Does Broker-Dealer Health Affect Stock Prices?*

Daniel Barth† Nicholas Zarra‡

November 20, 2024

Most Recent Version Here

Abstract

Not unless distress spreads to multiple broker-dealers. Broker-dealers do not participate directly in equity markets in large quantities; instead, they participate indirectly by lending to hedge funds via their prime brokerage divisions. We show that shocks to broker-dealer financial health affect their credit supply; however, hedge funds are typically able to diversify away these shocks. This is consistent with a high ability to substitute borrowing to non-distressed broker-dealers. This ability is not unlimited: when the shock to broker-dealer health is sufficiently broad and spills over to non-affected broker-dealers, it triggers hedge fund equity sell-offs. This results in lower abnormal returns for stocks held more by exposed funds. We show that such a broad broker-dealer shock occurred in the first quarter of 2016 when several European broker-dealers became distressed. Overall, our results indicate that broker-dealer health matters for equity prices under conditions of broad distress.

*Zarra is deeply grateful to Sydney C. Ludvigson and Thomas Philippon for their invaluable guidance and advice and also wants to thank Toomas Laarits, Robert Richmond, Anthony Saunders, and Alexi Savov for their excellent support. We also are thankful for the excellent comments by Yakov Amihud, Sirio Aramonte, Dick Berner, Frederic Boissay, Dario Caldara, Will Cassidy, Ricardo Correa, Angela Crema, Josh Coven, Egemen Eren, Quirin Fleckenstein, Melanie Friedrichs, Gaston Gelos, German Guttierez, Sebastian Hillenbrand, Franz Hinzen, Sebastian Infante, Robert Kurtzman, Sai Ma, Quinn Maingi, Odhrain McCarthy, Todd Messer, Phillip Monin, Karsten Muller, Gaston Navarro, Friederike Niepmann, Stefano Pastore, Lubomir Petrasek, Gabor Pintor, Matt Richardson, Andreas Schrimpf, Julia Selgrad, Marti Subrahmanyam, Vlad Sushko, Richard Sylla, Karamfil Todorov, Davide Tomio, Bruce Tuckman, Pascal Ungersboeck, Kenji Wada, Olivier Wang, Courtney Wiegand, and Ram Yamarthy for their comments and suggestions. We also want to thank seminar participants at NYU and the Federal Reserve Board for their insightful comments. Zarra thanks NYU Stern's Center for Global Economy and Business (CGEB) for generously providing funding for data purchases. The views and opinions are those of the authors and do not necessarily represent the views of the Board.

†Federal Reserve Board of Governors. Email: Daniel.J.Barth@frb.gov

‡New York University Stern School of Business. Email: nzarra@stern.nyu.edu

"A few prime brokers dominate the provision of lending to hedge funds, and this concentration could amplify shocks and propagate them through the financial system."

Financial Stability Board [2023]

A prominent literature argues that factors constructed from broker-dealer aggregate leverage—a proxy for broker-dealer health—strongly explain returns across asset classes (Adrian et al. [2014], He et al. [2017]), suggesting that intermediaries are marginal investors in many markets and important for determining asset prices.[1] Puzzlingly, this pattern holds even in asset classes where broker-dealers have limited holdings. However, broker-dealers participate in asset markets in two distinct ways: directly through their own investments, and indirectly by providing credit to other intermediaries, such as hedge funds. Across all asset classes, indirect participation is substantial with nearly $4.5 trillion dollars of lending provided to US-regulated hedge funds in 2024.[2] In this work, we show that, in the stock market, indirect participation by broker-dealers is large (accounting for 87% of total broker participation in 2024), and therefore is crucial for understanding the role that brokers play in the stock market.[3]

To assess whether and when broker-dealer health transmits to asset prices via indirect participation, we study prime broker lending to hedge funds with equity investments. The prime brokerage market provides an ideal setting in which to study a credit supply mechanism because this market is large and the main way in which brokers participate. Moreover, its market structure reveals the core economic tension that makes the transmission of broker-dealer health to asset prices a priori ambiguous. On the one hand, the prime brokerage market is exceptionally concentrated—with the top 5 brokers making up 55% of lending according to the Office of Financial Research's Hedge Fund Monitor—suggesting that even an idiosyncratic shock could have an aggregate effect. On the other hand, large hedge funds have diversified prime broker counterparty networks, borrowing

[1] Moving forward, we use aggregate broker-dealer health to refer to measures of broker-dealer leverage to avoid confusion between the leverage of broker-dealers (assets over equity) and their leverage provision through their lending to hedge funds. This interpretation of leverage as a measure of health is similar to that of Haddad and Muir [2021].

[2] This statistic is taken from the Office of Financial Research's Hedge Fund Monitor (OFR monitor) and includes hedge fund borrowing from US and foreign globally systemically important banks (G-SIBs) as well as non-banks. It includes lending via both repurchase and prime-brokerage agreements. About 90% of this total comes from G-SIBs. This figure is large against total trading securities holdings for brokers ($875B) and G-SIB bank holding companies ($2.34T) as well as G-SIB commercial & industrial lending ($1.03T). See Section 3.4 for a further discussion of these facts.

[3] In 2024 Q2, total broker-dealer equity holdings was $343.7B from the Federal Reserve's Financial Accounts. Total prime brokerage borrowing by hedge funds—the predominant means of financing equity purchases—was $2337B per the OFR monitor. Both aggregate quantities are constructed from micro-data collected from the Securities and Exchange Commision (SEC) (FOCUS and Form PF).

from an average of 3.6 brokers, suggesting that hedge funds could diversify broker health shocks.[4] Ultimately, determining which of these forces dominates is an empirical question.

This paper provides causal evidence that broker-dealer health shocks can impact equity prices through changes in lending to hedge funds. However, hedge funds typically manage to diversify away from these shocks. Non-diversifiable shocks only arise when a shock to broker-dealer health is sufficiently broad and spills over to previously unaffected broker-dealers. To support these findings and disentangle the effect of hedge fund diversification, this paper addresses two main challenges in studying the topic: data limitations and identification constraints.

Empirically studying prime brokerage markets requires both fund- and broker-level data. We measure aggregate prime brokerage quantities using data from the Enhanced Financial Accounts starting in 2012. To estimate broker-level prime brokerage quantities, we use FR Y-9C data on loans to investors. We measure fund-level exposure to individual prime brokers using the SEC's public regulatory Form ADV dataset, which provides the full prime brokerage network for each hedge fund registered in the US, again since 2012. This allows us to map broker-level distress to individual hedge funds. We merge Form ADV balance sheet information with adviser-level equity securities holdings data from FactSet Ownership to examine the impact on hedge fund equity holdings and then equity prices.

To identify an effect, a broker-dealer health shock needs to be plausibly exogeneous to the macroeconomic environment and financial conditions. This latter concern is particularly important, as broker-dealers are deeply embedded in the financial system, making it difficult to disentangle their health from that of the broader financial system. Through a narrative analysis of large broker-dealer health shocks in the sample, we identify two plausibly exogenous large shocks for sets of broker-dealers: the European broker-dealer distress period in Q1 2016 and the broker-dealer losses due to the collapse of Archegos. These two broker-specific shocks are the largest in the sample in terms of losses, financial distress, and the set of broker-dealers affected.[5] For these two large shocks, we investigate three interrelated sub-questions: first, we examine how and to what extent do broker shocks affect their credit provision to hedge funds; second, we explore whether and when hedge funds cannot diversify away from these shocks by examining the change in the quantity of equity holdings; and third, when shocks are not fully diversified away, we analyze the

[4] We define a large hedge fund as one with at least \$1 billion in reported gross assets according to Form ADV. As of 2022 Q4, these large hedge funds collectively manage over \$2,500 billion in gross assets, while all other hedge funds hold slightly less than \$285 billion. We define a prime broker borrowing relationship if the hedge fund reports a prime brokerage relationship on Form ADV.

[5] In Appendix Section C, we report the full narrative analysis of possible shocks based on large losses, fines, and near defaults. We find that these two shocks are the largest under all measures studied.

return patterns on equities that are more exposed to distressed broker-dealers.

The European broker-dealer distress shock provides direct evidence that broker-dealer distress can propagate to equity markets. In early 2016, European broker-dealers experienced significant distress due to idiosyncratic write-downs and concerns over debt defaults, originating with Deutsche Bank and Credit Suisse. This broker-level distress triggered contagion among other European broker-dealers, especially those that were ex-ante less profitable and reliant on lower-tier capital. These European brokers were active brokers in American equity markets. We group the set most distressed brokers—as measured by credit default swap (CDS) spread changes—as the "Euro 5."[6] We document that hedge funds managers exposed to these distressed broker-dealers could not perfectly substitute away, as they were forced to sell-off their equity positions. Stocks more exposed to the equity sell-off had abnormally lower returns than other stocks—even controlling for standard factor exposure—which took at least four months to fully revert. We find evidence that the bulk of the sell-off was absorbed by non-levered investors who were ex-ante considered more inelastic in their demand, suggesting that the change in investor composition could help to explain these results.[7]

However, almost all other shocks during the public regulatory data period appear to have been perfectly diversifiable. Our Archegos experiment groups together broker-dealers that suffered over $10 billion in losses during the collapse of the large family office known as Archegos in late Q1 of 2021. We first show that broker-dealers that experienced losses in response to the Archegos collapse saw their total lending fall by 14.5% in Q2 2021. While these specific brokers reduced their credit provision, we find that other broker-dealers increased their credit provision, and aggregate lending quantities increased. At the hedge fund manager level, we find no significant differences in equity holdings between managers who ex-ante borrowed from the shocked broker-dealers and those who did not, suggesting that these managers perfectly substituted away from the shock. To generalize, we study broker distress in the full panel. Distressed brokers are identified as those with extreme CDS changes relative to others in the same quarter. First, we find that these broker-dealers had lower loan growth rates on average, indicating a credit supply shock. Second, consistent with Archegos, managers ex-ante exposed to distressed broker-dealers do not significantly reduce equity holdings growth, implying perfect substitution.

One relevant question that emerges is why hedge funds are unable to diversify shocks during the European broker distress event, unlike other events. We suggest that the key difference in the that experiment lies in the health of non-shocked brokers and their credit response. During the

[6] We will inter-changably use the term "Euro 5" event and European broker-dealer distress event

[7] See Koijen and Yogo [2019] and Koijen et al. [2023], who suggest that investor composition affects prices.

Archegos shock, we find no evidence of health impairment among non-directly shocked brokers, and these broker-dealers significantly increased their lending provision. Similarly, in our panel exercise, we find almost no cases where a broker classified as '‘distressed” in this exercise coincided with other brokers facing deteriorating health. By contrast, during the European broker distress period, CDS spreads for non-shocked brokers rose considerably, indicating impaired health. Since much of the market distress coincided with news releases about the Euro 5 broker-dealers, we attribute this to health spillovers.[8] To test whether spillovers affected credit supply, we examine how the lender behavior of non-shocked broker-dealers with below-median CDS spread changes during the announcement dates (i.e., healthier non-shocked brokers) differed compared with lending behavior of other non-shocked brokers. We find that healthier non-shocked brokers had higher loan growth rates than their peers, suggesting that the poor health of non-shocked brokers likely reduced the ability of funds to fully substitute away from distressed brokers.

The collapse of Lehman Brothers provides additional evidence that the health of broker-dealers not directly affected by a shock plays a role in transmitting broker-dealer distress to equity markets. This event—central to the Global Financial Crisis (GFC)—is the most extensively studied prime broker-related shock.[9] We document significant spillovers from the Lehman collapse to other major prime brokers, using CDS data and narrative analysis. Specifically, the narrative analysis reveals that Lehman's failure triggered a run on other broker-dealers, particularly Morgan Stanley, in critical funding markets, thereby resulting in funding market contagion.[10] Using vendor data from Lipper TASS on a subset of prime brokerage relationships, we document that stocks with higher ex-ante exposure to hedge funds connected to Lehman Brothers and other distressed broker-dealers exhibit lower excess returns during periods of broker-dealer distress.[11] These results indicate that widespread distress is critical for broker-dealer shocks to affect equity markets.

[8] In Section 5.1.2, we provide evidence that the spillovers resulted from sympathetic contagion, with investors extrapolating health outcomes across brokers with similar characteristics. While a full exploration of the contagion's source is beyond the scope of this study, we highlight three unique features of European broker-dealers that may have contributed to this contagion. First, during the period of European broker distress, several brokers impaired assets due to unrelated exposures, in contrast to the Archegos event, where losses stemmed from a common exposure source. Second, broker distress spread to key funding markets, particularly the subordinated debt market, potentially constraining the funding capacity for other brokers. Third, unlike in other periods of financial distress, there were no significant policy interventions by central banks or fiscal authorities to alleviate investor concerns or ease funding market stress.

[9] Aragon and Strahan [2012] first analyzed Lehman's collapse impact on the stock market, focusing on liquidity but also presenting evidence that stocks more exposed to Lehman Brothers saw lower raw returns.

[10] To our knowledge, this is the first paper to explicitly discuss a funding market run on "prime brokerage free credits."

[11] We classify Merrill Lynch and Morgan Stanley as the other distressed broker-dealers based on their realized health events and a stock-level turnover analysis, as detailed in Section 7.2.2.

Taken together, our analysis offers three key findings. First, when broker-dealers become distressed, they cut credit to hedge funds, consistent with a credit supply channel. Second, hedge funds demonstrate a remarkable ability to diversify away from this distress, whereby we observe imperfect substitution as proxied by equity holdings quantities only when the broker-dealer health shock is sufficiently broad. Third, when hedge funds cannot fully substitute away, the broker shock propagates to the equity market as affected hedge funds sell-off equities, leading to lower prices for stocks with greater exposure to those hedge funds.

1 Relating to the literature

Our primary contribution is to the intermediary asset pricing literature. This paper is the first to *directly* study whether and when a potentially first-order mechanism within this literature—the brokerage credit supply mechanism—exists. Using detailed public regulatory data, we can measure the full prime broker network, allowing us to trace the impact of broker-dealer health on hedge fund portfolios. In constructing each test, we build upon the literature on hedge fund leverage, broker-dealer relationships, and the economics of broker-dealers. By testing this mechanism, we specifically contribute to the debate on whether, when, and which intermediaries matter for asset prices by showing a credit supply mechanism specifically for brokers. Furthermore, by examining this mechanism in equity prime brokerage markets, we advance the broader discussion on the influence of intermediaries on equity markets.

Motivated by the Global Financial Crisis (GFC), theoretical work (e.g., He and Krishnamurthy [2013]; Brunnermeier and Sannikov [2014]) argues that if the marginal investor is a representative intermediary, asset prices could be explained by shocks amplified to these intermediaries. To test representative intermediary models, the first empirical work (Adrian et al. [2014]; He et al. [2017]) constructed proxies for intermediary health using time series innovations to broker-dealer leverage.[12] To be clear, the choice to use broker-dealer leverage was due to its empirical properties and because it would likely be a good proxy for intermediaries in general.[13] These leverage-based

[12]More precisely, both use different measures of broker-dealer leverage. The Adrian et al. [2014] factor is constructed from time series innovations of flow of funds aggregate broker-dealer leverage. The He et al. [2017] factor measures the time series innovation of market "capital ratios" for primary dealers, as a subset of the largest broker-dealers. Capital ratios (equity over assets) are defined as the inverse of leverage (assets over equity), as both studies clearly state. He et al. [2017] state that the primary dealer sector is a natural candidate for the representative financial intermediary," while Adrian et al. [2014] state that "we focus on measuring the SDF of a representative financial intermediary using the aggregate leverage of security broker-dealers."

[13]Adrian et al. [2014] explicitly make this claim: "Backed by recent theories that give financial intermediaries a central role in asset pricing, we argue that the leverage of security broker-dealers is a good empirical proxy for the marginal value of wealth of financial intermediaries and that it can thus be used as a representation of the intermediary SDF." (p. 2558)

factors explain returns well across many asset classes, including markets in which broker-dealers do not directly participate, such as equities. As factor models test whether an investor's Euler equation holds, these results provide evidence that a representative intermediary is marginal in various markets.

Highlighting the existence of a marginal representative financial intermediary raises important questions about the role of intermediaries and which brokers matter. An investor's Euler equation holds if the pricing kernel reflects optimal behavior, although this does not imply that every marginal investor moves or determines asset prices, such as if broker-dealer shocks drive prices. Moreover, the existence of a marginal representative intermediary does not necessarily mean that it is the broker-dealer. Aggregate broker-dealer leverage is unlikely to be exogenous to the health or actions of other intermediaries, such as hedge funds, which might de-risk when broker leverage becomes constrained, regardless of broker behavior. This type of endogeneity—which is useful for testing representative intermediary theories—complicates distinguishing among different intermediary types and mechanisms.[14] This paper directly aims to ascertain whether broker-dealer shocks move prices via credit supply.

One approach to mitigating endogeneity concerns is to use explicit micro-data that enables studying plausibly exogenous shocks and thus direct price impact. Several papers in the literature employ this strategy in other markets by studying intermediaries as direct investors, such as CDS markets (Siriwardane [2019]; Eisfeldt et al. [2022]) and catastrophe bond markets (Tomunen [2022]). For example, Siriwardane [2019] studies a direct mechanism through which intermediaries affect asset prices in a highly concentrated market with high participation costs, showing that capital or health shocks to large intermediaries—including broker-dealers—selling CDS protection affect the spread charged on protection using detailed cross-sectional data. We study similarly concentrated markets with a large set of overlapping key institutions but find strikingly weaker results for a broker credit supply mechanism: while broker health can affect prices via its effect on hedge funds, hedge funds have a strong capacity to diversify away these shocks.

A second approach to addressing the Euler equation and endogeneity critiques is to study whether asset classes or securities more strongly owned by intermediaries are more sensitive to aggregate innovations in intermediary or broker-dealer leverage. Notably, Haddad and Muir [2021] show that asset classes with greater intermediary involvement are more responsive to—and better explained by—time series measures constructed from broker-dealer leverage factors, concluding that intermediaries *matter* more for these asset classes.[15] Their definition of "intermediated" is

[14] Another concern is that intermediary leverage might correlate with the stochastic discount factor of other investors, such as households (Santos and Veronesi [2022]) or the super-wealthy (Lettau et al. [2019]).

[15] The term "matter"—as introduced by the authors—refers to intermediaries directly influencing or causing move-

based on whether intermediaries directly own the asset, meaning that equities are considered the least intermediated asset class.

By contrast, our paper tests a broker lending mechanism directly in equity markets. Seegmiller [2024] studies the cross-section of common equities, showing that equities owned more by institutions in general—not only broker-dealers—are more sensitive to intermediary factor measures, providing further and more direct evidence that equities might be intermediated. While Seegmiller [2024] suggests that some of these results might be driven by broker credit supply in some cases, his methodology does not enable testing whether it is present or can explain his results. By contrast, our paper directly tests the credit supply mechanism and finds evidence that it can exist but rarely seems to be present in the data.

We now focus on specific literature that holds importance for certain tests in our paper. First, the literature on hedge fund crowding—particularly Brown et al. [2021]—has shown that hedge funds tend to concentrate on specific strategies and often "crowd" into the same securities. Their research documents that equities with large hedge fund positions tend to (a) have above-average excess returns on average and (b) exhibit common downside "tail risk." In this paper, we explore whether and when broker-dealer shocks cause significant, negative equity returns, i.e. the downside "tail risk" of hedge fund crowded portfolios. Accordingly, we explicitly connect hedge fund crowding to intermediary asset pricing. First, we document that hedge fund crowded portfolios tend to underperform during periods when aggregate broker-dealer health deteriorates, which coincides with declines in aggregate prime brokerage quantities, as shown in our motivating fact section.[16] Second, we directly test whether deteriorating broker conditions empirically trigger crashes in hedge fund crowded portfolios. Our results provide evidence that this can happen, although such instances are relatively rare due to hedge fund diversification.

Several studies have examined individual shocks to prime brokers. Most prominently, Aragon and Strahan [2012] demonstrates that stock market liquidity deteriorated more sharply after the Lehman Brother collapse for stocks with greater exposure to hedge funds that had Lehman Brothers as a prime broker. While their primary focus is on stock market liquidity, our study focuses on the direct impact of prime brokerage borrowing-induced sell-offs on stock market returns. Additionally, Kruttli et al. [2022] analyzes the effects of a large, prolonged shock to Deutsche Bank in Q1 2016 on hedge fund borrowing using confidential Form PF data, but they do not investigate the transmission of such shocks to asset markets. In contrast to these papers, we study the broad conditions under which, and the reasons why, broker-dealer distress becomes non-diversifiable and

ments in asset prices.

[16] To the best of our knowledge, this paper is the first to directly document this.

impacts asset markets. In doing so, we provide direct evidence that, under normal circumstances, hedge funds are capable of diversifying broker-dealer health shocks. Furthermore, we show that the diversifiability of a shock depends on the health and willingness of non-directly shocked broker-dealers to extend additional credit, as evidenced during the European broker distress period and the collapse of Lehman Brothers.[17]

Dahlqvist et al. [2021] studies the impact of prime broker risk on hedge fund performance. First, they show that single-broker hedge funds have lower returns in response to adverse broker-specific shocks but find null results for multi-broker hedge funds. Second, they show that hedge funds returns load on the He et al. [2017] factor, which they assume captures "shocks to the health of these pivotal prime brokers." Based on this, they conclude that systematic prime brokerage risk is a determinant of hedge fund returns. While our paper shares an interest with Dahlqvist et al. [2021] in the impact of idiosyncratic primer broker events on hedge funds and how these funds manage risk, we differ in our question, methodology, and findings. In general, we study the impact of broker shocks on the total equity holdings of funds and broker-level lending quantities as opposed to returns. Second, much of our paper focuses on broker-specific shocks that arise during periods of broader distress—a type of shock that does not fit neatly into the idiosyncratic or systematic categories described in that paper. In response to such shocks, we find evidence that even multi-broker hedge funds fail to fully diversify away the shock's impact on hedge fund manager equity holdings and prices.[18] More importantly, the two studies ask fundamentally different questions, as our research aims to understand how hedge funds propagate shocks to asset markets.

As we study bank holding company-level health shocks for much of our analysis, we implicitly assume the importance of internal capital markets within these institutions. We use CDS spreads to (a) measure spillovers in our European broker distress experiment and (b) proxy for broker distress in our panel analysis in Section 7. Studies such as Caglio et al. [2021] and Correa et al. [2022] provide evidence of internal capital markets between bank holding companies and their broker-dealers, showing that brokers with access to holding company funding (a) avoided costlier external sources during the GFC, and (b) used BHC funding for repo and FX trades when more profitable. These papers substantiate the existence of internal capital markets. By contrast, we exploit negative

[17]While Kruttli et al. [2022] do not explore the mechanisms driving non-substitution, Aragon and Strahan [2012] attribute the inability to substitute in Lehman's case to bankruptcy-specific factors—namely, the loss of client collateral that had been rehypothecated (lent out) by Lehman Brothers. Our findings suggest a much broader set of circumstances in which broker-dealer health shocks propagate beyond bankruptcy proceedings.

[18]Both Dahlqvist et al. [2021] and this paper study the collapse of Lehman Brothers, but in very different ways. Dahlqvist et al. [2021] considers this shock as "idiosyncratic," affecting a single prime broker. In Section 7.2, we instead view the shock as broader—documenting spillovers and contagion across broker-dealers—which we argue are crucial for the transmission of broker-dealer health to equity markets in this period.

effects, focusing on how distress at the holding company level disrupts prime brokerage activity for a broker.

Much of this paper explores the capacity of funds (borrowers) to substitute away from broker credit supply shocks (lenders) in concentrated credit markets. This issue has been extensively studied in concentrated borrowing markets, particularly for non-financial firms. For instance, in the context of Japanese corporate loans, Amiti and Weinstein [2018] demonstrate that shocks to individual, concentrated banks significantly affect the firms that borrow from them. Similarly, Galaasen et al. [2023] draw analogous conclusions regarding Norwegian corporate loans, using a granular instrumental variable identification strategy to show that firms often struggle to diversify away from such shocks. By contrast, our findings in prime brokerage settings reveal different outcomes. While broker shocks affect broker-level quantities in concentrated markets, funds appear to be generally well diversified and capable of managing borrower credit supply shocks. Both our model and empirical results indicate that funds have a strong incentive to actively manage credit supply risk, which they seem to do effectively.

