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What Drives Repo Haircuts? Evidence from the UK Market*

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Abstract

Using a unique transaction-level data, we document that only 61% of bilateral repos held by UK banks are backed by high quality collateral. Banks intermediate repo liquidity among different counterparties, and use CCPs to reallocate high-quality collaterals among themselves and exploit netting benefits. Furthermore, maturity, collateral rating and asset liquidity have important effects on repo liquidity via haircuts. Counterparty types also matter: non-hedge funds, large borrowers, and borrowers with repeated bilateral relationships receive lower (or zero) haircuts. Furthermore, we observe a pecking order in the posting of collateral, with higher quality one more likely to be used first. Overall, the evidence supports a first order role of information frictions in driving haircuts. In contrast, we do not find significant roles in the data for lenders' liquidity position or default probabilities.

Keywords: repurchase agreement, systemic risk, repo market, margin, haircut.
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The repurchase agreement (repo) market is a major tool for short-term funding of financial institutions, potentially an important source of systemic risks in the financial system. There is ample interest from academics, policy makers and members of the public in better understanding and monitoring this market. However, due to the over-the-counter nature of repo transactions, repo contract terms are rarely disclosed except for tri-party repos financed by US Treasury securities. Limited studies on bilateral repo transactions have shown that bilateral repo markets are significantly different from tri-party repo markets in terms of collaterals and counterparties. However, due to various data restrictions, evidence on how collateral and counterparty characteristics affect contract terms is often only suggestive and limited.[1] Furthermore, even though the repo markets in the EU and the UK are much larger than that in the US, our understanding of the determination of repo contract terms is almost exclusively based on US databases.[2] As a result, we still know relatively little about patterns of deal characteristics in bilateral repo market or the market-wide cross-sectional relationships between haircuts, collaterals and counterparty characteristics, especially in the EU and UK repo markets.

Our paper fills this gap in the literature by establishing a novel understanding of bilateral markets, and estimating the cross-sectional relationships of contract terms and deal characteristics. We investigate a unique transaction-level UK dataset that has a cross-section of borrowers and lenders and, importantly, we show which *market frictions* (e.g., information asymmetries) are relevant for repo haircuts in general. In particular, thanks to the collateral and counterparty heterogeneity in our data we are able to document a rich set of novel findings that should guide theoretical modelling. First, deal-level intrinsic risk characteristics increase haircuts: longer maturity contracts, as well as collaterals with higher (market and default) risk measures, demand higher haircuts, and safer assets are rehypothecated more often. Second, identity of the borrower and its riskiness, as well as repeated interactions with the lender, are key determinants of haircuts: larger, better rated, less levered, and borrowers with repeated interactions get charged much less while hedge funds pay significantly larger haircuts. Furthermore, relationship lending is one of the main predictors of zero haircuts.

[1]For example, Gorton and Metrick (2012) focus on the impact of collateral rating/asset class on repo terms since their database does not contain counter-party information. The analysis in Auh and Landoni (2022) is limited to a single borrower since the data are collected from one hedge fund family. Baklanova et al. (2019) find the effect of collateral price volatility on repo haircut mixed and inconclusive using three time snaps of repo data from nine US bank holding companies.

[2]The total value of all outstanding repos reported under the Securities Financing Transactions Regulations (SFTR) in the EU and the UK on December 10, 2021 was EUR 9,396 billion in the EU and EUR 8,448 billion in the UK, totalling EUR 17.8 trillion (https://www.icmagroup.org/assets/European-Repo-Market-Survey-April-2022.pdf). The Federal Reserve estimates the total repo assets (or investments in repos) in the US at around $4.6 trillion as of September 30, 2020 (https://www.sec.gov/files/mmfs-and-the-repo-market-021721.pdf).

Overall, counterparty characteristics have *larger* effects on haircuts than asset characteristics, whereas lender characteristics (except collateral concentration) do not appear to be primary drivers of haircuts. Third, we observe a pecking order of collateral choice by borrowers, with higher quality securities more likely to be posted first. Fourth, the main driver of repo transactions with CCPs (that are characterised by higher quality collateral) appears to be the netting benefit that they offer.

To our knowledge, our database is one of the few databases that cover transaction-level haircut information for collaterals with a wide range of qualities and a rich set of counterparty characteristics.[3] It also provides an opportunity to analyse an understudied major repo market segment. The dataset allows us to gain a market-wide view on how UK banks use bilateral repo contracts to intermediate liquidity across different counterparties and to study how the supply of this liquidity is affected by collateral quality, counterparty characteristics, bilateral relationships, and contract terms.

Our bird's-eye investigation reveals four distinct features about the UK bilateral repo market. First, we find that only 61% of collaterals used in the UK market can be categorized as high quality collaterals—government securities rated AA and above. Among the 39% of the riskier collaterals, 7% are nongovernment securities such as corporate bonds, securitized products and others. In contrast, the existing studies using tri-party repo data in the US market find that high quality securities such as US Treasuries are predominately used as collaterals (e.g., Copeland et al. (2010), Baklanova et al. (2019)).[4] The cross-sectional variation in the qualities of collateral used in the bilateral repo transactions leads to significant heterogeneity in haircuts among repo contracts in the UK market.

Second, we find a clear pattern on how banks intermediate liquidity among each other using central clearing counterparties (CCPs), and from asset managers to hedge funds via the UK bilateral repo market. Banks obtain liquidity from asset managers, while providing liquidity to hedge funds. In doing so, banks also earn intermediating spreads as they charge higher haircuts to their (net) borrowers – hedge funds – and are charged less by their (net) lenders – asset managers. For example, the banks charge intermediation spreads in terms

[3]The Office of Financial Research (OFR) has started to collect such data for the U.S. and Hempel et al. (2023) describe the pilot data collection of non-centrally cleared bilateral repurchase agreement spanning nine dealers over three reporting dates. In the E.U. the Money Market Statistical Reporting (MMSR) collects all repo transactions made by 38 dealer banks and Eisenschmidt et al. (2024), focusing on repos backed by government collateral, studies the monetary policy transmission in this market segment.

[4]The EU and UK repo markets have a larger share of lower-quality securities than the US market for several reasons. First, the supply of the high quality of government bonds is relatively low. For example, Germany is one of the main suppliers for safe assets in the EU area. The government debt to GDP ratio is much lower for Germany than the US, implying that the supply of the safest asset is relatively limited. Second, ECB accepts EU area government bonds of lower quality in their repo operations, albeit with higher haircuts. Hence, banks might have incentives to hold low quality government bonds which offer access to central bank liquidity.

of haircut as high as 1.3% to hedge funds and as low as 30 bps to broker dealers.[5] We also find that CCP trades are significantly different from non-CCP trades: banks tend to use high quality collaterals and to trade in large notional values when transacting with CCPs. These patterns indicate the important role of CCPs for banks when reallocating high quality collaterals among themselves.

Third, we find evidence for collateral rehypothecation. For government securities rated AA and above, the rehypothecation rate ranges from 26.3% for government bonds with maturity of 20 year and longer to 61.6% for government bonds with maturity from 10 to 20 years. This rate is much lower for non-government securities, which is 8.9% for bonds with maturity 20 year and longer to 27.7% for bonds with maturity of five year or less.

Fourth, we find that a significant portion of bilateral contracts have zero haircut—about 35% of all transactions—with relationship lending being the key driver.

After revealing these unique characteristics of the UK repo market in allocating liquidity, we turn to investigating the drivers behind the cross-sectional heterogeneity in haircuts, including the probability of receiving a zero haircut.

In particular, we build six testable hypotheses motivated by the existing theoretical work on collateralized borrowing and repo runs, and we also provide a stylized model with information frictions (in Appendix A.1) to illustrate the key mechanisms at play.[6] Our six hypotheses can be broadly categorised into three groups: collaterals', borrowers', and lenders' characteristics. Characteristics include typical quality variables such as default probability and credit rating but also liquidity indicators, concentration risks, counterparty types and some other variables. Existing theoretical models based on various market frictions have different predictions on how these characteristics affect haircuts.

To test our six hypotheses in the empirical investigation, we group the potential explanatory variables into five categories: deal, collateral, counterparty type, counterparty characteristics, and miscellaneous factors including concentration measures. We then examine their impact on the magnitude of haircuts and the probability of zero haircuts (given the

[5]We do not find that our reporting banks intermediate funds when trading with central banks and government agencies, insurance companies and pension funds, and other reporting banks. In fact, they often pay higher haircuts when borrowing from these counterparties.

[6]The theoretical literature in this area can be categorized into two main streams. One is based on the difference of opinion approach in a general equilibrium setting (e.g., Geanakoplos (1997) and Simsek (2013)). The other is based on contractual and/or information frictions (e.g., Dang et al. (2013), Dang et al. (2011), Ozdenoren et al. (2023) and Gottardi et al. (2019)).These theoretical models have been applied to explain repo runs which were prevalent during the financial crisis in 2008. The existing theories point out two types of repo runs: one is liquidity runs, which focuses on coordinations by extending Diamond and Dybvig (1983) either to the repo setting (Martin et al. (2014)), short-term borrowing (Acharya et al. (2011)), or endogenous information acquisition (Gorton and Ordonez (2014)); the other is inter-temporal coordination runs based on an adverse selection mechanism (Ozdenoren et al. (2023)).

large number of contracts with zero haircut in the data). In the main analysis of the paper, we focus on the non-CCP subsample because the institutional setups are different when repo trades are cleared via CCPs. The reported haircuts by borrowers tend to be lower because they establish separate margin accounts with CCPs. Our regression analysis exploits heterogeneity in collateral and counterparty characteristics, yielding the following main results.

First, we find that transaction maturity – a deal characteristic – has a first order effect: haircuts are larger for longer maturities of the contract. Haircuts are also increasing in the Value at Risk (VaR) of the collateral and in collateral concentration, but decreasing in collateral rating. Haircuts are also generally lower for portfolios that include a safe asset. This set of findings indicates that collateral quality and asset liquidity are important determinants of haircuts.

Second, we find that counterparties matter in haircut determination. This finding is especially useful as it allows to untangle various economic mechanisms that affect banks' intermediation of liquidity via repos. We find that hedge funds are charged significantly higher haircuts, especially when using nongovernment collateral: the haircut increases by a staggering 25%–28% when hedge funds borrow using such collaterals. Moreover, larger borrowers with higher ratings receive lower haircuts, which shows that there is significant tiering in the repo market. We also find that borrower-lender relationships affect haircuts significantly: some borrowers receive consistently lower haircuts when interacting with certain counterparties, and one–two banks in our sample account for the bulk of repo trades with zero haircuts. These findings are hard to explain by the difference of opinion theory since the significant borrower-lender relationships are often for agents from different lines of business. The results are, however, supportive of the idea that relationship banking lowers information frictions.

Third, we find little evidence that lenders' liquidity position or default probabilities affect haircuts, suggesting that the traditional bank run mechanism cannot explain repo runs. This lends support to the alternative inter-temporal feedback/coordination explanations of repo runs instead.

Fourth, when examining the likelihood of receiving zero haircuts, we find that, in addition to the determinants mentioned above, bilateral relationships explain large part of the variation in the probability of receiving a zero haircut. This finding indicates that banks filter out repo clients in conducting repo business and give preferential haircuts to certain counterparties.

Fifth, we examine the CCP subsample of our database departing from the main part of the paper. It is still interesting to examine why banks clear certain repo trades through CCPs, and whether the haircuts charged by repo lenders to CCP are any different to non-CCP borrowers, since the existing understandings on CCP repo trades is limited. We find that banks earn a smaller average intermediation spread (in terms of haircuts) through CCPs than through non-CCP counterparties. That is, banks' lending (reverse repo) trades have lower haircuts when transacting with CCPs, whereas their borrowing (repo) trades have higher haircuts. Furthermore, trades in which banks lend to a CCP have a higher percentage of zero haircuts and the net position of banks with CCPs is close to zero (on average). Given that bank-CCP trades often involve high quality collaterals and have large notional values, this new set of findings indicates that banks' repo transactions with CCPs might be motivated by netting benefits and affected less by asymmetric information.

We investigate this further by computing a proxy variable capturing bilateral netting opportunities between our reporting banks and each of their counterparties. We find that this proxy variable is significantly larger when CCPs act as counterparties. Furthermore, we find that netting benefits seem to be one of the main drivers of CCP trades in that the probability of a trade with a CCP increases by 40–43% when full netting can be achieved.

Sixth, we find that counterparties of our reporting banks seem to choose high quality collaterals first when borrowing via repo contracts. We interpret this pecking order in collateral selection as evidence of an information friction channel being at play in the repo market. This evidence supports information frictions as an important driver of haircuts.

Last but not least, we examine if there are any substitution effects between repo rates and haircuts by using a complementary dataset which contains information on both contract terms. We find strong evidence that repo rate is irrelevant in explaining haircuts, suggesting that haircuts and repo rates have different drivers. This finding is in line with the evidence in the existing literature. For example, Eisenschmidt et al. (2024) (see table 3 therein) find no statistical association between rates and haircuts in the Money Market Statistical Reporting (MMSR) European repo dataset from the ECB.

The rest of the paper is organized as follows. In Section 1 we provide a brief description of repurchase agreements and summarize the relevant literature. Section 2 outlines the main hypotheses that we test in the data. Section 3 describes the data. Section 4 analyzes the determinants of haircuts and presents the results for the six hypotheses. Section 5 concludes.

1 Background Information on Repurchase Agreements and Related Literature

1.1 Background Information on Repurchase Agreements

A repurchase agreement is the simultaneous sale of, and forward agreement to repurchase, securities at a specific price, at a future date (Duffie, 1996). In effect, a repo is a collateralized loan where the underlying security serves the collateral role. The party that borrows cash and delivers collateral is said to be doing a repo, and the party that lends cash and receives collateral is doing a reverse repo.[7]

Repurchase agreements are broadly classified into two categories. Tri-party repo is a transaction for which post-trade services such as collateral management (e.g., selection, valuation, and verification of eligibility criteria), payments and margining are outsourced to a third-party agent which is a custodian bank.[8] A tri-party agent settles the repos on its book. Most existing repo studies are about tri-party repos. By comparison, in a bilateral repo, settlement usually occurs on a delivery versus payment basis, and the cash lender must have back-office capabilities to receive and manage the collateral (Adrian et al., 2013). Our dataset reflects this second category of repo contracts.

An interesting feature about repo/reverse repo market is that CCPs are starting to clear a growing number of repos. CCPs place themselves between the two sides of a trade, leading to a less complex network of exposures (Rehlon and Nixon, 2013). They provide benefits such as multilateral netting and facilities to manage member defaults in an orderly manner, but can also pose systemic risks to the financial system. CCPs always impose a haircut in the form of initial margin, whether in a reverse repo or repo[9]. So banks doing a reverse repo transaction with a CCP will need to give a haircut, which amounts to a negative value for the haircut. Our dataset covers CCP trades with the reporting banks and hence offers an opportunity for us to examine characteristics and assess the benefits of these trades.

[7] The difference between the original loan value and the repayment specifies the repo rate. The haircut, or margin is determined by the difference between the loan and the collateral value. (Krishnamurthy et al., 2014). For example, if a borrower receives \$98 against \$100 value of collateral, the haircut is 2%. In Europe, the legal title to the collateral is transferred to the cash lender by an outright sale. In the US, this is not the case, but the repo collateral is not subject to an automatic stay and can be sold by the lender, should the borrower default (International Capital Market Association, 2019).

[8] There are two tri-party agents in the US: Bank of New York Mellon and JP Morgan. In Europe, the main tri-party agents are Clearstream, Euroclear, Bank of New York Mellon, JP Morgan, and SegaInterSettle.

[9] Although if the collateral is a portfolio of assets, the haircut may be imposed on a subset of them to meet the initial margin requirement. Counterparties to CCP also need to meet variation margin requirements. Since CCPs are purely intermediaries, these variation margins are pass through between lenders and borrowers.

1.2 Related Literature

The financial crisis rekindled interest in the theoretical and empirical study of the short-term funding market. The theoretical work on collateralized borrowing can be categorized into two streams. One is based on the difference of opinion approach in a general equilibrium setting such as in Geanakoplos (1997; 2002; 2003); Fostel and Geanakoplos (2012); and Simsek (2013). The other is based on contractual and/or information frictions such as in Dang et al. (2013); Dang et al. (2011); Ozdenoren et al. (2023) and Gottardi et al. (2019). We discuss the theoretical literature in detail when forming testable hypotheses in the next section of the paper.

There is also a body of literature that models crisis and runs in the repo market. One approach is based on the classical setting of Diamond and Dybvig (1983) extended to the repo setup as in Martin et al. (2014). In this framework, the liquidity needs of the lender, the capital position of the borrower, and the market microstructure of the repo market play important roles in determining the magnitude of the run. Acharya et al. (2011) model freezes in the market for short-term financing in the form of sudden collapse in debt capacity of collateral in an information-theoretic framework. Gorton and Ordonez (2014) focus on the information in-sensitivity of debt contract and how a sudden switch of information environment might trigger a deep discount and collateral crisis. Ozdenoren et al. (2023) emphasize the inter-temporal feedback of (expected) future asset price and the decisions of today's borrowers and lenders. In that setting, dynamic mis-coordination might lead to a run in the repo market.

The empirical studies of repurchase agreements are mostly focused on the US repo market. Several papers study developments in this market during the financial crisis. Broadly speaking, two distinct phenomena can be identified in the US bilateral and tri-party repo markets. In the bilateral market, as argued by Gorton and Metrick (2012), a run occurred during the 2008-2009 financial crisis in the form of rapid increases in haircut levels. This is further supported by multiple hedge funds failing due to margin calls (Adrian et al., 2013). Adrian and Shin (2010) empirically show that repo transactions have contributed the most to the procyclical adjustments of the leverage of banks. From this perspective, the rapid increase of haircuts in bilateral repos during the crisis can also be viewed as (forced) deleveraging of broker-dealers (Adrian et al., 2013).

In contrast, in the tri-party market haircuts moved very little during the 2008-2009 financial crisis and the amount of funding remained fairly stable but, instead, lenders refused to extend financing altogether to the most troubled institutions—namely, Bear Stearns and Lehman Brothers (Copeland et al., 2010). Krishnamurthy et al. (2014) argue that there was a run in the tri-party market but only for non-agency MBS/ABS, which constituted a relatively small and insignificant part of the short-term debt market. In the tri-party market, tension seemed to affect specific institutions rather than the broad collateral classes, except maybe for the private-label securitized assets (Adrian et al., 2013). Martin et al. (2014) relate the differences between the behaviour of these two markets with respect to their microstructure: In the tri-party market, haircuts are fixed in custodial agreements that are revised infrequently, but this is not the case in the bilateral market. Weymuller (2013) studies the role of reputation and relationship in a repeated bargaining game between borrowers and lenders in tri-party repo transactions involving one of the 145 largest money market U.S. funds over the 2006-2012 period. He finds empirically that persistent relationships are able to achieve lower rates for the borrower, albeit the evidence is less conclusive for haircuts.

