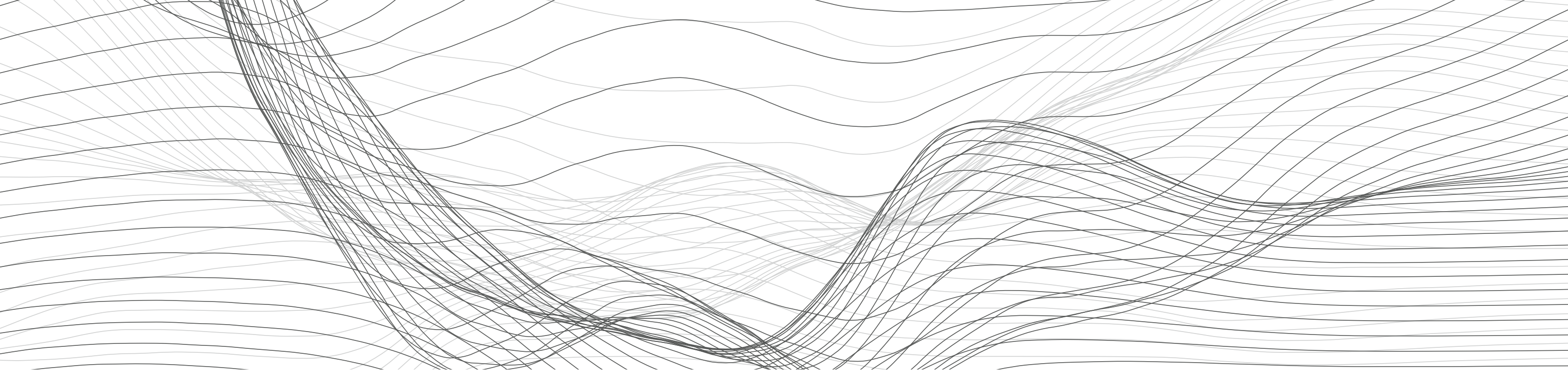

Beyond interbank: Identifying critical participants in integrated RTGS systems using payment type and temporal dynamics

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Beyond Interbank: Identifying Critical Participants in Integrated RTGS Systems Using Payment Type and Temporal Dynamics[*]

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Abstract

As modern economies increasingly adopt digital and instant payments, ensuring the resilience of payment systems and maintaining public trust have become more critical. This paper extends the network and clustering approach of Glowka et al. (2025) to identify critical participants in real-time gross settlement (RTGS) systems – those whose failure could disrupt system continuity. Our extension incorporates three key dimensions: payment type (interbank vs. customer), intrayear temporal frequency, and transaction view (value vs. volume). With these dimensions, we derive an extensive set of granular criticality scenarios and weight each scenario result by its economic activity to reflect its operational relevance. Applying this method to transaction data from SIC, Switzerland's RTGS system, we find that, beyond large international banks, mid-sized domestic banks and, occasionally, financial market infrastructures also play critical roles, especially during periods of heightened economic activity and night-time settlement hours. These criticality results are consistent, although some participants feature more prominently in the volume-based view. Our findings provide system operators and regulators with complementary tools to meet the Principles for Financial Market Infrastructures (PFMI), enabling context-specific assessment of criticality in RTGS systems and informing realistic stress test scenarios amid a rapidly evolving payment landscape.

Keywords: Payment system, Systemic risk, Settlement, Central bank, Customer payments

JEL Codes: E42, D62, E44, E58, G21, J33

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1. Introduction

The increasing adoption of digital payments in modern economies is largely driven by technological innovation and the demand for convenience (Di Iorio et al. 2025 and 2024, Brown et al. 2025 and 2022, Auer et al. 2022). Real-time, 24/7 payment systems have become essential to economic activity. However, their increasing complexity presents challenges for system operators and authorities to ensure operational resilience and maintain public trust (Cornelli et al. 2024, Khiaonarong et al. 2021, BIS CPMI 2021, World Bank 2021).

A payment system outage during periods of heightened economic activity may, for example, disrupt business and consumer transactions, leading to economic losses, reputational risk for system operators, and increased recourse to alternative, possibly nondomestic, payment providers. Repeated incidents could undermine public trust in domestic financial market infrastructures (FMIs), emphasising that systemic risk identification and mitigation must evolve alongside developments in the payment landscape.

FMIs such as *Swiss Interbank Clearing* (SIC), Switzerland's real-time gross settlement (RTGS) payment system, play a central role in financial stability. To support this role, FMIs are expected to comply with the Principles for Financial Market Infrastructures (PFMIs) established by the BIS Committee on Payments and Market Infrastructures (CPMI) and the International Organization of Securities Commissions (IOSCO). A key component of the PFMIs is the identification of "critical participants" – those whose operational failure could significantly impair the system's functioning. While research has mostly concentrated on liquidity and financial stability risks in interbank payments (Henggeler-Müller 2006, Soramäki et al. 2007, Iazzetta and Manna 2009), customer payment systems introduce distinct concerns linked to continuous service availability and public trust (Bech et al. 2008, BIS CPMI-IOSCO 2012, World Bank 2021). These evolving demands highlight the need for updated methods to assess participant criticality.

This paper extends a methodology based on network analysis and clustering introduced by Glowka, Müller, and Weber (2025) for identifying critical participants and applies it to SIC, incorporating additional dimensions such as customer payments, intrayear transaction frequency, and a volume-based view. Existing methods for identifying critical participants fall into three main categories: (1) activity-based metrics focusing on turnover and transaction volumes (Schmitz and Puhr 2009, European Central Bank 2010); (2) simulation-based contagion models that evaluate systemic risks from participant failures (Furfine 2003, Bedford et al. 2005); and (3) network-based analyses focusing on centrality measures (Boss et al. 2004, Soramäki et al. 2007). Recent studies, especially those by Glowka (2020) and Glowka et al. (2025), have applied clustering to identify critical participants. However, few studies have explicitly addressed the growing importance and increasing number of customer payments in RTGS systems – nor have they considered how seasonal patterns influence participant criticality.

To address this gap, we incorporate payment type (interbank vs. customer), intrayear frequency and transaction view (value vs. volume) into an extended version of the Glowka, Müller, and Weber (GMW) approach. This allows us to generate a wide range of specific scenarios in which participant criticality is assessed. To provide a final comprehensive assessment, we aggregate the individual scenario results using a payment-activity-weighted approach, which considers the economic relevance of each scenario. Our guiding research question is as follows: *How does integrating customer payments and the intrayear frequency alter the identification of critical participants in an integrated RTGS system?* Specifically, we examine whether participants beyond large international banks become critical under certain conditions. Using transaction data from SIC, which provides an ideal setting because of its integration of interbank and customer payments and near-continuous operations, we evaluate how participant criticality varies across different economic conditions. We conduct this analysis from two transaction views: a value-based view, where payment network flows are assessed by their monetary value and scenario results are weighted accordingly; and a volume-based view, where each transaction is weighted equally – regardless of its value – and scenario results are weighted by the number of transactions. Our findings show that while large international banks remain critical, mid-sized domestically oriented banks – and in some cases domestic FMIs – become critical, particularly during periods of heightened economic activity and night-time settlement hours. These findings hold true for both transaction views – payment values and payment volumes.

Our approach helps system operators meet the PFMI requirements to identify critical participants by offering a detailed and context-specific method for recognising these participants across different payment types and timeframes. This enhanced identification process contributes directly to the implementation of PFMI Principle 17 (Operational Risk) and Principle 21 (Efficiency and Effectiveness), which require operators to ensure continuous service and the capacity to manage participants' risk profiles under a variety of scenarios. Our work contributes to several strands of the literature. First, it builds on foundational studies by Furfine (2003), Boss et al. (2004), and Soramäki et al. (2007) by extending the GMW (2025) network/clustering approach with added granularity in the dimensions of payment type, intrayear frequency, and transaction view. Second, it advances the understanding of frequency-dependent participant behaviour in networks of interbank payments, extending the research by Bech et al. (2010), Craig and von Peter (2010), and GMW (2025), particularly for domestic FMIs during night-time hours. Third, it deepens the emerging literature on customer payments, identifying previously overlooked critical participants, particularly among mid-sized domestically focused institutions. Finally, it underscores the necessity of conducting independent assessments of various payment types within integrated RTGS systems and thus complements previous research conducted in Denmark (Rørdam and Bech 2009) and Mexico (Alexandrova-Kabadjova and Solís-Robleda 2012, Martinez-Jaramillo et al. 2014). Notably, it facilitates the identification of critical participants in customer payment transactions, which may be overlooked in broader or interbank-focused analyses.

The paper proceeds by presenting the data, followed by the methodology, results, and a concluding discussion.

2. Data and sample construction

This chapter outlines the data sources, preprocessing steps, and criteria used to define the sample to ensure consistent identification of interbank and customer payments across intrayear frequencies and transaction views.

Data dimensions

We use transaction-level payment data from the SIC system for 2021 to 2023. The SIC system, operated by SIX Interbank Clearing Ltd on behalf of the Swiss National Bank (SNB), differs from other RTGS systems such as Fedwire or TARGET2. Unlike these systems, SIC processes both interbank and customer payments individually and in real time, effectively blurring the traditional divide between the two. For example, in 2023, SIC handled more than 3.8 million customer transactions per day, a volume far exceeding that of both Fedwire and TARGET2 (both of which focus primarily on large-value interbank payments; see Table 1). The high volume of daily transactions processed through SIC underscores its vital role in facilitating a large share of Switzerland's cashless payments (see Figure A1 in the appendix). Looking only at interbank payments, SIC is in line with other payment systems, as shown by similar average transaction values (see Table 1). SIC applies a broad access policy, admitting not only domestic and foreign banks but also financial market infrastructures and nonbank entities such as cash processors, provided they meet SNB requirements. This approach contrasts with payment systems such as CHAPS and Lynx, which limit direct participation to a more narrowly defined set of banks and regulated institutions. The SIC system had 313 direct participants in 2023, including both domestic and foreign institutions (see Table 1).[2]

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[2] SIC also exemplifies a forwards-looking RTGS system that combines innovation, resilience, and regulatory compliance. Launched in 1987 as the world's first nationwide RTGS platform, SIC has remained at the technological forefront – adopting the ISO 20022 standard in 2018, integrating instant payments by 2024, and preparing for quantum-resistant security by 2026. Its evolution reflects a future-proof design that balances interoperability and innovation with strong alignment to CPMI–IOSCO principles.

Table 1: International comparison of RTGS payment systems in 2023

Payment System	Number of direct participants	Number of transactions settled per day (in 1000s)	Total value settled per day (in bn USD)	Average value per trans. (in 1000 USD)
Fedwire (US)	6,819	770	4,331	5,624
TARGET2 (XM)	956	416	2,411	5,797
CHAPS (GB)	38	204	453	2,228
Lynx (CA)	17	52	306	5,828
SIC (CH) – Interbank	304	69	223	3,241
SIC (CH) – Customer	304	3,786	27	7
SIC (CH) – Overall	313	3,855	250	65

Note: The table illustrates key statistics from national sources, converted to US dollars with annual average exchange rates vis-à-vis the USD. (National sources are https://frbservices.org, https://www.ecb.europa.eu, https://www.bankofengland.co.uk, https://www.payments.ca, and https://data.snb.ch). Please note that the number of direct participants in SIC for all of 2023 differs from the figure reported in the Report on the SIC System (Swiss National Bank 2024), which reflects the number of SIC participants at the year end. Additionally, the SIC participant numbers shown here differ from those in Table A2 in the appendix, where the number of 'economic units' is reported, each of which may comprise multiple SIC participants.

Next, we show that there is substantial variation in SIC payments across two key dimensions: payment type and intrayear frequency.

Payment type: different distributions and network topologies

The SIC system is an *integrated* payment system that settles both interbank and customer payments.[3] The distribution between these two payment types is asymmetrical, with large-value interbank payments accounting for 89% of the total value settled in 2023, even though they represent only approximately 2% of the total number of transactions processed. Most payments were therefore small-value customer payments (see Swiss National Bank 2024).[4]

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[3] All payment messages follow the ISO 20022 standard (see Table A4 in the appendix for data preprocessing). Interbank payments include pacs.009 messages exchanged between financial institutions or triggered by third-party systems, along with their associated pacs.004 return messages. Customer payments include pacs.008 messages initiated by individuals or businesses and any corresponding pacs.004 returns. The overall category combines all three message types – pacs.004, pacs.008, and pacs.009 – encompassing transactions of both interbank and customer payment types.

[4] It is essential to note that customer payments processed through the SIC system do not represent fast payments (or instant payments) in the conventional sense, as the system experiences regular daily interruptions in the examined timeframe. These interruptions vary in duration, with a short disruption on weekdays and a longer one on weekends (see Swiss National Bank 2024). Genuine fast payments were introduced in Switzerland in August 2024; however, this analysis does not focus on that development.