2 Data

We describe the main datasets used in the analysis.

2.1 Cross-sectional Regulatory Datasets

Central to our analysis is the SEC's Form ADV dataset. Form ADV is an annual regulatory disclosure form filed by investment advisers registered with the SEC who manage at least $150 million in private fund assets must. All SEC-registered investment advisers must file regardless of the fund's domicile, meaning that this includes foreign-domiciled hedge funds.[19] As part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Form ADV was revised to include information on the full set of prime broker counterparties for each regulated fund starting in 2012.[20] For this study, the key data from this form are the private fund-level data reported in Item 7 of Form ADV's Part 1, namely the legal identifiers for each fund, the prime brokerage counterparty network (Question 24), and fund-level gross asset value. From Question 24, we clean and assemble a list of all prime brokers for each fund. We then use this dataset to create a cross-walk to 13-F filings from FactSet.

[19] The SEC Private Fund statistics report that 34.2% of the total net asset value of reporting hedge funds is domiciled in the US.

[20] Form ADV shows a larger prime broker network than TASS Lipper, a leading vendor database.

2.2 Time Series Regulatory Datasets

The SEC's Form PF dataset is a confidential regulatory dataset that includes borrowing quantities for funds and fund-by-counterparty pairings. While this data is not publicly accessible, aggregates from the Form PF data are publicly available through the Federal Reserve's Enhanced Financial Accounts, the Office of Financial Research's Hedge Fund Monitor, and the SEC Private Fund statistics. Each dataset provides aggregated information on fund borrowing patterns and counterparty type.

2.3 Broker/Bank Holding Company Health and Balance Sheet Information

We collect information on the balance sheets and health of the ultimate parent or bank holding companies for the broker-dealers in the sample. As many large broker-dealers are foreign, we strive to measure the full balance sheet of the foreign parent or bank holding company. First, we collect balance sheet information from Compustat's North America, Global, and Bank databases, in particular on total assets and total liabilities.

Second, we collect market measures of broker health from Markit and FactSet. We collect Markit's Credit Default Swap spread data, match each broker to its parent company's main identifier, and then choose the senior primary five-year CDS spread identifier.[21] From FactSet Ownership's Security files, we collect the common market net worth for each bank holding company, which we call NW_t^b.[22]

2.4 Security Holdings Data

Based on the SEC's 13-F filings, FactSet Ownership provides quarterly data on institutional equity holdings, shares outstanding, and other relevant information from 2000 Q1 to 2022 Q4. FactSet also provides a proprietary classification of institutional investors into investor types.[23] We clean the data as described in Koijen et al. [2023]. As institutional holdings can exceed shares outstanding in certain periods in those cases, we rescale institutional holdings proportionally to sum to shares outstanding.

Merge with Form ADV: FactSet also provides a proprietary cross-walk between its manager-level identifiers and FINRA CRD identifiers. We update this cross-walk if we hand-identify a large fund or adviser that is not in the cross-walk. We remove hedge funds with large mutual fund holdings and those owned by bank holding companies.

[21] We use the senior five-year CDS spread as it has the most comprehensive set of matches.

[22] We use FactSet to measure market net worth as it provides the fullest coverage of global bank holding companies.

[23] We adopt Koijen et al. [2023]'s classification of FactSet identifiers into key institutional types such as hedge funds, investment advisers, and brokers.

2.5 Security- and Firm-Level Outcomes and Characteristics

We collect stock-level return information, volume, and volatility data from the CRSP US Stock Database. From the CRSP-Compustat Merged database, we collect standard firm-level balance sheet information—including firm-level assets. From this dataset, we can compute standard measures such as Amihud illiquidity and stock-level betas. For certain robustness tests, we collect firm-level syndicated loan exposure via DealScan. We merge this dataset with the holdings data via CUSIP.

Sample Selection: Our main sample includes common stocks traded on the New York Stock Exchange, the American Stock Exchange, or Nasdaq. As standard, we remove financial stocks based on the Standard Industrial Classification (SIC) code. We also remove stocks in the bottom quintile of market capitalization in the last period and those with prices less than $5 in the previous period.

3 Institutional Details and Aggregate Facts

This section outlines key institutional details and motivating facts about the interaction between broker-dealer health and hedge fund activities.

3.1 Prime Brokers and Equities Financing

A prime broker is a specialized type of broker-dealer that offers a range of services to hedge funds and other institutional clients, including financing long equity positions through margin loans, lending securities for short selling, and efficiently processing trades. Prime brokerage services are frequently bundled together. Prime brokers are usually units within broker-dealers, catering to high-value clients and providing more comprehensive services. Over time, many prime brokers have become part of larger bank holding companies, particularly following the partial repeal of Glass-Steagall and the consolidation that occurred after the GFC.

Prime brokers provide leverage to their clients through various contracts, including repurchase agreements, margin loans, and securities lending to facilitate short sales, as well as synthetic financing. Lending for equity purchases primarily occurs through the latter three types of contracts. Margin loans are the primary method to extend credit to clients to finance long equity positions. These loans are secured by the client's portfolio, with terms based on the client's creditworthiness and the risk profile of the assets held as collateral.

The liability management of broker-dealers is complex and segmented. Broker-dealers primarily finance their margin loans through a pecking order based on implied cost. To fund a margin loan, brokers first attempt to source the funds internally from their existing hedge fund clients, through either matched-book financing or internalization. Matched-book financing involves offsetting one client's lending needs with another's, such as matching long and short positions between two clients. Similarly, internalization refers to using the unencumbered cash balances of hedge fund clients held in their brokerage accounts, commonly known as prime brokerage free credits. Internalization and matched-book financing are generally near-zero cost. However, if brokers lack sufficient client resources, they might need to turn to external financing or use their own capital, which becomes more costly, especially during periods of financial distress. In such cases, the increased cost comes from the direct financing expense and potential opportunity costs if the broker's parent company needs to allocate additional funds to support margin lending activities.

Appendix Section A provides a more detailed description of the key institutional details for prime brokerage.

3.2 Hedge Funds

Hedge funds are the primary institutional investors employing leverage for equity investing in the US. The Investment Company Act of 1940 strongly restricts the use of leverage for many institutional investors that accept outside money, such as mutual funds. However, hedge funds are exempt from these restrictions because they raise funds from qualifying investors, typically high-net-worth individuals or institutions. Other institutional investors in the US—such as pension funds—generally do not employ leverage to the same extent. Other levered investors such as family offices and proprietary trading firms are typically smaller in scale but tend to behave similarly to hedge funds in their use of leverage.

Beyond being levered, hedge funds are large in terms of assets under management and equity holdings. According to the most recent SEC Private Fund statistics, gross hedge fund assets under management were $10.8 trillion in Q4 2022. Hedge funds participate actively in equity markets, although there is substantial nuance to their exposure. On *aggregate*, FactSet identified that hedge funds held 3.4% of the stock market in Q4 2022 and 3.9% of the total institutional share. However, from Table 1, we see that hedge funds are significant players in equity markets for the *average* security, owning 10.9% of the average equity security's shares outstanding and roughly 15.3% of the total institutional share of securities. Their importance is amplified by their trading activity, which accounts for up to 27.4% of institutional turnover at the security level. Moreover, stocks have heterogeneous exposure to the hedge fund sector, as the 90th percentile stock has a large 35.2% institutional share (25.7% market share). Similarly, the average stock is held by approximately 55 hedge fund managers, with the 90th percentile being held by around 74 funds.

3.3 Hedge Fund and Prime Brokerage Borrowing Patterns

The prime brokerage market is highly concentrated, predominantly intermediated by prime brokers associated with largest global systemically important banks (G-SIBs). The Office of Financial Research's Hedge Fund Monitor provides the total borrowing share by each broker, with counterparty identity anonymized. Table 3 reports the total lending share of brokers across the broker size distribution. The top five brokers provide 55.7% of total brokerage loans on average, while the top ten brokers account for about 80.2% of loans. This concentration level is high: for comparison, total commercial & industrial lending concentration ratios computed from Y-9C data show respective concentrations of 30.4% and 49.7% in 2022 Q4. Indeed, this concentration level raises the motivating concerns that idiosyncratic shocks to a large broker might have significant effects.

However, while lenders are concentrated, hedge funds borrow from multiple broker-dealers. Table 2 reports summary statistics on the number of prime broker relationships that hedge funds report on Form ADV. The average filing hedge fund has prime brokerage relationships with 2.6 broker-dealers, with this number being much higher for funds with at least \$1 billion (3.6 relationships) and \$5 billion (5.1) in gross assets. These latter groups account for over 89% and 69% of total gross assets, respectively, suggesting that those hedge funds that are more likely to affect prices actively diversify their counterparty network.

These two facts set up the core tension in the paper: while prime brokerage is concentrated and granular from the brokers' perspective, hedge funds appear to borrow from many brokers, introducing a potential diversification force.

3.4 Four Aggregate Facts

We now document four crucial aggregate facts suggesting a potentially prominent and important role of broker-dealer credit supply in relation to asset prices.

Fact 1: Broker-dealers predominantly intermediate securities market lending Figure 1 highlights the scale of broker-dealer involvement in securities markets through both direct and indirect channels. Column (1) shows that broker-dealers regulated by the SEC hold approximately \$875 billion in fixed income and equity securities, while lending about \$4.552 trillion to hedge funds. Notably, around 90% of this lending activity is concentrated within G-SIBs and their broker-dealer units. In Column (2), we present the total direct holdings of G-SIB bank holding companies. [24]

[24] This dataset includes American broker-dealer affiliates of US and foreign G-SIBs, as well as foreign broker-dealers for US G-SIBs. Foreign affiliates likely contribute to the discrepancy observed in equity holdings between Columns (1) and (2).

In this dataset, fixed income exposure is measured by holdings classified as "available-for-sale," reflecting securities held for active trading. Even under this more comprehensive measurement, brokers' lending remains approximately twice the scale of their direct securities holdings, particularly in equity and prime brokerage markets.[25] Additionally, broker-dealer credit supply via repurchase agreements—primarily used to lever fixed income assets—exceeds G-SIB direct fixed income holdings by roughly 30%.

Fact 2: Prime brokerage borrowing is strongly correlated with broker health: Figure 2 plots total prime brokerage lending from the SEC Private Funds Statistics against aggregate broker health. To proxy for aggregate health, we use the intermediary capital ratio of the parent companies of the primary dealer sector introduced by He et al. [2017].[26] When the aggregate intermediary state is good (i.e. the factor is high), aggregate prime brokerage lending is high, although this is an equilibrium quantity reflecting both supply and demand forces.

Fact 3: Investor borrowing has long correlated with equity market returns: We plot the year-over-year change in the equity market against FINRA margin loans. Margin loans are an important part of broker lending to equity investors. Figure 3 shows that total margin credit provision—across all investors—has a strong relationship with the market, extending back to the 1960s.[27] This figure shows equilibrium lending quantities have long been procyclical to the market.

Fact 4: Equity portfolios sorted by hedge fund exposure experience negative tail events when aggregate broker health is poor: Using FactSet's hedge fund classification system to consistently study hedge fund exposure to 2023, we sort stocks into value-weighted quintiles based on the share of the stock held by hedge funds.[28] Figure 4 provides the binscatter coefficients for the following spanning regression where we regress the long-short portfolio return on the intermediary capital factor:

$$LongMinusShortHFExposure_t = \alpha + \beta HKM_t + \beta_2 MKTRF_t + \varepsilon_t \tag{1}$$

In this approach, we control for the market factor for consistency with He et al. [2017].

[25] It is important to clarify that prime brokerage loans include not only equity-related lending but also lending for other instruments, such as convertible bonds, and securities lending to facilitate equity short positions.

[26] Based on Form ADV data, we know that most large prime brokers are parts of broker-dealers with primary dealers.

[27] Similar patterns exist for hedge fund specific borrowing in the Enhanced Financial Accounts since 2012. One pervasive issue with margin and prime brokerage loan datasets—including FINRA and the SEC Private Funds Statistics—is that these series co-mingle loans to facilitate short positions that are frequently marked-to-market.

[28] The literature refers to portfolios with the substantial presence of hedge funds as "hedge fund crowded" portfolios. This approach is similar to one of the empirical strategies proposed by Brown et al. [2021] in their paper on hedge fund crowding. They document that hedge fund-sorted portfolios have common tail risk, although they do not make the connection with broker-dealer factors.

Figure 4 shows that when long-minus-short hedge fund-sorted equity portfolios perform poorly, intermediary capital risk factors demonstrate extremely negative returns (i.e., suggesting constraints). In periods when these equity portfolios earn positive returns, intermediary capital risk factors are positive.

These three aggregate patterns suggest that (a) hedge fund borrowing is procyclical with broker health *in aggregate*, (b) equilibrium margin quantities are procyclical to the equity markets, and (c) equities more exposed to hedge funds perform poorly when aggregate broker health is poor. However, these aggregate patterns cannot ascertain whether broker health actually (ever) affects equities prices via their lending to hedge funds.

4 Simple Model and Empirical Design

We introduce a model of hedge fund borrowing dynamics from broker-dealers, which provides testable predictions regarding the conditions under which broker-dealer shocks may disrupt hedge fund investments. This framework, inspired by the prime brokerage funding pressures observed following the collapse of Lehman Brothers in 2008 (see Giannone [2009]), operates through broker-dealers' funding costs and associated risks, shedding light on the potential vulnerability of hedge funds to disruptions in their prime brokerage relationships.

4.1 Model

To fix ideas, we present a model of a fund borrowing from multiple brokers. Hedge funds have mean-variance preferences over the the returns on their levered asset and the cost of credit provision by the broker sector.

Based on their health, brokers offer different loan supply terms, modeled as the interest rate that they offer on a loan. This interest rate proxies for explicit financing rates, haircuts, and quantity terms that brokers are known to set. However, funds believe that credit supply is risky, namely that there is some chance that the cost of funding from the broker might be different than the rate implied by the contemporaneous broker health. In reduced form, this risk term captures many real risks associated with brokerage, including explicit costs from a broker-dealer's health deteriorating (increased spreads or transition costs to other broker-dealers) and implicit costs (the possible portfolio impact of losing credit access). Importantly, this friction generates non-zero borrowing quantities from multiple brokers. In this model, this risk term governs the capacity for funds to substitute between two broker-dealers.

To motivate our empirical tests, we compare predictions for the case where broker-dealers have purely uncorrelated health with the case where health is correlated. Our correlated case represents periods in which distress might spread across multiple brokers, such as when there is contagion.[29] In both cases, hedge funds substitute to non-directly shocked broker-dealers when a broker's health deteriorates. However, in the latter case, the extent of substitution is further dampened by the effect of health on indirectly shocked brokers' health. In the limit, we find that funds can perfectly substitute away uncorrelated shocks but cannot substitute away correlated shocks.

4.1.1 Simple Model with Uncorrelated Borrowing Costs

We consider a hedge fund that can borrow from two brokers, A and B.

Broker Problem: Brokers set the rate at which they charge funds for a unit of leverage (P_i) based on their expected marginal cost, determined by the broker's current financial health and a stochastic cost factor. The borrowing costs are given by:

$$P_A = D_A + \varepsilon_A \quad \text{and} \quad P_B = D_B + \varepsilon_B \tag{2}$$

where D_A and D_B represent the marginal cost of a unit of funding based on the level of bank distress, and ε_A and ε_B are independent stochastic components with mean zero and variance σ^2. In this model, the stochastic cost factor generates non-corner solutions by introducing a motive for funds to diversify away this risk. Fixing broker-level distress, costs are linear.

Hedge Fund Problem: Hedge funds have a simplified mean-variance optimization problem. The hedge fund leverages its capital by borrowing from multiple brokers to invest in a risky asset that provides a return $R \in \mathcal{N}(E[R], \sigma_R^2)$. As bank-level borrowing is costly and risky, the hedge fund chooses how much to borrow from broker A (L_A) and B (L_B) by maximizing:

$$U(L_A, L_B) = \mathbb{E}[R_L] - \frac{\lambda}{2} \cdot \text{Var}(R_L) \tag{3}$$

where λ is the risk aversion coefficient and R_L is the levered return net of borrowing costs:

$$R_L = R_L' - C(L_A, L_B) \tag{4}$$

where R_L' is the return on the levered investment

$$R_L' = R \cdot (1 + L_A + L_B) \tag{5}$$

[29] In our main experiment, we study spillovers along the line of sympathetic contagion in which we believe that certain brokers observe health spillovers based on investors extrapolating along business models.

and the cost associated with the borrowing is:

$$C(L_A, L_B,) = L_A \cdot (D_A + \varepsilon_A) + L_B \cdot (D_B + \varepsilon_B). \tag{6}$$

where P_i is the (expected) cost to borrow one unit from broker i and ε_i is the disturbance term above.

Optimal Borrowing Quantities: To solve the model, we begin by taking the first-order conditions. We find that the total borrowing from each bank i is given by:

$$L_i = \frac{1}{\lambda \cdot (\sigma_R^2 + \sigma^2)} \left(\underbrace{\mathbb{E}[R] - D_i}_{\text{Risk-adjusted financing spread}} - \underbrace{\lambda \cdot \sigma_R^2 \cdot (1 + L_{-i})}_{\text{Borrowing Risk Trade-off}} \right) \tag{7}$$

The first term represents the risk-adjusted financing spread. Hedge funds will borrow more from a broker when the expected cost of financing is lower due to distress, as a higher spread between expected returns and financing costs makes borrowing more attractive.

The second term reflects the borrowing risk trade-off. With mean-variance utility, higher borrowing levels from broker $-i$ increase the marginal risk associated with borrowing an additional dollar from broker i. In other words, as borrowing from one broker increases, the additional risk from borrowing more from the other broker increases due to the combined effect of return volatility and borrowing size.

Comparative Statics: To understand equilibrium borrowing in response to higher levels of distress, we re-compute the steady state if broker A's distress increases, i.e. $\partial D_A > 0$. By solving the system of linear differential equations, we find:

$$\frac{\partial L_A}{\partial D_A} = \frac{-(\sigma_R^2 + \sigma^2)}{\lambda \sigma^2 (2\sigma_R^2 + \sigma^2)} \tag{8}$$

$$\frac{dL_B}{dD_A} = \frac{\sigma_R^2}{\lambda \cdot \sigma^2 \cdot (2\sigma_R^2 + \sigma^2)} \tag{9}$$

These expressions predict that borrowing from broker A decreases while borrowing from broker B increases. In particular, the degree of substitution towards broker B is inversely related to σ^2, implying that higher levels of broker risk diminish the willingness of funds to substitute borrowing between brokers. Total borrowing unambiguously declines:

$$\frac{\partial L_{tot}}{\partial D_A} = \frac{-(\sigma^2)}{\lambda \sigma^2 (2\sigma_R^2 + \sigma^2)} \tag{10}$$

To understand why total borrowing declines, the initial conditions $D_A = D_B$ are fixed. In a model with no diversification motive or substitution frictions, funds would only borrow from broker B after distress from broker A. However, in this model, broker concentration risk (σ^2) breaks perfect substitution as funds balance the cost of funding with their disutility of concentration. The extent of substitution is determined by σ^2.

4.1.2 Simple Model with Correlated Health

We can trivially adjust this model to study correlated health events, considering the possibility that distress to one broker might affect the funding decisions of another broker.[30] These shocks are broader than idiosyncratic broker shocks; however, unlike standard aggregate shocks, they generate predictions about how cross-sectional differences in broker health impact total borrowing. Without lost of generality, broker B's cost curve is set as:

$$P_B = D_B + \rho D_A + \varepsilon_B \tag{11}$$

where $\rho \in (0,1)$ is the impact of broker A's health on broker B. The environment otherwise remains the same. Solving for the optimal demand of credit, the optimal loan quantity from B is now:

$$L_B = \frac{\mathbb{E}[R] - D_B - \rho D_A - \lambda \cdot \sigma_R^2 \cdot (1 + L_A)}{\lambda \cdot (\sigma_R^2 + \sigma^2)} \tag{12}$$

which is is identical to Equation 7 except for the direct impact of broker A's distress level on broker B's cost (ρD_A). Since loan supply is determined simultaneously when lending changes, we observe different responses to a shock to broker A's health:

$$\frac{dL_A}{dD_A} = \frac{\rho \sigma_R^2 - \sigma^2 - \sigma_R^2}{\lambda \left(2\sigma^2 \sigma_R^2 + \left(\sigma^2 + \sigma_R^2\right)^2\right)} \tag{13}$$

$$\frac{dL_B}{dD_A} = -\frac{\rho}{\lambda(\sigma_R^2 + \sigma^2)} - \frac{\sigma_R^2}{\sigma_R^2 + \sigma^2} \cdot \frac{\rho \sigma_R^2 - \sigma_R^2 - \sigma^2}{\lambda(\sigma_R^2 + \sigma^2)^2 + 2\lambda \sigma_R^2 \sigma^2} \tag{14}$$

[30] Our correlated events framework could also be used to study aggregate shocks with broker-level heterogeneous exposures.

Due to the correlated health effects, we observe that borrowing responses from both brokers adjust. In the context of this paper, the more important change lies with the non-directly shocked broker's health response. For broker B, we observe that the first term $-(\frac{\rho}{\lambda(\sigma_R^2+\sigma^2)})$—which represents broker B's increased broker funding cost due to the correlated health—is unambiguously negative while the second term representing the substitution motive is positive. The relative dominance of these two terms will determine whether borrowing from broker B increases in response to broker A retracting credit supply.

4.1.3 Model Propositions with Many Brokers

In the simple two-broker case, we observe that hedge funds cannot perfectly substitute away from broker distress. As large hedge funds on average borrow from 4.6 prime brokers, we now generalize our model to N brokers and study the asymptotic limiting behavior. For simplicity, we consider N brokers where broker A sets prices at

$$P_A = D_A + \varepsilon_A \tag{15}$$

For the uncorrelated health case, each broker $i \in B - N$—which we study as the non-directly shocked brokers—shares common health:

$$P_i = D_b + \varepsilon_i \qquad \text{(no spillover case)}$$

where D_b sets the initial mean level of distress to the same level for all brokers.[31] For the correlated health case, we assume:

$$P_i = D_b + \rho D_a + \varepsilon_i \qquad \text{(spillover case)}$$

In Appendix B, we directly solve for equilibrium quantities and comparative statics, which generates two key propositions:

Proposition 1. *Taking N to infinity, funds can perfectly substitute away from broker distress as* $\frac{dL_{tot}}{dD_A} \to 0$ *if* $\rho = 0$.

Proposition 2. *Taking N to infinity, funds cannot substitute away from broker distress as* $\frac{dL_{tot}}{dD_A} \neq 0$ *if* $\rho > 0$.

As we know that funds borrow from a finite number of brokers, we also ask whether or not the behavior in the data is well approximated by the limiting behavior.

[31] This assumption helps to generate analytical solutions.

4.2 Empirical Design

4.2.1 Ideal Specifications

Our model predicts how shocks propagate from broker-dealers to hedge funds, depending on the extent to which hedge funds are diversified across primer brokers. By "well diversified," we refer to hedge funds' ability to spread their borrowings across multiple primer brokers,i reaching the limit of full diversification as suggested in Section 4.1.3.

We test a credit supply in the cross-section, whereby our model provides clear, testable implications for the cross-sectional impact of broker health shocks. The core of our analysis relies on natural experiments and event studies, which allow us to isolate shocks to broker-dealers and observe their effects on credit supply, helping to address concerns about confounding demand-side effects. Additionally, since broker health events are relatively infrequent, we observe limited cross-sectional variation in most quarters when conducting panel analyses. The general structure of our experiments and empirical tests follows a common pattern, as described below.

When a shock to broker-dealer health occurs, we first validate that the affected (treated) brokers on aggregate reduce their credit supply during the event study. This can be conducted at either the broker or aggregate level. Ideally, one would test:

$$\Delta PBL^b = \alpha + Distress^b + \varepsilon^b \tag{16}$$

where $Distress^b$ is the broker-level distress measurement and PBL^b is the fund representative fund's prime brokerage borrowing from bank b. Our model suggests a clear cross-sectional test to identify the effect for the representative fund:

$$\Delta PBL^{f,b} = \alpha + \beta Distress^b + \varepsilon^{f,b} \tag{17}$$

Yet, in the data, there are many funds and, in our event study shock framework, $Distress^b$ will a discrete indicator variable for whether or not a broker is considered "shocked." As is common in the literature, one would ideally control for each fund's common demand via a Khwaja and Mian [2008] estimation strategy:

$$\Delta PBL^{f,b} = \alpha_f + \beta BorrowFromTreatedBroker^{f,b} + \varepsilon^{f,b} \tag{18}$$

where $BorrowFromTreatedBroker^{f,b}$ is an indicator variable for if fund f borrows from broker b and broker b is consider distressed while $PBL^{f,b}$ is the prime brokerage borrowing quantity from fund f and broker b. The fund fixed effect α_f controls for fund-level factors, namely common hedge fund demand. A negative coefficient for β suggests that on average the treated brokers reduced their credit supply.

