectively. In case a single bank has large net bilateral flows, it might want to keep more collateral for (intraday) credit from the central bank, as a precautionary measure.

Figure 9 shows the net bilateral flows (NBF) of all transactions per day (9a) and the 1.1 and 1.2 transactions (9b). A cyclical flow of 1% for all transactions corresponds to a value of approximately EUR 19 billion, which is a large amount participants cannot necessarily absorb (on average 1,900 billion per day for 2014, see Table 1 . In other words, if the cyclical flows are high the liquidity dependence between participants also high. The steep increase of the NBF observed in Figure 9a is partly caused by the extensive use of the Eurosystem's overnight deposits. This is in itself not risky as banks choose to transfer liquidity at the end of the day to the deposit facility and in the morning this is returned. Therefore, banks do not run the risk of having insufficient liquidity available to make payments.

A red light is given if one of the following two equations is met:

$$NBF_{t_0}(fc99) \geq 3 \tag{16a}$$

$$(\text{NBF MA})_{t_0}(max) > 5\% \tag{16b}$$

And a yellow light is given if the following equations is met:

$$NBF_{t_0}(fc95) \geq 3 \tag{17a}$$

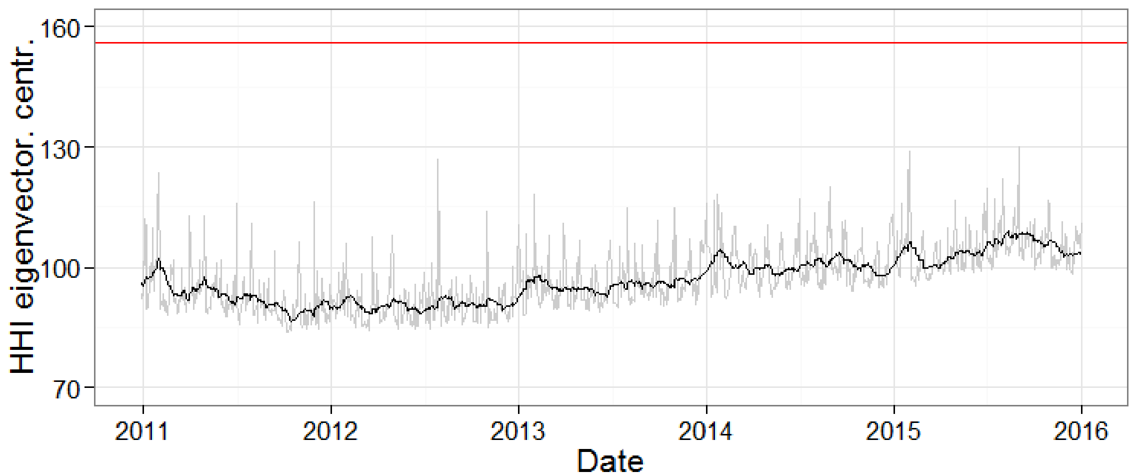
where $NBF_{t_0}(fc99)$, and $NBF_{t_0}(fc95)$ are the number of days in month t_0 that the actual value of the cyclical flows lies above the forecasted 99% and 95% confidence interval, respectively. $(\text{NBF MA})_{t_0}(max)$ the maximum value of the 20 day moving average of of the cyclical flows in month t_0. The threshold has been set to 5%, which corresponds to a value of almost EUR 100 billion when all transactions have been included. Banks cannot absorb such an amount as a loss (easily).