Furthermore, SIC interbank and customer payments are distinguished by disparate network structures, which are illustrated in Figure 1 below and quantified in Table A2 in the appendix. The SIC interbank network differs from the customer payments network in that it is broader (larger diameter), sparser (typically lower values for edge density, reciprocity and transitivity) and less concentrated (lower proportion of participants/nodes in the core of the network). Furthermore, the data in Table A2 also illustrate pronounced intraday variability in these measures, with the disparate structures being more evident during morning and afternoon periods but somewhat less pronounced during night-time periods.[5] These findings align with those previously documented by Rørdam and Bech (2009) in Denmark and Martinez-Jaramillo et al. (2014) in Mexico.

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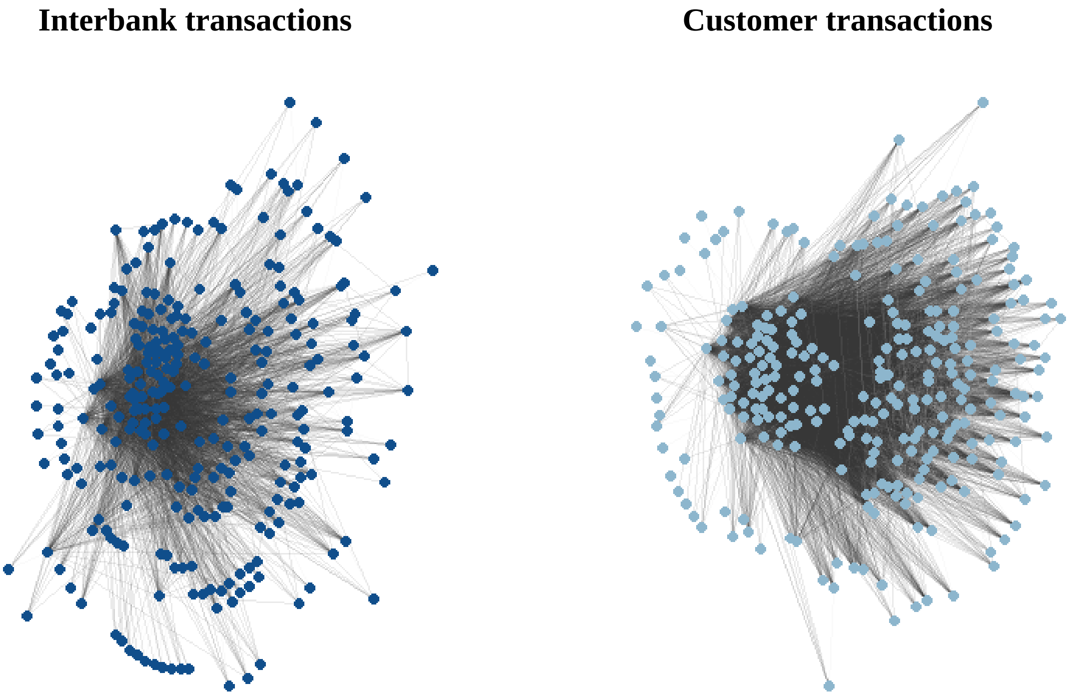
[5] Despite the differences in the networks of the two payment types, their centrality indicators, which are then included in the extended GMW network/clustering approach, are nevertheless similar. Correlation analyses between the four indicators per payment type show that two indicators are highly correlated with each other in both payment types, namely, the two indicators of degree as well as the eigenvector centrality and the turnover share. All other correlations are relatively low, with values less than 0.5. Overall, the correlation patterns of the payment types across all intraday periods are similar to those of GMW (2025), increasing comparability of the results between the two studies.

Figure 1: SIC payment networks by payment type (2023)



Interbank transactions

Customer transactions

Note: The figure illustrates the two distinct SIC payment network structures for 2023 from a value-based view: one for the interbank payment type and the other for the customer payment type. (Analogous network figures from a volume-based view would appear identical, provided the edges between the nodes are unweighted.)

Owing to their different distributions and network structures, the two payment types are well suited for the separate identification of critical SIC participants.

Intrayear frequencies and their seasonalities

Intrayear cyclical patterns of payments in RTGS systems are a well-documented phenomenon; see, for example, Armantier et al. (2008) for Fedwire in the U.S., Ball et al. (2011) for CHAPS in the U.K., Timmermans et al. (2017) for TARGET2 in the euro area, and Chande et al. (2023) for Lynx in Canada. Similarly, SIC payments show distinct but relatively consistent seasonal patterns across intrayear frequencies, which justifies a separate, granular analysis of this dimension (see Figure A3-1 and Figure A3-2 in the appendix). The patterns of the monthly, monthdaily[6] and weekdaily payment

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[6] The ‘monthdaily’ dimension is defined such that each day within a calendar month falls into one of three buckets: it is either one of the first five days with SIC settlement, one of the last five days with SIC settlement, or any day in between.

activities reflect varying levels of general economic activity. We document statistically significant differences within each of these intrayear frequencies in Table A3 in the appendix, justifying our treatment of these as distinct dimensions in the analysis.[7] For example, high levels of payment activity are observed in the second quarter of the year, towards the year end, at the turn of the month, and on weekends; in contrast, low levels of payment activity are observed in February, during the summer vacation months, and around the middle of each month and week. The only clear exception is the year 2022, in which the monthly interbank turnover by value exhibited an anomalous pattern. This anomaly was driven by significantly increased financial market turnover resulting from exceptional volatility in the securities markets and the implementation of monetary policy measures (Swiss National Bank 2022).[8] Within the intraday cycle, payment activity tends to peak during morning office hours (07:00–12:00). However, heightened activity is also observed at night, around midnight, when bundles of precollected payments are released by participants. In contrast, payment activity generally decreases to low levels in the afternoon.

Data preprocessing

Our objective is to specify a robust dataset that allows for a comprehensive understanding of critical participants in the SIC system. To achieve this, we focus on the "economic unit" level, wherein payments made over multiple settlement accounts belonging to the same economic unit are aggregated. This approach ensures that the data reflect the true economic activity and

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[7] Note that in our analysis, we do not focus on the specific seasonal patterns of the selected intrayear frequencies. Instead, we aim to identify economically relevant variations in activity across different time periods, which supports the use of these frequencies as distinct dimensions of analysis. To achieve this, we conduct an ANOVA test for both value- and volume-based payment networks for each intrayear frequency. This test compares the variance within each seasonal group (e.g., January, February, etc.) to the variance between these groups. The results can be found in Table A2 of the appendix. For most frequencies and payment types, at least one group's mean differs significantly from those of the other groups, indicating economically relevant variations in activity across different time periods. We recognise that a three-year dataset may not provide enough data points across all frequencies to generate fully reliable estimates and statistically robust conclusions. Nonetheless, we proceed with the ANOVA, as the quantitative results align with our qualitative assessments derived from visual inspection from Figure A3-1 and Figure A3-2 in the appendix.

[8] The ANOVA tests conducted on interbank payments (from a value view) at both monthly and weekdaily frequencies are the only analyses in Table A2 where we cannot statistically reject the null hypothesis of equal means across all time periods within each frequency.

interconnections of the participants rather than just the activity on individual accounts. For simplicity, we still refer to the "economic units" in the remainder of the paper as "participants". Furthermore, we remove obvious liquidity transfers between accounts to consider only payments with an economic basis. Additionally, we exclude SNB transactions to maintain the integrity of the analysis and reduce noise, as these transactions are related primarily to monetary policy and financial stability rather than to typical payment activities.

Table A4 in the appendix summarises the data selection and preprocessing steps, including the categorisation of payment types and their corresponding messages, as well as the division into intrayear frequencies and the thresholds applied.

3. Methodology

This chapter presents the methodological approach used to granularly identify critical participants in SIC by extending a network and clustering-based framework. It also presents the disaggregation into scenarios by payment type and intrayear frequency, as well as the weighting schemes used to aggregate scenario-specific results into a comprehensive criticality assessment.

The network/clustering approach by Glowka, Müller, and Weber (2025)

Our work is based on the network/clustering approach proposed by Glowka, Müller, and Weber (GMW 2025), which effectively differentiates between critical and noncritical participants in payment systems. We do not provide a mathematical derivation of the approach, as it is thoroughly detailed in GMW (2025). Instead, we qualitatively outline the key steps of their approach. It involves calculating network centrality indicators and combining them with traditional turnover share indicators, followed by the application of a hierarchical clustering method to identify groups of participants with similar sets of indicator values. Network centrality indicators provide a measure of interconnectedness and identify critical participants based on their position in the payment system network (see Soramäki et al. 2007, Bech et al. 2008 or Galbiati and Stanciu-Vizeteu 2015).

GMW (2025) utilise the three network indicators in-degree, out-degree and eigenvector centrality, in addition to the traditional turnover share indicator. In the context of a payment network, the in-degree represents the number of counterparties from which a participant receives transactions. The out-degree reflects the number of counterparties to which a participant sends transactions. Eigenvector centrality considers both the number and the importance of a participant's connections, emphasising those who are well connected to other influential participants; this highlights their systemic importance within the network.[9] Using the turnover share as an indicator places strong emphasis on the participants' transaction activity within the payment network. Clustering is an unsupervised machine-learning technique that aids in categorising participants on the basis of similarities in the data. The GMW approach employs the participants' values for the four indicators and applies agglomerative hierarchical clustering to categorise participants into three distinct clusters based on their importance for the payment system network; these groups are called 'critical', 'potentially critical' and 'not critical'.[10] Indicator-specific median threshold values are then derived from the indicator values of the participants in the central 'potentially critical' cluster. In the last step of the GMW approach, these thresholds are employed to categorise those participants in the 'critical' cluster who exceed the median threshold values for all indicators as *fully above-median critical* (for an illustration of this procedure, see the left panel beneath the blue number 1 in Figure 2).

GMW (2025) concluded that the network/clustering approach they proposed is a relatively fast, straightforward, and less complex alternative to simulation-based methods for payment system operators. Furthermore, the visual representation of the hierarchical clustering method can assist in explaining regulatory decisions based on complex models and multidimensional data structures.

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[9] Analogous to GMW (2025), we calculate the eigenvector centrality values of the participants based on the 'reversed' payment network. This means that the eigenvector centralities are calculated according to the participants' outgoing payments, as opposed to the standard definition which uses the participants' incoming payments.

[10] Analogous to GMW (2025), we conduct the agglomerative hierarchical clustering with the following parameter settings: the actual algorithm used is *agglomerative* clustering, the distance function is *squared Euclidean distance*, and the linkage criterion applied is *Ward's (1963) clustering criterion*. The distance threshold for cutting the tree is not applied, as the *number of clusters* is *predetermined to be three*. Note, however, that our 'critical' cluster is called 'very critical' in GMW (2025).

GMW (2025) also indicate that their network/clustering approach can be tailored to the requirements of individual payment systems and the preferences of policymakers.

Our extension of the GMW approach

In this paper, we utilise the network/clustering approach by GMW (2025) and integrate it into a two-step process of divergence and convergence (see the illustration in Figure 2).

Step 1: Granular scenario generation (divergence phase)

In the first step, we construct an extensive set of 276 distinct scenarios by combining payment types with various time frequencies (see Table 2 for an overview). This allows us to account for the seasonal patterns observed for each payment type across different time frequencies.

We consider three payment categories – interbank payments, customer payments, and the combined overall payments – and five temporal frequency windows: yearly, monthly, monthdaily, weekdaily, and intradaily. Each scenario is defined by a specific pairing of a payment type and a time frequency window. Crucially, we introduce an intraday cycle layer (with four segments: night, morning, afternoon, and whole day) as a meta dimension applied across all other time frequencies. This means that for every frequency (year, month, monthday, weekday), we not only examine the aggregate whole-day activity but also break it down into separate night, morning, and afternoon subscenarios. In doing so, we obtain a fine-grained scenario grid that captures both the seasonal and daily cyclical variations in the payment system.

Table 2: Overview of the 276 scenarios for the period 2021–2023

	Yearly				**Monthly**				**Monthdaily**				**Weekdaily**				
Intraday	Ni.	Mo.	Af.	WD	Ni.	Mo.	Af.	WD	Ni.	Mo.	Af.	WD	Ni.	Mo.	Af.	WD	
Interbank	3	3	3	3	12	12	12	12	3	3	3	3	5	5	5	5	**92**
Customer	3	3	3	3	12	12	12	12	3	3	3	3	5	5	5	5	**92**
Overall	3	3	3	3	12	12	12	12	3	3	3	3	5	5	5	5	**92**
																	276

Note: The table displays the number of scenarios defined for each combination of payment category and time frequency. We use the *intraday* time frequencies night (Ni), morning (Mo), afternoon (Af) and whole day (WD) as a meta dimension, applying it not only to payment types but also to other time frequencies because of pronounced daily cyclical patterns. For example, we analyse interbank scenarios for January as a whole and separately for January nights, mornings, and afternoons.