Next, one would want to ascertain whether hedge funds' total borrowing decreases by estimating:

$$\Delta PBL^f = \alpha + \beta BorrowFromTreatedBroker^f + \varepsilon^f \tag{19}$$

where PBL^f represents total fund-level borrowing. $BorrowFromTreatedBroker^f$ is an indicator variable for if a fund f borrows from any broker considered distressed in that period of time. A negative β indicates that hedge funds did not fully substitute away from the affected brokers, implying that the credit supply shock had a significant impact on total borrowing. Conversely, a coefficient near zero would imply that hedge funds could fully diversify their borrowing and offset the shock.

If the shock leads to a contraction in prime brokerage lending without sufficient substitution, we then examine the subsequent impact on equity prices. To investigate this, using the regulatory data, we first validate that hedge funds' equity holdings decline:

$$\Delta Equity^f = \alpha + \beta BorrowFromTreatedBroker^f + \varepsilon^f \tag{20}$$

4.2.2 Possible Specifications

Unfortunately, due to public data limitations, we cannot test Equations 18 and 19 as there are no public fund-level prime brokerage datasets. However, there are publicly available datasets for broker credit supply and hedge fund manager equity holdings, so instead we test versions of Equations 16 and 20. We take our broker-level credit supply proxy from FR Y-9C Bank Holding Company Datasets,"Loans for the Purchase or Carrying of Securities."[32] This series includes hedge fund margin loans at the broker level. To measure equity holdings, we study manager-level equity holdings constructed from FactSet Ownership 13-F filings.

4.2.3 Event Studies: Identification and Inference

Identifying the pass-through of broker health to equity prices via prime brokerage credit supply requires cross-sectional shocks to large broker-dealers that (a) impact their financial health and (b) are unlikely to correlate with other fundamentals. To find candidate shocks, we take a narrative

[32] One limitation of this approach is that non-US broker-dealers only began systematically filing these reports in late 2016.

approach. In Appendix C, we identify a set of potential shocks to the bank holding companies of major prime brokers by gathering events including (a) near-default scenarios, (b) significant one-time losses, and (c) regulatory fines. We classify these as shocks by conducting CDS spread change event studies to determine whether each announcement was unexpected. Related losses or events are grouped together accordingly.

From this approach, we focus on the "largest" shocks—the European broker-dealer distress in Q1 2016 and the losses associated with the collapse of Archegos in the first half of 2021. These two events stand out in the sample period due to the total magnitude of losses experienced by the impacted brokers, the critical nature of these losses for the broker-dealers, and the market's reaction to them. These two events also represent the only plausibly exogenous multi-broker distress events in the sample.

Our analysis is structured around detailed narrative event studies for these two shocks. For these event studies, we trace out the impact of the health shock on lending, hedge fund equity holdings, and then prices. Thereafter, we provide additional analysis of how broker-dealer distress—proxied by CDS spread changes—affects hedge funds.

The first experiment examines the contraction of prime brokerage lending by distressed European brokers in early Q1 2016, triggered by large reported losses and default concerns. The second experiment explores the contraction of prime brokerage credit following the Archegos defaults. These shocks are comparable in several respects, given that both involved significant capital losses (roughly \$10 billion) and clear treatment groups for broker-dealers. Based on available data, both experiments led to large contractions of credit by the shocked broker-dealers compared to other broker-dealers.

However, despite the similarities between the shocks, we find very different equilibrium effects on total equity holdings in these two cases. In Section 6.3, we provide evidence that these shocks crucially differ in the extent to which the health metrics of non-directly shocked broker-dealers also deteriorate.

5 European Broker Distress in Q1 2016

In early 2016, a set of leading European banks became distressed as concerns emerged over their asset quality and ability to raise market-based funding, triggered by idiosyncratic asset shocks at two major European banks (Bank for International Settlements [2016]). As investors grew worried about one of the bank's ability to repay its subordinated debt (AT1 capital), some—but not all—other European G-SIBs saw their market health indicators deteriorate following these announcements. These distressed G-SIBs—directly and indirectly affected—contracted credit during this period.

First, we introduce our shock and treatment groups, before studying the credit supply reaction and showing imperfect substitution. Finally, we highlight asset pricing implications.

5.1 Evidence of Shocks and Contagion

5.1.1 Direct Broker Shocks

Deutsche Bank: From Q4 2015 to Q1 2016, Deutsche Bank faced a series of negative health shocks, first concerning the quality of its assets and then later its ability to repay its liabilities. In Q4 2015, Deutsche Bank reported a "record net loss" of 6.0 billion Euros, announced on October 29 as part of its "Strategy 2020" restructuring. In this period, Deutsche Bank conducted an "impairment test" identifying over 5.8 billion Euros of assets to be impaired, namely the anticipated disposal of Postbank (its German retail bank) and Hua Xia Bank (a Chinese commercial bank in which it had significant exposures). Deutsche Bank also attributed these impairments to changing regulation, namely "higher expected regulatory capital requirements." In its end-of-year reports on January 20, 2016, Deutsche Bank confirmed larger-than-expected end-of-year losses of 6.7 billion Euros. However, in the following weeks, investor concerns expanded to include not only Deutsche Bank's assets but also its liabilities.

On January 28, 2016, concerns emerged over Deutsche Bank's ability to repay its subordinated debt, as a key source of wholesale funding for the bank. During a media conference on that date, Deutsche Bank's management directly addressed the possibility that it might not be able to repay its debt, although they argued that "we expect sufficient capacity to service AT1 coupons" (Cryan [2016]). Despite this reassurance, market participants reacted with heightened concerns about the bank's likelihood of missing future payments (see Glover [2016]), further amplifying worries about Deutsche Bank's financial stability. These concerns intensified throughout the following month, prompting additional communications on February 8 regarding the bank's ability to service its debt, and culminating in attempts to repurchase its debt on February 23.

Credit Suisse: Deutsche Bank was not the only major institution facing significant financial challenges with large-scale impairments during this period. On February 4, 2016, Credit Suisse reported substantial asset impairments from its acquisition of an American investment bank during the dot-com bubble more than fifteen years earlier, amounting to nearly 9% of its total market net worth. These two events represent the largest quarterly write-downs among banks with large broker-dealers covered by regulatory data. [33]

[33] We define large prime brokers based on the number of Form ADV prime brokerage relationships, whereby a broker is considered as large if it ever features in the top ten most common counterparties in a quarter.

5.1.2 Spillovers and Sympathetic Contagion

The concerns surrounding these banks highlighted vulnerabilities across the financial system, raising fears of broader contagion effects, especially among banks with similar asset and liability characteristics as the directly shocked banks. To highlight this, Figure 5 plots the change in CDS spreads—a widely used measure of funding costs and financial distress—for a select group of European G-SIBs, alongside the average for this group. Several important patterns emerge, whereby most notably the banks directly affected by the shocks saw significant increases in their CDS spreads following the announcements. Deutsche Bank in particular experienced a sharp rise in its CDS spread, which reached levels not seen since the Lehman Brothers collapse.

Additionally, we observe that many brokers experienced a rise in their CDS spreads after Deutsche Bank's media conference on January 28, even if they were not directly affected by asset shocks. This increase was seen both within the group of European G-SIBs and in the broader market. For example, following Credit Suisse's announcement on February 4, Barclays saw a 21-basis-point increase in its spread, while RBS/NatWest experienced a 19-basis-point rise, almost matching the impact on Credit Suisse.

The fact that banks not directly exposed to the shocks still saw significant increases in CDS spreads suggests broader market spillovers. This indicates that investor concerns extended beyond the banks directly hit by asset quality shocks and default concerns, leading to contagion effects throughout the financial system. One potential channel for these spillovers is sympathetic contagion, as described in Deutsche Bank's 2015 annual report: "Negative developments concerning other financial institutions perceived to be comparable to us and negative views about the financial services industry in general have...affected the prices at which we have accessed the capital markets" In this case, investor worries spread beyond Deutsche Bank and Credit Suisse, affected other European banks perceived to be similarly at risk.[34] Since European G-SIBs strongly rely on market-based financing for their dollar operations, these market pressures could directly constrain their lending activities.

To empirically study spillovers, we consider CDS responses by non-directly shocked brokers to distress from the directly shocked brokers, defined in two ways. First, we compile a list of key event announcements related to negative news about the directly affected broker, as shown in Table 4. These announcements include the main subordinated debt announcements proposed by Gleason et al. [2017] as well as Credit Suisse's announcement on February 4. We then aggregate the one-day CDS spread changes following these events, which captures other brokers' response

[34]Notably, media sources such as Rennison and Jackson [2016] reported that investors were actively purchasing CDS protection due to "anxiety about the health of Europe's banks" and concern over "European banks' junior debt."

to these news events. Second, we study the cumulative CDS spread changes between Deutsche Bank's first subordinated bond announcement on January 28 and its first CDS peak on February 9. This approach includes three announcements from Table 4 but also considers CDS movements outside of these windows, accounting for potential market speculation and precautionary responses to uncertainty.

Appendix Table 23 reports the cumulative CDS spreads under both sorting methods, whereby we observe three main patterns. First, the five brokers with the highest CDS spreads consistently include the same set of European G-SIBs, including the two directly shocked banks: Deutsche Bank, Credit Suisse, Barclays, RBS (NatWest), and Credit Agricole. Second, there is substantial variation in which brokers experience significant CDS spread increases outside of these five, depending on the sorting method used. Third, we observe considerable spillovers to the median broker: under the event-based sorting, the median broker saw a twelve-basis-point increase in CDS spreads, while under the start-to-peak sorting, the median broker experienced a 33-basis-point increase.

We group these five European G-SIBs—which consistently fall into the top quintile of CDS spreads—as our treatment group. Our model shows that even brokers not directly shocked could reduce their credit supply.

Appendix Section D.1.2 examines the characteristics of the spillover set, finding that the bank holding companies of these broker-dealers (a) are ex-ante less profitable—as measured by their market-to-book ratio—and (b) rely more on lower-tier capital for financing. These characteristics suggest that investors extrapolated from the asset quality of the directly shocked broker-dealers to the reliance of these banks on distressed forms of capital for financing.

5.2 Was There a Credit Supply Shock?

A key step to demonstrate is a clear retraction in credit supply during this period. Unfortunately, there is no dataset covering European broker-dealer activities in the US for this timeframe, as Y-9C coverage only begins in Q3 2016. Fortunately, Kruttli et al. [2022] studied a series of shocks to Deutsche Bank from Q4 2015 to 2016 Q4 that affected its market health. The shocks in the first two quarters—namely Deutsche Bank's impairments and CoCo bond distress—are the same events that motivate our paper. Their study shows three steps: first, they show that Deutsche Bank's aggregate lending declined throughout the period, with a pronounced decrease in Q1 2016; second, they provide evidence that funds substituted away from Deutsche Bank, controlling for fund effects to account for demand, similar to Equation 18; and third, they show that hedge funds brokered by Deutsche Bank contracted their portfolio sizes.

To substantiate the presence of a credit supply shock, we ultimately examine changes in equity holdings by exposed managers. This is effectively a test of the final step in the de-leveraging mechanism discussed in Section 5.3. In this paper, we study the Euro 5 brokers together due to their common shock exposure. In Appendix Section D.2, we provide evidence that non-DB Euro 5 brokers play a significant role in the sell-off. Specifically, we document (a) sell-off pressure being concentrated among managers exposed to both Deutsche Bank and at least one other Euro 5 broker, and (b) differential equity holding patterns between managers who borrow only from Deutsche Bank and those who borrow from at least one of the non-DB Euro 5 brokers.

5.3 Evidence for Equity Market Sell-0ff

To study whether the "Euro 5" shock affects prime broker clients (hedge fund managers) and then asset prices, we link our fund-level portfolio network to FactSet Ownership's security-level holdings. Specifically, we create a cross-walk that connects each hedge fund manager—identified by their SEC filing number—to FactSet's proprietary identifier, based on their FINRA CRD. Since hedge fund managers might oversee multiple funds, we aggregate the fund-level data to the manager level.

5.3.1 Euro 5 Broker Managers' Equities Sold

We examine whether managers exposed to the "Euro 5" shock reduced their equity holdings more than other managers on aggregate. First, we construct the total market value of 13-F holdings for these managers at market value, plotted in the left panel of Figure 6. However, portfolio values change due to both price and quantity changes and, in particular, we want to focus on de-leveraging induced asset sales. To eliminate the impact of the former, we deflate the value of the market portfolio by the hypothetical return on a buy-and-hold strategy where one purchases the aggregate Euro 5 and non-Euro 5 portfolios at time t and holds until $t+1$. Accordingly, this is:

$$Return_t^i = \sum_s ret_{t\to t+1}^s \cdot \frac{MarketValue_t^{s,i}}{\sum_s MarketValue_t^{s,i}} \tag{21}$$

for each group $i \in \{E5, nonE5\}$, where $MarketValue_{t-1}^{s,i}$ is the dollar value of group i's holdings in stock s at time t. We then deflate the total portfolio holdings by this return in the right panel of Figure 6.

In the left panel of Figure 6, we observe that the market value of Euro 5 affiliated managers fell by 12% in Q1 2016, while the market value of non-Euro 5 managers declined by about 6%. While this implies that exposed funds saw their portfolio size decrease, the same is evident for the non-exposed funds. In the right panel, we plot the portfolio size controlling for the returns on the underlying assets. This measure more closely proxies for aggregate sell-off pressure: Euro 5 managers saw their holdings decline by 6% in Q1 2016, while non-Euro 5 managers' holdings remained constant, implying that on aggregate these managers did not sell-off.

In order to ascertain whether the sell-off holds for the average fund manager as well for the aggregate hedge fund manager sector, we construct two distinct measures of equity holding size derived from the holdings data:

$$MarketPricePort_t^m = \sum_s Price_t^s \cdot SharesHeld_t^{m,s} \tag{22}$$

$$StalePricePort_t^m = \sum_s Price_{2015q4}^s \cdot SharesHeld_t^{m,s} \tag{23}$$

where *Price* is the security-level price at the respective time, and $SharesHeld_{2015q4+\tau}^{m,s}$ represents the number of shares held at time $2015q4+\tau$. We then compute the respective log-difference. The subscript m refers to an individual manager and s refers to an individual stock. The first measure computes the change in 13-F holdings for a manager, incorporating variations due to price changes of the underlying securities. The second measure—the stale price portfolio—fixes prices at the pre-period level and calculates changes based solely on the number of shares held. We then regress:

$$\Delta \ln(Port_{2016q1}^m) = \alpha + \underbrace{\beta}_{<0} BorrowsFromTreated^m + \varepsilon_{2016q1}^m \tag{24}$$

for $Port \in \{MarketPricePort_{2016q1}^m, StalePricePort_{2016q1}^m\}$.

Table 5 reports the estimates for these regressions, for both market price portfolios (Columns 1-3) and stale price portfolios (Columns 4-6). In Columns (1) and (4), we observe that this relationship holds across the full sample of managers. When restricting the sample to larger managers—those managing at least \$500 million (Columns 2 and 5) and \$1 billion (Columns 3 and 6)—-the magnitude of the effect increases, and the statistical significance becomes more pronounced, suggesting that we identify a cleaner effect. Importantly, the results are particularly robust for the stale price portfolios, where the estimates exhibit greater magnitude and statistical significance. This highlights the persistence of the sell-off effect, especially when eliminating variation driven by price changes.

5.3.2 Stock-Level Exposure and Abnormal Sell-Offs

As our ex-ante treatment variable from the credit supply regressions predicts manager-level sell-offs in the holdings data, we turn to study the performance of stocks more exposed to the distressed broker-dealers. For this purpose, we first need to construct stock-level exposure measures to distressed broker-dealers. Our main measure is:

$$Euro5MktShare^s_{t-1} = \sum_{m \in M_{t-1}(s)} MktShareHFs^{s,m}_{2015q4} BorrowsFromTreated^m \tag{25}$$

where $BorrowsFromTreated^m$ is defined as in the previous sections and $MktShareHFs^{s,m}_{2015q4}$ is the percentage of total shares in stock s outstanding held by manager m at the end of 2015. Under this measurement, a stock is more exposed to the shock if a greater proportion of the stock's shares outstanding are held by hedge fund managers with at least one Euro 5 broker relationship.

To assess the validity of this exposure measure, we directly test whether our security-level exposure measure predicts abnormal security-level sell-offs by those managers. In a stock-level panel from 2014-2020, we estimate:

$$\Delta Euro5MktShare^s_t = \alpha_t + \alpha_f + \beta Euro5MktShare^s_{t-1} + \beta_2 Euro5MktShare^s_{t-1} \times \mathbf{1}_{1=2016q1} + \varepsilon^s_t \tag{26}$$

where $\Delta Euro5MktShare^s_t$ is the change in market share of a stock exposed to the European broker-dealer distress via its counterparty network, and $Euro5MktShare^s_t$ is its lagged market share. As hedge fund managers frequently rebalance their portfolios, we control for mean reversion at the security level by estimating the β coefficient for our exposure measure for all quarters in the panel. With this control, β_2—the coefficient of the interaction term for our security-level exposure measure and the quarter of distress—measures the abnormal sell-off or turnover intensity.

In Column (1) of Table 6 we observe that in Q1 2016, for a one-percentage-point increase in the ownership stake of the shocked funds in a stock, there is a corresponding 0.0938 percentage point increase in the market share of that stock being sold by these funds on average. However, this effect conflates the normal rebalancing behavior of hedge funds with potentiall credit supply-induced sell-offs. To address this, we calculate the abnormal sell-off in Columns (2)-(5) of the panel, incorporating industry- and time-fixed effects. In Column (5), we find that on average hedge funds sell-off 0.0558% for each additional percentage point of holdings in a typical quarter, whereby the abnormal sell-off is -0.0440%, or about 80% above the average sell-off.

5.4 Evidence of Equity Price Impact

We now test whether stocks that are more ex-ante exposed to the Euro 5 brokers—and hence more likely to be sold off—perform worse. To investigate this, we regress realized returns on ex-ante exposure measures. Our baseline specification is the following regression:

$$ret^{s}_{2016q1} = \alpha + \beta Euro5MktShare^{s}_{2015q4} + X^{f} + \varepsilon^{s}_{2016q1} \tag{27}$$

where $ret^{s}_{t \to t+1}$ can be raw returns as well as returns residualized against the capital asset pricing model (CAPM) and the Fama-French three-factor model plus momentum (FF3+UMD). Our control set includes both industry fixed effects and the non-Euro 5 exposed hedge fund share. Standard errors are clustered at the three-digit SIC industry-code level.[**Table 7 approximately here**]

Table 7 reports the estimates for Equation 27. In Columns (1)-(3), we regress raw returns on our ex-ante return measures. In Column (1), we find that a stock that is one percentage point more exposed to the distressed broker-dealers has a roughly 40 basis point lower return. The point estimates are statistically significant and stable in order of magnitude. Controlling for the non-Euro 5 hedge fund share reduces the point estimate by about 15%. With this in mind, hedge fund exposures are not randomly assigned. To account for this, we residualize returns against standard factor models. In Columns (4)-(7), we regress residualized return from the CAPM and the Fama-French three-factor model plus momentum on the exposure measure. Our results are almost comparable to the estimates for non-residualized returns, implying that the variation identified is not driven by these factor exposures.

Our shock is ultimately a shock to levered investors. The betting-against-beta (BAB) factor by Frazzini and Pedersen [2014] is commonly perceived to measure sensitivity to leverage constraint changes for investors. Therefore, we residualize returns in Columns (8) and (9) to understand whether we are picking up common variation to this factor here. Again, our point estimates remain stable.

In Appendix Table 25, we confirm that the negative relationship observed between stock returns and exposure during this quarter is largely attributable to sell-offs, whereby this relationship remains robust even when controlling for other institutional sell-offs during this period. Specifically, in Column (2), we estimate that a one-percentage-point increase in realized sell-offs corresponds to a decrease in the stock's return by 2.894 percentage points. This effect size is larger than the typical micro-elasticity estimates found in the literature, such as those reviewed by Gabaix and Koijen [2021], although it remains within a similar order of magnitude. This higher estimate likely reflects that the shocks in question affect the primary arbitrageurs within these markets, leading to more pronounced sell-off effects.

5.4.1 Addressing Main Identification Threats

While standard factor exposures fail to account for our findings, several identification threats remain. Primarily, there is a possibility that this intermediary shock influenced asset prices through alternative channels. The first concern is that the shock might have also affected other institutional investors, who could be the actual drivers behind the observed price effects. The second concern is that the affected brokers might have had direct holdings of the securities or lending relationships with the the firms that underperformed, which could independently contribute to the observed declines in asset prices. Both concerns ultimately relate to the notion that Euro 5 hedge fund manager exposure measure might be correlated with another investor type.

To address the first concern, we construct stock-level exposures to institutional investors associated with these identification classes and run the following regression:

$$ret^{s}_{2016q1} = \alpha + \beta_1 Euro5MktShare^{s}_{2015q4} + \beta_2 StockExposure^{s,i}_{2015q4} + \varepsilon^{s}_{2016q1} \tag{28}$$

where $StockExposure^{s,i}_{2015q4}$ includes (a) the broker-dealer share, (b) the FactSet investment adviser share (an aggregate of non-discretionary levered and non-levered investment advisers, including mutual fund managers), and (c) the total institutional share excluding Euro 5 affiliated hedge funds.

Table 8 shows that across all three institution types, the point estimate on Euro 5 connected manager exposure remains significant and remarkably stable. Second, for the set of other institutional controls that are significant (for investment advisers and overall institutional shares), we find that relationship between returns and exposure is actually positive. We can conclude that there is limited evidence that the institutional share drives the relationship between Euro 5 brokered hedge fund exposure and returns.

Our second concern is that securities that performed poorly in this period are associated with firms disproportionately exposed to the shocked bank holding companies. This could occur through either (a) lending relationships or (b) equity exposure by associated investors. If hedge funds borrowing from these broker-dealers hold positions in the directly affected firms, our estimates could conflate the direct effect with our intended channel.[35] To address this concern, we estimate Equation 28 for investor shares explicitly related held by the Euro 5 bank holding companies and syndicated loan exposure to the Euro 5. For investor shares, we first control for

[35] Kumar et al. [2020] suggests that hedge funds connected to broker-dealers gain access to private information about the corporate strategies of the bank holding companies to which they are linked, which could induce a joint exposure measure.

FactSet-identified broker-dealers associated with the Euro 5, followed by controlling for all FactSet managers linked to the Euro 5. Next, we construct firm-level syndicated loan exposures. First, we estimate a dummy variable indicating whether a firm has had a lender relationship in the syndicated loan market over the past five years. Second, we create a continuous measure of total outstanding loans attributable to our treatment group, scaled by firm assets over the same period.

Table 9 reports the estimates. Our baseline estimates remain statistically significant, negative, stable, and of comparable magnitude to our estimates without controlling for direct exposure. Of the twelve robustness specifications, we only estimate a negative effect for the Euro 5 broker-dealer sector against the Fama-French 3 + Momentum model, and even then we do not estimate a meaningful effect on our point estimate.

5.4.2 Stock Prices Eventually Reverse

Without the release of any fundamental news or a permanent shock to intermediary capital, other investors should ultimately step in to arbitrage away any temporary mispricings. To test this, we study the impact on abnormal cumulative arithmetic returns. Since we are interested in reversions, we move from the quarterly (the frequency of the holdings data) to the monthly panel and examine two distinct specifications:

$$cumret^{s}_{2015m12+\tau} = \alpha + \beta Euro5MktShare^{s}_{2015q4} + \varepsilon^{s}_{2015m12+\tau} \tag{29}$$

for $\tau \in [-9, 9]$. We consider four different measures of cumulative returns: raw realized returns, BAB residualized returns, CAPM residualized returns, and Fama-French 3 + Momentum residualized returns.

