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Research Paper

Near-real-time monitoring in real-time gross settlement systems: a traffic light approach

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ABSTRACT

This paper develops a method to identify quantitative risks in financial market infrastructures (FMIs) that is inspired by the Principles for Financial Market Infrastructures. We convert transaction-level data into indicators that provide information on operational risk, concentration risk and liquidity dependencies. As a proof of concept we use TARGET2 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. Our method includes setting up the signaling threshold of relevant changes. For the signaling, we opt for a traffic light approach: a green light, an amber light or a red light for a small, moderate or substantial change in the indicator, respectively. The indicators developed in this paper can be used by overseers/regulators, by the operators of FMIs and by financial stability experts.

Keywords: risk indicators; central banks; granular data; TARGET2; oversight; financial stability.

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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 (PFMIs (CPSS–IOSCO 2012)). A number of the risks defined by the PFMIs are quantitative in nature.

The aim of this paper is to use FMI transaction-level data to develop risk indicators inspired by the PFMIs (CPSS–IOSCO 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. The benchmark value indicates the 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–June 2017. In addition to taking all transactions into account, we deepen our analysis by differentiating between the different payment types in TARGET2 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 PFMIs are also applicable to other FMIs. The approach to constructing our indicators (observation, benchmark) is as follows.

- First, we choose the risk indicator that is related to a certain PFMI and gather the observations.
- Second, we correct for seasonality and trends where needed (in line with Timmermans *et al* (2018)).
- Third, we determine the signaling thresholds (benchmark) at which an indicator should give an "alarm".

As we intend to propose a traffic light approach – or, as it is sometimes called in project status or risk reporting, an RAG approach (red, amber, green) – we need a two-valued benchmark to discriminate between the three possible colors. These signals help overseers, regulators, operators and financial stability experts in assessing the risk. Note that the signals (or "alarms") are primarily risk driven and not incident driven. They lend themselves more to helping operators identify issues for further investigation or helping overseers assess compliance with the PFMI, rather than for invoking crisis management. The indicators developed in this paper are therefore intended for near-real-time monitoring. The risk indicators are updated and evaluated every working day, meaning that overseers and financial stability experts have access to higher-frequency data than is the case for the existing weekly or monthly reporting. In addition, they provide the operator of the FMI with some daily data on the behavior of both the system and its participants, complementing the real-time monitoring process.

This paper adds to the strand of the literature on detecting risks and outliers in FMIs, particularly in large-value payment systems (LVPSs). Glowka *et al* (2018) and Klee (2010) develop an algorithm to detect the operational outages of individual participants in the European TARGET2 and US Fedwire systems, respectively. The algorithm uses transaction data to find periods with very few transactions or none at all. The operational problems of individual participants can cause severe liquidity problems for other participants in the system. Triepels *et al* (2018) use a neural network (autoencoder) to detect anomalous payment flows. Their method can, for example, be used to detect the beginning of bank runs in the LVPS. Li and Pérez-Saiz (2016) measure systemic risk in the network of FMIs by studying the probability that two or more FMIs have a large credit risk exposure to the same FMI participant, using extreme value methods. Heijmans and Heuver (2014) show how liquidity problems at individual bank level can be derived from LVPS data. Benos *et al* (2014) study the impact of the global financial crisis on counterparty risk in the UK real-time gross settlement (RTGS) system, CHAPS. Massarenti *et al* (2012) study the impact of disturbances to payments executed at different time points within the settlement day of the European RTGS system TARGET2. They find that the impact of a disruption is time dependent, ie, an outage late in the day can have larger consequences than one that occurs earlier on during the settlement day. Part of the literature focuses on detecting risks from LVPS data using network topology measures: see, for example, Soramäki *et al* (2007), Embree and Roberts (2009), Chapman *et al* (2010), Pröpper *et al* (2013) and León and Pérez (2014).

Our paper is also closely related to the literature on the visualization of financial data. Heijmans *et al* (2016) describe how information and risks can be identified from dynamic graphs (movies) based on payments data. Flood *et al* (2016) provide an overview of visual analytics for financial stability risk monitoring. They describe and categorize the analytical challenges faced by macroprudential supervisors. Sarlin (2016) discusses the role of risk communication in macroprudential risk. Besides data-driven research, game theory is also used to analyze LVPSs. For example, Bech and Garratt (2003, 2006) developed a game theoretical model to look at the impact of payment delay. They state that delaying payments is risky as it can cause so-called gridlock, in which every bank is waiting for others to make the first payment. This game has been executed in a laboratory by Abbink *et al* (2017) and Heemeijer and Heijmans (2015).

The rest of the paper is organized as follows. Section 2 briefly describes the FMI TARGET2 and the data we have used in our analysis. Section 3 explains how the risk indicators are developed. Section 4 discusses the risk indicators and their application to the transaction data of TARGET2. Section 5 summarizes and provides conclusions.

2 TARGET2

2.1 Overview of the system

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

In terms of the value processed, it is one of the largest payment systems in the world. It processes on average more than 350 000 transactions per day and has a turnover of €1900 billion. The average transaction value is €5.5 million. Most of the 1007 direct participants are euro area credit institutions, large banks established in the European Economic Area that are not in the euro area, and euro area central banks.[2]

2.2 Transaction data

Our data set contains all individual transactions settled in TARGET2 from June 2008 until June 2017. This corresponds to approximately 800 million transactions. TARGET2 distinguishes between several main and subcategories of payment. The payments are divided into four main categories.

(1) Main transactions, which contain the subtypes “customer” (1.1) and “interbank transactions” (1.2)).

(2) Payments with a central bank involved.

(3) Payments from and to ancillary systems (ASs).

(4) Liquidity transfers.

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

[2] There are formal access criteria that are defined in the TARGET2 guideline.

According to European Central Bank (2018b), the categories (1), (2), (3) and (4) account for, respectively, 42%, 11%, 20% and 27% of transactions by value and 77%, 7%, 13% and 3% by number, on average.

Technical transfers between the accounts of the same bank (category (4.4)) are seen not as an actual payment (or economic process) but as an administrative shift of liquidity between two accounts of the same legal entity. For this reason we exclude that transfer category (payment type (4.4)) when we look at all the transactions that should reflect an economic process. Categories (4.6) and (4.7) were introduced at the start of TARGET2 Securities (T2S) in 2015. The migration of T2S is done in migration waves. These payment categories will therefore increase over time.

The daytime opening of TARGET2 is between 07:00 and 18:00. Category (1.1) can only be processed by TARGET2 up to 17:00. Besides the daytime opening period, TARGET2 also allows some ASs to settle during the night (between 19:30 and 07:00). However, as these payments are limited in number and amount, and only reflect a small cross-section of the transaction types that are settled in TARGET2, we omit them from the scope of our analysis.