For each of the 276 scenarios, we apply our extended GMW network/clustering approach to evaluate participant importance. We compute the four indicators for every participant using the payment network observed in that scenario. Using the matrix of these network indicator values, we then perform a hierarchical clustering analysis (as per the GMW methodology) on the participants in the scenario. The participants are grouped into three clusters based on similarities in their indicator values. We interpret these clusters as three preliminary levels of criticality: “not critical”, “potentially critical”, and “critical”. Essentially, participants with relatively low values across the indicators fall into the *not-critical* cluster, those with moderate values cluster as *potentially critical*, and those with high values form the *critical* cluster. At this stage, we impose an additional rule to identify the most important actors per scenario. A participant in the *critical* cluster is labelled as fully above-median critical (FAMC) for that scenario if and only if its values exceed the median threshold (derived from the values of the participants in the *potentially critical* cluster) for all four indicators. This strict condition ensures that only participants who outperform their peers across every metric are marked as FAMC in that scenario. After this step, each participant obtains a binary outcome for the scenario – 1 if FAMC, 0 otherwise – resulting in a vector of 276 scenario-specific criticality flags per participant. This completes the divergence phase. We now have a comprehensive map of the participants who are deemed critical under each granular scenario.

Step 2: Weighted aggregation of the scenario results (convergence phase)

The second step is a convergence phase in which the 276 scenario-specific scores from step 1 are weighted and combined into a single binary classification of *ultimate criticality* for each participant. Each scenario is assigned a weight between 0 and 1 based on its economic importance, with scenarios involving larger payment activities receiving weights closer to 1.[11] For each participant, the 276 binary criticality scores obtained in step 1 are multiplied by their corresponding scenario weights. The resulting weighted scores are then summed, yielding a total that, by construction, ranges from 0 to 1. If this weighted sum is 0.1 or greater for any payment type, the participant is classified as *ultimate critical*, indicating systemic importance across the full range of scenarios. Conversely, a score less than 0.1 means that the participant is not considered *ultimate critical* in that payment type, even if it is critical in some isolated scenarios. The 0.1 threshold ensures that only participants who are critical in 10% or more of the total weighted scenarios are flagged as *ultimate critical*.

This two-step divergence and convergence process (illustrated in Figure 2) allows us to capture a wide range of temporal and transactional contexts, finally producing a robust single indicator of a participant's *ultimate criticality*. We apply this two-step process twice: once for value-based networks (such as GMW 2025), with value-based weighting of the scenarios, and once for volume-based networks, with volume-based weights of the scenarios. By extending the GMW (2025) approach with this methodology, we can consistently identify major players (such as large international banks) while also highlighting less obvious but important participants who dominate more niche but still significant

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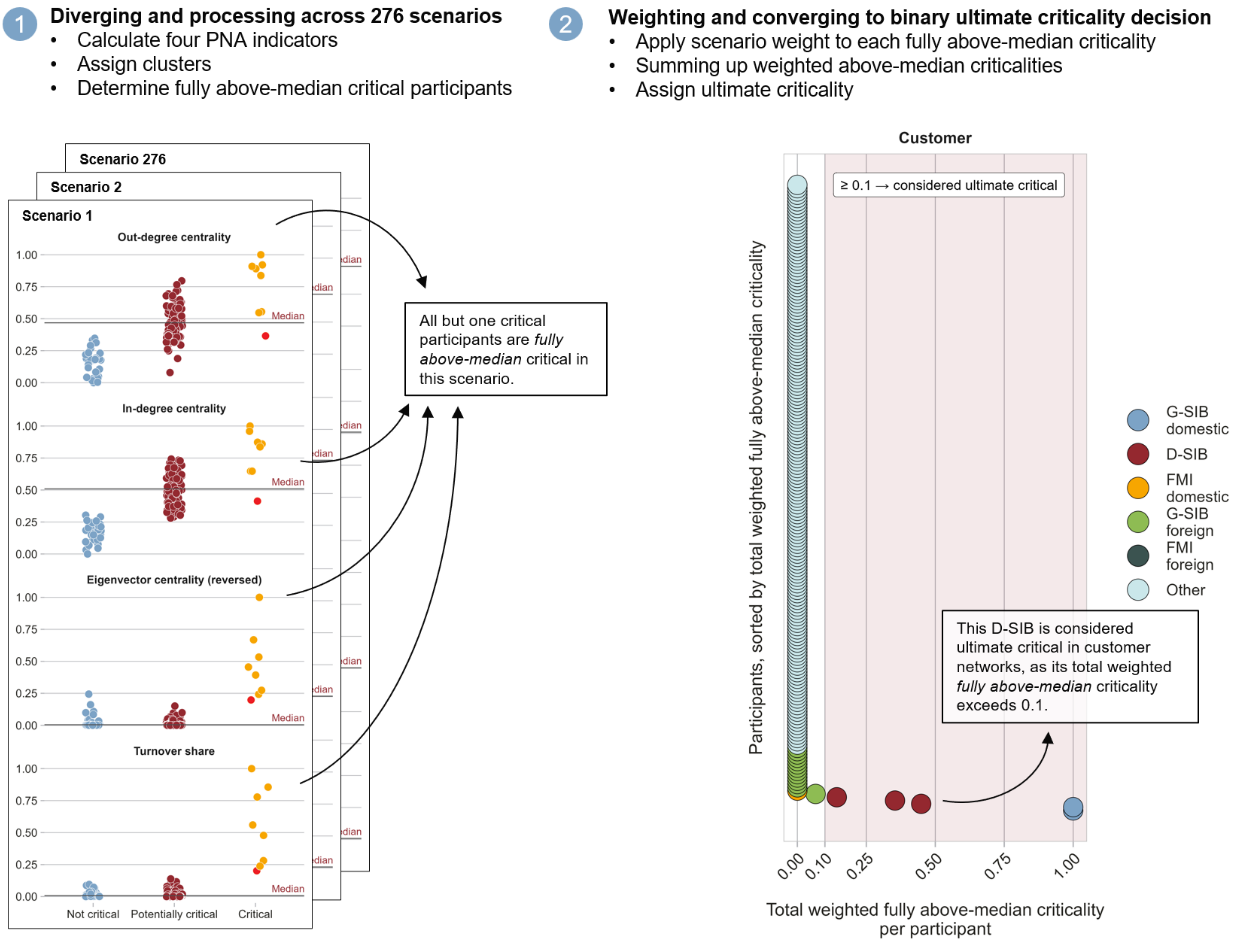
[11] The 276 weights of the scenarios from payment type and time frequency combinations are based on outlier-robust z-scores. The z-scores are computed by subtracting the year's median from each value and dividing by the median absolute deviation (MAD) of the same year. The resulting outlier-robust z-scores are then truncated to the range [-2, +2] to limit the influence of extreme values. After truncation, they are min–max scaled to the range (0, 1], and the scaled values are adjusted so that the weights sum to 1 across each payment type and time frequency (yearly, monthly, monthdaily, weekdaily, and intradaily). Figure A4-1 in the appendix details the used weights per scenario.

scenarios. Eventually, this approach provides a nuanced yet practical assessment of participant criticality based on network structure and economic activity.

Figure 2: Diverge-and-converge process for assigning participants' *ultimate criticality*



All but one critical participants are *fully above-median* critical in this scenario.

This D-SIB is considered ultimate critical in customer networks, as its total weighted *fully above-median* criticality exceeds 0.1.

Note: The figure outlines the process for assigning *ultimate criticality* to participants. It begins by diverging into 276 scenarios in which four indicators are calculated and the clusterings are conducted. For 'critical' participants, a rule assigns 'fully above-median criticality'. Each time a participant meets this criticality level, a scenario-specific economic weight, which is based on economic activity, is applied. The process converges to a binary criticality decision per participant by summing all weighted fully above-median criticalities per payment type and setting a threshold of 0.1 to determine *ultimate criticality*.

In summary, by extending the GMW approach into two dimensions, we want to investigate whether this changes the group of participants defined as critical in an RTGS system. We want to see whether, in addition to the 'usual suspects', i.e., Switzerland's large international banks, participants in other categories are also defined as critical. If so, in which payment types and at what time frequency?

4. Results

This chapter presents the results of our extended GMW (2025) approach to identifying *ultimate critical* participants in Switzerland’s SIC system. We apply the clustering methodology separately to networks constructed from transaction values and transaction volumes, each evaluated across 276 distinct operational scenarios. These scenarios are defined by combinations of payment types (interbank, customer, overall) and intrayear temporal frequencies (such as monthly, weekdaily or intraday segments) and are weighted according to their economic importance.[12]

Participants are classified as *ultimate critical* if their scenario-weighted FAMC score exceeds 0.1 in any payment-type dimension. The subsequent analysis proceeds in two parts: first, we present the value-based results, including both an example of intrayear temporal frequencies to show how participants’ roles may vary over time as well as benchmark comparisons with standard nominal activity thresholds and the TARGET2 findings from GMW (2025); second, we present the volume-based results and contrast them with their value-based counterparts. Finally, we illustrate how these results support practical application in PFMI-aligned operational risk assessments.

Value-based results

The results of the value-based analysis reveal a stable core of *ultimate critical* participants in the SIC system. As shown in the upper panel of Figure 3, the two domestic global systemically important banks (G-SIBs) consistently meet the criterion for *ultimate criticality* across all payment types, achieving a maximum weighted criticality score of 1.0 for all types. The three domestic systemically important banks (D-SIBs) are also classified as *ultimate critical*, although they surpass only the threshold of *ultimate criticality* in the customer payment network.

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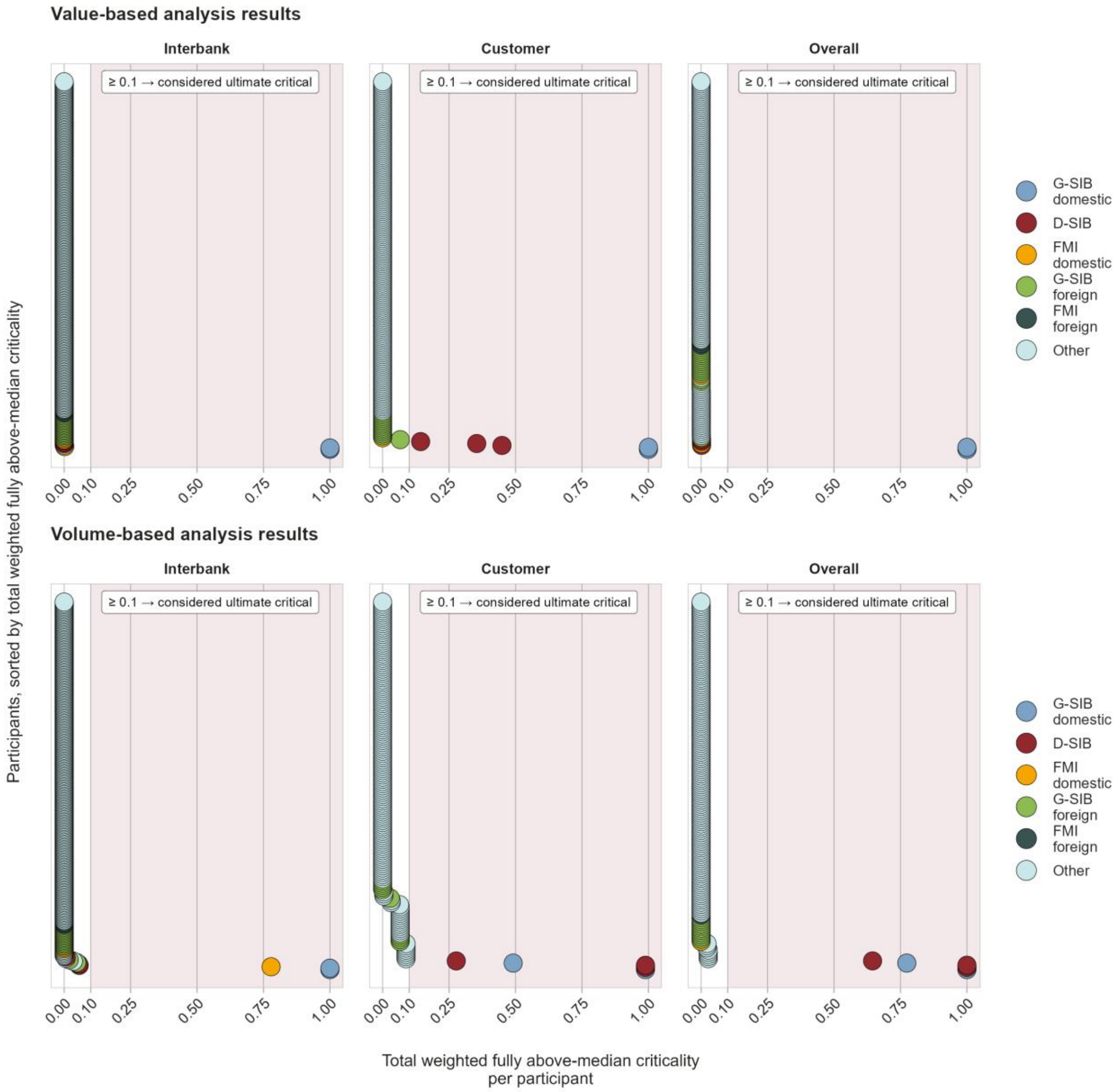
[12] In the value-based analysis, weights are based on the economic value of transactions in each scenario, whereas in the volume-based analysis, weights are based on the number of transactions transmitted in each scenario.

