Lending to Hedge Funds: Does Competition Erode Bank Risk Management?*

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Abstract

We analyze the impact of hedge funds' bargaining power on banks' risk management practices in secured lending. Our analysis shows that, for the same collateral, on the same day, and under identical repo conditions, the same bank requires significantly lower haircuts from hedge funds with greater bargaining power while controlling for hedge funds' probability of default. We confirm this effect through a quasi-natural experiment, using Credit Suisse's exit from the prime brokerage business as an exogenous shock to hedge funds' bargaining power. Furthermore, our findings suggest that stronger bargaining power among hedge funds increases the risk of insufficient haircuts based on standard value-at-risk models.

JEL Codes: G14, G21, G23, G24

Keywords: bank lending, hedge funds, risk management, competition, repurchase agreements

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1 Introduction

Non-bank financial intermediaries (NBFIs) have overtaken banks to become the largest financial intermediaries globally. Recent work by Acharya, Cetorelli, and Tuckman (2024) highlights this trend and emphasizes the growing interconnectedness between the activities and risks of NBFIs and banks. This trend is particularly pronounced in the growth of highly leveraged entities such as hedge funds. Over the past decade, the hedge fund industry's assets under management more than tripled, rising from $1.48 trillion in 2012 to $4.84 trillion in 2022.[1] Assessing the risks posed by the hedge fund sector to the broader financial system is challenging, yet several incidents highlight that these risks can be significant. One of the most notable examples occurred in 1998 when the Federal Reserve Bank of New York orchestrated the recapitalization of Long-Term Capital Management (LTCM) to avert its imminent collapse. This intervention stemmed from concerns that LTCM's failure could lead to widespread disruptions throughout the financial system. More recently, in March 2021, Archegos Capital Management, a family office employing strategies akin to those of hedge funds, defaulted on its loan agreements. This default led to a stock price decline of more than 20%, approximately $5.5 billion in losses for Credit Suisse, and over $10 billion in losses for banks worldwide.[2]

Despite these facts, there is still a limited understanding of how banks are interconnected with hedge funds and how banks manage their risk exposure to these highly leveraged and opaque market participants. A major concern among regulators is that, as hedge funds are lucrative clients, the competition for their business may compromise banks' risk management practices (Bernanke, 2006; FSB, 2024). Competitive pressure has evidently undermined Credit Suisse's credit standards with respect to Archegos Capital Management, as highlighted by an external report reviewing the case: *'In its negotiations with CS [Credit Suisse], Archegos told [...] that [...] other prime brokers had more favorable margin rates [...]. In an effort to offer a competitive rate*

[1] Source: BarclayHedge https://www.barclayhedge.com/solutions/assets-under-management/hedge-fund-assets-under-management/hedge-fund-industry. The total assets of the entire NBFI sector experienced a growth of 78% in the same time period, increasing from $122.46 trillion in 2012 to $217.88 trillion in 2022 (FSB, 2023).

[2] https://www.ft.com/content/c480d5c0-ccf7-41de-8f56-03686a4556b6

[...] CS agreed to a significant change'.[3] Moreover, as an increasing number of hedge funds have shifted from single to multiple broker relationships in the recent past (Dahlquist, Rottke, and Sokolovski, 2024)[4], their bargaining power in negotiations with banks has presumably grown even stronger. In this paper, we examine how greater bargaining power affects the bank-hedge fund relationship, specifically focusing on banks' risk management practices.

To explore this question, we examine banks' secured lending transactions with hedge funds through repurchase agreements (repos), which constitute the primary method of lending to hedge funds. Although substantial exposures to hedge funds can also arise through over-the-counter (OTC) derivative transactions, repo transactions offer an ideal testing ground for identifying shortcomings in risk management practices. Due to their standardization and high frequency, repos enable the comparison of numerous identical transactions executed by a single bank with various hedge funds on any given day. This feature makes it easier to detect potential deficiencies in risk management that might be less apparent in more complex or customized transactions, such as OTC derivatives. Building on these facts, we examine the variation in haircuts in relation to the bargaining power of hedge funds using a saturated regression framework approach. Specifically, our most saturated regression model investigates how haircuts on repos with the same tenor and identical collateral, transacted on the same day by the same bank, vary as a function of hedge funds' bargaining power, while controlling for the corresponding probability of default.

Building on the insights of Duffie, Gârleanu, and Pedersen (2005), we hypothesize that hedge funds with multiple banking relationships exert greater bargaining power in the bilateral repo market by exposing banks to sequential competition. Using the number of banking relationships as a proxy for bargaining power, we find that hedge funds with greater bargaining power receive lower haircuts. This relationship exhibits a pronounced non-linearity. An additional banking relationship has a larger impact on a hedge fund's bargaining power when the initial number

[3] See Credit Suisse Group Special Committee of the Board of Directors report on Archegos Capital Management by Paul, Weiss, Rifkind, Wharton & Garrison LLP: https://www.sec.gov/Archives/edgar/data/1159510/000137036821000064/a210729-ex992.htm

[4] Dahlquist, Rottke, and Sokolovski (2024) report that the proportion of hedge funds with multiple prime brokers in the Eurekahedge database rose significantly from approximately 10% in 2006 to about 45% in 2021.

of banking relationships is low. Conversely, for hedge funds that already maintain numerous banking relationships, the marginal effect of an additional relationship on bargaining power – and consequently on haircuts – is much smaller. Consistent with this intuition, hedge funds with three or more banking relationships receive significantly lower haircuts than those with fewer relationships. Based on this pattern, we classify hedge funds into high- and low-bargaining-power groups using a dummy variable. We document that the economic effect of bargaining power on haircuts is substantial. Hedge funds with high bargaining power experience haircuts that are up to 1.16 percentage points lower. For reference, the within-collateral-date variation of haircuts has a standard deviation of 0.91 percentage points. We find that the effect of bargaining power remains robust when controlling for observable and unobservable hedge fund characteristics through counterparty fixed effects. Moreover, our results hold consistently across a broad set of alternative proxies for bargaining power.

To address the endogeneity of hedge funds' funding structures, we exploit an exogenous shift in bargaining power provided by a quasi-natural experiment. Following the default of Archegos Capital Management, Credit Suisse announced its exit from the prime brokerage market. This decision acted as an adverse shock to the bargaining power of hedge funds that had existing relationships with Credit Suisse. In line with the hypothesis that bargaining power was reduced, our findings indicate a significant increase in haircuts for hedge funds previously associated with Credit Suisse following the announcement. On average, haircuts rose by 0.47 percentage points within a bank-hedge fund relationship using the same collateral, relative to counterparties without such a relationship. Consistent with the non-linear relationship between the number of banking relationships and bargaining power, haircuts increased only for hedge funds that, besides Credit Suisse, had few other broker relationships and, consequently, generally lower bargaining power.

Lastly, we assess the adequacy of haircuts imposed by banks by examining whether they are sufficient to cover large but plausible declines in the value of the underlying collateral. To this end, we employ a value-at-risk (VaR) framework, applying a range of parametric and non-parametric models. The resulting VaR estimates are used to derive model-implied haircuts, which we then compare to the actual haircuts observed in repo transactions. Our analysis consistently shows that, across all models and conventional VaR confidence levels, greater bargaining power is associated with a higher likelihood that haircuts will be insufficient to cover potential losses. This effect is particularly pronounced for short- to medium-term sovereign bonds rated in the medium to low investment-grade range, where increased bargaining power significantly heightens the risk of the haircut being inadequate.

2 Related Literature

Our study contributes to several strands of literature. Foremost, it sheds light on the growing interconnectedness between banks and non-bank financial institutions, as highlighted by Acharya, Cetorelli, and Tuckman (2024). We focus on a particular class of non-bank financial intermediaries — hedge funds — whose involvement has been scrutinized due to their significant role in leverage and their potential contribution to systemic risk. Brunnermeier and Pedersen (2009) explore how hedge funds' reliance on short-term funding can lead to liquidity spirals and market instability. Gennaioli, Shleifer, and Vishny (2013) provide a theoretical framework for how interconnectedness can lead to contagion and systemic risk, which is explored further by Acharya and Viswanathan (2011) examining the interplay between different types of institutions. To the best of our knowledge, this study is the first to provide a comprehensive empirical analysis of lending between banks and hedge funds using granular loan-level data.

In a related vein, our study contributes to the literature on the relationship between hedge funds and prime brokers. Kruttli, Monin, and Watugala (2022) show that an idiosyncratic liquidity shock to a prime broker decreases credit availability and worsens credit conditions of connected hedge funds, suggesting imperfect substitutability across credit sources. A sudden exit of a prime broker exposes hedge funds to severe funding risks (Di Maggio, Kermani, and Song, 2017) and has led to a change from single to multiple broker relationships after the collapse of Lehman

Brothers in 2008 (Agarwal, Ruenzi, and Weigert, 2017). Co-movement in returns of hedge funds sharing the same prime broker appear to be driven by information sharing rather than a result of the prime broker spreading funding liquidity shocks (Chung and Kang, 2016). Dahlquist, Rottke, and Sokolovski (2024) demonstrate that while idiosyncratic risks from prime brokers to hedge funds can be diversified across multiple brokers, hedge funds remain vulnerable to systematic prime broker risks. Extending this line of research, Dahlquist, Rottke, Sokolovski, and Sverdrup (2024) find that systematic financial intermediary risk is priced in the cross section of hedge fund returns. The findings of our analysis offer important insights into how competition shapes the broker-hedge fund relationship.

Our paper contributes to the existing literature on bank lending and competition. Petersen and Rajan (1995) argue that reduced competition results in higher interest rates for borrowers, and Hauswald and Marquez (2006) show that increased competition lowers loan costs by diminishing banks' market power. Additionally, Keeley (1990) suggests that greater competition can lead to higher risk-taking, a hypothesis further supported by Jiménez, Lopez, and Saurina (2013), who found that intense competition encourages banks to relax their lending standards. Consequently, competition impacts banks' profitability directly through adjustments in loan rates and indirectly by affecting the probability of counterparty default risk (Martinez-Miera and Repullo, 2010), and the literature presents mixed findings on the effect of competition on financial stability (Beck, De Jonghe, and Schepens, 2013; Goetz, 2018). Our paper contributes to the existing literature by examining the relationship between competition and non-price loan terms. While Besanko and Thakor (1987) and Jiménez, Salas, and Saurina (2006) suggest that bank competition increases the likelihood of collateral usage, we document that haircuts applied to a posted collateral decreases. Our results highlight the potential stability risks arising from a deterioration in collateral standards.

Our paper also contributes to the literature on over-the-counter markets. The theoretical framework of Duffie, Gârleanu, and Pedersen (2005) examines OTC markets with respect to search costs and bargaining power. A key hypothesis derived from this work is that clients with better access to alternative dealers exert greater bargaining power by exposing dealers to sequential competition. In line with this reasoning, empirical studies by O'Hara, Wang, and Zhou (2018), Hendershott, Li, Livdan, and Schürhoff (2020) and Hau, Hoffmann, Langfield, and Timmer (2021) provide evidence of discriminatory pricing in the corporate bond market and the OTC derivatives market. Eisenschmidt, Ma, and Zhang (2024) show that dealers' market power over clients leads to discriminatory pricing in the OTC segment of the repo market, which impedes monetary policy pass-through. Our study contributes to this literature by demonstrating that bargaining power not only shapes price formation in OTC markets but also weakens banks' prudential counterparty credit risk measures. While discriminatory pricing may have welfare implications for market efficiency, the consequences of inadequate counterparty credit risk management are potentially far more extensive. Exposures among systemically important banks could have broader repercussions for the stability of the financial system as a whole.

Our study also relates to the literature on repo markets. Auh and Landoni (2022) document higher margins and spreads for lower-quality loans in secured lending transactions. Copeland, Martin, and Walker (2014) and Julliard, Pinter, Todorov, and Yuan (2022) show that counterparty risk matters in addition to asset quality and liquidity. Furthermore, borrowers tend to pay a premium when their default risk is positively correlated with collateral risk Barbiero, Schepens, and Sigaux (2024). Gorton and Metrick (2012) provided a comprehensive analysis of the role of banks in the repo market during the financial crisis of 2007-2008, highlighting the liquidity issues that emerged. Extending this work, Krishnamurthy, Nagel, and Orlov (2014) examined the changes in banks' repo lending practices post-crisis, noting a shift towards greater risk aversion. Clark, Copeland, Kahn, Martin, McCormick, Riordan, and Wessel (2021) provided an up-to-date assessment of the evolving role of banks in the repo market. These studies collectively underscore the critical role of banks in maintaining the stability and efficiency of repo markets. Our study complements the existing literature by examining banks' risk management practices in repo transactions within the context of market competition.

3 Institutional Background

In the following section, we provide background on hedge funds and their linkages to the banking sector.

As discussed in detail by Kambhu, Schuermann, and Stiroh (2007), hedge funds are private and largely unregulated investment pools that provide managers with significant flexibility in both investment strategies and financial instruments. They can invest in a wide range of assets, employ complex tactics such as short-selling and derivatives, and make extensive use of leverage. Their regulatory exemptions are often justified by the fact that they primarily serve accredited investors and large institutions, which are deemed more capable of bearing the associated risks. However, when hedge funds are interconnected with other systemically important entities in the financial system, they can pose significant risks to the broader financial system. While banks, of course, maintain various relationships with both other banks and non-bank entities, Kambhu, Schuermann, and Stiroh (2007) emphasize that hedge funds warrant special attention due to their combination of unrestricted trading strategies, extensive use of leverage, lack of transparency to outsiders, and convex compensation structures. Notable examples of collapses with widespread repercussions include the failure of Long-Term Capital Management (LTCM) in 1998 and the default of Archegos Capital Management, a family office, in 2021.

