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Repo market networks: dynamics under financial stress

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Abstract

The smooth functioning of the repo market is essential to financial stability. However, the market has faced repeated episodes of stress in recent years. This paper examines the resilience of the euro-denominated repo market during recent episodes of elevated financial stress, drawing on transaction-level data and applying network analysis. The institutional repo network displays a core–periphery structure, with connectivity intensifying during stress periods. At the sectoral level, trading volumes and repo spreads remain broadly stable. For the euro repo market as a whole, financial stress is associated with lower spreads, consistent with the interpretation that the market functions as a shock absorber.

JEL Classification: G01, G21, G23, E44

Keywords: Network analysis, Non-banks, Haircuts, Repo spreads

Non-technical summary

Repurchase agreements (repos), mostly short-term collateralised cash loans, are essential for circulating liquidity through the financial system. The euro repo market has grown to become the largest segment of the euro money market, allowing banks and non-bank financial institutions (NBFIs) to obtain cash, deposit cash or acquire specific securities. In recent years, repo markets have occasionally faced shortages of liquidity and operational problems. Such disruptions can strain banks' funding, threaten the stability of the broader financial system, and interfere with the transmission of monetary policy. Examining the network of connections between repo market participants can reveal how the market functions and how it is affected by stress, which may weaken key links, alter borrowing strategies, or raise trading costs.

The paper finds that the euro repo market has a small core of highly active institutions that do most of the trading, along with a larger group of less active participants. Over time, connections between institutions, especially banks trading with other banks, have grown, even during periods of stress. Trading volumes and borrowing costs between different types of institutions remain stable under stress. At the market level, borrowing costs decline as financial stress increases, indicating that the euro repo market remains resilient and helps absorb shocks through adjustments in pricing.

The paper analyses transaction-level repo data using network metrics and regression techniques. Financial stress is defined using the Composite indicator of systemic stress (CISS). Institutional and sectoral networks are constructed to map repo market activity between counterparties. Key network measures, such as density and strength, are examined alongside important repo market variables, including trading volumes, spreads, haircuts, and maturities, over time and across periods of stress. A regression framework is then used to quantify how financial stress affects these variables, providing a clear picture of how the market adjusts under stress.

The analysis covers euro-denominated repo transactions from 2021 to mid-February 2025, using transaction-level data from the Securities Financing Transactions Data Store (SFTDS).

The paper offers insights for policymakers on how repo markets function during periods of elevated financial stress. The findings have important implications for designing repo market regulations and for developing comprehensive financial stability frameworks that track both individual institutions and sector-level interconnections.

1 Introduction

The repo market is an essential channel through which liquidity circulates across the financial system (Schaffner et al., 2019). A repurchase agreement (repo) is a secured borrowing arrangement in which a dealer sells securities, such as government or corporate bonds, to an investor, and pledges to repurchase them at a slightly higher, pre-specified price, often the next day[2] (e.g., Gottardi et al., 2019). Repos are primarily short-term instruments, functioning at their core as collateralized cash loans. Repos are essential financial instruments, particularly for major financial institutions within the non-depository banking sector, to obtain liquidity, deposit cash or receive specific securities. By enabling secured borrowing, repos offer an alternative to unsecured loans or the issuance of short-term debt instruments (ECB, 2010). Due to their role in providing financing and supporting the efficient allocation of securities, repos are vital to the functioning of financial markets.

Evidence from past crises reveals that repo markets can face vulnerabilities. Disruptions in the repo market can impair liquidity and the funding conditions of banks, potentially destabilising the broader financial system and obstructing the transmission of monetary policy (Ferrara et al., 2024; Bassi et al., 2024b). Moreover, with non-bank financial institutions (NBFIs) playing an increasingly prominent role in these markets, vulnerabilities in the repo market can propagate more rapidly throughout the entire financial system (ESRB, 2024). In recent years, repo markets have been subject to several episodes of illiquidity and operational dysfunction (ESRB, 2024). The financial crisis of 2007/2008 demonstrated the severe adverse consequences that can arise when the repo market fails to operate effectively (e.g. Martin et al., 2014; Gorton and Metrick, 2012). Runs on the repo market have the potential to quickly amplify and spread systemic risk to the whole financial system (Copeland et al., 2012). In March 2020, US hedge funds, using repos for basis trades, caused substantial liquidity stress in US Treasury markets (Financial Stability Board, 2020). In September 2022, euro area liability-driven investment (LDI) funds trading with UK counterparties leveraged their gilt exposure with repos, leading to solvency and liquidity issues when market prices for bonds dropped as yields for gilts rose (ESRB, 2023). These events highlight that especially vulnerabilities caused by leveraged trading strategies can spillover and lead to market and liquidity stress in other markets (Bassi et al., 2024b).

[2] Although repos typically have a short-term maturity, lasting only a few days, it is not uncommon to encounter repos with maturities extending up to two years, while open repos have no fixed end date.

The repo market has emerged as the largest segment of the euro money market, accounting on average for 56% of daily transactions and 30% of outstanding amounts (ECB, 2023). Moreover, the euro area repo market has been growing in recent years: according to a survey conducted by the International Capital Market Association (2024), which includes 61 financial institutions in Europe, primarily banks, there was a 4.9%[3] increase in the total value of outstanding repos from June 2023 to June 2024. Over the last ten years, daily turnover in the secured segment has more than doubled, whereas the interbank unsecured segment has contracted to just one-tenth of its former size. The secured segment has become increasingly attractive compared to the unsecured one, driven by reduced counterparty risk, more favourable regulatory treatment, and the efficiency of repos in acquiring securities. As a result, the euro area repo market has become the primary venue of short-term trading (ECB, 2023).

Despite the importance of the repo market in providing short-term liquidity to the financial system, there is little empirical work that uses recent data to study the dynamics in the network underlying the euro-denominated repo market and its resilience to financial stress. However, understanding the network dynamics within the repo market is crucial, as it can shed light on the cause of liquidity disruptions during periods of financial stress. For instance, critical links between counterparties may weaken, certain sectors might alter their borrowing strategies via the repo market due to risk considerations, or increased spreads could inflate trading costs. This paper seeks to address this gap by applying network analysis to transaction-level euro-denominated repo market data from the Securities Financing Transactions Data Store (SFTDS) to examine the interconnectedness among sectors active in the euro area repo market[4]. The analysis is closely following the framework introduced by Hüser et al. (2024) on the overnight gilt repo market. The focus of the analysis is how the structure of the repo network evolves and how different sectors, including NBFIs, adjust their borrowing and lending during stress episodes. In addition, a regression framework following Mancini et al. (2016) and Hüser et al. (2021) is employed to assess how financial stress affects key repo market variables, such as volumes, repo spreads, haircuts, and maturities.

[3] Adjustments for changes in the composition of the survey sample were made by calculating the growth rate using a consistent subset of 59 participants who had participated in the last three surveys.

[4] The analysis also provides further insights on the repo segment in the relatively new SFTDS dataset. To the best of my knowledge, there are currently only four papers studying various aspects of the repo market using SFTDS (Bassi et al., 2024b; Sliepenbeek, 2023; Grill et al., 2024; Hermes et al., 2025). In contrast, there is a larger body of literature on the repo market utilizing MMSR data, which has been available since 2016 (e.g., Eisenschmidt et al., 2024; de Souza and Hudepohl, 2024; Bassi et al., 2024a; Breckenfelder and Hoerova, 2023; Vela and Aguilar, 2024; Nicoletti et al., 2024).

In summary, this paper investigates three key research questions. First, to what extent are various institutions and sectors interconnected through trades in the euro-denominated repo market? Second, how is this network influenced by periods of financial stress? Third, how resilient is the euro-denominated repo market to financial stress?

The key findings are as follows. First, the institutional network displays a core–periphery structure. A tightly connected core of financial institutions conducts high-volume trades among themselves and with a loosely connected periphery of infrequent, lower-volume participants. Second, although the institutional network is generally sparse, its density shows an increasing trend over time, including during periods of financial stress. This rise in inter-institutional linkages is driven mainly by increased connections within the bank-to-bank sub-network. Third, the sectoral network analysis reveals no significant changes in trading volumes and repo spreads between sectors during periods of high financial stress. Fourth, financial stress is associated with a significant decline in repo spreads whereas volumes, haircuts and maturities remain stable. Overall, this points to resilience, with adjustment occurring mainly through pricing rather than through changes in activity or contractual terms.

This paper contributes to the empirical literature on how repo markets respond to financial stress. Gorton and Metrick (2012) report rising repo spreads and haircuts on the bilateral market during the Global Financial Crisis. Krishnamurthy et al. (2014) detect a sharp decline in the tri-party repo funding during the crisis consistent with a repo run[5]. However, the absolute decrease in funding is small relative to the aggregate amount of short-term securitised funding, but disproportionately impacting a few systemically important dealer banks. In contrast, Copeland et al. (2014) do not find evidence of a repo run in the tri-party repo segment during the crisis, as they observe that margins for most collateral and the level of funding remained stable. Mancini et al. (2016) study the central counterparty-based euro interbank repo market and find stable spreads, haircuts and maturities during periods of stress and conclude the resilience of the market, whereas the more recent study on the euro area sovereign debt crisis by Boissel et al. (2017) reports that repo rates in the centrally cleared segment were strongly affected by high sovereign risk. Also, Hüser et al. (2024) find increased repo rates in the gilt repo market during the COVID-19 crisis. The Bank of England's System-Wide Exploratory Scenario highlights the critical role of repo markets in providing liquidity (Bank of England, 2024). However, the exercise

[5] In a tri-party repo, a third-party agent handles collateral management between the borrower and lender. A repo run refers to a sudden withdrawal of funding by lenders, due to concerns about counterparty or collateral risk (e.g., Martin et al., 2014)

reveals that banks are unlikely to meet the increased demand for repo financing during market stress, despite having access to central bank facilities. In particular, banks are less willing to extend funding to non-banks than market participants expect, highlighting a potential funding gap under adverse conditions.

In addition to the broader strand of literature outlined above, the paper also contributes to a more specific subset of literature focused on how various non-bank sectors in the repo market react to periods of stress. For instance, Gorton et al. (2020) find that money market funds (MMF) increased their borrowing during the Global Financial Crisis, even as overall repo funding declined. Hüser et al. (2024) observe that, during the COVID-19 crisis, all non-bank sectors reduced their borrowing and increased their lending in the gilt repo market except for hedge funds, which increased their borrowing activities and MMF, which decreased their lending. Bassi et al. (2024b) report that the investment fund sector decreased their borrowing in the euro area repo market during times of crisis. In conclusion, there is little empirical evidence on how various sectors respond under stress, and no clear finding on how non-bank sectors adjust their activity in the repo market during times of crisis.

Analysing the network of institutions and sectors trading in the repo market is essential for assessing its functioning and resilience, particularly under conditions of financial stress. As mentioned, this paper builds on the work of Hüser et al. (2024), who examine the overnight gilt repo market and its response to funding liquidity stress during the COVID-19 crisis. The paper extends that analysis by using a different and larger dataset to study the euro-denominated repo market. In contrast to earlier studies focusing on crisis episodes such as the Global Financial Crisis or COVID-19, this paper examines a more recent period (2021 to February 2025) characterized by monetary tightening and geopolitical shocks. Given the expanding role of NBFIs in repo markets and international policy efforts that aim to address their vulnerabilities (Bassi et al., 2024b), the paper offers timely insights into the behavior and interconnectedness of both banks and NBFIs. The findings have implications for the design of repo market regulations and the development of more comprehensive financial stability frameworks that account for sectoral interlinkages. They contribute both to policy discussions and to the academic literature on market-based finance.

The paper is structured as follows: Section 2 describes the data sources and outlines the specifications used in the analysis. Section 3 presents the empirical strategies, including the definition of high-stress periods, as well as the construction of the institutional and sectoral networks and associated metrics. Section 4 provides descriptive statistics. Section 5 discusses the empirical findings, focusing on network analyses at both the institutional and sector levels, and assesses the overall resilience of the euro repo market. Section 6 concludes.

2 Data

The primary data source is transaction-level repo data from SFTDS. The new Composite Indicator of Systemic Stress (CISS) (Chavleishvili and Kremer, 2025) is used as a measure of financial stress. The euro short-term rate (€STR) and excess liquidity are also included in selected regression models. The following section provides a detailed description of data used in the analysis.

2.1 Transaction-level repo data

Transaction-level data on repos is inferred from SFTDS, which records all securities financing transactions (SFTs)[6] conducted within the euro area, along with all reported transactions involving entities under supervision in the euro area. SFTDS is a relatively new dataset available only as of July 2020. Moreover, since data quality from 2021 is more reliable (as, e.g., indicated by Bassi et al. (2024b)), the analysis in this paper only uses observations from that point onwards. Therefore, the analysis includes business days from 2 January 2021 until 15 February 2025. To ensure comparability in the subsequent analyses and to capture the most representative and connected segment of the market,[7] I focus on euro-denominated trades, the largest segment in the dataset. I refer to this subset as the *euro repo market* throughout the paper.

The SFTDS repo data used in this analysis are de-duplicated, ensuring that if the same trade is reported by more than one counterparty, only a single instance is retained. For centrally cleared trades, the transaction included reflects the final counterparties, those ultimately exchanging cash and collateral. Furthermore, the analysis concentrates on flow data rather than stock data, as the main interest is in newly agreed repo transactions rather than outstanding amounts. Consequently, only the first instance of a reported repo is included in the dataset.