Figure 3: Summary of results for value-based and volume-based analyses across 276 distinct scenarios by payment-type dimension



Note: Each dot represents a single SIC participant's aggregated criticality score, which is based on either transaction values (upper panel) or transaction volumes (lower panel). Scores are computed as the sum of weighted FAMCs across the 92 scenarios associated with each payment type. Participants with a weighted score above 0.1 for any payment type are classified as *ultimate critical* and are highlighted in the red-shaded area. A score of 1.0 indicates that the participant met the FAMC in all scenarios of that payment type. Dot colours reflect participant categories (e.g., G-SIBs, D-SIBs, FMIs, others).

Apart from these five institutions, no domestic or foreign FMI participant, nor any of the 'other participants' category, reaches *ultimate criticality* in the value-based analysis. Only one foreign G-SIB displays elevated criticality in specific scenarios but fails to qualify as *ultimate critical* in the weighted aggregation of scenario criticality. To illustrate how time-dependent patterns affect systemic relevance, we refer to a detailed example of our diverge-and-converge process for the ‘monthdaily’ frequency that is provided in Appendix A6.

Comparison with the standard criticality definition based on activity shares

To assess the sensitivity and added value of our extended GMW approach, we compare its outcomes with those of a standard threshold-based method. This benchmark approach, which is commonly applied in oversight practice, designates participants as critical based on their annual share of system activity, typically using a fixed nominal value threshold (we use 5 percent, although jurisdiction-specific variants exist).[13] The simplicity of this method facilitates comparability over time but comes at the cost of overlooking interaction structures and scenario-dependent dynamics.

Table 3: *Ultimate critical* participants by category,
network/clustering (value-based) vs. standard approach (2021–2023)

	Network/clustering approach (value-based)	**Standard: 5% turnover threshold**
	Critical participants/all participants	Critical participants/all participants
G-SIB domestic	2/2	2/2
D-SIB	3/3	2/3
FMI domestic	0/3	1/3
G-SIB foreign	0/18	1/18
FMI foreign	0/3	0/3
Other participants	0/271	0/271
Total	**5/300**	**7/300**

Note: The table compares the number of *ultimate critical* participants in the SIC system for the period 2021–2023, identified by the value-based network/clustering approach, with those identified by the standard method applying a 5% activity share threshold.

Table 3 summarises the differences in classification outcomes. While both methods identify the two domestic G-SIBs as critical, divergences emerge among the D-SIBs and other participant categories.

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[13] For example, the “Report on the SIC System and Disclosure Report 2022” refers to system-critical participants as being those participants who accounted for a share of at least 5% of annual SIC turnover (excluding the SNB) in each of the preceding three years. This report is available at the SNB’s website www.snb.ch.

Our approach identifies a slightly smaller set of critical participants overall, reflecting its focus on scenario-weighted network centrality rather than absolute transaction shares. These differences underscore a broader conceptual distinction: whereas the benchmark method captures activity concentration, the clustering model targets structural importance within operational contexts. The implications of this divergence become particularly evident at the scenario level, where the benchmark approach tends to flag a higher number of criticalities (7 versus 5; see last row in Table 3) but with greater volatility and less consistency across time frequencies (a total of 922 criticality identifications versus 785 in the case of the extended GMW approach; see Figure A5-1 vs. Figure A7-1 in the appendix).[14]

Comparison with results for TARGET2 presented by GMW (2025)

A complementary perspective is gained by comparing SIC's value-based results with those of the pan-European TARGET2 system using the analysis conducted by GMW (2025). TARGET2 differs from SIC in several fundamental respects: it is larger in scale, has a broader participant base, and is structurally geared towards interbank payments (see Table 1 and European Central Bank 2019). As such, it offers an instructive counterexample to SIC's integrated design.

As illustrated in Figure A8-1, the structural composition of the two systems' interbank networks yields distinct clustering outcomes.[15] In SIC, a greater share of participants falls into the potentially critical cluster, indicating a denser and more interconnected network. In contrast, TARGET2 displays a more distributed structure, with a larger proportion of participants classified as noncritical. While both systems identify a small set of core participants as critical, the nature of their systemic relevance

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[14] Members of the category 'Other participants' are excluded from this comparison because the network/clustering approach identifies between 23 and 28 additional FAMCs in some night-time scenarios, which could distort the interpretation of the differences between the two approaches. Nevertheless, these identified critical 'other participants' align with changes in the money market activity of these participants, especially in the year 2022 with its change in the course of monetary policy and the exceptionally high volatility in securities markets.

[15] With respect to GMW (2025), while their analysis is based primarily on transaction data from Q1 2022, they also conduct robustness checks using seven additional scenarios: Q2 2021, Q2 2022, Q3 2022, Q4 2022, January 2022, and the full years of 2021 and 2022.

differs. In SIC, critical participants are highly interconnected (reflected in their high values of in- and out-degree connectivity) and account for a substantial share of total turnover. Conversely, in TARGET2, these institutions play a less dominant role in network topology.

This comparison highlights the importance of contextualising criticality definitions within the institutional setting. In compact, integrated RTGS systems such as SIC, systemic relevance may be more tightly concentrated, with temporal and functional differentiation playing a crucial role. By comparison, larger, decentralised systems such as TARGET2 may exhibit more diffuse patterns of criticality, where network position and absolute size are less tightly aligned.

Together, these comparative insights emphasise the need for flexible, network-aware methodologies that account for both size and structure and that can be adapted to the operational characteristics of individual RTGS systems. Relying solely on nominal thresholds or annual aggregates risks overlooking the complex ways in which participants contribute to systemic resilience – or vulnerability – under specific conditions.

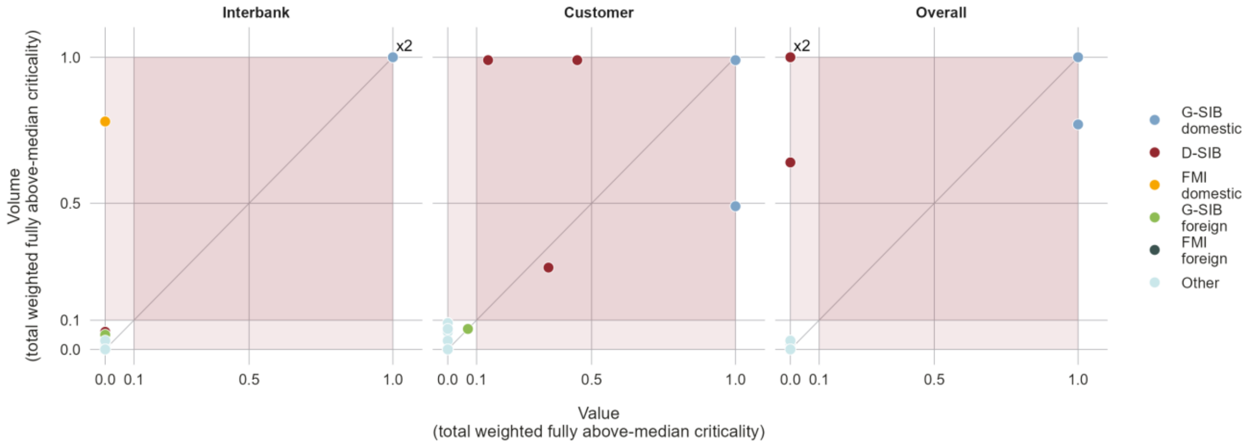
Volume-based results

The volume-based analysis, constructed from transaction counts and scenario weights based on transaction volumes, complements the value-based results by highlighting different aspects of systemic relevance. While the two domestic G-SIBs also remain critical across all payment types in the volume-based analysis, the rankings of mid-sized domestic institutions shift. The same three D-SIBs qualify as *ultimate critical*, but one becomes markedly more prominent than the others in volume terms, reflecting its role in high-frequency customer payment processing (see the lower panel of Figure 3). Interestingly, a domestic FMI reaches its *ultimate criticality* in the volume-based interbank network. Foreign G-SIBs, foreign FMIs and the other participants are not considered *ultimate critical* in either approach.

Differences between value- and volume-based network/clustering approaches

Despite similarities, the results of the value- and volume-based approaches diverge in important ways. The key difference emerges in the identification of a domestic FMI as *ultimate critical* in the volume-based interbank network. This FMI is highly active during low-traffic periods – particularly at night – and contributes a large share of transactions despite relatively low turnover. Its critical activity profile is invisible in the value-based results but fully captured in the volume-based results. These insights are summarised visually in Figure 4, which plots each participant's *ultimate criticality* score under the value-based approach (horizontal axis) against the corresponding volume-based score (vertical axis). Participants on or near the 45-degree line exhibit comparable importance under both lenses. Those above the line are more critical in volume terms (e.g., domestic FMIs), whereas those below are more critical in value terms (e.g., participants with comparably few high-value transactions). In summary, incorporating both value and volume views provides a more comprehensive view of systemic importance, illustrating the broad criticality of G-SIBs while also revealing participants whose criticality would be underestimated if only payment values were considered.

Figure 4: Comparison of participants' criticality in value- and volume-based views



Note: Each dot denotes a SIC participant's total weighted criticality score under the value-based (horizontal axis) and volume-based (vertical axis) views. Scores are computed for each payment type separately and reflect the sum of the scenario-weighted FAMC values. Participants located near the 45-degree line are assessed similarly in both views. Those above the line are more critical in volume terms, whereas those below are more critical in value terms. Red shading denotes the region of *ultimate criticality*. When multiple participants share a coordinate, labels such as "x2" indicate overlap.

The comparison in Figure 4 confirms that systemic relevance is multifaceted. Value-based approaches detect financial concentration, whereas volume-based analyses reveal operational centrality and customer-facing exposure. Relying exclusively on one view risks missing critical actors or misclassifying participants whose roles vary by context.

Taken together, the results show that RTGS systems contain layers of criticality that become visible only through disaggregated, scenario-based analysis. Nominal thresholds and aggregate yearly measures can provide a rough filter, but they lack the resolution needed for targeted supervision or operational planning. In the following discussion, we explore the broader implications of these findings for oversight, regulation, and systemic resilience.

Policy relevance

Our extended GMW approach is directly relevant to policy implementation and supervision, as it provides complementary tools that support two key principles of the PFMIs and provides discussion inputs on how to strengthen the oversight of the RTGS system.

PFMI alignment

In the context of the CPMI–IOSCO PFMIs, our approach offers concrete tools to support both Principle 17 (Operational Risk) and Principle 21 (Efficiency and Effectiveness). The identification of time- and function-specific criticality provides RTGS operators with a more granular, context-specific assessment and offers to target their business continuity planning with actual systemic exposure. For example, an FMI that is critical only during low-activity night-time settlement hours may pose fewer potential disruptions than a participant that is continuously central to the system. The incorporation of such temporal precision into resilience strategies strengthens robustness while ensuring proportionate resource allocation. From a supervisory standpoint, scenario-based network analysis further enables proportional oversight, distinguishing between structurally systemic participants and those whose criticality is occasional or situational. These criticality profiles can also be used to design more realistic scenario-based stress tests, enhancing the credibility and relevance of resilience testing. This facilitates more targeted monitoring and could be used to calibrate the application of liquidity or contingency requirements.

Lessons for RTGS system operators

The approach’s modular design and reliance on standard transaction data make it both scalable and adaptable. It can be applied to identify vulnerabilities in current systems and assess systemic roles under alternative configurations (e.g., postmerger, infrastructure upgrade, or changes in participant composition). As payment systems evolve – with greater automation, 24/7 operations, and new entrants on the user side – the ability to assess criticality with precision and context sensitivity will be an increasingly essential component of robust and efficient system design.

5. Discussion

The accelerating digitisation and instant availability of payments – driven by innovations and a growing demand for convenience – have significantly increased society’s expectations for and reliance on seamless and continuous transaction processing. Businesses and consumers now expect payment infrastructures to be available 24/7/365, especially for customer payments. This trend has also transformed the systemic profile of integrated RTGS systems. No longer confined to interbank liquidity transfers, these infrastructures now serve a much broader range of payment types and actors.