In Figure 7, we plot the coefficients for Equation 29. In the top-left panel, we observe that securities more commonly held by Euro 5 hedge funds experienced abnormally negative returns in both January and February. In March—after the main incidence of the shock—the cumulative returns relationship stabilizes, and a reversion begins, after which returns continue to revert in April 2016. In the other panels, we find similar patterns for the three residualized return measures, whereby returns decrease through February and then begin to revert. In three specifications, statistical reversion occurs in April, although the point estimate reversion is delayed for the CAPM and Fama-French 3 + Momentum residualized returns. These findings suggest that while the shocks are transient, they exhibit a relatively prolonged duration, requiring approximately four months for arbitrage to fully correct any mispricings.

5.5 Non-Levered Investors Absorb the Shock

In order to determine who buys when the Euro 5 set of brokers sells, conditioning on securities that Euro 5 hedge funds in aggregate sold off, we study which of the following investor groups increase their positions: hedge funds without a relationship with the Euro 5 (nonEuro5 HFs), FactSet-classified broker-dealers (Brokers), FactSet-classified investment advisers that are not Form ADV-identified hedge funds (Inv Adv), or the FactSet household sector (Households).[36] To examine statistical significance, we estimate:

$$\Delta MktShare^{i,s}_{2016q1} = \alpha + \beta \Delta Euro5MktShare^{s}_{2016q1} + \varepsilon^{s} \tag{30}$$

where i refers to the institutional types described above.

We present the coefficient estimates for Equation 30 in Table 10. In Columns (1) and (2), we report estimates of the portfolio changes by the aggregated non-Euro 5 hedge fund sector and the broker-dealer sector, the other main levered investor classes. In Column (1), we observe that for a security with an additional one percentage point of sell-off by the Euro 5 hedge fund sector, non-Euro 5 hedge funds increase their holdings on average by 0.1 percentage points. We do not find a statistically significant pass-through to broker-dealers. Instead, we find that over 90% of the sell-off appears to be absorbed by the FactSet household sector and other non-levered investor groups, with the bulk absorbed by the household sector.

These results are both interesting and unexpected. A priori, one might anticipate that other levered investors—represented in Columns (1) and (2)—would be the primary absorbers of these shocks, given their generally more flexible balance sheets, higher price elasticity, and lower risk aversion relative to other investor classes. However, we do not find a quantitatively large absorption effect among these groups.[37] Instead, our findings indicate that the sell-off is primarily absorbed by the household sector and the aggregated non-levered investment adviser sector. Given these observed quantity patterns, it is unsurprising that we observe a significant price impact associated with the sell-off. This finding aligns with traditional theoretical literature (He and Krishnamurthy [2013], Brunnermeier and Sannikov [2014]) and recent empirical studies estimating demand elasticities (Koijen and Yogo [2019], Koijen et al. [2023]), both of which predict substantial price effects when less elastic, non-levered investors absorb the sell-off.

[36] We define the household sector for a security as the difference between the total FactSet institutional sector holdings and the shares outstanding, as in Koijen et al. [2023]. This means that the household sector includes retail investors and institutional investors who do not file 13-F filings.

[37] The reason why other hedge funds do not absorb more of the sell-off is not immediately clear.

5.6 Other Effects

In the Appendix, we present additional results relating stock-level exposure to broker distress and various firm outcomes. We test for possible real effects by exploring issuance changes in terms of changes in equity issuances, buybacks, or debt issuance. We find no evidence of real effects in Table 26.

6 Archegos

In late March 2021, Archegos Capital Management—a large family office—collapsed after facing significant margin calls on its total return swaps. Nine major counterparties were exposed, and the disorderly liquidation resulted in five broker-dealers incurring losses exceeding $10 billion, as detailed in Table 11. Several brokers—including Nomura and Credit Suisse—experienced losses so severe (around 15% of their pre-shock net worth) that they exited the prime brokerage market altogether (Arons et al. [2021], Halftermeyer [2021]). The realization of these losses predominantly occurred in April 2021.

This credit supply shock was substantial as these shocked broker-dealers accounted for about 24% of the total investor loan share in 2020q4. We document that hedge funds appear to have diversified away from this large credit supply shock.[38]

6.1 Credit Retraction: Aggregate and Broker-Level Evidence

We analyze the Y-9C investor loan series to study the extent to which broker-dealers exposed to Archegos cut back on credit. Four of the six banks that suffered losses filed Y-9C reports with non-zero investor loans: Credit Suisse, Mizuho Financial Group, Morgan Stanley, and UBS.[39]

6.1.1 Cross-Sectional Credit Provision Evidence

We now test the broker-level credit reaction in the Y-9C data. At the broker level, we regress

$$\Delta ln(InvestorLoans^{b}_{2021q1\rightarrow 2021q2}) = \alpha + \beta ArchegosLosses^{b} + \varepsilon \tag{31}$$

where *ArchegosLosses* is a dummy that takes the value of one if a broker experienced losses to Archegos.

[38]This event study has two significant identification concerns: first, one of the shocked brokers saw large losses due to their investment in Greensill a few weeks before the Archegos event in 2021; and second, since these losses originated in the prime brokerage wing, they are not exogenous, and we might expect a larger-than-expected response. While these concerns are legitimate, both bias us towards finding stronger effects than those that truly exist. However, our ultimate result here is a null result.

[39]Foreign bank holding companies are not legally required to report loans not made in the US.

Table 8 presents estimates from this regression. In Columns (1)–(3), we estimate Equation 31 using the set of all Form ADV prime brokers in the Y-9C data. In Column (1), we find that broker-dealers who suffered losses due to Archegos reduced their growth rate of log lending by 0.293. One concern is that the relationship might be only driven by the broker with the greatest quantity of losses—Credit Suisse. In Column (2), we remove Credit Suisse from the analysis and find that the coefficient size decreases by over one-third but the relationship remains statistically significant. In Column (3), we test whether broker-dealers exposed to Archegos but who did not experience losses also saw decreases in credit provision. With an insignificant and economically small coefficient of around -0.03, this does not appear to be the case. In Columns (4)–(6), we limit our sample to the ten broker-dealers with the most Form ADV relationships in Q1 2021 and find similar results.

6.1.2 Aggregate Credit Provision

In Figure 8, we plot the total lending by broker-dealers by group to ascertain what happened to aggregate credit. While both broker-dealers who suffered losses from Archegos and those who did not behaved similarly in the lead-up, we observe that Archegos-exposed broker-dealers' credit quantities fell by about 17% in Q2 2021, while credit quantities increased for non-Archegos exposed broker-dealers in 2021q2. We also note that total credit provision slightly increased, which implies that aggregate credit conditions remained stable and the aggregate hedge fund sector did not reduce their borrowing.

6.2 Manager-Level Equity Holdings

Thus far, we have ascertained that brokers with Archegos losses saw lower equilibrium lending, although aggregate total lending increased due to offsetting increases by non-shocked brokers. This provides evidence that Archegos was not an aggregate credit supply shock. With this in mind, this might have occurred because borrowers exposed to the shocked brokers switched their borrowing to unshocked brokers—suggesting high degrees of substitution between lenders—or if a different set of borrowers increased their borrowing.

To dis-entangle these two results, we test whether portfolio growth rates differ based on exposure using the sample measures from Section 5.3.1. In the cross-section, we can test:

$$\Delta \ln(Port^{m}_{2021q2}) = \alpha + \beta BorrowsFromTreated^{m} + \varepsilon^{m}_{2021q2} \tag{32}$$

where m is a subscript for an individual hedge fund manager and $BorrowsFromTreated^{m}$ is an indicator variable that takes the value of one if a manager has at least one prime brokerage relationship with a broker-dealer with losses from Archegos exposure. If these results were driven by borrowers not exposed to the Archegos loss banks increasing borrowing, then we would expect β to be less than zero. However, in Table 13, we estimate the coefficient of interest and find an economically zero and statistically insignificant relationship across different portfolio size portfolios and holdings cut-offs. These results suggest that managers exposed to these shocks could fully mitigate their impact by reallocating their borrowing across alternative counterparties. In line with perfect substitution, Figure 9 shows that on aggregate managers exposed to these shocked brokers *increased* their portfolio holdings to a greater extent than other managers.

6.3 Archegos vs Euro 5: Spillovers

While the European broker distress and Archegos events appear similar upon first glance—as described in Section 4.2.3—they exhibit very different aggregate outcomes. In both cases, borrowing from the treated banks declined, although they differ in the extent to which fund-level holdings were affected. One hypothesis to explain this—supported by the model—is that the difference in credit provision by non-directly shocked brokers is determined by their health.

These experiments differ in the response of intermediary health for non-directly shocked brokers, both on aggregate and in the cross-section of untreated broker-dealers. First, market measures for non-shocked banks displayed differential patterns, as measured by CDS spreads. For both experiments, we choose a start date—March 24, 2021 for Archegos and January 27, 2016 for Euro 5—and examine CDS spread changes. In Figure 10, we plot the 25th, 50th, and 75th percentiles of CDS spread changes through the end of the next month, revealing drastically different patterns. After Archegos, the CDS spreads of non-treated brokers do not show significant movement. By contrast, after the European broker-dealer distress period, we observe large CDS spread movements for non-treated broker-dealers, with the median broker-dealer spread peaking at more than a 30-basis-point cumulative change and the 75th percentile peaking at more than a 50-basis-point cumulative change. This suggests that the health of other brokers deteriorated during this period. Furthermore, for the Euro 5 experiment, we show that a significant portion of this pattern occurs during our event windows—as shown in Table 23—implying that spillovers are important in explaining this pattern.

The increase in CDS spreads for non-shocked brokers suggests that aggregate intermediary conditions tightened during the European broker-dealer distress event but not during the Archegos event. Using the measure of intermediary capital in He et al. [2017], we find that aggregate intermediary capital increased from 5.5% in Q4 2020 to 6.4% in Q1 2021 and 6.7% in Q2 2021, while intermediary capital ratios tightened from 6.2% to 5.1% between Q4 2015 and Q1 2016.

To test this, we consider the total broker-level credit provision in the Y-9C data and test whether brokers who became more distressed in these periods but were not directly shocked cut back credit more.[40] To test this, we measure spillovers, proxied by the cumulative CDS spread change for brokers from January 28 to February 9. We then categorize each non-treated broker based on whether its CDS spread changes fall below or above the median. Finally, we test whether broker lending patterns are influenced by either of these broker health measures:

$$BorrOutcome^b = \alpha + \beta CumulativeEuroCDS^b + \varepsilon_{2016q1} \tag{33}$$

$$BorrOutcome^b = \alpha + \beta AboveMedian^b + \varepsilon_{2016q1} \tag{34}$$

where $BorrOutcome^b \in \{\Delta ln(PBL^b), BrokerCut\}$. $BrokerCut$ is a dummy that takes the value of one if a broker's total lending declined in Q1 2016.

We report the results in Table 14. In Column (1), we find that a one-percentage-point increase in CDS spread over these announcement dates is associated with a -0.257 decrease in the log-growth rate of loans. Similarly, in Column (2), we observe that brokers with above-median CDS spread increases have a -0.129 lower log-growth rate for investor loans. In Column (4), we find evidence that brokers with above-median CDS spread increases are more likely to experience negative lending growth rates. Collectively, these results suggest that non-directly shocked brokers—which became more distressed simultaneously with the Euro 5 brokers—had lower lending growth rates, indicating that their credit supply became more constrained.

7 External Validity

Based on our event study evidence, we suggest that the health of brokers not directly affected by shocks is important for the transmission of broker distress to equity markets. To further evaluate this claim, we examine how proxies for broker-dealer health relate to broker lending and hedge fund equity holdings using public regulatory data in Section 7.1.[41] We find evidence that broker-dealer distress affects lending; however, there is no period in which hedge fund managers fail to diversify away from these shocks outside of Q1 2016. In Section 6.3, we find limited evidence in CDS spreads of broad distress—characterized by the deteriorating health of non-directly shocked brokers—occurring to the same extent as observed during the European broker-dealer distress

[40] Unfortunately, most foreign brokers did not file in this quarter.

[41] The regulatory data sample is from 2012 onward and important for studying the cross-section of funds. Form ADV is the only dataset readily available for research that reports a fund's full prime brokerage network.

period.[42]

In Section 7.2, using vendor data, we provide evidence that the Lehman Brothers shock of Q3 2008 exhibited distress characteristics similar to those of the European broker distress shock. We find that the health of non-directly shocked broker-dealers deteriorated, as proxied by CDS markets, and provide narrative evidence of contagion in funding markets. Additionally, we present evidence that hedge funds exposed to more distressed broker-dealers—not limited to Lehman Brothers—experienced lower realized stock returns following Lehman's collapse.

7.1 Public Regulatory Data Panel Results

Are there other periods in the regulatory data sample where hedge fund managers were unable to diversify away from a broker-dealer health shock? To examine this, we first define a proxy for broker-level distress as follows:

$$Distress_t^b = CDS_{t,max}^b - CDS_{t-1,eoq}^b \tag{35}$$

where $CDS_{t,max}^b$ is the maximum CDS spread value in quarter t for a broker and $CDS_{t-1,eoq}^b$ is end of quarter value for that broker at the end of last quarter. We use this variable as a proxy for broker-level distress, as large CDS spread movements signal heightened credit risk and market concerns about a broker's solvency at any time during a quarter.[43].

Since we aim to capture plausible cross-sectional variation, we focus on abnormal CDS distress changes, which we define as the increase above the median broker, i.e.:

$$AbnormalDistress_t^b = Distress_t^b - \overline{Distress_t} \tag{36}$$

Abnormal CDS spread changes capture the relative distress of a broker-dealer compared to its peers, allowing us to focus on brokers experiencing disproportionately high levels of distress. In line with our experiment, we define an indicator variable for whether we consider a broker dis-

[42] The one exception to this is Q1 2020, during the height of the pandemic. In Appendix Section D.5, we show that broker-level distress does not statistically explain the cross-section of broker lending growth during this period for large brokers. Since we propose that broad shocks impact the willingness or ability of non-directly shocked brokers to expand credit supply in response to large shocks—rather than causing directly shocked brokers to reduce their credit supply—this pattern aligns with our findings.

[43] To clarify, this is akin to our approach with the Euro 5 experiment, where we group brokers by the start of distress to the peak CDS spread change.

tressed:

$$BigShock_t^b = \begin{cases} 1 & \text{if } AbnormalDistress_t^b \geq \mathrm{P}_\tau(AbnormalDistress), \\ 0 & \text{otherwise} \end{cases} \tag{37}$$

where τ is a percentile cut-off. We choose $\tau = 95\%$.[44] Moving forward, we will use the term "distressed broker" interchangeably with $BigShock_t^b$ taking a value of one.

7.1.1 Distressed brokers reduce credit provision

We first verify that on average, distressed broker-dealers under this measure cut back credit based on the following regression:

$$\Delta ln(PBL_t^b) = \alpha_t + \alpha_b + \beta BigShock_t^b + \varepsilon_t^b \tag{38}$$

where $\Delta ln(PBL_t^b)$ is the Y-9C lending quantities data.

We report the regression estimates in Equation 38 in Table 15. In Columns (1) and (2), we regress log investor loan growth on the continuous CDS spread measure, observing a sizable effect. In Columns (3) and (4), our independent variable is now $BigShock_t$. In Column (3), with quarter-fixed effects, we observe that on average, brokers with a top 5% $AbnormalDistress_t^b$ measurement have a -0.172 lower log investor growth rate, in line with these brokers reducing their credit.

7.1.2 Hedge fund managers always diversify away broker health shocks outside Q1 2016

Credit quantities declined by distressed brokers during both the Euro 5 and Archegos shocks; however, those two shocks differ in the capacity of managers to substitute away from distressed brokers. We now study when–if ever–managers are unable to diversify away these shock.

For each time t, we estimate the following cross-sectional regression:

$$\Delta \ln(Port_{t-1 \to t}^m) = \alpha + \beta BorrowsFromTreated_{t-1}^{m,\tau} + \varepsilon_{t-1 \to t}^m \tag{39}$$

where $BorrowsFromTreated_{t-1}^m$ is a variable indicating whether a manager has at least one prime brokerage relationship with a broker with $BigShock_t^\tau = 1$. In this case, our outcome variable is the stale price portfolio as previously defined.

In Figure 11, we plot β estimates for $\tau = 5\%$ as above but also $\tau \in \{1\%, 2\%, 10\%\}$. In the quarter of our (Euro 5) experiment, we find a point estimate of γ that is consistently negative and

[44] τ is robust to alternative threshold cut-offs. We choose $\tau = 95\%$ as it is sufficiently large to generate sufficient observations while focusing on tail events. These results are robust and interpretations are robust through $\tau = 10\%$.

statistically significant. This is robust for all cutoffs. Outside of this quarter, we never observe a negative and statistically significant point estimate for another quarter across all cutoffs. This implies managers were able to diversify away the effect of broker health shocks outside of the Euro 5 experiment.

Together, this evidence implies that (a) there are periods in the sample, outside of Q1 2016, during which broker-dealer health affects lending quantities consistent with a credit supply channel, but (b) there is no evidence that hedge fund managers are unable to fully diversify away from these shocks except for in Q1 2016.

7.1.3 The Health of Non-Distressed Broker-Dealers Rarely Deteriorates Outside of Q1 2016

In Section 6.3, we argue that the deteriorating financial health of non-directly shocked broker-dealers significantly limited the diversification response to the Euro 5 shock. We now confirm that broker-dealers not classified as distressed (i.e., those for which $BigShock_t^b$ is zero) experienced only minimal deterioration in financial health.

In Figure 12, we present the mean, 25th percentile, and 75th percentile of the continuous $AbnormalDistress_t^b$ variable for brokers we classified as non-distressed at the 5% cut-off threshold.[45] First, we observe that during the quarter of the European broker-dealer experiment, brokers classified as non-distressed showed increasingly poor distress metrics across all distribution measures. This quarter saw the largest increase at the 25th percentile, which rose by over 20 basis points. Second, there is very little distress observed outside this quarter, with only a few quarters showing slightly elevated levels (notably in 2022), and these increases are substantially smaller across all distribution moments.

Third, the Q1 2020 onset of the pandemic is the only quarter during which we observe a deterioration in the health of non-shocked broker-dealers, as was seen in Q1 2016. Both quarters exhibit comparable distress patterns for the mean and 75th percentiles of the distribution. We address this in Appendix Section D.5. In summary, we do not find that cross-sectional health differences explain lending growth during this period for large broker-dealers, which we attribute to the Federal Reserve System's stabilization policy that actively targeted large broker-dealers through the "Primary Dealer Credit Facility."[46]

Together, this section suggests that the European broker-dealer distress period is unique within the regulatory data sample due to the extent to which the health of non-directly shocked brokers

[45] All thresholds studied display similar patterns.

[46] Almost all large prime brokers are also primary dealers. During the period of European broker-dealer distress, there were no significant policy interventions. In fact, many market participants believed that the German government was unlikely to intervene even for the most distressed broker, Deutsche Bank (see Lee [2016]).

deteriorated. This evidence supports the view that the health of these non-directly shocked brokers is a crucial determinant of the transmission of broker health to equity prices.

7.2 Lehman Brothers and Prime Brokerage Market Spillovers

To provide additional evidence on the importance of non-directly shocked broker-dealers in transmitting health shocks to equity markets, we examine the collapse of Lehman Brothers on September 15, 2008—the most prominent prime-broker shock, as first analyzed in Aragon and Strahan [2012]. Our findings indicate that the health of non-directly shocked broker-dealers, such as Morgan Stanley, deteriorated following the collapse, suggesting sympathetic contagion. We find further evidence that this contagion may have amplified the transmission of the shock to equity markets.

For this event study, we use hedge fund by prime broker relationship data using vendor data from Lipper TASS.[47] Hedge funds voluntarily reports returns and prime-broker relationships for select funds to Lipper TASS. We use the December 2008 vintage of Lipper TASS.

7.2.1 CDS Spread and Narrative Evidence for Spillovers

Leading up to September 2008, major broker-dealers faced heavy losses on their trading books, primarily due to high-risk investments in Collateralized Debt Obligations and Mortgage-Backed Securities. This turmoil set the stage for two pivotal moments in the financial crisis: Bank of America's acquisition of Merrill Lynch on September 14, 2008, and the historic collapse of Lehman Brothers the next day. These events underscored vulnerabilities within major financial institutions and triggered a broader market panic.

While the brokers failed for specific reasons, CDS spreads showed an increased dispersion in funding costs for broker-dealers in response. Figure 13 plots the change in CDS spreads for major broker-dealers beginning in early February. Three key patterns emerge: First, there was an increase in CDS spreads leading up to the September 14-15 weekend for all brokers, particularly Goldman Sachs and Morgan Stanley; second, Goldman Sachs and Morgan Stanley experienced much larger CDS spread increases (214 basis points (bps) and 380 bps, respectively) from September 12 to September 16, indicating potential spillovers. At this time, Goldman Sachs and Morgan Stanley were the two largest prime brokers (see Giannone [2009]). However, after the initial distress, we see that Morgan Stanley's health continued to deteriorate through the end of the month, while Goldman Sach's stabilized.

Similar to the proposed sympathetic contagion associated with the European broker-distress

[47] George Aragon kindly provided his cleaned version of the prime broker-hedge fund relationships used which included hand-collected data of Lehman related hedge funds.

periods, Goldman Sachs and Morgan Stanley shared a crucial characteristic with the directly shocked broker-dealers—they were the only large, independent broker-dealers not within a bank holding company, meaning they lacked certain government regulatory support and stable funding sources.[48] This structural vulnerability led to sympathetic contagion as investors began withdrawing support. Financial press reports documented a significant run on prime brokerage free credits at these banks; for instance, Giannone [2009] noted that both Goldman Sachs and Morgan Stanley experienced funding outflows in their prime brokerage divisions during Lehman's collapse, suggesting potentially strong spillover effects.

While public data to directly study the prime brokerage run is unavailable, reports from the financial press depict its extent and speed as striking: per Ivry et al. [2011], the run was almost immediate. On the night of September 15, Morgan Stanley's Treasurer reported outflows to the NY Fed. The following morning, NY Fed communications revealed substantial withdrawals: Goldman Sachs lost \$5 billion, and Morgan Stanley, \$7 billion. This trend persisted throughout the subsequent week. Notably, Mackintosh [2008b] reported that Morgan Stanley lost a third of its prime brokerage assets overall and half in its critical London office, with Mackintosh [2008a] reporting similar effects for Goldman. In short, these brokers faced a rapid, spillover-driven run.[49]

7.2.2 Stock-level Turnover Abnormally High for Distressed Brokers

Did distress from the directly shocked and the spillover brokers lead to abnormal stock-level sell-offs? As in our Euro 5 experiment, we test for abnormal sell-offs by estimating:

$$\Delta MktShare_t^{s,b} = \alpha_t + \alpha_f + \beta MktShare_{t-1}^{s,b} + \beta_2 MktShare_{t-1}^{s,b} \times \mathbf{1}_{1=2008q3} + \varepsilon_t^s \tag{40}$$

where $\Delta MktShare_t^{s,b}$ is the change in market share of a stock exposed to a particular broker-dealer group via its counterparty network, and $MktShare_t^{s,b}$ is its lagged market share. We consider four main brokers: the two directly shocked broker-dealers, Lehman Brothers (*LEH*) and Merrill Lynch (*MER*), and the spillover brokers, Goldman Sachs (*GS*) and Morgan Stanley (*MS*), We also aggregate these four brokers as the Lehman 4 and construct the residual TASS Lipper identified hedge fund sector.

In Table 16, we present the estimates from our regression analyses. In Column (1), we observe

[48] On September 21, 2008, both firms announced reorganization into bank holding companies to access more stable funding.