2.3 Critical participants

The Eurosystem has defined extra technical requirements for participants that are considered critical: see the "Information guide for TARGET2 users" for details (European Central Bank 2018a).[3] These extra requirements should reduce the probability of these banks being unable to pay (for some time) because of technical problems. We will use the definition of critical participants later on to set an absolute threshold for the indicators.

3 CONSTRUCTING RISK INDICATORS

3.1 The 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. The benchmark value indicates the normal value of the indicator. If the observation deviates far enough from the benchmark, we have a signal.

[3] The Eurosystem considers a credit institution (commercial bank) to be critical in TARGET2 if it consistently settles at least 1% (by value) of the TARGET2 turnover on a daily average (excluding transactions submitted by third parties, eg, ASs). As well as credit institutions, there are several ASs that are considered critical.

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

(1) the regulatory quantitative measure;

(2) the quantitative (external) guidelines;

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

The regulatory measure provides the most straightforward indicators.[4] If an FMI has to follow a certain rule that can be quantitatively tested, then it is easy to establish the benchmark. An external guideline that is not legally binding but is nonetheless common practice may also serve as an adequate benchmark. The measure is known and can be easily calculated, as for 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 both of the following general requirements:

- they have to be easy to explain to an end user;
- they have to be relevant and scientifically correct.

The reason they have to be easy to explain is that end users, eg, managers, regulators and policy advisors, are the intended recipients of this type of information. This kind of information may be part of the enterprise risk reporting used at board level within an FMI, and therefore, owing to time constraints, the information needs to be self-evident and to be clear "at-a-glance". If it is not, the risk indicators are likely to stay unused. Besides, there will be many risk indicators that have to be understood. The second requirement is rather obvious, as the indicator has to be based on a solid foundation. Therefore, we will opt for the translation of an underlying indicator into the so-called traffic light approach (green, amber, red). In the case of a green light, there does not seem to be a problem with the given indicator relative to the benchmark. An amber light shows a moderate change and a red light shows a substantial change in the indicator relative to the benchmark.

3.2 Deseasonalizing and forecasting 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 in indicators based on TARGET2 transaction data. We follow the model developed by Timmermans *et al* (2018), which to

[4] An example of a strong rule laid down in the PFMIs is the two-hour recovery time objective.

our knowledge is the first to investigate outliers in our types of risk indicators. They have tested several models on a large set of risk indicators, including those in this paper. They find that a simple autoregressive integrated moving average (ARIMA) model with dummies performs best for this type of time series.[5] The dummies they include are the day of the week, the days before the end of the month and the days at the beginning of the month. We will filter our indicator time series using that model before applying the traffic light approach to it.

After the time series of the risk indicators that are based on their own history have been corrected for seasonality, we can define the thresholds for signaling (the red and amber lights of the traffic light approach). We use the forecasting method of Timmermans *et al* (2018) to forecast the next period, which can be between one day and one month. After the forecast has been made we can compare the actual values with the forecasted values. If the actual value deviates strongly from the forecasted value, this will be considered an outlier. To be more precise, if the actual value exceeds a 95% (respectively 99%) interval of the forecasted value several times, we set the traffic light to amber (respectively red). The 95% (respectively 99%) interval corresponds to 2.0 (respectively 2.6) standard deviations in the case of a normal distribution. However, the distribution of the actual values of the indicators is not a perfect normal distribution and contains fat tails. As a consequence, we choose for the signaling the number of times the actual value of the indicator lies outside the forecasted interval more than once. For more details on this method, we refer the reader to Timmermans *et al* (2018).

4 RISK INDICATORS

In this section we construct a total of seven risk indicators based on TARGET2 transactions and their corresponding thresholds. The three risks we focus on are (1) operational risk (Section 4.1), (2) concentration risk (Section 4.2) and (3) liquidity dependency risk (Section 4.3).

For each of the three indicators we describe how they are constructed and how the threshold for signaling is applied, leading to a traffic light signal. We also look at different layers of the TARGET2 payment network:

(1) all transactions;

(2) interbank transactions (payment types (1.1) and (1.2));

(3) AS transactions (payment types (3.1)–(3.5)).

[5] Their work is closely related to the detection of cyclical patterns in Van Ark and Heijmans (2016), which also looks at intraday patterns.

We leave the network layers of "payments with the central bank" (payment category (2)) and liquidity transfers (payment category (4)) out of the scope of this paper. However, these payment categories may also include relevant information.

4.1 Operational indicators

Operational risk indicators are obviously linked to the operational risk principle (PFMI 17). The two risk indicators developed below are related to the capacity of the system.[6]

4.1.1 Relative use of the system

Indicator setup. Looking simply at the number of transactions does not provide much information on the operational performance of the system. Figure 1 shows the number of transactions per day relative to the maximum number of transactions that TARGET2 guarantees to settle according to the service level agreement (SLA).[7] In Figure 1 all transactions have been used, including technical transfers (payment type (4.4)), as these transactions also have to be settled.[8] It 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.[9]

If the system is used too heavily, it may lead to delays in payments. Too heavily means, in this case, that the system has to settle more obligations than it is obliged to settle. As a consequence, payments may not be settled in time. This does not mean that the system is unable to settle more payments in a day: it means that the system does not "have to", contractually. If the system is used too heavily, the operator could decide to upgrade the system. This indicator could also support the overseer of an FMI in assessing capacity planning.

Indicator threshold. The question is, when should this indicator trigger a signal? If the actual number of transactions exceeds the maximum number guaranteed by the operator, a critical level has been reached and a "substantial risk" signal should be given. When it reaches a "high", but lower than maximum, level, it should give a "moderate" alarm signal, as it is possible that the maximum number will slowly