Hedge funds engage with the regulated banking sector primarily through prime brokerage relationships. Beyond trading and execution services, a key function of prime brokers is the extension of credit to hedge funds, typically through margin loans and repurchase agreements (repos). In our paper, we focus on repo transactions as they represent the predominant form of lending to hedge funds in our sample. In a repo transaction, the bank lends cash to the hedge fund in exchange for securities used as collateral. This structure ensures that in the event of a hedge fund default, the bank retains the securities as protection. To mitigate risk, banks apply a haircut or initial margin to the collateral, ensuring its value exceeds the loan amount and adequately covers potential fluctuations in the collateral's market value. Typically, a haircut is set to account for fluctuations in value up to a specified confidence level, such as 95%, over a defined time horizon (Value-at-risk, VaR) (Auh and Landoni, 2022). In addition to collateral being the primary determinant of loan conditions in the repo market, the risk profile of the borrower also influences these conditions (Copeland, Martin, and Walker, 2014; Julliard, Pinter, Todorov, and Yuan, 2022). If the value of the collateral drops below this threshold, banks apply a variation margin to rebalance their exposure. Our study focuses on the analysis of initial margin, as data on variation margin and margin calls are unavailable.

The prime broker plays a crucial role for a hedge fund by serving as the primary source of financing. This importance was highlighted by the bankruptcy of Lehman Brothers, which had a significant impact on hedge fund performance, as demonstrated by Aragon and Strahan (2012). Consequently, an increasing number of hedge funds have transitioned from relying on a single broker to establishing multiple broker relationships in recent years (Dahlquist, Rottke, and Sokolovski, 2024). However, establishing and maintaining a broker-hedge fund relationship is not without costs. First, to establish a relationship with a prime broker, an extensive onboarding process is required. Due to the high costs associated with onboarding and the ongoing monitoring required by the bank, contracts often stipulate a minimum transaction volume. Additionally, hedge funds incur administrative expenses to manage these relationships, creating friction for both the lender and the borrower. These factors effectively limit the ability of hedge funds to expand the number of brokers they engage with.[5,6,7]

In the context of banking regulation, a repo transaction in which a bank lends cash to a hedge fund in exchange for collateral represents an exposure with a credit risk mitigation (CRM) technique. While collateral reduces credit risk, it simultaneously introduces other types of risk, such as market risk. Consequently, banks are required to maintain robust risk management policies to evaluate the adequacy of margin requirements. Transactions utilizing CRM should not be subject to higher capital requirements than identical transactions without CRM. For uncollateralized exposures to hedge funds, the standardized approach typically assigns risk weights of 100% or 150%

[5]https://www.aima.org/article/five-key-considerations-when-selecting-a-prime-broker.html

[6]https://hedgelegal.com/prime-brokerage-agreement-negotiation-everything-a-hedge-fund-needs-to-know-part-1/

[7]https://thehedgefundjournal.com/the-balancing-act/

(Basel Committee on Banking Supervision, 2022), and typically somewhat lower when using the internal ratings-based approach. The risk weight associated with the counterparty can be substituted with the risk weight of the collateral, subject to a 20% floor (Basel Committee on Banking Supervision (2020), simple approach). Exemptions to the risk-weight floor are applicable to repo transactions under certain conditions. These conditions include overnight transactions or daily remargining and mark-to-market of both exposure and collateral, and the use of sovereign securities as collateral. Given the nature of the repo transactions observed in our dataset, it is very likely that the majority of these transactions fulfill the exemption requirements. As a result, a risk weight of 10% can be applied. Regulations currently do not mandate a minimum haircut when hedge funds act as counterparties in repo transactions. However, there is ongoing debate about whether implementing such minimum haircuts should be required (FSB, 2014; Basel Committee on Banking Supervision, 2021).

4 Data and Descriptive Statistics

4.1 Data Sources and Sample Construction

Our main data set comes from the Money Market Statistical Reporting (MMSR)[8] dataset, which provides transaction-level information on the European secured money market segment. This dataset encompasses detailed information, such as the identities of the lender and borrower, the characteristics of the collateral, and contract-specific attributes such as the rate, haircut, and tenor.

We restrict our sample to transactions where the reporting bank lends cash to hedge funds. To identify hedge funds, we proceed as follows. In the first step, we identify transactions with counterparties that are Non-MMF investment funds (ESA: S124) or financial auxiliaries (ESA: S126) that engage in economic activities related to 'fund management activities' or 'trusts, funds, and similar entities'. In the second step, these entities are further categorized based on SEC

[8]https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/money_market/html/index.en.html

filings listing the private fund type, e.g. hedge fund.[9] We classify a counterparty as a hedge fund if it is explicitly identified as such at the fund level. If the counterparty is matched at the asset management company level, we define it as a hedge fund if hedge fund activities account for more than 75% of the company's assets under management. Additionally, we require hedge funds to have more than ten transactions per month on average and the average monthly volume exceeding €10 million.

Our analysis focuses on the funding of hedge funds by banks. For this reason, we exclude observations with negative haircuts from our sample, as these typically represent instances where repos are used to borrow specific securities (Infante, 2019). To provide context, it is important to note that there are two primary motivations for entering into a repo transaction. The first motivation is for the cash lender (in our case the bank) to provide cash to the borrower (in our case the hedge fund). In such transactions, the parties first agree on the repo rate, after which a security is delivered from a basket of similar securities (e.g., the GC Pooling ECB Basket). This type of transaction is referred to as a *general collateral* (GC) transaction. The second purpose arises when the cash lender seeks to obtain a specific security from the cash borrower. In these instances, the parties first agree on the particular security to be delivered and subsequently determine the repo rate. Such transactions are referred to as *specific collateral* (SC) repos. Unlike GC transactions, SC repos typically feature negative haircuts, which serve to protect the collateral provider rather than the cash provider (Infante, 2019). We make use of this characteristic to filter out SC transactions.[10]

To assess the reliability of our filter in distinguishing between GC and SC transactions, we compare the rates of transactions with negative haircuts to those with non-negative haircuts.

[9] Form ADV: https://www.sec.gov/about/forms/formadv.pdf, Part 1A Schedule D 7.B.(1) A. Private Fund 10., obtained from the Investment Advisor Public Disclosure (IAPD) provided by the SEC. Our matching procedure consists of three steps: pre-processing, linking, and reviewing. 1. Pre-processing: In this initial step, we standardize the names of counterparties in both datasets used (MMSR and SEC) to ensure consistency and accuracy in the subsequent steps. 2. Linking: Next, we perform a fuzzy matching between entities in the relevant datasets based on the standardized names to identify potential matches even when there are minor discrepancies in the names. 3. Reviewing: Finally, we manually review the matched results to complement and verify the matches identified in the linking step. This procedure is applied at both the fund level and at the asset management company level, also utilizing the identity of the fund management company from GLEIF.

[10] The MMSR does not reliably distinguish between SC and GC transactions, as the reporting of this classification is only voluntary.

GC rates are predominantly influenced by the demand for cash and tend to trade close to unsecured money market rates. In contrast, SC rates are driven by the demand for specific securities and generally trade substantially below GC rates, a phenomenon known as the "specialness spread" (Duffie, 1996). Consistent with this distinction, we find that overnight transactions with non-negative haircuts, classified as GC, exhibit rates closely aligned with and slightly above (approximately 2 basis points) the STOXX GC Pooling EUR Extended ON Index rate. Conversely, transactions with negative haircuts, classified as SC, exhibit rates that are approximately 42 basis points lower.

We complement the MMSR data with various other data sources to obtain further information on lenders, borrowers and underlying collateral. For lender information, we merge bank balance-sheet characteristics from the EU-wide transparency exercise conducted by the European Banking Authority (EBA).[11] For additional information on borrowers (i.e., hedge funds) we use valid end-of-year information from annually updated SEC filings. Specifically, we use fund-level information about the number of brokers and exposure to Credit Suisse.[12] For counterparties matched at the asset management company level, we calculate the number of broker relationships as the average of broker relationships across the associated funds. We also incorporate data from the Analytical Credit Database (AnaCredit)[13], which covers the probability of default (PD) for each hedge fund. The PD is a forward-looking measure with a one-year horizon, as reported by the lender.[14] Finally, we use the Centralised Securities Database (CSDB) to merge collateral-specific information such as ratings, as well as daily prices from Refinitiv. We limit our sample to transactions involving fixed-income collateral, as it represents the most prevalent type of underlying collateral accounting for 98% of the observed transactions.

Lending to hedge funds by banks occurs in our sample exclusively through bilateral trans-

[11] https://www.eba.europa.eu/risk-and-data-analysis/data/data-analytics-tools

[12] Form ADV: https://www.sec.gov/about/forms/formadv.pdf, Part 1A Schedule D 7.B.(1) B. Service Providers 24., obtained from the Investment Advisor Public Disclosure (IAPD) provided by the SEC.

[13] https://www.ecb.europa.eu/stats/ecb_statistics/anacredit/html/index.en.html

[14] When the probability of default is unavailable for a specific date and bank counterparty relationship, data from previous reporting is used. It is important to note that the results remain robust when using only observations with directly reported PD information for a specific date and bank counterparty relationship.

actions, with no activity observed in triparty repo transactions. While the triparty repo market plays a relatively minor role in Europe compared to the U.S. (Heider, 2017), this pattern is a common characteristic of both regions. Baklanova, Caglio, Cipriani, and Copeland (2019) also highlight that hedge funds are predominantly active in the U.S. bilateral market compared to the triparty repo market.

4.2 Summary Statistics

The following section offers an overview of banks' lending relationships with hedge funds, providing descriptive statistics on the overall volume, the characteristics of both lenders and borrowers, and the collateral involved.

We begin with two key observations: First, lending to hedge funds has grown significantly during our sample period. Second, hedge funds have increasingly diversified their funding sources, relying on more banks and thereby adopting a less concentrated funding structure. The average daily transaction volume has more than doubled from 2019 to the end of 2023, with lending to hedge funds now constituting nearly 25% of total bilateral lending (see Figure 1).[15][16] In addition, hedge funds have increasingly diversified their broker relationships over the past years as can be seen in Figure 2. During our sample period, the average number of banking relationships for hedge funds increased from 3.7 in April 2019 to 5.9 in December 2024. Correspondingly, the funding concentration, measured by the Herfindahl-Hirschman Index (HHI), declined from 0.53 to 0.39 over the same period.

Hedge funds in our sample are larger both at the fund and company level and have more brokers compared to other hedge funds listed in SEC filings Form ADV. The identified hedge funds are almost exclusively domiciled in the Cayman Islands (96%), while the management companies are predominantly located in the United States (64%) and the United Kingdom (14%). Our sample

[15] In the repo market, banks also function as cash borrowers from hedge funds, effectively acting as securities lenders, while hedge funds primarily borrow securities to establish short positions. During our sample period, the average ratio of banks' secured lending to borrowing is 0.79, indicating that hedge funds used the European repo market to establish short positions in European securities to an even greater extent than for financing purposes.

[16] At the start of our sample period, bilateral lending accounts for 31% of total secured lending, rising to 38% by the end of the sample period.

includes 179 hedge funds, each managing, on average, more than $20 billion and engaging with about four broker (Table 1, Panel B). The funds in our sample have an average one-year probability of default exceeding 1.5%, corresponding to a non-investment grade rating B+.[17]

Banks in our sample are larger, more systemically relevant according to Financial Stability Board (FSB) standards, and tend to be less capitalized, with liquidity ratios similar to those of other banks participating in the EBA transparency exercise. Reflecting their business model, these banks hold more traded assets and exhibit higher exposure to counterparty credit risk. Data from AnaCredit contextualize the scale of lending to hedge funds, revealing that it constitutes 45% of total lending to the real economy for the average bank in our sample (Table 1, Panel A). Additionally, AnaCredit highlights the dominance of repurchase agreements (98.8%) in bank lending to hedge funds. For this reason, we rely on the secured segment of the MMSR in our analyses, as it provides additional crucial variables compared to AnaCredit, including information on haircuts and the specific collateral delivered.

Government bonds are the primary form of collateral in secured lending transactions, accounting for more than 90% of collateral value in our sample, followed by financial bonds (Figure A1). Nearly 40% of the total collateral value is rated as high-grade. Figure A2 provides a breakdown of collateral by country, showing a dominance of euro area countries, including Italy (30%), France (15%), Germany (14%) and Spain (13%).

Table 2 presents summary statistics on the variation in haircuts. Column (1) reports the standard deviation of haircuts for the full sample, as well as disaggregated by credit quality. Haircut variation increases with deteriorating credit quality, being lowest for high-grade collateral and highest for low-grade collateral. In Column (2), we examine the within-collateral variation by demeaning haircuts at the security level (i.e., by ISIN). This de-meaning reduces the standard deviation for the full sample from 5.74 percentage points to 1.59 percentage points. To further account for the time variation in haircuts within security, Columns (3) through (5) present standard deviations after demeaning by collateral-month, collateral-week, and collateral-date, respectively.