4.5 Fine tuning of signaling needed in practice

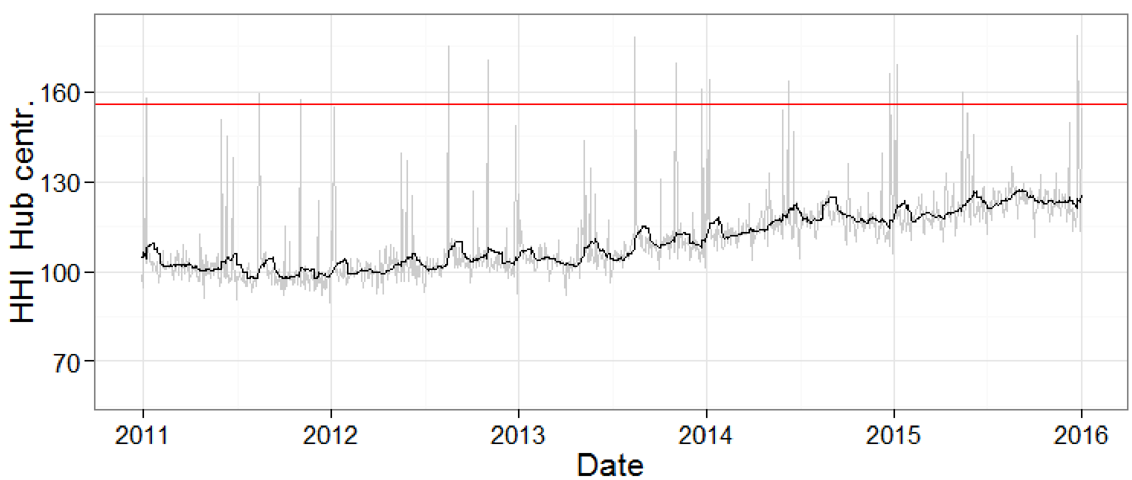
The traffic light approach applied in this section is a relatively rigid way of forcing a yellow or red alarm. We prefer rapid prototyping to looking for absolute academic certainty. First, because indicators become sooner available to the experts. Second, the usability and correctness can be discussed with these experts. Furthermore, in case of the signaling threshold of the indicators based on FMI transaction data it is highly questionable whether an analytical threshold can be defined. Moreover, it is not known what the best value would be for the network properties of an FMI. We are mainly interested in the changes over time. Feedback from the users (operator, overseers, regulators and financial stability experts) is required to fine tune the thresholds.

Figure 6: HHI centrality measures (1.1 and 1.2 transactions). Thick black line shows the 20-day moving average.

(a) Eigenvector centrality.



(b) Hub centrality.



(c) Authority centrality.

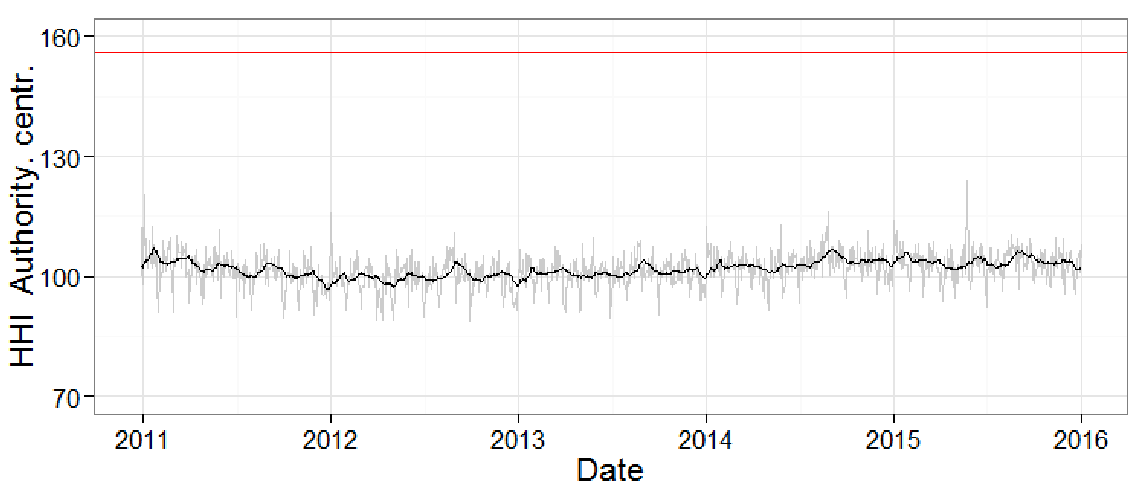


Figure 7: Share of AS turnover in TARGET2.