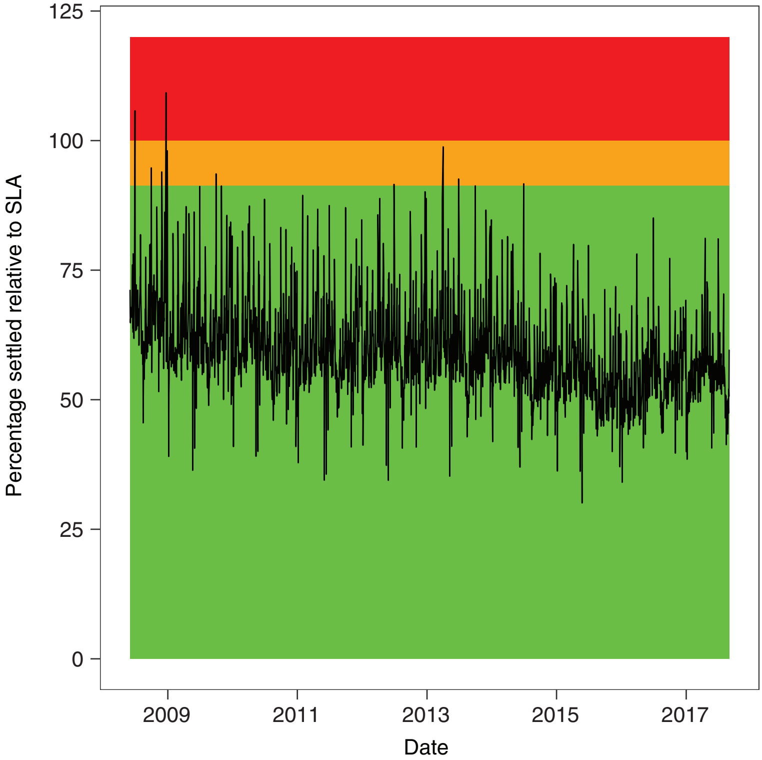
[6] The standard states: "An FMI should ensure that it has scalable capacity adequate to handle increasing stress volumes and to achieve its service-level objectives" (see CPSS–IOSCO 2012, p. 94, Key Consideration 17.4).

[7] For the purposes of the illustration we have set the maximum to an indicative 525 000 transactions with an increase of 3%. However, the principle involved does not change if these values are set to the actual values used in an LVPS.

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

[9] This can be done in the same way for higher-frequency data, eg, hourly.

FIGURE 1 Number of transactions per day relative to the maximum.



be reached. In other words, a red light should be given when the daily number of transactions (ie, the observation) in a calendar month (X) exceeds the maximum level ($X_{\max}$) agreed (ie, the benchmark) in the SLA:

$$\frac{X}{X_{\max}} \geqslant 1 \quad \text{for } X_{\max} > 0. \tag{4.1}$$

An amber light should be given when the daily number of transactions (X) in a calendar month exceeds a level lower than this maximum ($X_{\max-\sigma}$):

$$\frac{X}{X_{\max-\sigma}} \geqslant 1. \tag{4.2}$$

For σ we choose 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 specific alarm.

TABLE 1 Operational capacity risk indicator.

	June 2008	**March 2013**	**October 2015**
Number of times in a month $X \geqslant X_{\max}$	1	0	0
Number of times in a month $X \geqslant X_{\max-\sigma}$	2	1	0
Traffic light color	Red	Amber	Green

Table 1 is based on the data in Figure 1. It shows the traffic light information that is provided to the overseer for three selected months in our data sample. In addition to the information on the latest month, the traffic lights, eg, 6–12 months prior to the last month or the number of red, amber and green lights, could be reported.

4.1.2 Throughput risk indicator

Indicator setup. The previous operational risk indicator looked at the number of transactions settled in a day (or intraday). The throughput guidelines look at the cumulative value settled over the course of a day. These guidelines relate to intraday deadlines by which individual banks are required to send a predefined proportion of the average value of their daily payments. The Clearing House Automated Payment System (CHAPS), the United Kingdom's LVPS, enforces these guidelines (see Ball *et al* 2011). Enforcement of the throughput guidelines relies on peer pressure rather than financial or regulatory enforcement (Becher *et al* 2008).

In contrast to the indicator that shows the number of transactions settled relative to the TARGET2 service level agreement, the throughput guidelines do not have such a strict reference point. However, the throughput guidelines can be calculated easily and allow for a straightforward interpretation. They can therefore be used on RTGS systems other than CHAPS. The throughput guidelines (which act as the benchmark in this indicator) set up by CHAPS for each participant are as follows:

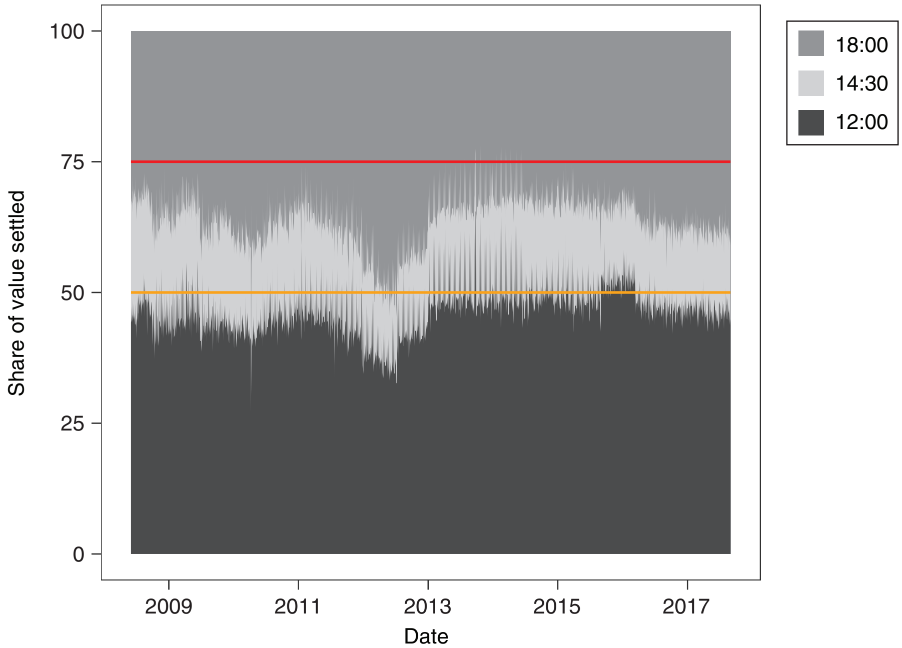
$$\text{transferred value before 12:00} \geqslant 50\%, \tag{4.3a}$$

$$\text{transferred value before 14:30} \geqslant 75\%. \tag{4.3b}$$

This means that more than half (respectively three-quarters) of the daily settlement value should be settled before noon (respectively 14:30).

Indicator threshold. We aggregate the individual bank throughput guidelines to arrive at a system-wide view for an early indication of potential delay in payments. This means that we look at all the liquidity settled by all banks before 12:00 and 14:30 (the observation in this indicator). The later in the settlement day that banks

FIGURE 2 Throughput guidelines.



(intentionally) settle their obligations, the more vulnerable the system is to operational problems. This is because there is less time to solve a problem if it occurs close to the end of the settlement day.