Most US studies on repos are on tri-party (instead of bilateral) contracts starting with Copeland et al. (2014); Krishnamurthy et al. (2014) and Hu et al. (2021). They generally find that the market is quite segmented and market power, collateral concentration and fund families might play important roles. To our knowledge, empirical studies on bilateral repos are rare due to lack of data availability. Therefore, the work by Gorton and Metrick (2012) using a proprietary database is important for the understanding of repo transaction where various types of collaterals are present. The dataset in Gorton and Metrick (2012) contains credit spreads on various products and repos between high-quality dealer banks. However, the dataset has limited deal level information. To control for counterparty risk, they use a market-wide pricing variable (the LIBOR-OIS spread), due to the lack of individual counterparty data. Auh and Landoni (2022) use bilateral repos data from the portfolio of multiple hedge funds under the same management. The authors find that lower-quality loans (backed by lower-rated collateral) have longer maturity, higher margins and spreads. However, since the dataset has only one borrower (the family of funds), it does not allow to analyse the role of counterparty borrower risk. Finally, Baklanova et al. (2019) use three data snapshots from nine BHC-affiliated securities dealers to study the use of collateral in bilateral repurchase and securities lending agreements. Their database is extensive, covering 51-53% of US bilateral Repo market for these three time snapshots. However, the data contains only counterparty types but not other individual characteristics. The authors find mixed results regarding the relationship between haircuts and potential price swings of the collaterals: the expected negative relationship is only found for transactions with positive haircuts. These inconclusive results on haircut drivers are in contrast with those in our paper.

Our dataset instead covers about 24% of the total repo activity in the UK market during the sample – a market estimated by the SFTR to be about twice the size of the the US one – and offers an extremely rich set of contract characteristics, underlying assets, and counterparty information. The richness of the dataset, hence, allows us to shed light on the key drivers of haircuts in bilateral repos by formally testing theoretical predictions.

The repo studies in the European area are mostly conducted on general collateral repos or through CCPs where regulations play a very important role (Mancini et al. (2016), Boissel et al. (2017), Corradin and Maddaloni (2020)). Other recent studies focused on safe assets and collateral use (Aggarwal et al. (2021) and Jank et al. (2021)). Compared to these studies, our repo haircut dataset is unique in that it covers a significant part of a bilateral repo market. In addition, our data set has a rich cross-sectional variation in the riskiness of the underlying collateral and in counterparty characteristics, which allows us to tease out the factors driving repo haircuts.

2 Testable Hypotheses on Haircuts

We now list the hypotheses on the determination of haircuts that we aim to assess in our empirical analysis. The conceptual motivation is grounded in existing theoretical models that explore haircut determination, which arises from various forms of information friction (such as Geanakoplos (2003), Simsek (2013), Dang et al. (2013), Dang et al. (2011), Ozdenoren et al. (2023), and Gottardi et al. (2019)). Additionally, in Appendix A.1, we provide a stylized model of a repo transaction focusing on one particular form of information friction to motivate our hypotheses.

Hypothesis 1 (collateral quality): The repo haircut is larger when the collateral is of lower quality and/or illiquid.

This hypothesis (that also follows from Proposition 1 of the stylised model in Appendix A.1) can be intuitively motivated. Less liquid and riskier collateral increases the recovery risk for the lender in the event of borrower default.

We measure collateral quality using VaR, maturity, rating, and asset types. Transaction maturity should also matter since as the duration of the repo contract increases, the potential loss from worsening collateral quality becomes greater. Note that the VaR we compute is a Market VaR (i.e. based on the uncertainty about the underlying asset price movements) rather than a Credit VaR (normally based on transition probabilities across asset ratings and default states). Furthermore, the VaR measure is at the very short horizon (5 days). Given that the main driver of market VaR is the volatility of the price, this is greatly affected by the liquidity of the underlying (due to the effect of price impact). Instead, credit rating is not directly related to liquidity: only the likelihood of default should in principle affect this measure. Nevertheless, a low credit rating can cause an illiquidity of the asset, and hence affect also the VaR.

Asset quality variables are not the only determinants of haircut if there are other information frictions between the borrowers and the lenders (see for instance Proposition 2 in Appendix A.1). Hence the counterparty types could also matter if these are associated with variable degrees of information asymmetries, and risk, for the different borrowers. Intuitively, the information friction is likely to be larger when borrowers are from a different line of business than lenders. This leads to our second hypothesis.

Hypothesis 2 (counterparty types): The repo haircut is larger when the counterparties in the contract are from different lines of business and hence have different opinions about the collateral value.[10]

Another potential proxy for information friction between the parties of a bilateral repo is the credit quality of the counterparty, rather than just the difference in types. This leads to our third testable hypothesis.

Hypothesis 3 (counterparty quality): The repo haircut is larger when the default probability (credit quality) of borrower is higher (lower).

Moreover, the existence of repeated bilateral relationships between borrower and lender is likely to lower the degree of information friction, and hence could drive the determination of haircuts. This leads to our fifth testable hypothesis.

Hypothesis 4 (bilateral relationship): Haircuts are lower for bilateral parties with stable banking relationships.

Nevertheless, as shown in Ozdenoren et al. (2023) (see Proposition 3 in Appendix A.1), there are contractual ways to mitigate the impact of asymmetric information between the counterparties, and alleviate the risks faced by the lender. For example, a portfolio of collateral assets will have a larger borrowing capacity if it includes some safe asset. This leads to our next testable hypothesis.

Hypothesis 5 (portfolio repos): Risky assets in a portfolio repo with safe assets have lower haircuts than purely risky asset repos.

The next hypothesis draws on the literature that models coordination and runs in the repo market. Gorton and Ordonez (2014) find that endogenous information acquisition can

[10] Geanakoplos (2003) explains haircut based on a model of difference of opinion.

cause a sudden increase in haircuts and a collateral crisis. Hence, lenders' characteristics might matter. Similarly, in a dynamic sequential trade model, Dang et al. (2011) find that the haircut size is increasing in the liquidity needs of the lender, and in the default probability of the lender in a subsequent repo transaction. In a series of dynamic Diamond and Dybvig (1983) models with an asset collateral market, Martin et al. (2014) find that collateral and liquidity constraints matter, and hence the liquidity of lenders affects haircuts. This leads to the last testable hypothesis.

Hypothesis 6 (lender's quality and liquidity): The repo haircut is larger when the default probability and/or liquidity need of the lender is higher.

3 Overview of the Data

The transaction-level dataset is a snapshot of the repo books of six banks that are major players in the UK repo market. The total size of their repo books—the sum of repos and reverse repos—is around £511 billion (including CCP transactions) at the end of 2012.[11] According to Financial Stability Board (2013), the UK-resident deposit-taking banks hold around £2.1 trillion in gross repo activity on their balance sheets, hence our dataset accounts for around 24% of the total repo activity in this market. That is, these six banks are, in terms of activity, central to the U.K. repo market, and are in our sample because the regulator deemed them systemically important for the repo market. The majority of this activity is with non-UK resident banks, including the activity between UK and foreign branches of the same consolidated group, and is highly concentrated (Financial Stability Board, 2013).

Each of the six banks reports its outstanding repo transactions as at the end of 2012, including the gross notional, maturity, currency, counterparty, haircuts and collateral information. We supplement this dataset with additional data on securities, counterparties, and the reporting banks from Datastream and Bloomberg. In what follows, we report information and results for reverse repos (REVR) and repos (REPO) separately. This classification is from the point of view of the reporting banks. Hence, *in a reverse repo the reporting bank is lending* to a counterparty, and *in a repo the reporting bank is borrowing* money from a counterparty.

3.1 General Sample

Table 1 presents an overview of our dataset in terms of key repo and reverse repo contract characteristics. It shows the breakdown of the data along four categories: maturity,

[11]The actual reporting periods differ slightly across the banks, but all are toward the end of 2012.

currency, counterparty type, and collateral type (Panels A, B, C, and D, respectively). Since repo indicates bank borrowing, we denote the repo values with negative numbers.

By comparing the values of reverse repos and repos, we find that the reporting banks are net borrowers in the repo market (see the row labeled "Total" in Table 1). Panel A of the table shows that most of the borrowing and lending transactions for these reporting banks have maturities less than three months. While borrowing exceeds lending for overnight contracts, lending is larger for transactions with maturities of less than three months. This observation suggests that the reporting banks conduct maturity transformation, to some extent. However, for maturities longer than one year they are still net borrowers. Panel B of the table shows that the reporting banks borrow and lend the most in GBP and EUR followed by USD. In net terms, they borrow in GBP and lend in other currencies.

Panel C of Table 1 shows that the reporting banks, in aggregate, borrow more via CCPs and from counterparties such as other banks, central banks and governments, broker-dealers and hedge funds. The reporting banks lend more via CCPs and to counterparties such as other banks, hedge funds, broker dealers, and other asset managers. This is in line with our general understanding of the money flow pattern in the wholesale funding market where banks and CCPs intermediate repo trades.[12] Finally, Panel D of Table 1 shows the breakdown based on collateral types. It shows that when the six banks borrow, only a small percent of their repo collateral is US government bonds. It also appears that the reporting banks intermediate in (and borrow against) relatively worse collaterals such as securitization products and corporate debt. UK government bonds are the most common collateral used both in repo and in reverse repo contracts followed by other high quality sovereigns such as German government bonds.

Inspecting the maturity-currency relationship in Figure 1, we see that the majority of contracts (frequency, not notional values) are in EUR and USD followed by GBP and JPY. Most of the contracts have maturity less than 3 months across all currency groups and only a very small fraction of the contracts have maturity more than half a year within each currency category. GBP has a relatively higher fraction of reverse repo contracts within 3 to 6 months, compared to other currencies. Repo (reverse repo) transactions in JPY and other currencies happen almost exclusively with maturity up to 1 (3) month(s).

In Table 2, we examine the breakdown of contract characteristics for the CCP sub-sample. There are six CCPs in our sample. Compared with the full sample, the CCP subset is less heterogenous in terms of maturity, currency denomination and types of collaterals. CCP

[12]The first row in Panel C describes the values when counterparty is a reporting bank. The reporting banks report on a UK-consolidated basis, but counterparties are reported on a global basis. Therefore, there may be discrepancies between the reverse repos and repos with the reporting banks.

trades are mostly short-term with 1 day to three-month maturity and without any maturities above five years. GBP-denominated transactions are above 82% for repo and above 55% for reverse repo CCP trades. UK government bonds are featured as collaterals in 86.7% of the repo and 59% of the reverse repo CCP trades.

Finally, to contrast the effect of the collateral quality, we provide summary statistics for three salient subsamples: Government securities rated AA and above, as well as rated below AA, and finally other securities. This exercise also serves to compare with studies using the US tri-party repo data where collaterals are high-quality US treasuries. The breakdown of these three types of contracts across maturity, currency, and counterparty types is shown in Table 3.

There are several notable differences between repos backed by highly-rated government securities and nongovernment ones. First, contracts with nongovernment assets as collateral are mostly overnight in reverse repo, and longer-term (1-5 years) in repo. This fact shows that when banks lend against riskier collateral (reverse repo), they do so only for very short maturities (overnight), whereas when they borrow against this risky collateral, they are able to do so for much longer contract maturities. In contrast, the safest collaterals (AA or higher government securities) are used both for repos and reverse repos with maturity up to 1 year, and the distribution across maturities is fairly similar. The intermediate quality collateral (government assets rated below AA) is used extensively for short term repos and reverse repos with maturity of less than three months. Second, the lower rated government securities and the nongovernment collateral have a larger share of USD-denominated trades, while the safest government assets are used to borrow mostly in GBP. The share of hedge funds as counterparty for nongovernment securities is larger when the reporting banks are lending compared to when they are borrowing. The larger share of hedge fund borrowers might explain the short overnight maturities of these contracts given the higher riskiness of hedge funds. In contrast to the case of nongovernment collateral, the repos backed by the safest assets have the majority of deals (both repo and reverse repo) with CCPs.

Comparing the total for the safest government collateral in repos and reverse repos in Table 3 (£314.4 billion) to the total in Table 1 (£511.2 billion) shows that a significant portion of the repo market – about 39% – is backed by riskier collaterals. This is a phenomenon that is unique to the European market and is a significant departure from the patterns observed in the US repo market. Among the 39%, about 7% is backed by nongovernment collaterals, which are of lower average quality. The discrepancy between our sample and the general US market stems from the fact that risky sovereign bonds such as those issued by GIIPS (Greece, Italy, Ireland, Portugal, and Spain) and developing countries are accepted as collaterals by central banks in the European markets, but not in the US market. Since the repo literature is dominated by studies that use US data, in the haircut analyses below we differentiate results for different collateral types. This investigation is in addition to the main analysis using the whole sample, in order to assess whether the overall results are mainly driven by a subsegment of the market.

We also analyse to what extent collateral is reused in our dataset by computing what percentage of the collateral received by banks in reverse repos is then reused to borrow as part of repo transactions. In particular, we report in Table 4 the average rehypothecation rates by maturity and collateral type. The overall pattern of rehypothecation across maturities is similar to recent findings for the US, as in Figure 4 of Infante et al. (2020). Table 4 shows that rehypothecation is more common for higher quality government securities particularly at 10-20 year maturity. Conversely, nongovernment collateral is rehypothecated at much lower frequency, especially for longer maturity.

Since we explore the heterogeneity of non-CCP deals in a large part of our regression analysis, Table 5 presents summary statistics on haircuts for the non-CCP subsample along four categories: maturity, currency, counterparty type, and collateral type (Panels A, B, C, and D, respectively). This sample is also smaller than that in Table 1 due to missing haircut information for some observations. The average haircuts for each category in Table 5 are weighted by the gross notional of transactions.

Panel A of Table 5 shows that, except for long maturities, the reporting banks are able to borrow at slightly lower haircuts than they lend. This observation means that they can use the collateral received in a reverse repo to obtain cheaper funding. A similar pattern exists for different currencies as shown in Panel B.

Panel C makes it clear that the above-mentioned haircut advantage for reporting banks arises from trades with hedge funds, other asset managers and, to a lesser extent, with other banks and broker-dealers. In the transactions with these counterparties, the banks can receive funding at significantly lower margins. The intermediation spread can be as high as 1.3% for hedge funds and as low as 30 bps for broker dealers. This advantage disappears when our banks trade with central banks and government agencies, insurance companies and pension funds, and other reporting banks.

Finally, Panel D in Table 5 shows the breakdown based on collateral types. It displays how margins depend on the quality of collateral. For example, both repos and reverse repos for German government bonds have a low average haircut, while haircuts for corporate debt and securitization are higher. The numbers also show that the six reporting banks are able to borrow at a lower haircut compared to the one they charge for the same type of collateral. This is true for all collateral types, except securitized debt. Note that the UK government collateral commands a relatively high haircut, but this is largely due to the longer maturity of the collateralized assets.

3.2 Zero-haircut Subsample

There are a lot of zero haircut observations in the data as illustrated by the histogram of haircuts in Figure 2: over 35% of the whole sample. Some of these zero haircuts are due to the way haircuts are reported in CCP trades as explained in the next section, but even excluding CCP trades, zero-haircut trades are still quite common.[13] This finding is not surprising and has been confirmed by other data collections undertaken at the global level. A summary of the zero-haircut trades among the non-CCP sample is presented in the last two columns of Table 5. The table shows that the vast majority of contracts are with other banks and are denominated in EUR. In terms of notional values, most repo contracts are overnight, whereas reverse repos have maturities below 3 months. As for number of contracts, most of the zero-haircut contracts are overnight (84% of all repo contracts, 72% of all reverse repos), as shown in Figure 3.

The network graphs in Figure 4 illustrate the topology of the zero-haircut trades. The size of each node reflects the number of counterparties with which a reporting bank has at least one zero-haircut deal. Edge widths show the total number of zero-haircut trades between two given nodes. The figures show that the zero haircut observations from the repo and the reverse repo samples are dominated by one or two banks. In the repo market, one of the banks (bank A in Figure 4) receives the majority of zero-haircut trades. This borrower has 89 zero-haircut lending counterparties but one particular counterparty accounts for 24% of these trades – C697 in Figure 4. In the reverse repo market, another bank (bank B in Figure 4) is involved in 95% of all the zero-haircut trades. The top-10 counterparties account for 68% of all zero-haircut repo trades and 71% of all zero-haircut reverse repo trades, which shows that a small number of counterparties contribute to the majority of zero-haircut observations. These facts suggest (and the fixed-effect analysis in Section 4.2 confirms) that there are important borrower-lender relationships among the determinants of the zero-haircut trades, supporting our fourth testable hypothesis highlighted above. We investigate the role of bilateral relations further in later sections.

3.3 Complementary data on Repo rates

Unfortunately, despite its richness, our baseline dataset does not include interest rates on the repo contracts. To fill this gap we employ the Bank of England Sterling Money Mar-

[13]We find that zero haircut trades are about 36% of the CCP sample and 30% of the non-CCP sample.

ket daily (SMMD) dataset, that contains detailed transaction-level information on repo and reverse repo agreements for which GBP cash borrowing and lending is secured against Treasury bills and government bonds (nominal and indexed-linked Gilts) issued by the UK government. Our data include trades reported by banks and major broker dealers between 2016 and 2019.[14] The data include, among other information, the counterparty Legal Entity Identifiers (LEI), the amount, the maturity of the transaction and corresponding interest rate, the ISIN identifier for the collateral backing the transaction, and the market value of the collateral. Summary statistics for this data are reported in Tables OA.I–OA.III of the Online Appendix.

4 The Drivers of Haircuts

4.1 Empirical approach

For the most part of the regression analysis, we focus on the sample excluding the trades with CCPs. In practice, CCPs often calculate haircuts (or initial margin requirements) on a portfolio basis. That is, the over-collateralization of repo positions is calculated at the portfolio or netting set level, without applying haircuts on individual transactions. In our dataset, firms still report a transaction-level haircut, but this is often zero given that the 'true' haircut is applied at the portfolio level. In such cases, it is not meaningful to look at haircuts on individual transactions that are centrally cleared. Therefore, we focus on the sample that excludes CCP transactions to conduct the main analysis. Nevertheless, we also study the possible reasons for choosing CCPs to conduct trades in Section 4.4.

In Table A.I of the Appendix, we describe all the explanatory variables used in the regressions. We have dummy variables for currencies, collateral types, counterparty types, bank-counterparty pairs and a dummy for collateral bundled in a portfolio with a very safe asset (rated AAA). Other than dummy variables, we use trade-specific variables, collateral-specific and counterparty-specific characteristics. We also have two measures for counterparty and collateral concentration. Counterparty concentration measures the share of transactions with a specific counterparty in total, evaluated using the notional amount of transactions. It represents how important that counterparty is to the bank. Similarly, collateral concentration is measured by the share of transactions against a specific collateral in total, evaluated using the notional amount of transactions. We also include an interaction between

[14] The Bank of England requires institutions with a significant activity in the money market to report their transactions. The population for the daily transaction reporting is chosen to capture all institutions whose activity falls within the top 95% of activity at either overnight or up to one-year maturity (measured using their reported annual turnover).

counterparty and collateral rating to check for substitution effects between the two types of ratings.