[6]SFTs are crucial to the financial system, offering funding, cash investment, collateral transformation, and facilitating hedging and liquidity provision. Data is gathered in accordance with the Securities Financing Transactions Regulation (SFTR), mandating that institutions report their securities financing transactions to a trade repository registered by the European Securities and Markets Authority (ESMA).

[7]Restricting the sample to euro-denominated repos enhances, e.g., the interpretability of the institutional network by avoiding an inflated set of potential connections with institutions active only in other currencies and thus unlikely to interact with euro area counterparties. This restriction is also applied in Bassi et al. (2024b).

For the sector classification of the borrower and lender of the repo transactions, I employ the matching of SFTDS and EMIR developed by Lenoci and Letizia (2021). For a further categorization of banks, I also differentiate whether banks are authorized primary dealers as published by European Securities and Markets Authority (ESMA) (2025), applying the approach used in Hermes et al. (2025). As a result, the analysis differentiates between the following sectors: dealer banks (DB), non-dealer banks (NDB), other financial intermediaries (OFI), central clearing counterparties (CCP)[8], investment funds (IF), pension funds (PF), insurance corporations (IC), and money market funds (MMF).

To ensure comparability, further data cleaning to detect reporting errors was performed prior to the analysis as described in Annex A.1.

2.2 Composite indicator of systemic stress

To define periods of elevated financial stress, I utilize the new CISS, which is available on a daily frequency for the euro area[9]. This new CISS was developed by Kremer and Chavleishvili (2021) and is based on the original CISS by Hollo et al. (2012). Throughout this paper, "CISS" refers exclusively to the new CISS. Systemic risk refers to the potential for financial instability to become so pervasive that it significantly disrupts the delivery of financial services to the economy, leading to substantial negative impacts on growth and employment (De Bandt and Hartmann, 2000). The CISS assigns greater weight to scenarios where stress is prevalent across multiple market segments simultaneously. This weighting reflects the notion that financial stress becomes more systemic and therefore more threatening to the overall economy when financial instability pervades the entire financial system (Hollo et al., 2012). The CISS is an established indicator widely used in the literature (e.g., Mancini et al., 2016; Creel et al., 2015; Duprey et al., 2017; De Santis, 2020; Burriel and Galesi, 2018).

The new CISS measures financial stress in the euro area by aggregating a representative set of 15 sub-indicators[10] capturing stress on the money market, bond market, equity market,

[8] A CCP appears as a borrower or lender in a SFTDS repo trade for one of two reasons. First, during the data cleaning of centrally cleared trades, when the ultimate counterparty could not be identified, the CCP was listed by default. Second, the trade is a genuine CCP investment: CCPs routinely place surplus margin cash in the market as reverse repos for short-term cash-management purposes. CCPs must re-invest at least 95% of the cash received from initial margin collateral requirement (Benos et al., 2022). The data do not allow to differentiate whether a reverse repo by a CCP is conducted as part of their clearing operations or their cash management activities. In the studied data, CCP are listed as borrowers or lenders for about 2.8% of observations.

[9] The new CISS is publicly available via the ECB Data portal under the series key: `CISS.D.U2.Z0Z.4F.EC.SS_CIN.IDX`.

[10] The 15 sub-indicators are as follows: money market: volatility of 3-month Euribor, rate spread 3-month

financial intermediaries, and foreign exchange market. It quantifies the severity of financial stress[11] on a continuous scale and is by construction bounded between zero and one.

2.3 Excess Liquidity, €STR and €STR transaction volume

In selected regression analyses, excess liquidity, €STR and €STR transaction volumes are incorporated. Excess liquidity is used as a measure of funding liquidity. It refers to surplus funds in the banking system that remain after commercial banks have fulfilled their minimum reserve requirements. These excess funds are typically held in banks' current accounts at their respective national central banks. The excess liquidity numbers are available on a daily basis and downloaded from Bloomberg.

The €STR captures the cost at which euro area banks obtain unsecured overnight funding in the wholesale market (ECB, 2021). The related volume[12] describes the total amount traded in the euro unsecured overnight market.

3 Empirical Strategy

This section outlines the empirical strategy. It begins by identifying periods of high financial stress using the CISS indicator, followed by formal definitions of the institutional and sectoral networks, along with the corresponding network metrics. The section then introduces the linear model used to estimate changes in sectoral trading volumes and spreads, as well as the bootstrap approach employed to assess the statistical significance of these changes.

3.1 Identifying periods of high financial stress

Figure 1a presents the time series of the CISS from 2000 to February 2025. The study period (shaded in grey) encompasses both episodes of pronounced financial stress and periods of

Euribor against French Treasury bill; bond market: volatility of German 10-year benchmark government bond price index, yield spread 10-year interest rate swap against German government bonds, yield spread 7-year A-rated non-financial corporate bonds against AAA-rated government bonds, yield spread 7-year A-rated financial corporate bonds against AAA-rated government bonds; equity market: volatility of non-financial stock price index, maximum cumulated loss (CMAX) of non-financial stock price index over moving 2-year window, book-price ratio of non-financial stock price index; financial intermediaries: volatility of financial stock price index, CMAX of financial stock price index, book-price ratio of financial stock price index; and foreign exchange market: volatility of euro exchange rate vis-a-vis US dollar, Japanese Yen, and British pound.

[11] For detailed information on the methodology of the CISS, such as the probability integral transformation of each sub-indicator, see Kremer and Chavleishvili (2021).

[12] €STR and the respective total volume are publicly available for each TARGET2 business day via the ECB Data Portal under the series keys `EST.B.EU000A2X2A25.WT` and `EST.B.EU000A2X2A25.TT`, respectively.

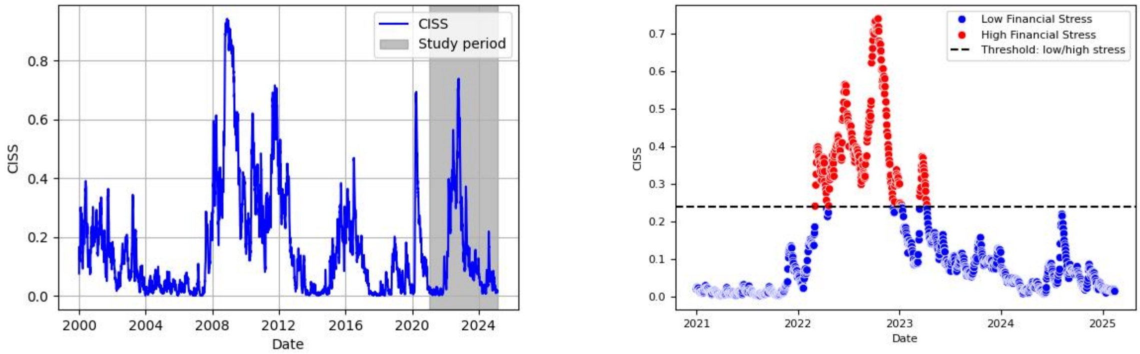
exceptionally low stress, with index values ranging from 0.002 to 0.738 and averaging 0.138. These fluctuations are comparable to earlier peaks and troughs in the sample, providing ample variation to analyse repo market dynamics under contrasting financial conditions.

To identify periods of high and low financial stress, I apply the k-means clustering algorithm with two clusters, a method introduced by MacQueen (1967), to the entire period where the CISS is available (3 January 1980 to 14 February 2025). K-means clustering is an unsupervised algorithm that partitions data into k clusters by minimizing the average distance between points within each cluster, effectively grouping similar data points together. Besides k-means clustering, several alternatives for classifications were explored, such as Hidden Markov models, using percentiles or thresholds obtained from the literature, further details are reported in Annex A.2. Given the limitations of alternative methods, this paper uses k-means clustering, which avoids strong distributional assumptions and arbitrary thresholds. Figure 1b shows the dates in the study period that are classified as low financial stress (depicted in light blue) and high financial stress (depicted in red). The algorithm classifies a day as experiencing high financial stress if the CISS value exceeds the threshold of 0.239.

The high level of the CISS observed between early March 2022 and early January 2023, as shown in Figure 1b, likely reflects the combined impact of several factors. First, financial stress may have been caused by interest rate hikes following a prolonged period of low inflation, along with the discontinuation of the net asset purchase programme in April 2022 and the pandemic emergency purchase programme in July 2022. Second, supply shocks affecting energy and agricultural commodities, triggered by the Russian invasion of Ukraine, likely added to market uncertainty. The smaller spike observed from mid-March to mid-April 2023 likely reflects market stress following the collapse of several US banks, such as the Silicon Valley Bank, and the rescue of Credit Suisse.

3.2 Defining the institutional network

I define the institutional network (indicated by the superscript I) of the euro repo market over the set of discrete business days $\mathcal{T} = \{t_1, t_2, \ldots, t_T\}$, where $t_1 =$ January 2, 2021 and $t_T =$ February 15, 2025. The sample comprises $T =$ 1,013 business days in total. $\mathcal{N}^{(I)} = \{1, \ldots, N^{(I)}\}$ represents the $N^{(I)} = 4572$ institutions active in the euro repo market at least once as a borrower or lender in $\mathcal{T}$. For each business day $t \in \mathcal{T}$, $V_{lb}^{(I)}(t)$ denotes the total nominal amount of cash (in euro) transferred from the lending institution l to the borrowing institution b through the



(a) Time series of CISS

(b) K-means clustering of the CISS: high vs. low stress

Figure 1 CISS time series and identification of stress periods

euro repo market. In the institutional repo network, each node represents a financial institution, and a directed edge from lender l to borrower b is created whenever $V_{lb}^{(I)}(t) > 0$, with the traded volume $V_{lb}^{(I)}(t)$ representing the edge weight.

For each business day $t \in \mathcal{T}$, I define the binary, asymmetric adjacency matrix $\mathbf{P}^{(I)}(t) = \left(p_{lb}^{(I)}(t)\right)_{l,b \in \mathcal{N}^{(I)}} \in \{0,1\}^{N^{(I)} \times N^{(I)}}$ for the institutional network, where each entry is given by

$$p_{lb}^{(I)}(t) = \begin{cases} 1, & \text{if } V_{lb}^{(I)}(t) > 0, \\ 0, & \text{otherwise.} \end{cases}$$

By construction, all diagonal entries of the defined adjacency matrix are zero, reflecting the fact that self-loops, edges connecting a node to itself, are excluded in the representation of simple graphs.

Focusing on the entire study period, the probability of a trade between two institutions l and b on a given business day is derived as $\overline{\mathbf{P}}^{(I)} = \left(\bar{p}_{lb}^{(I)}\right)_{l,b \in \mathcal{N}^{(I)}} \in [0,1]^{N^{(I)} \times N^{(I)}}$, with $\bar{p}^{(I)} := \frac{1}{T} \sum_{t \in \mathcal{T}} p_{lb}^{(I)}(t)$. T being the total number of business days in the studied period.

Let $\mathbf{V}^{(I)}(t) = \left(v_{lb}^{(I)}(t)\right)_{l,b \in \mathcal{N}^{(I)}} \in [0,\infty)^{N^{(I)} \times N^{(I)}}$ be the matrix of total notional cash flows in the institutional network on business day t, where each entry $v_{lb}^{(I)}(t)$ is the aggregate volume of cash lent from institution l to institution b via repo transactions on that day. If a pair of institutions engages in multiple repos on the same day, $v_{lb}^{(I)}(t)$ sums across all such transactions. The average daily transaction volume over the sample period is defined as $\mathbf{V}^{(I)} = \left(\bar{v}_{lb}^{(I)}\right)_{l,b \in \mathcal{N}^{(I)}} \in [0,\infty)^{N^{(I)} \times N^{(I)}}$, with $\bar{v}_{lb}^{(I)} := \frac{1}{T} \sum_{t \in \mathcal{T}} v_{lb}^{(I)}(t)$.

To assess whether certain pairs of institutions predominantly engage in repo transactions during periods of financial stress (denoted by FS), consider the matrix $\mathbf{F}^{\mathrm{FS}} = \left(f_{lb}^{\mathrm{FS}}\right)_{l,b\in\mathcal{N}^{(I)}} \in [0,1]^{N^{(I)}\times N^{(I)}}$, where each entry is defined as

$$f_{lb}^{\mathrm{FS}} := \begin{cases} \dfrac{\sum_{t\in\mathcal{T}_{\mathrm{FS}}} p_{lb}^{(I)}(t)}{\sum_{t\in\mathcal{T}} p_{lb}^{(I)}(t)}, & \text{if } \sum_{t\in\mathcal{T}} p_{lb}^{(I)}(t) > 0 \\ 0, & \text{otherwise.} \end{cases}$$

$\mathcal{T}_{\mathrm{FS}}$ denotes the subset of business days associated with heightened financial stress. The numerator captures the number of stress-period trading days during which institution l lent to institution b, while the denominator reflects the total number of trading days for the pair over the full sample period. High values of f_{lb}^{FS} indicate that the corresponding institution pair trades almost exclusively during stress episodes. Conversely, lower values suggest that their trading activity is not restricted to crisis periods and continues during low-stress times as well.

3.3 Defining the sectoral network

The sectoral repo network (indicated by the superscript S) is composed of a set of nodes $\mathcal{N}^{(S)} = \{1,\ldots,N^{(S)}\}$, each representing a distinct institutional sector active in the euro repo market. In this analysis, institutions are grouped into $N^{(S)} = 6$ sectors. For each trading day $t \in \mathcal{T}$, let $v_{lb}^{(S)}(t)$ denote the total nominal amount lent from sector l to sector b via a repo transactions. If $v_{lb}^{(S)}(t) > 0$, then there exists a directed edge from node l to node b at time t, with edge weight $v_{lb}^{(S)}(t)$.