Figure 2 shows the throughput guidelines of TARGET2 as defined by Ball *et al* (2011). The amber and red lines show the 50% and 75% benchmark of the value settled before 12:00 and 14:30, respectively. If the dark gray area is above the amber line, TARGET2 does not obey the first guideline (50% settled before 12:00); and if the white area is above the red line, it does not obey the second guideline (75% settled before 14:30). Since TARGET2 began, the first guideline has not been met a number of times. The second guideline, however, has been violated more often. In order to prevent false positives, we suggest that the guideline has to be violated three or more times in the same month before the alarm is triggered. We observe that banks started paying earlier on average from the end of 2011 to the beginning of 2012. This may have been due to the introduction of the Eurosystem's three-year long-term refinancing operation (3Y-LTRO). Banks in the Eurosystem have heavily used these 3Y-LTROs, and this has led to excess liquidity. Bech *et al* (2012) explain the link between monetary policy implementation and settlement liquidity. They find that large amounts of federal reserves unintentionally lead to an incentive to pay earlier.

Besides looking at the throughput guidelines of all the transactions of TARGET2, it is also possible to concentrate on only those transactions that are related to, for example, interbank payments (payment types (1.1) and (1.2)). It is important to understand that participants do not always have control over the timing of payments: for example, liquidity transfers to fund payments in other payment systems, such as Continuous Linked Settlement (CLS) for foreign-exchange transactions (see Berndsen (2018) for a short description of CLS), are made at specific times of the day. It is also possible to focus on the flows of only the critical participants, as defined by Section 2.3, as the impact of these participants is large in terms of liquidity.

4.2 Concentration risk

Concentration risk indicators can shed light on potential risks stemming from changes in the market share of a few large participants. This is relevant for assessing concentrations in credit risk (PFMI 4), liquidity risk (PFMI 7) and tiering risks (PFMI 19). The latter type of risk is concerned with the concentration of large numbers of indirect participants in a single direct participant, which may not be clearly visible to the operator of the system.[10]

We use the Herfindahl–Hirschman index (HHI) to measure the level of concentration in TARGET2. In general terms, the HHI is a measure of the size of firms (in our case, banks) in relation to the industry they are in, and it is an indicator of the amount of competition among them. It is calculated according to the following formula:

$$\mathrm{HHI} = \sum_{i=1}^{N} M_i^2, \tag{4.4}$$

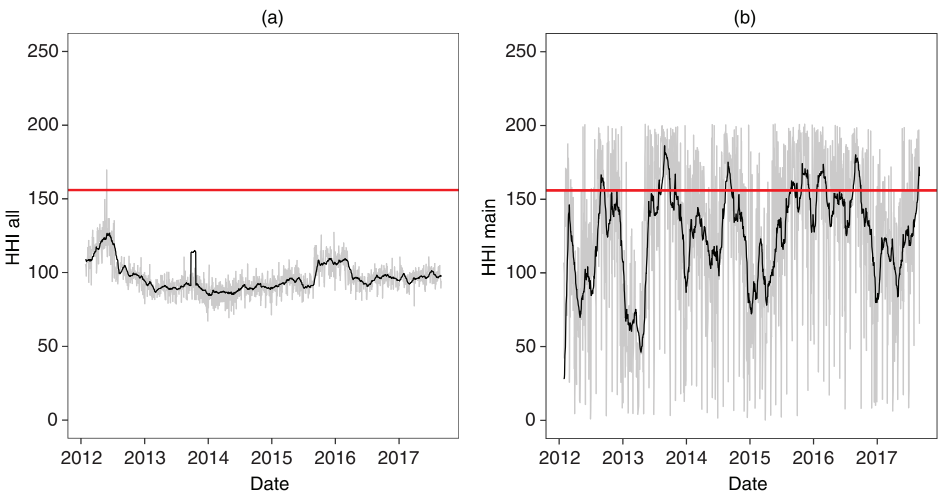
where M_i is the market share of participant i relative to the market total, and N is the number of participants in the system ($N \geqslant 1$). Whereas the HHI ranges from $1/N$ to 1, the normalized HHI ranges from 0 to 1. The normalized HHI can be calculated using

$$\mathrm{HHI}_{\mathrm{norm}} = \frac{\mathrm{HHI} - 1/N}{1 - 1/N}. \tag{4.5}$$

$\mathrm{HHI}_{\mathrm{norm}}$ gives insight into the distribution of the relative turnover of participants. It varies between 0 (all participants have the same share in turnover) and 1 (only one participant has outgoing transactions). The advantage of the HHI is that the

[10] In addition, PFMI 17 reads: "An FMI should identify, monitor, and manage the risks that key participants, other FMIs, and service and utility providers might pose to its operations. In addition, an FMI should identify, monitor, and manage the risks its operations might pose to other FMIs."

FIGURE 3 The HHI of the outgoing turnover: (a) all transactions and (b) main transactions.



The initial value has been set to 100. The thick black line shows the twenty-day moving average. The horizontal straight line represents the absolute threshold (see Section 4.2.4 and Appendix A (online)).

whole distribution is summarized by 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. In the following sections we calculate the HHI indicators for the banks' (1) outgoing daily payment value (Section 4.2.1), (2) degree (Section 4.2.2) and (3) eigenvector centrality (Section 4.2.3).

4.2.1 Concentration risk based on outgoing turnover

Indicator setup. Parts (a) and (b) of Figure 3 show the normalized index for all participants in TARGET2 and for only the main transactions, respectively. The M_i of (4.4) is in this case the value of all the 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. While Figure 3(a) provides a system-wide overview, Figure 3(b) provides a better understanding of the value of the payment flows between commercial banks and how they are distributed. An advantage of considering only the main transactions is that the participants (which are all commercial banks) are similar in nature. This makes the interpretation of an indicator more intuitive from, for example, a financial stability point of view.

Both graphs clearly show a volatile pattern (the light gray line), with occasional large spikes. Therefore, we smooth the HHI time series (by taking the twenty-day moving average) to get a better insight into the underlying trends (the thick black line). When one or more of the largest market participants has a significant increase in their outgoing payment flows, this will lead to an increase in the HHI. On the other hand, a market that becomes more homogeneous will lead to a decrease in the HHI. The size of a participant (often a bank) and its corresponding turnover do not usually change overnight but over the course of months or even years. Bank mergers could, however, result in a sudden increase. Likewise, the introduction of a new AS could cause substantial changes in turnover. But even though such an increase is sudden, they are known in the market and could easily be linked to a specific event.