[49] Previous studies document significant spillovers due to shared asset exposures with Lehman (see Ivashina and Scharfstein [2010], Chodorow-Reich [2013]). These studies focus on medium- or long-term impacts on non-financial corporate loans, with limited exploration of funding channels. To the best of our knowledge, we have the first study of the higher frequency common funding contagion channel.

a significant abnormal sell-off among Lehman-affiliated hedge funds: while these funds typically experience a sell-off of approximately 11 bps for each additional percentage point of holdings, the sell-off escalated to an additional 26 bps in 2008 Q3. Column (2) reveals that Merrill Lynch brokered hedge funds also experienced abnormal sell-offs, albeit at a quantitatively smaller rate. In Column (3), we find that Morgan Stanley had large and significant abnormal sell-off of 8.52bp. Perhaps surprisingly in Column (4), we see that Goldman Sachs had a significant but relatively smaller sell-off. In Column (5) we estimate the average security-level sell-off for the consolidated set of other Lipper TASS identified brokered hedge funds (*non LEH4*). We estimate a point estimate of -.0358—which is greater than the estimate for hedge funds brokered from Goldman Sachs. We take this as evidence that while Goldman Sachs might have experienced distress in this period, any possible credit supply effect was muted. These effects suggest stock-level sell-offs were more intense for stocks more exposed to funds that brokered with the directly shocked broker and Morgan Stanley, which we confirm in Columns (6) and (7).

7.2.3 Stocks more Exposed to Both Lehman and Other Distressed brokers have Lower Returns

Does the sell-offs affects returns? To investigate this, we regress realized returns on ex-ante exposure measures. Our baseline specification is the following regression:

$$ret^{s}_{15sep2008\rightarrow30sep2008} = \alpha + \beta MktShare^{s,b}_{2008jun30} + X^{f} + \varepsilon^{s}_{15sep2008\rightarrow30sep2008} \tag{41}$$

where $ret^{s}_{t\rightarrow t+1}$ can be raw returns as well as the Fama-French three-factor model plus momentum (FF3+UMD). Replicating Aragon and Strahan [2012], we study returns from September 15, 2008 through the end of the months. Standard errors are clustered at the three-digit SIC industry-code level.

In Table 17, we estimate Equation 41. In Column (1), we find that securities more exposed to Lehman Brothers have lower realized returns. In Column (2), we estimate a coefficient of similar magnitude to Column (1), which is now marginally statistically insignificant. In Columns (3) and (4), we observe statistically significant and negative return effects for exposure measures based on all three distressed broker-dealers. In Columns (5) and (6), we study the return effects for Lehman Brothers—as previously analyzed in the literature—alongside Morgan Stanley and Merrill Lynch (MS+MER). Here, we find that the hedge fund group exposed to Morgan Stanley and Merrill Lynch remains statistically significant and negative. Although Lehman Brothers is no longer statistically significant, the point estimate is large and negative, suggesting limited statistical power to distinguish between stocks exposed to Lehman Brothers and other treated stocks. In Columns

(7) and (8), we see that controlling for non-Lehman 3 hedge fund exposure (identified from Lipper TASS) does not materially affect our point estimates from Columns (3) and (4), suggesting that the exposure identified is distinct from the exposure of the aggregate hedge fund sector.

These results indicate that widespread distress was present and played a role in the transmission of the Lehman Brothers shock—the most widely recognized broker-dealer-specific health event—to equity markets. We find evidence of widespread distress and funding contagion following the Lehman Brothers bankruptcy, consistent with our findings from the European broker distress period. Additionally, we find that exposure to more distressed broker-dealers corresponded with higher stock-level turnover and lower realized returns. This pattern holds beyond a stock's exposure to Lehman Brothers or to other hedge funds.

8 Conclusion

Our paper provides direct evidence that broker-dealer health shocks affect equity prices through prime brokerage exposure. This causal evidence confirms the existence of a long-speculated channel in intermediary asset pricing—that broker-dealers can affect asset prices through indirect participation. We also find that the transmission to stock markets depends not only on the health of the directly shocked broker-dealer but also on the health of the non-shocked broker-dealers.

We find that hedge funds can diversify away from broker shocks when non-directly shocked brokers remain healthy. We document only one instance in the post-GFC period where this is not the case, underscoring the resilience of the post-GFC financial system. This fact carries important policy implications as both policy and industry experts have expressed concerns that prime brokerage credit supply poses a financial stability risk due to its size and concentration. For example, both the motivating quote by the Financial Stability Board [2023] and industry headlines such as 'Prime Brokerage a Growing Risk to Financial Stability' by Slok [2024] highlight the strong concern that broker risks could have widespread effects.[50] However, our study demonstrates that these concerns might be overstated, as hedge funds' private actions to diversify broker exposure effectively mitigate these risks in most cases. Nonetheless, policymakers should consider intervention if shocks spread across multiple brokers during periods of widespread distress, such as the European broker distress period in 2016.

This study underscores the need for further research. First, our findings show that broker-dealer health shocks must be very broad to impact asset prices; however, our methodology relies on the

[50]Policymakers are particularly concerned that price impacts in asset markets might extend beyond direct participants if other leveraged investors face deteriorating asset values from commonly owned assets, as noted by Bernanke [2006].

cross-sectional differences in these shocks to identify an effect. Causally identifying aggregate time-series credit supply shocks would be a valuable next step. Second, we motivate the potential importance of broker-dealercredit supply via a series of novel facts linking broker-dealer health, prime brokerage borrowing, and equity returns. Other non-credit supply mechanisms might also generate these effects in certain cases. For instance, shocks to the health or risk-seeking behavior of leveraged investors, such as hedge funds, could produce similar patterns through shifts in credit demand.[51] Identifying and quantifying these types of shocks alongside those presented in this paper would provide valuable insights. This study marks a first step toward uncovering when, why, and which types of leveraged intermediaries impact asset prices.

References

V. V. Acharya, R. Engle, M. Jager, and S. Steffen. Why did bank stocks crash during covid-19? *The Review of Financial Studies*, 37(9):2627–2684, July 2024. doi: 10.1093/rfs/hhae028. URL https://doi.org/10.1093/rfs/hhae028.

T. Adrian, E. Etula, and T. Muir. Financial intermediaries and the cross-section of asset returns. *The Journal of Finance*, 69(6):2557–2596, 2014. doi: 10.1111/jofi.12189. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12189.

M. Amiti and D. E. Weinstein. How much do idiosyncratic bank shocks affect investment? evidence from matched bank-firm loan data. *Journal of Political Economy*, 126(2):525–587, 2018. doi: 10.1086/696272. URL https://doi.org/10.1086/696272.

G. O. Aragon and P. E. Strahan. Hedge funds as liquidity providers: Evidence from the lehman bankruptcy. *Journal of Financial Economics*, 103(3):570–587, 2012. ISSN 0304-405X. doi: https://doi.org/10.1016/j.jfineco.2011.10.004. URL https://www.sciencedirect.com/science/article/pii/S0304405X11002364.

S. Arons, B. Hu, and T. Nakamichi. Nomura's prime brokerage pullback deals blow to global goals. *Bloomberg*, 2021. URL https://www.bloomberg.com/news/articles/2021-07-06/nomura-s-prime-brokerage-pullback-deals-blow-to-global-goals. Firm to stop offering prime-brokerage services in U.S., Europe. Brokerage has lost top-level bankers in wake of Archegos saga.

[51] See Packer et al. [2024] for one possible type of shock. They suggest that abnormal losses by multi-strategy hedge funds in carry trade markets during August 2024 could propagate across markets, including equity markets.

Bank for International Settlements. International banking and financial market developments, 2016. BIS Quarterly Review.

B. Bernanke. Hedge funds and systemic risk. 2006. Federal Reserve Bank of Atlanta's 2006 Financial Markets Conference, Sea Island, Georgia.

P. Bologna, A. Miglietta, and A. Segura. Contagion in the cocos market? a case study of two stress events. *The International Journal of Central Banking*, 2020.

G. W. Brown, P. Howard, and C. T. Lundblad. Crowded trades and tail risk. *The Review of Financial Studies*, 35(7):3231–3271, September 2021. doi: 10.1093/rfs/hhab107. URL https://doi.org/10.1093/rfs/hhab107.

M. K. Brunnermeier and L. H. Pedersen. Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6):2201–2238, 11 2008. ISSN 0893-9454. doi: 10.1093/rfs/hhn098. URL https://doi.org/10.1093/rfs/hhn098.

M. K. Brunnermeier and Y. Sannikov. A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421, February 2014. doi: 10.1257/aer.104.2.379. URL https://www.aeaweb.org/articles?id=10.1257/aer.104.2.379.

C. Caglio, A. M. Copeland, and A. Martin. The value of internal sources of funding liquidity: U.s. broker-dealers and the financial crisis. 2021.

G. Chodorow-Reich. The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis *. *The Quarterly Journal of Economics*, 129(1):1–59, 10 2013. ISSN 0033-5533. doi: 10.1093/qje/qjt031. URL https://doi.org/10.1093/qje/qjt031.

L. Clancy. Basel triggers new tussle on anti-archegos rules. *Risk.net*, May 2024. URL https://www.risk.net.

R. Correa, W. Du, and G. Liao. U.s. banks and global liquidity. 2022.

K. J. M. Cremers and A. Petajisto. How active is your fund manager? a new measure that predicts performance. *The Review of Financial Studies*, 22(9):3329–3365, August 2009. ISSN 0893-9454. doi: 10.1093/rfs/hhp057. URL https://doi.org/10.1093/rfs/hhp057.

J. Cryan. Db media conference, 2016. URL https://www.db.com/files/documents/newsroom/2016/Annual-Media-Conference-2016.pdf?language_id=1. Published report.

M. Dahlqvist, V. Sokolovski, and E. Sverdrup. Hedge funds and financial intermediaries. *Working Paper*, 2021.

A. L. Eisfeldt, B. Herskovic, S. Rajan, and E. Siriwardane. Otc intermediaries. *The Review of Financial Studies*, 36(2):615–677, September 2022. doi: 10.1093/rfs/hhac062. URL https://doi.org/10.1093/rfs/hhac062.

Financial Stability Board. The financial stability implications of leverage in non-bank financial intermediation, 2023.

A. Frazzini and L. H. Pedersen. Betting against beta. *Journal of Financial Economics*, 111 (1):1–25, 2014. ISSN 0304-405X. doi: 10.1016/j.jfineco.2013.10.005. URL https://www.sciencedirect.com/science/article/pii/S0304405X13002675.

X. Gabaix and R. S. J. Koijen. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Working Paper 28967, National Bureau of Economic Research, June 2021. URL http://www.nber.org/papers/w28967.

S. Galaasen, R. Jamilov, R. Juelsrud, and H. Rey. Granular credit risk. 2023.

J. A. Giannone. Prime broker ranks shaken up for good by crisis. *Reuters*, November 2009. URL https://www.reuters.com/article/world/prime-broker-ranks-shaken-up-for-good-by-crisis-idUSTRE5AG42I. Accessed: 2024-10-28.

K. Gleason, S. Bright, F. Martinez, and C. Taylor. Europe's cocos provide a lesson on uncertainty. *OFR Working Paper*, 2017.

J. Glover. Deutsche bank coco bonds have bumpy ride as lender struggles, 2016. URL http://www.bloomberg.com/news/articles/2016-01-28/deutsche-bank-coco-investors-have-bumpy-ride-as-lender-struggles.

V. Haddad and T. Muir. Do intermediaries matter for aggregate asset prices? *The Journal of Finance*, 76(6):2719–2761, 2021. doi: 10.1111/jofi.13086. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.13086.

M. Halftermeyer. Credit suisse to exit prime services in sharper wealth pivot. *Bloomberg*, 2021. URL https://www.bloomberg.com/news/articles/2021-11-04/credit-suisse-to-exit-prime-services-in-sharper-wealth-pivot. Bank to exit most of prime services business after Archegos. Will restructure wealth management businesses into single unit.

Z. He and A. Krishnamurthy. Intermediary asset pricing. *American Economic Review*, 103(2):732–70, April 2013. doi: 10.1257/aer.103.2.732. URL https://www.aeaweb.org/articles?id=10.1257/aer.103.2.732.

Z. He, B. Kelly, and A. Manela. Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35, 2017. doi: 10.1016/j.jfineco.2017.08.002. URL https://www.sciencedirect.com/science/article/pii/S0304405X1730212X.

V. Ivashina and D. Scharfstein. Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3):319–338, 2010. ISSN 0304-405X. doi: https://doi.org/10.1016/j.jfineco.2009.12.001. URL https://www.sciencedirect.com/science/article/pii/S0304405X09002396. The 2007-8 financial crisis: Lessons from corporate finance.

B. Ivry, B. Keoun, and P. Kuntz. Secret fed loans gave banks $13 billion undisclosed to congress. *Bloomberg Magazine*, November 2011. URL https://www.bloomberg.com/news/articles/2011-11-28/secret-fed-loans-undisclosed-to-congress-gave-banks-13-billion-in-income.

A. I. Khwaja and A. Mian. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42, September 2008. doi: 10.1257/aer.98.4.1413. URL https://www.aeaweb.org/articles?id=10.1257/aer.98.4.1413.

R. Koijen, R. Richmond, and M. Yogo. Which investors matter for equity valuations and expected returns? *Review of Economic Studies*, 2023.

R. S. J. Koijen and M. Yogo. A demand system approach to asset pricing. *Journal of Political Economy*, 127(4):1475–1515, 2019. doi: 10.1086/701683. URL https://doi.org/10.1086/701683.

M. S. Kruttli, P. J. Monin, and S. W. Watugala. The life of the counterparty: Shock propagation in hedge fund-prime broker credit networks. *Journal of Financial Economics*, 2022. ISSN 0304-405X. doi: https://doi.org/10.1016/j.jfineco.2022.02.002. URL https://www.sciencedirect.com/science/article/pii/S0304405X2200054X.

M. S. Kruttli, P. J. Monin, L. Petrasek, and S. Watugala. Ltcm redux? hedge fund treasury trading and funding fragility. *Working Paper*, 2023.

N. Kumar, K. Mullally, S. Ray, and Y. Tang. Prime (information) brokerage. *Journal of Financial Economics*, 137(2):371–391, 2020. ISSN 0304-405X. doi: 10.1016/j.jfineco.2020.02.010. URL https://www.sciencedirect.com/science/article/pii/S0304405X2030043X.

T. B. Lee. Germany's largest bank is facing a huge fine, prompting fear of a new financial crisis. *Vox*, October 4 2016. URL https://www.vox.com/2016/10/4/13156450/germanys-largest-bank-fine-financial-crisis. Accessed: [Date you accessed the article].

M. Lettau, S. C. Ludvigson, and S. Ma. Capital share risk in u.s. asset pricing. *The Journal of Finance*, 74(4):1753–1792, 2019. doi: https://doi.org/10.1111/jofi.12772. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12772.

J. Mackintosh. Lehman collapse puts prime broker model in question. *Financial Times*, September 24 2008a. URL https://www.ft.com/content/442f0b24-8a71-11dd-a76a-0000779fd18c.

J. Mackintosh. Morgan stanley suffers cash flight. *Financial Times*, September 25 2008b. URL https://www.ft.com/content/fc0e74be-8b43-11dd-b634-0000779fd18c.

F. Packer, A. Schrimpf, V. Sushko, and N. Zarra. Hedge fund exposure to the carry trade. *BIS Quarterly Review*, 2024.

R. W. . G. L. Paul, Weiss. Credit suisse group special committee of the board of directors report on archegos capital management, 2021. Published report.

J. Rennison and G. Jackson. Investors flock to cds amid fear over banks' bonds. *Financial Times*, February 9 2016. URL https://www.ft.com/content/449516ce-cebd-11e5-831d-09f7778e7377. Accessed: 2024-09-12.

T. Santos and P. Veronesi. Leverage. *Journal of Financial Economics*, 145(2, Part B):362–386, 2022. doi: 10.1016/j.jfineco.2021.09.001. URL https://www.sciencedirect.com/science/article/pii/S0304405X21003780.

B. Seegmiller. Intermediation frictions in equity markets. *SSRN*, 2024.

E. N. Siriwardane. Limited investment capital and credit spreads. *The Journal of Finance*, 74(5):2303–2347, 2019. doi: https://doi.org/10.1111/jofi.12777. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12777.

T. Slok. Prime brokerage: A growing risk to financial stability. *The Daily Spark*, 2024. URL https://www.apolloacademy.com/prime-brokerage-a-growing-risk-to-financial-stability/.

T. Tomunen. Failure to share natural disaster risk. *Working Paper*, 2022.

9 Tables

Table 1: **Stock-Level Exposure to Hedge Funds:** This table reports the distribution of stock-level exposure to hedge funds in 2022 Q4 based on data from FactSet Ownership. A security's "HF Institutional Share" is defined as the percentage of the total shares held by 13-F filing institutions that FactSet classifies as hedge fund managers. The "HF Market Share" of a security is defined as the percentage of the total shares outstanding of the security held by hedge fund managers, as classified by FactSet. "HF Institutional Turnover Share" refers to the share of total institutional turnover attributable to FactSet-identified hedge funds. "Number of Hedge " refers to the number of FactSet hedge fund managers holding a security.

	mean	p50	p1	p5	p10	p25	p75	p90	p95	p99
HF Institutional Share	15.3	10.3	1.1	1.8	2.6	4.7	20.5	35.2	46.1	68.3
HF Market Share	10.9	7.3	0.3	1.1	1.7	3.4	14.4	25.7	33.8	53.0
HF Institutional Turnover Share	27.4	25.4	0.1	1.9	4.8	12.5	39.4	52.6	60.9	81.2
Number of Hedge Funds	41.4	36.0	2.0	8.0	13.0	23.0	55.0	74.0	90.0	124.0
Observations	2180									

Table 2: **Equity Prime-Brokerage Network Characteristics in 2022 Q4:** This table reports the distribution of the number of prime brokerage counterparties across three groups of equity hedge funds: all hedge funds, hedge funds with at least $1B in gross assets, and hedge funds with at least $5B in gross assets under management. Columns (8) and (9) present the number of funds in each group and their total gross assets. Hedge fund data and prime brokerage networks are identified from Form ADV, while equity exposure is identified from FactSet Ownership.

	Number of Prime Brokers per Fund							
	mean	p50	p10	p25	p75	p90	Obs	Total Gross Assets ($ B)
HFs with at least 5B gross assets	5.1	4.0	1.0	2.0	8.0	10.0	105	1945
HFs with at least 1B gross assets	3.6	3.0	1.0	1.0	5.0	8.0	375	2505
All HFs	2.6	2.0	1.0	1.0	3.0	6.0	987	2790

Table 3: **Cumulative Borrowing Concentration:**: This first column reports the cumulative borrowing concentration for major hedge funds by counterparty rank from the OFR Hedge Fund Monitor, using data assembled by the OFR. The second column reports the cumulative concentration for BHC Total Loans from FR Y-9C Filings. Concentration measures are taken as of Q2 2024.

	(1) Hedge Fund Credit Concentration	(2) Y-9C Total Loan Concentration
1	14	12.3
2	27.9	22.3
3	40.3	30.7
4	48.2	36.9
5	55.7	40.3
6	63.1	43.2
7	69.8	46.1
8	75.4	48.9
9	77.8	51.3
10	80.2	53.7

Table 4: **News Events Concerning European Broker Distress:** Here, we take the news events first discussed by Gleason et al. [2017] to understand how news about the health of two large European BHCs is released.

Institution	Date	Event Description
DB	28-Jan-16	DB annual media conference clarifying losses and implying possible non-payment of AT1 debt
CS	4-Feb-16	CS announces unexpectedly large losses, driven by impairment of legacy acquisition worth 4bn or 9% of net worth
DB	8-Feb-16	DB releases press lease outlining cash available for CoCo bond repayments in attempt to calm market
DB	23-Feb-16	DB releases press lease describing Euro-denominated bond repurchase

Table 5: **Euro 5 Manager Sell-Offs:** This table presents estimates from Equation 24. We provide estimates for both market price portfolio changes and stale price portfolio changes. "Size" refers to the minimum equity cut-off last period to be included in this regression. The outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. Standard errors are heteroskedasticity-robust.

	$\Delta\ln(\text{Port})$					
Euro 5 Manager	-0.0470*	-0.0525*	-0.0739**	-0.0570**	-0.0631**	-0.0812***
	(0.0253)	(0.0280)	(0.0291)	(0.0247)	(0.0275)	(0.0281)
Intercept	-0.0606***	-0.0697***	-0.0645***	-0.0194*	-0.0309**	-0.0276*
	(0.0109)	(0.0141)	(0.0156)	(0.0106)	(0.0139)	(0.0151)
R-squared	0.008	0.015	0.037	0.012	0.022	0.047
N	454	232	170	454	232	170
Size	All	At Least 500m	At Least 1B	All	At Least 500m	At Least 1B
Port	Market	Market	Market	Stale	Stale	Stale

Standard errors in parentheses

Robust standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **Stock-Level Sell-Offs by Euro 5 Advisers** This table reports estimates for Equation 26. Equation 26 regresses the change in security-level market share held by Euro 5 advisers on the market share held by those same advisers. Column (1) presents estimates for the cross-section from the first quarter of 2016. Columns (2)-(5) present estimates based on a stock-by-quarter panel from 2014 to 2020, incorporating industry and quarter fixed effects. The exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the three-digit SIC industry-code level.

	Δ % Held Euro5 HFs				
(1)	(2)	(3)	(4)	(5)	
% Held Euro5 HFs	-0.0938***	-0.0447***	-0.0503***	-0.0490***	-0.0558***
	(0.00896)	(0.00341)	(0.00364)	(0.00387)	(0.00422)
% HeldEuro5HFs $\times$ Q12016		-0.0492***	-0.0435***	-0.0501***	-0.0440***
		(0.00857)	(0.00865)	(0.00856)	(0.00862)
Intercept	0.00360***	0.00281***	0.00311***	0.00301***	0.00337***
	(0.000425)	(0.000122)	(0.000134)	(0.000175)	(0.000196)
R-squared	0.076	0.029	0.037	0.040	0.049
N	1835	21972	21972	21969	21969
Q12016	X				
Quarter FE			X		X
IndustryFE				X	X

Table 7: **Realized Returns and Ex-Ante Exposure to Euro 5 Advisers** This table reports estimates for Equation 27, which regresses realized returns on Euro 5 exposure share measures (% Held Euro5 HFs). Returns are raw (Ret_t^s), residualized against the CAPM model, residualized against the Fama-French 3 + Momentum model ($\varepsilon^s_{FF4,t}$), or residualized against the bBetting-against-bBeta model ($BABRet_t$). In some specifications, we include controls for non-Euro 5 hedge fund exposure (% Held non-Euro5 HFs) and fixed effects based on industry codes (IndustryFE). Exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the three-digit SIC industry-code level.

	$Rets_{s,q}$			$\varepsilon_{CAPM,s,q}$		$\varepsilon_{FF4,s,q}$		$BABRet_t^s$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
% Held Euro5 HFs	-0.507***	-0.409***	-0.315***	-0.408***	-0.310***	-0.423***	-0.347***	-0.390***	-0.302***
	(0.129)	(0.104)	(0.0935)	(0.107)	(0.0952)	(0.0899)	(0.0876)	(0.105)	(0.0942)
% Held non-Euro5 HFs		-0.237	-0.0647	-0.261*	-0.0803	-0.235**	-0.113	-0.222	-0.0512
		(0.144)	(0.0842)	(0.147)	(0.0848)	(0.106)	(0.0721)	(0.143)	(0.0835)
Intercept	0.0351***	0.0433***	0.0284***	0.0388***	0.0233***	0.0478***	0.0366***	0.0537***	0.0392***
	(0.0119)	(0.00999)	(0.00608)	(0.0102)	(0.00616)	(0.00806)	(0.00530)	(0.00976)	(0.00610)
R-squared	0.018	0.024	0.283	0.025	0.288	0.033	0.239	0.022	0.278
Industry FE			X		X		X		X
N	1835	1835	1803	1834	1802	1832	1800	1835	1803

Table 8: **Realized Returns and Other Institutional Investors:** This table reports estimates for Equation 28, controlling for security-level exposures to other institutional investor classes. Other institutional classes include the broker-dealer sector (*Brokers*), non-hedge fund investment advisers (*IA*), and the aggregate institutional investor net of Euro 5-exposed broker-dealers. All institutional classes are identified using the taxonomy of FactSet classifications in Koijen et al. [2023]. Returns are raw (Ret_t^s) or residualized against the Fama-French 3 + Momentum model ($\varepsilon^s_{FF4,t}$). Exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the three-digit SIC industry-code level.