To confirm that the multitude of zero haircuts does not distort our results, in addition to the ordinary least square regressions, we also report Tobit estimation with truncation at zero (in the Appendix, Table A.II). We split the data and consider separately repo and reverse repo transactions since they are different samples: one has reporting banks as borrowers and the other has the reporting banks as lenders. Moreover, we observe heterogeneity in the counterparties in the two types of transactions which allows us to conduct a more detailed analysis of haircut determinants.

Table 6 reports summary statistics for haircuts and non-dummy explanatory variables for the sample used in the baseline regressions. Except collateral and counterparty ratings which are categorical, other variables in this table are continuous. The summary statistics are presented separately for reverse repos and repos in Panels A and B, respectively, given that haircut practices can potentially differ significantly between the two instruments. Variables are winsorized at the 0.5% level.

Even though haircuts can have a value as high as 46%, the weighted average of haircuts is about 6% for reverse repos and about 2% for repos. The weighted average of maturity for the transactions is about 22-29 days. Average collateral maturity used is between 7.5 and 12 years. Collateral and counterparty ratings are modified into a numeric scale from 1 to 20, with 20 being the highest rating. The average collateral quality in this scale is about 14, while the average counterparty rating is between 14 and 15 (which corresponds to between A- and A).

The summary statistics for counterparty return on assets (RoA), leverage, CDS spread, and cash ratio are also presented in Table 6, and the respective definitions are in Table A.I. We include RoA to see how profitability of the counterparty can affect haircuts. Cash ratio is intended to proxy for liquidity needs. Overall, the summary statistics for reverse repos and repos are not significantly different. We also present the same statistics for different subsets of collateral types in Table 7 and, overall, the counterparty characteristics seem similar across the three collateral categories.

Table 8 reports the baseline estimation results for the whole sample using the OLS specification. We conduct the analysis separately for reverse repo and repo contracts because for the same bilateral pair, the bargaining power often lies with one party regardless of whether this party is borrowing or lending. Therefore, haircuts would be different when the party with the larger bargaining power is borrowing (repo) compared to when it is lending (reverse repo), indicating that the counterparty fixed effect estimation should be different for the reverse repo and repo contracts. We also report the subsample analysis for different categories of collateral in Tables 9 (reverse repo) and 10 (repo), to isolate the information effect of the collateral on the haircut determination.

In these three tables, the dependent variable is haircut. The explanatory variables are classified into five categories: deal characteristics, collateral characteristics, counterparty types, counterparty characteristics, and miscellaneous variables. These categories are shown in the first column. Columns labeled with numbers display regression coefficients for different sets of explanatory variables. All continuous explanatory variables are standardized in order to simplify the comparison of coefficients for different variables. Standard errors, which are not reported for simplicity, are clustered at the counterparty level.[15] All regressions include bank fixed effects (FEs), relationship fixed effects and currency fixed effects. A relationship FE is a dummy taking the value of 1 if the given dealer-counterparty pair has more than 10 trades in the regression sample.[16] The main regression for Table 8 is:

$$Haircut_j = \beta \times determinants_j + BankFE + RelationshipFE + CurrencyFE + \epsilon_j, \quad (1)$$

where β is vector of estimates on the haircut determinants.

In columns (1)-(5) of Table 8 we report the results for reverse repo transactions. In these transactions, the reporting bank lends cash and receives collateral, whereas the counterparty borrows money and delivers collateral to the bank. Hence, counterparty characteristics correspond to borrower characteristics. In columns (6)-(10), we present analogous results for repos. In these transactions, the reporting bank borrows cash and delivers collateral, whereas the counterparty lends money and receives collateral. Hence, counterparty characteristics correspond to lender characteristics in these transactions. In both cases, we first report the result with the smallest set of explanatory variables (deal characteristics), then we include collateral variables, counterparty types and characteristics variables, and finally a set of miscellaneous variables.[17]

In Tables 9 (reverse repo) and 10 (repo), we present results for the three subsets of collateral: Government securities rated AA and above, those rated below AA, and non-government

[15]We have explored using two way clustering at the bank and counterparty levels, yielding similar results. However, given that we have only six banks in our sample, we have too few clusters at the bank level. Hence, we report standard errors using single clustering in all our tables.

[16]The results with larger cutoffs are similar.

[17]In Table A.III in the Appendix, we also run a robustness test for the main regression specification including month fixed effects, which shows that the main results are unchanged.

(other) securities. The regressions therein are of the form

$$
\begin{aligned}
Haircut_j = & \gamma \times determinants_j + \beta_1 \times determinants_j \times D_{j,<AA} \\
& + \beta_2 \times determinants_j \times D_{j,Other} + \delta_1 D_{j,<AA} + \delta_2 D_{j,Other} \\
& + BankFE + RelationshipFE + CurrencyFE + \epsilon_j,
\end{aligned} \tag{2}
$$

where the γ coefficients measure the base effect (corresponding to highly-rated government assets), shown in columns (1)–(5), and the β_1 and β_2 coefficients capture the marginal effects, i.e. the relative effect on using, respectively, government assets with ratings below AA (in columns (6)–(10)), and other collateral (in columns (11)-(15)).

In all tables, reverse repo regressions have a better fit (measured by R^2) than repo regressions. Importantly, the marginal R^2 pertaining to the various groups of explanatory variables is lower for repo than for reverse repos. For example, in Table 8, adding all our regressors in the repo case gives an $R^2 = 0.532$ (column 10) compared to having only the two contract-specific variables (column 6) with $R^2 = 0.511$. For reverse repos, adding all the regressors increases the R^2 from 0.539 to 0.669. Overall, this shows that our empirical model is better at explaining reverse repos than repos. This observation is also corroborated by the fewer significant coefficients in the case of repos compared to reverse repos.

The above observation can be partially explained by the nature of our sample. The reverse repo sample consists of the lending transactions by the six major banks to a variety of counterparties who use various types of collaterals. Hence, there is more heterogeneity in both collateral and counterparty characteristics for the regression analysis, which could explain the better fit. In contrast, the repo sample contains borrowing transactions by the same six major banks who use a relatively narrower list of collaterals and borrow from a relatively smaller set of counterparties (since typically only cash-rich counterparties lend to the banks). These unique features of our sample could help explain the difference in regression fit across the repo and reverse repo subsamples. Next, we elaborate on the main results presented in Tables 8–10 in light of the six hypotheses formulated in Section 3.

4.2 Tests of hypotheses

Test 1 (collateral quality): The haircut is larger when the collateral is of lower quality and/or illiquid.

As aforementioned, collateral quality can be measured using VaR, maturity, rating, and/or asset types. Transaction maturity is also a proxy because the longer the maturity, the riskier the underlying collateral becomes. Another measure of collateral riskiness is its concentration: when the concentration ratio increases, the collateral portfolio pool becomes riskier. To test hypothesis 1, we include VaR of each asset, collateral rating, maturity, transaction maturity, collateral concentration, and notional value in all baseline regressions. We compute VaR using two approaches. First, the measure is obtained using the historic approach, i.e. using the quintiles of the historical return distribution. We calculate simple returns and take the 5-days, 5% VaR as our main measure.[18] Second, we also compute VaR using the parametric approach (i.e., using the deciles of the normal distribution). The results are largely similar to the results obtained using the historic approach. In the main text, we provide the results obtained with the historic VaR.

Table 8 shows that the longer the contract maturity, the larger the haircut, and this relationship is statistically significant across most specifications. The estimate of 0.054 in column (5) of Table 8 shows that one standard deviation increase in maturity of reverse repo contracts (2 months) raises haircuts by 5.4%. Similarly, the coefficient of 0.035 in column (10) shows that one standard deviation increase in maturity of repo contracts (4 months) raises haircuts by 3.5%.

Among the collateral qualities, the results in Table 8 show that VaR has the most consistent, statistically significant impact on haircuts – both in reverse repo and repo markets. One standard deviation increase in the 5-day, 5% VaR is correlated with 100 bps rise in the repo haircut and with a 60 bps rise in the reverse repo haircut. The effect is robust to adding different controls – the estimates in columns 1-10 barely change. When inspecting the impact of VaR in the collateral subsets, we find that this effect is robust for reverse repo cash transactions, but the marginal effect is negative for lower rated government bonds and not significant for non-government collaterals (see Table 9). This reinforces the conjecture that, given its short horizon, VaR captures mostly liquidity rather than credit quality.[19] VaR is insignificant for repos for all collateral subsets (see Table 10).

We find that collateral rating has a statistically significant impact on reverse repo haircuts. One unit increase in collateral rating lowers the haircut by about 1.2% (Column (5) in Table 8). That is, the reporting banks rely on collateral rating to assess the haircut when lending. However, the statistical significance of this result disappears for the repo sample. The latter fact indicates that when reporting banks borrow, their counterparties rely less on collateral rating (a credit risk indicator) but more on VaR (a liquidity indicator) to set the haircut.

For the whole sample, higher collateral concentration – another measure for the riskiness of the collateral portfolio – increases the haircut, both for reverse repo and repo transactions (columns (5) and (10) in Table 8). Therefore, our reporting banks are charged (charge) sig-

[18]Using 1% or 10 days produces similar results.

[19]VaR is a measure of market liquidity risk in standard risk management textbooks.

nificantly higher haircut when borrowing (lending) relatively large sums against the same collateral. The results are more subtle when conditioning on the three collateral subsets. Collateral concentration has a positive and statistically significant effect on haircuts only when our reporting banks are lending against riskier collaterals (column (15) in Table 9).

In general, there is strong evidence that collateral quality and liquidity variables are important determinants of repo haircuts.

Test 2 (counterparty types): The haircut is larger when the counterparties in the contract are from different lines of business and hence have different opinions about the collateral value.

Table 8 shows that the reporting banks charge higher haircuts when lending to hedge funds and are charged higher haircuts when borrowing from central banks. However, there is more complexity to this finding. In Table 9 we further examine this effect in separate subsets of collateral. We find that hedge funds are charged much higher haircuts when using non-government assets as collateral: the haircut increases by a staggering 25-28% when banks lend to hedge funds in a repo backed by non-government securities. This finding is consistent with the idea that belief disagreement is more pronounced for repos backed by risky collaterals. Somewhat surprisingly, banks charge lower haircuts when hedge funds use highly-rated government assets as collateral. The latter observation might be related to the fact that the type of hedge funds that borrow using high quality collaterals is different from the one using riskier collaterals (Kruttli et al. (2021)). We also observe a similar dichotomy for insurance companies and pension funds, although the aggregate impact on the haircuts paid overall (shown in Table 8) is not statistically significant.

Since there is more disagreement about the value of riskier and more heterogeneous collaterals relative to the safest government bond collaterals, these observations support the view that when the two parties in a repo contract disagree on the collateral value, charging a higher haircut is a tool to mitigate the disagreement. We do not find strong evidence that banks charge significantly higher haircuts when lending to broker dealers, other banks, or asset managers. This pattern might reflect the fact that there is lower information friction between counterparties of similar types. This evidence is consistent with both the difference of opinion (see, e.g., Geanakoplos (1997)) and the adverse selection (see, e.g., Ozdenoren et al. (2023)) paradigms.

However, although our reporting banks are charged higher haircuts when borrowing from several types of counterparties in our sample, only haircuts from central banks are significantly larger from a statistical standpoint – about 4.9% higher (column (10) in Table 8). This effect is present only if banks use the safest government collateral (Table 10). Overall, the lack of significant counterparty type fixed effects in the repo sample (except the central banks one) may reflect the fact that there is little disagreement about the value of collaterals used by the reporting banks (since collaterals are mostly of the highest quality – see Table 3), and higher costs in accessing central bank liquidity.

Test 3 (counterparty quality): The haircut is larger when the default probability (credit quality) of the borrower is higher (lower).

To test hypothesis 3, we use the rating and the leverage ratio of the borrower in the reverse repo sample. The results from Table 8 show that both have a significant impact. Our reporting banks charge higher-rated (lower default probability) borrowers and lower-levered banks lower haircuts: one unit increase in rating decreases the haircut by 1.7% and one standard deviation drop in leverage lowers the haircut by 7.7% (column (5)). These findings are consistent with the third hypothesis. The results in column (5) of Tables 8–9 also show that larger counterparties are charged lower haircut by our reporting banks: one standard deviation increase in size massively reduces the haircut by 15.8% (and this seems to be driven mostly by the highly-rated government collateral, see Table 9). This finding shows that there is significant tiering in the repo market, similar to that in other short-term funding markets (Rime et al. (2022)). The results for the repo sample are not statistically significant although the positive sign indicates that larger lenders charge a higher haircut. Counterparties with missing data on counterparty characteristics charge a higher haircut as lenders, but receive a lower haircut as borrowers. The majority of these counterparties are small banks, asset managers, and some hedge funds.

Test 4 (bilateral relationship): The repo haircut is lower for bilateral parties with a stable banking relationship.

Albeit our baseline dataset comprises of a static snapshot of repo and reverse repo portfolios, we do actually observe repeated interactions across time. The snapshot covers trades initiated in the past at different moments in time, which allows us to observe several outstanding contracts between two counterparties. These repeated interactions enable us to tease out bank-counterparty variation that is unexplained by the controls, which is the base for our measure of relationships. In particular, we measure bilateral relationships with bank-counterparty fixed effects and focus only on pairs with at least 10 contracts outstanding. This allows us to distinguish between pairs that traded often in the past and those that did not. Table 11 reports the percentages of significantly negative and positive relationship fixed effects in specifications with and without bank fixed effects. It shows that an overwhelming majority of relationship fixed effects yield statistically significant negative haircuts. The reduction in haircut is around 7-10 basis points for reverse repo transactions, and 4-6 basis points for repo transactions. The results indicate that bilateral banking relationships indeed reduce the haircut.

Figure 5 presents a network graph of all the bank-counterparty relationship fixed effects, significant at the 5% (one-sided) level. Red colour means the regression coefficient on the fixed effect is negative (lower haircut if the given two nodes enter a repo contract). Blue colour means the coefficient is positive, i.e. higher haircut if the two nodes enter a contract. The thickness of the edge between two nodes shows the magnitude of the coefficient on the relationship fixed effect. The size of each node reflects the number of significant fixed effects involving the node.

The figure is consistent with the hypothesis that bilateral relationships matter in haircut determination since some entities are consistently able to borrow at a lower haircut from a set of counterparties. For example, bank B both borrows from and lends to counterparties C115, C167 and C189 at a significantly lower haircut. Interestingly, the same bank also lends at zero haircut to the largest number of counterparties, and also borrows at zero haircuts from many entities as seen from Figure 4. Bank A, which is also a major zero-haircut borrower and lender, is also involved in several significant relationships as seen from Figure 5 but the bank is charged or charges also higher haircuts when interacting with a set of counterparties as indicated by the blue lines. Overall, we find evidence in support of the fourth hypothesis and show the importance of bilateral relationships in determining haircuts.[20]

Test 5 (portfolio repos): Risky assets in a portfolio repo with safe assets have lower haircut than purely risky asset repos.

To implement this test, we define a dummy equal to one if an asset is part of portfolio which contains at least one highest-rated asset (AAA). The coefficient on the dummy for collateral bundled in a safe-asset portfolio from Table 8 shows that lower-rated assets in a portfolio with a safe asset have a lower haircut (about 60 bps) in the reverse repo sample compared to the same assets in a standalone arrangement. A more detailed analysis of the safe-asset portfolios shows that lower-rated counterparties are more likely to bundle assets in such portfolios. Hedge funds are the counterparties with the largest fraction of portfolios bundled with a safe asset. The effect of a safe asset in a portfolio is, however, not statistically significant for the repo sample and even becomes positive for credit collaterals. Overall, there is mixed evidence for this hypothesis.

[20]The bilateral relationships might stem from interactions between the two entities in markets other than the repo market. For example, a customer might also have an established trading relationship with the bank in other, non-repo assets. Examining the drivers of bilateral relationships is an interesting question that is out of the scope of this paper since we do not observe interactions beyond those in the repo market.

Test 6 (lender's quality and liquidity): The repo haircut is larger when the default probability and/or liquidity need of the lender is higher.

In the reverse repo regressions, the lenders are the reporting banks and borrowers are various counterparties. In the repo regressions, the lenders are various counterparties. Table 8 shows that none of the counterparties in the repo regressions affect the haircut except for central banks and government. In addition, none of the counterparty characteristics coefficients other than that of counterparties with missing data is consistently statistically significant. The estimates on lender's cash ratio, which could be a proxy for lender's liquidity needs, is insignificant. Similarly, the estimates on lender's CDS and leverage, which could proxy for default probability, are also not significant, whereas the coefficient on rating is positive but only marginally significant. These findings are not strongly supportive of hypothesis 6 and indicate that lender's default probability or liquidity needs do not affect how lenders set haircut in repo contracts.

4.3 Likelihood of zero-haircut repos

Given the multitude of zero haircuts in the data, we now study which transactions are more likely to get a zero haircut. To do that, we replace the independent variable with a dummy taking value 1 if the haircut is zero and value 0 otherwise: $D_{j,zero\ haircut}$. We then estimate a simple OLS (a linear probability model) where the regression coefficients on the independent variables can be interpreted as the marginal effects on the probability of observing zero haircut on a given contract:

$$D_{j,zero\ haircut} = \beta \times determinants_j + BankFE + RelationshipFE + CurrencyFE + \varepsilon_j. \quad (3)$$

Table 12 shows that the R^2 is very high in all regressions, suggesting that the explanatory variables capture most of the variation in zero vs non-zero haircuts. A closer look shows that the relationship FEs explain the largest part of that variation. In addition, collateral quality and liquidity variables affect the probability of receiving zero haircut in a way similar to the size of haircut, which we studied earlier. Lower contract maturity and higher collateral rating increase the probability of receiving a zero haircut in the reverse repo sample. Riskier counterparties (as measured by their CDS spreads) are less likely to receive a zero haircut. We also find that the probability of a zero haircut is higher when the counterparties are broker-dealers, central banks, asset managers, or even hedge funds (a marginally significant effect in reverse repo).[21]

[21] The evidence pertaining to the role of relationships in affecting zero haircuts adds to the recent US evidence

4.4 Determinants of CCP trades

We now examine the characteristics of trades with CCP as the counterparty. In unreported regressions we use the entire sample including the CCP deals and run the main regressions. None of the results mentioned above changes significantly, with one exception. We observe that including CCP transactions attenuates the impact of counterparty concentration on increasing haircuts. Overall, given the issues described in Section 4, it seems that CCP trades are motivated by different economic considerations and including CCP transactions introduces some noise in the way that the architecture of the market affects haircuts. In particular, as discussed in Schaffner et al. (2022) and Ballensiefen et al. (2023), by interposing themselves between borrowers and lenders CCPs greatly reduce counterparty risk, and apply the same collateral and risk policies to all CCP members, generating a more homogenous set of collaterals than for our non-CCP sample (see Panel D of Table 1 and Panel C of Table 2). Furthermore, positions with CCPs involve netting benefits as analysed below.

In Table 13, we compare CCP versus non-CCP transactions to shed light on the different economic motivations behind these trades. One immediate observation is that when our reporting banks transact through CCPs, they earn lower intermediating spreads, since they are borrowing at a higher average repo haircut via CCPs (at 0.044) than from non-CCP counterparties (at 0.039), and lending out at a lower average reverse repo haircut via CCPs (at 0.071) compared to non-CCP counterparties (0.096). Table 13 also shows that transactions with CCPs are more likely to have zero haircut.