Given the high volatility observed in Figure 3(b) and the lower volatility seen in Figure 3(a), we can conclude that the interbank transactions are not the ones that are dominant in the HHI based on all transactions. This can (partly) be explained by the large amounts of liquidity flowing between commercial banks and the central bank (such as stemming from main and long-term refinancing operation and deposit transactions) and, to a lesser extent, by flows between commercial banks and ASs.

4.2.2 Concentration risk based on a simple connectivity measure

The HHI of Section 4.2.1 showed a measure of the size of each participant or bank in terms of its outgoing turnover. This does not reveal much about the connectivity of each bank in the network. To get a better understanding of the distribution of the links in the network, we zoom in on the local structure of the network.

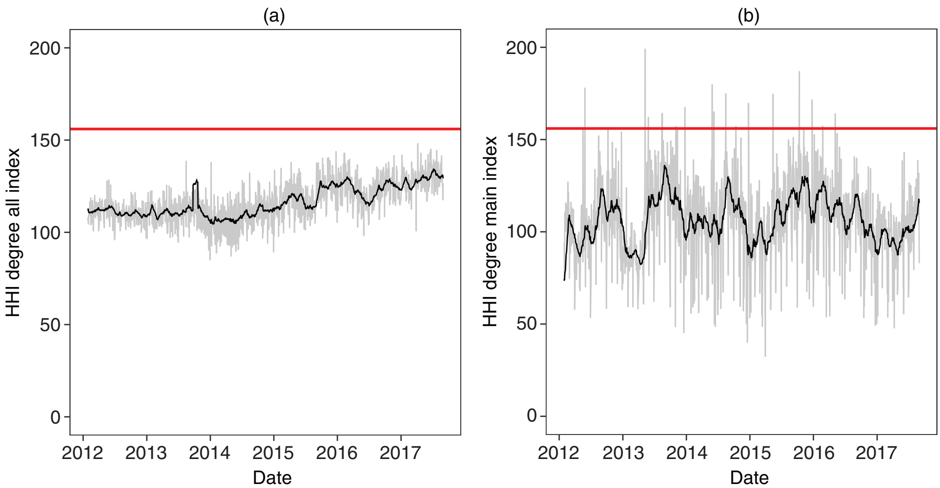
Indicator setup. We look first at the degree measure, which in our case is the number of links for each node (participant) per day. This simple network measure gives information about the direct surroundings of each participant. The total number of incoming and outgoing links is calculated for each node on every day. The links are value weighted, as a link with a high value is more important than a low-value link. The degree is calculated according to the following formula:

$$k_i = \sum_{j=1}^{N} A_{ij}, \tag{4.6}$$

where A_{ij} is the (value-weighted) adjacency matrix and N is the number of participants.

Parts (a) and (b) of Figure 4 show the normalized HHI based on the value-weighted degree for, respectively, all payments and main payments only. As for the turnover HHI, we have set the first value, in June 2008, to 100. In this case, the M_i of (4.4) corresponds to the value-weighted degree of participant i divided by the total degree

FIGURE 4 The HHI for the value-weighted degree: (a) all transactions and (b) main transactions.



The thick black line shows the twenty-day moving average. The horizontal straight line represents the absolute threshold (see Section 4.2.4 and Appendix A (online)).

of the system. As for the HHI for outgoing payment values, the bank that has the highest value-weighted degree contributes the most to the HHI.

4.2.3 Concentration risk based on an advanced connectivity measure

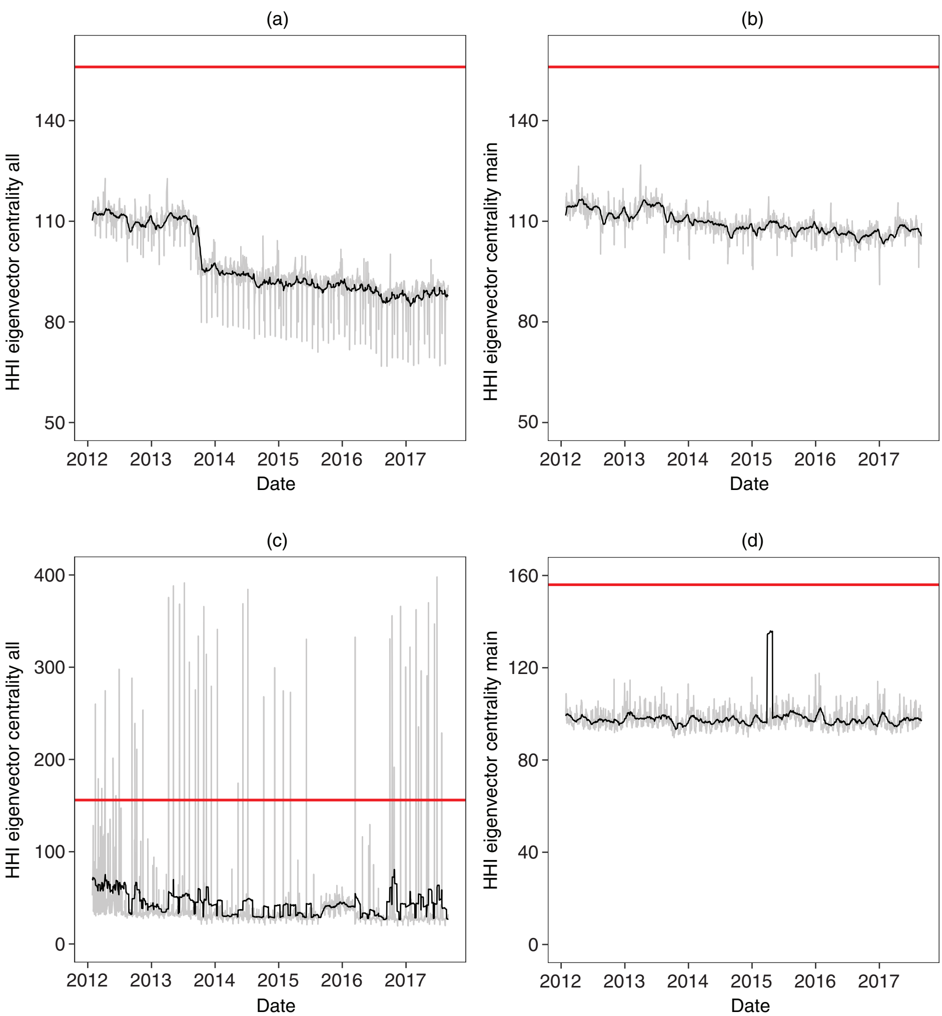
The degree provides information about the direct surroundings of each participant. Eigenvector centrality is a more advanced network property and captures the importance of connected nodes in the network. Besides looking at the (value-weighted) number of links that each participant has, eigenvector centrality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

Indicator setup. 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:

$$c_e(v_i) = \frac{1}{\lambda} \sum_{j=1}^{n} A_{j,i} c_e(v_j), \tag{4.7}$$

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

FIGURE 5 HHI eigenvector centrality: (a) all transactions (unweighted), (b) main transactions (unweighted), (c) all transactions (weighted) and (d) main transactions (weighted).