	$Ret_{s,t}$	$\varepsilon_{FF4,s,t}$	$Ret_{s,t}$	$\varepsilon_{FF4,s,t}$	$Ret_{s,t}$	$\varepsilon_{FF4,s,t}$
% Held Euro5 HFs	-0.519***	-0.461***	-0.503***	-0.518***	-0.554***	-0.550***
	(0.129)	(0.103)	(0.126)	(0.102)	(0.120)	(0.0976)
% Held Brokers	-0.0137	-0.798				
	(0.583)	(0.531)				
% Held non-HF IA			0.0671***	0.0442**		
			(0.0250)	(0.0220)		
% Held non E5 Inst.					0.0546***	0.0342*
					(0.0184)	(0.0202)
Intercept	0.0364***	0.0451***	-0.00239	0.0149	-0.00955	0.0117
	(0.0115)	(0.00833)	(0.0185)	(0.0145)	(0.0126)	(0.0131)
R-squared	0.019	0.028	0.024	0.028	0.024	0.028
N	1823	1820	1835	1832	1835	1832

Standard errors in parentheses

Standard errors are clustered at the three-digit SIC industry code level.

	$Ret_{s,q}$	$\varepsilon_{FF4,s,q}$	$Ret_{s,q}$	$\varepsilon_{FF4,s,q}$	$Ret_{s,q}$	$\varepsilon_{FF4,s,q}$	$Ret_{s,q}$	$\varepsilon_{FF4,s,q}$	$Ret_{s,q}$	$\varepsilon_{FF4,s,q}$	$Ret_{s,q}$	$\varepsilon_{FF4,s,q}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
% Held Euro5 HFs	-0.485***	-0.482***	-0.507***	-0.506***	-0.500***	-0.516***	-0.510***	-0.522***	-0.508***	-0.521***	-0.507***	-0.521***
	(0.120)	(0.0995)	(0.120)	(0.0993)	(0.125)	(0.101)	(0.129)	(0.104)	(0.128)	(0.103)	(0.129)	(0.103)
% Held E5 B/D	-1.147	-1.951**										
	(1.169)	(0.960)										
% Held E5 Affiliate			-0.183	-0.911								
			(1.022)	(0.854)								
E5 Bank in Syndicate					0.0356**	0.0204*						
					(0.0144)	(0.0112)						
SyndicatedLoansE5/FirmAssets							8.954	3.053				
							(7.006)	(4.800)				
E5 Bank Lead									-0.0196	-0.0189		
									(0.0315)	(0.0286)		
SyndicatedLoansLeadE5/FirmAssets											-46.72	-69.98
											(101.1)	(88.90)

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 9: **Realized Returns and Direct Euro 5 Exposure:** This table reports estimates for Equation 28, controlling for direct Euro 5 exposure measures. Columns (1)-(6) incorporate controls for FactSet managers associated with Euro 5 brokers, including Euro 5-affiliated FactSet-classified hedge funds (Euro5 HFs), Euro 5-affiliated broker-dealers (Euro5 B/D), and total Euro 5 affiliates identified by FactSet (E5 Affiliate). Columns (7)-(12) introduce controls for a security's Euro 5 syndicated loan exposure from DealScan. The variable "E5 Bank in Syndicate" is a binary indicator equal to one if a Euro 5 broker participated in a loan syndicate for the firm in the past five years, while "E5 Bank Lead" takes the value of one if a Euro 5 broker led a loan syndicate for the firm during that period. Both ($\frac{SyndicatedLoansE5}{FirmAssets}$) and ($\frac{SyndicatedLoansE5}{FirmAssets}$) scale the respective value of syndicated loans in which the bank participated or led over the past five years by the firm's total assets from Compustat in the previous quarter.

Table 10: **Other Institutional Shares and Euro 5 Sell-Offs** This table reports estimates for Equation 30, examining which investor classes appear to increase their exposure to stocks that are more commonly sold off by treated managers. The table conditions on the treated managers reducing their positions on aggregate. Standard errors are clustered at the three-digit SIC industry-code level.

	(1)	(2)	(3)	(4)
	Δ % Held nonEuro5 HFs	Δ % Brokers	Δ % Households	Δ % Inv Adv
Δ % Held Euro5 HFs	-0.106**	0.0137	-0.609***	-0.320***
	(0.0469)	(0.0164)	(0.107)	(0.0900)
Intercept	-0.00257***	-0.000612***	0.00402***	-0.00198
	(0.000655)	(0.000165)	(0.00121)	(0.00130)
R-squared	0.009	0.002	0.079	0.022
N	934	933	934	934

Table 11: **Losses from Archegos:** This table summarizes the losses and exposures of large broker-dealers due to Archegos, as reported by Bloomberg or in their financial reports. All losses are in billions of US dollars. The net worth of the bank holding company associated with each broker is reported as of December 31, 2020, also in billions of US dollars.

BHC	Reported Losses	BHC Market Net Worth	Losses to Net Worth	Loss Announcement
CS	5.5	31.3	17.6%	8-Apr-21
NMR	2.9	17.7	16.4%	27-Apr-21
UBS	0.774	54.5	1.4%	27-Apr-21
MS	0.911	123	0.7%	16-Apr-21
MUFG	0.27	111.1	0.2%	30-Mar-21
MFG	0.09	32	0.28%	N/A
GS	0	90.7	0.0%	N/A
DB	0	22.5	0.0%	N/A
WFC	0	124.7	0.0%	N/A

	(1)	(2)	(3)	(4)	(5)	(6)
Archegos Losses	-0.293***	-0.177**	-0.299***	-0.290**	-0.111 *	-0.311**
	-3.628	-2.507	-3.518	-2.477	-1.871	-2.269
Archegos Exposed/No Losses			-0.028			-0.050
			-0.297			-0.363
r2	0.422	0.270	0.425	0.434	0.333	0.445
N	20	19	20	10	9	10
Sample	All ADV PB	All ADV PB ex CS	All ADV PB	Lg ADV PB	All ADV PB ex CS	Lg ADV PB

Table 12: **Archegos Broker Cross-Section: Archegos Broker Cross-Section** This table reports estimates for Equation 31. The dependent variable is the log growth rate of investor loans.Outcome variables are winsorized at the 2.5% and 97.5% level. "Archegos Losses" is an indicator variable that equals one if a broker-dealer incurred losses due to exposure to Archegos. "Archegos Exposed/No Losses" is an indicator variable that equals one if a broker-dealer was exposed to Archegos but did not experience losses. Standard errors are heteroskedasticity-robust.

Table 13: **Change in 13-F Portfolio Size and Archegos Exposure:** This table presents estimates from Equation 32. We provide estimates for both market price portfolio changes and stale price portfolio changes. "Size" refers to the minimum equity cut-off last period to be included in this regression. The outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. Standard errors are heteroskedasticity-robust.

	(1)	(2)	(3)	(4)	(5)	(6)
				$\Delta\ln(\text{Port})$		
Archegos Manager	0.00860	0.0221	0.0280	-0.0132	-0.0135	-0.00119
	(0.0222)	(0.0207)	(0.0231)	(0.0182)	(0.0183)	(0.0210)
Intercept	0.133***	0.111***	0.111***	-0.0205***	-0.0308***	-0.0239**
	(0.00907)	(0.0100)	(0.0118)	(0.00746)	(0.00888)	(0.0107)
R-squared	0	0.004	0.007	0.001	0.002	0.000
N	562	320	222	562	320	222
Size	All	At Least 500m	At Least 1B	All	At Least 500m	At Least 1B
Port	Market	Market	Market	Stale	Stale	Stale

Standard errors in parentheses
Robust standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: **Broker Lending (Euro 5 Non Treated)** This table reports estimates for Equation 33 and 34. This sample excludes Euro 5 broker-dealers. "Cumulative Event CDS" is the cumulative CDS spread change over Euro 5 news announcements dates. "Above Median CDS" is an indicator variable that takes the value of one if "Cumulative Event CDS" is above median. Standard errors are heteroskedasticity-robust.

	(1)	(2)	(3)	(4)
	$\Delta ln(Loans_t^b)$	$\Delta ln(Loans_t^b)$	$\Delta Loans_t^b < 0$	$\Delta Loans_t^b < 0$
Cumulative Event CDS	-0.257*		0.901	
	-1.702		1.289	
Above Median CDS		-0.129**		0.429**
		-2.124		2.108
r2	0.106	0.285	0.107	0.257
N	13	13	13	13

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 15: **Large CDS Deviations and Investor Loan Growth:** This table reports estimates for Equation 38. The dependent variable is the log-growth rate of investor loans. The independent variable is either the continuous abnormal CDS spread change $AbnormalDistress_t^b$ or $BigShock_t^b$. $BigShock_t^b$ is an variable indicating whether $AbnormalDistress_t^b$ is in its top 5% of broker observations. All outcome variables are winsorized at the 2.5% level.

	(1)	(2)	(3)	(4)
$AbnormalDistress_t^b$	-0.182***	-0.157***		
	(0.0524)	(0.0495)		
$BigShock_t^b$			-0.172***	-0.155***
			(0.0549)	(0.0444)
_cons	0.0327***	0.0296***	0.0137**	0.0134***
	(0.00831)	(0.00501)	(0.00487)	(0.000541)
R-squared	0.163	0.233	0.148	0.224
N	669	669	669	669
brokers	All ADV	All ADV	All ADV	All ADV
FE	Q	Q and B	Q	Q and B

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: **Stock-Level Sell-Offs by Lehman spillover** This table reports estimates for Equation 40. Equation 40 regresses the change in security-level market share held by affiliated advisers on the market share held by those same advisers. Column (1)-(7) presents estimates for the cross-section from the third quarter of 2008 for a different set of hedge funds based on their prime brokerage relationships. Each specification controls for industry and quarter fixed effects The exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered by quarter.

	(1) Δ LEH	(2) Δ MER	(3) Δ MS	(4) Δ GS	(5) Δ nonLEH4	(6) Δ LEH3	(7) Δ non LEH3
LEH (t-1)	-0.109***						
	(0.0108)						
LEH X 2008q3	-0.260***						
	(0.0103)						
MER (t-1)		-0.0226					
		(0.0159)					
MS X 2008q3		-0.0768***					
		(0.0163)					
MS (t-1)			-0.108***				
			(0.00562)				
MS X 2008q3			-0.0852***				
			(0.00570)				
GS (t-1)				-0.0826***			
				(0.00579)			
GS X 2008q3				-0.0213***			
				(0.00555)			
non LEH4 HF (t-1)					-0.0582***		
					(0.00455)		
non LEH4 HF X 2008q3					-0.0358***		
					(0.00443)		
LEH3 (t-1)						-0.105***	
						(0.00545)	
LEH3 X 2008q3						-0.0795***	
						(0.00550)	
non LEH3 HF (t-1)							-0.0592***
							(0.00372)
non LEH3 HF X 2008q3							-0.0237***
							(0.00375)
R-squared	0.152	0.136	0.085	0.059	0.044	0.082	0.043
N	153591	153591	153591	153591	153591	153591	153591

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: **Realized Returns and Ex-Ante Exposure to Lehman** This table reports estimates for Equation 41, which regresses realized returns on various hedge fund exposure share measures. Returns are raw (Ret_t^s) or residualized against the Fama-French 3 + Momentum model ($\varepsilon^s_{FF4,t}$). Exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the three-digit SIC industry-code level.

	(1) $ret_{s,t}$	(2) $\varepsilon_{FF4,s,t}$	(3) $ret_{s,t}$	(4) $\varepsilon_{FF4,s,t}$	(5) $ret_{s,t}$	(6) $\varepsilon_{FF4,s,t}$	(7) $ret_{s,t}$	(8) $\varepsilon_{FF4,s,t}$
LEH (t-1)	-0.833*	-0.779			-0.650	-0.585		
	(0.436)	(0.501)			(0.432)	(0.500)		
LEH3 (t-1)			-0.503***	-0.496**			-0.484**	-0.477**
			(0.185)	(0.221)			(0.187)	(0.223)
MS+MER (t-1)					-0.683***	-0.724**		
					(0.245)	(0.287)		
non LEH3 HF (t-1)							-0.193**	-0.181**
							(0.0795)	(0.0878)
R-squared	0.002	0.001	0.007	0.005	0.009	0.008	0.010	0.007
N	1889	1889	1889	1889	1885	1885	1885	1885

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

‘

10 Figures

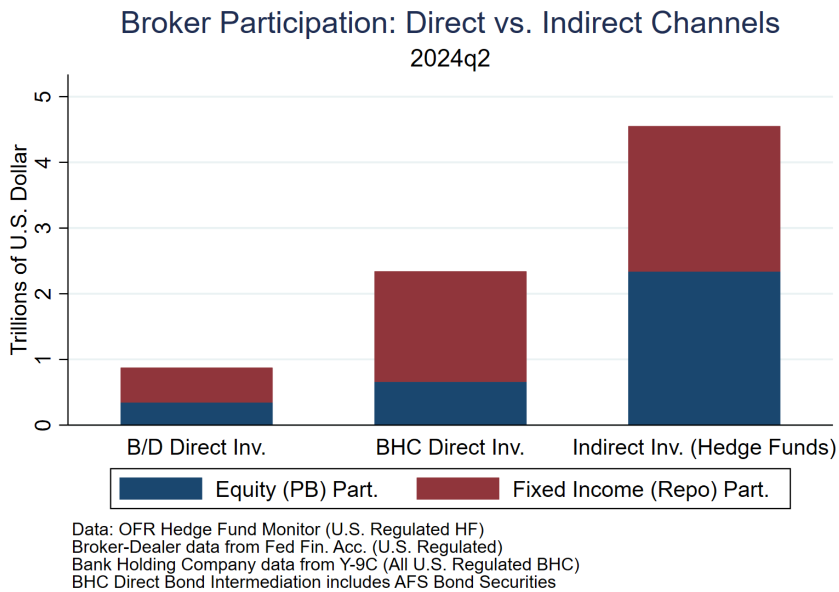


Figure 1: **Broker-Dealer Securities Market Participation: Direct vs. Indirect:** The figure reports broker-dealers’ total exposure to asset markets through both direct investments and indirect investments via lending to hedge funds. The blue bars represent exposure to equity holdings (or prime brokerage lending for indirect investments), while the red bars indicate exposure to fixed income securities (or lending via repurchase agreements for indirect investments). Column 1 shows direct broker-dealer holdings of US-regulated fixed income and equity assets based on Federal Financial Accounts data. Column 2 reports direct holdings at the bank holding company level (including both broker and bank holdings), calculated from Y-9C reports. Note that the discrepancy between broker and bank holding companies in equity holdings is likely due to the inclusion of foreign broker-dealers of US-regulated bank holding companies in Column 2. Column 3 reports total borrowings from hedge funds through repurchase agreements and prime brokerage margin agreements, as documented in the OFR Hedge Fund Monitor.

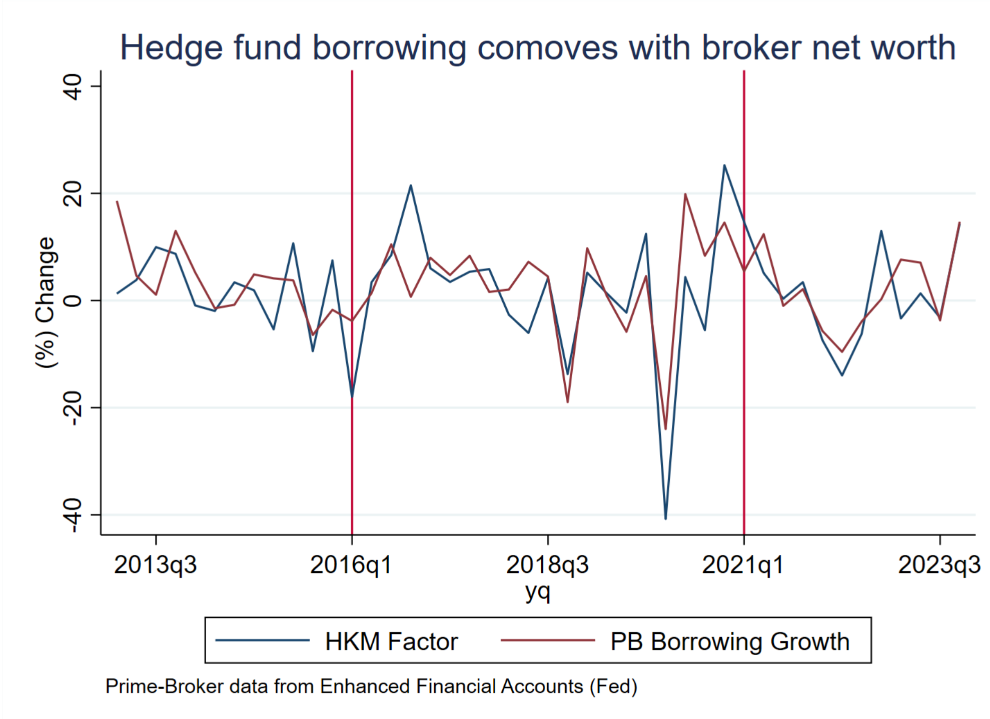


Figure 2: **Brokerage Lending and Intermediary Capital Factor:** The red line depicts the percentage change in total prime brokerage from the hedge fund sector, as measured by the SEC Private Funds Statistics. The blue line plots the He et al. [2017] intermediary capital risk factor, which measures innovations in primary dealer net capital ratio.

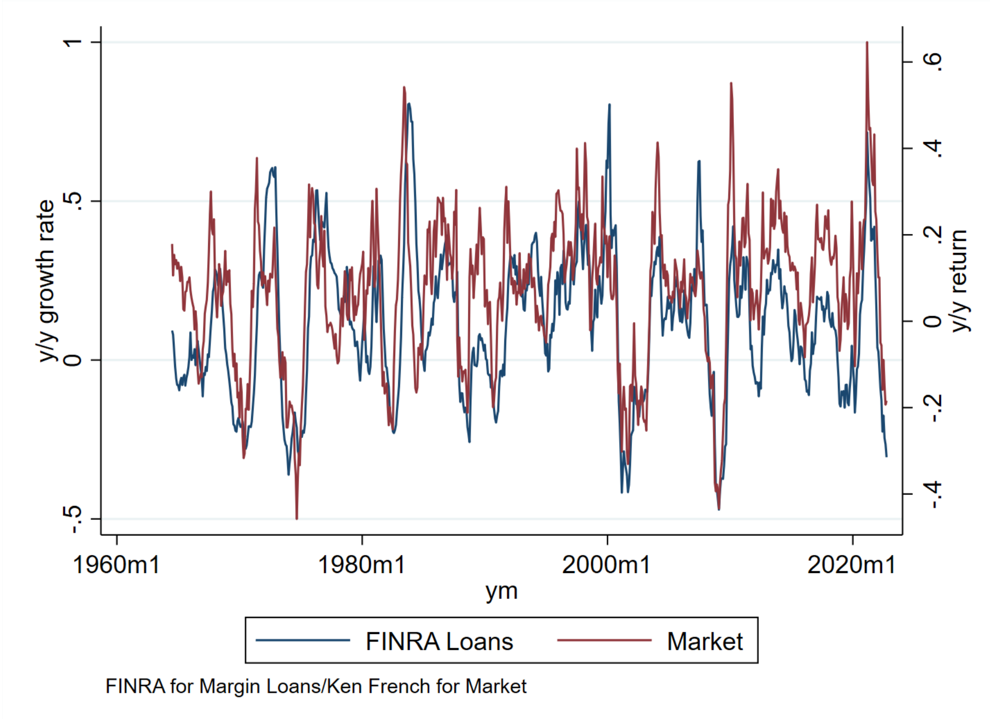


Figure 3: **FINRA Margin Loan Growth and the Market:** This figure plots the total margin lending (FINRA) against the market return since the 1960s.

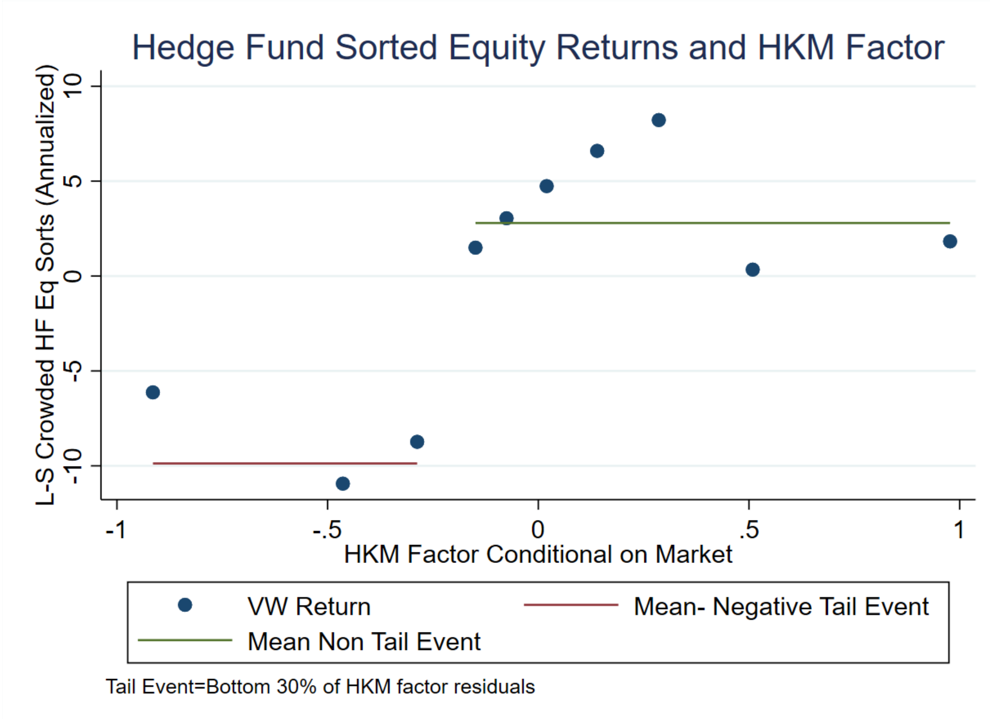


Figure 4: **Hedge Fund-Sorted Portfolio Returns and Intermediary Capital Factor:** This figure presents a binscattered regression of returns on long-minus-short portfolios, sorted by hedge fund exposure, constructed from FactSet's hedge fund database, against the He et al. [2017] intermediary net-worth factor. As proposed by He et al. [2017], we control for the market return factor within a two-factor model. We define a tail event when the He et al. [2017] factor (residualized to the market) falls within the bottom 30% of its distribution. The results show that hedge fund-sorted portfolios perform exceptionally poorly when intermediary capital—conditional on the factor—appears stressed.