Trades with CCPs offer a significant advantage over non-CCP transactions because CCP trades are netted and expand banks' balance sheet less. Due to this netting benefit, banks use CCPs often for collateral management and less so for earning intermediating spreads. To see if banks are indeed utilising this netting benefit, we compute the ratio of total repo and reverse repo positions against a given counterparty from the point of view of reporting banks in our sample. Table 13 shows that the mean ratio is 1.03 for CCPs, indicating that the net position with CCPs is close to zero. By comparison, the ratio is 5.77 for non-CCP counterparties, which shows that banks engage in one-directional trades with such counterparties. This fact suggests that banks use CCPs for collateral management purposes.

To investigate this formally we compute a proxy variable capturing netting opportunities between repo and reverse repo (as in Hempel et al. (2023)):

$$\text{netting}_{i,j} = \frac{2 \times \min\left(\sum_t \text{repo}_{i,j,t}\ ,\ \sum_t \text{revrepo}_{i,j,t}\right)}{\sum_t \text{repo}_{i,j,t} + \text{revrepo}_{i,j,t}}\ . \tag{4}$$

of Baklanova et al. (2019).

A value closer to 1 is indicative of higher netting benefits and we expect the subsample of transactions with CCP counterparties to have higher values of the proxy variable. Table 14 shows that the mean of the variable is higher for the subsample of CCP counterparties. In addition, the distribution is more tilted towards larger values than in the subsample of non-CCP counterparties. This is also confirmed by a comparison of the distributions of these measures across the two counterparty types in Figure OA.1 of the Online Appendix, although the two subsamples have very different sizes. We analyze the netting benefit hypothesis formally in Table 15 by reporting difference in mean tests between the two subsamples. The null hypothesis is equality of means against a 2-sided alternative in the first two rows, and against the alternative of a larger mean of the netting proxy for CCP counterparties for the last two rows. In both cases, we consider a version of the test assuming equal variance in the two subsamples and one version where equal variance is not assumed. The results indicate that the mean of the netting variable is significantly different across the two subsamples, and significantly larger when CCPs act as counterparties.

Next, we study whether the probability of zero haircuts is different for CCP trades. To control for collateral-level heterogeneity, we examine whether at the contract level, the probability of zero repo and reverse repo haircuts is different depending on whether the bank trades with a CCP or non-CCP counterparty. We run the following linear probability model:

$$D_j^{zero\ haircut} = \beta \times D_{j,CCP} + \gamma_1 \times notional_j + \gamma_2 \times maturity_j + CollateralFE + BankFE + \varepsilon_j, \tag{5}$$

where $D_{j,CCP}$ takes value 1 when the counterparty is a CCP. The results are reported in Table 16. They show that the probability of a zero haircut rises by about 17% when the reporting banks lend via CCPs relative to lending to non-CCP counterparties, but this probability is lower for transactions with large notional values.[22] The estimates on maturity show that longer-maturity trades are less likely to have zero haircut, which is consistent with collateral management for short periods. By comparison, for repo trades, whether the counterparty is a CCP or not does not affect the probability of receiving a zero haircut.

Finally, we investigate the determinants of trading with a CCP. To do so, we run the following linear probability model:

$$D_{j,CCP} = \beta \times determinants_j + BankFE + \varepsilon_j. \tag{6}$$

[22]This might also reflect the possibility that assets of low notional values are packaged in a collateral portfolio together with those of large notional values to back repo transactions. Therefore, haircuts are assessed on assets of large notional values to meet the initial margin requirement.

Table 17 shows that the probability of a trade with a CCP is greatly increased (by 40–43%) when the netting proxy is equal to one – that is, netting benefits seem to be one of the main drivers of CCP trades.

Additionally, the probability of trading with a CCP in Table 17 increases in the notional of the trade, in the collateral rating, and when the transaction is denominated in GBP, EUR and USD. Instead, the probability decreases for corporate and securitised debt collaterals, which suggests that CCP transactions are motivated by managing high quality collateral inventories of the reporting banks in our sample.[23] Together with the fact that CCP trades tend to involve high quality collaterals (See Table 2), these findings indicate that reporting banks use CCPs to reallocate high quality collaterals among themselves. Overall, Table 17 reveals that CCP repo trades have different drivers than bilateral contracts.

4.5 The pecking order of collateral choice

So far we have presented evidence that is in line with the predictions of an asymmetric information view of haircuts. A key ingredient of such models is the existence of information frictions between borrowers and lenders. The classical pecking order theory proposed by Myers (1984) and Myers and Majluf (1984), motivated by the adverse selection friction, suggests a hierarchical financing strategy. That is, to minimize the costs of borrowing, the source of capital with the lowest degree of information asymmetry should be used first when raising funds. In the repo setting this predicts that collaterals of the highest quality should be used first by repo borrowers.

Even though our dataset is based on a single snapshot, we observe trades initiated at different dates that allow us to test for a pecking order. For instance, for borrowing maturing at maturity T, we observe collateral posted in transactions initiated in period $T-1$, $T-2$ etc. Hence, we can test whether there is a systematic pattern in the quality of collateral used over time.

To test the pecking order hypothesis we first compute, for each bank-counterparty pair (i, j), the weighted average of the collateral quality backing borrowing in month t which will mature in month T, with $T \geq 2$.[24] We use the notation $\text{CollRating}_{i,j,t}^{T}$ to denote this measure. We then compare this measure with the corresponding average collateral quality backing new borrowing in the following months ($t+1$, $t+2$, ...) for *the same maturity date*, denoted

[23]A caveat of this analysis is that CCPs in our sample period did not experience stress. For an analysis of CCPs in turbulent times, see Duffie (2014) and Boissel et al. (2017).

[24]Recall that the numerical classification for collateral quality is on a scale from 1 to 20, with lower values representing lower collateral quality.

$\text{CollRating}^T_{i,j,t+k}$ in the following regression:[25]

$$\text{CollRating}^T_{i,j,t+k} = \beta_0 \times \text{CollRating}^T_{i,j,t} + \text{controls} + FEs + \varepsilon_{i,j,t+k}, \forall k \in [1, T-t) \quad (7)$$

where β_0 is the coefficient of interest. If there is no pecking order in the posting of collateral, we would expect the average collateral quality to be similar at different point in time, hence we would expect $\beta_0 = 1$. Instead if, for a given borrowing maturity, higher quality collateral tends to be posted first, we would expect $\beta_0 < 1$. We include the borrowing horizon, the initial amount borrowed and the time difference between the initial and new borrowing (k) as control variables. We consider different combinations of reporting banks, counterparty sector and time fixed effects. The standard errors are clustered at the counterparty and time level in all the cases.

Table 18 shows our estimation results for equation 7.[26] In addition, each row of Table 19 reports the 95% confidence interval around the estimate of our coefficient of interest for the corresponding column. In all specifications, the coefficient estimates are significantly smaller than one at canonical confidence levels. That is, counterparties of our reporting banks seem to choose high quality collaterals first when borrowing via repo contracts.

Overall, we interpret the findings on a pecking order in collateral selection as evidence of an information friction channel being at play in the repo market.

4.6 The link between repo interest rates and haircuts

Despite its richness in terms of repo deal informations, our baseline dataset does not contain the repo rates applied to the individual contracts. This is potentially problematic since demanding higher haircuts could be to some extent a substitute for offering lower interest rates. To check whether this issue might be at play, we complement our analysis with the Bank of England Sterling Money Market daily (SMMD) dataset. The SMMD data contains transaction-level information, including haircuts and deal rates, for which GBP denominated repos are secured against UK government bills and bonds (nominal and indexed-linked Gilts). Hence, in this dataset, we have no rating heterogeneity but the collateral quality is captured by its maturity, whether it is inflation linked or not, since the two market segments have quite different liquidity, and the VaR of the asset.

[25] In the analysis, we focus on the transactions reported during 2012, where most of the observations are concentrated. We aggregate the transactions taking place within a same month between a bank-counterparty pair to compute the variables entering our regression. Setting $t = 1$ in January 2012, we have $k \in [1, 11]$ and $T > k$.

[26] The final samples contains 327 observations between 81 unique clients and the 6 reporting banks.

In Table 20 we regress haircuts on these collateral quality proxies, deal characteristics, and importantly the rate spread relative to the central bank base rate. In a naïve regression of haircuts on only the deal rate in columns (1) and (2), we do indeed find a statistically significant link between the two variables (albeit the sign is the opposite of what a substitutability between the two would predict). Nevertheless, the simple addition of counterparty fixed effects, in column (3), or just controlling for the quality of the collateral, in columns (4) to (6) with or without fixed effects, make the rate irrelevant in explaining haircuts. Furthermore, when controlling for time fixed effects – hence for the overall credit condition on a given date – the coefficient associated with the repo rate is not only statistically indistinguishable from, but also very close to, zero.

This finding could prima facie look surprising, but is in line with the findings in the existing literature. For example, Eisenschmidt et al. (2024) (see table 3 therein) find no statistical association between rates and haircuts in the Money Market Statistical Reporting (MMSR) European repo dataset from the ECB.

This finding suggests that haircuts and repo rates have different drivers. A potential explanation is that repo rates are determined by the market makers to clear *aggregate* demand and supply of funds, while haircuts instead are determined at the *contract level* based on risk considerations. This explanation is in line with anecdotal evidence we have collected interviewing directly the credit officers and market makers of the repo desks at the reporting banks in our baseline dataset, The reason for this pooling of collaterals (with different haircuts) in the determination of the overall repo rate is driven by liquidity considerations in the market practice, as it would be costly to clear demand and supply of funds in collateral- and counterparty-specific markets.[27]

Hence, the absence of an empirical link between rates and haircuts of repo contracts alleviates concerns of our baseline analysis being affected by an omitted variable due to excluding repo rates.

5 Conclusion

In this study, we analyse the structure of the UK bilateral repo market using a unique transaction-level dataset. We uncover features of the repo market in the UK that are distinct from the US market. In this unique setting, we examine how banks intermediate liquidity among different counterparties via repo trades and how they use CCPs to reallocate high quality collaterals and exploit netting benefits.

[27]Note also that in tri-party repo markets haircuts are actually fixed in the custodian agreements, that are revised infrequently, while the rates are determined at higher frequency to clear demand and supply of funds.

We analyse the characteristics of contract terms including maturity structure, collateral and counterparty types associated with these trades and test various economic mechanisms that can affect the amount of repo liquidity provided via haircuts. Besides asset quality and liquidity, we find that counterparties matter in haircut determination. Furthermore, we observe a pecking order in the posting of collateral, with the higher quality ones used first when borrowing.

Overall, our findings are consistent with an asymmetric information explanation of haircuts, but not with effects related to lenders' liquidity position or default probabilities affecting the size of haircuts. Therefore, effective policy interventions to improve repo funding conditions during times of financial market stress should target measures that mitigate information frictions about repo collaterals.

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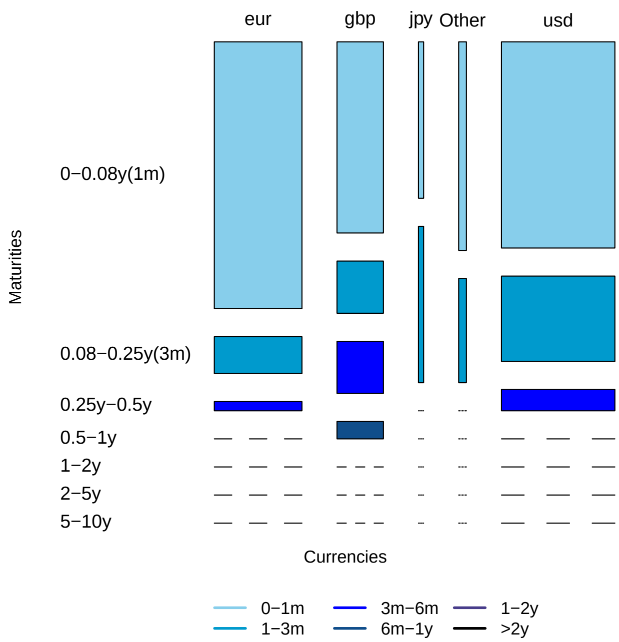
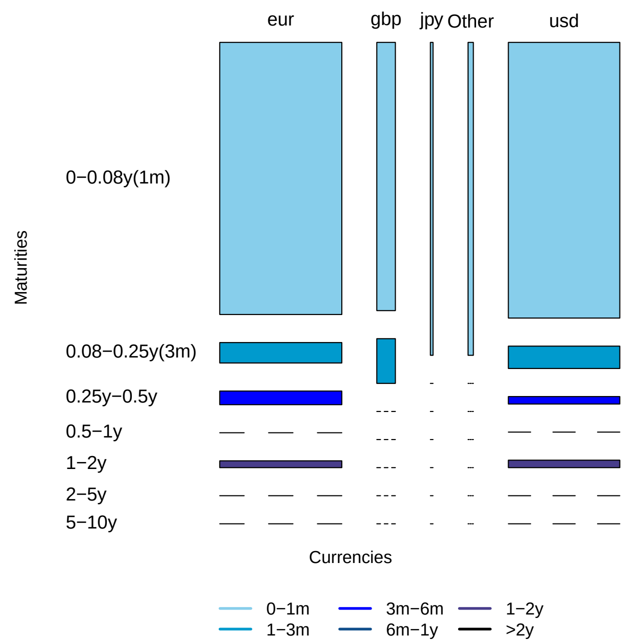
Figures

Figure 1: Currency vs. maturity of the contracts



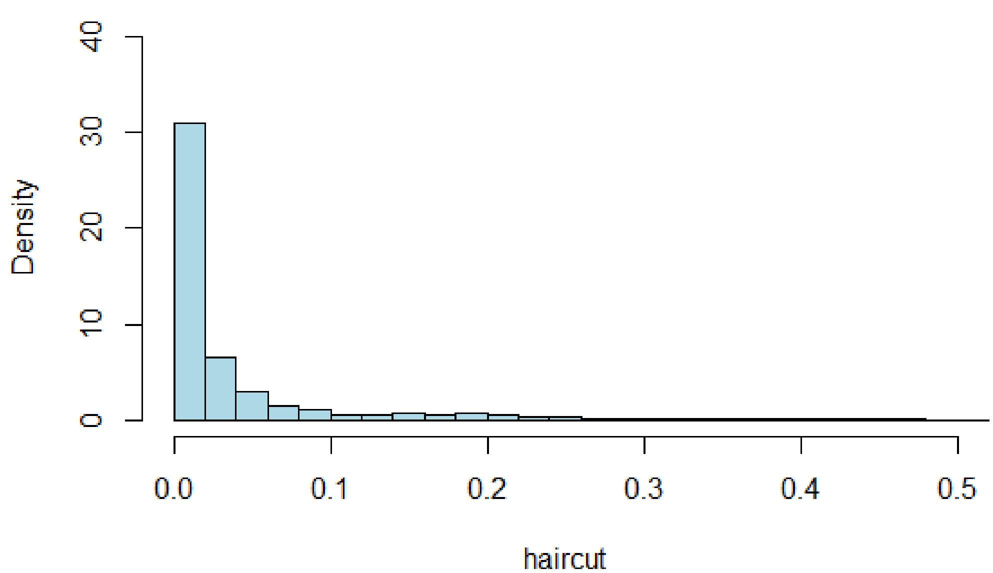
(a) Reverse Repo



(b) Repo

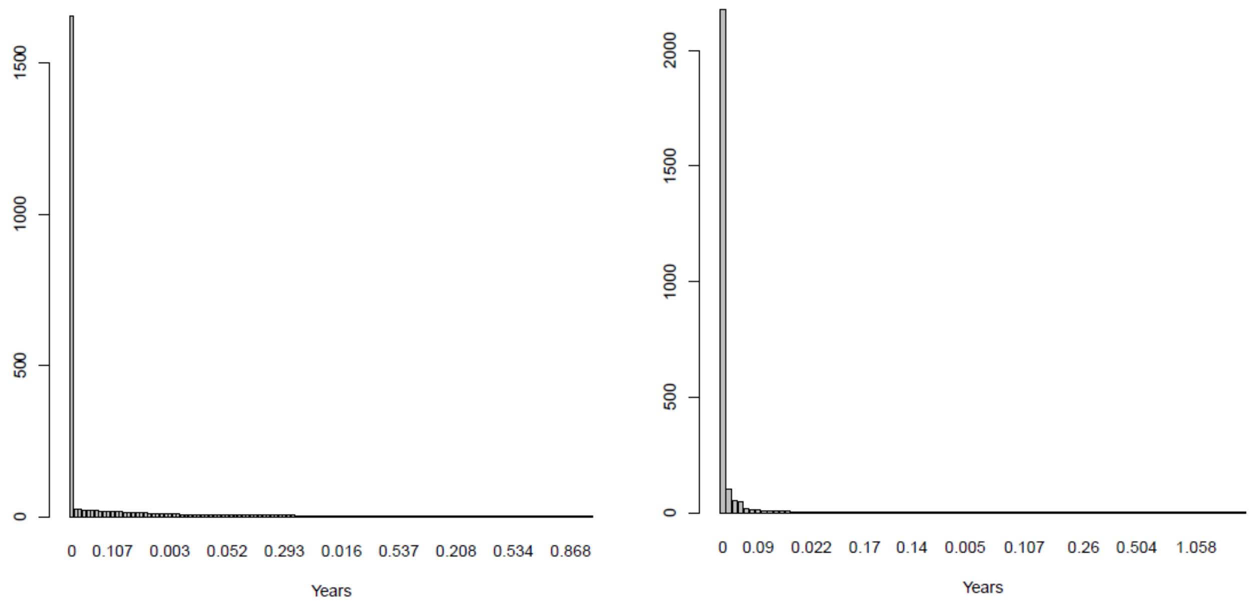
The area of each rectangle represents the fraction of contracts (in terms of frequency, not notional values) within a particular maturity-currency group. The area of the entire square is 100%.

Figure 2: Distribution of haircuts



The figure shows the density of haircuts for both Repo and Reverse Repo contracts.