The matrix of total nominal amount of repo borrowing at business day t is defined as:

$$\mathbf{V}^{(S)}(t) = \left(v_{lb}^{(S)}(t)\right)_{l,b\in\mathcal{N}^{(S)}} \in [0,\infty)^{N^{(S)}\times N^{(S)}}.$$

The corresponding adjacency matrix is given by:

$$\mathbf{P}^{(S)}(t) = \left(p_{lb}^{(S)}(t)\right)_{l,b\in\mathcal{N}^{(S)}} \in \{0,1\}^{N^{(S)}\times N^{(S)}}, \text{where } p_{lb}^{(S)}(t) = \begin{cases} 1, & \text{if } v_{lb}^{(S)}(t) > 0, \\ 0, & \text{otherwise.} \end{cases}$$

Here, $p_{lb}^{(S)}(t)$ indicates whether sector l lent to sector b on day t.

The average probability of sector l lending to sector b across the sample period is given by the matrix $\overline{\mathbf{P}}^{(S)} \in [0,1]^{N^{(S)} \times N^{(S)}}$, with entries defined as $\overline{P}^{(S)}_{lb} = \frac{1}{T}\sum_{t\in\mathcal{T}} p^{(S)}_{lb}(t)$. Each element $\overline{P}^{(S)}_{lb}$ thus represents the empirical frequency with which sector l lent to sector b on any given day in the sample.

3.4 Network metrics

The following outlines the calculation of the empirical survival function, network density, average degree, and average strength as applied to the institutional network. Network density is additionally computed for the sectoral network.

As one measure of connectedness, I calculate the empirical survival function of the average in- and out-degrees of nodes in the network. The degree of a node quantifies an institution's total number of transactions with other institutions. The in-degree of a node represents the number of edges directed towards it, corresponding to the number of borrowing transactions. Conversely, the out-degree captures the number of edges directed away from the node, reflecting its lending activity. The average in- and out-degrees of the network are obtained by averaging the daily degree measures across all institutions in the dataset. The survival function is derived as $1 - F(deg)$ from the empirical cumulative distribution function $F(deg)$, with $deg \in \{1, \ldots, N^{(I)} - 1\}$ denoting the degree, which is computed separately for borrowing and lending transactions. The function $F(deg)$ denotes the probability that a node's average degree is less than or equal to deg, while the corresponding survival function, $1 - F(deg)$, captures the probability that the average degree exceeds deg. Given that the institutional network comprises $N^{(I)} = 4572$ nodes[13], the maximum number of distinct counterparties any institution can engage with either as a lender or a borrower is bounded by $N^{(I)} - 1$, as self-interactions are excluded.

As a second measure of connectedness, I calculate the network density. At each business day t, network density is computed as

$$\text{Network density}(t) = \frac{1}{N^{(I)}(N^{(I)} - 1)} \sum_{l=1}^{N^{(I)}} \sum_{b=1}^{N^{(I)}} p^{(I)}_{lb}(t). \tag{1}$$

where $p^{(I)}_{lb}(t)$ is an indicator that equals one if institution l lent to institution b on day t, and zero otherwise. This metric captures the ratio of actual links observed in the network to the total number of possible links, excluding self-connections.

[13] For an evolution of the number of entities active over time see Figure 2b.

A complementary measure of network connectedness is the average degree, defined as the number of edges divided by the number of nodes in a directed network. It quantifies the average number of distinct trading partners per institution on a given day. Formally, it is given by

$$\text{Average degree } (t) = \frac{1}{N^{(I)}} \sum_{l=1}^{N^{(I)}} \sum_{b=1}^{N^{(I)}} p_{lb}^{(I)}(t). \tag{2}$$

This measure captures how widely institutions are connected through repo transactions, with higher values indicating greater interconnectivity.

In addition to evaluating connectedness through network density and average degree, I also assess the intensity of interactions by calculating the strength of the network. The strength of an active node is a volume-weighted measure of its degree, incorporating the total repo volumes transacted with each counterparty. It is defined as

$$\text{Average strength}(t) = \frac{1}{n^{(a)}(t)} \sum_{l=1}^{N^{(I)}} \sum_{b=1}^{N^{(I)}} v_{lb}^{(I)}(t), \tag{3}$$

where $n^{(a)}(t) \leq N^{(I)}$ denotes the number of active institutions at time t. An institution is considered active if it engages in at least one repo transaction, either as a lender or as a borrower. The average strength can also be interpreted as a normalized version of the aggregate transaction volume, adjusted for the number of institutions participating in the repo market on that day.

On the sectoral network, I define the network density for each day t as

$$\frac{1}{N^{(S)}(N^{(S)} - 1)} \sum_{l=1}^{N^{(S)}} \sum_{b=1}^{N^{(S)}} p_{lb}^{(S)}(t), \tag{4}$$

where $p_{lb}^{(S)}(t)$ is an indicator that equals one if sector l lent to sector b on day t, and zero otherwise. The metric captures the ratio of actual links between sectors observed in the network to the total number of possible links, excluding self-connections.

3.5 Defining the linear model to estimate changes in volumes and repo spread during high-stress periods

To analyse changes in volumes traded in the sectoral network, I estimate the following linear model on the sectoral level:

$$v_{lbt} = \sum_{l \in N^{(S)}} \sum_{b \in N^{(S)}} \left[\beta_{lb}^{\text{(Vol, Normal)}} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\} + \beta_{lb}^{\text{(Vol, Stress)}} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\} \cdot \mathbb{I}\{t \in \mathcal{T}^{\text{Stress}}\} \right] + \varepsilon_{lbt} \quad (5)$$

where v_{lbt} denotes the notional amount of cash in euro lent from sector l to b at business day t. $t \in \widetilde{\mathcal{T}}$ are all 886 business days in the sample, while excluding the 5 days before and after each quarter end to abstract from known window dressing behavior[14]. The indicator function $\mathbb{I}\{\}$ is 1 if the condition inside the brackets is met and 0 otherwise. $N^{(S)}$ represents the total number of lender and borrower sectors, which equals six. If no transaction occurs between a given sector pair on a given day, the corresponding volume is set to zero. Since the regression is estimated across 36 sectoral pairs for each day, it is based on a total of 31,896 observations. The specification is equivalent to a fully interacted sector-pair fixed-effects model.

In total, $2(N^{(S)})^2 = 72$ model parameters are estimated and can be expressed in two matrices with the dimensions $N^{(S)} \times N^{(S)}$. $\beta_{lb}^{\text{(Vol, Normal)}} \in \mathbb{R}_{>0}^{N^{(S)} \times N^{(S)}}$ represents the average daily volume traded between sector pairs in times of low financial stress $t \in \widetilde{\mathcal{T}} \setminus \mathcal{T}^{\text{Stress}}$. $\beta_{lb}^{\text{(Vol, Stress)}} \in \mathbb{R}^{N^{(S)} \times N^{(S)}}$ reflects the change in the average daily volume traded between sector pairs during the period of high financial stress $t \in \mathcal{T}^{\text{Stress}}$. Therefore, $\beta_{lb}^{\text{(Vol, Normal)}} + \beta_{lb}^{\text{(Vol, Stress)}}$ is the average daily volume traded between two sectors over the entire time frame studied.

To analyse changes in repo spreads within the sectoral network, I estimate the following linear model:

$$s_{lbt} = \sum_{l \in N^{(S)}} \sum_{b \in N^{(S)}} \left[\beta_{lb}^{\text{(Spread, Normal)}} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\} + \beta_{lb}^{\text{(Spread, Stress)}} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\} \cdot \mathbb{I}\{t \in \mathcal{T}^{\text{Stress}}\} \right] + \varepsilon_{lbt}, \quad (6)$$

where the dependent variable s_{lbt} is the average volume-weighted repo spread between two

[14] Repo volumes and rates fluctuate significantly at quarter-end due to regulatory accounting practices, independently of the stress episodes under analysis (see, e.g., Hüser et al. (2024); Mancini et al. (2016); Bassi et al. (2024a)). For a detailed explanation of the decline in repo activity around quarter- and year-end dates, see Bassi et al. (2024a). Consequently, it is common practice in the related literature to exclude these dates from the study period (e.g., Hüser et al., 2024; Mancini et al., 2016).

sectors. This sector-level repo spread is defined analogously to the transaction-level measure introduced in Equation 7. The estimation yields parameter matrices $\beta^{(Spread,Normal)}$ and $\beta^{(Spread,Stress)}$, representing the average repo spread during low-stress periods and the changes in repo spreads during high-stress episodes, respectively.

In addition to the baseline specifications presented in Equation 5 and 6 for ease of interpretability, I also estimate models that include controls for trade-level characteristics, such as whether the transaction is centrally cleared, the collateral issuer's country (via dummy variables), and maturity (via bucketed bins). While the results remain qualitatively similar and largely insignificant, the inclusion of these controls reduces statistical power. For brevity, these extended specifications are not shown in the main text.

3.6 Bootstrap approach to determine statistical significance

To determine statistical significance, I use a bootstrap approach for the linear model introduced in Section 3.5 that is more conservative than conventional p-values from standard hypothesis testing. To perform the bootstrap, I divide the data into consecutive blocks b of length 10 business days. This yields $N_B = T/b$ full blocks, along with a remaining block of $T - N_B \times b$ days if T is not an exact multiple of b. I then construct a resampled series by randomly drawing, with replacement, N_B blocks of size b and one additional block to account for the remaining days. These sampled blocks are joined together to form a new synthetic time series. Next, I re-estimate the linear model (see Equation 5 and Equation 6) on this resampled data. This procedure is repeated $R = 1000$ times, producing R different estimates of the model parameters.

4 Descriptive Statistics

The following section presents descriptive statistics based on the transaction-level SFTDS data. It focuses on the evolution of key repo market metrics over time, with particular attention to periods of high financial stress. In addition, the analysis examines the types of underlying collateral and the sectors of borrowers and lenders.

The analysis examines the period from January 1, 2021, to February 15, 2025, covering a total of 1,013 business days. Out of these, 219 days are identified as high-stress according to the CISS, while the remaining 794 days are categorized as low-stress. Within this time frame, the study analyses a total of 28,201,133 repo transactions after cleaning and filtering, amounting to a cumulative volume of approximately 715 trillion euros (7.148×10^{14}).

Figure 2a shows the daily number of repo transactions reported in SFTDS: On average, about 28,000 trades are closed each business day. Over the studied period, one can observe an increasing trend on the daily number of transactions. Declines at quarter-end, and more prominently at year-end, highlighted in the figure by the grey areas, are consistent with window dressing [15] as, e.g., documented by Bassi et al. (2024a). During the period of high financial stress, highlighted in light blue in the figure, the number of transactions remains rather constant, with a slight upward trend that aligns with the overall increase observed throughout the entire study period.

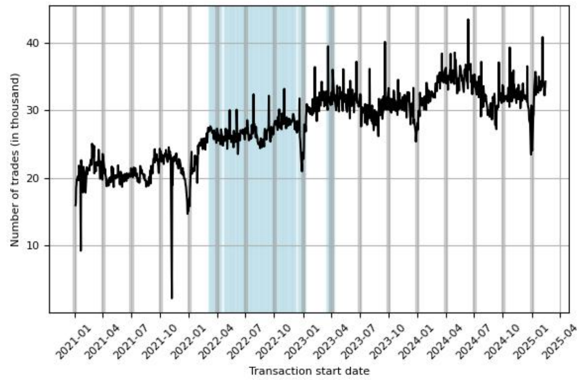
Figure 2b illustrates the total number of active institutions, as well as the number of active lenders and borrowers, for each business day. On average, 574 institutions are active in the repo market each day, with 473 acting as lenders and 252 as borrowers. Among them, 152 participate in both roles. This indicates that the number of active lenders is, on average, roughly twice the number of active borrowers. The time series reveals an upward trend in the number of active institutions, driven mostly by an increase in the number of lenders, whereas the number of borrowers only increases slightly over the studied period. During episodes of high financial stress (highlighted in light blue), the number of borrowers exhibits a stable pattern, whereas the number of lenders shows an increasing trend[16]. The number of active borrowers and lenders also displays temporary reductions around quarter-end and most notably at year-end, which aligns with patterns of window dressing (see Bassi et al., 2024a).

Figure 3 illustrates the dynamics of the key repo market variables: trading volumes, repo spreads, and haircuts, with the latter two commonly serving as measures of the cost of a repo transaction. Figure 3a shows the total nominal volume traded each day, averaging €706 billion euro. During high-stress periods (shaded in light blue), trading volume exhibits an upward trend, which is comparable in magnitude to the overall increase observed throughout the study period. Market activity contracts at year-end and, to a lesser extent, at quarter-end (as indicated by the grey shading), reflecting behavior consistent with window dressing.

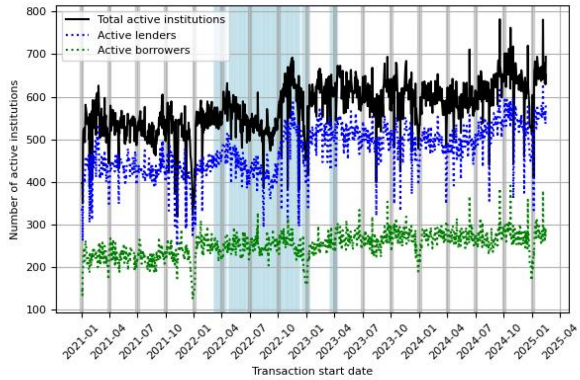
Figure 3b displays the daily volume-weighted repo spreads, expressed in percentage points,

[15] At quarter-end, volumes and repo rates fluctuate considerably due to regulatory accounting practices. For a more detailed explanation, please see Bassi et al. (2024a).