This development has implications for how the systemic relevance and criticality of participants in payment networks are defined, measured, and managed. Traditional methods for identifying critical participants – based on annual turnover shares or simple volume rankings – offer valuable simplicity but do not capture the multidimensional nature of modern systemic risk. They overlook interaction structures, operational timing, or customer-side dependencies. They also fail to consider factors such as reputational risk, public trust and the continuous availability of payment services, which are increasingly essential components of resilience assessments. By including customer payments and around-the-clock payment activity in our analysis, we highlight scenarios where an outage at a large customer bank might quickly undermine public confidence in the payment system or its operator, with major reputational consequences. Addressing these gaps, our results show the benefit of a scenario-based network approach that distinguishes between value- and volume-based criticality across different payment categories and time intervals.

In this paper, we investigate how payment type and intrayear temporal frequency affect the identification of critical participants in an integrated RTGS system. We extend the network/clustering methodology proposed by Glowka et al. (2025) and apply it to Switzerland's SIC system, an integrated RTGS infrastructure. This extended network/clustering approach enables a more granular analysis of participant criticality by incorporating functional distinctions – such as interbank versus customer payments – as well as temporal dynamics, including time-of-day and seasonality patterns.

Our findings confirm the systemic importance of Switzerland's domestic G-SIBs but also reveal additional critical players. When customer payments and temporal granularity are included in the analysis, mid-sized domestic banks and, in some cases, domestic FMIs emerge as critical participants – especially during night-time hours and periods of heightened economic activity. This effect is even more pronounced when analysed from a volume view, indicating that conventional assessments based solely on annual value measures may obscure systemic vulnerabilities.

The overlap between the results of the extended network/clustering methodology and traditional approaches is not a limitation but rather a strength. Such consistency ensures continuity in regulatory interpretation, while the increased resolution of our method offers two key benefits. First, it allows regulators to assess participant criticality in specific operational contexts – such as night-time processing or change-of-month peaks – thereby improving diagnostic accuracy. Second, it enables the design of scenario-based stress tests that reflect realistic operational scenarios that align with the temporal and functional risk profile of a participant – for example, simulating the effects of a night-time outage at an FMI identified by the analysis as being critical only during night-time operations. This targeted approach promotes resilience effectively and efficiently.

This granular view of participant criticality contributes directly to fulfilling key responsibilities under the CPMI–IOSCO PFMIs, namely, Principle 17 on operational risk and Principle 21 on efficiency and effectiveness. By helping system operators identify which participants are critical under which conditions, our method provides practical insights to support compliance with these obligations.

Additionally, the use of network-based metrics complements simulation-based stress testing, which remains the benchmark for analysing systemic risk under hypothetical disruptions. While simulations offer detailed scenario analyses, they are resource-intensive. Our method can serve as an effective screening tool, highlighting participants or time periods that warrant deeper investigation via simulation.

Future research could extend this framework by incorporating a geographical dimension to reveal regional clusters of criticality and support more localised resilience strategies. Another promising avenue is to simulate disruptions to participant-specific flows or timing structures, testing the network's resilience under targeted shocks. Furthermore, this method may enable international benchmarking, facilitating comparisons across jurisdictions with different institutional setups and operational constraints.

By uncovering the conditions under which participants become critical, this paper contributes to a more accurate and responsive form of systemic oversight. It demonstrates that effective RTGS supervision requires attention not only to transaction values but also to the intersection of network position, timing and functional role. As payment systems continue to evolve, so must the analytical tools used to safeguard their resilience. The framework presented here offers a robust baseline; however, its continued effectiveness depends on regular updates aligned with market developments and evolving policy priorities.

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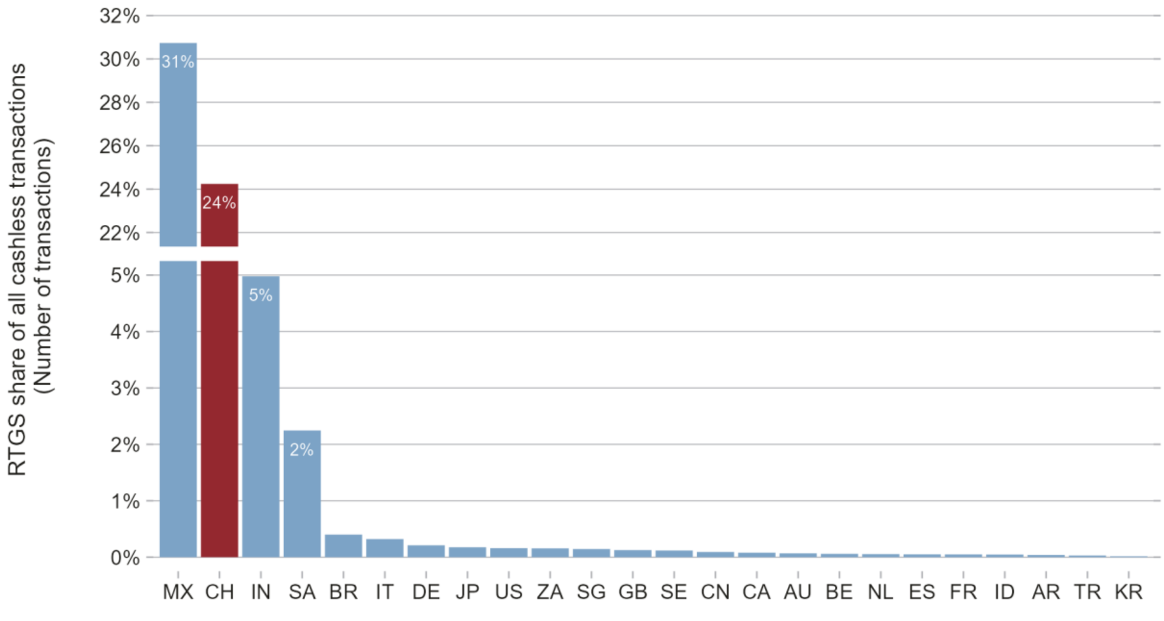
Appendix

A1. Importance of RTGS systems in a country's payment landscape

Figure A1: Proportion of RTGS-settled transactions in the country's overall cashless transactions (in %; 2022)



Source: BIS Red Book

Note: The figure shows the ratio of transactions settled in the RTGS system relative to the country's overall cashless transactions according to BIS Red Book statistics for the year 2022. Note the break on the y-axis between 5% and 22% to make the low values for most countries slightly easier to read. Only four countries out of 24 settle two percent or more of their cashless transactions in the national RTGS system.

A2. Payment networks in the SIC system 2023

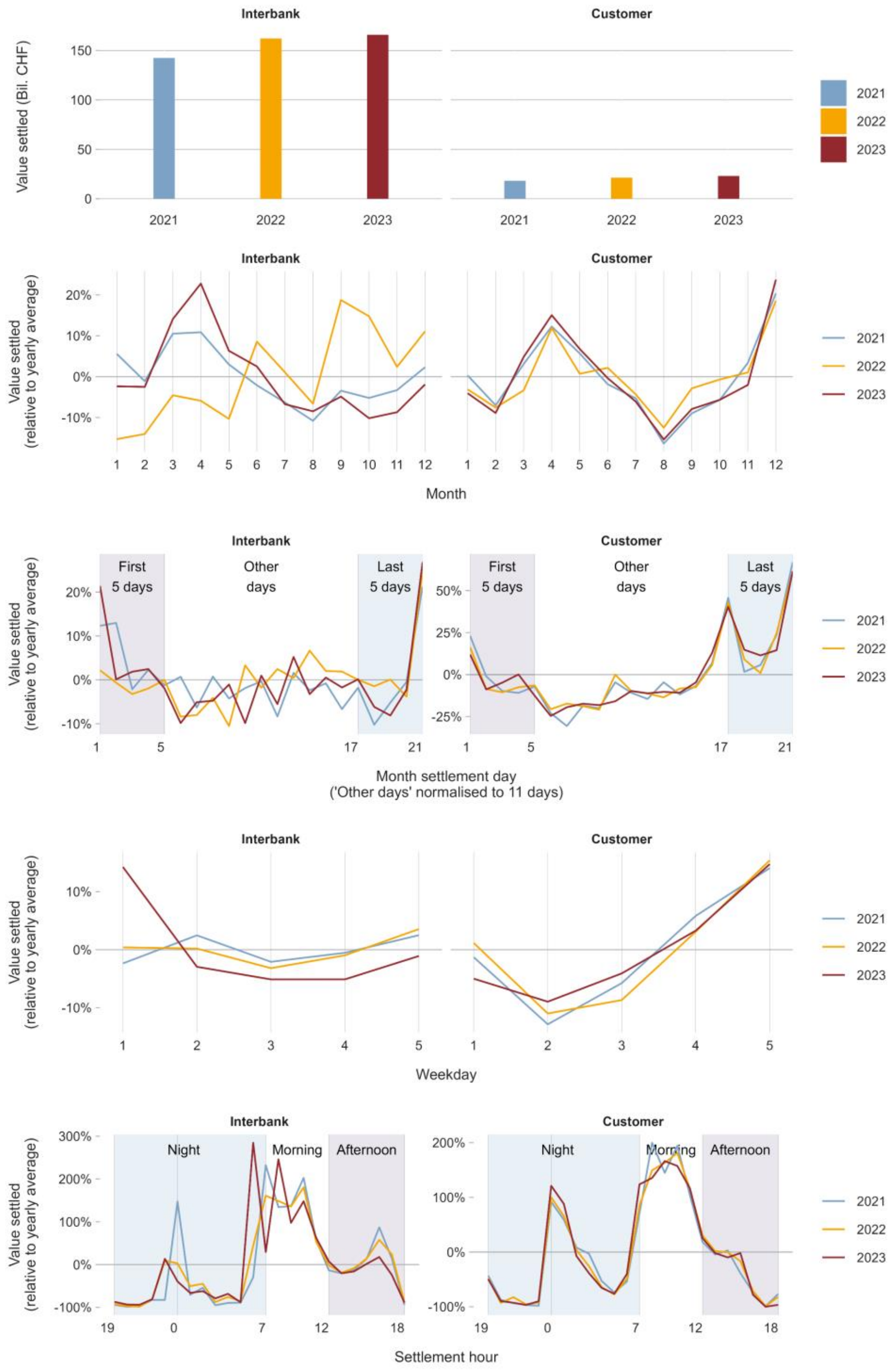
Table A2: Summary statistics of SIC payment networks (year 2023)

	Node count	Edge density	Com-ponents	Nodes in core, %	Diameter	Reci-procity	Transi-tivity
Interbank							
whole day	**271**	**0.38**	**15**	**27**	**4**	**0.80**	**0.54**
- night	255	0.23	47	25	5	0.73	0.58
- morning	268	0.15	21	16	5	0.74	0.38
- afternoon	267	0.13	27	15	5	0.68	0.35
Customer							
whole day	**271**	**0.85**	**34**	**36**	**3**	**0.81**	**0.66**
- night	260	0.43	55	35	4	0.72	0.63
- morning	262	0.51	34	35	4	0.78	0.65
- afternoon	264	0.46	36	31	3	0.76	0.63

Note: These indicators are based on SIC payment networks of the year 2023 between nodes at the level of the ‘economic unit’ and exclude all SNB transactions.