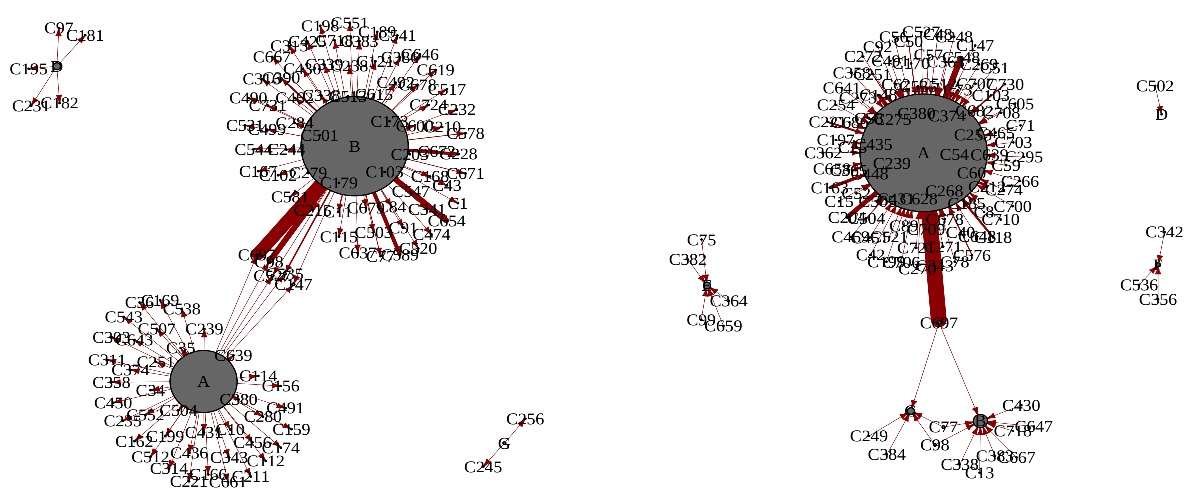
Figure 3: Maturity distribution of zero-haircut deals



(a) Reverse Repo (b) Repo

Number of zero-haircut contracts for each maturity in the zero-haircut subsample.

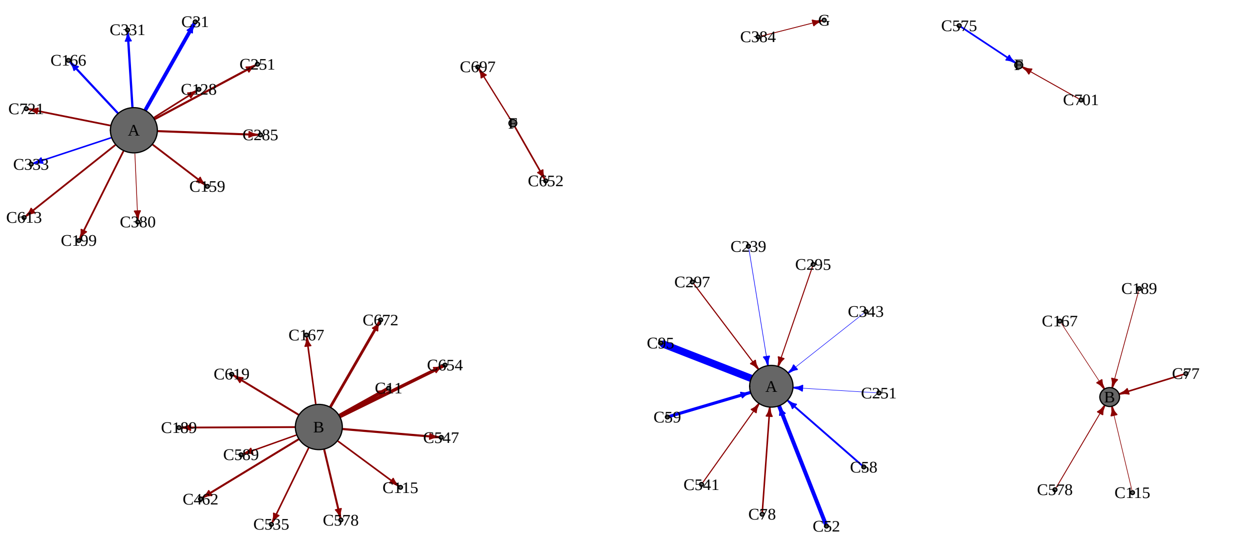
Figure 4: Zero-haircut network



(a) Reverse Repo (b) Repo

The size of each node reflects the number of counterparties with which it has at least one zero-haircut deal. Edge width is increasing in the total number of zero-haircut trades between two given nodes. A, B, D, E, F, and G denote the six reporting banks, and nodes labeled with C and numeric denote their counterparties.

Figure 5: Significant relationship fixed effects



(a) Reverse Repo

(b) Repo

Network graph implied by the statistically significant, at the 5% (one sided) level, relationship fixed effects for reverse repo (panel (a)) and repo (panel (b)) contracts. Estimates based on the regressions from columns 5 (reverse repo) and 10 (repo) of Table 8. A relationship is defined as having at least 10 bilateral transactions. Red (blue) arrows denote negative (positive) fixed effects while their direction represents the lending flow. Node sizes are proportional to the number of bilateral relationship fixed effects involving the given node. Edge width is increasing in the absolute magnitude of the estimate. A, B, D, E, F, and G denote the six reporting banks, and nodes labeled with C and numeric denote their counterparties.

Tables

Table 1: Breakdown of value of contracts (in bn GBP)

	REVR		REPO		
	Value	Percent	Value	Percent	Net
A. Maturity					
Overnight	29.7	12.2%	-38.1	14.3%	-8.5
1 day-3m	140.7	57.6%	-130.7	48.9%	10.0
3m-1y	65.8	26.9%	-78.1	29.2%	-12.3
1y-5y	8.0	3.3%	-18.5	6.9%	-10.5
5y+	0.0	0.0%	-1.7	0.6%	-1.6
Total	244.2	100.0%	-267.0	100.0%	-22.8
B. Currency					
GBP	110.2	45.1%	-149.8	56.1%	-39.6
EUR	90.6	37.1%	-86.7	32.5%	4.0
USD	30.5	12.5%	-26.8	10.0%	3.7
JPY	6.0	2.5%	-1.6	0.6%	4.4
Other	6.9	2.8%	-2.1	0.8%	4.8
Total	244.2	100.0%	-267.0	100.0%	-22.8
C. Counterparty type					
Another reporting bank [a]	8.2	3.4%	-10.2	3.8%	-2.0
Other banks	29.3	12.0%	-43.6	16.3%	-14.3
Broker-dealer [b]	15.0	6.1%	-15.8	5.9%	-0.8
Hedge fund	15.1	6.2%	-15.5	5.8%	-0.4
MMFs	0.0	0.0%	-1.9	0.7%	-1.9
Other asset managers [c]	11.5	4.7%	-8.3	3.1%	3.2
CCP	145.5	59.6%	-131.3	49.3%	14.2
Insurance and pension	9.5	3.9%	-8.5	3.2%	1.0
Central bank and government	5.5	2.3%	-28.6	10.7%	-23.0
Other [d]	4.4	1.8%	-2.8	1.0%	1.6
Total	244.1	100.0%	-266.6	100.0%	-22.5
D. Collateral type					
US govt	10.9	6.0%	-5.4	2.9%	5.5
UK govt	83.1	45.8%	-111.7	59.1%	-28.6
Germany govt	25.5	14.0%	-19.1	10.1%	6.4
France govt	16.9	9.3%	-7.2	3.8%	9.7
GIIPS [e]	4.1	2.2%	-4.4	2.3%	-0.3
Other sovereign	31.6	17.4%	-16.0	8.4%	15.7
Corporate debt	7.5	4.1%	-11.7	6.2%	-4.2
Securitisation	2.0	1.1%	-13.5	7.1%	-11.5
Other	0.0	0.0%	0.0	0.0%	0.0
Total	181.6	100.0%	-188.9	100.0%	-7.3

Breakdown of deals by maturity, currency, counterparty, and collateral (Panels A, B, C, and D respectively). Value of the trades is in billion (bn) GBP. The total values in Panels A, B, C and D are based on data from six reporting banks that report haircut and collateral information. Discrepancies in row Total are due to missing information.

[a] The reporting banks report on a UK-consolidated basis, but counterparties are reported on a global basis. Therefore, there may be discrepancies between the reverse repos and repos with the reporting banks. [b] Broker-dealers are mostly securities firms that are subsidiaries of large banks. [c] Non-leveraged non-MMF mutual funds—asset managers that are not hedge fund or MMF. [d] Includes corporations, schools, hospitals and other non-profit organizations. [e] Greece, Italy, Ireland, Portugal, and Spain government bonds.

Table 2: Breakdown of value of contracts with CCPs (in bn GBP)

	REVR		REPO		
	Value	Percent	Value	Percent	Net
A. Maturity					
Overnight	5.5	3.9%	-5.1	3.9%	0.4
1 day-3m	88.0	62.1%	-71.7	54.6%	16.3
3m-1y	42.2	29.8%	-50.5	38.4%	-8.3
1y-5y	6.0	4.2%	-4.0	3.1%	2.0
Total	141.7	100.0%	-131.3	100.0%	10.4
B. Currency					
GBP	80.2	56.6%	-108.5	82.6%	-28.3
EUR	59.2	41.8%	-21.3	16.2%	37.9
USD	2.4	1.7%	-1.5	1.1%	0.9
Other	0.0	0.0%	0.0	0.0%	0.0
Total	141.7	100.00%	-131.3	100.00%	10.4
C. Collateral type					
UK govt	65.5	59.0%	-93.8	86.7%	-28.3
Germany govt	20.1	18.1%	-6.2	5.7%	13.9
France govt	12.1	10.9%	-2.5	2.3%	9.6
GIIPS [a]	0.2	0.2%	-0.5	0.5%	-0.3
Other sovereign	12.7	11.4%	-5.2	4.8%	7.5
Corporate debt	0.5	0.5%	0.0	0.0%	0.5
Securitisation	0.1	0.0%	0.0	0.0%	0.0
Total	111.1	100.0%	-108.2	100.0%	2.8

Breakdown of the deals involving CCPs by maturity, currency, and collateral type (Panels A, B, C respectively). Value of the trades is in bn GBP. Total values in Panels A, B and C are based on data from six reporting banks that report haircut and collateral information. Discrepancies in row Total are due to missing information.
[a] Greece, Italy, Ireland, Portugal, and Spain government bonds.

Table 3: Breakdown of value of contracts by collateral type (in bn GBP)

	Gov ≥AA					Gov <AA					Other				
	REVR		REPO			REVR		REPO			REVR		REPO		
	Value	%	Value	%	Net	Value	%	Value	%	Net	Value	%	Value	%	Net
A. Maturity															
o/n	9.3	5.9%	-14.4	9.2%	-5.1	3.1	22.6%	-2.7	39.4%	0.4	4.8	50.3%	-7.9	30.5%	-3.1
<3m	92.2	58.4%	-81.9	52.4%	10.3	7.4	53.2%	-3.8	54.5%	3.6	3.4	35.4%	-0.9	3.3%	2.5
3m-1y	50.3	31.8%	-53.9	34.4%	-3.6	3.0	21.7%	-0.4	5.8%	2.6	1.4	14.4%	-4.9	18.9%	-3.5
1y-5y	6.1	3.9%	-6.0	3.8%	0.2	0.3	2.3%	-0.0	0.3%	0.3	0.0	0.0%	-10.9	42.2%	-10.9
5y+	0.0	0.0%	-0.2	0.1%	-0.2	0.0	0.2%	0.0	0.0%	0.0	0.0	0.0%	-1.3	5.2%	-1.3
Total	158.0	100.0%	-156.4	100.0%	1.6	13.9	100.0%	-6.9	100.0%	6.9	9.5	100.0%	-25.9	100.0%	-16.4
B. Currency															
GBP	83.4	52.8%	-111.8	71.5%	-28.4	0.0	0.1%	-0.0	0.0%	-0.0	0.9	9.8%	-5.6	21.8%	-4.7
EUR	55.7	35.2%	-32.6	20.8%	23.1	3.9	28.2%	-3.6	51.0%	0.4	3.3	34.6%	-11.7	45.2%	-8.4
USD	15.4	9.7%	-11.2	7.1%	4.2	6.5	46.8%	-2.6	38.0%	3.9	5.3	55.5%	-8.1	31.2%	-2.8
JPY	1.8	1.1%	-0.2	0.1%	1.6	2.2	15.7%	-0.8	11.0%	1.4	0.0	0.0%	-0.0	0.2%	-0.0
Other	1.7	1.1%	-0.7	0.4%	1.1	1.3	9.2%	0.0	0.0%	1.3	0.0	0.1%	-0.4	1.6%	-0.4
Total	158.0	100.0%	-156.4	100.0%	1.6	13.9	100.0%	-6.9	100.0%	6.9	9.5	100.0%	-25.9	100.0%	-16.4
C. Counterparty															
Another reporting bank[a]	4.6	2.9%	-1.0	0.6%	3.6	1.7	12.3%	-0.2	3.4%	1.5	1.0	10.9%	-3.8	14.6%	-2.7
Other banks	9.9	6.3%	-14.4	9.2%	-4.5	5.0	35.9%	-2.0	29.0%	3.0	2.3	23.8%	-9.8	37.6%	-7.5
Broker-Dealers[b]	5.2	3.3%	-2.9	1.9%	2.2	2.0	14.3%	-0.8	11.9%	1.2	2.1	21.8%	-6.3	24.4%	-4.3
Hedge Fund	2.2	1.4%	-5.6	3.6%	-3.3	3.0	21.8%	-1.9	27.1%	1.1	1.7	17.7%	-0.7	2.6%	1.0
MMFs	0.0	0.0%	-1.9	1.2%	-1.9	0.0	0.0%	0.0	0.0%	0.0	0.0	0.0%	-0.0	0.0%	-0.0
Other Asset Managers[c]	9.1	5.8%	-4.6	3.0%	4.4	0.4	2.6%	-0.2	3.1%	0.1	0.5	4.8%	-1.6	6.2%	-1.1
CCP	110.4	69.9%	-107.4	68.6%	3.0	0.1	0.8%	-0.5	6.6%	-0.4	0.6	5.9%	-0.0	0.1%	0.5
Insurance and Pension	5.4	3.4%	-1.8	1.1%	3.6	0.0	0.0%	-0.0	0.7%	-0.0	0.7	7.6%	-3.1	11.9%	-2.4
Central Bank and Government	4.2	2.7%	-15.4	9.8%	-11.2	1.3	9.0%	-1.2	16.6%	0.1	0.1	0.8%	-0.6	2.5%	-0.6
Other[d]	6.9	4.4%	-1.4	0.9%	5.5	0.5	3.3%	-0.1	1.7%	0.3	0.6	6.7%	-0.0	0.1%	0.6
Total	158.0	100.0%	-156.4	100.0%	1.6	13.9	100.0%	-6.9	100.0%	6.9	9.5	100.0%	-25.9	100.0%	-16.4

Breakdown for different collateral types of Repo and Reverse Repo deals by maturity, currency, and counterparty (Panels A, B, C respectively). Total values in Panels A, B and C are based on data from six reporting banks that report haircut and collateral information. Discrepancies in row Total are due to missing information.

[a] The reporting banks report on a UK-consolidated basis, but counterparties are reported on a global basis. Therefore, there may be discrepancies between the reverse repos and repos with the reporting banks.

[b] Broker-dealers are mostly securities firms that are subsidiaries of large banks.

[c] Non-leveraged non-MMF mutual funds—asset managers that are not hedge fund or MMF.

[d] Includes corporations, schools, hospitals and other non-profit organizations.

Table 4: Rehypothecation Rate of Assets

	<5Y	5-10Y	10-20Y	>20Y
Gov $\geq$ AA	33.4%	47.9%	61.6%	26.3%
Gov $<$ AA	30.5%	17.5%	26.4%	19.3%
Other	27.7%	23.9%	16.6%	8.9%

Rehypothecation rates computed at the CUSIP/ISIN-level as the total amount of collateral asset posted (via repo) divided by the total amount received (via reverse repo).

Table 5: Breakdown of haircuts for the non-CCP subsample

	Average haircut		Zero haircut % of notional	
	REVR	REPO	REVR	REPO
A. Maturity				
Overnight	1.9%	0.7%	42.2%	78.9%
1 day-3m	3.2%	1.4%	47.5%	15.0%
3m-1y	0.6%	0.5%	10.3%	5.3%
1-5y	0.0%	0.7%	0.0%	0.8%
5y+	0.0%	0.0%	0.0%	0.0%
B. Currency				
GBP	1.4%	0.8%	35.9 %	9.0 %
EUR	1.5%	1.4%	31.7 %	50.7 %
USD	2.6%	0.9%	24.4 %	36.1 %
JPY	0.1%	0.0%	4.2 %	2.1 %
Other	0.2%	0.1%	3.8 %	2.1 %
C. Counterparty type				
Another reporting bank [a]	0.1%	0.2%	4.3 %	4.8 %
Other banks	1.9%	1.4%	41.7 %	62.5 %
Broker-dealer [b]	0.9%	0.6%	8.3 %	10.2 %
Hedge fund	1.4%	0.1%	1.4 %	0.0 %
Other asset managers [c]	1.0%	0.1%	10.5 %	13.3 %
Insurance and pension	0.3%	0.5%	15.6 %	1.2 %
Central bank and government	0.0%	0.3%	6.6 %	7.3 %
Other [d]	0.3%	0.0%	11.5 %	0.8 %
D. Collateral type				
US govt	0.4%	0.0%	6.0 %	0.3 %
UK govt	1.0%	0.4%	24.5 %	1.5 %
Germany govt	0.1%	0.1%	8.7 %	17.3 %
France govt	0.1%	0.1%	3.4 %	7.9 %
GIIPS [e]	0.2%	0.1%	1.1 %	2.1 %
Other sovereign	1.1%	0.2%	19.2 %	30.4 %
Corporate debt	1.1%	0.6%	36.8 %	30.7 %
Securitisation	0.5%	0.8%	0.3 %	9.8 %
Other	0.0%	–	0.0%	–
Overall average	1.2%	0.7%		

The table presents the breakdown of the deals by maturity, currency, counterparty type, and collateral type (Panels A, B, C, and D, respectively). For each category, it shows the average haircut (columns 2 and 3), as well as the distribution of zero haircut deals (columns 4 and 5), for the reverse repos and repos, respectively. The averages are weighted by the gross notional of the transactions. The haircuts are based on the data from the six banks that report haircut and collateral information (excluding deals with CCPs).
[a] The reporting banks report on a UK-consolidated basis, but counterparties are reported on a global basis. Therefore, there may be discrepancies between the reverse repos and repos with the reporting banks.
[b] Broker-dealers are mostly securities firms that are subsidiaries of large banks. [c] Non-leveraged non-MMF mutual funds—asset managers that are not hedge fund or MMF. [d] Includes corporations, schools, hospitals and other non-profit organizations. [e] Greece, Italy, Ireland, Portugal, and Spain government bonds.

