Abstract

Reuse of collateral within repo markets is key in enabling participants to meet their short-term financing needs, maintaining market efficiency, and establishing collateral valuations. In addition, part of the literature relies on the premise that some market players, in special large dealers, take advantage of their market position to obtain "liquidity windfalls" through haircut differences when reusing collateral. However, despite the importance of this mechanism for market functioning, the result is mainly theoretical, as empirical work exploring the effects of collateral reuse is scant. Through the analysis of a novel database on European Securities Financed Transactions, this study aims to help fill this gap. We show that around 11 percent of transaction volume is based on reused securities, with chains averaging three links. Besides, contrary to the liquidity-windfalls hypothesis, we find that dealers do not impose systematic haircut wedges when interposing between non-dealers.

JEL Codes: G15, G21, G23.

Keywords: repo, collateral reuse, haircuts.

Non-technical summary

In Europe's repo market—where institutions borrow cash against securities as collateral—the same bond can be transferred multiple times. This "reuse" of collateral boosts market efficiency and liquidity by stretching scarce high-quality assets, but also creates interconnected chains of transactions (collateral chains) that can amplify stress when funding dries up. Moreover, theory suggests that large dealers might exploit these chains for "liquidity windfalls", earning extra cash by imposing steeper haircuts when taking collateral in and lower haircuts when re-pledging it.

To quantify how often and how far collateral really travels, we assemble a novel, transaction-level dataset from the Securities Financing Transactions Data Store (SFTDS), covering all repo trades across euro-area countries from July 2020 through February 2025. After rigorous cleaning (excluding quarter-end window-dressing, extreme outliers and intragroup trades), the sample comprises roughly 18 million repo transactions.

Building on the algorithm of Fuhrer, Guggenheim, and Schumacher (2016), we match each repo (the "initial" trade) to any subsequent repo in which the same bond, same counterparty, and overlapping dates indicate true reuse rather than fresh pledges. This lets us trace the full collateral "chain" from first pledge to final repurchase, and measure chain lengths directly.

On average, about 11 percent of collateral value in daily repo flows is in fact being reused from a previous trade. Each reused bond typically travels through three links (i.e. the original pledger plus two intermediaries) before returning to its original owner. We also explore the drivers of reuse; we find that smaller, shorter trades are significantly more likely to involve reused collateral—reflecting risk and timing considerations in layering chains. Counterparty characteristics matters far more than collateral features. Who the borrower is (e.g. dependence on a given lender, dealer vs. fund status, home country) is the primary determinant of whether they reuse. By contrast, haircuts, repo rates, bond maturity or specialness all have negligible effects once firm identity is controlled for. Market stress events (e.g. March 2023 turmoil) temporarily depress reuse, suggesting caution when chains become riskier.

As for liquidity windfalls, contrary to theory, dealers do not systematically pocket extra cash via haircut wedges when intermediating collateral. A two-stage Heckman correction model confirms that, after accounting for self-selection into reuse, dealers earn no outsized "windfall" through haircut arbitrage. The euro-area repo market relies on collateral chains of non-trivial length, heightening systemic interconnectedness, especially in stress.

Empirical reuse rates (11 percent) sit above earlier Swiss and Australian estimates but well below the 50–75 percent claims—highlighting the value of granular, repo-specific data.

Policy debates on collateral scarcity, special repo facilities or haircut regulations should

account for the dominant role of counterparty relationships rather than collateral characteristics per se.

The absence of haircut windfalls suggests that dealers' funding advantage comes through other mechanisms—perhaps rate spreads or central-bank facilities—inviting further research on how collateral intermediation shapes financial resilience.

1 Introduction

The market for Repurchase Agreements, or *repos*, where participants buy and sell securities with a simultaneous agreement to undo the transaction at a later date, plays a crucial role in the financial system, in practice acting as one of the main sources of wholesale funding. Collateral, the security deposited by the borrower to safeguard the transaction in case of default, is essential for these markets to function effectively. High-quality, liquid collateral mitigates counterparty credit risk, a major concern for lenders. It also allows for efficient use of cash and facilitates short-term financing needs for market participants. In addition, some repos are performed with the goal of sourcing specific security rather than cash, meaning that collateral is actually the main term.

In this framework, enabling the reuse of collateral – where the cash lender in a repo re-pledges the received collateral to another lender in a subsequent transaction – can bring several advantages. Allowing the same security to backstop multiple transactions tends to increase the overall efficiency of the repo market, given the additional allocation possibilities brought by a more abundant supply of available collateral. Additionally, reuse enhances market liquidity by allowing institutions to unlock the financing potential of their existing collateral holdings. This can be particularly beneficial during periods of financial stress, when access to cash becomes impaired.

However, collateral reuse also raises important concerns. A key risk lies in the creation and expansion of collateral chains—interlinked transactions where the same security is re-pledged[1] multiple times across institutions. While these chains can enhance liquidity, they also increase the interconnectedness of financial institutions, amplifying systemic vulnerabilities. In the event of market stress or the default of a major player, disruptions can propagate through these links, potentially triggering margin calls, fire sales, and broader instability. Moreover, empirical evidence suggests that higher reuse rates may be associated with increased volatility, failures to deliver, and asset mispricing, especially when reuse exceeds certain thresholds.

Additionally, part of the literature relies on the premise that some market players, in special large dealers, take advantage of their market stance to obtain additional temporary liquidity, the so-called “liquidity windfalls”, via haircut differences when reusing collateral. The existence of an additional funding mechanism for dealers could affect the way they react to changes in other forms of liquidity sourcing. These include outright sales of securities, which could potentially alter dealers’ balance sheets and asset allocation in the market as a whole, as well as the provision of liquidity by the central bank, impacting the transmission of monetary policy.

[1]The term ”transferred” would be more accurate instead of ”re-pledge”. We use ”(re-)pledge” for simplicity and within the repo market context

However, despite the importance of these topics, empirical investigation remains limited, much due to data restriction and the difficulty to map repo collateral reuse. This study aims to address this gap by analyzing reuse within the European repo market. For this, we rely on the Securities Financed Transactions Data Store (SFTDS), a novel dataset from ESMA. SFTDS offers a detailed picture of repo and securities lending transactions, including information on the reuse of collateral.

The subsequent sections of this paper delve deeper into this analysis. Section 2 presents the literature with the current academic stance on collateral reuse and liquidity windfalls; Section 3 details the dataset and the algorithm we employ to estimate collateral reuse in repo transactions; Section 4 details our reuse metrics and the obtained results for the estimation of collateral reuse in European repo markets; Section 5 details our empirical strategy and shows the results for our investigation of liquidity windfalls; Section 6 concludes.

2 Literature Review

2.1 Repo Collateral Reuse

Suppose a financial market participant seeks short-term funding to cover any necessity. It holds assets but does not want to get rid of them in exchange for cash. The repurchase agreement (commonly known as a *repo*) market offers a solution: a repo is a transaction in which one party (the repo seller) sells a security with a contractual commitment to buy it back for a price that includes an interest payment (referred to as the repo rate) on a pre-agreed date, while the counterparty (the repo buyer) commits to selling the security back.

In practice, repos function as a collateralized loan backed by the sold security. Repo markets have become a very important source of wholesale funding – if not the most important – for banks, funds, hedge funds, and many other market participants. For instance, the outstanding amount of repos and reverse repos (a repo from the perspective of the cash lender) in Europe has been reaching new highs, surpassing EUR 11 trillion in 2024 (ICMA, 2024).

One of the noteworthy features of the European repo arrangements is that the counterparty receiving the collateral gains partial or full legal rights over it. In other words, it is not uncommon for the cash lender to be allowed to do whatever it wishes with the security, as long as it is available to be returned to the original owner when the time to revert the transaction comes. This paves the way for institutions to do something very intuitive: pledge the same securities they have received as collateral in their own transactions. This process is known as *reuse* or *rehypothecation*. Although these terms are sometimes used interchangeably, rehypothecation is a subset of reuse. The former typically refers to the context where a prime broker, which gains

access to part or all of its client's portfolio as collateral, employs these securities for its own purposes (e.g., repos, short selling, etc.). The latter describes the broader case where collateral received from a transaction is pledged in a subsequent one (FSB, 2012b; Singh, 2014). Our focus in this work is reuse within the repo market, i.e., collateral received via repo and re-pledged in other repos.

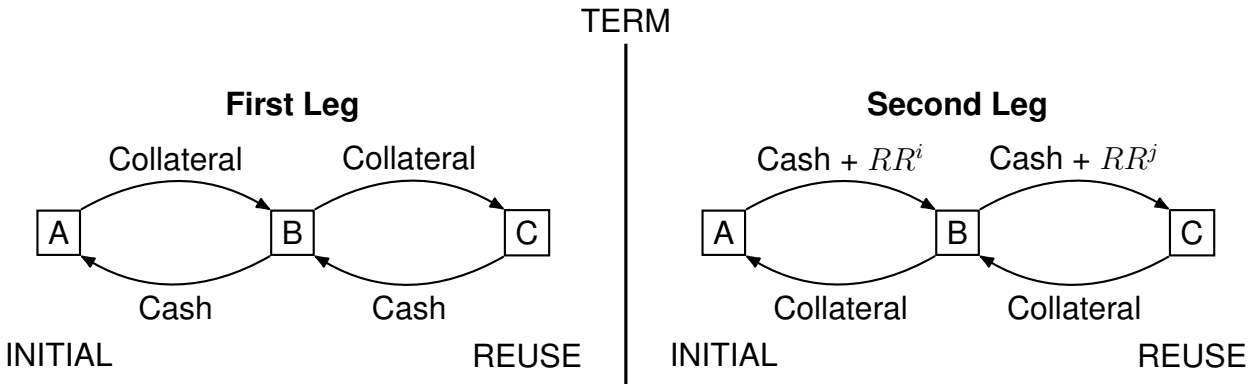


Figure 1: Illustration of collateral reuse in a Repurchase Agreement. Collateral goes from A to be B in the initial transaction, and B re-pledges it in a repo with C. In the repurchase date of the reuse transaction, C delivers the collateral to B, while B returns the collateral to A in the repurchase date of the initial transaction. RR^i and RR^j represent the repo rates agreed on in each transaction.

Although quite intuitive and apparently simple, this process has important implications for financial markets. Recent research highlights that collateral rehypothecation tends to boost market efficiency through increased liquidity and additional allocation possibilities, but also increases systemic risk and volatility due to additional interconnectedness (e.g., Infante, 2019; Gottardi, Maurin, and Monnet, 2019; Accornero, 2020; Brumm et al., 2023). This trade-off is also highlighted by regulators (e.g., CGFS, 2013; FSB, 2017a, 2017b). In a model set-up, Chang and Chuan (2025) find that more collateral reuse decreases the likelihood of the worst equilibrium (crises) and can unambiguously improve financial stability for a fixed degree of risk-taking behavior.

Re-pledging collateral also has links with asset valuation (Bottazzi, Luque, and Páscoa, 2012) and monetary policy (e.g., Muley, 2016; Andolfatto, Martin, and Zhang, 2017).

However, despite their importance, these works are all theoretical or normative. Empirical literature on the topic remains scant, mainly due to data availability issues. Aitken and Singh (2010), Singh (2011), and Kirk et al. (2014) pave the way, reporting a trade-off between collateral circulation and risks intrinsic to collateral rehypothecation, similar to that later brought up

by theoretical papers, and providing estimates of collateral velocity. Nonetheless, these early works were bound to rely on dealers' annual reports instead of proper transaction-level data, limiting the scope of their conclusions.

More recently, Infante, Press, and Saravay (2020) use U.S. supervisory data on securities financed transactions (SFTs) and incoming and outgoing collateral for the nine largest primary dealers to capture rehypothecation. They argue that this practice, although boosting liquidity and reducing issuance costs, also increases market fragilities through the creation and expansion of "collateral chains", i.e., links between different market participants connected to the same collateral through a series of transactions. Moreover, reuse of treasuries is positively related with scarcity, and highly connected with the central bank's balance sheet. Besides, they reported that 85% of incoming treasuries are later re-pledged.

Notably, in possession of transaction-level data, but no clear-cut indication of reuse, Fuhrer, Guggenheim, and Schumacher (2016) develop an algorithm to quantify collateral reuse in the Swiss repo market from early 2006 to early 2013. The method is based on coincidences of purchase and repurchase dates, counterparties, pledged security, and transaction amounts. The authors find an average reuse amount of CHF 2.2 billion (6.5% of the outstanding volume), and an average reuse rate[2] of 5%, peaking at around 20% in autumn 2007. They also show, among other things, that reuse decreases with collateral availability.

This approach became somewhat popular. Issa and Jarnecic (2024) use transaction-level data for repos from the Australian Securities Exchange, also from 2006 to 2013, to run a similar algorithm. They find an average reuse rate of 3.42%, in addition to finding evidence contradicting the hypothesis that dealers have access to extra temporary liquidity (or "liquidity windfalls") when intermediating collateral via reuse in repos. We further develop this last claim in Section 2.2. Inhoffen and van Lelyveld (2024) follow an analogous path, using their algorithm to capture repo collateral reuse with data from the European Money Market Statistical Reporting (MMSR) between 2016 and 2021. Their findings corroborate that the reuse rate positively responds to central bank-induced asset scarcity. Furthermore, the authors point out that demand for safe assets is more determinant of reuse than liquidity, and they find additional support for the financial stability concerns arising from collateral reuse. Finally, they report an average reuse rate of 53%. This is well above the numbers obtained by Fuhrer, Guggenheim, and Schumacher (2016) and Issa and Jarnecic (2024), but not entirely deviant from the whole literature. Jank, Moench, and Schneider (2022) measure reuse at the dealer-security level for German banks using the quarter-end reports from the Bundesbank's Securities Holdings Statistics and security-level data on incoming and outgoing collateral from repos and securities lending from 2008 to 2017. The authors present an average reuse rate of 75%, much closer to that of In-

[2]The ratio total reused to total pledged collateral in a given period.

hoffen and van Lelyveld (2024). They also report that increases in reuse beyond certain levels are linked to rising failures to deliver and interest rate volatility in the repo market, as well as additional mispricing in the secondary cash bond market.