[17] https://www.spglobal.com/ratings/en/research/articles/240328-default-transition-and-recovery-2023-annual-global-corporate-default-and-rating-transition-study-13047827

Even at the most granular level, haircut variation remains substantial: for the same security on a given day, the standard deviation is 0.91 percentage points. This within-security variation is modest for high-grade collateral (0.24 percentage points) but notably larger for medium-low-grade (0.84 percentage points) and speculative-grade or unrated collateral (1.43 percentage points). Hence, even for the same collateral on the same day, we observe significant dispersion in haircuts. The subsequent analysis investigates the role of bargaining power in explaining this variation in haircuts.

5 Bargaining Power and Haircuts

5.1 Empirical Strategy

To test the effect of bargaining power on haircut policies, we run the following regression:

$$\begin{aligned} \textit{Haircut}_{l(bfct)} = {} & \beta \textit{Bargaining power}_{ft} + \gamma PD_{bft-1m} \\ & + \alpha_{bc\tau} + \nu_t + \varepsilon_{l(bfct)}, \end{aligned} \tag{1}$$

where $Haircut_{l(bcft)}$ is the haircut (in percent) applied by bank b for collateral c in a repo transaction with hedge fund f at transaction day t as a function of loan l. The primary variable of interest, *Bargaining power*$_{ft}$, is a measure of hedge funds' bargaining power. In the baseline specification, this is measured by the number of banking relationships the hedge fund maintained in the previous month. This proxy is grounded in the theoretical framework of Duffie, Gârleanu, and Pedersen (2005), which demonstrates that in OTC markets, clients with better access to alternative dealers exert greater bargaining power by exposing dealers to sequential competition. Similarly, hedge funds approach different banks in the bilateral repo market. Hedge funds with a larger network of established banking relationships have more outside funding options, enhancing their ability to negotiate favorable terms with banks. Alternative measures of bargaining power or investor sophistication, as established in the literature (Hau, Hoffmann, Langfield, and

Timmer, 2021), will also be used in our robustness checks. Furthermore, we control for credit risk by including the probability of default, PD_{bft-1m}, which reflects the one-year default likelihood of hedge fund f, as reported by bank b in the previous month (*t-1m*). Our analysis utilizes a saturated regression framework that incorporates fixed effects, denoted by $\alpha_{bc\tau}$, which capture the interactions between banks and collateral within distinct time periods τ. The time periods are granularly defined and can represent a calendar month, a week, or even a trading day. Essentially, our most saturated regression model examines how haircuts for identical collateral on the same day from the same bank vary in relation to the concentration of hedge funds' funding, while adjusting for the respective probability of default. Throughout all our analyses we cluster standard errors at the bank-fund-collateral level.

5.2 Results

Table 3 presents the estimated coefficients from Equation (3). We begin with simpler models in specifications (1) to (4), which incorporate only collateral and day fixed effects and their interaction. The simplest specification in column (1) only includes collateral fixed effects and the number of banking relationships as a proxy for bargaining power. It yields a statistically significant coefficient for the number of banking relationships, implying that hedge funds with higher bargaining power face lower haircuts. The economic magnitude of this effect is substantial: an additional banking relationship reduces the haircut, on average, by 19 basis points. Notably, even this simple model, which includes only security fixed effects, demonstrates strong explanatory power, with an R^2 exceeding 92.5%. This high R^2 value can be attributed to the fact that haircut variations are predominantly driven by characteristics specific to the securities involved.

In specification (2), we include the probability of default as a control variable. As expected, the probability of default has the anticipated sign: higher default risk is associated with higher haircuts. Importantly, incorporating the probability of default has little impact on the economic magnitude of our bargaining power proxy. Hence, the observed relationship between bargaining power and haircuts is not driven by a spurious correlation between the number of banking relationships and the probability of default. Our estimated coefficients remain virtually unchanged when time fixed effects are included in column (3) to account for market-wide factors such as volatility. Similarly, including the interaction of collateral and day fixed effects in column (4) yields consistent results. This is an important finding as it highlights that, even for the same collateral on the same day, haircuts vary substantially and decline with increasing bargaining power.

In specifications (5) through (7), we address the possibility that haircuts may depend on bank-specific risk assessments of the collateral. We do this by including bank $\times$ collateral $\times$ time-period fixed effects. The time period granularity is narrowed down from a month to a week, and finally to a trading day. The economic magnitude of our bargaining power proxy remains remarkably consistent across all specifications, even in the most saturated model, which only exploits variation within bank-collateral-trading day. That is, for the same day and the same collateral, the same bank requires significantly lower haircuts from hedge funds with higher bargaining power. It is important to note that this most saturated model necessitates at least two distinct transactions involving different funds within the same bank-collateral-day combination. This requirement effectively halves the sample size

We next investigate potential non-linearity in the relationship between bargaining power and haircuts. Intuitively, an additional banking relationship should have a greater impact on a hedge fund's bargaining power when the initial number of banking relationships is low. Conversely, for hedge funds that already maintain numerous banking relationships, the marginal effect of an additional relationship on bargaining power - and consequently on haircuts - is expected to be much smaller. We test for this in our regression model by including dummy variables that group funds by the number of banking relationships. Figure 3 displays the coefficients of the dummy variables, with funds having seven or more banking relationships serving as the reference group. Relative to this base category, funds with four to six banking relationships do not exhibit a significant difference in haircuts. However, funds with three banking relationships face slightly higher haircuts compared to the reference group. More notably, funds with only one or two banking relationships incur significantly higher haircuts.

To account for this non-linearity, we construct a dummy variable, *Bargaining Power High*, which equals one for funds with three or more banking relationships and zero otherwise. This dummy is used in all subsequent analyses because it effectively captures the non-linearity of the bargaining power effect and provides an easy interpretation. Panel B of Table 3 repeats the previous analysis of Panel A using the dummy variable instead. For all specifications we yield a comparable estimate of the effect of bargaining power on haircuts. Haircuts of fund with high bargaining power are 1.04 to 1.16 percentage points lower compared to funds with low bargaining power. This effect is economically meaningful when compared to the within collateral-date standard deviation of haircuts, which amounts to 0.91 percentage points, as reported in Table 2.

5.3 Heterogeneity

In the subsequent analysis, we explore the variation in the influence of bargaining power on haircuts across different collateral characteristics. We focus on the two most saturated specifications, which account for bank-collateral-week and bank-collateral-day fixed effects. Although the bank-collateral-day specification yields the most precisely identified effects, it comes at the cost of a significantly smaller sample size, which in turn diminishes the statistical power relative to the within-week comparison of haircuts.

Table 4, Panel A presents the results categorized by the credit rating of the collateral issuer. Across all rating categories, higher bargaining power consistently reduces haircuts. Notably, the impact of bargaining power grows stronger as we move from high-grade collateral (-16 bps) to medium/low investment grade (-94 bps) and, finally, to speculative grade/non-rated collateral (-211 bps). Panel B examines the heterogeneity across the remaining maturity of the bonds, revealing a U-shaped relationship. For bonds with a remaining maturity of less than 5 years, the bargaining power effect is -114 bps. This effect decreases to -46 bps for bonds with maturities between 5 and 10 years. For bonds with maturities over 10 years—generally considered more illiquid and volatile—the effect is -238 bps. Finally, Panel C explores differences across collateral issuer sectors. We find that the bargaining power effect is most pronounced when the underlying collateral consists of sovereign bonds, but it is not present for financial issuers. For non-financial issuers, the the coefficient for the *Bargaining Power High* dummy is sizable, though imprecisely estimated, likely due to the limited number of observations.

5.4 Robustness Checks

We conduct a series of robustness tests on our baseline regression to ensure the reliability of our findings.

First, we incorporate the repo rate as an additional control variable in our regression specification. For a given transaction, the haircut is one component of the equilibrium outcome, with another crucial parameter being the rate. Theoretical models that incorporate collateral either as an enforcement mechanism (Geanakoplos, 2010) or to mitigate asymmetric information (Bester, 1985) predict a negative relationship between the haircut and the rate. From the lender's perspective, there exist combinations of the haircut and rate that provide the same profit. Empirical evidence regarding the relationship between haircuts and rates remains inconclusive. Baklanova, Caglio, Cipriani, and Copeland (2019) identify a negative correlation between these two variables, though the economic significance of this relationship is rather weak. In contrast, Chebotarev (2021) initially report a positive relationship using ordinary least squares, which reverses to negative when liquidity needs of the borrower are instrumented. In columns (1) and (2) of Table 5, we extend the analysis by including the repo rate as an additional control variable in our regression model. Consistent with the setup of Chebotarev (2021), our findings reveal a positive relationship between the repo rate and haircuts, indicating that funds with lower haircuts are associated with lower rates. Crucially, for the core question of this paper, we observe that the inclusion of the repo rate does not alter the coefficient for bargaining power.

In our next robustness test, we additionally control for hedge fund unobservables. Our empirical estimation strategy compares haircuts across hedge funds with different levels of bargaining power within the same bank-collateral-day pair. Our data allow us to control for a key theoretical determinant of haircuts at the counterparty level: the hedge fund's probability of default. However, a concern remains that other fund characteristics could spuriously affect our results. Given the intrinsic opacity of hedge funds, identifying sufficient controls in this setting is challenging. To address this issue, we take an alternative approach and include counterparty fixed effects, which account for all fund-specific characteristics, whether observed or unobserved. This approach, however, requires sufficient variation in bargaining power within each counterparty, which is challenging due to the relatively short time span of our panel dataset. Columns (3) and (4) of Table 5 present the results with counterparty fixed effects. Despite the short time period, we find a significant negative relationship between bargaining power and haircuts. When bargaining power is high, haircuts are up to 70 basis points lower. The results are almost identical to those in columns (5) and (6), where we extend the specification to include repo rates while retaining counterparty fixed effects.

We also explore the robustness of our main findings using alternative proxies for bargaining power. Specifically, we consider various measures of funding concentration that are commonly used in the literature (Hau, Hoffmann, Langfield, and Timmer, 2021). First, we examine the Hirschman-Herfindahl Index (HHI), which quantifies the concentration of a hedge fund's funding structure based on its bank relationships. Second, we consider various concentration ratios (CR) of hedge funds' funding structures. Specifically, CR_1 represents the market share of the largest funding bank, CR_2 measures the combined market share of the two largest funding banks, and CR_3 represents the combined market share of the three largest funding banks. Table 6 shows that, across all the measures mentioned above, lower market concentration—reflecting higher bargaining power—leads to lower haircuts.

We conduct several additional robustness checks. For the sake of brevity, we provide only a brief summary of the results. Detailed results are available in the online appendix for interested readers.

In our main analyses, we measure the number of bank relationships and funding concentration based on all transactions from the previous month. As a robustness check, we extend the measurement period to the previous three and six months. The results remain consistent across these alternative measurement horizons (see Table A1 in the online appendix).

Next, we distinguished between transactions with zero haircuts and those with positive haircuts. For this purpose, we re-estimate Equation (3), introducing a binary indicator that takes the value of one for zero haircuts and zero for positive haircuts similar to Julliard, Pinter, Todorov, and Yuan (2022). This analysis explores the influence of bargaining power on the likelihood of obtaining a zero haircut. Additionally, we re-run our analysis on the subset of transactions that involve positive haircuts. Our results show that higher bargaining power not only reduces the size of haircuts but also increases the probability of receiving a zero haircut (see Table A2, in the online appendix).

Our analysis concentrated on the overnight segment, which is the most prevalent maturity for secured lending to hedge funds. In a robustness analysis we broaden our scope to include the entire spectrum of repo tenors, encompassing tom-next, spot-next, and longer durations spanning several weeks or months. To control for repo maturity we include interactions between bank-collateral-week fixed effects and bank-collateral-day fixed effects with predefined maturity buckets. Additionally, in the most saturated model we include interactions for all dates defining a repo transaction, namely bank×collateral×trade date×settlement date×maturity date fixed effects. We find a consistent positive association between funding concentration and haircuts in the extended sample, covering all repo maturities (see Table A3, Panel A in the online appendix).

Some transactions classified as overnight may actually be open repos due to the specific reporting requirements of the MMSR. In a robustness check we therefore filter out open repos using reporting patterns in the unique transaction identifier (UTI) and we re-run our analysis on the filtered overnight segment. We find that bargaining power has an even greater effect on haircuts when applying this filtering (see Table A3, Panel B in the online appendix).

We assess the robustness of our findings by considering alternative measures of the probability of default (PD). The literature provides mixed evidence on the reliability of banks' internal estimates of borrowers' PD. Some studies (e.g., Beyhaghi, Howes, and Weitzner, 2024) suggest that banks' PD estimates incorporate private information, allowing them to predict defaults more accurately than public sources. Conversely, other research (e.g., Behn, Haselmann, and Vig, 2022) documents evidence of PD manipulation to reduce regulatory capital requirements. To address concerns about potential manipulation, we construct alternative PD proxies. First, we calculate the average PD across all banks that maintain a lending relationship with a given fund. Second, we compute the mean PD while excluding information from the actual lender in the respective transaction. Third, we use the maximum PD among all banks associated with a given fund. Regardless of the PD measure applied, we find a statistically and economically significant reduction in haircuts when bargaining power is high (see Table A4 in the online appendix). This result holds even when we exclude the lender's PD from the calculation of the average PD, thereby omitting all funds that maintain only one banking relationship. This approach works against detecting the effects of bargaining power, as it excludes funds with extremely low bargaining power (i.e., only one bank relationship) from the analysis. We also explore alternative approaches to clustering standard errors. Specifically, we cluster standard errors at the bank, counterparty, and collateral levels, as well as at the counterparty and date levels. As reported in Table A5, our findings remain robust under these alternative clustering methods.