The thick black line shows the twenty-day moving average. The horizontal straight line represents the absolute threshold (see Section 4.2.4 and Appendix A (online)).

Figure 5 shows the graphs for the eigenvector centrality for unweighted transactions (in parts (a) and (b)) and for value-weighted transactions (in parts (c) and (d)). The M_i of (4.4) corresponds to the unweighted and value-weighted eigenvector centrality of participant i divided by the total eigenvector value of the system.

We make two overall observations from Figure 5. First, as for the turnover and degree HHI, there is a difference between the network layer that includes all transactions (parts (a) and (c)) and the layer that includes only interbank transactions (parts (b) and (d)) in the eigenvector centrality HHI. Second, the value-weighted eigenvector centrality HHI for all transactions (part (c)) shows large spikes on several days, which are likely to have been caused by transactions with the central bank (eg, main and long-term refinancing operations, which are relatively high in value but low in number and come from the same account). A time series that contains large spikes like these on a regular basis, but not on a fixed interval, is not very useful as an indicator. The spikes cannot be corrected for with the methodology of Timmermans *et al* (2018), and as a consequence we will have many false positives; this is because the threshold method will pick up these spikes as potentially harmful, while in fact they represent normal behavior.

4.2.4 The indicator threshold for the three concentration risk indicators

In order to construct the indicator thresholds for the three concentration risk indicators, we proceed as follows. First, to convert the time series into an indicator, we compare the forecasted with the actual HHI of the current month or some other period of investigation. We count the number of times the actual HHI lies above the 99% ("fc99") and 95% ("fc95") intervals of the forecasted value for a red light and an amber light, respectively (see Timmermans *et al* (2018) for details of the forecasting procedure). We are interested only in the cases in which the actual HHI lies outside the 99% and 95% intervals at the top, and not at the bottom, as we perceive an increase in the HHI to represent higher (concentration) risk.

The fluctuations of the indicators' time series are not normally distributed. We observe that the actual value lies outside the 99% and 95% confidence intervals on a regular basis.[11] Therefore, we set the number of times in a month the actual value has to lie above the forecasted (99%) value to three for a red light value (4.8 a) and above the forecasted (95%) value to three for an amber light (4.9). Also, a red light will be created if the smoothed HHI index lies above 156 (4.8 b) at least once during the month (see Appendix A (online) for an explanation of this number). This threshold is required because the system could increase slowly over time without giving any amber or red lights.

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

$$\mathrm{HHI}_{t_0}(\mathrm{fc99}) \geqslant 3, \tag{4.8 a}$$

$$(\mathrm{HHI\ MA})_{(t_0)}(\max) > 156. \tag{4.8 b}$$

[11] These confidence intervals assume a normal distribution of the data.

An amber light is given when

$$\mathrm{HHI}_{t_0}(\mathrm{fc95}) \geqslant 3, \tag{4.9}$$

where $\mathrm{HHI}_{t_0}(\mathrm{fc99})$ and $\mathrm{HHI}_{t_0}(\mathrm{fc95})$ are the number of days in month t_0 on which the actual value lies above the forecasted 99%, respectively 95%, confidence interval, and $(\mathrm{HHI\ MA})_{(t_0)}(\mathrm{max})$ is the maximum value of the twenty-day moving average of the HHI in month t_0. If there is a trend in the indicators over time, it may be required to reset the "first" index to 100 again on a new date, to ensure that the indicator does not provide unwanted alarms every month.

4.3 Liquidity dependencies

In this section two indicators will be shown regarding Principle 20 on FMI links. This principle reads as follows: "An FMI that establishes a link with one or more FMIs should identify, monitor, and manage link-related risks."[12]

4.3.1 Liquidity interdependencies between FMIs

Indicator setup. TARGET2 settles many transactions that go from and to other FMIs (these are also called ASs in the context of TARGET2). These transactions are classified as "transactions with ancillary systems". Therefore, there is a liquidity interdependency between TARGET2 and these ASs. If an AS does not receive the liquidity, it cannot process its payments.[13] At the same time, if liquidity stays on the account of an AS (trapped liquidity), the participants do not receive their liquidity back, which may lead to a (temporary) liquidity shortage for these participants.

Figure 6 shows the turnover to and from all ASs in TARGET2 (the dark gray area) and other transactions in TARGET2 (the light gray area). The black area (right-hand scale) shows the percentage of payments, by value, that are related to payment categories (3.1)–(3.5). They are represented by the following equation:

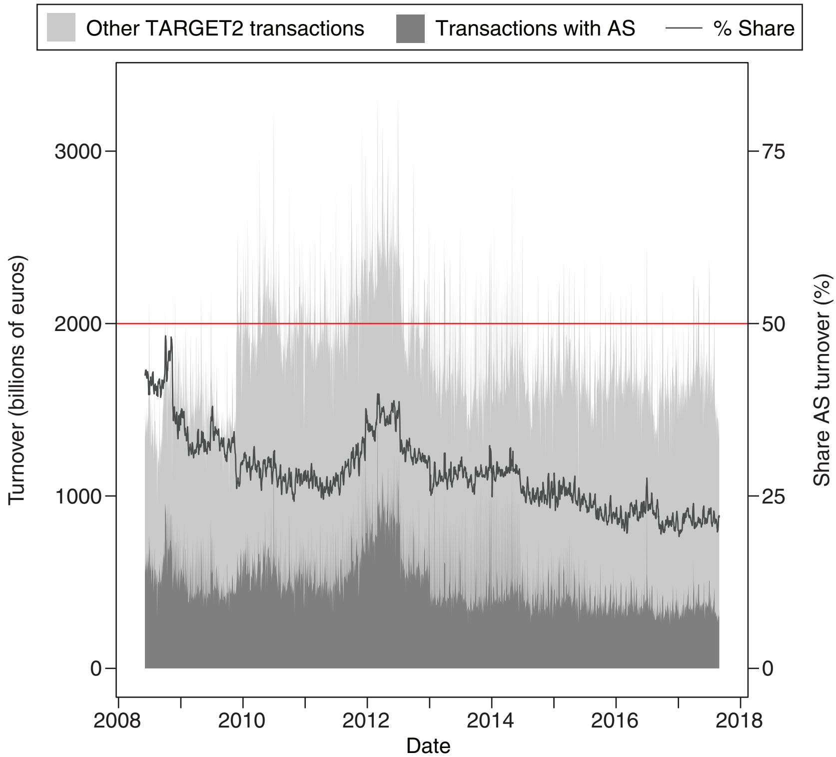
$$(\text{AS share MA }(\%)) = \frac{\text{AS turnover}}{\text{total TARGET2 turnover}} \times 100. \tag{4.10}$$

The horizontal red line is the absolute threshold for the share of ASs relative to all TARGET2 transactions. Given the high day-to-day volatility, it may be good to use a moving average.