[16] The rising number of lenders could reflect a broader "flight to safety" dynamic, where institutions prefer to hold secured, short-term assets, such as repos backed by high-quality collateral, instead of engaging in riskier activities.



(a) Time series on number of daily repo transactions



(b) Time series on daily number of active lenders, borrowers and institutions

Figure 2 Participation in the repo market over time

Note: The shaded light blue areas represent periods of elevated financial stress, while the grey areas highlight the five days preceding and following each quarter- and year-end.

which are calculated as

$$s_t = \frac{\sum_i (V_{it} \cdot (r_{it} - \mathrm{DFR}_t))}{\sum_i V_{it}}, \tag{7}$$

where t denotes the trading day, i indexes an individual repo transaction, V_{it} is the transaction volume, expressed in euro, r is the repo rate and DFR represents the ECB's deposit facility rate, both expressed in percentage. The average daily volume-weighted repo spread over the study period is -0.150 pp. and remains relatively stable over time. However, during the high-stress period, the repo spread exhibits a modest downward trend.

The daily volume-weighted haircuts (in percent) are shown in Figure 3c and calculated as

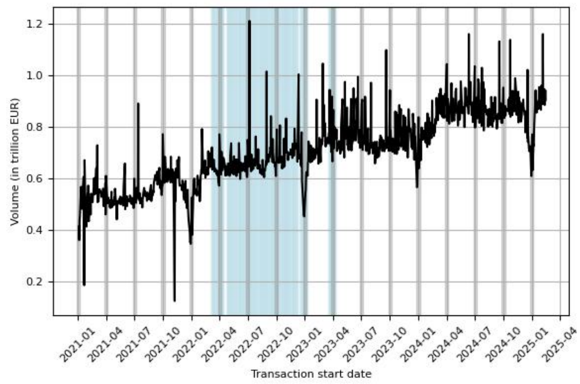
$$h_t = \frac{\sum_i V_{it} \cdot h_{it}}{\sum_i V_{it}}, \tag{8}$$

where V_{it} is the transaction volume and h_{it} the haircut[17] of an individual transaction. The average volume-weighted haircut across the study period is -0.034%, with the haircut remaining relatively stable throughout the entire study period, including during periods of high financial stress.

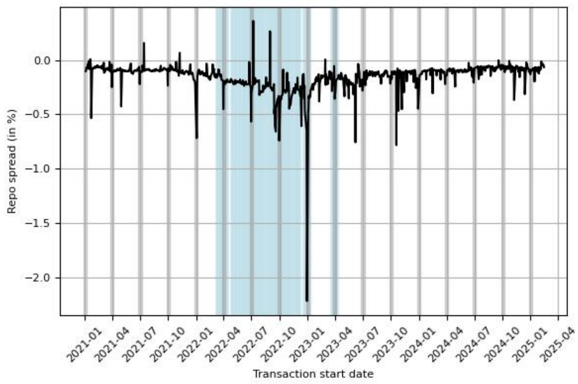
Figure 3d illustrates that most of the nominal amount traded in the repo market is centrally cleared. However, the share of centrally cleared volume has gradually declined over time,

[17]The haircut h_{it} of an individual transaction used in the following analysis is self-reported in SFTDS. According to the guidelines on SFTR reporting and repos issued by ICMA (2025a,b), it should be calculated as $h_{it} = (1 - \frac{\mathrm{V}_{it}}{\mathrm{C}_{it}}) \cdot 100$, where C_{it} is the market value of the collateral and V_{it} the purchase price of the repo. The self-reported SFTDS haircuts are also used in Hermes et al. (2025).

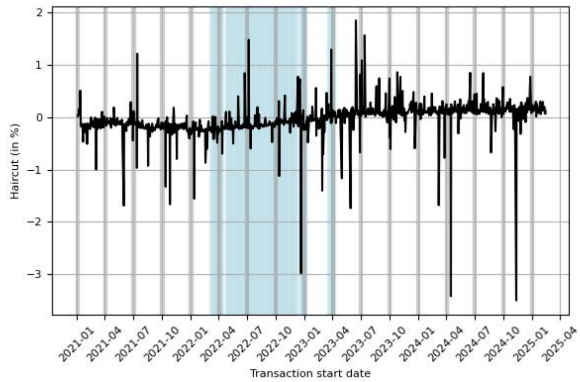
including during periods of elevated market stress.



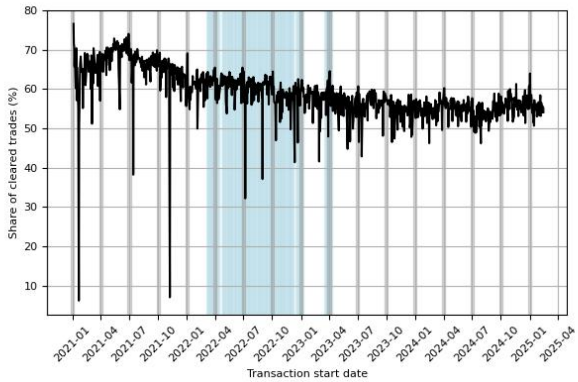
(a) Daily total nominal volume traded



(b) Daily volume-weighted average repo spread



(c) Daily volume-weighted average repo haircut



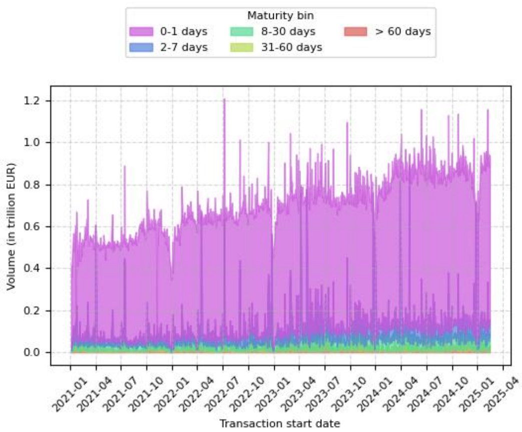
(d) Daily share of nominal amounts in centrally cleared transactions

Figure 3 Time series on volume traded, repo spread, haircut and share of cleared transactions

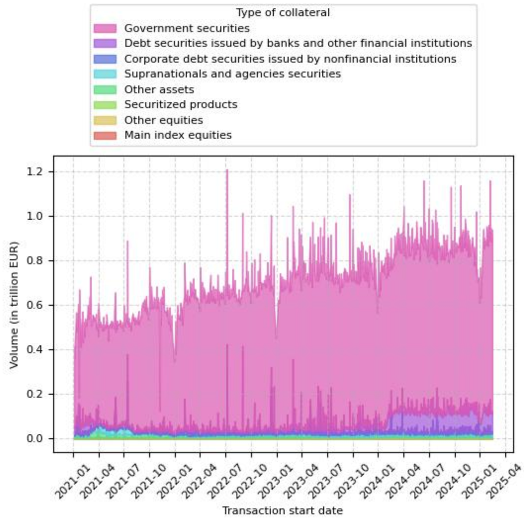
Note: The shaded light blue areas represent periods of elevated financial stress, while the grey areas highlight the five days preceding and following each quarter- and year-end.

Figure 4a displays the total daily repo volumes by maturity bin. The maturity of a repo is defined as the number of business days between the transaction start and maturity date. The majority of repos (84% of the trading volume) has a maturity of one day or less, followed by 7% with 2–7 days, 5% with 8–30 days, 3% with 31–60 days, and 1% exceeding 60 days. Over time, the share of overnight repos increased, alongside a modest rise in volumes for the 2–7 day bin.

Figure 4b shows the breakdown of repo trading volumes by collateral type. Government securities constitute the dominant collateral class (89%), followed by debt issued by financial institutions (5%). Supranational and agency securities, other assets, and corporate debt by non-financial institutions each account for 1–2%, while securitised products and equities represent less than 1% of the total volume. Repos with underlying debt securities issued by banks and other financial institutions exhibit a sharp increase in trading volume towards the end of 2023, after which volumes stabilize at an elevated level. This sudden increase likely reflects a change in reporting practices. A closer look at the pledged government securities reveals that 86% originate from just five countries: Italy, Germany, France, Belgium, and Spain. Italian government bonds constitute the largest share (30%), followed by German (23%), French (22%), Belgian (5%), Spanish (5%), and Dutch (4%) government securities. Securities from all other countries individually account for less than 3%.



(a) Time series on daily volume traded by maturity bin



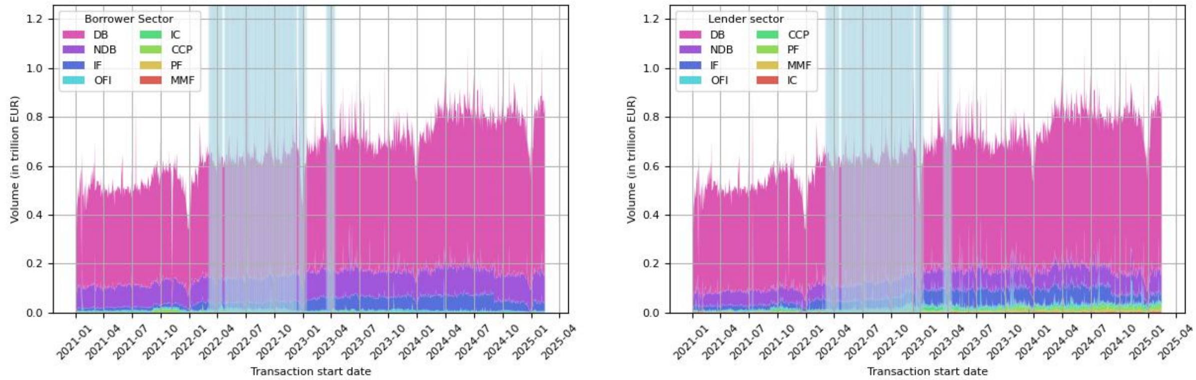
(b) Time series on daily volume traded by collateral type

Figure 4 Maturity and underlying collateral type in the repo market

Figure 5 displays the shares of repo volume borrowed and lent by each sector. Dealer banks are the largest participants on both the borrowing and lending sides, followed by non-dealer banks, investment funds, and other financial intermediaries. Figures 5a and 5b show that the overall increase in repo activity is driven by gradually rising volumes from banks and a notable expansion in investment fund activity over time.

5 Results

This section presents the empirical results, the network analyses at both the institution and sector levels, and an assessment of the overall resilience of the euro repo market.



(a) Time series on daily volume borrowed by sector

(b) Time series on daily volume lent by sector

Figure 5 Lender and borrower sectors share over time

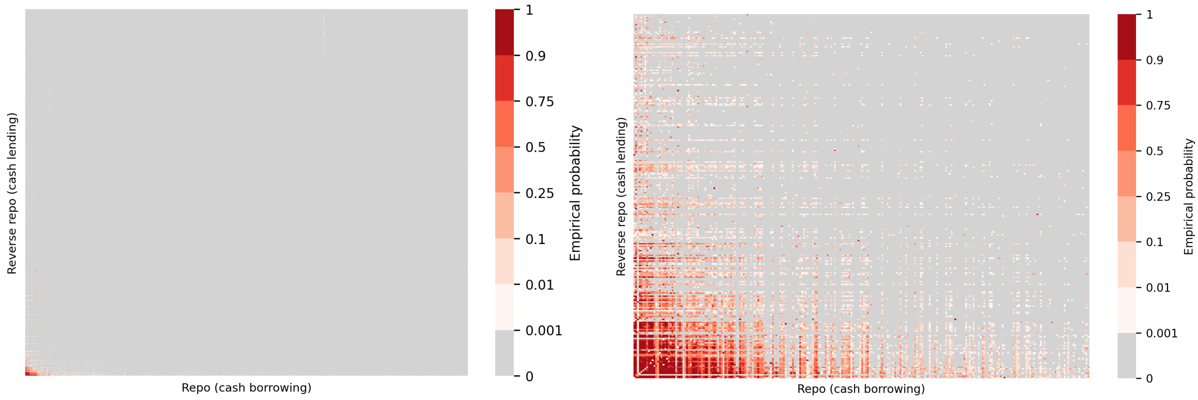
Note: The shaded light blue areas represent periods of elevated financial stress, while the grey areas highlight the five days preceding and following each quarter- and year-end. The following sectors are considered: dealer banks (DB), non-dealer banks (NDB), other financial intermediaries (OFI), central clearing counterparties (CCP), investment funds (IF), pension funds (PF), insurance corporations (IC), and money market funds (MMF). The volumes borrowed/lent by the studied sectors are below the total volume, since only selected sectors are included in this analysis; moreover, for some entities, no sector matching was possible. The sector labels are arranged in ascending order based on the total amounts borrowed and lent, respectively.

5.1 Network analysis on the institutional level

This section visualizes the network of transaction volumes between individual institutions, examines measures of network connectedness, and investigates how the network responds to financial stress.

Figure 6a presents a truncated version of the empirical transaction probability matrix, $\overline{\mathbf{P}}^{(I)}$ (as defined in Section 3.2), restricted to the subset of borrowers and lenders that participated in at least one transaction during the sample period, a total of 2,352 borrowers and 3,399 lenders. Each dot in the heatmap corresponds to the empirical transaction probability between a specific pair of institutions. The institutions are ordered by total trading volume, such that borrowers with the largest volumes appear on the very left, and lenders with the largest volumes are positioned at the bottom of the figure. Except for the lower-left corner, most of the figure is grey-shaded, indicating that institutions with generally low trading volumes, typically located at the periphery of the network, are unlikely to engage in repo transactions with one another.