6 Quasi-Natural Experiment: Credit Suisse's Exit from the Prime Brokerage Business

In this section, we leverage the exit of Credit Suisse from the prime brokerage business as a quasi-natural experiment to establish a causal relationship between bargaining power and haircuts. This methodology is akin to the approaches used by Di Maggio, Kermani, and Song (2017) and Gabrieli and Georg (2014), who analyzed the impact of a flagship dealer's exit in 2008 on intermediation chains in the corporate bond market and on liquidity allocation in the interbank market, respectively.

6.1 Chronology of Events

Figure 4 illustrates the timeline of events involving Credit Suisse and Archegos Capital Management during the sample period from April 1, 2019, to December 31, 2023.

Archegos Capital Management operated as a family office but employed investment strategies similar to those of hedge funds. By March 2021, Archegos was highly leveraged and heavily invested in equity derivatives of ViacomCBS and Disney Inc. When the underlying stock prices declined drastically, Archegos was unable to meet the margin calls from associated banks, which ultimately led to its default on March 26, 2021. Credit Suisse, which had significant exposure to Archegos, was forced to unwind its positions.[18] Consequently, the stock price of Credit Suisse dropped by more than 20% within the subsequent three trading days compared to pre-Archegos level. Credit Suisse was not the only broker affected by the default of Archegos. Among the largest 15 brokers, nearly half were exposed to Archegos at that time. While some banks managed to unwind their positions with minimal losses, Credit Suisse incurred the largest overall loss of approximately $5.5 billion (see Table A6).

Findings from an independent external investigation highlighted failures the in effective risk management. The final report highlighted key issues, including failures *'by both the first and second lines of defense as well as a lack of risk escalation. [...] it also found a failure to control limit excesses across both lines of defense as a result of an insufficient discharge of supervisory responsibilities in the Investment Bank and in Risk, as well as a lack of prioritization of risk mitigation and enhancement measures'*. As a result, Credit Suisse announced its exit from the prime brokerage business on November 4, 2021, which we use as a quasi-natural experiment.

The substantial losses from exposure to Archegos, failures in risk management practices, along with other adverse developments led Credit Suisse to agree to a merger with UBS Group AG on March 19, 2023. The legal merger between the two entities was completed on July 1, 2024, which is outside our sample period.[19] On July 24, 2023, the Federal Reserve Board and the Pruden-

[18] https://www.ft.com/content/073509cd-fe45-44d2-afac-cace611b6900
[19] https://www.ubs.com/ch/en/microsites/ubs-acquisition-of-credit-suisse.html

tial Regulation Authority imposed fines for Credit Suisse in the context of risk management failures in connection with Archegos amounting to $268.5 million and £87 million, respectively.[20,21]

6.2 Empirical Strategy

We utilize Credit Suisse's announcement to exit the prime brokerage business on November 4, 2021 as a quasi-natural experiment to establish a causal relationship between bargaining power and haircuts. We hypothesize that hedge funds with pre-existing relationships with Credit Suisse experience a negative shock to their bargaining power following the announcement.

We posit that the announcement of Credit Suisse's exit from the prime brokerage business was an unanticipated, exogenous event for the affected hedge funds. The announcement was an ad-hoc disclosure pursuant to article 53 Listing Rules, which mandates issuers of securities to disclose price-sensitive information.[22] This highlights the significance of the announcement, as it provides new and relevant information to the market. The planned exit from the prime brokerage business formed part of a broader strategic initiative aimed at significantly reducing capital requirements over the subsequent two years.[23] Although Credit Suisse did not immediately exit the prime brokerage business, hedge funds that relied on its services faced the prospect of a future reduction in available funding options. The announcement itself plausibly weakened their bargaining power in negotiations with other banks, as these funds anticipated an impending need to secure alternative funding relationships.

We classify hedge funds as treated if they maintained a prime brokerage relationship with Credit Suisse as of 2020 (CS_f = 1, and 0 otherwise), the year preceding Credit Suisse's announced exit (reference period). Exposure to Credit Suisse can reasonably be viewed as predetermined with respect to the exit decision, as it reflects historically established client preferences and Credit Suisse's prior service offerings, rather than any anticipation of the announcement. To construct our treatment variable, we make use of the SEC Form ADV filings, which provide annual in-

[20]https://www.federalreserve.gov/newsevents/pressreleases/enforcement20230724a.htm
[21]https://www.bankofengland.co.uk/news/2023/july/the-pra-imposes-record-fine-of-87m-on-credit-suisse
[22]https://www.ser-ag.com/dam/downloads/regulation/listing/listing-rules/lr-en.pdf
[23]https://www.sec.gov/Archives/edgar/data/1159510/000137036821000077/a20211104-6k.htm

formation on hedge funds' prime brokerage relationships. We utilize official SEC filings in our analysis, as Credit Suisse, not being a euro area bank, is not included in our repo transaction dataset (MMSR). Despite this, we are still able to investigate how the shock to bargaining power induced by the exit of Credit Suisse influences the determination of haircuts among the euro area banks in our sample.

In order to validate the suitability of the quasi-natural experiment, we analyze the impact of the exit announcement on the broker growth of hedge funds in Table 7. The results indicate that hedge funds with a prior relationship with Credit Suisse experienced a 7 to 9 percentage point lower growth in broker relationships relative to those without such a relationship following the announcement. To account for time-invariant fund characteristics and broader temporal trends, we include fund and year fixed effects in our analysis. The estimates for hedge funds in our main sample, presented in columns (1) and (2), align with the results for the full universe of hedge funds reporting to the SEC, as shown in columns (3) to (5), thereby supporting the external validity of our findings. Moreover, hedge funds with and without prior relationships to Credit Suisse exhibit no significant differences in broker relationship growth in the years prior to the exit announcement, validating the parallel trends assumption (see Table 7, columns (2) and (4)). Column (5) provides the detailed broker growth year by year. Broker growth for treated funds declined for all years following the announcement, with a particularly notable decline in 2023. The pronounced decline in broker growth in 2023 may reflect a substantial number of relationship terminations as Credit Suisse neared the completion of its planned exit from the prime brokerage business.[24] Overall, these findings present strong support that the announcement of Credit Suisse's exit from the prime brokerage business had a significant and lasting impact on the bargaining power of exposed hedge funds.

To identify the impact of bargaining power on haircuts, we estimate the following loan-level

[24] Additionally, the publicity surrounding the merger between Credit Suisse and UBS may have increased awareness and led to improved reporting quality of broker relationships by hedge funds, resulting in Credit Suisse being reported less often as a broker. It is important to note that we only have information on reported broker relationships, and their relevance cannot be inferred. However, transaction- and performance-based revenues, primarily from brokerage, based on annual reports of Credit Suisse indicate a steady decline in the years following the exit announcement.

specification:

$$Haircut_{l(bfct)} = \beta POST_t \times CS_f + \gamma PD_{bft-1m} + \delta_{bfc} + \eta_{bct} + \varepsilon_{l(bfct)}, \tag{2}$$

where $Haircut$ is the dependent variable and reflects the haircut on collateral *c* at date *t* for a loan l provided by bank *b* to hedge-fund *f*. CS_f equals one if Credit Suisse provided brokerage services to a given hedge funds as of 2020, and zero otherwise. $POST_t$ equals one after Credit Suisse announced its exit from the prime brokerage business on November 4, 2021, and zero otherwise. We introduce bank-hedge fund-collateral fixed effects to identify the effects of ex-ante broker composition on haircut policy over time within bank, counterparty and collateral relationships. This set of fixed effects captures, among other aspects, structurally different demand for and supply of funding and services within a given relationship. Additionally, we control for credit risk by including the default probability of hedge fund f from the previous month at date *t-1m* reported by bank *b*. To further refine our model, we saturate the specifications with fixed effects including bank-collateral-trade date to control for time-varying characteristics at the bank and collateral levels.

6.3 Results

Table 8 presents the estimated coefficients from Equation (2). We begin with the least restrictive model in column (1), which controls for characteristics at the bank, collateral, and counterparty levels as well as the default probability of the counterparty reported by the bank. The negative coefficient for $POST_t$ suggests lower haircuts, consistent with the general trend of stronger broker diversification over time (see Figure 2). The interaction of $POST_t \times CS_f$ is positive, implying 35 basis points higher haircuts for hedge funds with pre-existing relationships with Credit Suisse after Credit Suisse announced its exit from prime brokerage business. Notably, the increase in haircuts for affected counterparties exceeds the size of the overall trend, leading to a net increase of haircuts for affected hedge funds by 18 basis points.

In column (2), we include date fixed effects to control for general trends over time. From column (3) onwards, we start identifying effects within relationships: bank-counterparty relationships in column (3), and bank-counterparty-collateral relationships in column (4) to (7). Interestingly, the main coefficient of interest, the interaction of $POST_t \times CS_f$, remains very similar across all specifications and ranges between 0.29 and 0.47. Specifically, haircuts increased by 0.47 percentage points within the same bank and hedge fund relationship using identical collateral (see column (4)) compared to counterparties without such a prior relationship. The specification controls for differences in lending relationships and dependencies between collateral and counterparty as outlined by Barbiero, Schepens, and Sigaux (2024). By including collateral-trade date fixed effects in column (5), we control for changes in collateral liquidity and quality. This set of fixed effects effectively restricts our sample to loans with collateral that is posted more than once on a given date. In column (6), we also incorporate bank-trade date fixed effects to control for unobserved bank-specific changes over time. The most saturated specification in column (7) also controls for changing collateral preferences of a given bank over time by introducing bank-collateral-trade date fixed effects.

We conduct several robustness checks to our main estimation. To rule out the influence of confounding events, we restrict our sample to a short post-announcement period ending in June 2022. This period excludes the European Central Bank´s monetary policy tightening, which began with the first rate change on July 27, 2022. The change in monetary policy could potentially bias our results from both the supply and demand side. Supply could be differentially affected if brokers of Credit Suisse related hedge funds had different sensitivities to interest rate changes. Additionally, hedge funds themselves might experience heterogeneous changes in demand during a period of rate increases, leading to bias if correlated with exposure to Credit Suisse. Our findings remain robust with this short post-announcement period in columns (1) and (2) of Table 9. In columns (3) and (4), we introduce $POST_{Archegos \rightarrow Exit,t}$, an indicator variable that equals 1 for the period between the default of Archegos Capital Management on March 26, 2021, and the exit announcement of Credit Suisse on November 4, 2021. The results show no significant pre-treatment effect in the period leading up to the announcement. Moreover, this finding suggests that the higher haircuts are not driven by banks reassessing the riskiness of Credit Suisse's counterparties following the information revelation event associated with Archegos' default. Only after the exit announcement of Credit Suisse, we find an increase in haircuts for treated hedge funds, which is of similar magnitude and statistical significance.

Finally, we present results in Table 10, analyzing the effect of Credit Suisse´s exit from brokerage on haircut policies and exploiting the non-linearity in banking/broker relationships. We split the sample based on the number of broker relationships each counterparty has, using the mean as cutoff. Counterparties with up to four broker relationships are labeled as having low bargaining power, as shown in columns (1) and (2), while those with more than four broker relationships are labeled as having high bargaining power, as shown in columns (3) and (4). The results show that the negative shock to bargaining power increased haircuts only for hedge funds that had few other broker relationships. In contrast, hedge funds with many brokers and hence high bargaining power do not appear to be significantly affected by Credit Suisse's exit announcement. We redo the analysis based on lending relationships instead of broker relationships, splitting the sample by the number of lending relationships as suggested by our results in Section 5.2 (see, Figure 3). Hedge funds with up to two lending relationships are labeled as having low bargaining power, as shown in columns (5) and (6), while those with more than two lending relationships are labeled as having high bargaining power, as shown in columns (7) and (8).[25] The findings are consistent and show that the results are concentrated in the subsample of hedge funds with low bargaining power.

We conduct a series of robustness tests in the context of the quasi-natural experiment to ensure the reliability of our findings. Detailed results are available in the online appendix. These robustness tests are applied consistently with those shown in Section 5.4, where the rationale for these tests is discussed in detail. In Table A7, we control for the interest rate applied to a lending

[25]The difference in cutoff values between the two definitions arises from the fact that broker relationships cover all brokers, whereas the number of lending relationships is limited to euro area banks.

transaction as part of an equilibrium outcome, and results remain virtually unaffected. Next, we differentiate between transactions with zero haircuts and those with positive haircuts, as shown in Table A8. Our findings show that treated funds are both less likely to receive a zero haircut and experience an increase in haircuts when they are positive. Furthermore, we show the robustness of our results regarding repo maturity by including the entire spectrum of repo tenors and by excluding potentially open repo transactions (see Table A9). We also assess the robustness of our findings by considering alternative measures of probability of default (see Table A10). Finally, we show in Table A11 the robustness of our findings with respect to alternative methods of clustering standard errors.