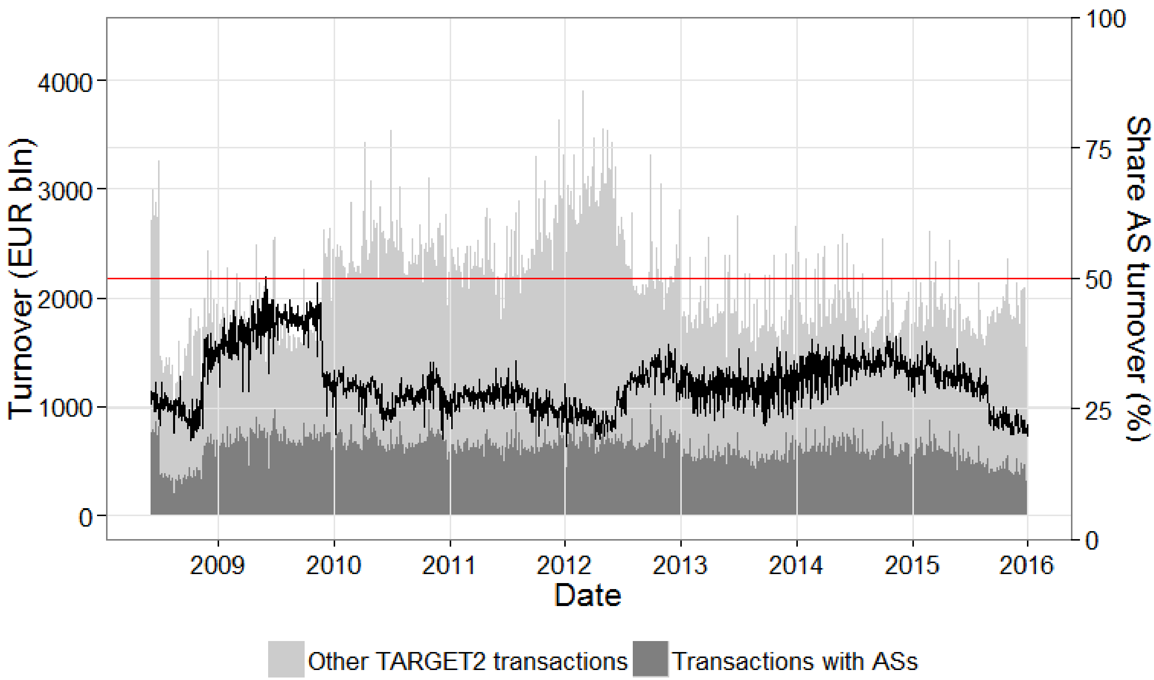


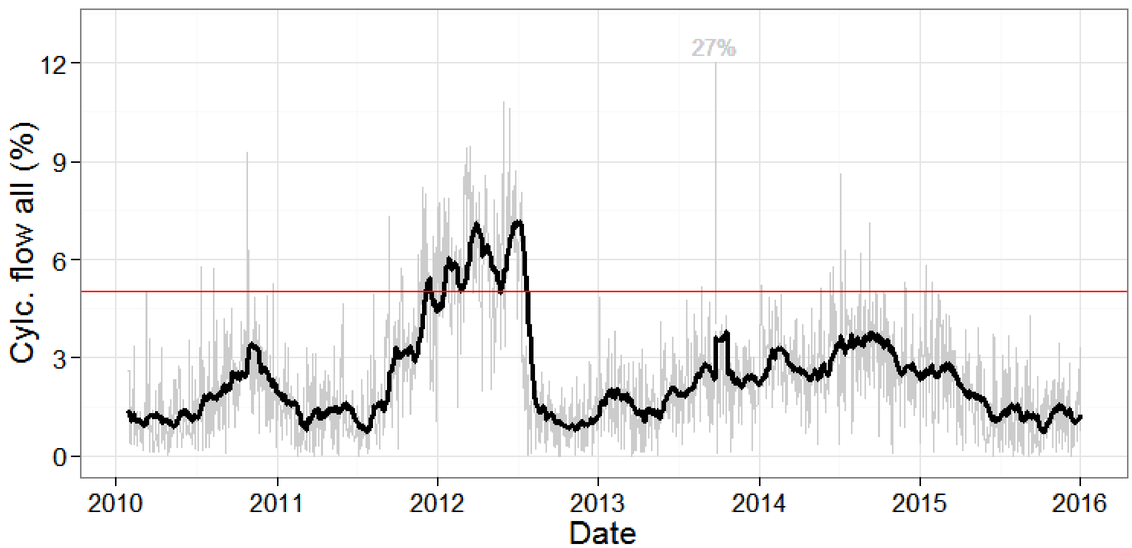
Figure 8: Bilateral net flows matrices with a net zero flow (top matrix) and a positive net flow (bottom matrix).