Figure 6b provides a zoomed-in view of the lower-left corner of Figure 6a, illustrating the empirical transaction probabilities for the subset of the 250 borrowers and lenders with the highest cumulative trading volumes over the study period. In particular, the lower-left corner contains many dark-red cells as well as in the far left columns and the lower rows, indicating a repo contract formed almost every day.



(a) Empirical transaction probability between all borrowers and lenders in the sample

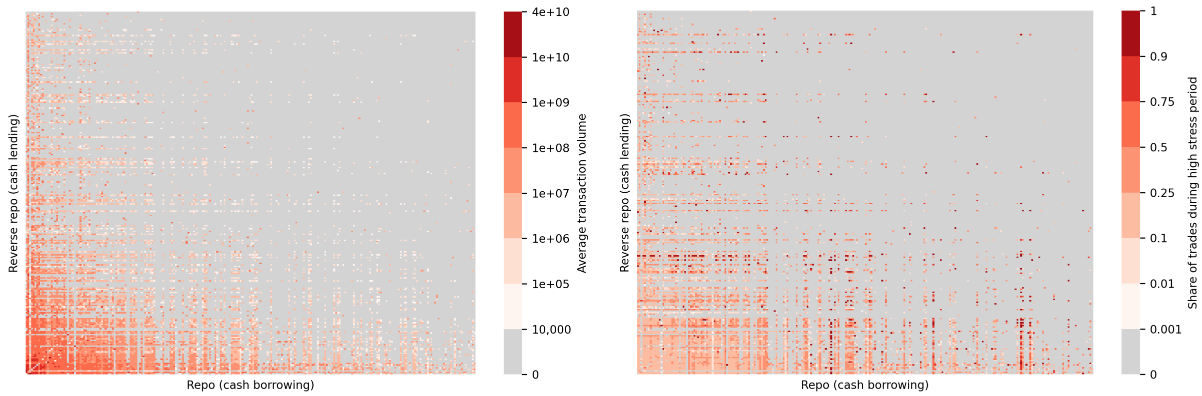
(b) Empirical transaction probability among the 250 borrowers and lenders with the highest total trading volume

Figure 6 Heatmaps on empirical probability of transaction between individual institutions on a given day

Figure 7a displays the average daily transaction volume $\bar{v}_{lb}^{(I)}$ (as defined in Section 3.2) between the 250 borrowers and lenders with the highest cumulative trading volumes over the sample period. As the visualization of the full network including all active borrowers and lenders closely mirrors the structure shown in Figure 6a, it is omitted for conciseness. Similar to the empirical transaction probabilities, institutions with the highest aggregate volumes tend to engage in large transactions both among themselves and with less active counterparties.

In summary, the institutional network exhibits a small, densely connected core of high-volume participants that are not only tightly linked with one another but also maintain substantial trading relationships with peripheral institutions. The vast remainder of the network is only sparsely connected, comprising mainly institutions that participate infrequently and with low trading volumes. Moreover, the borrower and lender structures appear broadly symmetric, suggesting similar interaction patterns on both sides of the market.

To assess whether certain institution pairs predominantly transact during periods of financial stress, Figure 7b visualizes $\mathbf{F}^{\mathrm{FS}}$ (as defined in Section 3.2) for the 250 most active institutions by total trading volume. Dark red cells identify institution pairs that trade almost exclusively during periods of stress. The full matrix for all active institutions (not shown for brevity) exhibits similar patterns, with some dark red areas towards the leftmost columns and bottom rows, suggesting that some of the most active market participants increase trading with both core and peripheral institutions in times of distress. Nonetheless, the prevalence of lighter shades across most cells indicates that repo market activity between most institutions persists across a range of market conditions and is not solely confined to stress periods.



(a) Average daily transaction volume **(b)** Share of trades during high-stress period

Figure 7 Heatmaps for the subset of the 250 lenders and borrowers with the highest total trading volume

5.1.1 Aggregate metrics of the institutional repo market network

In this subsection, I visualize the metrics of network connectedness and intensity as defined in Section 3.4 and analyse their evolution over time, particularly during periods of high financial stress.

Figure 8 displays the empirical survival functions of institutions' average in-degrees (blue circles) and out-degrees (red crosses), plotted on a log-log scale for clearer visibility of tail behavior. For example, at a degree of 3 on the x-axis, the survival probability is approximately 0.05 for in-degree and 0.03 for out-degree. This implies that only around 3–5% of institutions maintain more than three incoming or outgoing connections on average, whereas the vast majority—about 95–97%—are connected to at most three counterparties. As the degree threshold increases, the survival probability declines rapidly. For instance, the maximum average number of daily lending transactions per institution is 118, while the maximum for borrowing transactions reaches 192. This suggests that even the most connected nodes in the network fall short of being fully connected to all other institutions. Overall, the distribution of average degrees reveals a network in which most nodes are only sparsely connected, while a small subset of institutions exhibits much higher connectivity.

Figure 9a presents the time series of network density for the entire institutional repo network

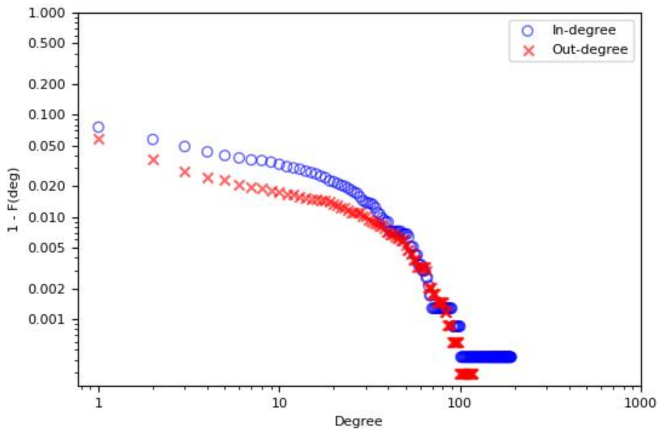


Figure 8 Log-log scaled plot of the survival function, reflecting the connectedness of institutions based on their average in- and out-degrees

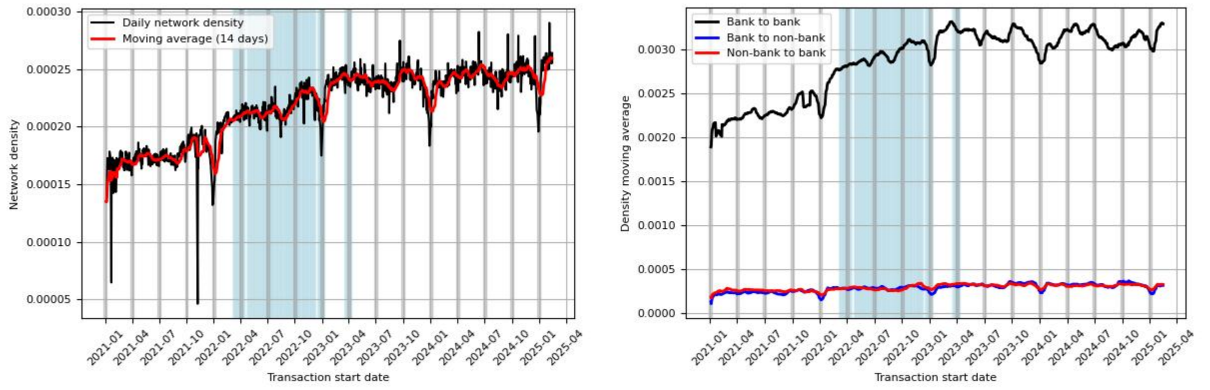
as defined in Equation 1. The average network density over the sample period is approximately 0.0002%, indicating that, on average, fewer than one in 500,000 possible borrower–lender connections is active on any given day. This confirms the high sparsity of the institutional repo network. Despite the overall sparsity, the network density, depicted in Figure 9a, shows an increasing trend over time, suggesting a gradual rise in inter-institutional activity[18]. Notably, the data reveal recurring drops in density at year-end, consistent with window-dressing practices (Bassi et al., 2024a). During the high-stress period, network density increases, suggesting that institutions either reactivated existing repo relationships or formed new connections with counterparties with whom they had not previously traded.

A complementary measure of network connectedness is the average degree (defined in Equation 2), which captures the average number of distinct trading partners per institution. Higher values indicate broader engagement in repo transactions. Over the sample period, the average daily degree is 0.499, suggesting that institutions transact with fewer than one distinct counterparty per day on average. Aggregated over a business week, this rises to 0.773, reflecting slightly broader but still limited interconnectivity.

In addition to examining the density of the full network, I disaggregate the nodes into banks and NBFIs and analyse the sub-networks corresponding to bank-to-bank, bank-to–non-bank, and non-bank-to–bank interactions. The densities of the sub-networks involving NBFIs (represented by the red and blue lines) remain low and rather stable over the sample period

[18]Since the SFTDS is a relatively recent dataset, the observed upward trend may, to some extent, reflect improvements in reporting practices or broader institutional coverage.

(see Figure 9b). I conclude that the overall dynamics in the daily network density observed in Figure 9a are driven by changes in the bank-to-bank sub-network.



(a) Daily density of the institutional network

(b) Moving average of daily density for bank and non-bank institutional sub-networks

Figure 9 Timeseries on density of the institutional network and sub-networks

Note: The shaded light blue areas represent periods of elevated financial stress, while the grey areas highlight the five days preceding and following each quarter- and year-end.

To assess the intensity of interactions, I use network strength (as defined in Equation 3), a volume-weighted measure of degree. Figure 10 shows the evolution of average node strength among active institutions over time. On average, the strength of the institutional repo network amounts to €2.978 billion, with a gradual upward trend observed across the sample period. However, during the high-stress period, average strength exhibits considerable volatility without a clear directional trend, reflecting substantial fluctuations in average transaction volumes.

In summary, the network metrics reveal that between 2021 and early 2025, both the density and strength of the institutional repo network exhibit an increasing trend, suggesting a rise in the number and average size of transactions. During episodes of elevated financial stress, the frequency of interactions between institutions tends to rise, while the average transaction volume per relationship remains ambiguous. This suggests that stress episodes are associated with an expansion in the number of active trading relationships, rather than systematic changes in transaction size.

5.2 Network analysis on the sectoral level

The following section examines the structure of the euro repo market at the sectoral level by aggregating individual institutions into sectors and analysing the resulting trading network. The

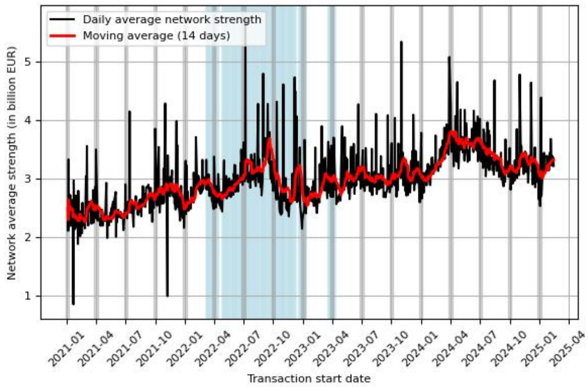


Figure 10 Daily average strength of the institutional network

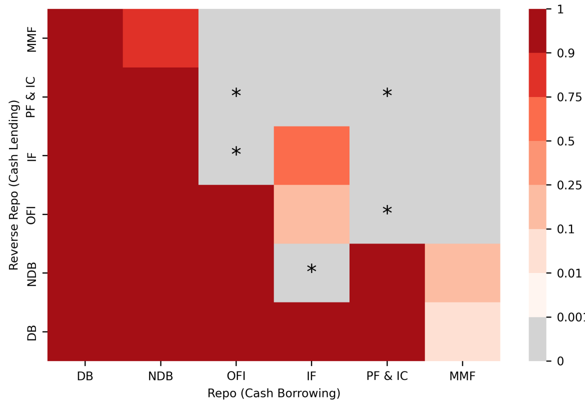
Note: The shaded light blue areas represent periods of elevated financial stress, while the grey areas highlight the five days preceding and following each quarter- and year-end.

sectors considered are dealer banks, non-dealer banks, OFI, investment funds, insurers, pension funds, MMFs and CCPs.

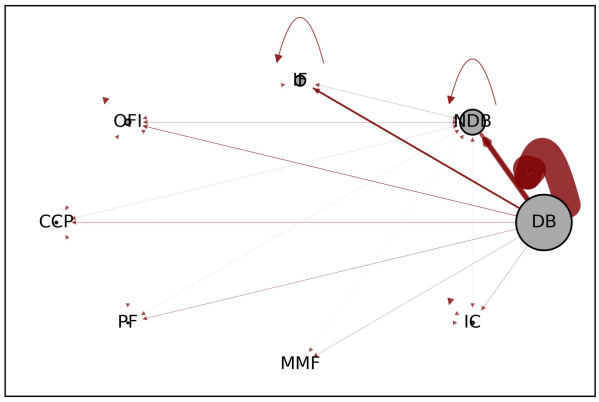
Figure 11a presents a heatmap of $\overline{\mathbf{P}}^{(S)}$ over the full sample period as defined in Section 3.3. Darker red cells indicate more frequent interactions between sectors. Both dealer and non-dealer banks are active in borrowing from and lending to all sectors on an almost daily basis, with the notable exception of MMFs, which rarely borrow from any sector. OFIs and investment funds are heavily involved in repo transactions within their own sector.