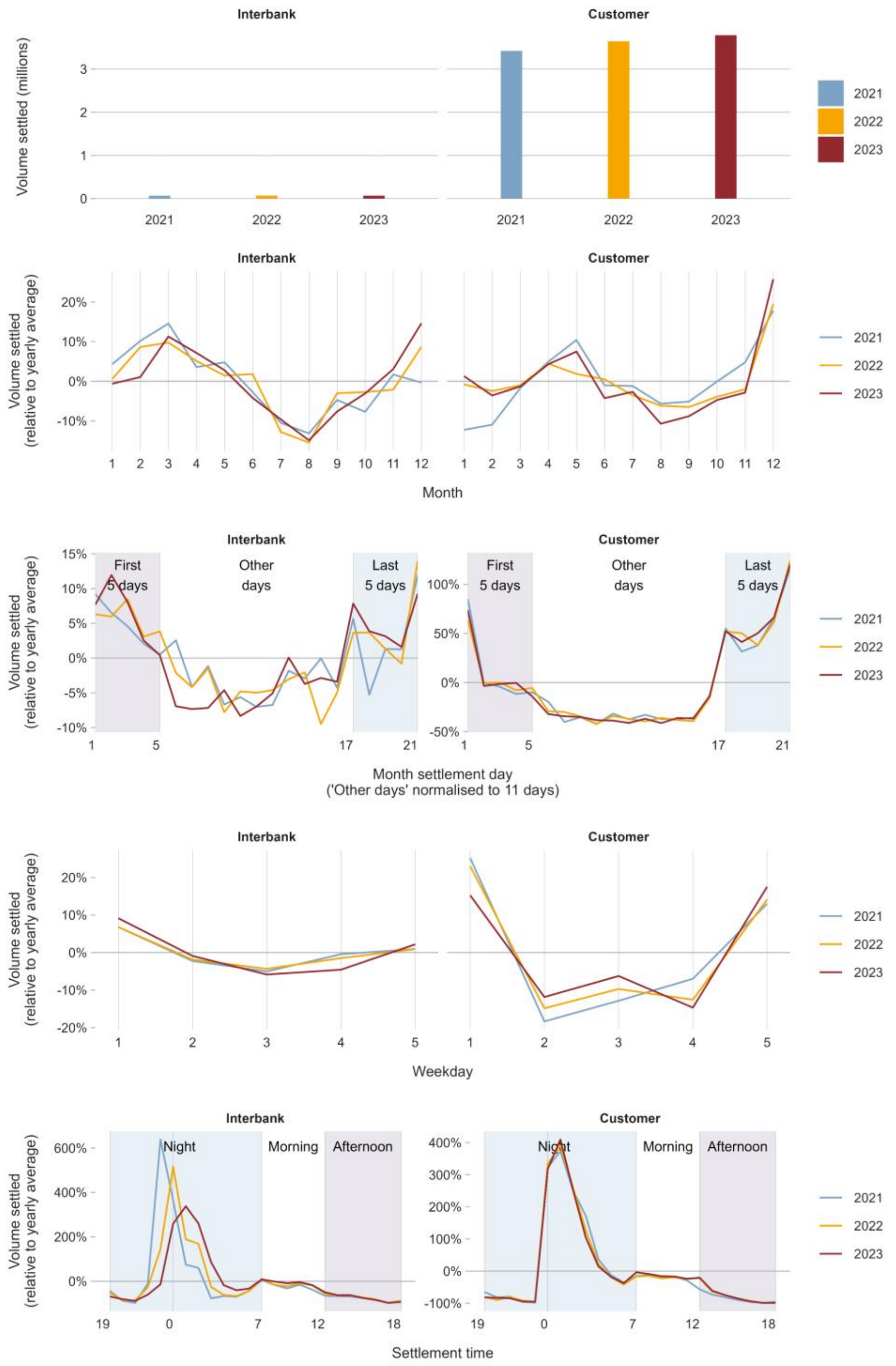
A3. Seasonality patterns in SIC payment types

Figure A3-1: Value-based yearly and intrayearly seasonality patterns in SIC (2021–2023)



Note: The charts in the figure illustrate SIC values, disaggregated by payment type and frequency, for the three-year period from 2021 to 2023. For each intrayear frequency, the charts present the percentage difference between the respective annual frequency average and the observed value. The monthly interbank turnover by value in 2022 exhibits an anomalous pattern, reflecting markedly elevated financial market turnover. This is attributable to the volatility of securities markets and the implementation of monetary policy measures.

Figure A3-2: Volume-based yearly and intrayearly seasonality patterns in SIC (2021–2023)



Note: The charts in the figure illustrate SIC volumes, disaggregated by payment type and frequency, for the three-year period from 2021 to 2023. For each intrayear frequency, the charts present the percentage difference between the respective annual frequency average and the observed volume.

Table A3-1: ANOVA p-values across frequencies (of SIC payments for the years 2021–2023; volume and value views)

		Volume		Value	
		p-value	signif.	p-value	signif.
Monthly	Interbank	0.00000	***	0.46174	
	Customer	0.00000	***	0.00000	***
Month-daily	Interbank	0.00001	***	0.04305	**
	Customer	0.00002	***	0.00014	***
Week-daily	Interbank	0.00001	***	0.33374	
	Customer	0.00000	***	0.00004	***
Intra-daily	Interbank	0.00021	***	0.00341	***
	Customer	0.00022	***	0.00002	***

Note: A significant p-value in the ANOVA summary suggests that at least one group's mean differs significantly from those of the other groups at the 1%, 5%, or 10% significance level, denoted by ***, **, or *, respectively.

A4. Data preprocessing

Table A4: Data preprocessing steps

Step	**Reason**	**Procedure**
Initialisation	Initial data source: SIC transaction data and selected data fields - Settlement period: 2021–2023 - Settlement date and timestamp - Message types (ISO 20022 standard): o pacs.009 – Interbank payments and third-party system payments o pacs.008 – Customer payments o pacs.004 – Return payments (Note that these payments will later be split between the interbank and customer payments; see step 'Recoding' below.) - Settlement account numbers of both sender and receiver	
Exclusion of SNB accounts	SNB transactions are excluded because they primarily fulfil specific monetary policy and financial stability roles, which do not reflect the activities of typical participants in the SIC system.	Remove transactions from SNB accounts or to SNB accounts.
Construction of economic units	An *economic unit* may comprise multiple SIC participants, each of whom may hold more than one settlement account. In our analysis, we treat economic units as the network nodes, as this approach most accurately reflects the actual economic activities and interconnections within the network. In	- Merging settlement accounts (senders and receivers) that belong to the same SIC participant. - Consolidating SIC participants based on a mapping of economic units to participants, compiled from multiple sources – one of which is SwiftRef.

	contrast, analysing data at the participant or account level would also encompass internal transfers within the same financial institution, which do not represent genuine interinstitutional activity.	
Recoding	Recoding variables into the categories used to distinguish between scenarios and participant groups.	Time variables and frequencies: - Years: 2021–2023 - Month: January to December - Monthdaily: Organised into three categories: the first five settlement days, the last five settlement days, and all other settlement days within the month. - Weekdaily: settlement days from Monday to Friday - Intradaily: *Night*: From the beginning of the settlement day until 06:59:59 *Morning*: 07:00:00 to 11:59:59 *Afternoon*: 12:00:00 until the end of the settlement day Payment types: - Interbank: Includes all messages of type pacs.009 and pacs.004 that refer to a pacs.009. This category also covers transactions between participants triggered by third-party systems. - Customer: Includes all messages of type pacs.008 and pacs.004 that refer to a pacs.008. - Overall: Includes all interbank and customer payments (i.e., messages of type pacs.004, pacs.008, and pacs.009). Participant categorisation: Participants are classified into categories such as domestic/foreign G-SIBs, D-SIBs, and domestic/foreign FMIs using the following data sources: - G-SIBs: FSB list of Global Systemically Important Banks - D-SIBs: FINMA list of Domestic Systemically Important Banks - FMIs: Internal classification based on the SIC participant’s financial institution category

A4. Economic weights by time frequency

Figure A4-1: Economic weights used for weighting for the results of the time frequencies

Value-based weighting scheme

Yearly

	Night	Morning	Afternoon	Whole day
2021	0	.025	.025	.05
2022	0	.012	.012	.025
2023	0	.025	.025	.05

Monthly

	Night	Morning	Afternoon	Whole day
January	0	.004	.004	.009
February	0	.003	.003	.005
March	0	.007	.007	.014
April	0	.01	.01	.021
May	0	.006	.006	.013
June	0	.006	.006	.011
July	0	.003	.003	.006
August	0	0	0	0
September	0	.004	.004	.008
October	0	.004	.004	.008
November	0	.005	.005	.009
December	0	.01	.01	.021

Monthdaily

	Night	Morning	Afternoon	Whole day
First 5 days	0	.018	.018	.036
Other days	0	0	0	0
Last 5 days	0	.044	.044	.089

Weekdaily

	Night	Morning	Afternoon	Whole day
Monday	0	.019	.019	.039
Tuesday	0	.006	.006	.012
Wednesday	0	0	0	0
Thursday	0	.01	.01	.02
Friday	0	.027	.027	.054

Economic weighting score

0.00 0.02 0.04 0.06 0.08 0.10

Volume-based weighting scheme

Yearly

	Night	Morning	Afternoon	Whole day
2021	.022	.006	.022	.05
2022	.011	.003	.011	.025
2023	.022	.006	.022	.05

Monthly

	Night	Morning	Afternoon	Whole day
January	.004	.001	.004	.01
February	.005	.001	.005	.011
March	.007	.002	.007	.015
April	.007	.002	.007	.016
May	.007	.002	.007	.016
June	.004	.001	.004	.009
July	.002	.001	.002	.005
August	0	0	0	0
September	.002	0	.002	.004
October	.003	.001	.003	.007
November	.005	.001	.005	.011
December	.01	.002	.01	.022

Monthdaily

	Night	Morning	Afternoon	Whole day
First 5 days	.027	.007	.027	.062
Other days	0	0	0	0
Last 5 days	.028	.007	.028	.063

Weekdaily

	Night	Morning	Afternoon	Whole day
Monday	.028	.007	.028	.064
Tuesday	.002	.001	.002	.005
Wednesday	0	0	0	0
Thursday	.004	.001	.004	.008
Friday	.021	.005	.021	.048

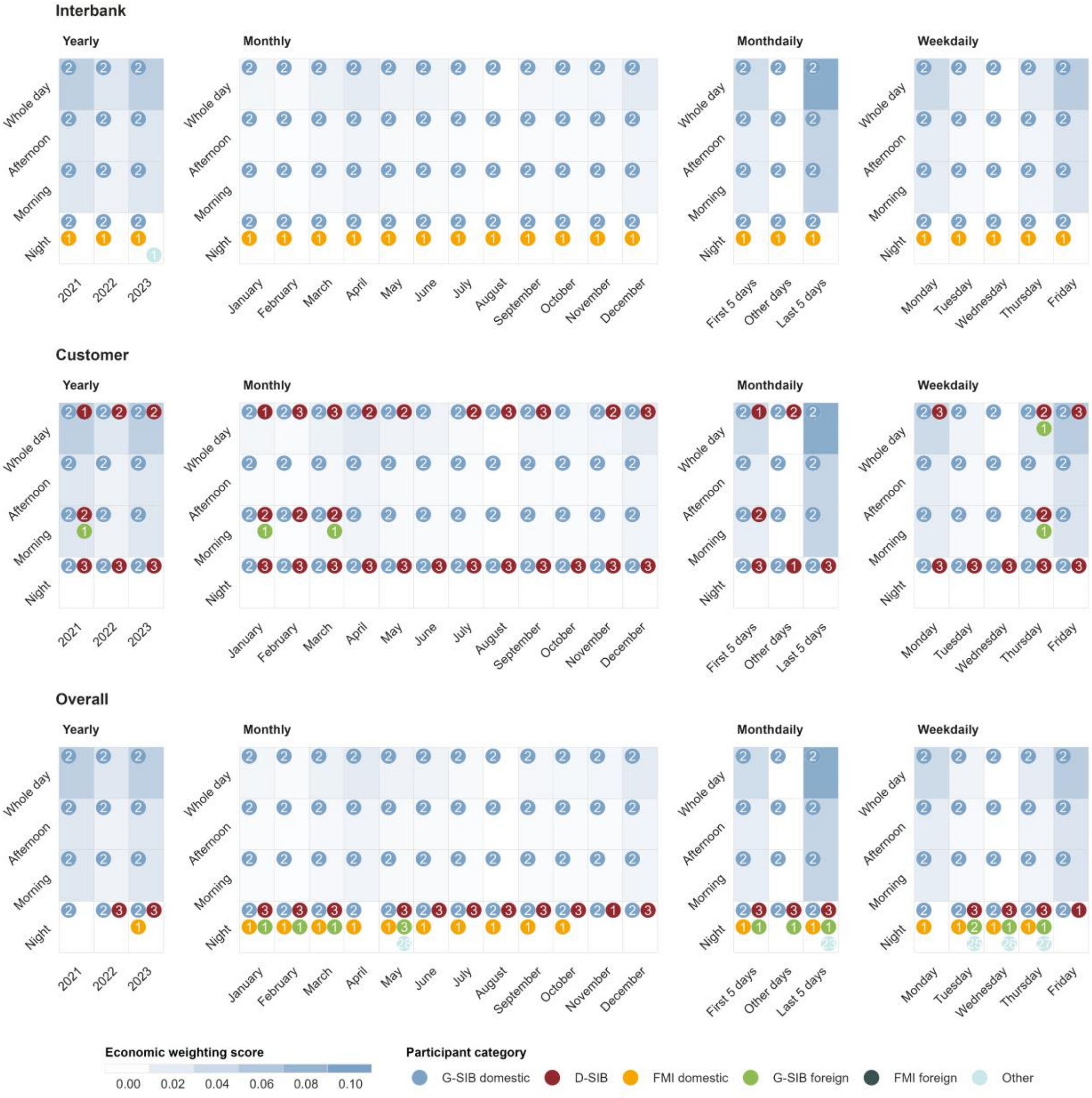
Economic weighting score

0.00 0.02 0.04 0.06 0.08 0.10

Note: The table shows the economic weights assigned to the different time frequencies, based on economic activity (value or volume) and qualitative assessment. These weights are applied consistently across all the payment types – interbank, customer, and overall – within the corresponding transaction view (value vs. volume). The weights for each of the time frequency categories (yearly, monthly, monthdaily, and weekdaily) sum to 0.25, ensuring that the maximum possible weighted criticality for any participant in a payment type totals 1.