$$
M_0 = \begin{array}{c} \\ a \\ b \\ c \end{array} \begin{array}{c} \begin{array}{ccc} a & b & c \end{array} \\ \begin{bmatrix} 0 & 10 & 50 \\ 10 & 0 & 80 \\ 50 & 80 & 0 \end{bmatrix} \end{array}
$$

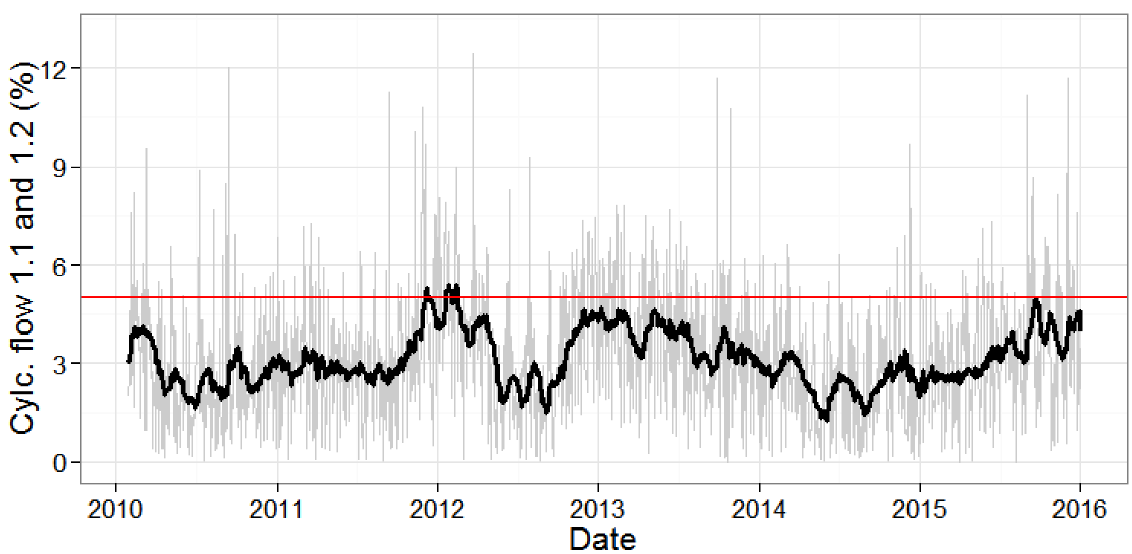
$$
M_+ = \begin{array}{c} \\ a \\ b \\ c \end{array} \begin{array}{c} \begin{array}{ccc} a & b & c \end{array} \\ \begin{bmatrix} 0 & 10 & 50 \\ 100 & 0 & 200 \\ 150 & 80 & 0 \end{bmatrix} \end{array}
$$

Figure 9: Cyclical flows of all transactions in TARGET2. Thick black line shows 20 days moving average and the thin gray the daily data.

(a) All transactions.



(b) 1.1 and 1.2 transactions.