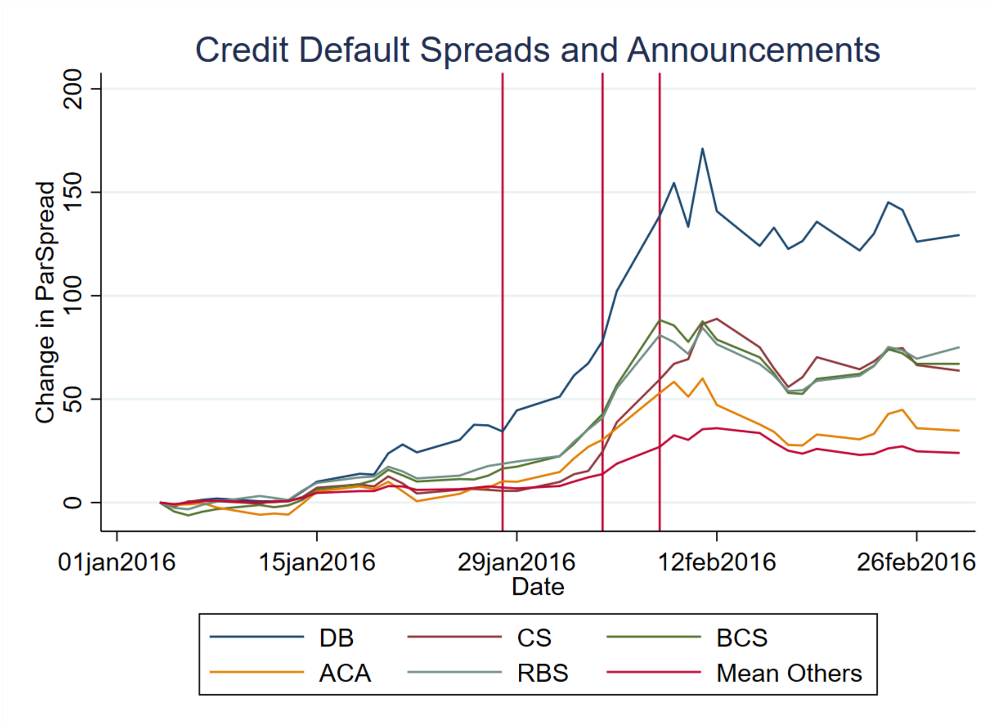
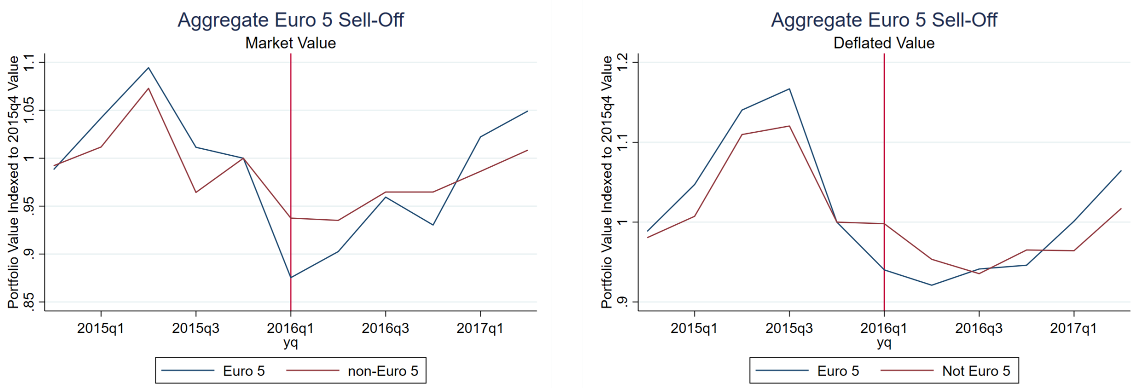
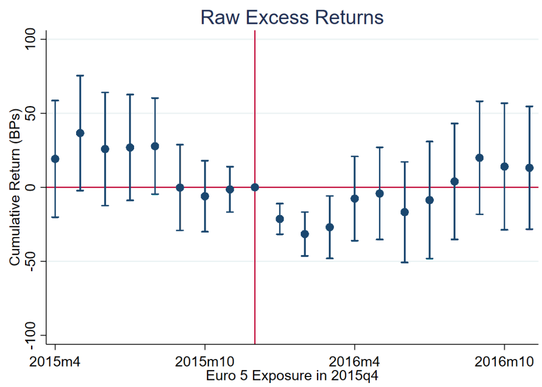


Figure 5: **CDS Spread Changes in Early Q1 2016:** In this figure, we plot the cumulative change in CDS spreads for a select group of European G-SIBs from the start of the quarter. The legend reports the tickers on individual broker-dealers. In order, the tickers are Deutsche Bank ("DB"), Credit Suisse ("CS"), Barclays ("BCS"), Credit Agricole ("ACA") and Royal Bank of Scotland/Natwest ("RBS"). "Mean Others" refers to the mean CDS spread change for all other broker-dealers in the Form ADV sample.

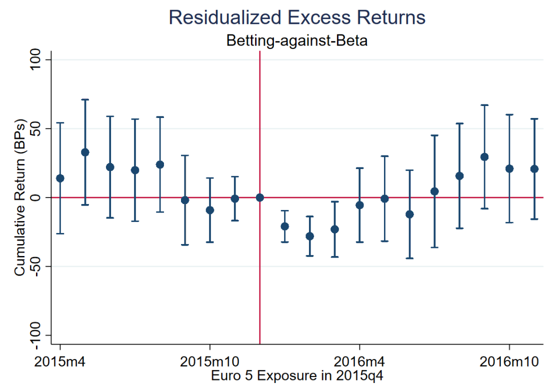


(a) Market Value **(b) Deflated Value**

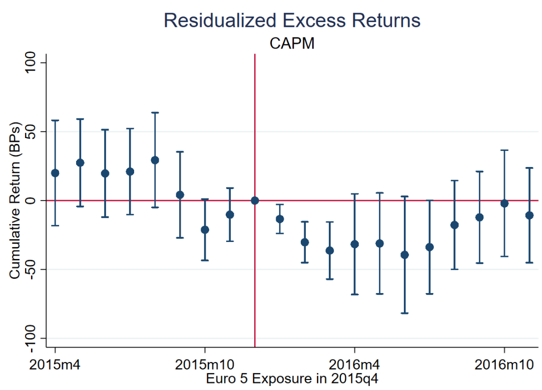
Figure 6: **Aggregate Sell-Off by Euro 5:** We plot the time series of the total value of holdings for hedge fund managers exposed to the Euro 5 (in blue) and funds that are not exposed to DB (in red). The right panel shows the cumulative change in the market value of aggregate holdings, while the left panel deflates aggregate holdings by the aggregate value-weighted returns each quarter.



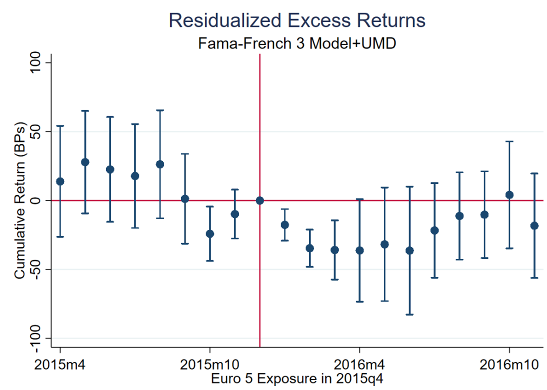
(a) Raw Realized Returns



(b) Betting-Against-Beta Residuals



(c) CAPM Residuals



(d) Fama-French 3 + Momentum Residuals

Figure 7: **Reversal Plots:** This figure presents estimates for Equation 29 from April 2015 to December 2016. Each point represents the regression estimate of cumulative returns, $CumRet_t^s$, on the market share of holdings by Euro 5 brokers as of Q4 2015. The four panels show different measures of returns: raw realized returns (top-left), returns residualized to the betting-against-beta model (top-right), returns residualized to the CAPM (bottom-left), and returns residualized to the Fama-French 3 + Momentum model (bottom-right). Standard errors are clustered at the three-digit SIC industry-code level.

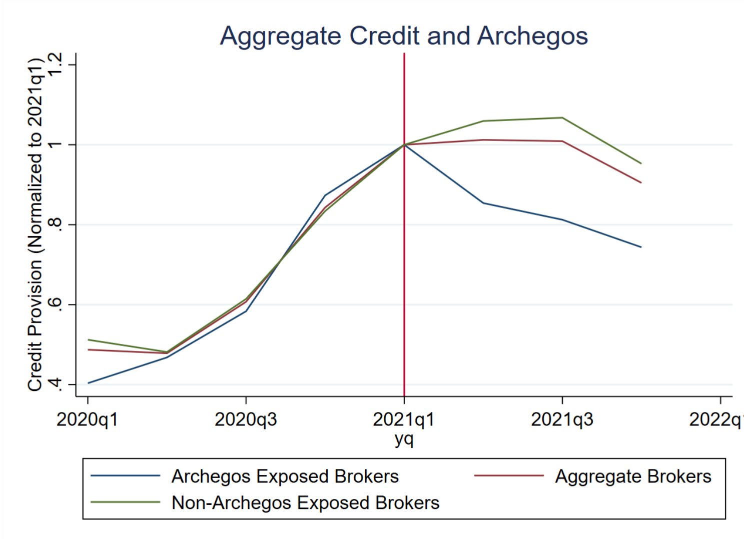
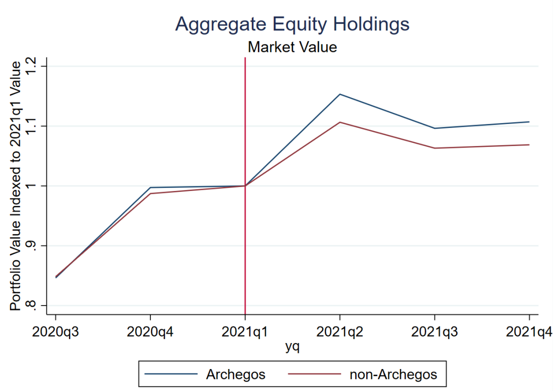
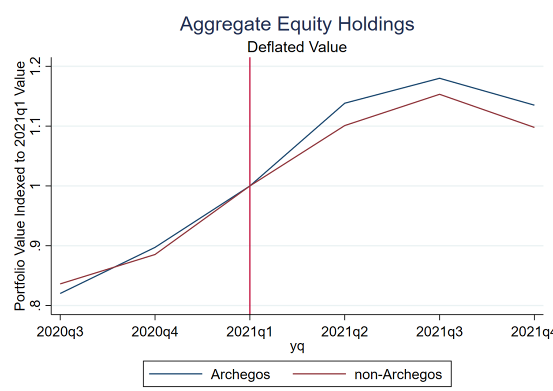


Figure 8: **Time Series of Credit** This figure shows the time series of investor loans by group. Lender by broker-dealers who suffered losses from Archegos is plotted in blue, normalized to Q1 2021 values. Lending by broker-dealers who did not suffer losses from Archegos is shown in green, also normalized to Q1 2021 values. Aggregate lending for all broker-dealers is presented in red.

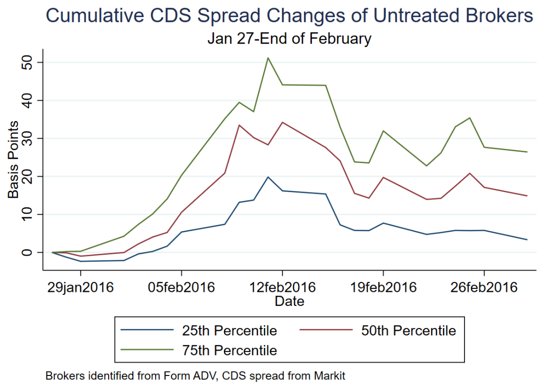


(a) Market Value

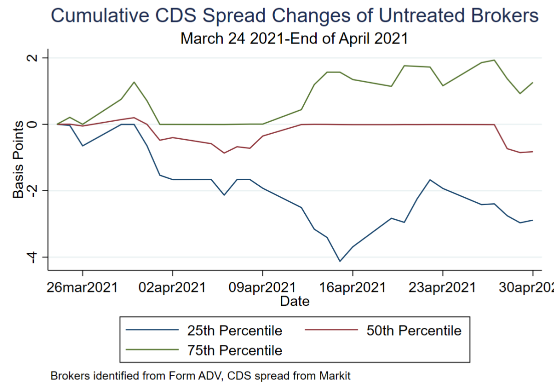


(b) Deflated Value

Figure 9: **Aggregate Equity Holdings by Archegos Exposure:** We plot the time series of the total value of holdings for hedge fund managers exposed to the Archegos brokers (in blue) and funds that are not exposed to Archegos brokers (in red). The right panel shows the cumulative change in the market value of aggregate holdings. The left panel deflates aggregate holdings by the aggregate value-weighted returns each quarter.

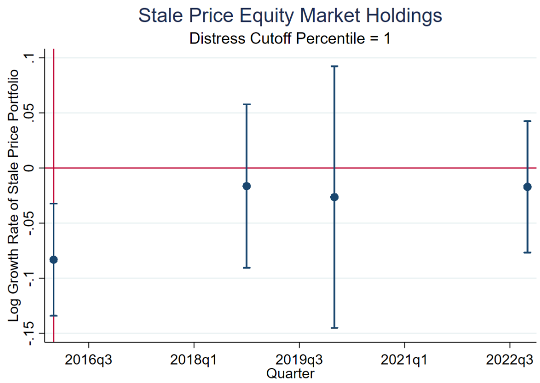


(a) **Euro 5**

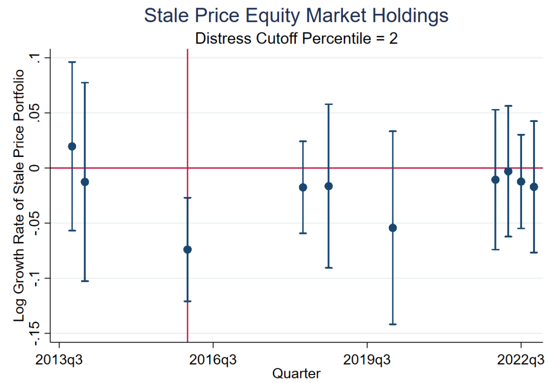


(b) **Archegos**

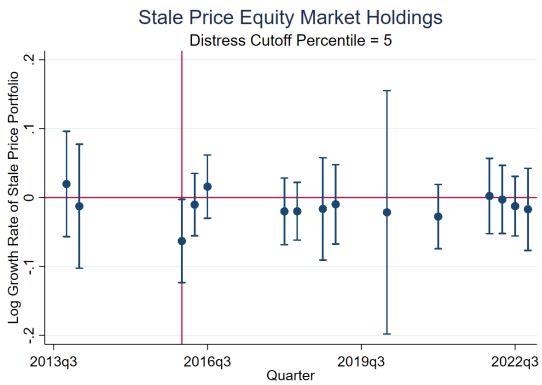
Figure 10: **CDS Spread Responses of Untreated Brokers:** This figure presents the unshocked broker-dealers' cumulative CDS spread changes after the onset of distress. We report the 25th, 50th, and 75th percentile of broker-dealers (identified by Form ADV) through until the end of the following calendar month. In the left panel, we report CDS spread changes for broker-dealers not assigned to the treatment group from January 27 onwards, observe that the median broker-dealer saw an increase of almost 30 basis points in their CDS spread after the event. In the right panel, we study the same CDS spread change patterns in response to Archegos, where we see no significant movement in untreated brokers' CDS spreads thereafter.



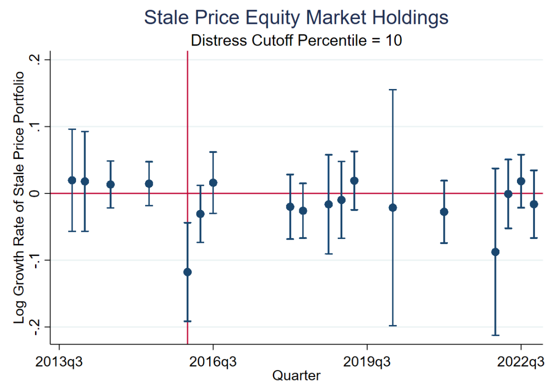
(a) Top 1%



(b) Top 2%



(c) Top 5%



(d) Top 10%

Figure 11: **Stale Price Portfolios in the Panel:** This figure presents estimates for Equations 39 across four different thresholds. The outcome variable is winsorized at 2.5% and 97.5% level. Robust standard errors are reported.

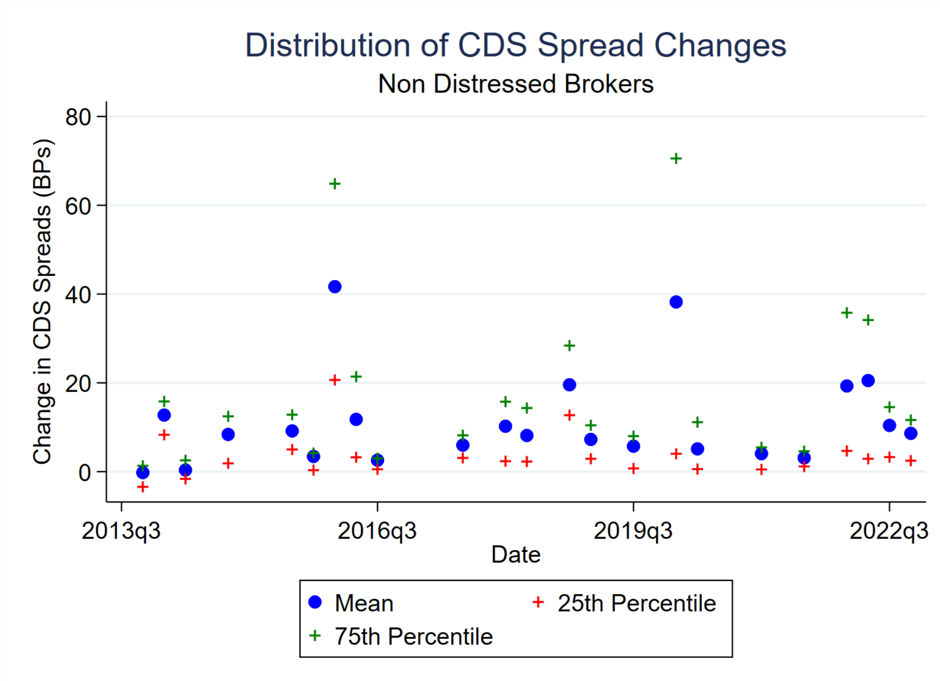


Figure 12: **Non-Shocked Brokers Health and the Panel:** This table reports the quarterly mean, 25th percentile, and 75th percentile of $Distress_t^b$ for brokers with $BigShock_t^b = 0$. $Distress_t^b$ is defined as the maximum CDS spread value in a quarter minus the end-of-quarter CDS spread value from the previous quarter. $BigShock_t^b$ is an indicator variable that equals one if a broker's $Distress_t^b$ value is in the top 5% of all observations in the sample.

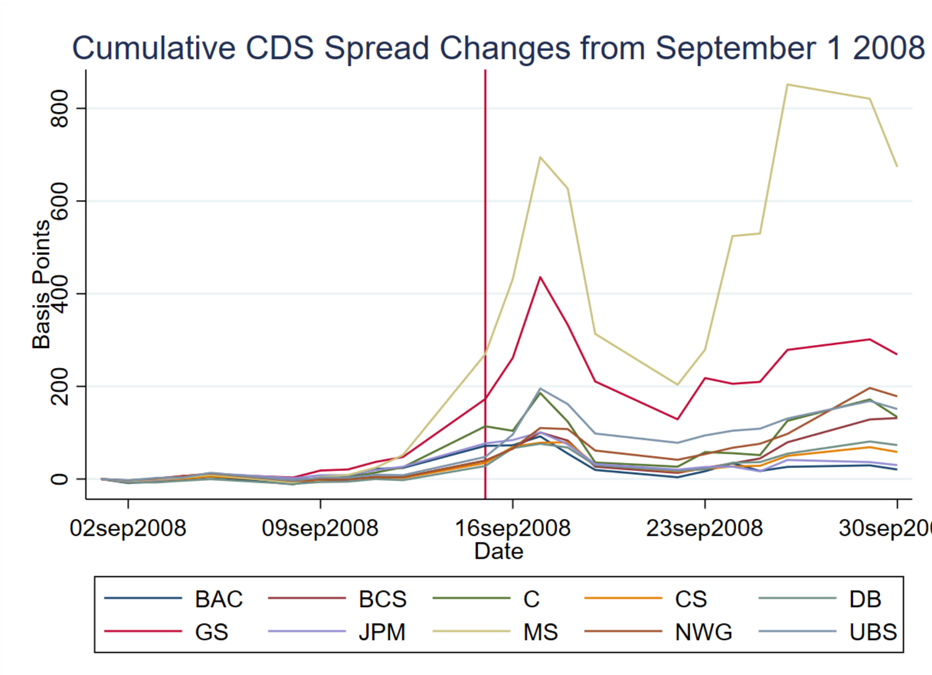


Figure 13: **CDS Spread Changes in September 2008:** This figure plots the cumulative CDS spread changes from September 1st 2008 for large broker-dealers. The red bar identifies the week-end of September 14th-15th when Merrill Lynch was acquired by Bank of American and Lehman Brothers failed.

A Institutional Details Appendix

This paper tests how intermediary health affects how brokers provide leverage to hedge funds for the purchase of equities. In this section, we provide key institutional details on institutional types, identities, and loan types. We also provide key aggregate facts when relevant.

A.1 Primer on (Prime) Brokers

Broker-dealers play a crucial role in intermediating securities and derivative markets. Brokers, by definition, facilitate transactions on behalf of their clients, while prime brokers specialize in servicing "prime" clients, namely hedge funds or family offices. Prime brokers offer a range of services to their clients, including financing long positions in equities through margin loans, lending securities to facilitate short positions, and efficiently processing trades.[52]

Broker-Dealer Balance Sheet

Cash	Customer Payables
Instruments Owned	Repurchase Agreements
Reverse Repo	**Securities Lent**
Securities Borrowed	Commercial Paper
Margin Loans	Financing from Parent Company
Customer Receivables	...
...	**Equity**

Figure 14: Stylized Broker-Dealer Balance Sheets

Figure 14 presents a simplified representation of a broker-dealer's balance sheet. On the asset side, the "dealer" subsidiary directly holds various assets. Brokers facilitate a significant volume of short-term secured borrowings through reverse repurchase agreements and securities borrowings. In these transactions, the broker transfers cash in exchange for a security and receives interest. The asset of particular interest in this paper is margin loans, which will be further described below.

Broker-dealers are large, sophisticated institutions with a complicated liability structure. Today, they rely heavily on equity, transfers from their parent holding companies, short-term secured borrowing, and short-term unsecured borrowing. Historically, brokers could also rely on long-

[52] Equities financing is a non-trivial revenue for large intermediaries. In its 2019 annual report, Goldman Sachs reported $3.02 billlion of revenues related to equities financing, contributing over 8% of total revenues for the consolidated bank holding companies.

term funding markets such as broker-specific equity and long-term debt, but these activities are now conducted by the parent company. Brokers match their liabilities to assets: brokers finance certain assets with certain liabilities and contracts to minimize risk and financing costs. To provide leverage to safe fixed income markets such as Treasuries and Agency securities, broker-dealers rely heavily on external financing via repo markets. For other assets classes (including margin credit), broker-dealers rely on the strength of their own balance sheet to finance these loans. In aggregate, due to the substantial secured transactions they facilitate, broker-dealers tend to be highly leveraged intermediaries.[53]

The partial repeal of Glass-Steagall in 1999 and distress from the Global Financial Crisis resulted in the consolidation of many systematically important broker-dealers into bank holding companies by the early 2010s. This consolidation occurred either through banks acquiring broker-dealers, as seen with J.P. Morgan's purchase of Bear Stearns, or by converting existing broker-dealers into bank-holding companies, as exemplified by Goldman Sachs. Consequently, these broker-dealers became subject to the regulatory reporting and limitations faced by bank holding companies (such as bank holding company capital regulation such as the Supplemental Leverage Ratio). Conversely, consolidation also led to potential spillovers between different subsidiaries within these institutions. Internal spillovers between subsidiaries could manifest through internal capital markets, where liquidity is funneled between different subsidiaries, external capital markets where the bank holding company might raise long-term debt and equity, or via indirect spillovers influenced by common policies. To counter these spillover, Federal Reserve Regulation W limits the scale of internal transfers between commercial banks and their sibling broker-dealers; however, internal capital markets due exists especially given exemptions for certain risk-free assets such as Treasuries. [54] For this project, the key dimension is that the market health of the broker-dealer is best proxied for using its bank holding company market health.

A.2 Primer on Equities Financing

Broker-dealers offer three forms of leverage to equity market investors: writing equity-market derivatives, facilitating short positions through securities lending, and providing margin loans to clients for the acquisition of equities. The latter two forms of leverage, which involve securities transactions by the broker-dealer's counterparty, are known as traditional leverage. Using publicly available aggregates, we see that funds readily use all three types of leverage in Figure 15. The

[53]For instance, via their public 2019 FOCUS balance sheet report, the main broker-dealer subsidiaries of Goldman Sachs had a book-leverage of over 31.

[54]See Correa et al. [2022] for a detail explanation for the internal capital markets of banks and a discussion for how binding Reg W is.

long prime brokerage market is roughly a 1$ trillion dollar market in this sample with a maximum market size of 1.2$ trillion dollars in 2021 Q4. In this paper, our focus is on traditional long leverage, as we only observe security-level long equity holding positions.