Table 6: Summary statistics for the sample excluding deals with CCPs

Variable	Obs	Mean	Std dev	Min	Max	Average [a]
A. REVR						
Haircut	8754	6.25%	10.13%	0.00%	46.15%	6.15%
Notional	10435	6.25	0.86	3.45	8.32	6.25
Maturity	10435	0.07	0.14	0.00	3.00	0.06
Collateral maturity	7085	11.88	10.42	0.22	43.18	12.01
Collateral rating	5729	14.54	4.83	3.00	20.00	14.60
Ctpy size	6512	5.17	0.70	3.57	6.25	5.16
Ctpy RoA	6506	0.29	0.41	-1.26	1.98	0.29
Ctpy leverage	6469	5.56	1.33	2.97	11.00	5.56
Ctpy CDS	5593	0.01	0.01	0.01	0.04	0.01
Ctpy cash ratio	6484	-0.01	5.48	-81.44	4.37	-0.03
Ctpy rating	6495	14.59	1.28	8.00	20.00	14.60
VaR	5875	1.89	1.31	0	7.01	1.87
B. REPO						
Haircut	7386	2.37%	5.82%	0.00%	46.15%	2.36%
Notional	11896	6.18	0.79	3.45	8.32	6.21
Maturity	11905	0.08	0.35	0.00	3.00	0.08
Collateral maturity	8993	7.50	7.81	0.22	43.18	7.50
Collateral rating	8629	14.34	4.99	3.00	20.00	14.33
Ctpy size	8380	5.37	0.62	3.57	6.25	5.37
Ctpy RoA	8367	0.36	0.39	-1.26	1.98	0.36
Ctpy leverage	7300	5.87	1.42	2.97	11.00	5.86
Ctpy CDS	5908	0.02	0.01	0.01	0.04	0.02
Ctpy cash ratio	8160	0.01	6.63	-81.44	4.37	0.01
Ctpy rating	8445	15.19	1.94	8.00	20.00	15.19
VaR	5579	1.74	1.2	0	7.01	1.74

The table shows the summary statistics of variables used in the regressions excluding the deals with CCPs, for repo and reverse repo transactions. The sample only includes the six banks that provided data on haircuts and collateral. Variables have been winsorized at 0.5% level. Rating scale is 1–20, with 20 being the highest rating.
[a] Average is weighted by the gross notional of transactions.

Table 7: Summary statistics by collateral type (excluding deals with CCPs)

	Gov $\geq$ AA						Gov < AA						Other					
Variable	Obs	Mean	Sd	Min	Max	Av	Obs	Mean	Sd	Min	Max	Av	Obs	Mean	Sd	Min	Max	Av
A. REVR																		
haircut	1344	4.14%	7.86%	0.00%	39.57%	4.30%	640	9.52%	13.67%	0.00%	47.35%	9.58%	2878	7.92%	13.07%	0.00%	47.47%	7.88%
notional	1432	6.99	0.72	4.11	8.44	7.06	975	6.66	0.74	3.96	7.98	6.74	3558	6.01	0.54	4.16	7.81	6.06
maturity	1432	0.15	0.20	0.00	1.01	0.16	975	0.09	0.16	0.00	1.02	0.09	3558	0.04	0.11	0.00	1.50	0.04
collmaturity	1432	12.36	11.89	0.25	47.40	12.46	975	9.80	7.60	0.20	31.40	9.77	3479	9.66	9.74	0.21	40.07	9.64
collrating	1432	19.78	0.57	18.00	20.00	19.78	975	11.18	4.05	3.00	17.00	11.20	3322	13.26	4.30	4.00	20.00	13.30
cptysize	661	5.44	0.71	3.57	6.24	5.43	599	5.51	0.59	3.55	6.21	5.52	2094	5.30	0.62	3.57	6.24	5.30
cptyroa	657	0.35	0.49	-0.42	4.33	0.36	589	0.31	0.52	-1.26	1.98	0.32	2108	0.15	0.32	-1.21	1.55	0.15
cptyleverage	651	5.67	1.14	2.97	8.40	5.70	586	6.13	1.42	3.19	11.00	6.15	2093	5.37	1.33	3.19	9.42	5.40
cptycds	539	0.02	0.01	0.01	0.04	0.02	455	0.02	0.01	0.01	0.04	0.02	1826	0.01	0.00	0.01	0.04	0.01
cptycashratio	655	0.45	0.84	0.03	12.60	0.45	589	-0.49	9.75	-99.11	4.83	-0.55	2098	0.36	0.46	0.01	4.59	0.36
cptyrating	659	14.67	1.14	11.00	20.00	14.68	595	14.13	1.80	9.14	20.00	14.10	2094	14.57	1.10	9.00	20.00	14.56
VaR	1422	1.98	1.57	0.02	6.55	1.99	955	1.94	1.04	0.07	5.51	1.92	3207	1.86	1.28	0.00	7.92	1.86
B. REPO																		
haircut	1651	1.25%	5.30%	0.00%	39.57%	1.41%	494	1.83%	5.14%	0.00%	46.50%	1.96%	3317	2.52%	6.54%	0.00%	47.47%	2.73%
notional	1891	6.51	0.94	4.11	8.44	6.65	1239	6.19	0.72	3.96	7.98	6.27	5838	5.96	0.59	4.16	7.89	6.02
maturity	1891	0.06	0.18	0.00	1.01	0.07	1240	0.03	0.09	0.00	1.02	0.03	5839	0.11	0.49	0.00	3.65	0.12
collmaturity	1891	7.19	7.31	0.25	47.40	7.43	1240	9.76	8.23	0.20	31.40	9.75	5692	6.99	7.58	0.21	40.07	6.98
collrating	1891	19.75	0.60	18.00	20.00	19.77	1240	11.21	4.33	3.00	17.00	11.26	5498	13.18	4.59	4.00	20.00	13.24
cptysize	1232	5.32	0.63	3.57	6.24	5.33	833	5.39	0.55	3.57	6.21	5.39	4212	5.45	0.54	3.57	6.25	5.45
cptyroa	1232	0.45	0.81	-0.42	8.23	0.46	833	0.37	0.40	-1.26	1.98	0.37	4203	0.33	0.35	-1.21	1.55	0.33
cptyleverage	1029	5.65	1.49	2.97	8.40	5.69	758	5.62	1.28	3.19	11.00	5.64	3490	5.89	1.47	3.19	9.42	5.90
cptycds	670	0.02	0.01	0.01	0.04	0.02	671	0.02	0.01	0.01	0.04	0.02	2780	0.02	0.01	0.01	0.04	0.02
cptycashratio	1181	0.75	1.49	0.03	12.60	0.76	818	-0.04	6.99	-99.11	5.69	-0.06	4103	0.63	0.89	0.01	4.59	0.62
cptyrating	1234	15.49	2.02	11.00	20.00	15.38	834	14.94	1.80	9.14	20.00	14.90	4277	15.48	1.91	9.00	20.00	15.45
VaR	1221	1.47	1.09	0.02	6.25	1.50	928	2.09	1.12	0.07	5.51	2.09	3313	1.75	1.22	0.00	7.92	1.74

The table shows the summary statistics of variables used in the regressions excluding the deals with CCPs, for repo and reverse repo transactions across the subsamples of a) government securities with AA+ and above rating, b) government securities with ratings smaller or equal to A, and c) other securities. Variables have been winsorized at 0.5% level. Rating scale is 1–20, with 20 being the highest rating. Average is weighted by the gross notional of transactions.

Table 8: The drivers of haircuts (excluding deals with CCPs)

	Reverse Repo					Repo				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deal vars:										
notional	-0.013**	-0.002	-0.002	-0.004	-0.003	0.003	0.002	0.001	0.001	0.001
maturity	0.070**	0.072**	0.066**	0.041	0.054*	0.029**	0.031***	0.033***	0.034***	0.035***
Collateral vars:										
collrating		-0.009***	-0.008***	-0.007***	-0.012***		-0.000	-0.001	-0.001	0.000
collmaturity		0.000	0.000	0.000	0.004		0.002*	0.002	0.002	0.002*
securitisation		0.017	0.029*	0.023	0.019		-0.000	0.001	0.001	0.002
var		0.006*	0.005*	0.006**	0.005**		0.011**	0.010**	0.010**	0.010**
asset in safe portf		-0.004	-0.006*	-0.005*	-0.006*		0.002	0.001	0.002	0.002
Cpty type:										
brokerdealers			-0.017	-0.003	0.004			0.002	0.004	0.005
hedgefund			0.114***	0.085***	0.072**			0.003	0.008	0.013
otherassetmanagers			0.035*	0.026	0.024			0.011	0.016	0.014
insurance&pension			0.006	-0.021	-0.003			0.001	0.004	-0.000
centralbank&government			-0.007	-0.006	0.009			0.048**	0.053***	0.049**
other			0.083*	0.055	0.044			0.003	0.003	0.000
Cpty vars:										
cptysize				-0.141**	-0.158**				0.039	0.029
cptyroa				-0.012*	-0.011*				-0.005*	-0.003
cptyrating				-0.003	-0.017***				0.003	0.006*
cptyleverage				0.081***	0.077***				0.011	0.005
cptycds				0.005	0.000				0.001	0.001
cptycashratio				0.011	0.016**				-0.001	-0.001
nocptydata				-0.137	-0.238*				0.143*	0.120*
Misc:										
cptycon					0.009					0.009**
collcon					0.007**					0.005**
cptyandcollrating					0.001***					-0.000*
N	3907	3907	3907	3907	3907	2915	2915	2915	2915	2915
R^2_{adj}	0.539	0.606	0.634	0.645	0.669	0.511	0.521	0.526	0.527	0.532

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

OLS regressions (equation (1)) for reverse repo, columns (1)-(5), and repo, columns (6)-(10), excluding deals with CCPs. The dependent variable is haircut and explanatory variables are listed in the first column. All quantitative variables (notional, maturity, collmaturity, VaR, cptysize, cptyroa, cptyleverage, cptycds, cptycashratio, cptycon, collcon) are standardized. All regressions include bank, relationship, and currency fixed effects. Standard errors are clustered at the counterparty level.

Table 9: Reverse repo haircut drivers by collateral type (excluding deals with CCPs)

	Gov ≥AA (γ, baseline effect)					Gov <AA (β_1, marginal effect)					Other (β_2, marginal effect)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Deal vars:															
notional	-0.007	-0.010**	-0.005	-0.008**	-0.005	0.020	0.027**	0.018	0.015	0.018*	-0.007	0.004	0.0006	0.002	-0.002
maturity	0.121***	0.076***	0.053**	0.046*	0.056**	-0.087	-0.009	0.041	0.002	-0.018	-0.123**	-0.043	-0.015	-0.059	-0.056
Collateral vars:															
collrating		0.002	0.003	0.007	0.006		-0.019*	-0.023***	-0.026***	-0.030***		-0.010	-0.006	-0.009*	-0.010
collmaturity		0.003	0.005	0.004	0.006		-0.006	-0.012	-0.011	-0.012		-0.010	-0.009	-0.007	-0.008
var		0.022**	0.024**	0.025**	0.022**		-0.021**	-0.023**	-0.022**	-0.023**		-0.007	-0.017	-0.018	-0.016
asset in safe portf		-0.009**	-0.005	-0.004	-0.005		-0.016	-0.019*	-0.020*	-0.015		0.011**	0.002	0.001	0.001
Cpty type:															
brokerdealers			-0.023	-0.010	-0.011			-0.030*	-0.051**	-0.018			0.034*	0.029	0.027
hedgefund			-0.047***	-0.061***	-0.063***			0.076***	0.050	0.049			0.281***	0.256***	0.245***
otherassetmanagers			0.013	0.020	0.017			-0.100**	-0.146***	-0.146**			0.056	0.015	0.010
insurance&pension			-0.034*	-0.044**	-0.050***			0.258***	0.222***	0.202***			0.035***	0.011	0.017
centralbank&government			-0.023	-0.021	-0.026			0.045*	0.219***	0.138***			0.009	0.024	0.034
other			0.078	0.065	0.056			0.035	0.002	0.009			0.070*	0.046	0.043
Cpty vars:															
cptysize				-0.153**	-0.110*				0.026	-0.065				-0.009	-0.050
cptyroa				-0.011*	-0.009*				0.002	0.013				-0.001	-0.004
cptyrating				-0.002	0.011				-0.014	-0.044***				0.001	-0.018
cptyleverage				0.070***	0.046*				-0.067	-0.011				-0.014	0.010
cptycds				-0.003	-0.002				0.012	0.000				0.011	0.009
cptycashratio				0.016*	0.017*				0.005	-0.002				-0.012	-0.010
nocptydata				-0.218	-0.158				-0.220	-0.324**				0.033	-0.077
Misc:															
cptycon					0.009					0.020***					-0.002
collcon					0.002					0.020					0.110*
cptyandcollrating					-0.0006					0.002***					0.0008
N	3,907	3,907	3,907	3,907	3,907										
R^2_{adj}	0.554	0.628	0.717	0.728	0.740										

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

OLS regressions for the reverse repo subsamples excluding deals with CCPs (equation (2)). The dependent variable is haircut and explanatory variables are listed in the first column. Columns (1)-(5) capture the baseline—corresponding to highly-rated government securities—effects, while columns (6)-(10) and (11)-(15) capture the marginal effects, respectively, of lower-rated government securities and other collaterals. All quantitative variables (notional, maturity, collmaturity, VaR, cptysize, cptyroa, cptyleverage, cptycds, cptycashratio, cptycon, collcon) are standardized. All regressions include bank, relationship, and currency fixed effects. Standard errors are clustered at the counterparty level.

Table 10: Repo haircut drivers by collateral type (excluding deals with CCPs)

	Gov ≥AA (γ, baseline effect)					Gov <AA (β_1, marginal effect)					Other (β_2, marginal effect)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Deal vars:															
notional	0.003**	0.001	0.000	-0.0001	-0.001	0.002	0.006	0.006	0.007	0.011*	-0.0009	-0.0003	0.001	0.002	0.004
maturity	0.007	0.001	-0.0007	-0.006	-0.005	0.049	0.051	0.074	0.071	0.037	0.025	0.033	0.032	0.042*	0.042*
Collateral vars:															
collrating		0.002	0.002	0.002	0.000		-0.001	-0.002	-0.001	0.006		-0.003**	-0.003**	-0.003*	0.0001
collmaturity		0.006	0.004	0.004	0.004		-0.008	-0.008	-0.008	-0.009		-0.003	-0.0008	-0.0007	-0.0002
var		0.009	0.012	0.012	0.012		-0.024	-0.022	-0.023	-0.015		0.004	0.002	0.002	0.002
asset in safe portf		-0.002	-0.002	-0.001	-0.001		0.002	0.0006	-0.002	0.003		0.005	0.004	0.004	0.004
Cpty type:															
brokerdealers			-0.0002	0.005	0.003			0.007	-0.002	-0.002			0.004	0.003	0.006
hedgefund			0.002	0.000	0.012			0.000	0.000	0.000			0.000	0.000	0.000
otherassetmanagers			0.006	0.014	0.010			-0.005	-0.027	-0.016			0.011	0.011	0.014
insurance&pension			-0.008	-0.002	-0.006			-0.037	-0.038*	-0.009			0.000	0.000	0.000
centralbank&government			0.047**	0.054**	0.051**			-0.006	-0.013	-0.026			0.007	0.004	0.001
other			-0.008	-0.005	-0.011			0.000	-0.005	-0.007			0.029	0.024	0.023
Cpty vars:															
cptysize				0.006	-0.026				0.057	0.087*				0.032	0.052
cptyroa				-0.009**	-0.009**				0.015**	0.016**				0.004	0.005
cptyrating				0.002	-0.008				0.000	0.015				-0.004	0.011
cptyleverage				0.056**	0.050*				-0.063	-0.068*				-0.057*	-0.061**
cptycds				0.006	0.005				-0.003	-0.003				-0.013	-0.009
cptycashratio				-0.007	-0.008				-0.005	0.004				0.009	0.008
nocptydata				0.159	0.088				0.016	0.019				-0.134	-0.064
Misc:															
cptycon					0.008					0.016*					0.001
collcon					0.003					-0.003					0.013
cptyandcollrating					0.001					-0.001**					-0.001*
N	2,915	2,915	2,915	2,915	2,915										
R^2_{adj}	0.512	0.534	0.539	0.542	0.551										

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

OLS regressions for repo subsamples excluding deals with CCPs (equation (2)). The dependent variable is haircut and explanatory variables are listed in the first column. Columns (1)-(5) capture the baseline—corresponding to highly-rated government securities—effects, while columns (6)-(10) and (11)-(15) capture the marginal effects, respectively, of lower-rated government securities and other collaterals. All quantitative variables (notional, maturity, collmaturity, VaR, cptysize, cptyroa, cptyleverage, cptycds, cptycashratio, cptycon, collcon) are standardized. All regressions include bank, relationship, and currency fixed effects. Standard errors are clustered at the counterparty level.

Table 11: The role of bilateral relationships

	With Bank FE			Without Bank FE		
Significance level	negative %	cond. mean of neg. (bps)	positive %	negative %	cond. mean of neg. (bps)	positive %
Panel A: Reverse Repo						
10%	40.3%	-7.5	9.0%	44.8%	-9.9	22.4%
5%	32.8%	-7.9	6.0%	43.3%	-10.1	17.9%
Panel B: Repo						
10%	27.9%	-3.9	23.3%	55.8%	-5.4	25.6%
5%	25.6%	-4.1	18.6%	51.2%	-5.8	23.3%

The table reports the share of significantly negative and positive relationship fixed effects for different significance levels reported in the first column, for a specification with (columns two to four) and without (columns five to seven) reporting bank fixed effects. The specification with bank fixed effects is from columns 5 and 10 of Table 8, whereas the specification without is based on the same regressions but excluding bank FEs. The conditional means (columns three and six) are the average of the significantly negative fixed effects.

Table 12: The probability of zero haircuts (excluding deals with CCPs)

	Reverse Repo					Repo				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deal vars:										
notional	-0.003	-0.011	-0.012	-0.010	-0.010	0.001	0.002	0.004	0.004	0.005
maturity	-0.139***	-0.156***	-0.169***	-0.137***	-0.148***	-0.023	-0.031	-0.039	-0.044	-0.050
Collateral vars:										
collrating		0.006***	0.006***	0.006***	0.007***		0.004	0.005	0.005	0.004
collmaturity		0.011***	0.010***	0.009***	0.008***		-0.015**	-0.012*	-0.012*	-0.011*
securitisation		0.014	0.009	0.019	0.018		-0.072**	-0.074**	-0.074**	-0.079**
var		0.000	0.000	-0.000	0.001		-0.022	-0.009	-0.009	-0.009
asset in safe portf		-0.012	-0.013	-0.015*	-0.014*		0.009	0.011	0.011	0.009
Cpty type:										
brokerdealers			0.058*	0.050	0.049			0.152**	0.189**	0.185**
hedgefund			0.027	0.069	0.077*			0.040	0.070	0.065
otherassetmanagers			0.040*	0.056	0.060*			-0.150	-0.119	-0.115
insurance&pension			0.060	0.099*	0.104*			-0.481***	-0.441***	-0.437***
centralbank&government			0.110***	0.086	0.089*			-0.059	-0.022	-0.016
other			0.107**	0.148***	0.157***			-0.066	-0.028	-0.023
Cpty vars:										
cptysize				0.260	0.299*				-0.203	-0.165
cptyroa				-0.005	-0.006				-0.006	-0.007
cptyrating				0.007	0.007				0.037	0.034
cptyleverage				-0.134	-0.137				0.134	0.139
cptycds				-0.039***	-0.039***				0.030	0.033
cptycashratio				-0.029	-0.030*				-0.021	-0.018
nocptydata				0.278	0.324				0.436	0.528
Misc:										
cptycon					-0.024**					-0.013
collcon					-0.007					-0.029**
cptyandcollrating					-0.000					0.000
N	3907	3907	3907	3907	3907	2915	2915	2915	2915	2915
R^2_{adj}	0.910	0.912	0.913	0.915	0.915	0.663	0.667	0.679	0.681	0.684

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Linear probability model for zero haircuts in reverse repo, columns (1)-(5), and repo, columns (6)-(10), deals (excluding deals with CCPs). The dependent variable is a dummy taking value 1 if the haircut is zero and value 0 otherwise: see equation (3). Explanatory variables are listed in the first column. All quantitative variables (notional, maturity, collmaturity, VaR, cptysize, cptyroa, cptyleverage, cptycds, cptycashratio, cptycon, collcon) are standardized. All regressions include bank, relationship, and currency fixed effects. Standard errors are clustered at the counterparty level.