Our goal in this work is to contribute to this discussion by directly matching reuse and initial transactions and analyzing the corresponding haircut differentials. This approach aims to provide a clearer understanding of how collateral reuse affects dealers' liquidity and funding costs, thereby shedding light on the practical implications of the liquidity windfall phenomenon. We explore these issues in detail in Section 5.

2.2 Liquidity Windfalls

Given that one part in a repo receives cash and the counterparty receives the security as to fulfill the role of collateral, it is naturally considered upfront that the market value of the security might vary, eventually leaving the cash lender exposed. For that reason, repos usually include certain degree of over-collateralization. This takes the form of a discount on the initial market value of the collateral *vis-à-vis* its purchase price, widely known as "haircut". Haircuts are calculated as[3]:

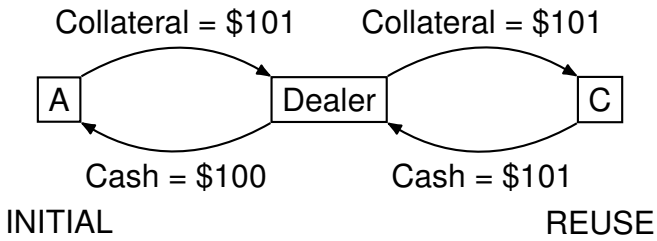
$$\left(\frac{P_m - P_p}{P_m}\right) \times 100$$

where P_m is the market value of collateral and P_p is the purchase price. For instance, this means that a cash borrower searching for \$100 in the repo market, while facing a haircut of 2%, actually needs to pledge collateral with a market value of $\frac{100}{0.98} \approx 102.04$.

Haircut determination is in the center of a significant chunk of the research focusing on repo markets. Importantly for our purposes, Infante (2019) designs a model where dealers intermediate collateral through reuse, receiving additional temporary liquidity by imposing a larger haircut in the first transaction (dealer as collateral taker, larger haircut implies more collateral) relative to the second one (dealer as collateral provider, smaller haircut implies more cash), which is referred to as a "liquidity windfall". In other words, dealers would receive more securities in their repo transactions than they need to pledge in order to obtain the same amount of cash they lent out. They would then pledge the whole amount in subsequent repos, pocketing the cash difference at least until the repurchase date. The author argues that larger haircut in bilateral repo markets (where dealers tend to be the lenders) when compared to the tri-party market (where dealers are likely to be borrowers) corroborate the existence of this phenomenon. This is in line with the model of Eren (2014), where dealers' sourcing for funding determines

[3]For further details, see: ICMA ERC Repo Margining Best Practices 2012.

repo rates and haircuts, this last one influenced by dealers charging higher haircuts one providing repo funding to hedge funds than the ones they face when reusing the sourced collateral, exactly the same idea presented in the concept of liquidity windfall.



Liquidity Windfall = $101 - $100

Figure 2: Illustration of the concept of liquidity windfalls. Counterparty A pledges $101 in collateral value in exchange for $100 in cash, meaning it faces a positive haircut. The dealer re-pledges the collateral in another repo, now facing lower haircuts (zero, in this example). In this way, the dealer can get more cash than it has lent out, retaining this surplus until the repurchase date.

Infante and Vardoulakis (2021) model coordination failures introduced by dealers' reliance on liquidity windfalls in the repo market. Also based on this concept, Kruttli, Monin, and Watugala (2022) argue that distressed prime brokers might not reduce credit to hedge funds due to the benefits of the extra liquidity resulting from collateral reuse. Besides, intuitively, the existence of an additional funding mechanism for dealers could affect the way they react to changes in other forms of liquidity sourcing. These include outright sales of securities, which could potentially alter dealers' balance sheets and asset allocation in the market as a whole, as well as the provision of liquidity by the central bank, impacting the transmission of monetary policy.

Naturally, as in the research on collateral reuse in general, empirical evidence on these results is very rare. Data availability is in the root of this problem, given high-quality granular data on repo transactions is hard to obtain. Perhaps more surprising is the fact that one of the only papers to investigate this issue finds results that actually contradict the postulate of liquidity windfalls (Issa and Jarnecic, 2024). Using transaction-level data from the Australian Securities Exchange (ASX), the authors, also employ an algorithm based on Fuhrer, Guggenheim, and Schumacher (2016), find that dealers in reality set a negative spread between the haircuts of the initial versus reuse repos, the opposite of what theory predicts. They offer a compelling conjecture to rationalize the outcomes: it might as well be that dealers focus on the repo rate spread between initial and reuse transactions rather than on the haircut differential. For theoretical models to adapt to this, one needs to drop the hypothesis that dealers strictly prefer

immediate cash, present in Infante's (2019) model. Instead, one could suppose that banks prefer permanent rather than temporary liquidity, making the rate spread more attractive relative to the haircut spread.

We believe the apparent mismatch between theoretical predictions and recent empirical findings calls for further investigation. Our objective is to explore this discrepancy and gain a deeper understanding of the factors influencing haircut differentials and their role, if any, in dealers' funding strategies. This analysis will be the focus of Section 5.

3 Data and Reuse Estimation

3.1 The Dataset

The Securities Financing Transaction Data Store (SFTDS) is a joint project of the ECB and seven national central banks (Belgium, Germany, Spain, France, Italy, Luxembourg, and the Netherlands), with the goal of creating a common database for Secured Financing Transactions (SFTs). This resulted in a transaction-level dataset capturing all SFTs conducted involving entities in these countries, corresponding to the vast majority of transactions in Europe. Data is collected under the Securities Financing Transaction Regulation, which requires institutions to report their SFTs to a trade repository registered by the European Securities and Markets Authority (ESMA).

SFTDS covers three types of SFTs: i) repurchase agreements (repos) and buy/sell-backs, ii) securities lending, and iii) margin lending. Data is available on a daily basis since July 2020, and includes comprehensive information including counterparty LEIs[4], transaction dates, transaction amount, repo rate, haircut, currency, counterparty sector, collateral ISIN[5], collateral issuer, among other trade characteristics.

The dataset has key advantages over Money Market Statistical Reporting (MMSR), a widely used data source on European Securities Financing Transactions. First, the dataset contains separate tables for distinct SFTs. This makes it possible to fully disentangle collateral reuse in repos from pledging activity in any of those markets, establishing a true repo–repo reuse nexus. SFTDS also broadens repo reporting requirements, previously restricted to larger banks, to more segments of the financial sector, including non-bank financial institutions (e.g., hedge funds, pension funds)[6]. This provides a more complete view of overall repo market activity, capturing flows that banks might not see directly. For example, when examining specifics of collateral

[4]LEI stands for "Legal Entity Identifier"

[5]ISIN stands for "International Securities Identification Number", and is a code that uniquely identifies a security globally.

[6]For more details, see: ECB SFTDS Description.

reuse, such as haircut differentials, we can now restrict our sample to non-bank transactions. This allows us to investigate whether liquidity windfalls (or their absence) stem from collateral intermediation by dealers or if such windfalls are simply an inherent characteristic of reuse in repos. Moreover, centrally cleared trades in MMSR do not include the final cash borrower and lender, whereas in SFTDS these entities can be identified, enabling a deeper counterparty-based analysis.

We start with around 24.6 million observations, ranging from July 2020 to February 2025. Those are composed by repos involving sovereign and corporate bonds, as well as a small fraction of Asset-Backed Securities and Agency debt, from 12 Euro Area countries plus securities issued in the European Union but not relating to a specific EU country jurisdiction, and international securities cleared through pan-European clearing systems, such as Euroclear and Clearstream in Europe (i.e., ISINs starting with EU and XS). Goverment bonds represent the bulk of pledged collateral, figuring in around 90% of all transactions, as can be seen in Figure 3. We drop data from the first half of 2020 (5.5%) due to known data quality issues in this part of the sample. The same applies for transactions with the Eurosystem (0.14%) and intragroup transactions (8.85%), due to the distinct nature of these repos. We understand that, when a bank moves cash or collateral between its own branches or subsidiaries, the volume and terms of that transfer might be standardized or set in advance. Because these intragroup repos exist solely to shift assets within the same institution—rather than to fund external trades—they serve a fundamentally different purpose from ordinary repo transactions. Consequently, treating any subsequent trades as 'collateral reuse' can stem from a simple misinterpretation of their true intent.

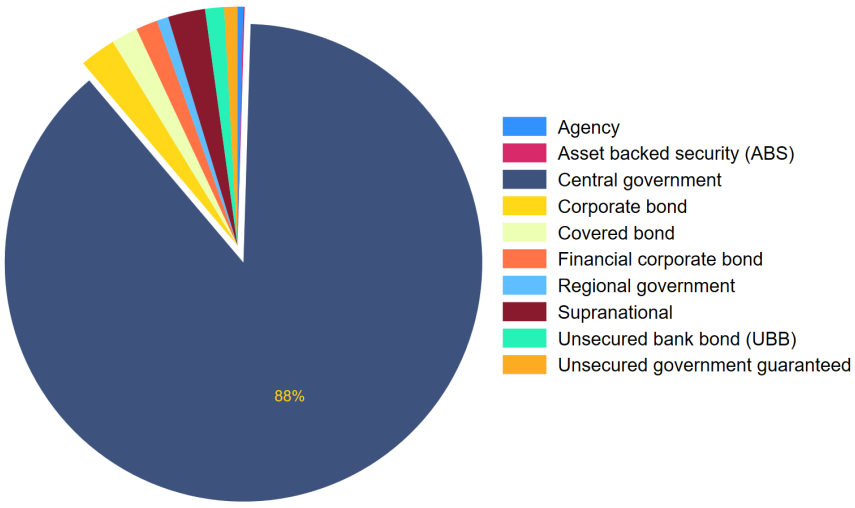


Figure 3: Asset Class Breakdown

Another important data aspect that we should be careful about is window-dressing behavior. The practice of window-dressing by banks has been a topic of debate for decades as of now (e.g., Griffiths and Winters, 1997; Munyan, 2017; Bassi et al., 2024). In essence, window dressing "(...) involves the use of short-term financial transactions to manipulate accounting numbers around the quarter-end reporting date" (Jaafar, Pollizi, and Reghezza, 2023, p. 635). Thus, it is normally identified by spotting a consistent difference in the size of certain variables between in-quarter and quarter-end operations. Repos lead to an expansion in banks' balance sheet by allowing borrowing against their assets. The incoming cash means additional exposure, which ends up increasing Leverage Ratio as defined in Basel III delimitations (BCBS, 2014). Searching to report a better version of this metric, banks can reduce their positions in repo at quarter-ends, something that has been widely documented. This could even be done by closing reverse repo positions and employing the cash to decrease repo exposure (Jaafar, Pollizi, and Reghezza, 2023), further decreasing the outstanding repo volumes.

Thus, window-dressing in repo is observed through sharp reductions of volume at quarter-ends. This tends to affect reuse both in size and motivation, adding confounding effects to the analysis. For these reasons, we drop observations at quarter-ends for all years. We follow the analysis in Bassi et al. (2024, p. 27) to decide for an adequate window, which stays at $T-2$ to $T+2$ for the three first quarters and at $T-10$ to $T+3$ for the last quarter, coming to around 8.9% of our sample.

Finally, we drop the 1 and 99 percentiles for haircuts (1.43%), volume (1.1%), and repo rate (0.75%), also to avoid reported data quality issues resulting in made up outliers. The whole process reduces our sample to 52% of the original aggregate volume (entire sample). 16% of the excluded value is due solely to the 1% winsorizing process on volumes, corroborating the problems affecting extreme values and substantiating our decision to clean it. The final sample gathers around 18 million observations.

In terms of collateral setting, there are two kinds of repos: General Collateral (GC) repos allow the cash borrower to choose from a predetermined set (or "basket") of securities, and this choice usually cannot be refused by the lender. On the other hand, Specific Collateral (SC) repos allow the repo buyer to pick the pledged security. This distinction naturally affects deal terms and changes the motivation for the transactions. For instance, if one is studying collateral intermediation, it would make little sense to look at GC repos as a means of sourcing collateral, which is why they are sometimes referred to as "cash-drive" repos[7]. Based on this, some might argue that General Collateral transactions should be ignored when analyzing collateral reuse. Inhoffen and van Lelyveld (2024) also point out that in centrally cleared transactions the Central

[7]In contrast, SC transactions are referred to as "security-driven" repos.

Clearing Counterparty (CCP)[8] usually does not allow collateral reuse in GC repos, apart from transactions with the Eurosystem. Against this background, our view is that it is not necessarily optimal to drop GC transactions. In bilateral (i.e., over-the-counter) transactions, even though the security is not selected by the cash lender, it still can be re-pledged if the occasion arises, especially considering that ISINs included in GC baskets tend to be good-quality collateral. For centrally cleared operations, the security, although encumbered post-transaction, could still have been sorted via reuse initially, and thus excluding it from the sample would mean removing at least one initial-reuse pair. This makes for an inconclusive trade-off. Adding to this the small representation of GC repos in our sample, both in number of transactions (5.45%) and total volume (5.1%), we have decided against dropping those.