7 Adequacy of Haircuts

We now examine whether the haircuts required by banks are adequate when judged by standard value-at-risk models following similar approaches put forth in the literature (e.g., Baklanova, Caglio, Cipriani, and Copeland, 2019). To examine this question, we run the following regression

$$\begin{aligned} \mathbb{1}(Haircut_{bfct} < Haircut^{m}_{ct}) = \beta \, \textit{Bargaining power high}_{ft} + \gamma PD_{bft-1m} \\ + \alpha_{bc\tau} + \nu_t + \varepsilon_{bfct}, \end{aligned} \tag{3}$$

where the dependent variable is defined by a binary indicator, which is set to one if the haircut $Haircut_{bcft}$, applied by bank b to collateral c in a repurchase agreement with fund f on day t, is lower than the model-predicted haircut $Haircut^{m}_{ct}$ for the same collateral and day, as determined by model m. To calculate these model-implied haircuts, we employ various value-at-risk (VaR) models at distinct confidence intervals.

Initially, we utilize the historical approach to identify the empirical 1st, 5th, and 10th percentiles of the collateral's return distribution over the preceding 12 months. This method provides a non-parametric estimate of the VaR based on actual historical returns. Subsequently, we estimate the conditional variance using two parametric methods: the Exponentially Weighted

Moving Average (EWMA) and the Generalized Autoregressive Conditional Heteroskedasticity GARCH(1,1) model. By forecasting the one-step-ahead conditional variance with these methods, we can compute the VaR at various confidence levels under the assumption that returns follow a normal distribution. These calculated VaRs serve as the benchmarks for the model-implied haircuts against which the actual haircuts applied in repo transactions are compared.

Table 11 presents the results of our empirical analysis. Across all employed estimation techniques and at every conventional Value-at-Risk (VaR) confidence level, we consistently find that greater bargaining power significantly increases the probability of an insufficient haircut in a given transaction. The estimated coefficients on the bargaining power dummy exhibit considerable stability across model specifications and show little variation across different confidence levels. Specifically, for hedge funds with higher bargaining power, the probability of an inadequate haircut is elevated by approximately 11 to 15 percentage points relative to those with lower bargaining power. Furthermore, our analysis indicates an inverse relationship between the probability of default and the likelihood of an insufficient haircut. However, this effect is not statistically significant across all model specifications, particularly when lower VaR confidence levels are employed. Overall, the findings presented in Table 11 provide robust evidence that bargaining power significantly amplifies the risk of insufficient haircuts, as measured by standard VaR models.

In the subsequent analysis, we explore the influence of bargaining power on the likelihood of insufficient haircuts across different collateral characteristics. Given the consistency of results across various models, we focus on the findings derived from an EWMA model at a 5% confidence level. Table 12 displays sample splits by rating, maturity remaining, and issuer sector. The results highlight that the risk of inadequate haircuts, as affected by bargaining power, is particularly significant for securities sovereign bonds, which are rated as medium to low investment grade and with a remaining maturity between 0 and 10 years. Note that there are subtle differences when comparing Table 12 to Table 4. Higher bargaining power reduced haircuts in non-rated or speculative bonds as well as in long-term bonds ($\geq$ 10 years) by more than two percentage points. However, Table 12 shows that the discount in haircuts does not lead to the conclusion that haircuts are inadequate judged by our benchmark models. This suggest that banks employ rather high haircuts for these very risky bonds to begin with.

8 Conclusion

In recent years, an increasing number of hedge funds have transitioned from single-broker to multi-broker relationships, diversifying their funding sources and altering their interactions with banks. This paper examines the implications of this structural shift for the prudential risk management practices of banks. Our findings indicate that hedge funds maintaining multiple banking relationships exert greater bargaining power in the bilateral repo market and obtain significantly lower haircuts. Crucially, from a regulatory perspective, we show that greater bargaining power is associated with an elevated risk that haircuts are insufficient to absorb potential losses, particularly in transactions involving medium to low investment-grade sovereign bonds. These results contribute to ongoing policy discussions on minimum haircut requirements for hedge funds (FSB, 2024), highlighting the potential vulnerabilities arising from the evolving dynamics in the bank-hedge fund nexus.

While our analysis focuses on the bargaining power implications of hedge funds' multi-broker relationships, this trend carries broader implications for financial stability. To begin with, greater diversification of funding sources naturally strengthens the resilience of hedge funds to idiosyncratic shocks affecting individual prime brokers, reducing their exposure to the distress of any single lender. However, as noted by Dahlquist, Rottke, and Sokolovski (2024), hedge funds remain vulnerable to systemic risks affecting the prime brokerage sector as a whole. Moreover, a more diversified lender base may lead to greater opacity and higher leverage, enabling hedge funds to expand their balance sheets while weakening the incentives for individual lenders to engage in rigorous risk monitoring (Hauswald and Marquez, 2006). The presence of multiple lenders can also complicate creditor coordination during periods of stress, potentially amplifying instability when a hedge fund faces distress. These considerations underscore the complex interconnectedness between banks and hedge funds, highlighting the need for further research into the associated risks and their broader implications.

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Figures

Figure 1: **Secured lending to hedge funds**
The graph displays the lending activity of Euro area banks to hedge funds, as well as the proportion of these loans in comparison to the overall bilateral lending volume. The data reflect the average daily lending volume on a quarterly basis, encompassing all transactions reported by MMSR agents from April 2019 to December 2023.

Figure 2: **Hedge funds' funding structure over time**

The figure depicts the evolution of hedge funds' banking relationships and their funding concentration. For each fund, we calculate the number of banking relationships and the concentration of funding using the Hirschman-Herfindahl Index (HHI) on a monthly basis. We report volume-weighted averages of these funding concentration measures each month. The data encompass MMSR agents' lending transactions to hedge funds from April 2019 to December 2023.

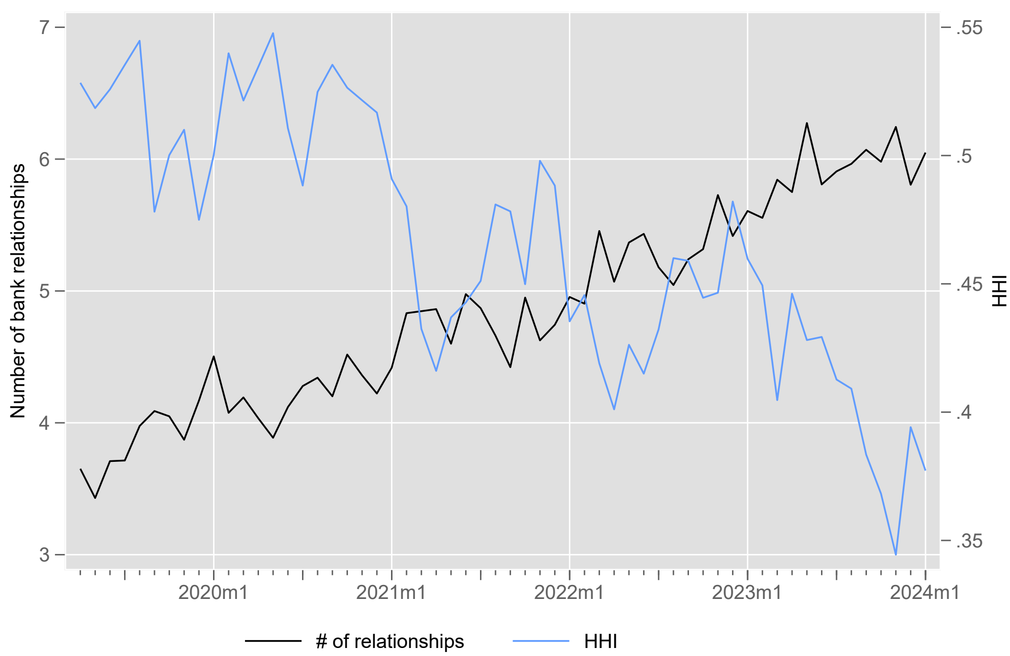


Figure 3: **Nonlinearity in the relationship of bargaining power and haircuts**
The graph illustrates the relationship between haircuts and the number of banking relationships. Haircuts are regressed on dummy variables representing different numbers of banking relationships, while controlling for the probability of default and including time and collateral fixed effects. The graph shows the coefficients of the dummy variables for each number of banking relationships, with funds having seven or more banking relationships serving as the reference group. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-fund-security level. Whiskers indicate 95% confidence intervals.

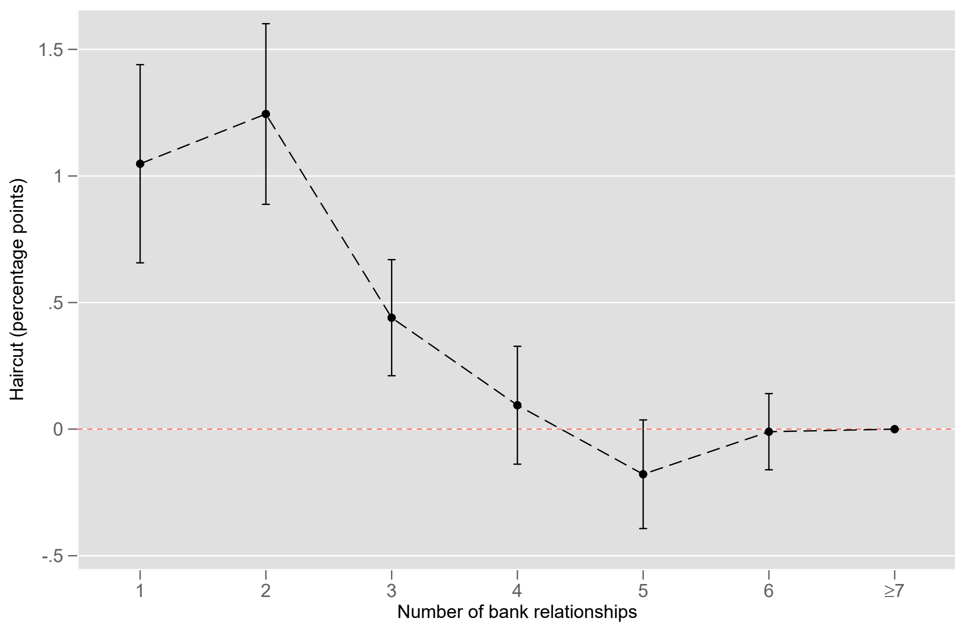
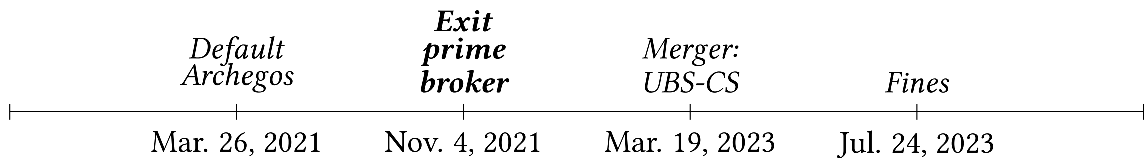


Figure 4: **Timeline of events**

The figure shows a timeline of events related to Credit Suisse and Archegos Capital Management during the sample period from April 1, 2019, to December 31, 2023. These events include the default of Archegos, the exit of Credit Suisse from the prime brokerage business, the merger announcement of Credit Suisse and UBS, and fines imposed by the Federal Reserve Board and the Prudential Regulation Authority in the context of risk management failures by Credit Suisse in connection with Archegos.



Tables

Table 1: **Summary statistics: banks and hedge funds**
The table presents summary statistics for lenders and counterparties in 2020. Panel A reports summary statistics for lenders at the bank level, comparing banks in the sample with other banks participating in the EBA transparency exercise. Panel B reports summary statistics for counterparties, comparing hedge funds in the sample with other hedge funds based on SEC filings in Form ADV.

Panel A: Bank	Sample			Reference				
	Mean	SD	*N*	Mean	SD	*N*	t	p-value
Assets (in € bn)	928.16	629.57	14	142.72	211.74	66	8.30	.00
G-SIB Bucket[26]	.79	.97	14	.06	.30	66	5.11	.00
CET1 Ratio	.15	.03	14	.19	.08	66	-1.66	.10
Traded Assets / Total Assets	.15	.03	14	.04	.07	66	4.36	.00
Liquid Assets / Total Assets	.12	.05	14	.15	.10	66	-0.99	.32
CCR / CET1	.28	.16	14	.11	.17	66	3.41	.00
Lending to (Hedge Funds / Economy)	.45	.58	14	.00	.00	66	6.54	.00
Panel B: Hedge Fund	Sample			Reference				
	Mean	SD	*N*	Mean	SD	*N*	t	p-value
Number of Broker Relationships	4.08	2.64	179	1.95	1.90	6,864	16.29	.00
AUM (in $ bn, Company)	161.55	190.63	179	23.34	68.62	6,864	24.60	.00
Assets (in $ bn)	20.65	43.94	112	.71	4.29	6,864	29.96	.00

Table 2: **Variation in haircuts by rating and within collateral-time dimensions**
The table presents the standard deviation of haircuts (in percentage points) by rating category in column (1). Columns (2) through (5) report the standard deviation measured within collateral (i.e., at the ISIN level), and further within collateral-month, collateral-week, and collateral-date, respectively.