Table 13: CCP versus non-CCP trades

	Mean $\frac{Repo\ Position}{Reverse\ Repo\ Position}$	Mean REVR haircut	Mean REPO haircut	% of zero haircuts
Non-CCP counterparties	5.77	0.096	0.039	0.300
CCP counterparties	1.03	0.071	0.044	0.359

Summary statistics of contracts with and without CCPs as counterparties.

Table 14: Summary statistics of the netting proxy variable

	Min	Max	Mean	Obs	Std dev	q25	q50	q75
CCP trades	0.00	0.98	0.43	15	0.39	0.00	0.32	0.81
Non-CCP trades	0.00	1.00	0.15	851	0.29	0.00	0.00	0.13

Table 15: Tests for equality in mean of netting proxy in CCP and non-CCP subsamples

Test	T-stat	Dof	Std error	P-val
2-sided same var	3.688	864.000	0.076	0.000
2-sided diff. var	2.740	14.268	0.102	0.016
1-sided same var	3.688	864.000	0.076	0.000
1-sided diff. var	2.740	14.268	0.102	0.008

Table 16: Probability of zero haircuts and CCP trades

	(1) REVR	(2) REPO
$D_{j,CCP}$	0.168***	0.026
$notional_j$	-0.015**	0.001
$maturity_j$	-0.196**	-0.121**
N	5048	8258
R^2_{adj}	0.409	0.275

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model estimation of zero haircut trades: equation (5). The specifications include reporting banks and collateral fixed effects. The dependent variable takes value 1 if the trade has zero haircut, and $D_{j,CCP}$ is a dummy variable equal to one 1 if the trade involves a CCP. Standard errors are clustered at the counterparty level.

Table 17: Determinants of trading with CCPs

	(1) REVR	(2) REPO	(3) REVR	(4) REPO
notional	0.1000***	0.0410*	0.0804***	0.0335**
maturity	-0.1614	-0.072	-0.1361	-0.0674
collrating	0.0167**	0.0065	0.0164**	0.0083*
collmaturity	-0.0039	0.0145	-0.0109	0.0060
corpdebt	-0.2305***	-0.1982**	-0.1787***	-0.1254**
securitisation	-0.3028***	-0.2603**	-0.3120***	-0.1725**
gbp	0.2195***	0.2213***	0.1635***	0.1929***
eur	0.2859***	0.1173	0.2791***	0.1231*
usd	0.0920*	0.0139	0.1193**	0.0469
jpy	-0.3762***	-0.1272**	-0.1981**	-0.0338
netting			0.3957***	0.4301***
N	6959	10074	6959	10073
R^2_{adj}	0.549	0.384	0.614	0.475

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model estimation of trades with a CCP. The dependent variable takes value 1 if the trade involves a CCP: equation (6). Standard errors are clustered at the counterparty level.

Table 18: The pecking order of collateral choice

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	5.3663***						
	(0.7430)						
collrating	0.6585***	0.6650***	0.5050***	0.6501***	0.6541***	0.4799***	0.4742***
	(0.0449)	(0.0561)	(0.0360)	(0.0522)	(0.0650)	(0.0378)	(0.0573)
maturity	1.6310	3.1552**	0.9191	2.4441*	4.1158	0.8779	2.9814
	(1.6464)	(1.3620)	(1.1970)	(1.2976)	(2.6289)	(1.7999)	(2.8021)
notional	-1.3264	-1.8675	-2.2637	-1.5793	-1.8069	-2.0190	-1.8536
	(5.2306)	(5.9901)	(4.2678)	(5.6729)	(6.5339)	(4.7429)	(4.9714)
k	0.0950	-0.0037	0.0575	0.2019	0.0423	0.0833	0.1185
	(0.1472)	(0.1221)	(0.1173)	(0.1722)	(0.1528)	(0.1390)	(0.1681)
Bank FE		Yes			Yes		Yes
Sector FE			Yes			Yes	Yes
Time FE				Yes	Yes	Yes	Yes
N	327	327	327	327	327	327	327
R^2_{adj}	0.61151	0.62382	0.67057	0.61074	0.61695	0.67866	0.68199

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

OLS regressions for the reverse repo subsamples excluding deals with CCPs (equation (7)). The dependent variable is the average collateral quality backing new borrowing for the same maturity date as the initial transaction. Explanatory variables are listed in the first column and include the average collateral quality backing initial borrowing (our variable of interest), the maturity and total notional amount borrowed initially, and the time difference between initial and new borrowing. Columns (1)-(7) consider different combinations of bank, counterparty sector, and time fixed effects. Standard errors are clustered at the counterparty and time levels, and reported below the coefficient estimates between parentheses.

Table 19: 95% confidence intervals around pecking order coefficient estimates

Specification	2.5 %	97.5 %
No FEs	0.5585	0.7585
Bank FEs	0.5399	0.7901
Sector FEs	0.4249	0.5851
Time FEs	0.5339	0.7663
Bank + Time FEs	0.5094	0.7989
Sector + Time FEs	0.3956	0.5641
Bank + Sector + Time FEs	0.3465	0.6020

Each row reports the 95% confidence interval around the estimate of our coefficient of interest for the specification in the corresponding column of Table 18.

Table 20: The role of Repo rates

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	10.7348***			24.1247***		
	(3.4324)			(8.0501)		
rate spread	3.9543**	1.9282**	0.2821	0.9173	0.2494	0.0889
	(1.8261)	(0.8187)	(0.7293)	(1.3738)	(0.3002)	(0.3437)
notional				-1.6342**	-0.0691	-0.0315
				(0.6051)	(0.1906)	(0.1767)
maturity				-0.4168	0.1477	0.1626
				(0.4398)	(0.1347)	(0.1627)
collmaturity				4.2095***	3.7027***	3.6572***
				(1.1471)	(1.2223)	(1.1765)
inflationlinked				11.6760***	8.6546***	8.5814***
				(3.0265)	(3.0994)	(3.0351)
var				0.0869	0.7844***	0.2390*
				(0.4498)	(0.2395)	(0.1265)
Bank FE		Yes			Yes	Yes
Counterparty FE			Yes		Yes	Yes
Time FE						Yes
N	251,573	251,573	251,573	242,713	242,713	242,713
R^2_{adj}	0.04964	0.57768	0.23623	0.19723	0.67924	0.68578

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

OLS regressions for the reverse repo subsamples of the SMMD data. The dependent variable is haircut and explanatory variables are listed in the first column. Columns (1)-(3) consider a baseline specification controlling only for the transaction spread relative to the central bank policy rate, and columns (4)-(6) add other control variables. In both cases, different combinations of bank, counterparty, and time fixed effects are considered. Standard errors are clustered at the bank and counterparty levels, and reported below the coefficient estimates between parentheses.

Appendix

A.1 A stylized model of Repo haircut determination

We present here a stylized model to motivate the testable hypotheses on haircut of repo loans. Consider an economy with two dates, date 0 and date 1 where all agents are risk neutral. There are agents who need funds for starting productive projects at date 0 with a deterministic gross return $z > 1$ at date 1. There is also a representative lender with deep pockets. To overcome the limited commitment problem, the borrowers need to use the collateral asset to back the borrowing at date 0, that is, they use a form of repo loan.

We assume that the collateral asset yields a random payoff $\tilde{\delta}$ at date 1.[1] The asset can be of high or low quality. The probability of low type is λ. Quality is i.i.d and privately known to the borrower. For expositional clarity, we derive the comparative statics using a two-point distribution. Specifically, the high (low) quality asset pays one unit of payoff with probability π_H (π_L) and pays $e \in (0, 1)$ otherwise, where $0 \leq \pi_L < \pi_H \leq 1$. We assume that, when the ownership of the collateral asset is transferred, a fraction $\gamma \in (0, 1)$ of the asset value is destroyed (e.g., due to illiquidity, transaction cost or lost of convenience yield). To raise funds, borrowers can issue a security that promises to pay y and is backed by the collateral payoff. The debt contract takes a simple form. It pays $y = \min\{d, (1-\gamma)\tilde{\delta}\}$. That is, in the case of default, the lender can only obtain a $1-\gamma$ fraction of the collateral value, and receive the face value of debt contract (d) otherwise.

Next, we discuss the market microstructure. We assume that the lending market is competitive. The representative (risk neutral) lender, hence, earns zero profit. The cost of lending for the representative lender is normalized to 1. There are gains from trade since $z > 1$. We also assume that the gains from trade parameter is small enough, that is, $z < 1/(1-\lambda)$ so that it will not make the impact of the information friction irrelevant in this model. Furthermore, the collateral price ϕ is set as $\phi = \mathbb{E}\{\tilde{\delta}\}$ due to the risk neutral assumption. The amount of lending offered by the lender is the price of the loan contract, which is denoted by q. The haircut is, hence, defined as $h = 1 - q/\phi$.

This is a model of lemons since the borrowers with the low quality collateral always issue asset-backed securities to raise fund in order to access a return of z. The borrowers with the high quality collaterals, however, might not participate since their asset-backed security would be pooled with the low quality borrowers and priced at a lower value. Hence, the

[1] We denote random variable with $\tilde{}$.

participation constraint is

$$z\mathbb{E}\{y\} = z\left(\lambda\mathbb{E}_L\{y\} + (1-\lambda)\mathbb{E}_H\{y\}\right) \geq \mathbb{E}_H\{y\} \tag{A.8}$$

where the left side of the inequality is the payoff from issuing an security priced at the pooling price and investing in the project with return z, and the right side of the inequality is the payoff from holding onto the collateral.

Note that in this stylised model quality of the borrower and quality of the collateral are isomorphic. That is, we bundle together two information frictions: the adverse selection with respect to both borrower default risk and the credit quality of the posted collateral.

Next, we define the information sensitivity ratio of a security issued by the borrowers in this economy, denoted by $\zeta(y) \equiv \mathbb{E}_L\{y\}/\mathbb{E}_H\{y\}$. The smaller is $\zeta(y)$, the more there is a difference in payoffs of high and low collaterals, and the more information sensitive is the security's payoff, which in turn leads to more adverse selection. When condition (A.8) holds with equality, we obtain a threshold $\bar{\zeta}$ which is the lowest possible information sensitivity ratio of a security that the borrowers with high quality collaterals are willing to issue knowing that they will be pooled with the borrowers with low quality collaterals.

$$\zeta(y) \equiv \frac{\mathbb{E}_L\{y\}}{\mathbb{E}_H\{y\}} \geq 1 - \frac{z-1}{z\lambda} \equiv \bar{\zeta} \tag{A.9}$$

where $\bar{\zeta}$ measures the adverse selection level of the lemon market. It is decreasing in the productivity parameter z and increasing in the probability of low type, λ.

The information sensitivity ratio of the repo debt is

$$\zeta\{d,\tilde{\delta}\} = \frac{\mathbb{E}_L \min\{d,(1-\gamma)\tilde{\delta}\}}{\mathbb{E}_H \min\{d,(1-\gamma)\tilde{\delta}\}}. \tag{A.10}$$

We assume that parameters π_L π_H, e are such that $\zeta\{1,\tilde{\delta}\} < \bar{\zeta}$ to ensure that the information friction is severe enough for the haircut problem to be non-trivial.

We are now ready to characterize the face value of the loan. We first obtain the price of the loan contract, q, which satisfies the following zero profit condition:

$$\begin{aligned} q &= \mathbb{E}\{\min\{d,(1-\gamma)\tilde{\delta}\}\} \\ &= \mathbb{E}\{\tilde{\delta}\} - [\lambda\pi_L + (1-\lambda)\pi_H](1-d) - \gamma e\left[(1-\pi_L)\lambda + (1-\pi_H)(1-\lambda)\right] \end{aligned} \tag{A.11}$$

The indifference condition for the high type borrowers to participate in this market for lemons is

$$\zeta\{d,\tilde{\delta}\} = \bar{\zeta}. \tag{A.12}$$

We assume that lenders want to maximize the lending by setting the face value high enough to meet this indifference condition. Hence, the face value of the debt, d, can be obtained by solving equation (A.12), which is

$$d = (1-\gamma)e\left(1+\frac{1-\bar{\zeta}}{\bar{\zeta}\pi_H - \pi_L}\right). \tag{A.13}$$

Combining equations (A.11) and (A.13), we obtain the haircut for repo loans,

$$\begin{aligned} h &= \frac{1}{\phi}\left[1-(1-\gamma)e\left(1+\frac{1-\bar{\zeta}}{\bar{\zeta}\pi_H-\pi_L}\right)\right][\lambda\pi_L+(1-\lambda)\pi_H] \\ &\quad +\frac{\gamma}{\phi}e\left[(1-\pi_L)\lambda+(1-\pi_H)(1-\lambda)\right] \end{aligned} \tag{A.14}$$

where $\phi = \mathbb{E}\{\tilde{\delta}\}$. Equation (A.14) shows that the repo loan haircut depends on the distribution parameter $\pi_H - \pi_L$, illiquidity γ, and adverse selection parameter $\bar{\zeta}$. We categorize these parameters into two types. One type is related to the risk of asset payoff such as $(\pi_H - \pi_L)$ and illiquidity (γ). The other type is related to adverse selection. The following results follow directly from (A.14).

PROPOSITION 1: Haircuts are larger for risky assets and illiquid assets.

Equation (A.14) also shows that the higher the adverse selection parameter $\bar{\zeta}$, the larger the haircut, which leads to the following result.

PROPOSITION 2: Haircuts are increasing in the degree of adverse selection.

Additionally, we find that the participation constraint is relaxed when the borrowing is backed by a portfolio of one unit of risky collateral and one unit of the safe asset that pays 1 unit irrespective of the state since

$$\zeta^{safe}(d,\tilde{\delta}) = \frac{1+\mathbb{E}_L \min\{d,(1-\gamma)\tilde{\delta}\}}{1+\mathbb{E}_H \min\{d,(1-\gamma)\tilde{\delta}\}} > \frac{\mathbb{E}_L \min\{d,(1-\gamma)\tilde{\delta}\}}{\mathbb{E}_H \min\{d,(1-\gamma)\tilde{\delta}\}}. \tag{A.15}$$

Intuitively, the portfolio that combines safe with risky collaterals is less information sensitive. Therefore, the adverse selection is lower and the haircut on this portfolio is smaller.

PROPOSITION 3: Haircuts are lower when safe assets are included in the portfolio of collateral assets.

Table A.I: Description of the explanatory variables

Variable	Description
gbp	Dummy variable = 1 if transaction is in GBP.
eur	Dummy variable = 1 if transaction is in EUR.
jpy	Dummy variable = 1 if transaction is in JPY.
othercurrency	Dummy variable = 1 if transaction is not GBP, EUR or JPY.
notional	Log notional of the transaction in millions GBP.
maturity	Maturity of the transaction in years.
collrating	Rating of the collateral: 20 is highest and 1 is lowest.
collmaturity	Maturity of the collateral in years.
corpdebt	Dummy variable = 1 if collateral is corporate bond.
securitization	Dummy variable = 1 if collateral is securitisation.
var	Historical 5-day, 5% Value-at-Risk of the asset.
asset in safe portf	Dummy variable = 1 if the asset is in a portfolio with at least one asset rated AAA.
brokerdealers	Dummy variable = 1 if counterparty is a broker-dealer.
hedgefund	Dummy variable = 1 if counterparty is hedge fund.
otherassetmanagers	Dummy variable = 1 if counterparty is other asset managers.
insurance&pension	Dummy variable = 1 if counterparty is insurance company or pension fund.
centralbank&government	Dummy variable = 1 if counterparty is central bank or government.
other	Dummy variable = 1 if counterparty is other type.
cptysize	Log size of the counterparty in millions GBP.
cptyroa	RoA of the counterparty.
cptyrating	Rating of the counterparty: 20 is highest and 1 is lowest.
cptyleverage	Leverage ratio of the counterparty (RWA over equity).
cptycds	CDS spread of the counterparty.
cptycashratio	Cash ratio of the counterparty (cash over short-term debt).
nocptydata	Dummy variable = 1 there is no counterparty data.
cptycon	Concentration of the counterparty measured by the share of transactions with that counterparty in total: higher number indicates more concentration.
collcon	Concentration of the collateral measured by the share of transactions against that collateral in total: higher number indicates more concentration.
cptyandcollrating	Interaction term between counterparty rating and collateral rating

Table A.II: Tobit estimation of drivers of haircuts (excluding deals with CCPs)

	Reverse Repo					Repo				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deal vars:										
notional	-0.016**	0.002	0.002	-0.001	-0.001	0.003	0.002	0.001	0.001	0.001
maturity	0.119**	0.116***	0.106**	0.070*	0.084**	0.029**	0.031**	0.034***	0.035***	0.037***
Collateral vars:										
collrating		-0.013***	-0.012***	-0.011***	-0.015***		-0.001	-0.001	-0.001	0.000
collmaturity		0.003	0.002	0.004	0.008		0.003*	0.003*	0.003*	0.003**
securitisation		0.022	0.031*	0.021	0.018	0.003	0.004	0.004	0.006	
var		0.006*	0.005*	0.005**	0.005*		0.013***	0.012***	0.012***	0.012***
asset in safe portf		-0.007	-0.009	-0.007	-0.009		0.001	0.000	0.001	0.001
Cpty type:										
brokerdealers			-0.027	-0.006	0.001			-0.011	-0.012	-0.011
hedgefund			0.098***	0.067**	0.057*			-0.000	0.003	0.007
otherassetmanagers			0.031	0.018	0.017			0.022	0.026*	0.024
insurance&pension			0.009	-0.019	-0.004			0.034**	0.034**	0.030**
centralbank&government			-0.033	-0.016	0.001			0.054***	0.057***	0.051**
other			0.078	0.049	0.038			0.005	0.002	-0.002
Cpty vars:										
cptysize				-0.203**	-0.225***				0.049*	0.039
cptyroa				-0.018**	-0.015**				-0.006*	-0.005
cptyrating				0.001	-0.015*				-0.000	0.003
cptyleverage				0.107***	0.100***				0.007	-0.000
cptycds				0.020*	0.012				-0.000	-0.002
cptycashratio				0.008	0.014				0.001	0.001
nocptydata				-0.124	-0.274				0.104	0.075
Misc:										
cptycon					0.013					0.009*
collcon					0.012**					0.007***
cptyandcollrating					0.001***					-0.000*
N	3907	3907	3907	3907	3907	2915	2915	2915	2915	2915
R_p^2	2.379	2.628	2.689	2.734	2.790	-0.460	-0.476	-0.486	-0.489	-0.495

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tobit regressions for reverse repo, columns (1)-(5), and repo, columns (6)-(10), excluding deals with CCPs. The dependent variable is haircut and explanatory variables are listed in the first column. All quantitative variables (notional, maturity, collmaturity, VaR, cptysize, cptyroa, cptyleverage, cptycds, cptycashratio, cptycon, collcon) are standardized. All regressions include bank, relationship, and currency fixed effects. Standard errors are clustered at the counterparty level.