3.2 Identifying Collateral Reuse

To identify collateral reuse in SFTDS, we developed a two-fold algorithm *à la* Fuhrer, Guggenheim, and Schumacher (2016), which works as follows:

1. The data is sorted by purchase date, maturity, and collateral value, starting with the oldest purchase date, smallest maturity, and smallest traded amount. After the data is sorted, an index is assigned to each transaction.

2. For each transaction, the algorithm iterates over all subsequent transactions included in the dataset and checks whether the following conditions hold at the same time: i) the purchase date of the second transaction is not earlier than the first transaction, ii) the same securities (i.e., ISINs) is used in both transactions, iii) the collateral provider in the second transaction is the same as the collateral taker in the first transaction, and iv) the purchase date of the second transaction is not later than the repurchase date of the first transaction. If all conditions are fulfilled, the first repo transaction is flagged as a "possible initial transaction" and the second one as a "possible reuse transaction".

In the process of identifying reuse transactions, the algorithm iterates through possible initial transactions and searches for possible reuse transactions. Once it is done with one transaction, it moves on to the next possible initial transaction and labels the previous one as drained. This is important to avoid overestimation, as otherwise in case two transactions with identical ISINs take place on the same date, between the same two entities, but with opposite directions (i.e., cash borrower and lender), the algorithm would identify simultaneously both transactions as reuse cases of each other, which is implausible.

[8] A CCP is a financial clearinghouse that becomes the buyer to every seller and the seller to every buyer, reducing counterparty risk.

In the last step, the algorithm checks whether second transactions are overlapping in time and calculates the maximum possible value to be reused at once, in order to reduce possible overestimation. For this reason, the ordering of the dataset is very important. In the end, for every transaction flagged as initial transaction, the algorithm outputs the total amount that has been reused in the subsequent reuse transactions.

One important deviation from the baseline approach in Fuhrer, Guggenheim, and Schumacher (2016) is that, contrary to the authors, we do not impose the repurchase date for reuse transactions to happen before the repurchase date of the initial transaction. The rationale for this is that it would not be unexpected for an entity reusing collateral to source the same bond elsewhere if the second lag of the initial transaction happens before that of the reuse one. This means this condition can be fairly strict, leading to significant underestimation of collateral reuse. This is corroborated by the fact that the authors, when dropping this condition, report as much as double collateral reuse than otherwise, what, as we will see in the next sections, would make their reuse rate very similar to the one we find.

Additionally, our algorithm does not allow more than one initial transaction to back a unique reuse transaction. This means that as soon as an initial-reuse pair is established, any value in the reuse transaction not covered by the initial one is considered own inventory. This differs from Inhoffen and van Lelyveld (2024), where more than one initial transaction can feed the same reuse one. We consider this approach more realistic in face of securities' fungibility and the fact that traders might have limited information on which fraction of collateral pledged in a transaction comes from reuse or own holdings[9].

For a concrete illustration of the algorithm, consider the example of a reuse chain in Figure 4, where the transactions are identified by their transaction index. The output in terms of data can be seen in Table 1.

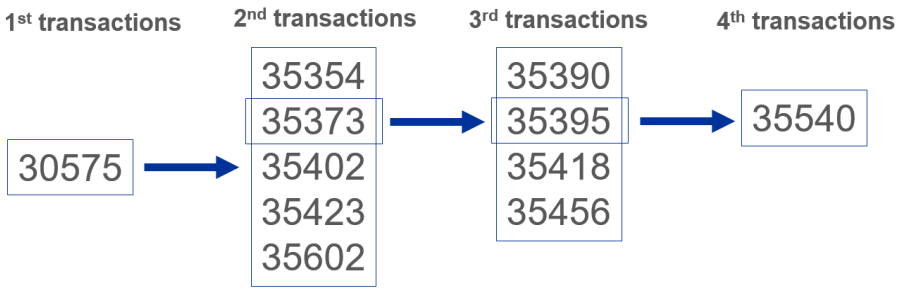


Figure 4: Example of reuse chain.

Note that the algorithm identifies pairs of initial-reuse transactions, meaning the initial transaction in one pair might be a reuse transaction in a previous pair. Ideally, a complete overview

[9]We thank some repo traders for clarifying the usual approach to reuse from trading desks' perspective.

Table 1: Example of output of the algorithm for identification of reuse pairs.

ISIN	Transaction index	Purchase date	Repurchase date	Collateral provider	Collateral taker	Transaction amount	Value of reuse	Total reuse	Reuse	Count of reuse
DE001	30575	07/08/2023	11/08/2023	Entity A	Entity B	42750000	0	0	1	10
DE001	35354	07/08/2023	08/08/2023	Entity B	Entity C	19057200	19057200	1	1	0
DE001	35373	07/08/2023	08/08/2023	Entity B	Entity D	66704400	42750000	6000	1	4
DE001	35390	08/08/2023	09/08/2023	Entity D	Entity E	43276	43276	1	1	0
DE001	35395	08/08/2023	09/08/2023	Entity D	Entity F	950450	950450	1	1	1
DE001	35418	08/08/2023	09/08/2023	Entity D	Entity G	9410944	9410944	1	1	0
DE001	35456	08/08/2023	09/08/2023	Entity D	Entity H	86549184	56299732	1	1	0
DE001	35402	08/08/2023	09/08/2023	Entity B	Entity I	3811640	3811640	1	1	0
DE001	35423	08/08/2023	09/08/2023	Entity B	Entity J	11435280	11435280	28000	1	0
DE001	35602	10/08/2023	11/08/2023	Entity B	Entity K	20013000	20013000	1	1	0
DE001	35540	09/08/2023	10/08/2023	Entity F	Entity L	105237128	950450	62000	1	0

of the reuse chains is desired. To achieve this, the second fold of the algorithm produces a list of transaction indexes involved in each chain, the chain length, and the corresponding ISIN. A visual representation of this can be found in Table 2.

Table 2: Example of output of the algorithm for full reuse chain identification.

ISIN	Chain (transaction index)	Chain length	Reuse count
DE001	[30575, 35354]	2	10
DE001	[30575, 35373, 35390]	3	10
DE001	[30575, 35373, 35395, 35540]	4	10
DE001	[30575, 35373, 35418]	3	10
DE001	[30575, 35373, 35456]	3	10
DE001	[30575, 35402]	2	10
DE001	[30575, 35423]	2	10
DE001	[30575, 35602]	2	10

4 Collateral Reuse in European Repo Markets

4.1 Description of Reuse

We analyze 983 trading days, during which 2668 institutions participated and pledged 6654 distinct securities. During the sample period, settled repos amounted to around EUR 449 trillion, averaging around EUR 456 billion per day and 24.5 million per transaction. We identify 1,705,492 trades (10.7%) serving as initial transactions and 3,848,031 reuse trades (21%), where 5585 unique securities were re-pledged. Besides, we find 1398 institutions acting as cash lenders in reuse transactions, but only 588 acting as cash borrowers (i.e., collateral providers). This pattern is consistent both for sovereign bonds (1338 lenders vs. 536 borrowers) and corporate bonds (314 lenders vs. 141 borrowers). Altogether, the information we gather suggests that (i) most securities are reused to some extent and (ii) there is much more space or sense for more market participants to serve as collateral suppliers in reuse transactions relative to being

cash suppliers, corroborating the need for certain market conditions to fulfill the first role. As shown in Table 3, initial and reuse transactions amount to EUR 40 trillion and EUR 50.9 trillion, respectively.

Table 3 shows that reuse activity is heavily concentrated in short maturities—essentially one day—for both the number of transactions and trade volume. In contrast, the volume of initial transactions is more dispersed across the maturity bands, with the 1M–3M and Over 6M tenors also being prominent, even though the number of transactions remains focused on day-to-day terms.

Table 3: Distribution of Initial vs. Re-use by Maturity

	Share of Transactions		**Share of Volume**	
Maturity	**Initial**	**Re-use**	**Initial**	**Re-use**
Day-to-Day*	87.5%	94%	35.8%	89.4%
1W	5.6%	3.7%	8.2%	5.5%
1M–3M	6.4%	2.2%	38.3%	5%
3M–6M	0.2%	0.04%	6.6%	0.1%
Over 6M	0.3%	0.1%	11.2%	0.1%
Total	1,705,492	3,848,031	40T	50.9T

* Day-to-Day includes Overnight, Spot-Next, and Tom-Next.

Figure 5 shows the evolution of the daily value of collateral delivered in repos over the course of our sample. As we can see, there is a noticeable growth in the European repo market during this period, with the total collateral value going from EUR 330 billion to around EUR 559 billion, a 69% increase. The value of reused collateral also experiences a significant expansion in the period, jumping from EUR 39 billion to EUR 62 billion a day, 59% higher. This data highlights that (i) repo markets are becoming increasingly important as a source of wholesale funding for European institutions, and (ii) the value of reused collateral within these markets has been following this growth, and thus so is the exposure of the European financial system to its effects – good and bad.

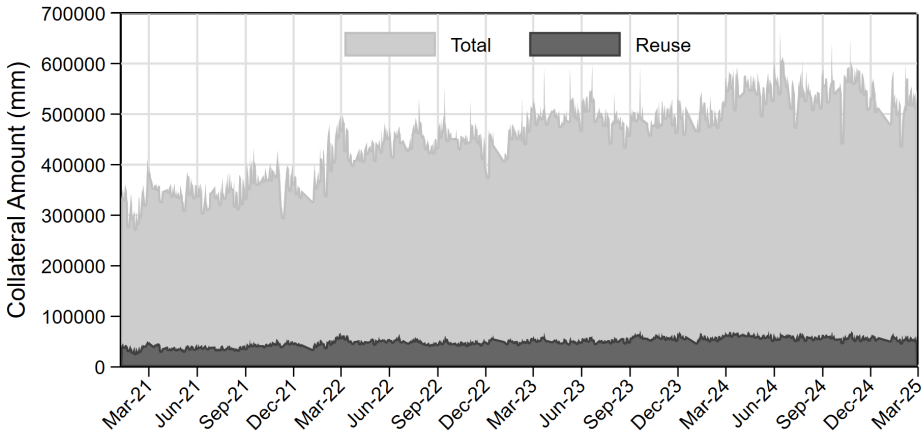


Figure 5: Pledged Collateral - Total vs. Reuse

The set of graphs in Figure 6 shows the counterparty-country decomposition for the three largest euro-area countries (Germany, France, and Italy), depicting the proportion of reused collateral issued in one of these countries that is being reused by entities from the other two, plus British counterparties. We can see that the latter are quite active in the reuse of French and German bonds, while they are basically absent when it comes to Italian collateral. Also noteworthy is the fact that counterparties from the issuer countries are not always the ones reusing domestic securities the most, as can be seen for German bonds at the beginning of the sample and Italian bonds at the end.

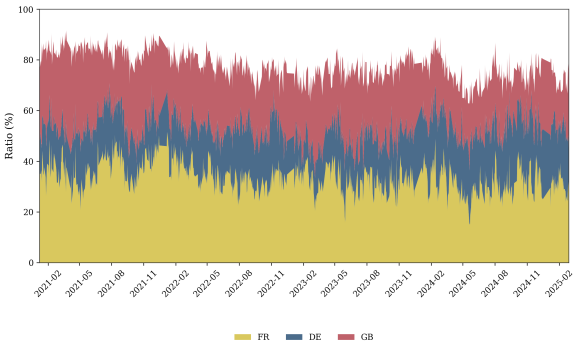
We pick two metrics to report the extent of collateral reuse in the repo market. The first one is the reuse rate, consisting of:

$$rr_t = \frac{\sum_{i=1}^{N} Reuse_{it}}{\sum_{i=1}^{N} Repo_{it}}$$

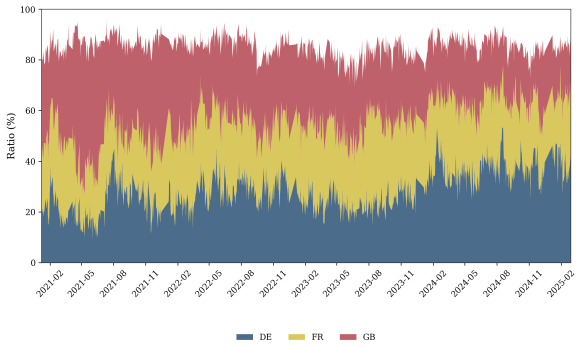
For each transaction in our sample, we calculate the collateral value corresponding to reuse from past repos, which corresponds to $Reuse_{it}$. $Repo_{it}$ is the traded amount for a given transaction. In simple terms, we calculate the ratio of reused collateral to outstanding collateral per period (in our case, daily). This measure provides insight into the ability of market participants to generate additional liquidity by re-using collateral (FSB, 2017b).

The second one is the average reuse chain length. As presented in Section 3.2, our algorithm is capable of tracking the path from the first collateral provider to the last collateral taker.