Figure 11b illustrates the sectoral repo market network of volumes. The size of each node represents the total borrowed amount within the studied time frame, with the largest nodes corresponding to dealer banks, non-dealer banks, and investment funds. The directed edges are scaled according to the total amount of cash exchanged between sectors, with edge thickness reflecting the volume of transactions. Notably, dealer banks, non-dealer banks, and investment funds engage in sizable repo transactions within their own sectors, while other sectors generally only trade outside of their sector. Dealer banks, non-dealer banks, and OFIs maintain connections with all other sectors, whereas the remaining sectors are involved in transactions with a more limited set of other sectors.

Table 1 provides an overview of the number of borrowers and lenders active in the euro repo market, along with borrowing and lending volumes for both the full sample period and during episodes of high financial stress. Banks and investment funds account for the largest borrowing and lending volumes. Except for non-dealer banks, which are net borrowers both overall and during high stress periods, all other sectors are net lenders. Investment funds are the largest



(a) Heatmap on empirical probability of transaction between sectors



(b) Volume-weighted sectoral repo network

Figure 11 Sectoral repo market network

Note: In the heatmap, cells marked with * are omitted to preserve confidentiality, in line with rules that prohibit reporting values based on fewer than three entities or where a single entity accounts for more than 85% of the total. For the same reason, CCPs are excluded from the analysis, and pension funds and insurance companies are aggregated into a single category. Each grey node's size is proportional to the sector's average borrowed cash volume during the sample period. Direct red edges, whose thickness is proportional to the average transaction size, depict the average cash loaned between sectors. Arrow heads point towards the borrowing sector.

net lenders across the full study period, while dealer banks take on this role specifically during high stress episodes. Also in the high-stress period, investment funds, dealer banks, and insurers increase their net lending volumes, whereas pension funds, MMFs, OFIs, and non dealer banks reduce theirs.

	Full study period					High-stress period				
Sector	n. borrowers	n. lenders	rev. repo vol.	repo vol.	net vol.	n. borrowers	n. lenders	rev. repo vol.	repo vol.	net vol.
IF	755	1234	45.35	37.32	8.03	431	836	40.62	29.16	11.46
CCP	8	9	6.50	1.39	5.11	6	9	3.26	1.73	1.53
PF	64	118	5.55	0.71	4.84	26	69	3.75	1.36	2.39
DB	67	71	526.55	522.51	4.04	57	63	518.23	504.66	13.57
MMF	19	56	3.83	0.02	3.81	6	21	1.59	0.01	1.58
OFI	115	109	10.13	7.08	3.06	68	58	9.99	9.40	0.58
IC	104	63	3.09	2.18	0.92	68	33	3.81	2.23	1.57
NDB	505	371	75.92	105.71	-29.80	294	211	73.09	105.78	-32.68

Table 1 Breakdown of sector-level average daily trading volumes in the euro repo market for the entire sample period and during times of high financial stress

Note: This table reports the average across all trading days of the number of borrowers and lenders, as well as transaction volumes (in billion euro) by sector. Volumes are broken down into reverse repo (lending), repo (borrowing), and net volumes (net lending). Figures are reported for both the full sample period and periods of high financial stress. Sectors are ordered by their net volumes over the full sample. The sectors are denoted as: dealer banks (DB), non-dealer banks (NDB), other financial intermediaries (OFI), investment funds (IF), central clearing counterparties (CCP), pension funds (PF), insurance corporations (IC), and money market funds (MMF).

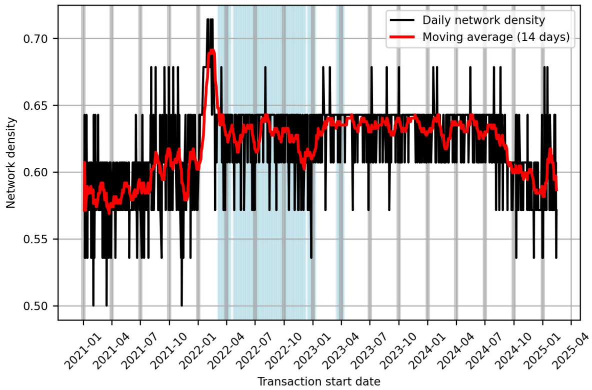


Figure 12 Daily density of the sectoral network

Note: The shaded blue areas represent periods of elevated financial stress, while the grey areas highlight the five days preceding and following each quarter- and year-end.

Aggregate metrics on the sectoral repo market network

Figure 9a shows that the average daily density of the institutional network is increasing over time and during periods of high financial stress, indicating that the connectedness increases since additional trading links are established. To determine whether these additional links formed between already connected sectors or increased the connectedness of the different sectors, Figure 12 depicts the density of the sectoral network (as defined in Equation 4).

In contrast to the institutional network, the sectoral network density exhibits a declining trend during the high-stress period, suggesting that new or renewed trading relationships predominantly occur between sectors that were already previously connected. Prior to this high-stress phase, the sectoral density showed an increasing trend, indicating a rise in trading activity between sectors that had not traded before. From 2023 onward, sectoral density stabilizes, with a noticeable dip towards the end of 2024.

In summary, the overall increase in institutional network density during high-stress periods is accompanied by a corresponding decline in sectoral network density, implying that the intensification of trading activity is driven primarily by increased interactions within sectors rather than across them.

5.2.1 Regression-based analysis of volume and repo spread dynamics under stress

This section employs a regression approach to examine how the volumes traded between sector pairs, as well as the repo spread, vary during periods of heightened financial stress[19]. To enhance comparability of the results, the sample is limited to repos collateralised by government bonds from Italy, Germany, France, Spain, and Belgium, with a maturity of up to 30 days.

Volumes traded in the sectoral network

To evaluate how trading between sector pairs varies between low- and high-stress periods, I estimate the regression framework introduced in Section 3.5. The matrices of the model parameters are visualized as heatmaps in Figure 13. The color scale represents the magnitude of the parameter estimates, with red indicating positive estimates and blue indicating negative estimates. Darker shades within each color signify more extreme values.

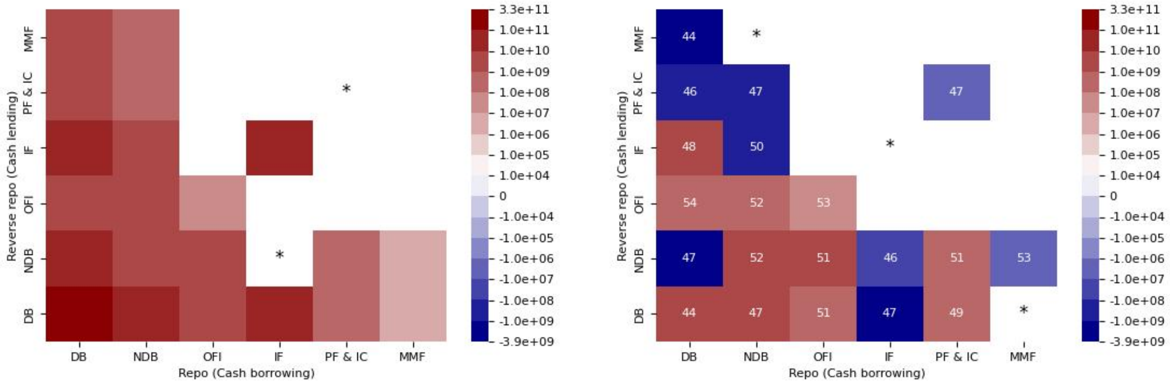
Figure 13a displays $\beta_{lb}^{(\text{Vol, Normal})}$, the average daily trading volume for each borrower-lender pair during low-stress times. The heatmap is populated with shades of red and white, as only non-negative volumes can be traded. The highest trading volumes are observed within the banking sectors and in transactions between banks and other sectors. Investment funds exhibit substantial inter-sector trading activity. The white cells between various non-bank sectors indicate that, on average, no trading activity is observed between those pairs.

Figure 13b visualizes $\beta_{lb}^{(\text{Vol, Stress})}$, the change in the daily trading volume during times of high financial stress for each borrower-lender pair. The chart has a similar amount of blue and red fields indicating that a similar number of sector pairs decreased and increased their trading volume during times of stress. None of the volume changes are statistically significant, as indicated by the bootstrapped percentiles shown in each cell. Based on the procedure outlined in Section 3.6, all percentiles fall between 1.5 and 98.5, remaining well within conventional significance thresholds.

Aggregate volumes traded as borrower or lenders by sector

Beyond changes in volumes between individual sector pairs, I also examine the aggregate daily volumes borrowed and lent by each sector during periods of low and high financial stress, as

[19] The analysis could be extended by also studying dynamics in haircuts. However, the data quality of granular haircuts is in general worse compared to volumes and repo rates.



(a) $\beta^{(Vol,Normal)}$: Volumes traded between sector pairs during normal time

(b) $\beta^{(Vol,Stress)}$: Changes in average volumes traded between sector pairs during high-stress times

Figure 13 Heatmaps of regression coefficients on average repo volumes in normal and changes in volume during stress periods (in euro)

Note: Parameter estimates are visualized using colors, while their corresponding percentiles in the bootstrap distribution are shown as numbers. Percentiles less than or equal to 1, or greater than or equal to 99, indicate that the estimate falls in the extreme tails of the distribution, implying a high level of statistical significance. Cells marked with * are omitted to preserve confidentiality, in line with rules that prohibit reporting values based on fewer than three entities or where a single entity accounts for more than 85% of the total. For the same reason, CCPs are excluded from the analysis, and pension funds and insurance companies are aggregated into a single category.

shown in Figure 14[20]. The average daily repo volume for sector b during normal times is calculated as $\sum_{l \in N_S} \beta_{lb}^{(\text{Vol, Normal})} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\}$. For high-stress periods, it is derived as $\sum_{l \in N_S} \left(\beta_{lb}^{(\text{Vol, Normal})} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\} + \beta_{lb}^{(\text{Vol, Stress})} \cdot \mathbb{I}\{t \in \mathcal{T}^{\text{Stress}}\} \cdot \mathbb{I}\{l\} \cdot \mathbb{I}\{b\} \right)$, with $\mathcal{T}^{\text{Stress}}$ denoting the high-stress periods. Reverse repo volumes are obtained analogously, by summing across borrowing sectors rather than lending sectors.

Figure 14 reveals that during high-stress periods, borrowing increases marginally for banks, and OFIs, while it declines for investment funds. On the lending side, dealer banks and OFIs expand their lending, whereas investment funds and MMFs reduce theirs; other sectors remain rather unaffected. Overall, absolute changes in borrowing and lending between stress and non-stress periods are small in magnitude.

Repo spreads traded in the sectoral network

The following analyse changes in repo spreads within the sectoral network derived by estimating the linear model as described in Section 3.5. Figure 15a presents the heatmap of $\beta^{(\text{Spread, Normal})}$, where red shades represent positive average repo spreads during low-stress periods, blue shades

[20] A corresponding figure for average repo and reverse repo spreads could be constructed, but since it would reflect averages of weighted spreads, its interpretation could be misleading and is therefore omitted.

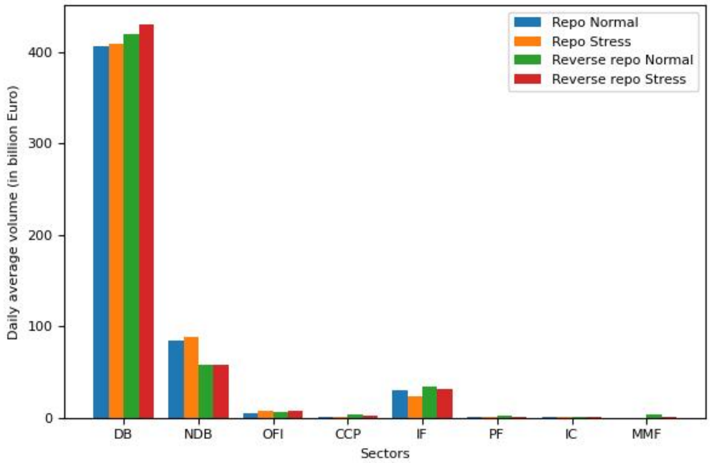


Figure 14 Sector-level daily average volumes in repo and reverse repo trades across normal and high-stress periods.

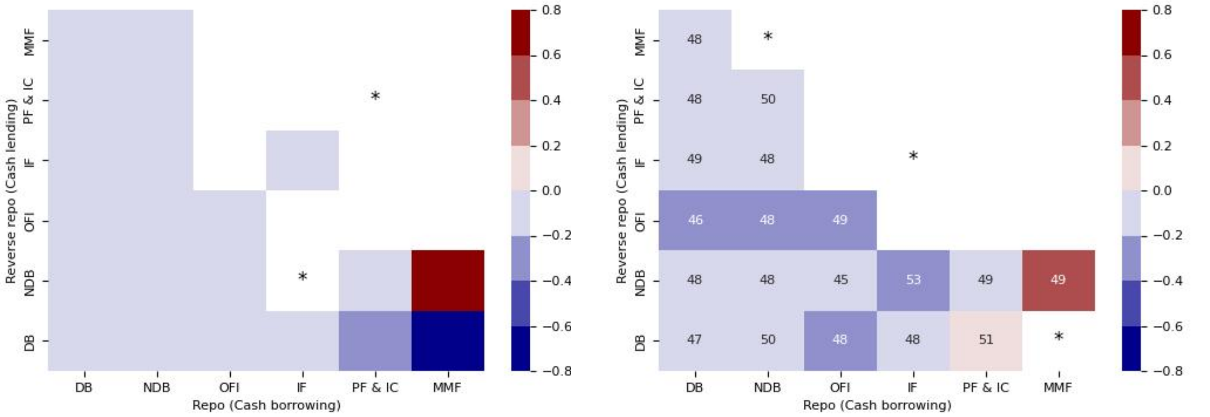
indicate negative spreads, and darker colors correspond to larger absolute values. The heatmap is dominated by light blue fields, indicating that average repo spreads between most sector pairs are small and negative. A notable exception in the pattern of repo spreads is observed for dealer banks, which lent at particularly favorable rates to pension funds and insurers as well as MMFs, with average spreads of -0.28 pp. and -0.65 pp., respectively. The highest repo spread occurs in transactions where non-dealer banks lend to MMFs, reaching 0.61 pp.