Haircut std. dev. (pp)	(1)	(2)	(3)	(4)	(5)
		Haircuts demeaned by…			
Rating		collateral	collateral-month	collateral-week	collateral-date
High Grade	1.08	0.37	0.27	0.25	0.24
Medium-Low Grade	4.57	1.43	0.9	0.86	0.84
Speculative Grade (or NA)	6.33	2.53	1.53	1.45	1.43
Full Sample	5.74	1.59	0.98	0.93	0.91

Table 3: **The effect of bargaining power on haircuts**

This table presents the estimation results, regressing hedge funds' haircuts (in percentage points) on measures of hedge funds' bargaining power, controlling for their probability of default. In Panel A, bargaining power is measured using the number of banking relationships hedge funds had in the previous month. In Panel B, bargaining power is measured using a dummy variable that is equal to one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-fund-security level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Number of banking relationships as proxy for bargaining power							
# Bank relationships	-0.19***	-0.18***	-0.20***	-0.19***	-0.19***	-0.20***	-0.20***
	(-7.23)	(-6.83)	(-7.19)	(-4.79)	(-4.81)	(-4.36)	(-3.71)
PD		16.45***	16.83***	13.16***	17.60**	19.56*	20.69
		(6.47)	(6.90)	(4.72)	(1.99)	(1.83)	(1.58)
Constant	4.92***	4.59***	4.68***	4.40***	4.63***	4.63***	4.89***
	(40.17)	(39.29)	(37.55)	(26.91)	(22.33)	(20.16)	(18.19)
R^2 (%)	92.5	92.6	92.8	95.9	98.0	98.2	96.8
N	450,787	450,787	450,787	286,688	449,578	446,519	229,561
Panel B: Dummy specification							
Bargaining power high	-1.08***	-1.04***	-1.07***	-1.12***	-1.09***	-1.06***	-1.16***
	(-5.96)	(-5.85)	(-6.16)	(-4.43)	(-3.92)	(-3.63)	(-3.14)
PD		17.70***	18.43***	13.92***	27.60***	29.09**	30.93**
		(6.95)	(7.42)	(5.02)	(2.93)	(2.54)	(2.20)
Constant	4.87***	4.56***	4.57***	4.37***	4.44***	4.41***	4.68***
	(35.29)	(34.27)	(35.19)	(25.45)	(24.40)	(22.52)	(20.31)
R^2 (%)	92.6	92.7	92.9	95.9	98.1	98.2	96.8
N	450,787	450,787	450,787	286,688	449,578	446,519	229,561
Fixed effects:							
Collateral	✓	✓	✓	–	–	–	–
Trade date	–	–	✓	–	✓	✓	–
Collateral × trade date	–	–	–	✓	–	–	–
Bank × collateral × trade month	–	–	–	–	✓	–	–
Bank × collateral × trade week	–	–	–	–	–	✓	–
Bank × collateral × trade date	–	–	–	–	–	–	✓

Table 4: **The effect of bargaining power on haircuts across collateral type**
This table repeats the two most saturated regression specifications from Table 3 for different subsamples based on the characteristics of the underlying collateral. The dependent variable is the haircut, expressed as a percentage. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sample split by rating category						
	High grade		Medium to low investment grade		Speculative and not rated	
Bargaining power high	-0.15***	-0.16**	-0.87***	-0.94***	-1.99**	-2.11**
	(-2.61)	(-2.10)	(-3.25)	(-2.81)	(-2.51)	(-2.23)
R^2 (%)	99.1	98.2	98.1	96.7	96.0	92.4
N	137,015	65,075	199,959	100,794	108,358	63,620
Panel B: Sample split by bonds' maturity remaining (in years)						
	maturity < 5		$5 \leq$ maturity < 10		$10 \leq$ maturity	
Bargaining power high	-1.07**	-1.14*	-0.41*	-0.46*	-2.09***	-2.38***
	(-2.19)	(-1.90)	(-1.88)	(-1.75)	(-3.66)	(-3.30)
R^2 (%)	97.4	95.4	98.1	96.7	98.7	97.7
N	152,333	79,643	132,065	64,441	146,687	78,360
Panel C: Sample split by issuer sector						
	Sovereign		Financial		Non-financial	
Bargaining power high	-1.13***	-1.19***	-0.22	-0.30	-1.69	-2.07
	(-5.19)	(-4.51)	(-0.22)	(-0.22)	(-1.45)	(-1.26)
R^2 (%)	98.1	97.5	96.9	91.7	96.8	88.6
N	316,067	173,444	90,737	42,442	38,288	13,121
Controls & fixed effects:						
PD	✓	✓	✓	✓	✓	✓
Trade date	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓

Table 5: **Robustness tests: controlling for repo rates and accounting for counterparty unobservables**

This table replicates the two most saturated regression specifications from Table 3, with additional robustness checks. The dependent variable is the haircut, expressed as a percentage. The variable *Bargaining power high* is a dummy variable that is equal to one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. In Columns (1) and (2), the repo rate is included as an additional control variable. Columns (3) and (4) introduce counterparty fixed effects to control for unobserved hedge fund characteristics. Columns (5) and (6) incorporate both the repo rate and counterparty fixed effects. $Rate_{l(bft)}$ is the interest rate applied to a transaction between bank b and hedge fund f at time t. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)
Bargaining power high	-1.04***	-1.13***	-0.54***	-0.70**	-0.54***	-0.70**
	(-3.56)	(-3.04)	(-2.77)	(-2.35)	(-2.79)	(-2.38)
Rate	0.01***	0.02***			0.01***	0.02**
	(3.68)	(2.96)			(2.67)	(2.07)
R^2 (%)	98.3	96.9	98.7	97.6	98.7	97.7
N	446,378	229,547	446,517	229,560	446,376	229,546
Controls and fixed effects:						
PD	✓	✓	✓	✓	✓	✓
Trade date	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓
Counterparty	–	–	✓	✓	✓	✓

Table 6: **Robustness tests: alternative measures for bargaining power based on funding concentration**
This table replicates the two most saturated regression specifications from Table 3, using alternative proxies for bargaining power. The dependent variable is the haircut, expressed as a percentage. The primary explanatory variable is *Funding concentration*, with lower concentration indicating higher bargaining power for hedge funds. We use several measures of funding concentration: HHI denotes the Hirschman-Herfindahl Index, which quantifies the concentration of a hedge fund's funding structure based on its bank relationships. CR_n denotes the n-firm concentration ratio within a hedge fund's funding structure. Specifically, CR_1 represents the market share of the largest funding bank, CR_2 measures the combined market share of the two largest funding banks, and CR_3 denotes the combined market share of the three largest funding banks. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Concentration measure:							
	HHI		CR_1		CR_2		CR_3	
Funding concentration	1.23***	1.30***	1.31***	1.40***	2.10***	2.23***	2.81***	3.01***
	(3.03)	(2.60)	(3.28)	(2.80)	(4.62)	(3.95)	(5.40)	(4.60)
R^2 (%)	98.2	96.7	98.2	96.7	98.2	96.7	98.2	96.7
N	446,519	229,561	446,519	229,561	446,519	229,561	446,519	229,561
Controls and fixed effects:								
PD	✓	✓	✓	✓	✓	✓	✓	✓
Trade date	✓	–	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓	–	✓

Table 7: **Broker relationship growth and Credit Suisse exit from brokerage**
The sample is a panel at the hedge fund level f from 2017 to 2023 with yearly frequency. $POST_t$ equals 1 from 2021 onward, the year when Credit Suisse announced to exit prime brokerage, and 0 otherwise. The variable $PRE_{2017\to2019,t}$ equals 1 for the years 2017 to 2019 and 0 otherwise. 2017_t to 2023_t are yearly indicator variables that take the value of 1 in their respective year and 0 otherwise, with 2020 as the base category. CS_f equals 1 if Credit Suisse acts as a broker for hedge fund f as of 2020, and 0 otherwise. Columns (1) and (2) include hedge funds from our main analysis (see Table 8), whereas Columns (3) to (5) cover all hedge funds in SEC filings. Standard errors are clustered at the fund level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Relationship Growth	(1)	(2)	(3)	(4)	(5)
	in-sample		external validity		
$POST \times CS$	-0.09**	-0.08*	-0.07***	-0.07***	
	(-2.03)	(-1.79)	(-7.98)	(-5.77)	
$PRE_{2017\to2019} \times CS$		0.01		0.00	
		(0.28)		(0.26)	
$2017 \times CS$					0.03
					(1.60)
$2018 \times CS$					0.00
					(0.28)
$2019 \times CS$					-0.01
					(-1.08)
$2021 \times CS$					-0.05***
					(-3.23)
$2022 \times CS$					-0.03**
					(-2.53)
$2023 \times CS$					-0.13***
					(-9.16)
R^2 (%)	26.9	26.9	21.2	21.2	21.3
N	733	733	40,667	40,667	40,667
Fixed effects:					
Fund FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Table 8: **Effect of Credit Suisse exit on haircut**

This table presents the estimation results based on equation 2, regressing hedge funds' haircuts (in percentage points) on their exposure to Credit Suisse, controlling for their probability of default. CS_f is a dummy variable indicating exposure to Credit Suisse; it equals 1 if Credit Suisse acted as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals 1 after Credit Suisse announced its plan to leave prime brokerage on November 4, 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$POST \times CS$	0.35***	0.32**	0.33**	0.47**	0.29**	0.34**	0.42**
	(2.73)	(2.51)	(2.39)	(2.28)	(2.09)	(2.14)	(2.09)
$POST$	-0.17**						
	(-2.09)						
Constant	4.69***	4.62***	4.42***	4.47***	4.45***	4.61***	5.54***
	(37.87)	(38.04)	(28.49)	(22.16)	(88.80)	(64.53)	(46.12)
R^2 (%)	94.9	95.0	95.4	97.4	98.3	98.3	98.1
N	356,063	356,063	356,061	355,840	204,994	204,299	167,289
Controls & fixed effects:							
PD	✓	✓	✓	✓	✓	✓	✓
Bank	✓	✓	–	–	–	–	–
Counterparty	✓	✓	–	–	–	–	–
Collateral	✓	✓	✓	–	–	–	–
Trade date	–	✓	✓	✓	–	–	–
Bank × counterparty	–	–	✓	–	–	–	–
Bank × counterparty × collateral	–	–	–	✓	✓	✓	✓
Collateral × trade date	–	–	–	–	✓	✓	–
Bank × trade date	–	–	–	–	–	✓	–
Bank × collateral × trade date	–	–	–	–	–	–	✓

Table 9: **Effect of Credit Suisse exit on haircut: identification**

This table presents the estimation results based on equation 2, regressing hedge funds' haircuts (in percentage points) on their exposure to Credit Suisse, controlling for their probability of default. CS_f is a dummy variable indicating exposure to Credit Suisse; it equals 1 if Credit Suisse acted as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals 1 after Credit Suisse announced its plan to leave prime brokerage on November 4th 2021, and 0 otherwise. $PRE_{Archegos \to Exit,t}$ represents the period after the default of Archegos but before the exit announcement; it equals 1 for the period from March 26, 2021 (the date of Archegos Capital Management's default), to November 4, 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to June 30, 2022. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)
$POST \times CS$	0.24**	0.28*	0.24**	0.23*
	(2.05)	(1.83)	(2.22)	(1.69)
$PRE_{Archegos \to Exit} \times CS$			-0.00	-0.06
			(-0.08)	(-1.39)
R^2 (%)	98.1	97.9	98.1	97.9
N	118,005	97,946	118,005	97,946
Controls & fixed effects:				
PD	✓	✓	✓	✓
Bank × counterparty × collateral	✓	✓	✓	✓
Collateral × trade date	✓	–	✓	–
Bank × trade date	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓

Table 10: **Effect of Credit Suisse exit on haircut: bargaining power**

This table presents the estimation results based on equation 2, regressing hedge funds' haircuts (in percentage points) on their exposure to Credit Suisse, controlling for their probability of default. The sample is split based on the number of a hedge fund's brokers, $N, broker_{f,2020}$, as of 2020. Hedge funds with up to 4 brokers are shown in columns (1) and (2), while hedge funds with more than 4 pre-existing broker relationships are shown in columns (3) and (4). Similarly, the sample is split based on the number of a hedge fund's lending relationships, $N, lender_{f,2020}$, as of 2020. Hedge funds with up to 2 lending relationships are shown in columns (5) and (6), while hedge funds with more than 2 pre-existing lending relationships are shown in columns (7) and (8). CS_f is a dummy variable indicating exposure to Credit Suisse; it equals 1 if Credit Suisse acted as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals 1 after Credit Suisse announced its plan to leave prime brokerage on November 4, 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bargaining power:							
	by broker relationships				*by lending relationships*			
	low		high		low		high	
$POST \times CS$	3.11***	3.20***	0.34	0.44	2.73***	2.73***	0.05	0.08
	(6.53)	(7.15)	(1.49)	(1.56)	(16.60)	(16.75)	(0.86)	(1.49)
R^2 (%)	97.1	96.9	98.8	98.7	97.7	97.6	97.2	97.0
N	154,448	85,774	201,586	72,161	163,219	83,577	192,818	71,686
Controls & fixed effects:								
PD	✓	✓	✓	✓	✓	✓	✓	✓
Bank × counterparty × collateral	✓	✓	✓	✓	✓	✓	✓	✓
Collateral × trade date	✓	–	✓	–	✓	–	✓	–
Bank × trade date	✓	–	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓	–	✓