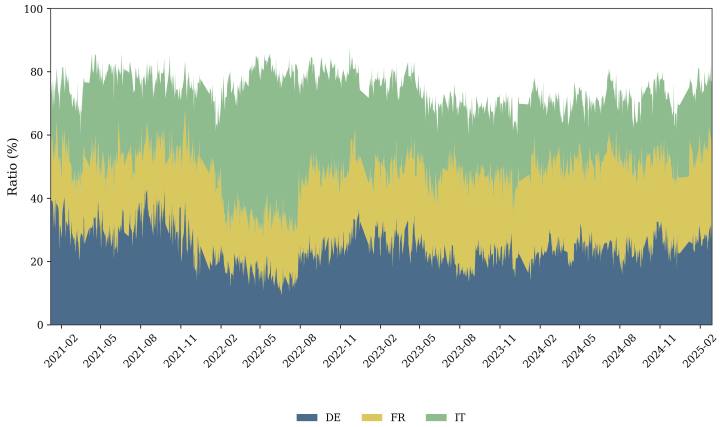
The number of players involved in this trail is the size of that specific reuse chain. We measure the daily average chain length by:



(a) French Bonds – Reuse Counterparty Composition



(b) German Bonds – Reuse Counterparty Composition



(c) Italian Bonds – Reuse Counterparty Composition

Figure 6: Selected bonds reuse volume composition

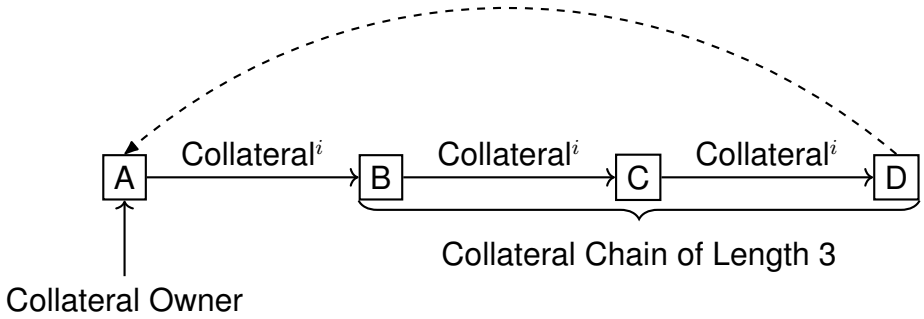


Figure 7: Illustration of the concept of collateral chains. In the example, collateral pledged by counterparty A is subsequently re-pledged from B to C and finally from C to D. When the time comes to reverse the transaction, the security has to make its way back to A. The collateral chain counts institutions linked by the same collateral, excluding the owner, and is a measure of interconnectedness among market participants.

$$\overline{Chain}_t = \frac{\sum_{i=1}^{N} Chain_{it}}{N}$$

where $Chain_{it}$ is the number of nodes in chain i, and N is the total number of chains in period t.

As highlighted by the FSB (2017b), the average chain length is a measure of interconnectedness among market participants, linked by the same collateral being re-pledged in subsequent transactions. Any issue faced by one node in the chain may cause distress along the entire sequence, potentially triggering problems in transaction settlements (e.g., a cascade of failures to deliver reused collateral) that can undermine market confidence and worsen deal terms for those seeking collateral. To the best of our knowledge, our work is the first to directly measure collateral chains, rather than estimating them through other measures of reuse.[10]

As shown in Figure 8, the reuse rate within the repo market is somewhat volatile, even though its range appears relatively stable. While 1–2 percentage point variations might seem minor, given the average daily volume, they can represent up to EUR 8 billion in additional collateral circulating in the market—something far from negligible. One can also observe a sudden and persistent change in level from July-2022 on. This coincides with the beginning of the ECB's interest rate hiking cycle (July 21st, 2022), and might be evidence of a reduction in collateral demand in a market that has just turned cash-driven.

The average reuse rate stands at 11.35%, with a standard deviation of 0.87%. It reaches a minimum of 9.4% in October 2022, and a maximum of 14.73% in November 2021. This result is significantly higher than those reported by Issa and Jarnecic (2024) (3.42%) and Fuhrer, Guggenheim, and Schumacher (2016) (5%). This discrepancy may stem from our algorithm, which, unlike those used by these authors, does not restrict reuse based on repurchase dates. In other words, our approach allows reuse transactions to have a later repurchase date than their corresponding initial transactions. As discussed in Section 3, Fuhrer, Guggenheim, and Schumacher (2016) find a reuse rate of 10% after relaxing this condition, which is in line with what we obtain.

On the other hand, our estimate is well below those reported by Jank, Moench, and Schneider (2022) (75%) and Inhoffen and van Lelyveld (2024) (53%). One possible explanation lies in the scope of the underlying data. Due to the structure of their datasets, both studies are effectively unable to distinguish repos from other securities financing transactions (SFTs), such as

[10] For instance, FSB (2017b, pp. 7–8) presents an estimate of collateral chain length given by $length_k = \frac{1}{1-ReuseRate_k}$. This approach is valid only for estimating unconditional chains (i.e., regardless of *de facto* collateral reuse), which is the best one can do when employing aggregate reuse measures instead of tracing how much of the collateral value in each transaction actually originates from previously pledged sources.

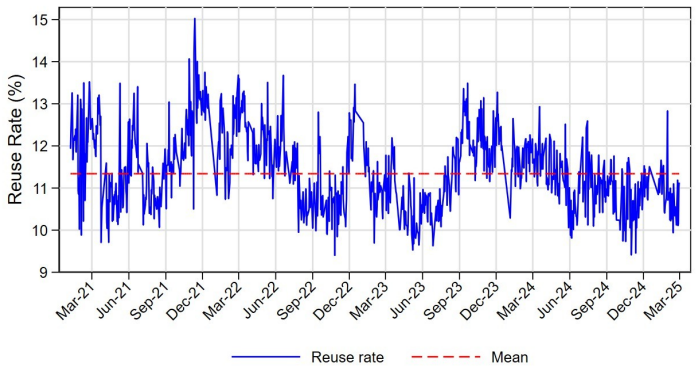


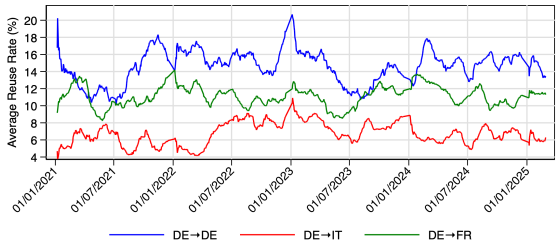
Figure 8: Average Reuse Rate

securities lending or margin lending. This would naturally result in a higher reuse rate if other SFTs constantly employ collateral obtained via repo or vice-versa. A second explanation relates to our methodological constraint on initial–reuse pairs: we require that each reuse transaction be backed by only one initial transaction. This differs from the algorithm used by Inhoffen and van Lelyveld (2024), and—as also discussed in Section 3—can significantly reduce our reuse estimates relative to theirs.

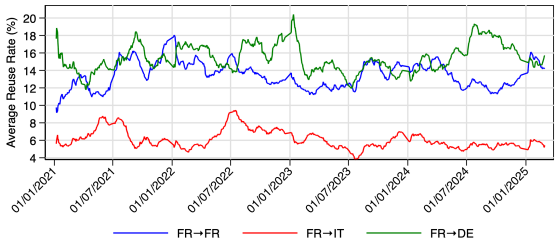
Figure 9 outlines the reuse rate profiles of the three main countries in the sample when trading among each other. One can notice that it is not uncommon for institutions located in one country to have a higher reuse rate when dealing with institutions from other countries compared to their own (as an aggregate). Not only that, there are countries, such as Italy, where the "domestic" reuse rate is consistently lower than the "international" ones. This may indicate that the demand profile for securities in other countries creates greater opportunities for reuse gains compared to the domestic Italian market, highlighting the allocation potential of collateral driven by reuse. In plot (d), we can also observe what happens when entities in the aforementioned countries trade with those of a non-EU but highly interconnected market, in the form of the British market. British counterparty also reuse collateral in different rates when trading with German, French, or Italian entities. In special, the volatility of the reuse rate when facing Italian counterparties relative to the other two origins might signal that factors that turn reuse advantageous in this market for British players (e.g., better deal terms, better allocation of securities) change more frequently in the Italian market.

Not only the counterparties' origin influences reuse, but also that of the securities. Figure 10 breaks down the reuse rate by the issuing country for the five largest Euro area countries. The reuse rate for French and German bonds is consistently higher and lower than the others, respectively, with the French rate always above average and the German one usually below it. The rate for Spanish bonds is noticeably more volatile in comparison. Interestingly, there seems

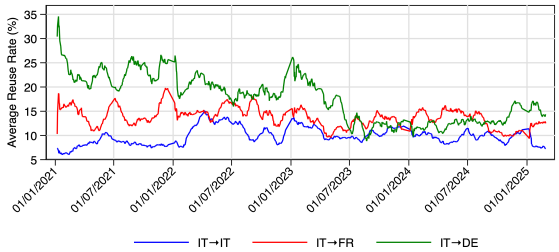
to be some convergence among most or all of the rates, especially in the early part of each year.



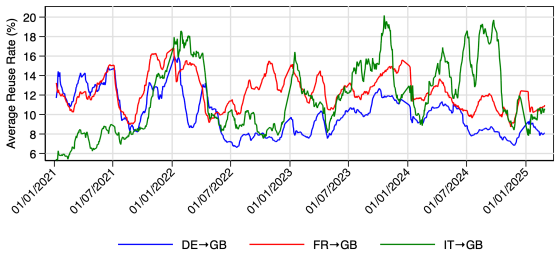
(a) Reuse Rates by Counterparty Country Pair - German Lender



(b) Reuse Rates by Counterparty Country Pair - French Lender



(c) Reuse Rates by Counterparty Country Pair - Italian Lender



(d) Reuse Rates by Counterparty Country Pair - British Borrower

Figure 9: Reuse Rates by Counterparty Country Pair (%, MA-30). Country A → Country B means that an entity located in A lends cash to an entity in B. For instance, the data represented by DE → IT is the average daily reuse rate for when Italian counterparties borrow cash (and, therefore, transfer securities) from a German counterparty.

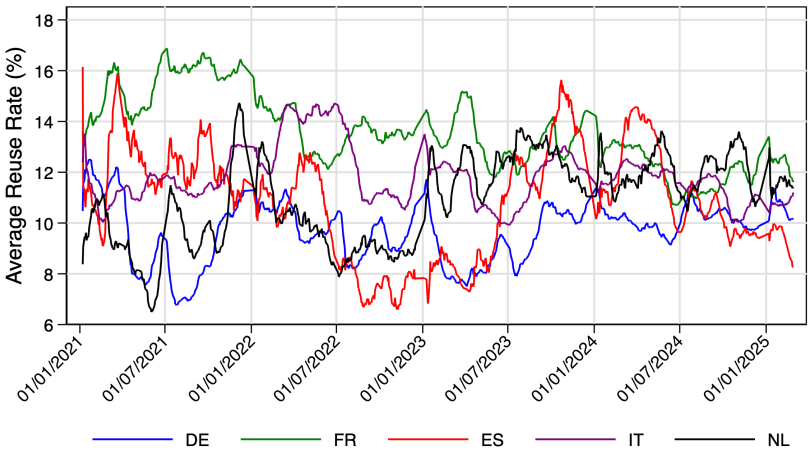


Figure 10: Reuse Rate by Issuer Country (MA-30)

Figure 11 shows that, aside from a few short periods, short-dated (one year or less) bonds usually have the lowest reuse rates, typically around 8–11%, while the longest maturity buckets

tend to show higher rates in the 12–14% range. Reuse rates for bonds with shorter remaining maturities are also more volatile, whereas the >1Y–5Y, >5Y–10Y, and 10Y+ buckets generally follow smoother and often similar trends.

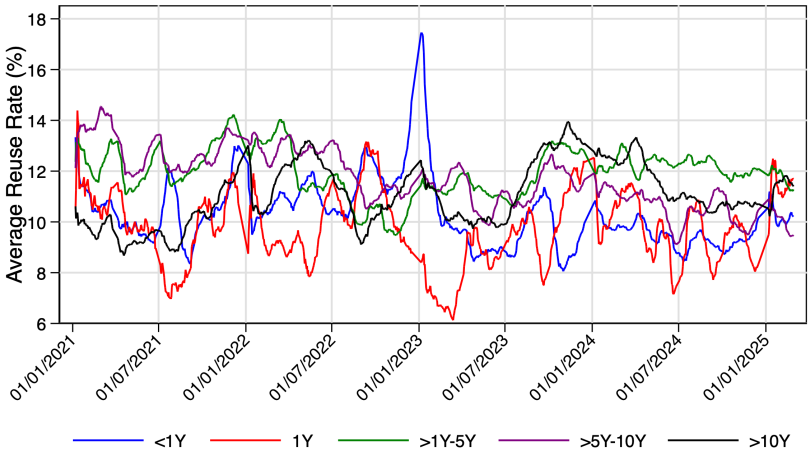


Figure 11: Reuse Rate by Bond Remaining Maturity (MA-30)

Figure 12 reveals that, across most counterparty relationships, the reuse rate has generally been stable and close to the overall average throughout the sample period, with a few notable excursions. Bank-to-fund transactions exhibit the most pronounced volatility, spiking above 18% during late 2021 and early 2022, potentially reflecting the surge in funding pressures and balance-sheet arbitrage around that time. In contrast, reuse flowing from banks into hedge funds remains consistently subdued, dipping below 8 percent in recent quarters—a pattern that underscores persistent caution (and perhaps higher operational friction or haircuts) when banks extend reusable collateral to more leveraged trading entities. In terms of reuse volumes, reuse activity is mainly a bank to bank phenomenon.