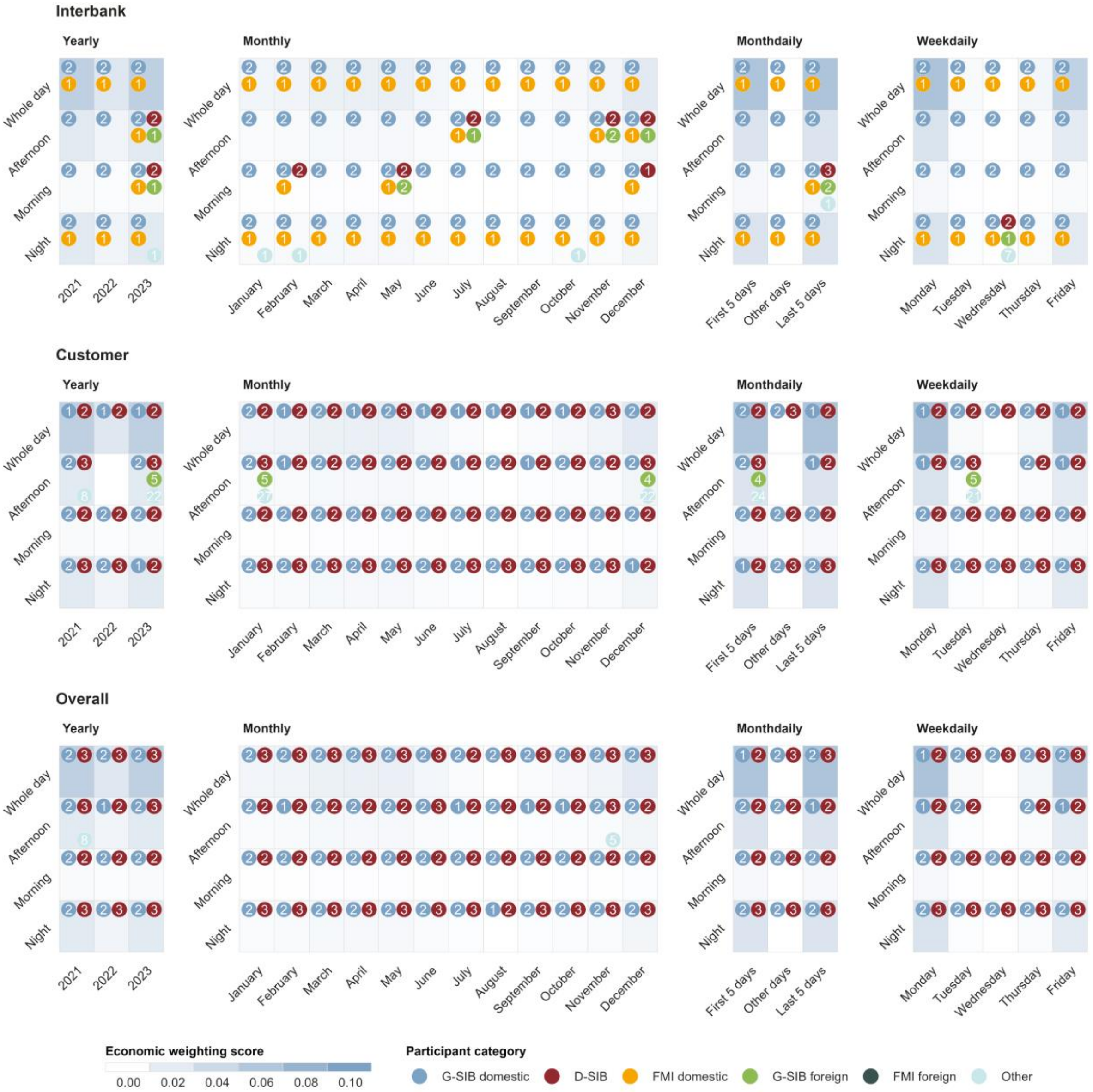
A5. Fully above-median critical (FAMC) participants in 276 scenarios

Figure A5-1: Illustration of the 276 scenarios of the value-based transaction view with their respective economic weights and numbers of FAMC participants



Note: The numbers above the circles indicate the number of FAMC participants in each scenario (tile), grouped by economic unit category. The shading of each tile reflects the value weight assigned to that specific scenario.

Figure A5-2: Illustration of the 276 scenarios of the volume-based transaction view with their respective economic weights and numbers of FAMC participants



Note: The numbers above the circles indicate the number of FAMC participants in each scenario (tile), grouped by economic unit category. The shading of each tile reflects the volume-based weight assigned to that specific scenario.

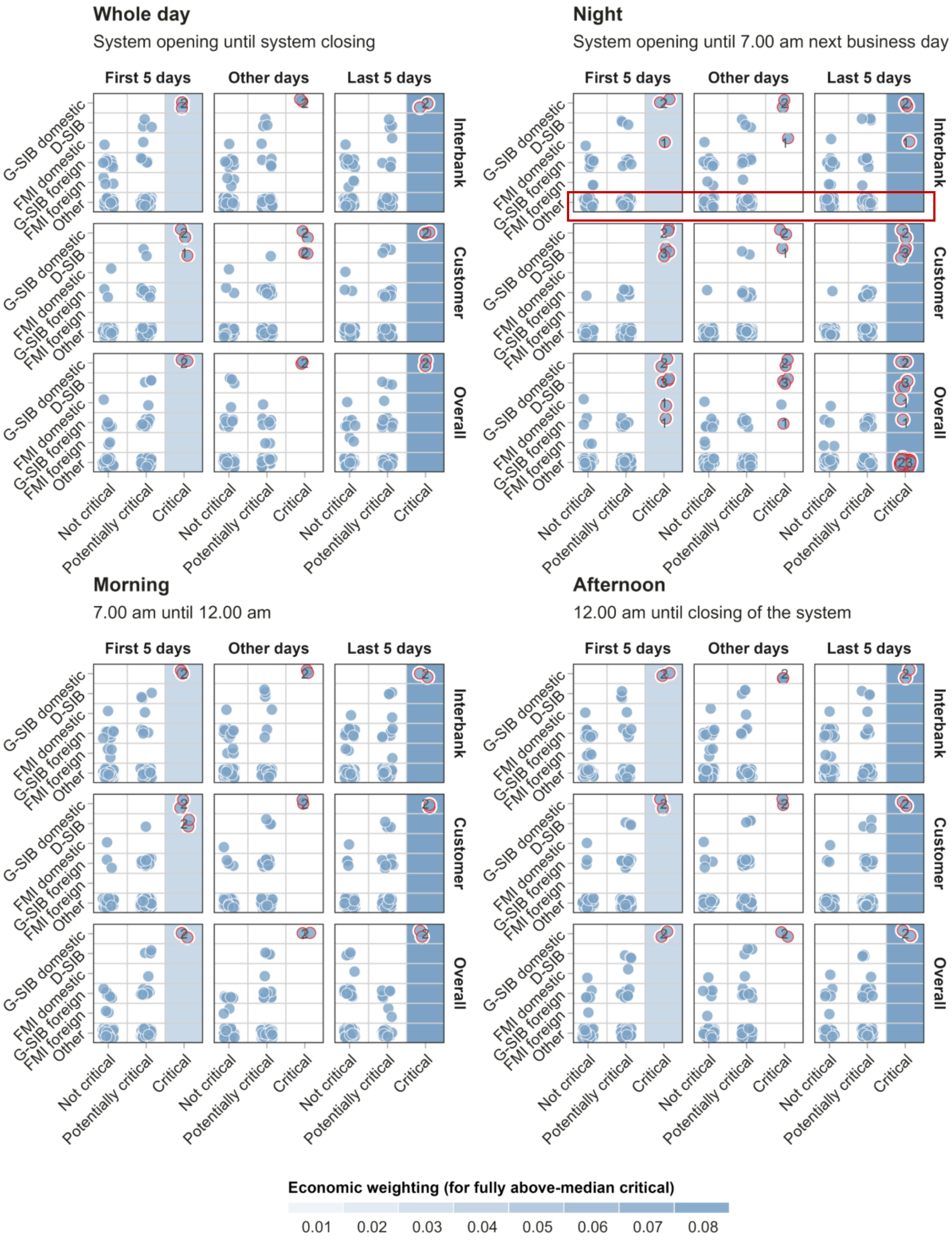
A6. Detailed example of the diverge-and-converge process: the value-based transaction view at ‘monthdaily’ frequency

To illustrate the value of temporal disaggregation in identifying systemic relevance, we present the diverge-and-converge process of our extended GMW approach to obtain value-based results at the “monthdaily” temporal frequency. This frequency divides each calendar month into three segments: the first five settlement days, its last five settlement days, and the remaining settlement days. Each segment is further subdivided into four daily time windows (whole day, night, morning, afternoon), resulting in 36 scenarios across all three payment types.

In each scenario, participants are clustered – to *critical*, *potentially critical* or *not critical* clusters – on the basis of their four network centrality indicators. A participant is considered FAMC if it is in the *critical* cluster and if all its four network indicators exceed their respective median of the *potentially critical* cluster in that scenario. These FAMC instances are then weighted by the economic relevance of each scenario and aggregated to produce the final *ultimate criticality* score. The full monthdaily clustering outcomes are visualised in Figure A6-1, with red-outlined dots indicating FAMC participants in that specific scenario and background shading in the right columns reflecting scenario weights, with which the FAMC instances are weighted to converge to a binary decision regarding *ultimate criticality*. In this monthdaily example, the last five settlement days carry the highest weight (dark shading), whereas the first five days have a lower weight (lighter shading), and the remaining days are assigned a weight of zero (see Figure A4-1 in the appendix for the numeric scenario weights).

These detailed value-based results show that some participants exhibit FAMC only during specific time windows. For example, one of the two domestic FMIs in interbank payments is critical at night but not during other intraday segments or whole days at the monthdaily frequency (see the red rectangle in the *night* panel of Figure A6-1). These contributions are masked in aggregate yearly analyses but become apparent when temporal detail is considered.

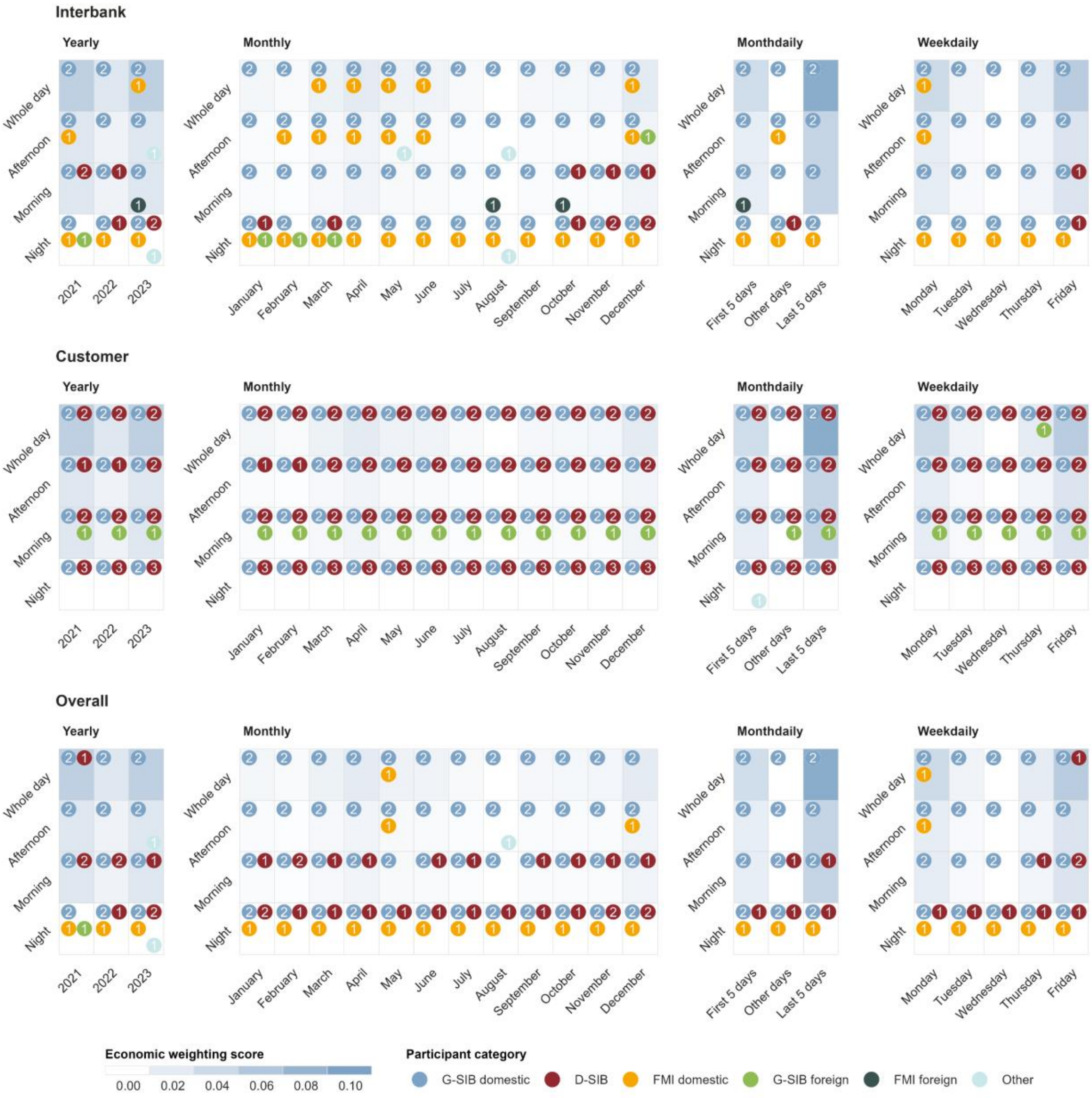
Figure A6-1: Monthdaily clustering results of the value-based transaction view, by intraday and payment category type



Note: The figure displays the 36 monthdaily scenarios (2021–2023) of the value-based transaction view for the interbank, customer, and overall payment types, further broken down into whole day, night, morning, and afternoon. The right columns show the number of critical participants in each cluster, and a participant's dot outlined in red indicates that it exhibits FAMC, meaning that all four of its network indicators exceed the medians of the potentially critical cluster. The background colour in these columns reflects the assigned weights for each scenario, which determine how the FAMCs are aggregated.