Table 11: **The effect of bargaining power on the likelihood of insufficient haircuts**
The dependent variable is a dummy variable that equals one if a given haircut is deemed insufficient based on the chosen value-at-risk model and confidence level, and zero otherwise. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. To determine the VaR, we employ the historical method in specifications (1) and (2), the Exponentially Weighted Moving Average (EWMA) in specifications (3) and (4), and a GARCH (1,1) model in specifications (5) and (6). Panels A to C vary with regard to different VaR confidence levels. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Historical		EWMA		GARCH	
Panel A: Dependent variable: Insufficient haircut (VaR 1%)						
Bargaining power high	0.11***	0.12***	0.13***	0.14***	0.14***	0.15***
	(4.14)	(3.59)	(3.69)	(3.20)	(4.36)	(3.81)
PD	-1.69	-1.58	-2.00**	-1.93*	-1.19	-1.09
	(-1.64)	(-1.30)	(-2.26)	(-1.85)	(-1.45)	(-1.13)
R^2 (%)	96.7	94.6	95.8	94.4	94.4	94.3
N	297,584	153,535	298,071	153,547	317,078	164,528
Panel B: Dependent variable: Insufficient haircut (VaR 5%)						
Bargaining power high	0.12***	0.13***	0.13***	0.14***	0.14***	0.15***
	(3.17)	(2.72)	(3.54)	(3.07)	(4.07)	(3.53)
PD	-2.64***	-2.55**	-2.38**	-2.29**	-1.44*	-1.37
	(-2.61)	(-2.14)	(-2.46)	(-2.00)	(-1.72)	(-1.38)
R^2 (%)	96.3	93.6	95.8	93.6	94.2	93.2
N	297,584	153,535	298,071	153,547	317,185	164,531
Panel C: Dependent variable: Insufficient haircut (VaR 10%)						
Bargaining power high	0.14***	0.15***	0.13***	0.14***	0.14***	0.15***
	(3.71)	(3.20)	(3.58)	(3.10)	(3.97)	(3.46)
PD	-3.22***	-3.23**	-3.23***	-3.16**	-2.39***	-2.41**
	(-2.97)	(-2.52)	(-3.02)	(-2.53)	(-2.66)	(-2.26)
R^2 (%)	96.0	92.9	95.4	92.8	94.6	93.0
N	297,584	153,535	298,071	153,547	317,239	164,534
Fixed effects:						
Trade date	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓

Table 12: **The effect of bargaining power haircut adequacy across collateral type**
The dependent variable is a binary indicator that takes the value of one if a particular haircut is considered inadequate according to the selected value-at-risk (VaR) model and confidence level, and zero otherwise. To calculate the VaR, we utilize the EWMA approach with a confidence level of 5%. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable: Insufficient haircut (VaR 5%, EWMA)						
Panel A: Sample split by rating category						
	High grade		Medium to low investment		Speculative	
Bargaining power high	0.05	0.05	0.23***	0.24***	0.00	0.00
	(0.73)	(0.51)	(3.80)	(3.32)	(0.44)	(0.56)
R^2 (%)	96.4	93.7	92.8	89.3	90.7	86.9
N	92,844	38,910	126,658	63,522	77,904	51,074
Panel B: Sample split by bonds' maturity remaining (in years)						
	maturity <5		$5\leq$ maturity <10		$10\leq$ maturity	
Bargaining power high	0.20***	0.21***	0.16***	0.17**	-0.05	-0.06
	(3.55)	(3.10)	(2.71)	(2.26)	(-1.52)	(-1.35)
R^2 (%)	93.5	88.7	95.8	93.3	97.4	96.8
N	120,819	64,967	75,285	33,659	91,843	48,683
Panel C: Sample split by issuer sector						
	Sovereign		Financial		Non-financial	
Bargaining power high	0.17***	0.18***	-0.01	-0.01	0.00	0.00
	(3.76)	(3.25)	(-1.42)	(-1.34)	(1.53)	(1.34)
R^2 (%)	95.0	92.4	91.9	85.9	92.8	85.7
N	212,040	106,036	61,761	36,351	24,014	11,004
Controls & fixed effects:						
PD	✓	✓	✓	✓	✓	✓
Trade date	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓

ONLINE APPENDIX

Figure A1: **Collateral: breakdown by rating and issuer type**
The figure illustrates the collateral used in secured lending activities of Euro area banks to hedge funds. Hedge funds are categorized based on SEC filings in Form ADV. The figure plots the breakdown by rating (High-Grade vs. Non-High-Grade) and issuer type (Financial, Government, Other) based on the nominal amount of posted collateral for the sample period from April 1, 2019, to December 31, 2023.

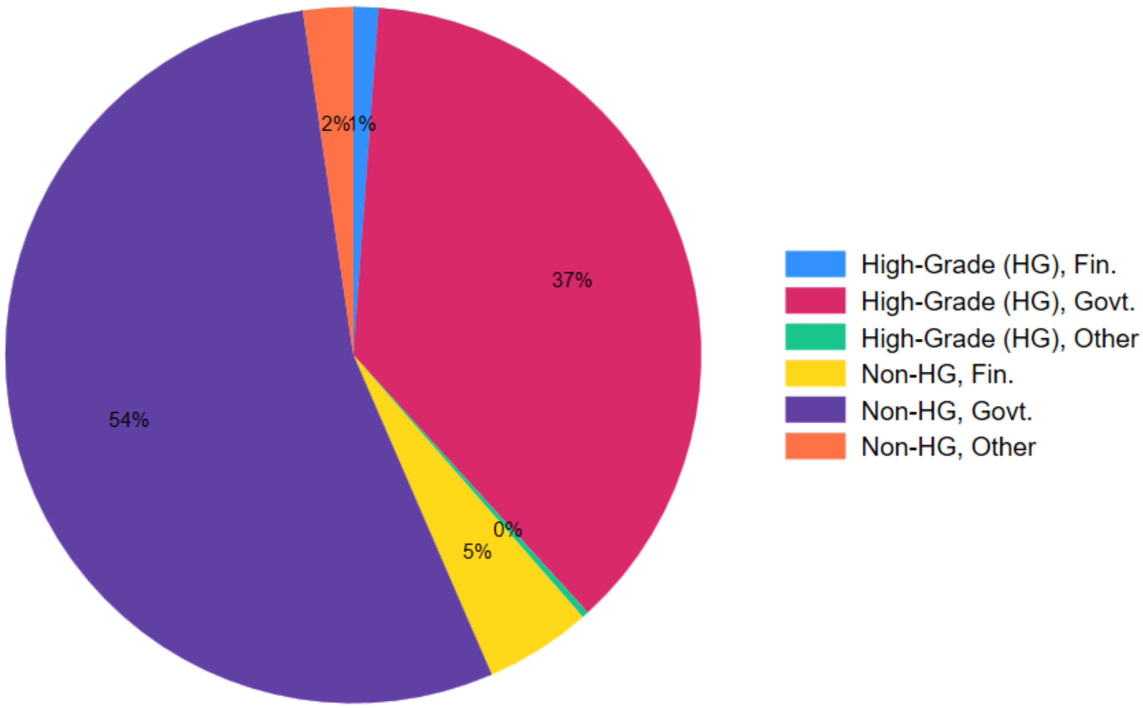


Figure A2: **Collateral: breakdown by country**
The figure illustrates the collateral used in secured lending activities of Euro area banks to hedge funds. Hedge funds are categorized based on SEC filings in Form ADV. The figure plots the breakdown by country based on the nominal amount of posted collateral for the sample period from April 1, 2019, to December 31, 2023.

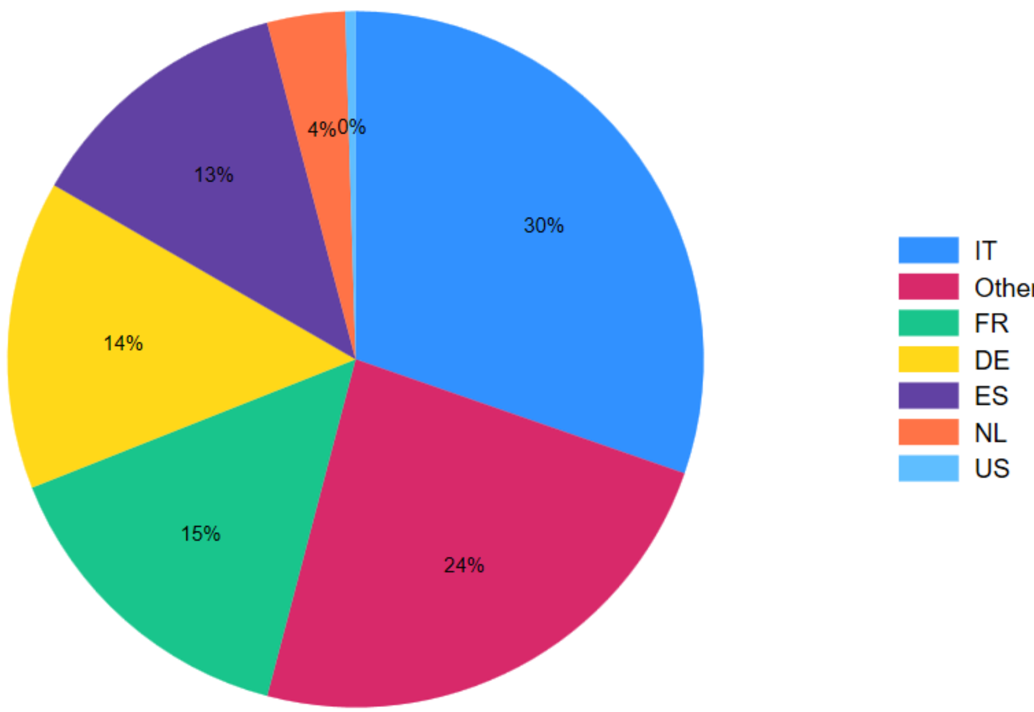


Table A1: **Robustness tests: alternative measures for bargaining power across different measurement horizons**

This table repeats the two most saturated regression specifications from Table 3, using alternative proxies for bargaining power that are measured over different horizons. The dependent variable is the haircut, expressed as a percentage. The primary explanatory variable is *Funding concentration*, where lower concentration is associated with higher bargaining power for hedge funds. We use several measures of funding concentration: # banks refers to hedge funds' number of banking relationships, HHI refers to the Hirschman-Herfindahl Index, which quantifies the concentration of a hedge fund's funding structure based on its bank relationships. CR_n denotes the n-firm concentration ratio within a hedge fund's funding structure. Specifically, CR_1 represents the combined market share of the largest funding bank, CR_2 measures the combined market share of the two largest funding banks, and CR_3 represents the combined market share of the three largest funding banks. The concentration measures are calculated over different time horizons. In Panel A, we use the preceding three months, while in Panel B, we use the previous six months. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Horizon for concentration measures: previous 3 months										
	Concentration measure:									
	# banks		HHI		CR_1		CR_2		CR_3	
Funding concentration	-0.20***	-0.21***	1.29***	1.31**	1.41***	1.44***	2.39***	2.46***	3.25***	3.35***
	(-4.35)	(-3.70)	(3.00)	(2.56)	(3.21)	(2.73)	(4.50)	(3.84)	(5.28)	(4.49)
R^2 (%)	98.3	96.9	98.3	96.9	98.3	96.9	98.3	96.9	98.3	96.8
N	433,786	222,517	433,786	222,517	433,786	222,517	433,786	222,517	433,786	222,517
Panel B: Horizon for concentration measures: previous 6 months										
	# banks		HHI		CR_1		CR_2		CR_3	
Funding concentration	-0.20***	-0.20***	1.10***	1.11**	1.23***	1.24**	2.65***	2.70***	3.78***	3.84***
	(-4.19)	(-3.57)	(2.59)	(2.20)	(2.77)	(2.35)	(4.29)	(3.67)	(5.10)	(4.34)
R^2 (%)	98.3	96.9	98.3	96.9	98.3	96.9	98.3	96.9	98.3	96.9
N	409,588	209,633	409,588	209,633	409,588	209,633	409,588	209,633	409,588	209,633
Controls and fixed effects:										
PD	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Trade date	✓	–	✓	–	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓	–	✓	–	✓

Table A2: **The effect of bargaining power on haircuts: zero vs. positive haircuts**

This table repeats the regression from Table 3, differentiating between zero and positive haircuts. The dependent variable in columns (1) and (2) is a dummy variable that equals one if a given haircut is zero, and zero otherwise. The dependent variable in columns (3) and (4) is the haircut percentage for the sample with positive haircuts. The dependent variable is the haircut, expressed as a percentage. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dep. variable:	**$\mathbb{1}$(Haircut = 0)**		**Haircut**	
Sample:	*full*		*Haircut > 0*	
Bargaining power high	0.12***	0.13***	-1.31***	-1.42***
	(4.08)	(3.54)	(-3.39)	(-2.94)
Constant	0.31***	0.30***	6.23***	6.63***
	(13.01)	(10.93)	(21.96)	(20.38)
R^2 (%)	95.4	91.7	97.8	95.8
N	446,519	229,561	300,210	153,342
Controls & fixed effects:				
PD	✓	✓	✓	✓
Trade date	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓

Table A3: **The effect of bargaining power on haircuts: robustness regarding repo maturity**