Finally, the average chain length sits at around 2.95. As shown in Figure 13, it is also quite stable throughout the analyzed period, consistently above 2.5 and never dropping below 2. This chain length refers to the complete universe of bonds (government and corporate). If we include only government bonds in our sample, the average chain length is around 3.05, consistently above 2.9 and never dropping below 2.7. This is an interesting but expected observation, since we expect corporate bonds to be less reused in the financial system than sovereign ones. Singh (2011) introduced the concept of "collateral velocity", which is essentially the ratio of total pledged collateral to incoming collateral. This gives an idea of how many market transactions are simultaneously secured by the same security, on average. In other words, it is an estimate of the reuse chain length, something we are now able to observe more directly. Singh found that

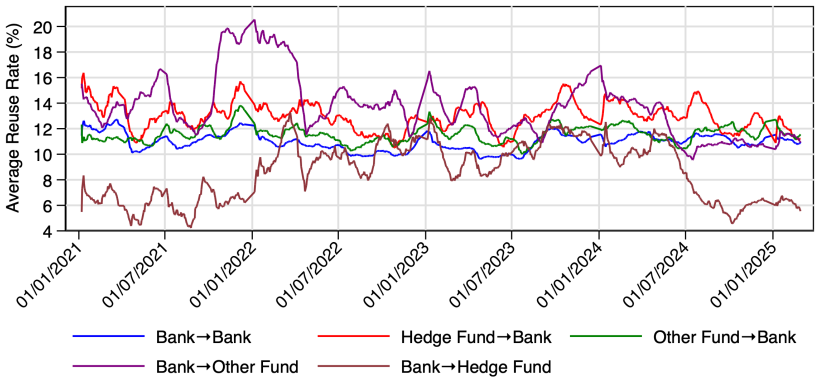


Figure 12: Reuse Rate by Counterparty Sector Pair (MA-30)

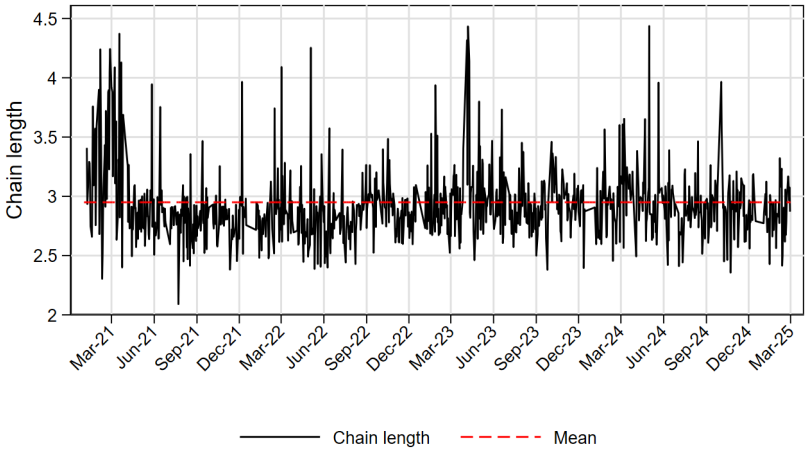


Figure 13: Average Reuse Chain Length

collateral velocity (or chain length) was around 3 before the collapse of Lehman Brothers at the end of 2007, falling to 2.4 by the end of 2010. Our results suggest that collateral chains have since rebounded to pre-crisis levels. Greppmair and Jank (2023) estimate that when the central bank lends out one unit of collateral, it expands the total collateral in the repo market by 3.13 units.

4.2 Drivers of Reuse

We proceed to identify the determinants of collateral reuse in the repo market. For this, we employ different specifications under the following general form:

$$Reuse_i = \beta_0 + \Phi X + \beta_1 OISSpread_i + \beta_2 Hike_i + \beta_3 March23_i + \gamma_{t,b,cp} + u_i$$

where $OISSpread$ is the spread between the 3-month €STR-based Overnight Index Swap (OIS) and the realized €STR for a given date, capturing agents expectations on future market developments; $Hike$ and $March23$ are dummies flagging the dates coming after July 2022 and the whole month of March 2023, isolating the effects of the new ECB monetary policy cycle and the financial turmoil in 2023 (e.g., Credit Suisse downfall, Silicon Valley Bank bankruptcy); $\gamma_{t,b,cp}$ are combinations of time (week), bond (security ISIN) and counterparty fixed effects; and Φ and X are, respectively, vectors of coefficients and independent variables corresponding to each group that we test for. The groups refer to different aspects of trade, namely transaction, counterparty, and collateral characteristics. Table 4 presents a joint summary of statistics for all the variables that we use in the different specifications.

$Reuse_i$ is a binary variable taking the value 1 if transaction i is reusing collateral, and 0 otherwise. This turns our model into a Linear Probability Model (LPM), where coefficients can be directly interpreted as changes in the probability of collateral reuse. Importantly, while non-linear models such as logit and probit are theoretically preferable for binary outcomes due to their bounded predictions and efficient estimation, they are computationally intensive and often incompatible with high-dimensional fixed effects structures. In other words, employing any of those would prevent us from taking full advantage of our vast data availability to make use of more rigorous specifications. In this setting, we opt for a LPM, which allows us to flexibly incorporate strict fixed effects that capture unobserved heterogeneity across several dimensions. Although LPM has known limitations, including heteroskedasticity and potential predictions outside the [0,1] range, the use of robust standard errors and the consistency of the estimates under standard assumptions make it a pragmatic and credible choice for causal inference in this context.

GROUP 1: TRANSACTION CHARACTERISTICS

To analyze this group, we opt to specify our regressions as:

$$Reuse_i = \beta_0 + \phi_1 ln(Notional_i) + \phi_2 ln(Term_i) + \phi_3 Haircut_i + \phi_4 RepoRate_i$$

$$+ \beta_1 OISSpread_i + \beta_2 Hike_i + \beta_3 March23_i + \gamma_{t,b,bw} + u_i$$

where $Notional$ is the transaction amount and $Term$ is the transaction tenor in days, both in natural logarithm; $Haircut$ and $RepoRate$ are the remaining transaction terms; and $\gamma_{t,b,bw}$ are $time \times bond \times borrower$ fixed effects. The choice of the borrower, rather than the more strict counterparty-pair fixed effects, is justified by the fact that the lender generally does not know the source of the pledged collateral; therefore, the decision and the capacity to reuse it lies with

Table 4: Descriptive Statistics

Variable name	Unit	Freq.	Obs.	Mean	Std. dev.	Min	Max
Reuse	dummy	t	17,956,478	0.21	0.41	0	1
Notional	millions	t	17,956,478	24.50	37.10	0.04	279
Term	days	t	17,956,478	2.20	10.20	1	720
Haircut	pp	t	17,956,478	0.14	1.19	-9.00	12.97
Repo Rate	pp	t	17,956,478	1.87	1.91	-1.03	4.02
Dealer Borrower (DB)	dummy	t	17,956,478	0.44	0.50	0	1
Dealer Lender (DL)	dummy	t	17,956,478	0.44	0.50	0	1
OIS Spread	pp	d	17,956,478	0.09	0.28	-0.44	1.05
Ask–Bid	euro	d	14,087,374	0.12	0.16	0.00	3.70
March 2023	dummy	d	17,956,478	0.02	0.16	0	1
ECB Hike	dummy	d	17,956,478	0.71	0.45	0	1
Dealer Borrower	dummy	t	17,956,478	0.44	0.50	0	1
Hedge Fund Borrower	dummy	t	17,956,478	0.03	0.17	0	1
German Borrower	dummy	t	17,956,478	0.19	0.40	0	1
French Borrower	dummy	t	17,956,478	0.24	0.43	0	1
Italian Borrower	dummy	t	17,956,478	0.14	0.34	0	1
OTC Trade	dummy	t	17,956,478	0.23	0.42	0	1
Borrower Rating	integer	d	14,464,256	17.7 (A+)	1.82	8 (B)	22 (AAA)
Borrower-Lender Exposure	ratio	q	17,956,478	0.13	0.26	0	1
Lender-Borrower Exposure	ratio	q	17,956,478	0.13	0.23	0	1
Bond Remaining Maturity	years	t	17,908,240	8.15	8.91	0.003	100
Bond Outstanding Amount	millions	d	17,894,344	19164	12167	6.96	67270
German Issuer	dummy	t	17,956,478	0.25	0.44	0	1
French Issuer	dummy	t	17,956,478	0.20	0.40	0	1
Italian Issuer	dummy	t	17,956,478	0.30	0.46	0	1
Specialness	pp	t	17,956,478	0.15	0.22	-4.52	5.02
ECB Haircut	pp	d	17,905,732	4.61	4.04	0.40	40.00

Notes: Freq. = Frequency of variables: t = for each transaction, d = daily, q = quarterly. Obs. = Number of observations for each variable. Unit: pp = percentage points.

the borrower.

GROUP 2: COUNTERPARTY CHARACTERISTICS

Our specification to test for the attributes of borrowers and lenders is:

$$Reuse_i = \beta_0 + \phi_1 DB_i + \phi_2 HFB_i + \phi_3 DEB_i + \phi_4 FRB_i + \phi_5 ITB_i + \phi_6 RATB_{bwi}$$

$$+ \phi_7 EXPOB_{bwi} + \phi_8 EXPOL_{li} + \phi_9 OTC_i + \beta_1 OISSpread_i + \beta_2 Hike_i + \beta_3 March23_i + \gamma_{t,b} + u_i$$

where DB and HFB are dummies flagging if the borrower is, respectively, a dealer[11] or a hedge fund; DEB, FRB, and ITB are dummies indicating if the borrower is located in Germany, France, or Italy; OTC indicates if the transaction is bilateral (which naturally makes the central clearing the baseline case); $RATB$ is the borrower's rating in a numeric scale that goes from 1 (equivalent to D) to 22 (equivalent to AAA)[12]; and $EXPOB$ and $EXPL$ represent, respectively, the exposure of the borrower to the lender and vice-versa in a given transaction, quantified as fraction of the cash amount, in that quarter, that the borrower (lender) received (lent out) from a given lender (to a given borrower). The subscripts bwi and li refer, respectively, to borrower and lender characteristics when transaction i is sealed. $\gamma_{t,b}$ are $time \times bond$ fixed effects.

GROUP 3: COLLATERAL CHARACTERISTICS

At last, we proceed to capture the influence of collateral specifics on reuse with:

$$Reuse_i = \beta_0 + \phi_1 REMMAT_{bi} + \phi_2 ln(Outstanding_{bi}) + \phi_3 IssuerDE_{bi} + \phi_4 IssuerFR_{bi}$$

$$+ \phi_5 IssuerIT_{bi} + \phi_6 ASKBID_{bi} + \phi_7 Specialness_{bi} + \phi_8 ECBHC_{bi} + \beta_1 OISSpread_i$$

$$+ \beta_2 Hike_i + \beta_3 March23_i + \gamma_{t,bw} + u_i$$

where $REMMAT$ is the bond remaining maturity in years; $Outstanding$ is the natural logarithm of the security's outstanding amount in the trade date; $IssuerDE$, $IssuerFR$, and $IssuerIT$ are dummies indicating if the issuer is located in Germany, France, or Italy; $ASKBID$ is the different between the ask and the bid prices for the pledged security on a given that date, pinning down liquidity elements; $Specialness$ is the difference between the repo rate for a given transaction and the ongoing ECB Deposit Facility Rate (DFR)[13]; $ECBHC$ is the haircut

[11] Further explanation on our classification of dealers is available in the next section.

[12] Ratings follow Standard and Poor's model.

[13] It might be argued that specialness in this definition fits better as a transaction characteristic. Our understand-

attributed to the security in the ECB collateral framework on the trade date, which we understand to be a suitable quantitative substitute for bond ratings as a measure of credit risk. The subscript bi refers to the bond b serving as collateral for transaction i. Finally, $\gamma_{t,bw}$ are $time \times borrower$ fixed effects.

Table 5 presents the results for transaction characteristics, beginning with two very intuitive takes: smaller and shorter transactions are more likely to reuse collateral. This appeals to considerations of risk exposure on the notional side and to the repurchase date dynamics on the term side, meaning that reusing collateral from longer maturities in shorter-maturity repos makes more sense if one aims to constrain exposure. Despite being statistically significant in some setups, the haircut and repo rates are not economically meaningful for determining reuse. The negative coefficients for the OIS spread and the dummy flagging the turbulent month of March 2023 signal that higher financial instability reduces collateral reuse in the repo market, indicating that players are concerned with potential heightened risks when entangled in collateral chains during turmoil. Finally, the ECB-hike dummy is, at most, not economically significant, signaling that the decision to reuse is unrelated to traditional monetary policy tools.

Almost none of this, however, applies to corporates, which are much more dependent on counterparty characteristics, as one can see in Table 6. Not only those, though; once we drop our borrower fixed effects in favor of a looser specification, the explanatory power of our model, as measured by the R-squared, decreases dramatically for every setup (complete sample, sovereigns, and corporates). That said, given that we have a comprehensive set of those counterparty characteristics (country, sector, rating, connections, etc.) and still remain far from achieving a similar explanatory power (relative to the stricter set of fixed effects) when it comes to sovereign reuse probability, we conclude that what really matters is not the characteristics of the institution but, indeed, who they really are. This essentially boils down to market stance in a way that can hardly be captured by statistical tools, but one can now be aware this is the case.

Dealer activity does not seem to be a determinant of the probability of reuse, except for corporates, where it becomes very significant. Hedge fund participation, on the other hand, notably reduces this probability when those funds act as borrowers. For corporates, the coefficient is omitted for collinearity issues, mostly due to the low participation of these institutions in repos involving privately issued securities. Both results indicate that reuse of corporate bonds is feasible mostly for counterparties with a stronger market stance. But it does not stop there: the importance of this factor for the entire repo market can be seen in the coefficients for borrower and lender exposure. A borrower being more dependent on the lender for its transaction vol-

ing, however, is that this is an attribute closely tied to bond specifics, and significant variation between transactions with the same underlying collateral should rarely be observed over short periods of time unless there is significant distress in the market, something we already control for.

ume decreases the probability of reuse, while a lender more dependent on the borrower has the opposite effect—at least for sovereigns—further highlighting the importance of counterparties' competitive position. The issuer of the bond also matters, with Italian bonds less likely to be reused, and the same holds for French corporates. The clearing structure matters, with over-the-counter transactions becoming more likely to accommodate collateral reuse. The statistical insignificance of this coefficient for corporates, just as in the case of lender exposure, further strengthens the conjecture that the borrower's stance is crucial for repo reuse involving these bonds.