5 How to use the indicators?

5.1 Economic interpretation

The question is how the indicators presented in section 4 have to be interpreted by operators, overseers and financial stability experts. The operational indicators in section 4.1 will mainly be useful for operators and overseers of payments systems. Operators gain a good understanding of whether the system's capacity is still adequate. If overseers observe that the guaranteed capacity is inadequate they can demand an increase of the capacity. When there is an increasing trend visible, the overseer can already demand an upgrade of the capacity before the maximum has been reached.

The HHIs described in section 4.2 give information on the concentration of participants. Operators and overseers are usually more interested in the system-wide view of the FMI. Therefore, they will in general be more interested in indicators containing all transactions. In case concentration increases it is important to know why. If this is caused by commercial banks showing a (much) higher concentration it may want to set extra requirements to these banks in line with the critical participant approach already in place. Just preventing a technical failure of such a participant leads to large liquidity problems in the FMI. For financial stability experts, the banking view (including only transaction 1.1 and 1.2) will usually be most relevant. In case the HHI increases suddenly or shows an increasing trend, the impact of a large participant failing to meet its obligation will most likely have a larger impact on the market.

An increasing trend or an upward shock in the indicators providing information on the flow from TARGET2 and other FMIs shows an increasing dependence of these FMIs with respect to TARGET2 liquidity, which is of interest to operators and overseers. Also a decreasing trend or downward shock may be a sign of decreasing use of central bank money by FMIs. Central banks encourage the use of central bank money by banks and ancillary systems as this is safer. For the cyclical flows, a similar reasoning can be held as for the HHI. The larger the cyclical flows, the larger the impact is of a (large) participant failing to meet its payment obligations.

5.2 Dashboard

To give the expert in charge a good overview of our indicators (combined with other indicators) we provide a proposed dashboard with the traffic light of the indicators. Figure 10 depicts this dashboard of the indicators of section 4 for the year 2015. For each month and each indicator in the year 2015 a green, yellow or red traffic light is presented. The expert in charge gains a very quick overview of the 'traffic lights' of each indicator and how it has developed over time. Only the yellow and red lights have to be investigated.

Figure 10: Traffic light dashboard for the indicators for the year 2015.

Indicator	01	02	03	04	05	06	07	08	09	10	11	12
Capacity (daily)	G	G	G	G	G	G	G	G	G	G	G	G
Capacity (hourly)	G	G	G	G	G	G	G	G	G	G	G	G
Throughput	Y	Y	Y	Y	G	Y	Y	G	Y	Y	Y	Y
HHI turnover	G	G	G	Y	G	G	G	G	Y	G	G	G
HHI 1.1, 1.2	G	G	G	G	Y	G	G	Y	G	G	G	G
HHI Degree all	G	G	G	G	G	G	G	G	G	G	G	G
HHI Deg 1.1, 1.2	G	G	G	G	Y	G	G	Y	G	G	Y	G
HHI eigenvector all	G	G	G	G	G	G	G	G	G	G	G	G
HHI eigenv 1.1, 1.2	R	G	G	G	G	Y	G	G	G	G	G	G
HHI Hub all	G	G	G	G	G	G	G	G	G	G	G	R
HHI Hub 1.1, 1.2	G	G	G	G	G	G	G	G	G	G	G	R
HHI Auth all	G	Y	G	G	G	G	G	G	G	G	G	G
HHI Auth 1.1, 1.2	G	Y	G	G	G	G	G	G	G	G	G	G
HHI AS share	G	G	G	G	G	G	G	G	Y	G	G	G
Cyc. Fl. all	G	G	G	G	G	G	G	G	G	G	G	G
Cyc. Fl. 1.1, 1.2	G	G	G	G	G	G	G	G	Y	G	G	G

As each expert type is interested in different indicators, it is possible to create a dashboard for each type. This way the expert in charge sees only the indicators that are of interest to his/her expertise.