This table repeats the analysis from Table 3 considering alternative samples with regard to repo maturity. The dependent variable is the haircut, expressed as a percentage. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. Panel A extends the analysis to all repo maturities. The specifications vary in terms of the fixed effects employed. Specifications (1) and (2) adjust for repo maturity by incorporating interactions between bank-collateral-week fixed effects and bank-collateral-day fixed effects with predefined maturity buckets. Week and day correspond to the trade date of the transaction. Specification (3) represents the most saturated model, controlling within a bank-collateral pair for all dates defining a repo transaction, namely transaction, settlement, and maturity date. Panel B applies a refined filtering of overnight transactions by excluding observations that may represent open repos. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent variable: Haircut	(1)	(2)	(3)
Panel A: Extended sample of all repo maturities			
Bargaining power high	-0.76***	-0.93***	-0.93***
	(-3.48)	(-3.09)	(-3.06)
R^2 (%)	99.2	98.0	98.0
N	603,752	313,826	305,192
Controls & fixed effects:			
PD	✓	✓	✓
Trade date	✓	–	–
Bank × collateral × trade week × maturity bucket	✓	–	–
Bank × collateral × trade date × maturity bucket	–	✓	–
Bank × collateral × trade date × settlement date × maturity date	–	–	✓
Panel B: Filtered overnight transactions (excl. potential open repos)			
Bargaining power high	-1.35***	-1.44***	
	(-3.54)	(-3.09)	
R^2 (%)	97.5	95.6	
N	227,544	133,738	
Controls & fixed effects:			
PD	✓	✓	
Trade date	✓	–	
Bank × collateral × trade week	✓	–	
Bank × collateral × trade date	–	✓	

Table A4: **The effect of bargaining power on haircuts: robustness using alternative PD measures**

This table repeats the two most saturated regression specifications from Table 3 using alternative measures for the probability of default (PD). The dependent variable is the haircut, expressed as a percentage. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. In columns (1) and (2), we calculate the average PD across all banks that maintain a lending relationship with a given fund in the previous month $t-1m$. In columns (3) and (4), we compute the mean PD while excluding information from the actual lender in the respective transaction in the previous month $t-1m$. In columns (5) and (6), we use the maximum PD among all banks that maintain a lending relationship with a given fund in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)
	Mean PD		Mean PD (exl. lender)		Max PD	
Bargaining power high	-0.91***	-0.99***	-0.61**	-0.78*	-0.95***	-1.03***
	(-3.43)	(-2.97)	(-2.09)	(-1.86)	(-3.17)	(-2.74)
PD	27.00**	28.41*	0.82	0.50	-0.73	-0.18
	(2.11)	(1.79)	(0.20)	(0.10)	(-0.24)	(-0.05)
R^2 (%)	98.2	96.8	98.6	97.4	98.2	96.8
N	446,519	229,561	342,675	163,053	446,519	229,561
Controls & fixed effects:						
Trade date	✓	–	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓

Table A5: **The effect of bargaining power on haircuts: robustness clustering**
This table repeats the regression from Table 3, employing alternative clustering when standard errors are computed. In columns (1) and (2), we cluster by bank, counterparty and collateral; in columns (3) and (4) we cluster by counterparty and date. The dependent variable is the haircut, expressed as a percentage. *Bargaining power high* is a dummy variable that equals one if a hedge fund had three or more banking relationships in the previous month, and zero otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors in columns (1) and (2) are clustered at the bank, counterparty, and collateral level and clustered at the counterparty and date level in columns (3) and (4). t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)
	Clustering:			
	Bank, counterparty, collateral		Counterparty, date	
Bargaining power high	-1.06***	-1.16***	-1.06***	-1.16***
	(-4.50)	(-5.04)	(-2.84)	(-3.07)
PD	29.09*	30.93*	29.09*	30.93**
	(2.08)	(2.11)	(1.93)	(2.15)
R^2 (%)	98.2	96.8	98.2	96.8
N	446,519	229,561	446,519	229,561
Controls & fixed effects:				
Trade date	✓	–	✓	–
Bank × collateral × trade week	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓

Table A6: **Broker to hedge funds**
Volume is the sum of banks' customer (hedge funds) assets in $ bn. *Count* shows the number of hedge funds for a given bank. *Size* shows the average hedge fund size for a given bank in $ bn. *Exposure* equals *yes* in case of a relationship to Archegos prior to its default. *Loss* expresses the bank-specific loss incurred after the default of Archegos. The largest 20 broker represent about 90% of the market. Information is based on SEC filings Form ADV in 2020 and public sources for exposure to Archegos.

Rank	Bank Name	Broker Segment		Hedge Fund	Archegos	
		Volume ($ bn)	Count	Size ($ bn)	Exposure	Loss
1	Barclays	5,739	656	8.75		
2	Morgan Stanley	5,195	2,162	2.40	yes	$911m
3	Citigroup	4,888	778	6.28		
4	Credit Suisse	4,452	1,092	4.86	yes	$5.5bn
5	Goldman Sachs	4,626	2,363	1.96	yes	~ 0
6	J.P. Morgan	4,623	1,562	2.96		
7	UBS	3,481	841	4.14	yes	$861m
8	ING	3,401	1,083	3.14		
9	Deutsche Bank	3,101	645	4.81	yes	~ 0
10	Merrill Lynch	2,631	328	8.02		
11	BNP Paribas	1,983	347	5.72		
...						
14	Wells Fargo	805	361	2.23	yes	~ 0
15	Nomura	705	54	13.05	yes	$2.9bn
...						
20	Société Générale	405	37	11.0		

Table A7: **Effect of Credit Suisse exit on haircut: robustness rate**

This table presents the estimation results based on equation 2, regressing hedge funds' haircut (in percent) on their exposure to Credit Suisse, controlling for their probability of default. Exposure to Credit Suisse, CS_f, equals one if Credit Suisse acts as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals one after Credit Suisse announced its plan to leave prime brokerage on November 4th 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. $Rate_{l(bft)}$ is the interest rate applied to a transaction between bank b and hedge fund f at time t. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$POST \times CS$	0.35***	0.33***	0.34**	0.48**	0.32**	0.38**	0.47**
	(2.74)	(2.63)	(2.46)	(2.36)	(2.40)	(2.46)	(2.44)
POST	-0.15*						
	(-1.95)						
Constant	4.69***	4.08***	3.92***	4.05***	3.27***	3.31***	4.11***
	(37.91)	(16.45)	(15.10)	(13.36)	(4.54)	(4.00)	(4.45)
R^2 (%)	94.9	95.0	95.4	97.4	98.3	98.3	98.1
N	356,053	356,053	356,051	355,830	204,984	204,289	167,279
Controls & fixed effects:							
PD	✓	✓	✓	✓	✓	✓	✓
Rate	✓	✓	✓	✓	✓	✓	✓
Bank	✓	✓	–	–	–	–	–
Counterparty	✓	✓	–	–	–	–	–
Collateral	✓	✓	✓	–	–	–	–
Trade date	–	✓	✓	✓	–	–	–
Bank × counterparty	–	–	✓	–	–	–	–
Bank × counterparty × collateral	–	–	–	✓	✓	✓	✓
Collateral × trade date	–	–	–	–	✓	✓	–
Bank × trade date	–	–	–	–	–	✓	–
Bank × security × trade date	–	–	–	–	–	–	✓

Table A8: **Effect of Credit Suisse exit on haircut: zero vs. positive haircuts**

This table presents the estimation results based on equation 2, differentiating between zero and positive haircuts. The dependent variable in columns (1) and (2) is a dummy variable that equals one if a given haircut is zero, and zero otherwise. The dependent variable in columns (3) and (4) is the haircut expressed as a percentage. Exposure to Credit Suisse, CS_f, equals one if Credit Suisse acts as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals one after Credit Suisse announced its plan to leave prime brokerage on November 4th 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral and covers all observations in columns (1) and (2), but only observations with haircuts greater than zero in columns (3) and (4). The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
Dep. variable:	**1(Haircut = 0)**		**Haircut**	
Sample:	*full*		*haircut > 0*	
$POST \times CS$	-0.16**	-0.19**	0.44*	0.51*
	(-2.29)	(-2.26)	(1.77)	(1.70)
Constant	0.45***	0.41***	7.05***	7.64***
	(6.82)	(4.42)	(43.74)	(34.23)
R^2 (%)	97.2	96.9	97.7	97.5
N	204,299	167,289	137,187	123,071
Controls & fixed effects:				
PD	✓	✓	✓	✓
Bank × counterparty × collateral	✓	✓	✓	✓
Collateral × trade date	✓	–	✓	–
Bank × trade date	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓

Table A9: **Effect of Credit Suisse exit on haircut: robustness regarding repo maturity**
This table presents the estimation results based on equation 2, regressing hedge funds' haircut (in percent) on their exposure to Credit Suisse, controlling for their probability of default. Exposure to Credit Suisse, CS_f, equals one if Credit Suisse acts as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals one after Credit Suisse announced its plan to leave prime brokerage on November 4th 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample in Panel A consists of lending transactions from MMSR reporting agents to hedge funds with fixed income securities as collateral of all repo maturities. The specifications vary in terms of the fixed effects employed. Specifications (1) and (2) adjust for repo maturity by incorporating interactions between bank-collateral-week fixed effects and bank-collateral-day fixed effects with predefined maturity buckets. Week and day correspond to the trade date of the transaction. Specification (3) represents the most saturated model, controlling within a bank-collateral pair for all dates defining a repo transaction, namely transaction, settlement, and maturity date. Panel B applies a refined filtering of overnight transactions by excluding observations that may represent open repos. The sample consists of transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent variable: Haircut	(1)	(2)	(3)
Panel A: Extended sample of all repo maturities			
$POST \times CS$	0.37**	0.39**	0.39**
	(2.09)	(2.12)	(2.12)
R^2 (%)	98.5	98.4	98.5
N	258,655	238,675	232,947
Controls & fixed effects:			
PD	✓	✓	✓
Bank × counterparty × collateral	✓	✓	✓
Bank × collateral × trade date	✓	✓	✓
Bank × collateral × week × maturity bucket	✓	–	–
Bank × collateral × trade date × maturity bucket	–	✓	–
Bank × collateral × trade date × settlement date × maturity date	–	–	✓
Panel B: Filtered overnight transactions (excl. potential open repos)			
$POST \times CS$	0.52**	0.52**	
	(2.06)	(2.06)	
R^2 (%)	97.4	97.4	
N	115,075	114,522	
Controls & fixed effects:			
PD	✓	✓	
Bank × counterparty × collateral	✓	✓	
Collateral × trade date	✓	–	
Bank × trade date	✓	–	
Bank × collateral × trade date	–	✓	

Table A10: **Effect of Credit Suisse exit on haircut: robustness using alternative PD measures**

This table repeats the two most saturated regression specifications from Table 8 using alternative measures for the probability of default (PD). This table presents the estimation results based on equation 2, regressing hedge funds' haircut (in percent) on their exposure to Credit Suisse, controlling for their probability of default. Exposure to Credit Suisse, CS_f, equals one if Credit Suisse acts as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals one after Credit Suisse announced its plan to leave prime brokerage on November 4th 2021, and 0 otherwise. In columns (1) and (2), we calculate the average PD across all banks that maintain a lending relationship with a given fund in the previous month $t-1m$. In columns (3) and (4), we compute the mean PD while excluding information from the actual lender in the respective transaction in the previous month $t-1m$. In columns (5) and (6), we use the maximum PD among all banks that maintain a lending relationship with a given fund in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors are clustered at the bank-counterparty-collateral level, and t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. variable: Haircut	(1)	(2)	(3)	(4)	(5)	(6)
	Mean PD		Mean PD (exl. lender)		Max PD	
$POST \times CS$	0.24**	0.29**	0.26**	0.26*	0.25**	0.29**
	(2.27)	(2.12)	(2.46)	(1.75)	(2.26)	(2.10)
PD	6.01	10.14	8.76	9.54	2.83	4.42
	(1.02)	(1.42)	(1.53)	(1.38)	(1.10)	(1.26)
R^2 (%)	98.4	98.2	97.8	97.6	98.4	98.2
N	288,478	233,915	214,089	164,988	288,478	233,915
Controls & fixed effects:						
Bank × counterparty × collateral	✓	✓	✓	✓	✓	✓
Collateral × trade date	✓	–	✓	–	✓	–
Bank × trade date	✓	–	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓	–	✓

Table A11: **Effect of Credit Suisse exit on haircut: robustness clustering**
This table presents the estimation results based on equation 2, applying different clustering. The dependent variable is the haircut expressed as a percentage. Exposure to Credit Suisse, CS_f, equals one if Credit Suisse acts as a broker for hedge fund f as of 2020, and 0 otherwise. $POST_t$ equals one after Credit Suisse announced its plan to leave prime brokerage on November 4th 2021, and 0 otherwise. PD_{bft-1m} denotes the probability of default of hedge fund f, as reported by bank b in the previous month $t-1m$. The sample consists of all overnight lending transactions of MMSR reporting agents to hedge funds with fixed income securities as collateral. The sample period is from April 1, 2019, to December 31, 2023. Standard errors in columns (1) and (2) are clustered at the bank, counterparty, and collateral level and clustered at the counterparty and date level in columns (3) and (4). t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Dep. variable: Haircut	(1)	(2)	(3)	(4)
Sample:	Clustering:			
	Bank, counterparty, collateral		Counterparty, date	
$POST \times CS$	0.34**	0.42**	0.34**	0.42**
	(3.02)	(4.24)	(2.05)	(2.01)
R^2 (%)	98.3	98.1	98.3	98.1
N	204,299	167,289	204,299	167,289
Controls & fixed effects:				
PD	✓	✓	✓	✓
Bank × counterparty × collateral	✓	✓	✓	✓
Collateral × trade date	✓	–	✓	–
Bank × trade date	✓	–	✓	–
Bank × collateral × trade date	–	✓	–	✓