Table 5: Results Group 1 – Transaction Characteristics

	Dependent Variable: *Reuse*		
	All	Sovereigns	Corporates
ln(Notional)	-0.03^{***}	-0.03^{***}	0.01
	(–10.82)	(–11.03)	(1.24)
ln(Term)	-0.02^{***}	-0.02^{***}	-0.002
	(–5.42)	(–5.35)	(–0.51)
Haircut	0.000^{***}	0.000^{***}	0.001^{**}
	(3.32)	(2.67)	(1.99)
Repo Rate	-0.006^{*}	-0.006	-0.002
	(–1.96)	(–1.56)	(–0.74)
OIS Spread	-0.01^{**}	-0.01^{*}	-0.02
	(–2.17)	(–1.89)	(–1.09)
March 23	-0.01^{*}	-0.01^{*}	0.0005
	(–1.92)	(–1.87)	(0.04)
ECB Hike	-0.01^{***}	-0.01^{***}	-0.009^{*}
	(–4.38)	(–4.06)	(–1.69)
Constant	0.63^{***}	0.65^{***}	-0.08
	(16.47)	(16.91)	(–0.70)
Time × Bond × Borrower FE	Yes	Yes	Yes
Adj. R-squared	0.61	0.61	0.54
Number of obs	17,343,690	15,826,380	1,016,673

Notes: t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the borrower level.

Finally, table 7 shows that collateral features seem to not matter too much in the decision to reuse. This might emerge from the fact that collateral pledged in most repos is already restricted to securities held to a certain high standard. One can confirm this by checking, in Table 4, that the average ECB haircut in our sample is 4.61, something only feasible for bonds rated AAA to A-[14]. This conclusion is reinforced by the fact that those haircuts themselves

[14]See: ECB Haircut Schedule.

Table 6: Results Group 2 – Counterparty Characteristics

	Dependent Variable: *Reuse*		
	All	Sovereigns	Corporates
Dealer Borrower	0.03	0.03	0.29**
	(1.35)	(1.24)	(2.58)
Hedge Fund Borrower	-0.11***	-0.10***	
	(-3.04)	(-2.77)	
German Borrower	0.04	0.04	-0.08
	(0.89)	(0.92)	(-0.80)
French Borrower	-0.01	-0.01	-0.14**
	(-0.45)	(-0.34)	(-2.16)
Italian Borrower	-0.11***	-0.11***	-0.23***
	(-3.77)	(-3.71)	(-3.79)
Borrower Rating	0.004	0.00	0.002
	(1.01)	(1.14)	(0.42)
Borrower Exposure	-0.14***	-0.14***	-0.10***
	(-4.14)	(-3.72)	(-2.79)
Lender Exposure	0.18***	0.21***	-0.02
	(4.08)	(4.92)	(-0.60)
OTC	0.05***	0.04**	0.05
	(2.71)	(2.11)	(0.54)
OIS Spread	-0.01*	-0.01	-0.04
	(-1.79)	(-1.30)	(-1.38)
March 2023	0.01	0.01	0.004*
	(1.36)	(1.46)	(1.74)
ECB Hike	0.001	0.00	-0.01
	(0.31)	(0.33)	(-1.37)
Constant	0.12	0.13*	0.05
	(1.65)	(1.74)	(0.46)
Time × Bond FE	Yes	Yes	Yes
Adj. R-squared	0.10	0.09	0.41
Number of obs	14,417,039	12,904,489	1,035,455

Notes: t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the borrower level.

are neither statistically significant nor economically meaningful. The bond issuer, on the other hand, seems to matter: German and French bonds—at least sovereigns—seem less likely to be reused. One explanation could be that, seen as safer assets from the EU's largest countries, they might have better uses other than being consecutively pledged in repos. Finally, the coefficient on the outstanding amount seems to contradict the hypothesis that bond scarcity necessarily prompts collateral reuse. However, this applies only to corporates, while most studies concluding for the existence of this relationship focus on Treasuries or ECB-induced scarcity for sovereigns (Fuhrer, Guggenheim, and Schumacher (2016); Infante, Press, and Saravay (2020); Jank, Moench, and Schneider (2022); Inhoffen and van Lelyveld (2024)).

Table 7: Results Group 3 – Collateral Characteristics

	Dependent Variable: *Reuse*		
	All	Sovereigns	Corporates
Remaining Maturity	0.000	-0.000	-0.000
	(0.84)	(-1.19)	(-0.80)
ln(Outstanding)	0.04***	0.02	0.02**
	(5.29)	(1.43)	(2.38)
German Issuer	-0.04***	-0.04***	0.01
	(-4.02)	(-3.18)	(0.92)
French Issuer	-0.03**	-0.02**	-0.03
	(–2.37)	(–1.97)	(–0.98)
Italian Issuer	0.05**	0.01	-0.01
	(1.99)	(0.39)	(–1.01)
Ask-Bid	-0.03**	-0.01	0.001
	(–2.32)	(–0.74)	(0.12)
Specialness	-0.01	0.002	-0.005
	(–0.65)	(0.18)	(–0.61)
ECB Haircut	-0.000	0.004	0.000***
	(–0.17)	(1.42)	(3.70)
OIS Spread	-0.01*	-0.01**	-0.02
	(–1.91)	(–2.08)	(–1.20)
March 2023	0.01	0.01	0.005
	(1.55)	(1.61)	(1.43)
ECB Hike	0.000	0.000	-0.01*
	(0.08)	(0.20)	(–1.74)
Constant	-0.12*	0.03	-0.04
	(–1.91)	(0.28)	(–1.00)
Time × Borrower FE	Yes	Yes	Yes
Adj. R-squared	0.10	0.08	0.31
Number of obs	14,022,814	12,453,234	1,018,062

Notes: t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the borrower level.

5 Investigating Liquidity Windfalls

We now proceed to test the hypothesis of existence of liquidity windfalls via collateral reuse in repo transactions. As mentioned in Section 2, literature develops the idea that some market players, essentially dealers due to their privileged market position, are able to intermediate collateral by running a reverse repo (or initial transaction) to source collateral and a posterior

repo (or reuse transaction) to source liquidity using the same security. Since intermediating bond trades is a dealer's core business, this would not bring anything new. The noteworthy twist is on the deal terms: according to this theory, dealers would impose a larger haircut in the initial transaction than they face in the reuse one, and by doing so would be able to obtain a temporary free cash buffer, named as liquidity windfall.

Because this windfall frees internal liquidity, it could reshape dealer incentives in nontrivial ways. First, it encourages a dealer to include the same bond in a larger matched book: each fresh reverse-repo is mirrored by an offsetting repo, so net exposure stays tiny while gross positions snowball. Because the extra bonds are financed almost entirely with borrowed cash, assets rise while equity does not, pushing textbook leverage to levels that must tumble the moment haircuts move against the dealer. This leverage spiral itself is spelled out in Brumm et al. (2023). Wallen and Lu (2025) show that the balance sheet capacity of dealers is an important driver of their leverage supply, which is cyclical and increases the US Treasury market fragility. Still on this point, by insulating cash lenders while leaving collateral providers exposed, this mechanism leaves dealers exposed to collateral runs following a cascade of events where:

1. Collateral providers (the over-collateralized counterparties in the initial reverse-repo) may refuse to roll their trades when the dealer shows signs of stress;

2. The dealer must return securities that are no longer in its possession (they have been reused in onward repos);

3. It is therefore forced to scramble for replacement collateral or fire-sell assets.

This sequence matches the "repo runs" documented during the 2008 GFC by Copeland, Martin and Walker (2014).

At the macro level, haircut-driven liquidity windfalls can blur the transmission of monetary policy and affect bond pricing. By working like a quiet subsidy slashing the dealer's effective funding cost, they might weaken the policy-rate pass-through to repo rates. This is consistent with recent evidence pointing that dealer market power muffles the signal that central banks try to send (Eisenschmidt, Ma and Zhang 2024). Besides, cheaper balance-sheet space lets dealers enlarge their matched books and quote skinnier bid-ask spreads, a pattern traced in both structural models and data (Huh and Infante 2021; Adrian, Boyarchenko and Shachar 2017). If those balance-sheet costs later rise—for example because leverage ratios tighten—the entire yield curve shifts between the "net-short" and "net-long" bounds as derived by Du, Hébert and Li (2022).

Given the context, a logical first step is to distinguish the institutions that are central to this analysis. Our identification of dealers relies on the official list of Primary Dealers (PDs)

for the reporting countries. A dealer is considered active in a transaction when (i) it acts as the cash borrower or lender and (ii) the issuer of the pledged security is a country where the bank has PD status. The list of active dealers in our sample can be found in Appendix A. We observe 52 distinct dealers in our sample, of whom 47 trade sovereign bonds at least once and 45 trade corporate bonds. Dealers borrow cash in 44% of transactions and lend cash in 47%, while dealer-dealer transactions account for the remaining 19%. These numbers remain similar when we look only at government bonds, but they vary considerably for corporates: dealers pledge these bonds in 15% of cases and lend against them in 72% of corporate-bond trades. There are essentially no dealer-dealer transactions with corporate bonds as collateral. In reuse transactions, 51 dealers act as cash providers, while 44 act as collateral providers. The same ordering holds for sovereigns (45 lenders and 41 borrowers) and for corporates (38 lenders and 31 borrowers), suggesting that, even among dealers, only a smaller subset is capable of reusing collateral. They also seem to intermediate collateral via reuse: dealers are collateral providers in more than 50% of reuse trades.

We then move on to compute our variable of interest: haircut differentials (or spreads). The procedure is straightforward: we match initial and reuse transactions and compute:

$$Haircut_{initial} - Haircut_{reuse}$$

An entity intermediating collateral via reuse receives a liquidity windfall whenever $Haircut_{\text{initial}} > Haircut_{\text{reuse}}$. Thus, consistently positive haircut differentials would corroborate the hypothesis that this extra cash cushion is common.

Before starting our analysis of haircut spreads, it is crucial to note that we define the haircut as the ratio of cash notional to collateral market value inclusive of any margin the parties know they will have to post, whether a dealer-set bilateral buffer or a CCP-imposed initial margin. Because traders negotiate terms only after considering the full equity they must lock up, the combined margin stack is part of the economic rationale for entering the trade in the first place. A dealer will agree to intermediate, and an investor will agree to lend or borrow, only if the all-in funding cost implied by both the bilateral haircut and any CCP margin is acceptable. Measuring the haircut this way therefore lets us compare trades on the basis of the total liquidity they tie up, and any differential we observe later reflects genuine differences in expected funding costs across clearing structures, not an artifact of leaving out a piece of the margin that traders have already priced in.

Figure 14 documents that, across the entire collateral reuse chain captured in our sample of 2.7 million chains, the average haircut differential is slightly negative (-9 bps). In other words, collateral is priced at a modest liquidity cost. This is the first piece of empirical observation

that acts as evidence against the existence of liquidity windfalls for the dealers, which predicts a positive differential whenever an intermediary dealer can pocket the spread between a reverse repo and a subsequent repo reusing collateral.

Figures 15 and 16 sharpen this discrepancy. The negative differential is more prominent in links where a dealer actually stands in the middle of the chain (-22 bps on average), whereas transactions executed directly between two cash investors clear often at parity. Moreover, the haircut penalty is amplified when a position moves from bilateral OTC trading into central clearing (-23 bps) and mildly reversed when it flows in the opposite direction (+6 bps). Taken together, these results provide the first empirical evidence that, contrary to the hypothesis, intermediation in real-world repo chains tends to erode rather than enhance immediate liquidity for the entity reusing collateral.