Table A.III: The drivers of haircuts (excluding deals with CCPs) with time (month) fixed effects

	Reverse Repo					Repo				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deal vars:										
notional	-0.012**	-0.000	-0.000	-0.002	-0.001	0.002	0.001	0.001	0.001	0.001
maturity	0.073*	0.072**	0.064*	0.031	0.048	0.060**	0.061**	0.061**	0.060**	0.060**
Collateral vars:										
collrating		-0.009***	-0.008***	-0.007***	-0.012***		-0.001	-0.001	-0.001	0.000
collmaturity		0.000	0.000	0.000	0.004		0.002*	0.002*	0.002*	0.002**
securitisation		0.018	0.029*	0.023	0.019		0.002	0.003	0.003	0.003
var		0.007**	0.006**	0.007***	0.006***		0.012***	0.012***	0.012***	0.011***
asset in safe portf		-0.003	-0.005	-0.004	-0.006*		0.001	0.000	0.001	0.002
Cpty type:										
brokerdealers			-0.017	-0.004	0.002			0.001	0.000	0.001
hedgefund			0.108***	0.079***	0.065**			-0.011	-0.004	-0.001
otherassetmanagers			0.032	0.023	0.019			0.012	0.016	0.014
insurance&pension			0.004	-0.024	-0.007			-0.006	-0.002	-0.006
centralbank&government			-0.007	-0.006	0.008			0.046**	0.052***	0.048**
other			0.080	0.053	0.041			-0.001	-0.000	-0.003
Cpty vars:										
cptysize				-0.136**	-0.153**				0.044*	0.033
cptyroa				-0.015**	-0.013**				-0.004	-0.002
cptyrating				-0.005	-0.020***				0.001	0.003
cptyleverage				0.079***	0.074***				0.005	-0.002
cptycds				-0.009	-0.013				-0.004	-0.005
cptycashratio				0.008	0.013*				-0.000	-0.000
nocptydata				-0.193	-0.297**				0.101	0.071
Misc:										
cptycon					0.010					0.011*
collcon					0.007*					0.004*
cptyandcollrating					0.001***					-0.000
N	3907	3907	3907	3907	3907	2915	2915	2915	2915	2915
R^2_{adj}	0.545	0.614	0.640	0.651	0.676	0.530	0.543	0.548	0.549	0.553

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
OLS regressions for reverse repo, columns (1)-(5), and repo, columns (6)-(10), excluding deals with CCPs. The dependent variable is haircut and explanatory variables are listed in the first column. All quantitative variables (notional, maturity, collmaturity, VaR, cptysize, cptyroa, cptyleverage, cptycds, cptycashratio, cptycon, collcon) are standardized. All regressions include bank, relationship, currency, and time (month) fixed effects. Standard errors are clustered at the counterparty level.

Online Appendix

Table OA.I: Breakdown of value of contracts in the complementary dataset (in bn GBP)

	REVR		REPO		
	Value	Percent	Value	Percent	Net
A. Maturity					
Overnight	20893.1	44.9%	-22640.1	45.4%	-1747.0
1 day-3m	24846.2	53.4%	-27027.0	54.2%	-2180.7
3m-1y	808.3	1.7%	-239.4	0.5%	568.9
1y+	12.8	0.0%	-0.7	0.0%	12.1
Total	46560.4	100.0%	-49907.1	100.0%	-3346.7
B. Counterparty type					
Other reporting banks	839.4	1.8%	-789.3	1.6%	50.1
Other banks	380.8	0.8%	-432.9	0.9%	-52.1
Hedge fund	6446.9	13.8%	-6864.5	13.8%	-417.7
MMFs	131.3	0.3%	-2643.7	5.3%	-2512.3
Other asset managers	631.9	1.4%	-3269.2	6.6%	-2637.3
CCP	34692.0	74.5%	-32336.8	64.8%	2355.2
Insurance and pension	2265.8	4.9%	-1738.5	3.5%	527.3
Central bank and government	638.6	1.4%	-1408.7	2.8%	-770.1
Other	533.6	1.1%	-423.5	0.8%	110.1
Total	46560.4	100.0%	-49907.1	100.0%	-3346.7
C. Collateral type					
Nominal bonds					
<1y	1550.0	3.3%	-1775.2	3.6%	-225.2
1y-7y	14245.6	30.6%	-13797.4	27.6%	448.2
7y-15y	13505.5	29.0%	-12159.5	24.4%	1345.9
15y-25y	3420.0	7.3%	-3790.6	7.6%	-370.5
25y+	5081.4	10.9%	-6527.5	13.1%	-1446.1
Inflation-linked bonds					
<1y	431.5	0.9%	-468.4	0.9%	-36.8
1y-7y	2019.9	4.3%	-2576.5	5.2%	-556.6
7y-15y	2060.3	4.4%	-2827.6	5.7%	-767.3
15y-25y	1738.4	3.7%	-2537.2	5.1%	-798.8
25y+	2507.7	5.4%	-3447.2	6.9%	-939.5
Total	46560.4	100.0%	-49907.1	100.0%	-3346.7

Breakdown of deals by maturity, counterparty, and collateral (Panels A, B, and C respectively). Value of the trades is in billion (bn) GBP. The total values in Panels A, B, and C are based on transaction data for the period 2016-2019 between 28 reporting banks and 660 counterparties.

Table OA.II: Breakdown of value of contracts with CCPs in the complementary dataset (in bn GBP)

	REVR		REPO		
	Value	Percent	Value	Percent	Net
A. Maturity					
Overnight	18755.1	54.1%	-15635.7	48.4%	3119.5
1 day-3m	15877.8	45.8%	-16619.0	51.4%	-741.2
3m-1y	58.9	0.2%	-82.2	0.3%	-23.3
1y+	0.3	0.0%	0.0	0.0%	0.3
Total	34692.0	100.0%	-32336.8	100.0%	2355.2
B. Collateral type					
Nominal bonds					
<1y	1190.6	3.4%	-1205.9	3.7%	-15.4
1y-7y	11515.1	33.2%	-10481.2	32.4%	1033.9
7y-15y	9951.4	28.7%	-8454.4	26.1%	1497.0
15y-25y	2353.9	6.8%	-2398.0	7.4%	-44.0
25y+	3338.1	9.6%	-3399.9	10.5%	-61.8
Inflation-linked bonds					
<1y	405.8	1.2%	-339.9	1.1%	65.9
1y-7y	1503.0	4.3%	-1604.8	5.0%	-101.9
7y-15y	1499.4	4.3%	-1581.8	4.9%	-82.4
15y-25y	1178.4	3.4%	-1172.8	3.6%	5.6
25y+	1756.3	5.1%	-1698.1	5.3%	58.3
Total	34692.0	100.0%	-32336.8	100.0%	2355.2

Breakdown of deals involving CCPs by maturity and collateral (Panels A and B respectively). Value of the trades is in billion (bn) GBP. The total values in Panels A and B are based on transaction data for the period 2016-2019 between 28 reporting banks and 7 CCPs.

Table OA.III: Summary statistics for the covariates in the complementary dataset

Variable	Obs	Mean	Std dev	Min	Max	Average[a]
Haircut	251580	11.44%	17.75%	-10.57%	72.66%	9.17%
Rate spread	251573	0.02%	0.12%	-0.42%	0.37%	0.01%
Notional	251580	16.83	1.30	13.90	19.43	18.06
Repo maturity	251580	32.20	66.94	1.00	364.00	29.40
Collateral maturity	251389	18.03	13.72	0.16	52.30	14.86
VaR	242717	-0.01	0.11	-0.60	0.49	-0.00

The table shows the summary statistics of variables used in the regressions excluding the deals with CCPs for reverse repo transactions. Variables have been winsorized at 0.5% level.

[a] Average is weighted by the gross notional of transactions.

Table OA.IV: The breakdown of value of contracts (in bn GBP) by maturity, currency, counterparty type, and collateral type. Sample of six banks excluding CCPs.

	REVR		REPO		
	Value	Percent	Value	Percent	Net
A. Maturity					
Overnight	23.4	23.7%	-33.0	24.4%	-9.6
1 day-3m	51.6	52.4%	-58.6	43.3%	-7.0
3m-1y	21.8	22.1%	-27.5	20.3%	-5.7
1y-5y	1.8	1.8%	-14.5	10.7%	-12.7
5y+	0.0	0.0%	-1.7	1.2%	-1.6
Total	98.6	100.0%	-135.3	100.0%	-36.7
B. Currency					
GBP	26.9	27.3%	-41.0	30.3%	-14.2
EUR	31.4	31.9%	-65.4	48.3%	-33.9
USD	27.4	27.8%	-25.2	18.6%	2.2
JPY	6.0	6.1%	-1.6	1.2%	4.4
Other	6.9	7.0%	-2.1	1.6%	4.8
Total	98.6	100.0%	-135.3	100.0%	-36.7
C. Counterparty type					
Another reporting bank [a]	8.2	8.3%	-10.2	7.6%	-2.0
Other banks	29.3	29.7%	-43.6	32.2%	-14.3
Broker-dealer [b]	15.0	15.2%	-15.8	11.7%	-0.8
Hedge fund	15.1	15.3%	-15.5	11.5%	-0.4
Other asset managers [c]	11.5	11.7%	-8.3	6.2%	3.2
Insurance and pension	9.5	9.7%	-8.5	6.3%	1.0
Central bank and government	5.5	5.6%	-28.6	21.1%	-23.0
Other [d]	4.4	4.5%	-4.7	3.5%	-0.3
Total	98.6	100.0%	-135.3	100.0%	-36.7
D. Collateral type					
US govt	10.2	15.3%	-5.4	6.7%	4.8
UK govt	14.5	21.7%	-17.6	21.9%	-3.1
Germany govt	5.4	8.0%	-12.9	16.0%	-7.5
France govt	4.9	7.3%	-4.7	5.9%	0.1
GIIPS [e]	3.9	5.8%	-3.9	4.8%	0.0
Other sovereign	18.9	28.4%	-10.8	13.4%	8.2
Corporate debt	7.0	10.5%	-11.7	14.5%	-4.7
Securitization	1.9	2.9%	-13.5	16.8%	-11.6
Other	0.0	0.1%	0.0	0.0%	0.0
Total	66.7	100.0%	-80.4	100.0%	-13.8

The table presents the breakdown of the deals by maturity, currency, counterparty type, and collateral type (Panels A, B, C, and D respectively) for the sample of six banks excluding CCPs. For each category, it shows the value of the trades in billions GBP and the percentage of total trades for the reverse repos and repos respectively. The total values in Panels A, B, C and D are based on the data from the six reporting banks that report haircut and collateral information. Discrepancies in row Total between the Panels are due to missing information.

[a] The reporting banks report on a UK-consolidated basis, but counterparties are reported on a global basis. Therefore there may be discrepancies between the reverse repos and repos with the reporting banks.
[b] Broker-dealers are mostly securities firms that are subsidiaries of large banks. [c] Non-leveraged non-MMF mutual funds—asset managers that are not hedge fund or MMF. [d] Includes corporations, schools, hospitals and other non-profit organizations. [e] Greece, Italy, Ireland, Portugal, and Spain government bonds.

Table OA.V: The breakdown of reverse repos

	Counterparty type								
	1	2	3	4	5	6	7	8	Total
A. Maturity									
Overnight	1.4	18.8	8.0	4.0	2.0	2.1	0.0	2.2	38.4
1 day-3m	0.81	17.5	9.3	10.1	5.6	5.5	2.6	2.2	53.9
3m-1y	0.3	1.7	0.3	0.3	2.5	1.6	0.5	0.5	7.6
1-5y	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1
5y+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	2.5	38.2	17.7	14.4	10.1	9.2	3.1	4.9	100.0
B. Currency									
GBP	1.1	2.8	1.5	2.6	6.3	5.8	0.1	2.6	22.8
EUR	0.6	16.1	2.9	6.3	1.4	3.0	1.3	1.2	32.6
USD	0.7	15.6	11.1	4.0	2.2	0.2	0.7	0.9	35.6
JPY	0.0	1.5	0.9	1.3	0.3	0.0	0.0	0.2	4.0
Other	0.1	2.3	1.3	0.2	0.0	0.1	1.0	0.1	5.0
Total	2.5	38.2	17.7	14.4	10.1	9.2	3.1	4.9	100.0
C. Collateral type									
US govt	0.2	3.1	6.2	0.9	1.4	0.0	0.8	0.0	13.0
UK govt	0.1	0.6	0.9	0.3	7.4	4.9	0.2	2.4	16.8
Germany govt	0.3	1.2	0.4	0.6	0.6	0.6	1.1	0.1	4.9
France govt	0.0	1.7	0.2	0.4	0.3	1.1	0.1	0.2	4.0
GIIPS	0.0	0.2	0.0	3.6	0.1	0.2	0.4	0.0	4.6
Other sovereign	0.6	14.2	3.9	1.5	1.1	0.6	1.7	0.9	24.4
Corporate debt	1.0	10.9	3.3	4.8	1.8	1.9	0.1	2.6	26.4
Securitization	0.1	1.7	1.4	1.4	0.2	0.4	0.1	0.5	5.5
Other	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.2
Total	2.3	33.7	16.5	13.6	12.9	9.6	4.5	6.8	100.0

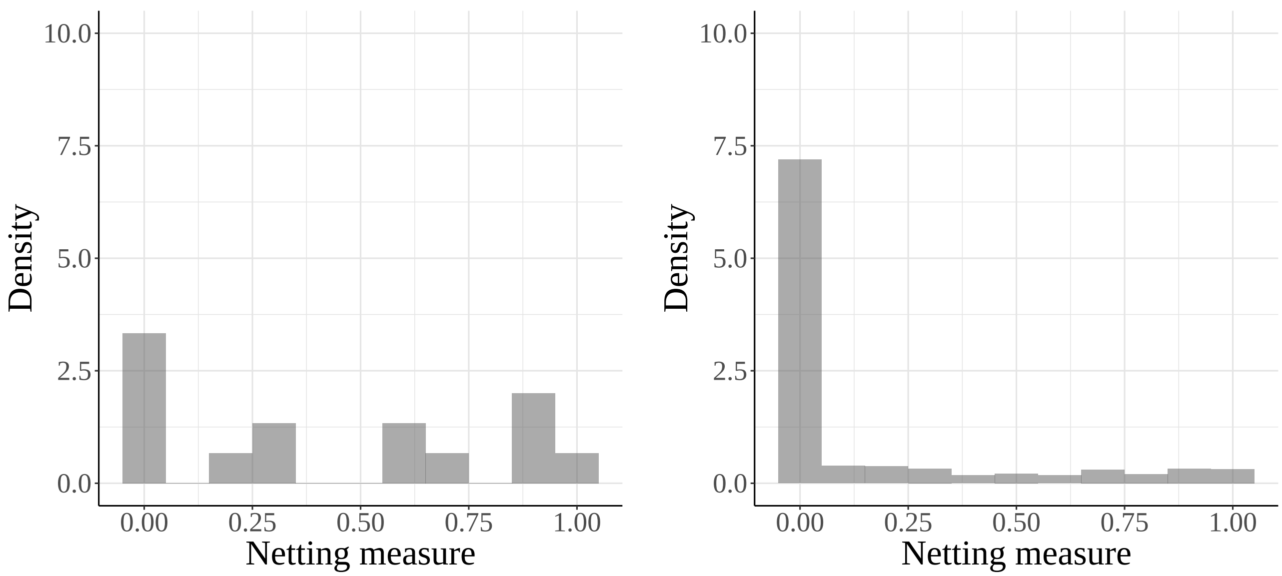
This table exhibits a finer breakdown of the reverse repo contracts. The numbers are in percentage points and indicate the percentage of notional value in each category. The data is double sorted by counterparty type (columns) and maturity, currency and collateral type in Panels A, B, and C respectively. The table is based on the data from the six banks that report haircut and collateral information. Columns 1–8 refer to the following counterparty types:
1. Another reporting bank; 2. Other banks; 3. Broker-dealer; 4. Hedge fund; 5. Other asset managers; 6. Insurance and pension; 7. Central bank & govt; and 8. Other

Table OA.VI: The breakdown of repos

	Counterparty type								Total
	1	2	3	4	5	6	7	8	
A. Maturity									
Overnight	3.5	25.6	10.7	4.8	5.8	1.0	1.7	0.4	53.2
1 day-3m	0.8	10.3	5.8	7.3	2.7	3.9	4.4	0.8	36.3
3m-1y	0.2	2.4	0.8	0.5	0.2	0.5	2.1	0.0	6.7
1-5y	0.3	1.7	1.5	0.0	0.0	0.3	0.0	0.0	3.8
5y+	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	4.8	40.0	18.8	12.6	8.7	5.7	8.2	1.2	100.0
B. Currency									
GBP	0.6	1.9	2.2	2.3	2.3	2.8	2.2	0.4	15.1
EUR	1.4	20.9	7.3	6.8	4.5	0.9	4.9	0.5	46.9
USD	2.0	15.5	8.3	3.0	1.8	2.0	0.9	0.3	33.6
JPY	0.8	0.2	0.0	0.2	0.0	0.0	0.0	0.0	1.4
Other	0.0	1.5	1.0	0.2	0.1	0.0	0.1	0.0	2.9
Total	4.8	40.0	18.8	12.6	8.7	5.7	8.2	1.2	100.0
C. Collateral type									
US govt	0.5	1.9	0.6	0.1	0.2	0.0	0.4	0.0	3.7
UK govt	0.3	0.7	0.2	0.7	2.0	1.0	1.9	0.4	7.9
Germany govt	0.4	4.1	0.6	1.9	0.5	0.0	2.2	0.1	10.0
France govt	0.1	2.0	0.2	0.9	0.6	0.0	0.7	0.0	4.4
GIIPS	0.0	1.0	0.5	2.4	0.3	0.0	0.8	0.0	5.0
Other sovereign	2.2	8.3	4.1	2.5	0.8	0.3	2.1	0.3	20.5
Corporate debt	1.3	15.6	7.5	2.9	5.2	3.8	1.0	0.1	37.1
Securitization	0.6	6.5	2.9	0.2	1.1	0.2	0.1	0.0	11.4
Other	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	5.3	40.0	16.6	11.7	10.8	5.5	9.2	0.9	100.0

This table exhibits a finer breakdown of the repo contracts. The numbers are in percentage points and indicate the percentage of notional value in each category. The data is double sorted by counterparty type (columns) and maturity, currency and collateral type in Panels A, B, and C respectively. The table is based on the data from the six banks that report haircut and collateral information. Columns 1–8 refer to the following counterparty types:
1. Another reporting bank; 2. Other banks; 3. Broker-dealer; 4. Hedge fund; 5. Other asset managers; 6. Insurance and pension; 7. Central bank & govt; and 8. Other

Figure OA.1: Comparison of netting measure across CCP and non-CCP counterparties.



(a) CCP counterparties

(b) Non-CCP counterparties

Previous volumes in this series

All volumes are available on our website www.bis.org.