Figure 15b presents the heatmap of $\beta^{(\text{Spread, Stress})}$, which represent the change in the average volume-weighted repo spread in times of high financial stress. The figure indicates that for most sector pairs repo spreads decrease during high stress. Based on the bootstrap percentiles reported in each cell, calculated using the method described in Section 3.6, none of the changes are statistically significant, with all percentiles falling outside the conventional significance thresholds of ≤ 1.5 or ≥ 98.5.

These results of the linear model indicate that no statistically significant shifts in transaction volumes or spreads occur between sector pairs during periods of financial stress, pointing to a high degree of persistence in sectoral trading patterns.

5.3 Overall repo market resilience to stress

This section examines the resilience of the euro repo market. Using a regression approach, I analyse how financial stress impacts repo volumes, spreads, haircuts, and maturity. I find that higher financial stress is associated with a significant decline in repo spreads, while no



(a) $\beta^{(Spread,Normal)}$: Heatmap on average repo spread during normal time (in percentage points)

(b) $\beta^{(Spread,Stress)}$: Heatmap on average repo spread during high-stress times (in percentage points)

Figure 15 Heatmap of regression coefficients on repo spreads in normal and stress periods

Note: Parameter estimates are visualized using colors, while their corresponding percentiles in the bootstrap distribution are shown as numbers. Percentiles less than or equal to 1, or greater than or equal to 99, indicate that the estimate falls in the extreme tails of the distribution, implying a high level of statistical significance. Cells marked with * are omitted to preserve confidentiality, in line with rules that prohibit reporting values based on fewer than three entities or where a single entity accounts for more than 85% of the total. For the same reason, CCPs are excluded from the analysis, and pension funds and insurance companies are aggregated into a single category.

statistically significant effects are found for repo volumes, haircuts, or maturity. These findings suggest that the euro repo market remains resilient in times of heightened financial stress.

Following Mancini et al. (2016), I define a resilient repo market as one in which, during periods of financial stress, lending volumes and maturities do not decline, while repo rates and haircuts do not rise. Their empirical anlysis shows that the euro repo market demonstrates resilience in times of crisis and may even act as a shock absorber, as higher risk levels, measured by the CISS, are associated with increased repo lending, while spreads, maturities, and haircuts exhibit little to no deterioration.

To test the correlation of CISS with repo volume, spreads, haircuts and maturity, I estimated the following regression model,

$$\begin{aligned} Y_t = {} & \beta_0 + \beta_1 t + \beta_2 \text{CISS}_{t-1} + \beta_3 \text{€STR}_{t-1} + \beta_4 \log\left(\text{Volume €STR}_{t-1}\right) \\ & + \beta_5 \log\left(\text{Excess Liquidity}_{t-1}\right) + \beta_6 \log\left(\text{Volumes}_{t-1}\right) + \beta_7 \text{Spreads}_{t-1} \\ & + \beta_8 \text{Haircuts}_{t-1} + \beta_9 \text{Maturity}_{t-1} + \beta_{10} \text{Cleared}_t + \varepsilon_t \end{aligned} \tag{9}$$

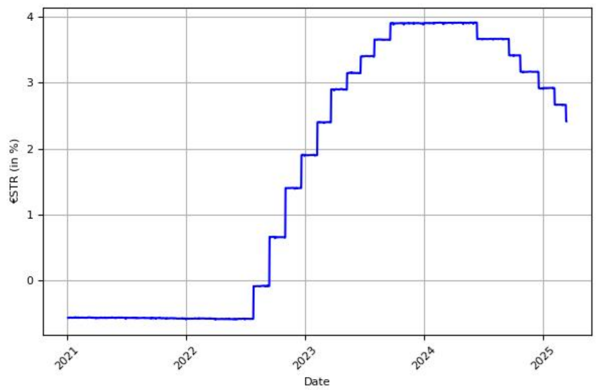
where $Y_t \in \{\log\left(\text{Volumes}_t\right), \text{Spreads}_t, \text{Haircuts}_t, \text{Maturity}_t\}$ denotes the dependent variable in each of the four specifications. Volume is calculated as the total amount of all repos initiated on that business day, while spreads, haircuts, and maturity are computed as volume-weighted averages, following the definitions in Equation 7 and Equation 8, and equivalently applied to maturity. Dependent and independent volume variables are log-scaled to normalize their distribution and allow for interpretation in terms of relative changes. To account for any general trend in the dependent variable, a linear time trend is included as a control. Additionally, I add the lagged repo volumes, spreads, haircuts and maturities to control for autocorrelation and dynamic interdependencies among key repo market variables. To account for differences between cleared and uncleared trades, a dummy variable equal to 1 for cleared repos is added to the regression. To control for central bank policy, the lagged €STR, related volume, and excess liquidity are added to the regression as controls. The €STR reflects the cost at which euro area banks access unsecured overnight funding in the wholesale market (ECB, 2021). The corresponding €STR volume measures the total amount transacted in the euro unsecured overnight market. Excess liquidity represents the surplus reserves in the banking system beyond what is required to meet minimum reserve obligations and serves as an indicator of funding liquidity[21]. The parameters to be estimated are given by $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_9)^\top$. The term ε_t captures the stochastic error component.

The time series of selected explanatory variables are depicted in Figure 16. The €STR largely mirrors the movements of the deposit facility rate, rising steadily from mid-2022 and declining again from mid-2024 onwards. The €STR volume shows an upward trend from 2021 to 2023, followed by a decline thereafter. Excess liquidity also exhibited an upward trend until the end of 2022, followed by a declining trajectory afterwards. However, when considering excess liquidity over a longer timeframe, i.e., 2015 onwards, also the lower levels in 2025 are still high in historical perspective (for a more detailed discussion on recent developments in excess liquidity, see, e.g., Hudepohl et al., 2024).

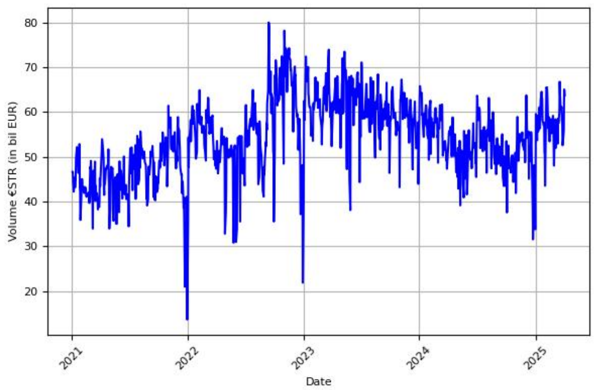
I estimate the regression specified in Equation 9 for the full sample of repos backed by government collateral (see Table 2). As a robustness check, I then focus on subsamples comprising the largest sovereign collateral types, Italy, Germany, and France, which together account for approximately 78% of total euro-denominated repo volume in Tables 3, 4, and 5 in Annex A.3.

First, focusing on the full-sample results in Table 2 the coefficients on the time trend indicate a statistically significant positive trend in repo volumes, while no significant trend is observed

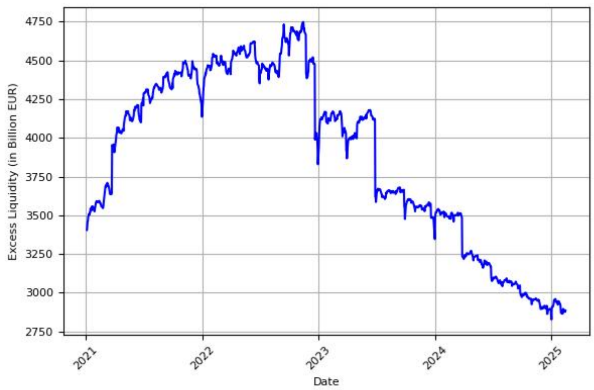
[21]For more detailed information on these explanatory variables see Section 2.3.



(a) Time series of €STR



(b) Time series of €STR volume



(c) Time series of excess liquidity

Figure 16 Time series of independent variables of the regressions defined in Equation 9

Table 2 Regression results for whole sample

	Dependent variable:			
	Log (Volume in EUR)	Spreads (in %)	Haircuts (in %)	Maturity (in days)
Constant	3.128	3.863***	1048.337*	119.340
	(3.057)	(0.926)	(407.248)	(185.942)
Trend	0.000***	0.000	0.012	0.000
	(0.000)	(0.000)	(0.011)	(0.006)
$\text{CISS}_{(t-1)}$	0.100	-0.117***	-12.606	0.392
	(0.068)	(0.030)	(9.167)	(5.654)
$\text{EUROSTR}_{(t-1)}$ (in %)	0.019*	-0.003	1.695	-0.204
	(0.008)	(0.002)	(0.878)	(0.442)
Log $(\text{Volume EUROSTR in EUR})_{(t-1)}$	0.026	-0.031	-3.508	4.505
	(0.042)	(0.020)	(6.572)	(3.736)
Log $(\text{Excess liquidity in EUR})_{(t-1)}$	0.256*	-0.081**	-6.624	-3.409
	(0.108)	(0.028)	(14.240)	(7.234)
Log $(\text{Volume in EUR})_{(t-1)}$	0.557***	-0.032**	-30.720***	-4.708
	(0.119)	(0.011)	(7.004)	(3.131)
$\text{Spreads}_{(t-1)}$ (in %)	-0.107	0.494***	17.341	3.434
	(0.093)	(0.087)	(15.902)	(4.849)
$\text{Haircuts}_{(t-1)}$ (in %)	-0.001	-0.000	0.173**	-0.025
	(0.000)	(0.000)	(0.059)	(0.034)
$\text{Maturity}_{(t-1)}$ (in days)	-0.002*	-0.000	0.186*	0.124
	(0.001)	(0.000)	(0.089)	(0.070)
Cleared	0.408***	0.023*	46.918***	-4.050
	(0.120)	(0.011)	(7.570)	(3.142)
R-squared	0.874	0.532	0.222	0.098
R-squared Adj.	0.874	0.529	0.217	0.092
N	1738	1738	1738	1738

Notes: The table reports the estimated coefficients (β_i) for each variable, with Newey–West heteroskedasticity- and autocorrelation-consistent standard errors with five lags shown in parentheses. The regressions are estimated using daily data (TARGET2 business days) from 1 January 2021 to 15 February 2025. To mitigate potential window-dressing effects, observations from the five trading days preceding and following each quarter-end are excluded from the sample. Intra-group repos, defined as transactions between counterparties sharing the same ultimate LEI, are excluded from the sample. Statistical significance is denoted by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

for repo spreads, haricuts or maturities.

Second, and most importantly, I examine how financial stress, measured by the CISS, affects activity in the euro-denominated repo market. The results show a statistically significant decline in repo spreads as financial stress increases, implying that secured funding becomes cheaper during periods of heightened stress. This pattern is consistent with a flight-to-quality mechanism, whereby stronger demand for high-quality collateral compresses secured funding premia. By contrast, repo volumes, haircuts, and maturities do not respond significantly to changes in financial stress. Conditional on the included controls, stress does not systematically affect aggregate trading activity, the degree of collateralisation, or the maturity structure of transactions. Overall, the findings suggest that adjustment in the euro repo market during stress episodes occurs primarily through pricing rather than through changes in trading activity or contractual terms.

Third, the results reveal significant correlations between key repo market variables and monetary policy indicators. Repo volumes are positively correlated with both the €STR rate and excess liquidity. This indicates that higher unsecured short-term money market rates, as well as more ample central bank liquidity provision, are associated with increased activity in the secured market. Together, these relationships suggest that repo trading responds both to prevailing funding conditions in the unsecured segment and to the overall liquidity environment. Repo spreads, by contrast, are negatively associated with lagged excess liquidity. This suggests that when excess liquidity is higher, secured borrowing costs tend to be lower. The result is consistent with the view that more abundant liquidity conditions are accompanied by compressed secured funding premia. Overall, the findings highlight the sensitivity of repo market volumes and pricing to monetary conditions and underscore the close interaction between secured and unsecured funding markets.

Fourth, the dynamic interdependencies among key repo market variables reveal systematic adjustment patterns. Lagged volumes are positively associated with current volumes and negatively related to both current spreads and haircuts. This suggests persistence in trading activity and indicates that periods of elevated market participation are followed by lower funding premia and less stringent collateral requirements. Lagged repo spreads exhibit a positive association with current spreads, pointing to persistence in pricing conditions. Similarly, lagged haircuts are positively related to current haircuts, indicating continuity in collateral requirements. Lagged maturities are negatively associated with current volumes and positively related to current haircuts. This pattern suggests that longer past contract horizons are followed by reduced trading activity and tighter collateral terms. Overall, these results point to significant dynamic relationships among repo market variables, highlighting persistence and cross-variable linkages in volumes, spreads, haircuts and maturities.