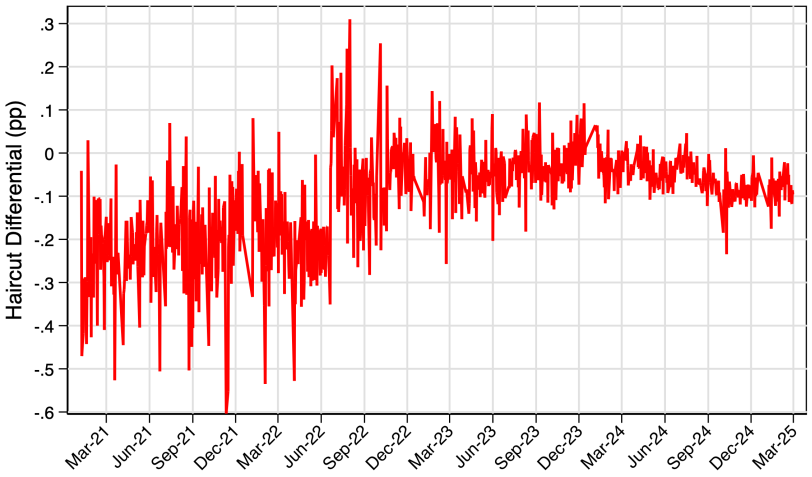


Figure 14: Average Haircut Differentials - Complete sample

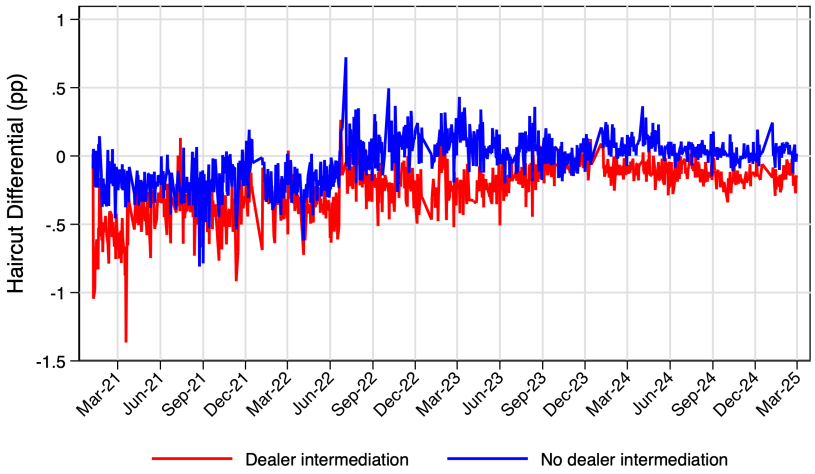
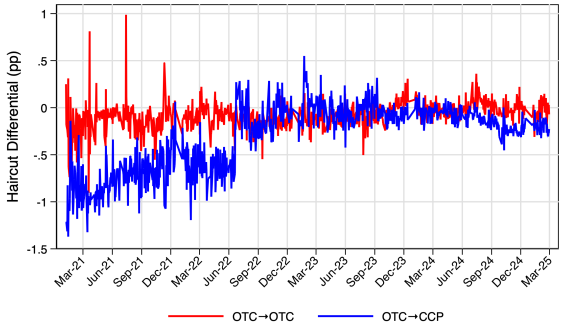
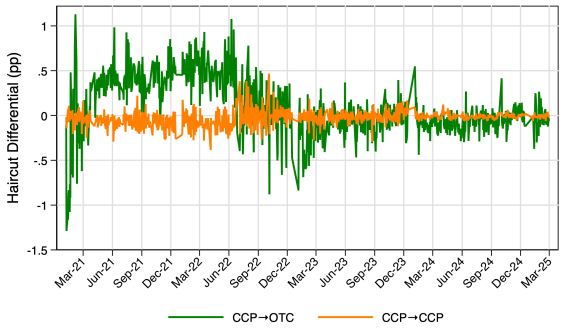


Figure 15: Average Haircut Differentials - Dealer and non dealer intermediation



(a) Average haircut differential - OTC bond sourcing



(b) Average haircut differential - CCP bond sourcing

Figure 16: Average haircut differential per clearing structure pair

In order to avoid confounding effects, we econometrically assess haircut differentials. As observed by Issa and Jarnecic (2024), this estimation is likely to suffer from self-selection bias, given there might exist factors influencing both the decision to reuse collateral and the haircut differential between the initial and the reuse transactions. We then follow the authors' approach in estimating a two-stage Heckman (1979) model that goes by:

STAGE I

$$\Pr(\text{reuse}_i = 1) = \Phi\Big(\beta_0 + \beta_1 \ln(\text{Notional}_i) + \beta_2 \ln(\text{Term}_i) + \beta_3 \,\text{Haircut}_i + \beta_4 \,\text{Repo Rate}_i$$

$$+ \beta_5 \,\text{OISSpread}_i + \beta_6 \,\text{Hike}_i + \beta_7 \,\text{March23}_i + \gamma_{t,b,bw}\Big)$$

As we have seen in Section 4.2, our most strict fixed effects specification adds considerable explanatory power to the estimates. Additionally, our main goal in the first stage of the model is to obtain the inverse Mills ratio (IMR). This corresponds to standard-normal density divided by its cumulative probability at each observation's estimated selection score. The IMR controls for the non-random selection mechanism: it represents the conditional expectation of the outcome disturbance given that an observation enters the sample, and including it in the outcome equation removes the resulting selection bias from coefficient estimates. That said, we impose a specification very similar to that pinning down reuse drivers for Group 1 (transactions characteristics), which should allow us to obtain a more accurate IMR by soaking up $time \times bond \times borrower$ attributes while also controlling for observable deal terms.

When estimating haircut differentials, however, we notice that the sample available for corporates is quite small, given the low ratio of reuse transactions with those bonds as collateral. This makes the usual sovereign-corporate comparison much less relevant, as estimates for the second group would be compromised. On the other hand, we know that clearing structure tends to be important when it comes to reuse. As seen in Table 6, bilateral transactions are more likely to be reused. Furthermore, dealers and larger banks usually have direct access to central clearing counterparties, while smaller institutions have only indirect access (if any) due to the costs associated with engaging in CCP arrangements. This means that not only can the clearing structure influence the decision (or the possibility) to reuse collateral, but sourcing and reusing collateral in distinct setups might also affect the terms. For instance, one could expect dealers to source collateral via CCPs, where haircuts are generally smaller. If it is possible to reuse this collateral in OTC trades, where they can negotiate higher haircuts, we would expect haircut differentials to be larger in this combination. Nonetheless, our descriptive measures seem to contradict this logic, possibly due to the piling up of pre-novation haircuts and CCP-imposed initial margins, as explained earlier. To further explain the issue, we turn our attention to clearing structures, reporting the results for this section accordingly, as shown in Table 8 and Table 9.

An important point to address is that, while our transactions vary considerably in size (i.e., collateral amount), running an ordinary least-squares regression would assign the same weight to all trades; the resulting coefficients would therefore describe the haircut differential for the *average trade* rather than for the *average euro* of collateral. To focus the fit on economic exposure, we estimate the Stage II model by weighted least squares (WLS), assigning each observation a weight equal to the size (in euros) of the reuse transaction,

$$w_i = C_i \; > \; 0, \qquad \hat{\beta}_{\text{WLS}} = (X^\top W X)^{-1} X^\top W d,$$

where d_i is the haircut differential for trade i, X_i its covariate vector, and $W = \text{diag}(w_1, \ldots, w_n)$. Because each squared residual is multiplied by w_i, a reuse trade involving twice as much collateral influences the fit twice as strongly. The resulting coefficients therefore quantify how the explanatory variables affect the haircut differential *per euro of collateral*, preventing the results from being driven disproportionately by small transactions.

Table 8 presents the results of Stage I, a probit model estimating the probability that a given repo transaction involves reused collateral. The results are naturally quite similar to those in Table 5, given that the regressors are identical. Now, however, we can compare these results across different clearing arrangements, and a couple of changes are noticeable.

First, transaction maturity reduces the probability of reuse only in OTC transactions. One possible explanation is that counterparties are more concerned with failing to deliver due to repurchase date mismatches in bilateral trades, where the other counterparty does not hold any kind of additional margin or collateral to cover for the security's absence—unlike CCPs, which usually do. This would then leave the counterparty reusing collateral exposed to a high fee in such situations, reducing risk-taking behavior in this segment conditionally. On the other hand, the recent change in the ECB's monetary policy stance reduces reuse only in centrally cleared transactions. This could have a more straightforward explanation: large banks and dealers are primarily responsible for monetary policy transmission and, thus, are the first to be affected by these changes. At the same time, these are the entities directly affiliated with central clearing agreements, which would make centrally cleared trades more reactive to policy shifts. With that in mind, we advance to the Stage II.

STAGE II

$$\Delta HC_j = \phi_0 + \phi_1 ln(Notional_{j2}) + \phi_2 ln(Term_{j2}) + \phi_3 NDN_j + \phi_4 NNN_j$$
$$+ \phi_5 \Delta R_j + \phi_6 OISSpread_{j2} + \phi_7 Hike_{j2} + \phi_8 March23_{j2} + \phi_9 IMR_{j2} + \gamma_{t,b,bw} + \varepsilon_j$$

where ΔHC_j is the haircut differential between the reuse and the initial and transaction for the transaction pair j; NDN is a dummy that takes the value of 1 if a reuse chain is established such that collateral goes from a non-dealer to a dealer and later to another non-dealer, and NNN signals a connection solely between non-dealers; ΔR_j is the repo rate differential between reuse and initial transactions, and IMR is an inverse Mills ratio from the predicted values of STAGE I. The subscript $j2$ signals that the aforementioned attributes refer to the second transaction (i.e., the reuse transaction). Our abundant sample allows us to impose $time \times counterparty\ pair \times ISIN$ fixed effects or variations of this combination. Note that time

fixed-effects at day-level control for risk and liquidity factors, counterparty pair accounts for prior relationships and interconnectedness, and ISIN pins down all the collateral characteristics (e.g., rating, liquidity, etc.).

Table 8: Stage I Heckman correction model — Probit Analysis

	Dependent Variable: $Prob(\text{Reuse} = 1)$		
	All	OTC	CCP
ln(Notional)	-0.03^{***}	-0.02^{***}	-0.03^{***}
	(–10.73)	(–3.24)	(–10.40)
ln(Term)	-0.02^{***}	-0.02^{***}	0.002
	(–6.23)	(–7.29)	(1.18)
Haircut	0.001^{***}	0.002^{***}	0.000^{***}
	(3.84)	(3.40)	(3.58)
Repo Rate	-0.01^{*}	-0.01^{**}	-0.01^{***}
	(–1.95)	(–2.25)	(–2.88)
OIS Spread	-0.02^{**}	-0.02^{**}	-0.01^{**}
	(–2.21)	(–2.36)	(–2.34)
March 23	-0.01^{*}	-0.01	-0.01
	(–1.93)	(–1.51)	(–1.44)
ECB Hike	-0.02^{***}	0.002	-0.02^{***}
	(–4.43)	(–0.51)	(–4.99)
Time × Bond × Borrower FE	Yes	Yes	Yes
Pseudo R^2	0.65	0.62	0.61
Number of obs	17,343,690	3,667,205	13,538,482

Notes: The table reports *marginal effects*. t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the borrower level.

Table 9 presents Stage II results. Looking at the constants, we already find important information on the average haircut differential: the same bond being traded in the same week with the same borrower averages -0.54% for the entire sample, i.e., counterparties reusing collateral surrender, on average, an extra 54 bps of its value relative to the haircut they themselves charged when first sourcing the bond. With roughly EUR 60 billion of collateral being reused each day, this implies a systemic liquidity shortfall of about EUR 320 million per trading day. The direction of the clearing switch is decisive. In practice, there is zero spread when collateral moves within bilateral transactions (OTC $\rightarrow$ OTC), but the gap remains at an almost identical level when an OTC position is novated to a CCP. Surprisingly, providing CCP-sourced securi-

ties bilaterally does not generate gains from haircut differentials, which are also virtually zero on average. Finally, CCP $\rightarrow$ CCP rolls command a sizable –65 bps surcharge.

Size and tenor behave as expected, but the sensitivity is clearly venue-dependent. In pure bilateral trade pairs, an 1% increase in notional or term lifts the haircut by 12-19 bps (col. 2). Once collateral is reused in a centrally cleared transaction, the elasticities jump: haircut spreads climb by 15–30 bps per log-point of size or maturity in OTC $\rightarrow$ CCP deals and by 18-35 bps in CCP $\rightarrow$ CCP ones. The effect vanishes once the collateral cycle returns to the OTC book (col. 3), which squares with CCP margin models that scale more aggressively with exposure than dealer credit desks do.

Turning to counterparty mix, which is where our crucial parameters are, remember that NDN refers to a chain where a dealer wedged between two non-dealers, whereas NNN features only nondealers. For NDN the coefficients are small and insignificant almost everywhere; the single borderline result is the mild 2.5 bps discount when an OTC position is unwound via CCP, and a 2 bps gain when the opposite happens. This second output might bring evidence of a liquidity gain made by dealers in CCP $\rightarrow$ OTC collateral allocation, consistent with intuition, but it is hard to argue for economic significance given its size. Pure non-dealer chains (NNN) show the same directional pattern at an even lower statistical significance, which is compatible with the weaker market stance of the involved counterparties.

The fact that the coefficient on NDN is virtually indistinguishable from zero is directly at odds with the "liquidity windfalls" hypothesis. Its absence might suggest that any potential surplus from collateral reuse is neutralized by practical frictions: balance-sheet and leverage-ratio costs make an asymmetric haircut unattractive; competitive pressure from money-market funds limits a dealer's ability to widen margins; and operational risk from daylight exposures encourages matching rather than stacking of haircuts. Crucially for any conjecture, we see no evidence that lower haircut differentials are offset by wider repo-rate spreads. If anything, haircut and repo-rate differentials occasionally rise and fall together, hinting that counterparties able to profit from collateral reuse push for better terms on both margins at once.