[12] More precisely, PFMI 20 requires an FMI to identify, monitor and manage all potential sources of risk, including credit and liquidity risks, arising from the link arrangement.

[13] The reason for an AS not receiving liquidity could be (1) because of an outage of TARGET2 or (2) because one or more participants have insufficient liquidity available on their TARGET2 account to make the payment to the AS.

FIGURE 6 Share of AS turnover in TARGET2.



Indicator threshold. Just by looking at Figure 6 we learn that the total TARGET2 turnover (the sum of the dark gray and light gray areas) shows significant variation over time. The turnover of ASs (the dark gray area) also shows some jumps and spikes. It is clear from (4.10) that the variation in this ratio can be caused by two things: (1) a change in the TARGET2 turnover (the denominator) and (2) a change in AS-related turnover (the 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% interval or the 95% interval. However, for this indicator we look at both the upper and lower limits. An increase in the relative and absolute shares leads to a stronger liquidity dependency between TARGET2 and the ASs. On the other hand, a decrease could be a sign of less liquidity being settled in central bank money, which is not preferred from a financial stability point of view. PFMI 9 (money settlements) encourages the use of central bank money, as it carries a lower settlement bank risk. We suggest the following for a red light:

$$\mathrm{AS}_{t_0}(\mathrm{fc99}) \geqslant 3, \tag{4.11a}$$

$$(\mathrm{AS\ share})_{t_0}(\mathrm{fc99}) \geqslant 3, \tag{4.11b}$$

$$(\mathrm{AS\ share\ MA})_{t_0}(\max) > 50\%. \tag{4.11c}$$

We define an amber light by

$$\mathrm{AS}_{t_0}(\mathrm{fc95}) \geqslant 3, \tag{4.12a}$$

$$(\mathrm{AS\ share})_{t_0}(\mathrm{fc95}) \geqslant 3, \tag{4.12b}$$

where $\mathrm{AS}_{t_0}(\mathrm{fc99})$ and $\mathrm{AS}_{t_0}(\mathrm{fc95})$ are the number of days in month t_0 on which the actual value of the AS turnover lies above the forecasted 99% and 95% confidence intervals, respectively. $(\mathrm{AS\ share})_{t_0}(\mathrm{fc99})$ and $(\mathrm{AS\ share})_{t_0}(\mathrm{fc95})$ are the number of days in month t_0 on which the actual share of the value of the AS turnover relative to the total TARGET2 turnover lies above the forecasted 99% and 95% confidence intervals, respectively. $(\mathrm{AS\ share\ MA})_{t_0}(\max)$ is the maximum value of the twenty-day moving average of this relative turnover in month t_0.

A red light will be given if (4.11 a) and (4.11 b) show that the observation is higher than the benchmark (99% interval) at least three times a month. Equation (4.11 c) is an absolute threshold for the AS share. If this threshold has been met, a red light will also be given. The reason for introducing this threshold is the same as in the case of the HHI index indicators. In theory, all transactions in TARGET2 could be related to ASs but not picked up as signals. The value of this threshold has been set to 50% as this value was only reached once in 2009 and has substantially decreased since then.

Figure 6 gives an overview of liquidity flows between TARGET2 and all other ASs. It is also possible to create the same indicator for each (independent) AS, eg, the flows between TARGET2 and CLS, or the delivery versus payment settlement of the securities settlement system (3.1). However, due to the sensitivity of the data we are not allowed to present graphical representations of such an indicator.

4.3.2 TARGET2 liquidity intradependence

Indicator setup. Besides the dependency between TARGET2 and ASs, banks also depend heavily on each other's liquidity (TARGET2 liquidity intradependence). We measure this by looking at the remaining net bilateral flows (NBF) of payments between banks in the system, which are defined by

$$\mathrm{NBF} = \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{|P_{ij,t} - P_{ji,t}|}{2}, \tag{4.13}$$

FIGURE 7 Bilateral net flows matrixes with a zero net flow (left matrix) and a positive net flow (right matrix).

$$M_0 = \begin{array}{c} \\ \mathrm{a} \\ \mathrm{b} \\ \mathrm{c} \end{array} \begin{array}{c} \begin{array}{ccc} \mathrm{a} & \mathrm{b} & \mathrm{c} \end{array} \\ \begin{bmatrix} 0 & 10 & 50 \\ 10 & 0 & 80 \\ 50 & 80 & 0 \end{bmatrix} \end{array}, \qquad M_+ = \begin{array}{c} \\ \mathrm{a} \\ \mathrm{b} \\ \mathrm{c} \end{array} \begin{array}{c} \begin{array}{ccc} \mathrm{a} & \mathrm{b} & \mathrm{c} \end{array} \\ \begin{bmatrix} 0 & 10 & 50 \\ 100 & 0 & 200 \\ 150 & 80 & 0 \end{bmatrix} \end{array}$$

where N is the number of participants in the system, the $P_{ij,t}$ are the total amounts of payments from participant i to participant j on day t, and the $P_{ji,t}$ are the total amounts of payments from participant j to participant i. The division by 2 is necessary to avoid double counting.

To illustrate the cyclical flow, Figure 7 shows two schematic examples of how net bilateral flows appear for three banks. In the left matrix of Figure 7 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 the right matrix of Figure 7 the net bilateral flows between two banks are not equal to zero. In this example there is a net flow from bank b to bank a of €90, from b to c of €120, and from c to a of €100. The total net bilateral flow in this example would be €310.