Tables 3, 4, and 5 in Annex A.3 indicate that the relationship between financial stress and repo spreads is consistent across collateral types. In all cases, higher values of the CISS are associated with a significant decline in repo spreads, pointing to a robust pricing effect across countries. For Italian and French collateral, financial stress is also positively associated with repo volumes. In the case of French collateral, it is additionally linked to lower haircuts.

6 Conclusion

This paper examines the functioning of the euro repo market during recent episodes of financial stress, with particular attention to its resilience as a key source of short-term funding. Leveraging SFTDS, a transaction-level dataset, and applying network analytical tools, I study dynamics in the network of individual institutions and sectors as well as the aggregate resilience of the market.

The analysis reveals several key findings regarding dynamics in the institutional and sectoral network as well as on the aggregate level. The institutional-level repo market network confirms a core–periphery structure, characterized by a tightly connected core of high-volume institutions interacting with a more fragmented periphery of infrequent, lower-volume traders. Over time, network density has gradually increased, even during episodes of financial stress, driven primarily by greater interconnectedness within the bank-to-bank segment. At the sectoral level, trading volumes and repo spreads between sector pairs remain stable under stress. At the aggregate level, financial stress is associated with a significant decline in repo spreads for euro-denominated transactions backed by government collateral, while no significant effects emerge for volumes, haircuts or maturities. The negative relationship between the CISS and repo spreads holds across Italian, German and French collateral, underscoring the robustness of the pricing effect. Overall, the results suggest that the euro repo market remains resilient during periods of stress, with adjustment occurring primarily through pricing rather than through changes in market activity or contractual terms.

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A Appendix

A.1 Data cleaning on transaction-level SFTDS data

The steps described in the following section are applied to the data after the initial cleaning and enrichment procedures already implemented.

Repo trades are excluded when the Legal Entity Identifier (LEI) of the repo borrower or lender is missing. Only transactions with a cash amount borrowed between 1 EUR and 100 billion EUR are considered. Open-term repo, where no fix maturity date is agreed, are excluded. The repo rate (interest rate on the repo fund) is cleaned by identifying and correcting cases where entities mistakenly reported rates in basis points rather than as percentages and restricted between -10 and 10%. To avoid double counting, trades are excluded when there are multiple pieces of collateral pledged (leading only to the exclusion of less than 0.01% of repo volume traded). Maturity dates are required to be below 2099 and the number of business days between the start of the repo contract and maturity must be smaller than 800 days. The starting date of the transaction contract must be before the reference date for a transaction to be active, which is assumed to be before the maturity date of the transaction contract. The self-reported repo haircut[22] is assumed to be equal or above -100 % and equal or below 100%. TARGET2 closing days[23] (e.g., due to weekends or public holidays in the euro area) as well as public holidays in the US are excluded as well as four days that are known to be low in reporting quality[24].

For the regression analysis, the five days before and after each quarter end are excluded to abstract from so called window dressing[25] (as e.g., reported by Hüser et al. (2024); Mancini et al. (2016); Bassi et al. (2024a)).

A.2 Alternatives to define periods of high and low financial stress

This section evaluates alternative methods to the k-means clustering approach employed in this paper for classifying periods of high and low financial stress. A notable limitation of k-means clustering is its inability to account for temporal dependencies or state transitions. By

[22] A haircut refers to the difference between a collateral's initial market value and the price paid for it at the beginning of the repo transaction.
[23] For a list of closing days, see ECB (2025).
[24] The excluded days are 2021-06-11, 2021-07-29, 2022-02-08, and 2022-02-09.
[25] At quarter-end, volumes and repo rates fluctuate considerably due to regulatory accounting practices (for a more detailed explanation, please see Bassi et al. (2024a)), which are independent of the stress episodes under investigation.

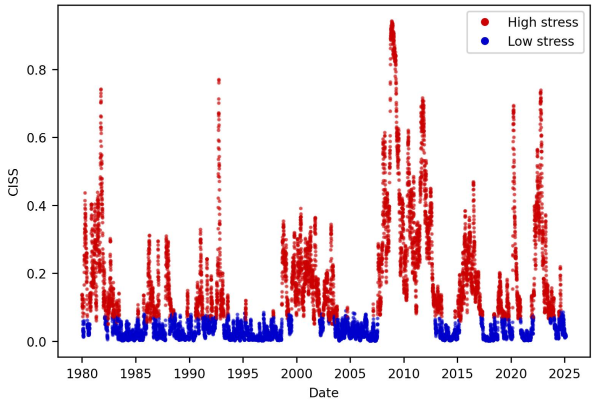

Figure 17 Financial stress states identified by applying the Hidden Markov Model to the CISS

treating each observation independently, k-means may fail to capture the sequential dynamics and persistence inherent in financial stress.

A common approach defines high financial stress as periods when the stress indicator exceeds its historical mean by one or more standard deviations (e.g., Illing and Liu, 2006; Cardarelli et al., 2011). However, this method implicitly assumes the stress measure follows a normal distribution, an assumption contradicted by empirical evidence for the CISS (Kremer and Chavleishvili, 2021). Alternatively, percentile-based thresholds, such as the 90th or 95th percentile, can be applied, though the choice of percentile remains inherently arbitrary.

Another method explored is the use of a Hidden Markov Model to identify latent stress regimes, as illustrated in Figure 17. While the Hidden Markov Model provides a probabilistic framework for state classification, in this application it assigns a disproportionately large share of observations to the high-stress state, thereby limiting interpretability and complicating its practical use.

Another option considered is to use thresholds reported in the literature. Several studies propose threshold values for the CISS based on empirical modeling approaches. For instance, Kremer and Chavleishvili (2021) report a threshold of 0.123, while Hollo et al. (2012) put forward two alternatives: 0.323 based on a threshold regression model, and 0.46 derived from an autoregressive Markov switching framework. However, these thresholds vary considerably across sources, are not calibrated to the most recent data, and were estimated using the original version of the CISS rather than the updated indicator (see Chavleishvili and Kremer, 2025).

Considering these limitations, this paper adopts k-means clustering as the method for classifying periods of high and low financial stress.

A.3 Regression analysis on repo market resilience by subsample of underlying collateral

Table 3 Regression results for subsample of Italian government collateral pledged

	Dependent variable:			
	Log (Volume in EUR)	Spreads (in %)	Haircuts (in %)	Maturity (in days)
Constant	1.173	1.634*	-561.653	-49.581
	(3.129)	(0.762)	(423.302)	(225.460)
Trend	0.000**	0.000**	0.028*	0.002
	(0.000)	(0.000)	(0.011)	(0.005)
$\text{CISS}_{(t-1)}$	0.268**	-0.087*	-18.028	5.743
	(0.100)	(0.038)	(10.522)	(9.776)
$\text{EUROSTR}_{(t-1)}$ (in %)	0.044***	-0.005**	2.575*	-0.272
	(0.012)	(0.002)	(1.036)	(0.516)
Log (Volume EUROSTR in EUR)$_{(t-1)}$	0.054	-0.017	-12.570	0.062
	(0.050)	(0.024)	(6.922)	(5.054)
Log (Excess liquidity in EUR)$_{(t-1)}$	0.323*	-0.018	47.758***	2.147
	(0.126)	(0.023)	(14.260)	(6.040)
Log (Volume in EUR)$_{(t-1)}$	0.500***	-0.030*	-22.473***	-0.182
	(0.094)	(0.012)	(6.093)	(1.626)
$\text{Spreads}_{(t-1)}$ (in %)	-0.049	0.555***	5.578	13.808
	(0.144)	(0.082)	(20.546)	(11.308)
$\text{Haircuts}_{(t-1)}$ (in %)	-0.001	-0.000	0.310**	0.053*
	(0.000)	(0.000)	(0.095)	(0.024)
$\text{Maturity}_{(t-1)}$ (in days)	-0.002*	-0.000	0.350*	0.101*
	(0.001)	(0.000)	(0.171)	(0.046)
Cleared	0.693***	0.033*	49.566***	-7.850***
	(0.138)	(0.016)	(9.940)	(2.360)
R-squared	0.902	0.454	0.250	0.064
R-squared Adj.	0.901	0.451	0.245	0.058
N	1738	1738	1738	1738

Notes: The table reports the estimated coefficients (β_i) for each variable, with Newey–West heteroskedasticity- and autocorrelation-consistent standard errors with five lags shown in parentheses. The regressions are estimated using daily data (TARGET2 business days) from 1 January 2021 to 15 February 2025. To mitigate potential window-dressing effects, observations from the five trading days preceding and following each quarter-end are excluded from the sample. Intra-group repos, defined as transactions between counterparties sharing the same ultimate LEI, are excluded from the sample. Statistical significance is denoted by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Table 4 Regression results for subsample of German government collateral pledged

	Dependent variable:			
	Log (Volume in EUR)	Spreads (in %)	Haircuts (in %)	Maturity (in days)
Constant	-5.999	3.046***	3.546	46.417
	(3.287)	(0.713)	(283.072)	(79.116)
Trend	0.000***	-0.000	0.018*	-0.002
	(0.000)	(0.000)	(0.009)	(0.002)
$\text{CISS}_{(t-1)}$	0.087	-0.079***	0.594	-0.727
	(0.075)	(0.023)	(6.937)	(1.132)
$\text{EUROSTR}_{(t-1)}$ (in %)	0.012	0.002	-0.259	0.286
	(0.008)	(0.002)	(0.684)	(0.192)
Log $(\text{Volume EUROSTR in EUR})_{(t-1)}$	0.005	-0.024	-0.868	-0.290
	(0.049)	(0.018)	(4.768)	(1.254)
Log $(\text{Excess liquidity in EUR})_{(t-1)}$	0.552**	-0.082**	18.021	0.259
	(0.172)	(0.028)	(12.396)	(2.818)
Log $(\text{Volume in EUR})_{(t-1)}$	0.570***	-0.005	-21.703***	-1.607*
	(0.113)	(0.006)	(6.428)	(0.688)
$\text{Spreads}_{(t-1)}$ (in %)	-0.090	0.753***	40.929***	1.496
	(0.076)	(0.044)	(12.241)	(0.977)
$\text{Haircuts}_{(t-1)}$ (in %)	-0.001	0.000	0.378***	0.007
	(0.001)	(0.000)	(0.104)	(0.007)
$\text{Maturity}_{(t-1)}$ (in days)	-0.002	0.001*	0.277	0.013
	(0.002)	(0.000)	(0.154)	(0.025)
Cleared	0.504***	0.006	45.783***	-3.774***
	(0.153)	(0.008)	(10.814)	(1.019)
R-squared	0.864	0.826	0.498	0.173
R-squared Adj.	0.864	0.825	0.495	0.168
N	1738	1738	1738	1738

Notes: The table reports the estimated coefficients (β_i) for each variable, with Newey–West heteroskedasticity- and autocorrelation-consistent standard errors with five lags shown in parentheses. The regressions are estimated using daily data (TARGET2 business days) from 1 January 2021 to 15 February 2025. To mitigate potential window-dressing effects, observations from the five trading days preceding and following each quarter-end are excluded from the sample. Intra-group repos, defined as transactions between counterparties sharing the same ultimate LEI, are excluded from the sample. Statistical significance is denoted by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Table 5 Regression results for subsample of French government collateral pledged

	Dependent variable:			
	Log (Volume in EUR)	Spreads (in %)	Haircuts (in %)	Maturity (in days)
Constant	3.435	5.821***	560.435**	-170.125
	(2.907)	(1.308)	(207.202)	(94.637)
Trend	0.000***	0.000	-0.008	-0.003
	(0.000)	(0.000)	(0.006)	(0.003)
$\text{CISS}_{(t-1)}$	0.123*	-0.135***	-12.143*	1.153
	(0.059)	(0.036)	(5.478)	(3.909)
$\text{EUROSTR}_{(t-1)}$ (in %)	0.015*	-0.013*	0.239	0.236
	(0.006)	(0.005)	(0.563)	(0.408)
Log (Volume EUROSTR in EUR)$_{(t-1)}$	0.030	-0.006	5.354	4.135
	(0.044)	(0.020)	(5.010)	(3.372)
Log (Excess liquidity in EUR)$_{(t-1)}$	0.145	-0.181***	-16.937*	3.733
	(0.098)	(0.044)	(8.225)	(2.841)
Log (Volume in EUR)$_{(t-1)}$	0.648***	-0.021**	-8.359	-1.237
	(0.072)	(0.007)	(4.474)	(1.100)
$\text{Spreads}_{(t-1)}$ (in %)	0.026	0.303*	11.111	13.605*
	(0.085)	(0.130)	(6.697)	(6.397)
$\text{Haircuts}_{(t-1)}$ (in %)	-0.000	0.000	0.530***	-0.016
	(0.000)	(0.000)	(0.081)	(0.015)
$\text{Maturity}_{(t-1)}$ (in days)	-0.001	0.000	0.048	0.376**
	(0.001)	(0.000)	(0.047)	(0.118)
Cleared	0.315***	0.017	15.707**	-5.212***
	(0.073)	(0.010)	(4.924)	(1.191)
R-squared	0.849	0.310	0.416	0.202
R-squared Adj.	0.848	0.306	0.413	0.197
N	1738	1738	1738	1738

Notes: The table reports the estimated coefficients (β_i) for each variable, with Newey–West heteroskedasticity- and autocorrelation-consistent standard errors with five lags shown in parentheses. The regressions are estimated using daily data (TARGET2 business days) from 1 January 2021 to 15 February 2025. To mitigate potential window-dressing effects, observations from the five trading days preceding and following each quarter-end are excluded from the sample. Intra-group repos, defined as transactions between counterparties sharing the same ultimate LEI, are excluded from the sample. Statistical significance is denoted by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

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