Table 9: Stage II — Haircut-differential analysis

	Dependent Variable: ΔH				
	All	OTC → OTC	OTC → CCP	CCP → OTC	CCP → CCP
ln(Notional)	-0.26^{***}	-0.12^{**}	-0.15^{***}	-0.11	-0.18^{***}
	(–2.68)	(–2.49)	(–2.86)	(–1.48)	(–2.93)
ln(Term)	-0.25^{**}	-0.19^{**}	-0.3^{***}	-0.15	-0.35^{***}
	(–2.45)	(–2.58)	(–2.82)	(–1.27)	(–2.93)
NDN	0.006	0.08	-0.025^{**}	0.02^{***}	-0.015
	(0.63)	(0.48)	(–2.00)	(3.07)	(–1.03)
NNN	-0.002	-0.02	-0.025^{*}	0.07	-0.003
	(–0.16)	(–0.27)	(–1.99)	(1.31)	(–0.43)
ΔR	0.07^{**}	0.008	-0.02	0.14^{**}	-0.053
	(2.19)	(0.12)	(–0.47)	(2.25)	(–1.55)
OIS Spread	-0.082	-0.004	-0.2^{**}	0.07	-0.25^{**}
	(–0.98)	(–0.04)	(–2.44)	(1.16)	(–2.17)
March 23	-0.001	0.04	0.03	0.07	-0.08
	(–0.03)	(0.51)	(0.58)	(1.59)	(–0.84)
ECB Hike	-0.13^{***}	-0.15	-0.16^{**}	0.09^{***}	0.18^{*}
	(–3.42)	(–1.06)	(–2.18)	(2.85)	(1.94)
IMR	3.36^{***}	1.39^{***}	2.06^{***}	1.13	2.42^{***}
	(2.76)	(2.65)	(2.98)	(1.29)	(3.02)
Constant	-0.54^{***}	0.008	-0.55^{***}	0.14	-0.65^{***}
	(–4.07)	(–0.05)	(–4.68)	(1.04)	(–3.51)
Time × Bond × Borrower FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.65	0.73	0.79	0.63	0.44
Number of obs	2,314,122	288,949	771,624	171,243	980,268

Notes: t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the borrower level.

Discussions with market participants indicate that, within financial institutions, securities remaining after necessary coverage has been finalized (e.g., margin adjustments, outright sales) are swept into a collateral pool, and decisions about where to allocate them usually depend on the potential repo rate alone[15], suggesting that banks eye permanent liquidity rather than temporary, even though the former comes at a later date, as suggested by Issa and Jarnecic (2024).

For the broader market, this finding implies that collateral reuse, while pervasive, is not

[15]We thank repo traders are specialists for providing detail on institutions' daily repo operations.

amplifying leverage through ever-thinner equity buffers on reused bonds. Haircuts do not seem to display the systematic dealer-imposed wedge predicted by the windfall hypothesis; instead, the data show no consistent asymmetry when a dealer reuses collateral between non-dealers. This means that secured funding system is less prone to collateral runs than windfall models predict. In practical terms, repo desks manage liquidity primarily via pricing and term, not via margin concessions, which stabilizes funding conditions for bond dealers and non-dealer investors alike. For monetary policy, it means that central bank actions aimed at easing or tightening financial conditions will transmit more through the rate channel of repos than through sudden shifts in collateral valuation haircuts, reducing the risk that policy shocks inadvertently trigger a margin-induced liquidity crunch in sovereign-bond markets.

6 Conclusion

This paper provides new empirical insights into collateral reuse and liquidity dynamics in European repo markets. By leveraging a novel, transaction-level dataset from the Securities Financing Transaction Data Store (SFTDS), we have been able to directly measure collateral chains and examine the occurrence of liquidity windfalls—a topic that has, until now, received mainly theoretical treatment.

We first establish the prevalence and scope of reuse, showing that it is an integral component of the repo market rather than a marginal activity. Our findings indicate that securities pledged in repurchase agreements often move through multiple hands, effectively unlocking additional liquidity. This dynamic helps meet short-term funding needs, yet it also brings risks. The interconnected nature of these chains means that a disturbance at one node could quickly spread, creating broader vulnerabilities in the financial system.

Building on this descriptive evidence, we evaluate the "liquidity windfalls" hypothesis — that dealers extract funding benefits by imposing wider haircuts when they intermediate collateral via repo, taking advantage of their market stance.

All in all, the evidence fails to confirm the "liquidity windfall" mechanism that is included in much of the recent debate. Dealers do reuse collateral, but they do not systematically gain a haircut advantage between the sourcing and onward legs of the chain, so the assumed free-cash buffer never materializes. Without that cushion, the leverage-pyramiding logic that would otherwise amplify balance-sheet growth and heighten the risk of collateral runs loses traction, and haircut shifts cease to be a primary trigger of stress. Market-wide effects also look different from the windfall narrative. Since haircut wedges are absent, monetary policy shocks and funding squeezes may reach collateral reuse through different channels.

References

Accornero, M. (2020). *Collateral reuse, Liquidity and Financial Stability*. DiSSE Working Paper Series (No. 10/2020).

Adrian, T., Boyarchenko, N., and Shachar, O. (2017). Dealer balance sheets and bond liquidity provision. *Journal of Monetary Economics*, 89, 92–109.

Aitken, J., and Singh, M. M. (2010). *The (sizable) role of rehypothecation in the shadow banking system. International Monetary Fund*.

Andolfatto, D., Martin, F. M., and Zhang, S. (2017). Rehypothecation and liquidity. *European Economic Review*, 100, 488-505.

Bassi, C., Behn, M., Grill, M., and Waibel, M. (2024). Window dressing of regulatory metrics: evidence from repo markets. *Journal of Financial Intermediation*, 58, 101086.

Basel Committee on Banking Supervision (BCBS), 2014. *Basel III Leverage Ratio Framework and Disclosure Requirements*. Bank for International Settlements.

Bottazzi, J. M., Luque, J., and Páscoa, M. R. (2012). Securities market theory: Possession, repo and rehypothecation. *Journal of Economic Theory*, 147(2), 477-500.

Brumm, J., Grill, M., Kubler, F., and Schmedders, K. (2023). Reuse of collateral: Leverage, volatility, and welfare. *Review of Economic Dynamics*, 47, 19-46.

Chang, J.-W. B., and Chuan, G. (2025). *Collateral Reuse and Financial Stability*. Finance and Economics Discussion Series (FEDS), 2025-035. Washington, DC: Board of Governors of the Federal Reserve System. https://doi.org/10.17016/FEDS.2025.035.

Committee on the Global Financial System (CGFS) (2013). *Asset encumbrance, financial reform and the demand for collateral assets*. CGFS Papers, N. 49.

Copeland, A., Martin, A., and Walker, M. (2014). Repo runs: Evidence from the tri-party repo market. *The Journal of Finance*, 69(6), 2343-2380.

Du, W., Hébert, B., and Li, W. (2023). Intermediary balance sheets and the treasury yield curve. *Journal of Financial Economics*, 150(3), 103722.

Eisenschmidt, J., Ma, Y., and Zhang, A. L. (2024). Monetary policy transmission in segmented markets. *Journal of Financial Economics*, 151, 103738.

Eren, E. (2014). Intermediary funding liquidity and rehypothecation as determinants of repo haircuts and interest rates. In *27th Australasian Finance and Banking Conference*.

Financial Stability Board (FSB) (2017a). *Re-hypothecation and collateral reuse: Potential financial stability issues, market evolution and regulatory approaches*. Report, Financial Stability Board, Basel, Switzerland.

Financial Stability Board (FSB) (2017b). *Non-Cash Collateral reuse: Measure and Metrics*. Report, Financial Stability Board, Basel, Switzerland.

Financial Stability Board (FSB) (2012b). *Strengthening Oversight and Regulation of Shadow*

Banking. A Policy Framework for Addressing Shadow Banking Risks in Securities Lending and Repos.

Fuhrer, L. M., Guggenheim, B., and Schumacher, S. (2016). Re-use of collateral in the repo market. *Journal of Money, Credit and Banking*, 48(6), 1169-1193.

Greppmair, S., and Jank, S. (2023). Collateral scarcity and market functioning: Insights from the Eurosystem securities lending facilities. *Deutsche Bundesbank Discussion Paper*, 31/2023.

Gottardi, P., Maurin, V., and Monnet, C. (2019). A theory of repurchase agreements, collateral reuse, and repo intermediation. *Review of Economic Dynamics*, 33, 30-56.

Griffiths, M. D., and Winters, D. B. (1997). On a preferred habitat for liquidity at the turn-of-the-year: Evidence from the term-repo market. *Journal of Financial Services Research*, 12(1), 21-38.

Heckman, J., 1979. Sample selection bias as a specification error. *Econometrica*, 47, 153–161.

Huh, Y., and Infante, S. (2021). Bond market intermediation and the role of repo. *Journal of Banking & Finance*, 122, 105999.

ICMA [International Capital Market Association] (2024). *European Repo Market Survey Number 47*.

Infante, S. (2019). Liquidity windfalls: The consequences of repo rehypothecation. *Journal of Financial Economics*, 133(1), 42-63.

Infante, S., Press, C., and Saravay, Z. (2020). Understanding collateral reuse in the US financial system. In *AEA Papers and Proceedings*, Vol. 110, pp. 482-486.

Infante, S., and Vardoulakis, A. P. (2021). Collateral runs. *The Review of Financial Studies*, 34(6), 2949-2992.

Inhoffen, J., and van Lelyveld, I. (2024). *Safe asset scarcity and reuse in the European repo market*. Tinbergen Institute Discussion Paper (No. TI 2024-018/IV).

Issa, G., and Jarnecic, E. (2024). Collateral reuse as a direct funding mechanism in repo markets. *Pacific-Basin Finance Journal*, 86, 102449.

Jaafar, A., Polizzi, S., and Reghezza, A. (2023). Persistency of window dressing practices in the US repo markets after the GFC: The unexplored role of the deposit insurance premium. *European Financial Management*, 29(2), 634-663.

Jank, S., Moench, E., and Schneider, M. (2022). *Safe asset shortage and collateral reuse*. CEPR Discussion Papers, No. 16439.

Kirk, A., McAndrews, J., Sastry, P., and Weed, P. (2014). Matching collateral supply and financing demands in dealer banks. *FRBNY Economic Policy Review*, Vol. 20, No 2.

Kruttli, M. S., Monin, P. J., and Watugala, S. W. (2022). The life of the counterparty: Shock propagation in hedge fund-prime broker credit networks. *Journal of Financial Economics*, 146(3), 965-988.

Muley, A., (2016). *Rehypothecation and monetary policy*. Working Paper, Massachusetts Institute of Technology.

Munyan, B. (2017). *Regulatory arbitrage in repo markets*. SSRN.

Singh, Manmohan (2011). *Velocity of pledged collateral: analysis and implications*. International Monetary Fund, Working Paper 11/256.

Singh, Manmohan (2014). *Collateral and Financial Plumbing. London*, UK: Risk Books.

Wallen, J., and Lu, L. (2025). *Negative Treasury Haircuts*. SSRN Working Paper. https://doi.org/10.2139/ssrn.5239611.

Appendix A - Dealer List

Institution	AT	BE	DE	DK	ES	FI	FR	GR	IT	LU	NL	PT	SK	EU
ABN AMRO Bank N.V.			✓							✓	✓			
Alpha Bank S.A.								✓						
Banco Bilbao Vizcaya Argentaria S.A.					✓				✓	✓		✓		✓
Banco Cooperativo Español S.A.					✓									
Banco Monte dei Paschi di Siena S.p.A.									✓					✓
Banco Santander S.A.					✓				✓			✓		✓
Barclays Bank Ireland PLC	✓		✓		✓	✓	✓	✓	✓		✓	✓		✓
BofA Securities Europe S.A.	✓	✓				✓	✓	✓	✓		✓	✓		✓
BNP Paribas	✓			✓	✓	✓	✓	✓	✓			✓		✓
BNP Paribas Fortis		✓												
Bred Banque Populaire	✓										✓			✓
CaixaBank S.A.					✓									✓
Cecabank S.A.					✓									✓
Citibank Europe PLC	✓	✓			✓	✓	✓		✓		✓	✓	✓	
Citibank Global Markets Europe AG								✓						✓
Commerzbank AG	✓		✓		✓			✓						✓
Cooperatieve Rabobank U.A.			✓											
Credit Agricole CIB S.A.		✓			✓	✓	✓		✓			✓		✓
Danske Bank A/S			✓	✓		✓								✓
DekaBank			✓											
Deutsche Bank AG	✓	✓	✓		✓	✓	✓	✓	✓			✓	✓	✓
DZ Bank AG			✓											✓
Erste Group Bank AG	✓									✓			✓	✓
Eurobank S.A.								✓						✓
Goldman Sachs Bank Europe SE	✓		✓		✓	✓	✓	✓	✓		✓	✓		✓
HSBC Continental Europe S.A.	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
ING Bank N.V.											✓			
Intesa Sanpaolo S.p.A.			✓					✓	✓	✓			✓	✓
Jefferies GmbH			✓					✓			✓	✓		
J.P. Morgan SE	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
KBC Bank N.V.		✓											✓	✓
Landesbank Baden-Württemberg	✓		✓											✓
Landesbank Hessen-Thüringen			✓											
Mediobanca Banca di Credito Finanziario S.p.A.									✓					
Mizuho Securities Europe GmbH			✓						✓					
Morgan Stanley Europe SE	✓	✓		✓	✓		✓	✓	✓		✓	✓		✓
National Bank of Greece S.A.								✓						✓
Natixis S.A.	✓	✓	✓		✓		✓		✓	✓	✓			✓
NatWest Markets N.V.		✓					✓		✓		✓			✓
Norddeutsche Landesbank			✓											
Nordea Bank Abp			✓	✓		✓								✓
Nomura Financial Products Europe GmbH	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓		✓
Piraeus Bank S.A.								✓						✓
Raiffeisen Bank International AG	✓													✓
Scotiabank Designated Activity Company			✓											
Société Générale S.A.	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓			✓
SEB				✓										✓
TD Global Finance Unlimited Company														✓
UBS Europe SE			✓					✓	✓					✓
UniCredit Bank AG (Munich)			✓											
UniCredit S.p.A.	✓								✓					✓
Volksbank Wien AG	✓													

The list of potential dealers is based on registered primary dealers (PD) in any of the reporting countries. A dealer is registered as active in a transaction if: (i) it acts as the cash borrower or cash lender and (ii) the pledged security's issuer is in a country where it holds PD status. XS ISINs have their PDs equalized to EU ones.