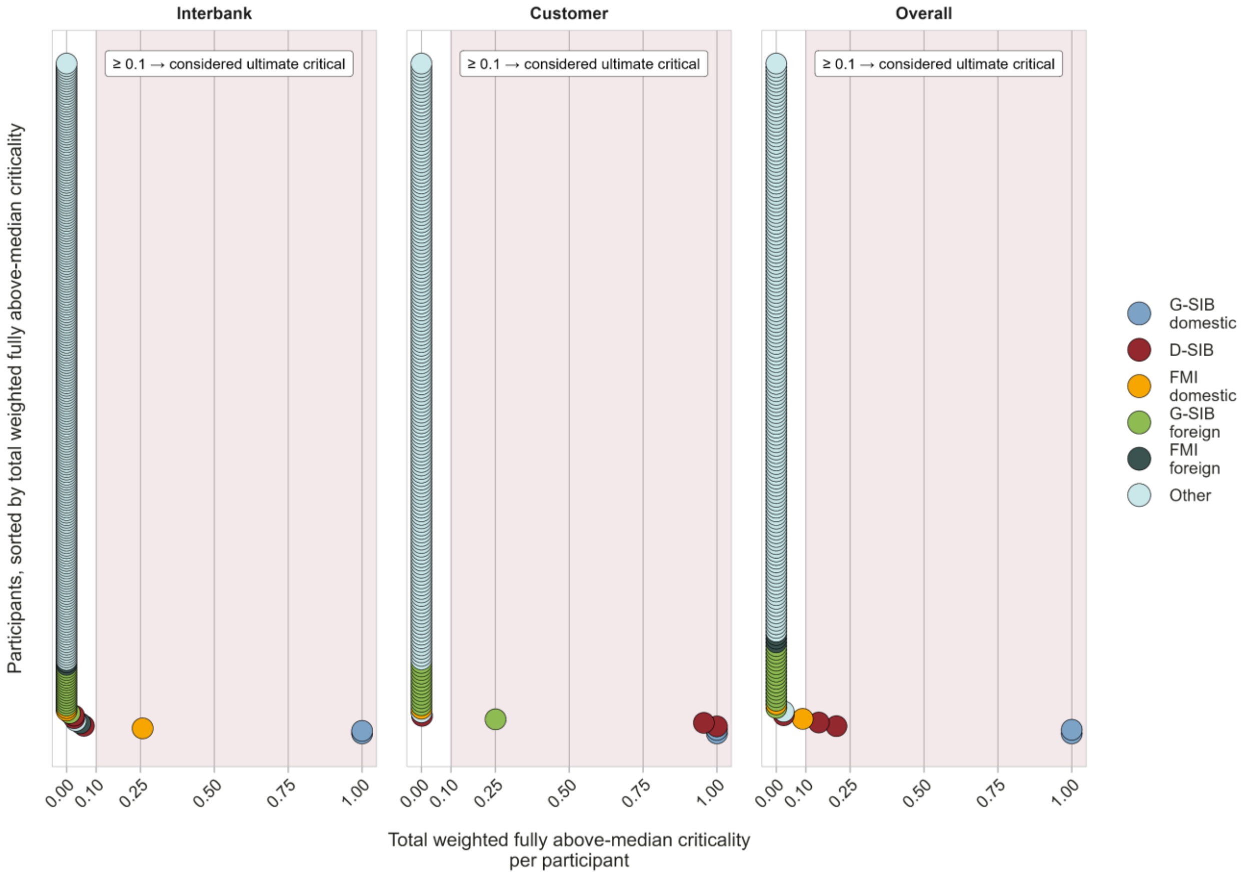
A7. Standard: Critical participants according to the conventional 5% turnover share threshold in 276 scenarios

Figure A7-1: Illustration of the 276 scenarios with their respective value-based economic weights and numbers of critical participants according to the conventional 5% turnover share criterion



Note: The numbers above the circles indicate the number of critical participants according to the 5% turnover share benchmark in each scenario (tile), grouped by economic unit category. The shading of each tile reflects the value-based weight assigned to that specific scenario.

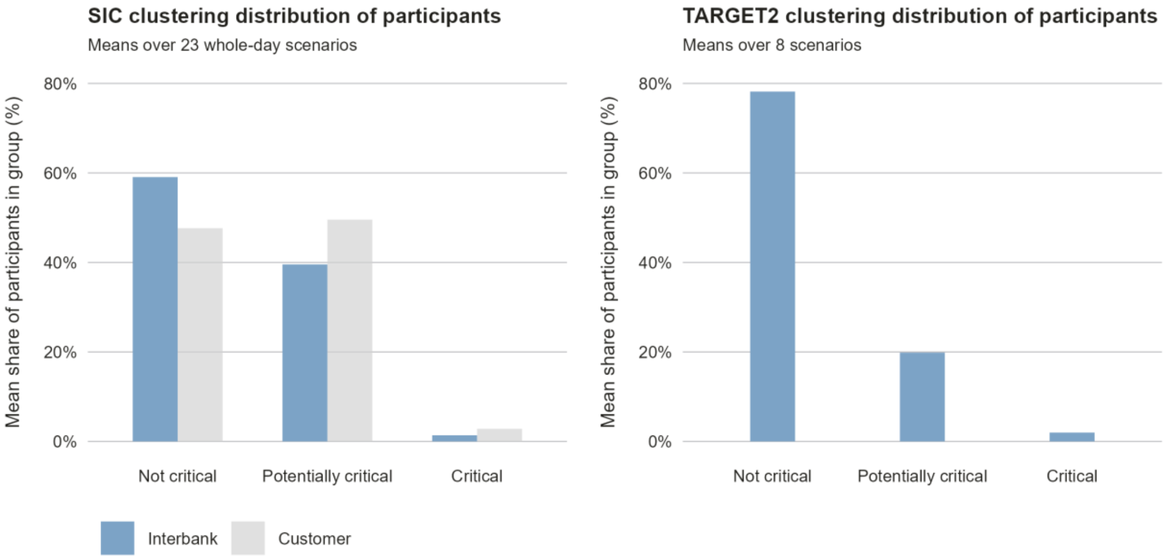
Figure A7-2: Summary of standard results across 276 distinct scenarios by payment type



Note: Each point represents the results of one SIC participant per payment type, based on the results of the conventional 5% turnover share in 276 scenarios, after value-based economic weighting. When a participant reaches a total weighted criticality above the threshold value of 0.1 for at least one payment type, the participant is deemed *ultimate critical* with respect to the standard. If a participant reaches *ultimate criticality* in all scenarios of a payment type, this is represented by a total weighted criticality of 1 for that payment type.

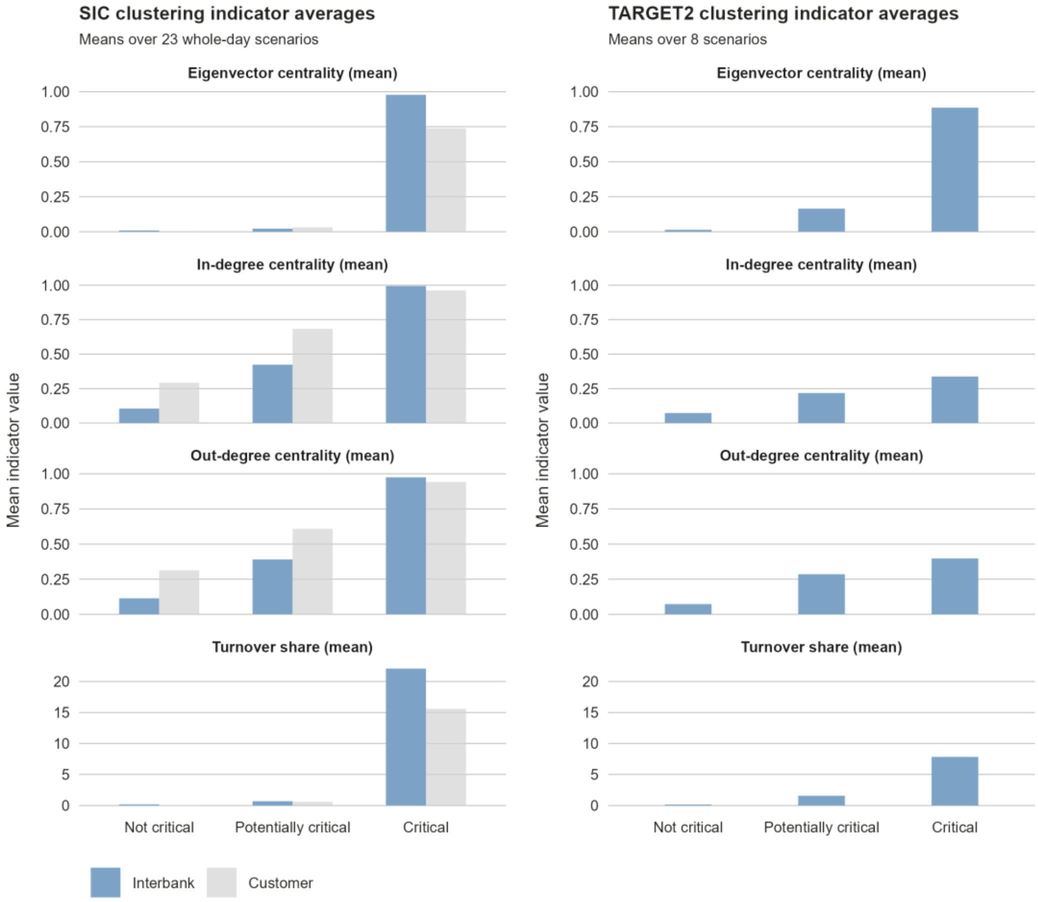
A8. TARGET2 comparison: Participant and indicator distribution by cluster

Figure A8-1: TARGET2 comparison: Participant distribution by cluster



Note: To compare the SIC distribution of participants across clusters with the TARGET2 results reported in GMW (2025), we first averaged the SIC clustering outcomes of the value-based transaction view (before assigning FAMC) over 23 whole-day scenarios to improve comparability. These distributions were compared with the average participant distribution from the eight TARGET2 scenarios in GMW (2025). The SIC results were broken down into the two payment types – interbank and customer – with the interbank category offering the closest comparison to TARGET2. This is because TARGET2 primarily handles large-value interbank and urgent customer payments, while regular customer payments are typically processed in bulk via retail clearing systems (e.g., SEPA-compliant automated clearing houses) and not settled individually in real time (European Central Bank 2019).

Figure A8-2: TARGET2 comparison: Indicator distribution by cluster



Note: To compare the SIC distribution of the indicator values across clusters with the TARGET2 results reported in GMW (2025), we first averaged the SIC clustering outcomes of the value-based transaction view (before assigning FAMC) over 23 whole-day scenarios to improve comparability. These distributions were compared with the average indicator distribution from the eight TARGET2 scenarios in GMW (2025). The SIC results were broken down into three payment types – interbank, customer, and overall – with the interbank category offering the closest comparison to TARGET2. This is because TARGET2 primarily addresses large-value interbank and urgent customer payments, while regular customer payments are typically processed in bulk via retail clearing systems (e.g., SEPA-compliant automated clearing houses) and not settled individually in real time (European Central Bank 2019).

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