6 Conclusions

This paper investigates how granular financial market infrastructure (FMI) data can be used to identify risks in this FMI. We have looked at indicators providing information on 1) operational risk (number of transactions settled and the throughput of the value over the day), 2) changes in the network structure (degree and centrality measures) and 3) liquidity dependency (liquidity flows between TARGET2 and ancillary systems, and between commercial banks. These indicators can be seen as a contribution to existing indicators provided in the literature. Besides, it is possible to look at many other aspects of risks, which may be supported by transaction data of an FMI.

We describe how to convert the massive amount of transactions processed in our TARGET2 case into risk indicators. These indicators follow two general requirements: 1) they should be easy to explain to an end-user and 2) should be meaningful. As these two requirements often contradict we opt for a traffic light approach. This means that the signaling for changes has to be brought back to a simple choice: low (green light), moderate (yellow light) or substantial (red light) changes with respect to the Benchmark. The operational indicators are based on legislation and guidelines. This means that it is clear when an indicator should provide an alarm (yellow or red light). In case of the other indicators we base the signaling of our indicators on their own history. We use the forecasting method of Timmermans and Heijmans (2017) to set the alarms, after correcting the indicator time series for cyclical patterns. If the real value of the indicator in a given month lies outside the forecasted value (99% or 95% interval), a red or yellow light should be given. Depending on the indicator this is either outside the interval on the top side or both sides. Indicators providing information on network properties usually are considered riskier when they increase. However, the liquidity flow from TARGET2 to ancillary systems should provide an alarm for both a moderate, or substantial increase or decrease. An increase means a stronger dependence of liquidity by ancillary systems, which may potentially be riskier. A decrease could be a sign of decreased use of central bank money. PFMI 9 encourages banks to make use of central bank money.

The indicators can be used by overseers, who have to check whether the respective FMI follows the Principles for financial market infrastructures, operators of FMIs who want to monitor potential risky developments in their FMI and also by financial stability experts who are interested in e.g. changes in concentration of the banking network or increasing dependencies between participants in an FMI. This means that depending on the focus and interest of an expert, you have to look at different layers (payment categories) in the network. To fine tune the thresholds for signaling, the experts have to be involved as they have to clarify when they would like to receive alarms.

A Seasonal correction and forecasting

The basis of the model of Timmermans and Heijmans (2017) is a simple ARIMA model:

$$d_t = \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{18}$$

where Y_t corresponds to the data (risk indicators), p denotes the number of lagged values and q the number of past error terms that are taken into account. The optimal number of included lags of the Auto Regressive parts p and Moving Average parts q is found based on the minimization of the Akaike Information Criterion (AIC). The AIC optimizes the $\mathrm{Log-Likelihood}$ while penalizing for adding more explanatory variables. Hence, a parsimonious model with high $\mathrm{Log-Likelihood}$ is selected. The standard ARIMA model is extended by including dummy variables that capture the effect of seasonality. This extended model can capture M different cycles with period lengths P_i:

$$Y_t = \mu + \sum_{i=1}^{M} \sum_{j=1}^{P_i-1} \gamma_{i,j} D_{i,j,t} + d_t \tag{19}$$

They have included dummy variables for business days of the week and business days of the month. For each different cycle (week, month) one dummy will be omitted to avoid the dummy variable trap. This way, the effect of a day in a category is measured relative to the omitted day in the category. The advantage of the ARIMA dummy model is that dummies can be constructed for different period lengths. This means that for each month a different period length can be used. Because the number of business days in a month varies across months between 19 and 23 it is an advantage that this model can capture the monthly cycles by using different lengths for each monthly cycle.

B Absolute HHI threshold critical participants

We use the ECB definition of critical participants (ECB, 2014) to determine the value for 'acceptable HHI'. First we calculate the HHI of the critical participants. As the largest participants contribute to the HHI the most, this gives us clear HHI of the market. We do this for the first quarter of 2014. We increase the outgoing value of each of these critical participants by 25%. The threshold value (the HHI value above which a red light should be given at all times) will be determined by increasing the turnover of all participants by 25% having at least 1% of the original turnover. This leads to an increase of 56% of the HHI or in other words a value of 156.

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