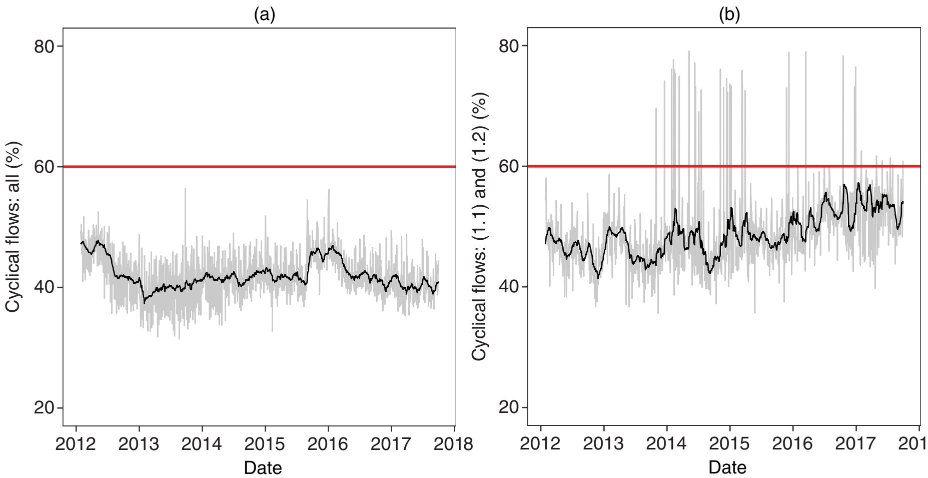
Large net bilateral flows for the banking community when a single bank suffers technical problems pose a bigger challenge. In such a case, the receiving banks lack part of their incoming liquidity, which they need to make their own payments to other banks. Such technical problems can be mitigated by the receiving bank if they implement 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 the individual bank level. A large net bilateral inflow means that, on average, a given bank receives liquidity from some banks that is used to pay others. A stop sending rule applied to the problem bank might therefore not work effectively. If 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.

Indicator threshold. Figure 8 shows the NBF of all transactions on a given day (part (a)) and of the main transactions ((1.1) and (1.2)) (part (b)) relative to the total turnover of all transactions and main transactions, respectively. A cyclical flow of 1% for all transactions corresponds to a value of approximately €17 billion, which is a large amount that participants may not easily absorb.[14] In other words, if the

[14] The turnover was, on average, €1700 billion per day for 2017 (European Central Bank 2018b).

FIGURE 8 Cyclical flows of transactions in TARGET2: (a) all transactions and (b) main transactions.



The thick black line shows the twenty-day moving average and the thin gray line shows the daily data.

cyclical flows are high, the liquidity dependence between participants is also high. We see from the two figures that the day-to-day volatility of the "main transactions" NBF is much larger than that for "all" NBF.

Given the potential impact of large net bilateral flows in the system, the operator may also mark those banks that consistently contribute the most to the NBF as critical – not only the banks that are large in total outgoing turnover.

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

$$\mathrm{NBF}_{t_0}(\mathrm{fc99}) \geqslant 3, \tag{4.14a}$$

$$(\mathrm{NBF\ MA})_{t_0}(\max) > 60\%. \tag{4.14b}$$

An amber light is given if the following equation is met:

$$\mathrm{NBF}_{t_0}(\mathrm{fc95}) \geqslant 3, \tag{4.15}$$

where $\mathrm{NBF}_{t_0}(\mathrm{fc99})$ and $\mathrm{NBF}_{t_0}(\mathrm{fc95})$ are the number of days in month t_0 on which the actual value of the cyclical flows lies above the forecasted 99% and 95% confidence intervals, respectively. $(\mathrm{NBF\ MA})_{t_0}(\max)$ is the maximum value of the twenty-day moving average of the cyclical flows in month t_0. The threshold has been set to 60%, which corresponds to a value of almost €1200 billion when all transactions have been included. Banks may experience severe liquidity pressures above this threshold. It has to be noted that the net bilateral flow between banks often changes from one day to the next. There may be a net positive outflow from bank a to bank b on one day and a net positive inflow on another. Further, most banks, and especially large banks, will simultaneously be on both the paying end and the receiving end of the NBF, as the NBF is the aggregate of all bilateral bank pairs.

4.4 Economic interpretation

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

The HHIs described in Section 4.2 provide information about the concentration of participants. Operators and overseers are usually more interested in the system-wide view of the FMI. Therefore, they will generally be more interested in indicators that contain all transactions. If concentration increases, it is important to know why. If any increase is caused by commercial banks having a (much) higher concentration, operators and overseers may want to set additional requirements for these banks in line with the critical participant approach that is already in place. For financial stability experts, the banking view (including only the main transactions) will usually be most relevant. If the HHI increases suddenly or shows an increasing trend, the impact of a large participant failing to meet its obligations will probably 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. In addition, 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 ASs because of lower settlement bank risk. For the cyclical flows, a similar reasoning can be held as for the HHI. The larger the cyclical flows, the larger the impact when a (large) participant fails to meet its payment obligations.

5 CONCLUSIONS

This paper investigates how granular transaction-level data can be used to identify risks in FMIs. In so doing, it is possible to monitor compliance with the relevant international standards (PFMIs) in a formal and quantitative way. We have investigated indicators that provide information on (1) operational risk (the number of transactions settled and the throughput of the value over the course of the day), (2) concentration risk and (3) liquidity dependency (liquidity flows between TARGET2 and ASs, and between commercial banks). These indicators can be seen as an addition to the existing indicators provided in the literature.

We describe how to convert the massive number 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) they should be well founded. To satisfy both requirements simultaneously we opt for a traffic light approach. This means that the signaling for changes must be brought back to a simple choice: low (green light), moderate (amber light) or substantial (red light) changes with respect to the relevant benchmark. The operational indicators are based on legislation and guidelines. This means that it is clear when an indicator should provide an alarm (an amber or red light). In the case of the other indicators, we base the signaling of the indicators on their own history. We use the forecasting method of Timmermans *et al* (2018) to set the alarms, after correcting the indicator time series for cyclical patterns. The indicators developed in this paper are by no means intended to be exhaustive: more useful indicators will surely be developed on the basis of granular data.

The indicators can be used by overseers, who have to check whether the respective FMI follows the PFMIs; by operators of FMIs who want to monitor potential risky developments in their FMI; and by financial stability experts who are interested in, for example, changes in the concentration of the banking network or increasing dependencies between participants in an FMI. This means that, depending on the focus and the areas of interest of an expert, you have to look at different layers (payment categories) in the network.

DECLARATION OF INTEREST

Ronald 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 July 29, 2010 on access to and use of certain TARGET2 data. De Nederlandsche Bank (DNB) and the Market Infrastructures and Payments Committee of the Eurosystem (MIPC) have checked the paper against the rules for guaranteeing the confidentiality of transaction-level data imposed by the MIPC pursuant to Article 1(4) of the abovementioned decision. The views expressed in the paper are solely those of the authors and do not necessarily represent the views of the authors' affiliations.

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