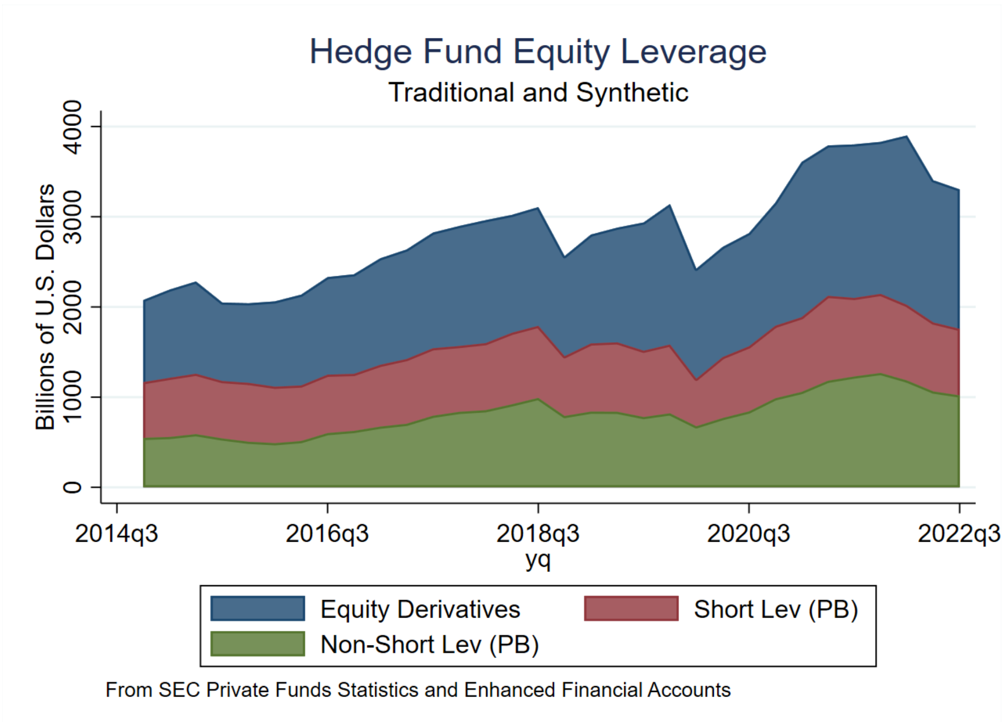


Figure 15: **Sources of Financing:** Using SEC Private Funds Statistics, we depict total leverage provided by brokers to hedge funds in equity derivative markets and prime brokerage markets. We decompose borrowings into three categories: traditional long leverage, traditional short borrowings, and synthetic borrowings for equities (equity derivatives). All three sources of borrowings are intermediated by prime brokers. It is straightforward to see that hedge fund borrowings for equities are large.

Margin loans are short-term collateralized loans provided by brokers to individual investors. In this arrangement, brokers offer cash to investors in exchange for a portfolio of securities, which serves as collateral for the loan. For hedge funds, margin loans represent the primary source of leverage for their equities positioning. These loans are considered callable, meaning the lender can demand repayment at any time, and they typically lack a fixed repayment schedule. Interest is charged periodically on the outstanding loan amount. To mitigate risk for the lender, margin loans are subject to margin requirements both at the loan's initiation and throughout its term. These requirements aim to limit the amount of leverage that can be obtained through such loans. In the United States, regulatory limitations are imposed on the amount of leverage allowed from margin loans. Regulation T specifies an initial debt-financing limit of 50% of the purchase value for securities bought on margin.[55]

Brokers set the terms of loans individually for each client and require that the collateralized securities be within the client's own margin account at the broker-dealer. While prime brokerage loans are over-collateralized, brokers take on risk as the collateral is risky and wrong-way risk exists. In particular, wrong-way risk can be exacerbated by asymmetric information between brokers and funds regarding a fund's riskiness and trading strategies, as funds have incentives to conceal proprietary trading strategies.[56] Later in this paper, we show that relationships between brokers and funds appear to be present in this market in response to this.

Brokers finance their margin loans using the following pecking order.[57] Broker-dealers first "internalize" their margin loan their demand by matching customer long and short position demand as it is the cheapest source of financing. Internalization also includes brokers borrowing from their own clients through individual investor "free credit balances." These free credit balances represent cash held in their margin accounts at broker-dealers, typically earning interest and subject to withdrawal on demand.[58] If internal sources of financing do not satisfy demand, broker-dealers turn to short-term secured funding markets. In such cases, brokers pledge either their own securities or rehypothecate the client's securities to secure cash necessary to fund these long positions. While we do not observe directly the funding sources in these markets, we see that the key funding sources are in debt-like markets.

Since the crisis, funds have become aware of counterparty risk from the brokers and have altered terms. First, prime brokerage agreements are more likely to include margin lock-ups agreement which prevents broker-dealers from changing margin and collateral terms for a fixed period of time—usually 1-4 months, see Paul [2021]. Second, funds borrow from a wider-range of counterparties than before the market

A.3 Hedge Funds

Hedge funds are private investment funds that pool capital from multiple investors and have a broad mandate to invest across various asset classes. They exclusively raise funds from high net-

[55] Brunnermeier and Pedersen [2008] argues that Regulation T might not be binding due to portfolio margining and the use of offshore transactions, see Page 30 of the published paper.

[56] Clancy [2024] quotes a risk manager for a large broker succinctly identifying this asymmetric information by saying funds "never disclose detailed risk pieces because of the nature of proprietary trading strategies."

[57] The following paragraph is based on substantial conversations policy-makers and industry participants; there is almost no literature or public sources discussing

[58] Free credits are essentially uninsured deposits to the broker-dealer. Conversation with market participants imply that this is the cheapest form of financing.

worth individuals and other institutional investors, commonly referred to as "accredited investors." Hedge funds are exempt from the Investment Company Act, which grants them the ability to use significant levels of leverage, and are main levered equity market investor. Managed by skilled investors, hedge funds play a crucial role as a source of active capital in equity markets.

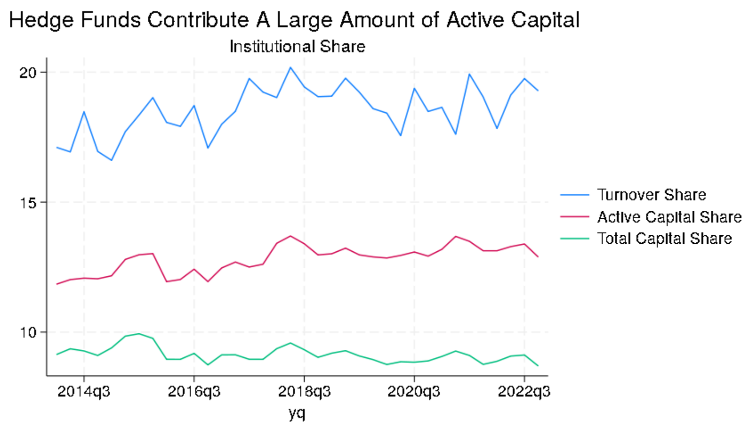


Figure 16: **Hedge Fund Size from 13-F Filings:** We employ several measures to gauge the size of hedge funds, derived from Form ADV and Factset Institutional Holdings data. The Total Capital Share is calculated by dividing the total holdings of hedge funds by the total holdings of all investors filing 13-F reports. For a more refined assessment, the Total Active Capital Share adjusts the holdings of each investor based on their activeness measure following Cremers and Petajisto [2009]. Additionally, the Total Turnover quantifies the turnover of each fund in their 13-F filings. Overall, our findings reveal that hedge funds contribute significantly as a source of active capital, as evidenced by the 13-F filings.

In Figure 16, we present the size of the equity hedge fund sector, based on Form ADV and holdings data from Factset. On average, these funds make up approximately 9% of the total value of institutional market holdings. However, more importantly for pricing, we see that hedge funds are substantially more active compared to other investors. gauge their activeness in two ways: first, the blue line illustrates that hedge funds account for approximately 20% of total quarterly turnover. Second, we use an alternative measure of activeness based on Cremers and Petajisto [2009]'s deviation from index portfolios, represented by the pink line, which also demonstrates that hedge funds provide active capital in the market.

B Model Appendix

B.1 Model with uncorrelated health

We consider a hedge fund that can borrow from N brokers with uncorrelated cost structures.

Broker Problem: The borrowing costs from each broker are influenced by the health of the broker and a stochastic cost factor. Each broker set their credit supply at expected marginal cost. The borrowing costs for each broker i are given by:

$$P_i = D_i + \varepsilon_i \tag{42}$$

where D_i is the baseline health index for broker i, and ε_i is a stochastic shock with $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$. Each random draw is independent of each other. D_i is an abstraction that represents th, either due to direct costs such as the cost of wholesale funding or as the shadow cost of a funding for prime-brokerage within the broker holding company's optimization problem.[59]

Hedge Fund Problem: Hedge funds have a simplified mean-variance optimization asset. The hedge fund leverages its capital by borrowing from multiple banks to invest in a risky asset that provides a return R. The total amount borrowed by the hedge fund is denoted by $L_{\text{total}} = \sum_{i=1}^{N} L_i$, where L_i is the borrowing from bank i (for $i = 1, 2, \ldots, N$.[60] The hedge fund's objective is to maximize its utility, which is a function of the expected return on the leveraged investment minus the risk (variance) associated with the return:

$$U(L_1, L_2, \ldots, L_N) = \mathbb{E}[R'_L] - \frac{\lambda}{2} \cdot \text{Var}(R'_L) \tag{43}$$

where λ is the risk aversion parameter, and $\text{Var}(R'_L)$ is the variance of the return on the leveraged investment. The return on the leveraged investment R'_L is given by:

$$R'_L = R \cdot (1 + L_{\text{total}}) - C(L_1, L_2, \ldots, L_N) \tag{44}$$

where $C(L_1, L_2, \ldots, L_N)$ is the total cost of financing. The total cost of financing $C(L_1, L_2, \ldots, L_N)$

[59]In reality, broker-dealers typically finance a substantial portion of their prime-brokerage activities in near-zero-cost funding markets, either by matching clients' positions (matched book) or by utilizing prime-brokerage free credits. However, during periods of extreme distress, broker-dealers may be compelled to raise external funding through wholesale funding markets. During these stress periods, the opportunity cost of a dollar of funding within the broker holding company is also likely to increase. We abstract away from these details

[60]Here, we view L as being the total borrowing scaled by net-assets in line with our main empirical specifications.

is the sum of the borrowing costs across all brokers:

$$C(L_1, L_2, \dots, L_N) = \sum_{i=1}^{N} P_i \cdot L_i = \sum_{i=1}^{N} H_i \cdot L_i + \sum_{i=1}^{N} \varepsilon_i \cdot L_i. \tag{45}$$

Given the distributional assumptions, the expected return on the leveraged investment is:

$$\mathbb{E}[R_L'] = \mathbb{E}[R] \cdot (1 + L_{\text{total}}) - \sum_{i=1}^{N} H_i \cdot L_i. \tag{46}$$

The variance of the leveraged return is driven by the idiosyncratic risks from each bank's borrowing cost:

$$\text{Var}(R_L') = \underbrace{\sigma_R^2 \cdot (1 + L_{\text{total}})^2}_{\text{asset risk}} + \underbrace{\sum_{i=1}^{N} \sigma^2 \cdot L_i^2}_{\text{financing risk}} \tag{47}$$

where σ_R^2 is the variance of the return on the risky asset.

B.1.1 Solution Comparative Statistics

we solve for the equilibrium of this model. Given a set of parameters, we derive equilibrium borrowing quantities for the borrowing from each broker:

$$L_i = \underbrace{\frac{\mathbb{E}[R] - D_i}{\lambda \cdot (\sigma_R^2 + \sigma^2)}}_{\text{Risk-Adjusted Financing Spread}} - \underbrace{\frac{\sigma_R^2 \cdot \left(1 + \sum_{j \neq i}^{N} L_j\right)}{\cdot (\sigma_R^2 + \sigma^2) \cdot (N+1)}}_{\text{Concentration Penalty}} \tag{48}$$

The first term reflects the mean effect of the financing spread: Adjusting for risk, hedge funds will borrow more from a broker that has better health as the financing spread will be higher. The second term reflects a concentration penalty if the hedge fund takes on too much borrowing relative to the risks associated with the total leverage. It discourages excessive concentration of borrowing and encourages diversification across banks.

Total borrowing can then be expressed as:

$$L_{\text{total}} = \frac{N\mathbb{E}[R] - \sum_{i=1}^{N} D_i - \lambda \sigma_R^2 N}{\lambda (\sigma^2 + N\sigma_R^2)} \tag{49}$$

where total borrowing is pinned down by each bank's bank-health and the structural parameters.

Now, what happens if broker A's health deteriorates? Accounting for both direct and indirect effects, we can set up the system of equations as

$$\frac{\partial L_A}{\partial D_A} = \frac{-1}{\lambda(\sigma^2+\sigma_R^2)} - \frac{\sigma_R^2}{\sigma^2+\sigma_R^2}\sum_{j\neq A}\frac{\partial L_j}{\partial D_A} \tag{50}$$

We see that the fund has two counter-acting forces for total borrowing: First, funds want to borrow less from the shocked broker due to the credit supply shock. In the second term, as if funds now borrow more from other brokers and the the broker has convex preference, the total quantity of brokerage risk attributable to other brokers is increasing, putting an additional incentive to borrow less.

The borrowing from any other broker j (where $j \neq A$) also changes in response to the shock to D_A:

$$\frac{\partial L_i}{\partial D_A} = -\frac{\sigma_R^2}{\sigma^2+\sigma_R^2}\frac{\partial L_A}{\partial D_A} - \frac{\sigma_R^2}{\sigma^2+\sigma_R^2}\sum_{j\neq i, j\neq A}\frac{\partial L_j}{\partial D_A} \tag{51}$$

The first term reflects that fund will substitute away from shocked broker-dealer to the other broker-dealers in the choice set. This effect is also tempered by the endogeneous response to increased concentration of other broker-dealers, but, the interesting effect we will study is the first term which reflects the substitution effects in this model.

The borrowing from any other broker j (where $j \neq A$) also changes in response to the shock to $\bar{D}_A$:

$$\frac{\partial L_i}{\partial \bar{D}_A} = -\frac{\sigma_R^2}{\sigma^2+\sigma_R^2}\sum_{j\neq i}\frac{\partial L_j}{\partial \bar{D}_A} = \frac{\sigma_R^2}{\sigma^2+\sigma_R^2}\sum_{j\neq i, j\neq A}\frac{\partial L_j}{\partial \bar{D}_A} - \frac{\sigma_R^2}{\sigma^2+\sigma_R^2}\frac{\partial L_A}{\partial \bar{D}_A} \tag{52}$$

Solution: First, note that the effect for indirectly shocked banks should be symmetric, i.e. that $\frac{\partial L_k}{\partial \bar{D}_A} = \frac{\partial L_j}{\partial \bar{D}_A}$ for all $j \neq A, k \neq A$. The only heterogeneity between banks in this model is heterogeneity of their own health, which does not interact with health A. Let $\frac{\partial L_A}{\partial \bar{D}_A} = x_A$ denote the derivative of Bank A's borrowing with respect to its own health shock, and let $\frac{\partial L_i}{\partial \bar{D}_A} = x$ for all indirectly affected banks $i \neq A$.

The derivative for Bank A is given by:

$$x_A = \frac{-1}{\lambda(\sigma^2+\sigma_R^2)} - \frac{\sigma_R^2(N-1)}{\sigma^2+\sigma_R^2}x \tag{53}$$

For any indirectly affected bank $i \neq A$, the derivative is:

$$x = -\frac{\sigma_R^2}{\sigma^2 + \sigma_R^2}\left(x_A + (N-2)x\right) \tag{54}$$

Solving for x and x_A

We solve for x by rearranging the equation:

$$x\left(1 + \frac{\sigma_R^2(N-2)}{\sigma^2 + \sigma_R^2}\right) = -\frac{\sigma_R^2}{\sigma^2 + \sigma_R^2}x_A \tag{55}$$

$$x = -\frac{\frac{\sigma_R^2}{\sigma^2+\sigma_R^2}x_A}{1 + \frac{\sigma_R^2(N-2)}{\sigma^2+\sigma_R^2}} = -\frac{\sigma_R^2 x_A}{(\sigma^2 + \sigma_R^2) + \sigma_R^2(N-2)} \tag{56}$$

Substituting this expression for x back into the equation for x_A:

$$x_A\left[1 + \frac{\sigma_R^4(N-1)}{(\sigma^2 + \sigma_R^2)\cdot((\sigma^2 + \sigma_R^2) + \sigma_R^2(N-2))}\right] = \frac{-1}{\lambda(\sigma^2 + \sigma_R^2)} \tag{57}$$

Solving for x_A:

$$x_A = \frac{-1}{\lambda}\cdot\frac{(\sigma^2 + \sigma_R^2)\cdot((\sigma^2 + \sigma_R^2) + \sigma_R^2(N-2))}{(\sigma^2 + \sigma_R^2)\cdot((\sigma^2 + \sigma_R^2) + \sigma_R^2(N-2)) + \sigma_R^4(N-1)} \tag{58}$$

B.1.2 Behavior as N Becomes Large

Next, we analyze the behavior of the derivatives as the number of banks N becomes very large.

B.1.3 Derivative for Indirectly Affected Banks x

As N becomes large, the term $\sigma_R^2(N-2)$ dominates the denominator in the expression for x:

$$x \approx -\frac{\sigma_R^2 x_A}{\sigma_R^2 N} = -\frac{x_A}{N} \tag{59}$$

Thus, x becomes very small as N increases.

Derivative for Bank A x_A

Similarly, the term $\sigma_R^4(N-1)$ dominates in the denominator of the expression for x_A:

$$x_A \approx \frac{-1}{\lambda\sigma_R^2 N} \tag{60}$$

Therefore, x_A also decreases as N increases, but more slowly than x.

Sum of All Derivatives

The sum of all derivatives is given by:

$$\sum_{i=1}^{N} \frac{\partial L_i}{\partial \bar{D}_A} = x_A + (N-1)x \tag{61}$$

Substituting the expressions for x and x_A:

$$\sum_{i=1}^{N} \frac{\partial L_i}{\partial \bar{D}_A} \approx x_A \cdot \frac{1}{N} = \frac{-1}{\lambda\sigma_R^2 N^2} \tag{62}$$

Summing the contributions to $\frac{dL_{\text{total}}}{d\bar{D}_A}$:

$$\frac{dL_{\text{total}}}{d\bar{D}_A} = \frac{-1}{\lambda\cdot(\sigma_R^2+\sigma^2)} + (N-1)\cdot\left(-\frac{\lambda\cdot\sigma_R^2}{\lambda\cdot(\sigma_R^2+\sigma^2)}\right)\cdot\frac{1}{\lambda\cdot(\sigma_R^2+\sigma^2)} \tag{63}$$

Simplifying:

$$\frac{dL_{\text{total}}}{d\bar{D}_A} = \frac{-1}{\lambda\cdot(\sigma_R^2+\sigma^2)}\cdot\frac{1}{1+\frac{(N-1)\cdot\sigma_R^2}{\sigma_R^2+\sigma^2}} \tag{64}$$

Further simplification gives:

$$\frac{dL_{\text{total}}}{d\bar{D}_A} = \frac{-1}{\lambda\cdot\left(\sigma_R^2+\sigma^2+(N-1)\cdot\sigma_R^2\right)} \tag{65}$$

B.1.4 Behavior as N Becomes Large

As N becomes large, the term $(N-1)\cdot\sigma_R^2$ dominates the denominator:

$$\frac{dL_{\text{total}}}{d\bar{D}_A} \approx \frac{-1}{\lambda \cdot N \cdot \sigma_R^2} \tag{66}$$

Taking the limit as N tends to infinity:

$$\lim_{N\to\infty} \frac{dL_{\text{total}}}{d\bar{D}_A} = \lim_{N\to\infty} \frac{-1}{\lambda \cdot N \cdot \sigma_R^2} = 0 \tag{67}$$

B.2 Model with correlated health

We consider a model with N banks similar to above:

- **Bank A** has a distinct health index D_A and borrowing quantity L_A.
- **Banks B through N** are identical, with the same health index D_b and the same borrowing quantity L_b.

The borrowing costs for Bank A is given by:

$$P_A = \bar{D}_A + \varepsilon_A \tag{68}$$

and The borrowing costs for Bank A is given by:

$$P_B = \bar{D}_B + \rho\bar{D}_A + \varepsilon_B \tag{69}$$

where $\bar{D}_i$ is the baseline health index for bank i, $\rho \in (0,1)$ is the impact of Bank A's health on other banks, and ε_i is a stochastic shock with $\varepsilon_i \sim \mathcal{N}(0,\sigma^2)$. Each random draw is independent of each other.

The hedge fund borrows from these banks and maximizes its utility based on the expected return and the risk associated with the leveraged investment with the following objective function:

$$U(L_A,L_b) = [\mathbb{E}[R]\cdot(1+L_A+(N-1)L_b) - (D_A\cdot L_A + \varepsilon_A\cdot L_A + (N-1)\cdot(D_b\cdot L_b + \rho D_A\cdot L_b + \varepsilon_b\cdot L_b))] \tag{70}$$

$$-\frac{\lambda}{2}\left[\sigma_R^2\cdot(1+L_A+(N-1)L_b)^2 + \sigma^2\cdot\left(L_A^2+(N-1)L_b^2\right)\right] \tag{71}$$

B.3 Deriving the First-Order Condition for L_A

To maximize the utility $U(L_A, L_b)$, we take the derivative of U with respect to L_A and set it to zero:

$$
\begin{aligned}
\frac{\partial U}{\partial L_A} =& \frac{\partial}{\partial L_A}\left[\mathbb{E}[R]\cdot(1+L_A+(N-1)L_b)\right] \\
&- \frac{\partial}{\partial L_A}\left[D_A \cdot L_A + (N-1)\cdot(D_b \cdot L_b + \rho D_A \cdot L_b)\right] \\
&- \frac{\partial}{\partial L_A}\left[\frac{\lambda}{2}\left[\sigma_R^2\cdot(1+L_A+(N-1)L_b)^2 + \sigma^2\cdot L_A^2 + (N-1)\sigma^2\cdot L_b^2\right]\right]
\end{aligned}
$$

Putting it all together:

$$\frac{\partial U}{\partial L_A} = \mathbb{E}[R] - D_A - \lambda\sigma_R^2\cdot(1+L_A+(N-1)L_b) - \lambda\sigma^2\cdot L_A$$

Setting this derivative to zero gives the first-order condition for L_A:

$$\mathbb{E}[R] - D_A = \lambda\sigma_R^2\cdot(1+L_A+(N-1)L_b) + \lambda\sigma^2\cdot L_A$$

B.3.1 Solving for L_A

Finally, solve for L_A:

$$L_A = \frac{\mathbb{E}[R] - D_A - (\lambda\sigma_R^2)(1+(N-1)L_b)}{\lambda\left(\sigma^2+\sigma_R^2\right)}$$

B.3.2 Deriving the First-Order Condition for L_b

$$L_b = \frac{E[R] - D_A\rho - D_b - \lambda(1+L_A\sigma_R^2)}{\lambda\left(N\sigma_R^2+\sigma^2-\sigma_R^2\right)} \tag{72}$$

B.4 Derivatives with respect to D_A

The system of differential equations is:

Differential equation for L_A:

$$\frac{dL_A}{dD_A} = \frac{\partial L_A}{\partial D_A} + \frac{\partial L_A}{\partial L_b}\cdot\frac{dL_b}{dD_A}$$

Where:
$$\frac{\partial L_A}{\partial D_A} = -\frac{1}{\lambda(\sigma^2 + \sigma_R^2)}$$
$$\frac{\partial L_A}{\partial L_b} = -\frac{(N-1)\lambda\sigma_R^2}{\lambda(\sigma^2 + \sigma_R^2)}$$
Thus:
$$\frac{dL_A}{dD_A} = -\frac{1}{\lambda(\sigma^2 + \sigma_R^2)} - \frac{(N-1)\lambda\sigma_R^2}{\lambda(\sigma^2 + \sigma_R^2)} \cdot \frac{dL_b}{dD_A}$$

Differential equation for L_b:

$$\frac{dL_b}{dD_A} = \frac{\partial L_b}{\partial D_A} + \frac{\partial L_b}{\partial L_A} \cdot \frac{dL_A}{dD_A}$$

Where:
$$\frac{\partial L_b}{\partial D_A} = -\frac{\rho}{\lambda(N\sigma_R^2 + \sigma^2 - \sigma_R^2)}$$
$$\frac{\partial L_b}{\partial L_A} = -\frac{\lambda\sigma_R^2}{\lambda(N\sigma_R^2 + \sigma^2 - \sigma_R^2)}$$
Thus:
$$\frac{dL_b}{dD_A} = -\frac{\rho}{\lambda(N\sigma_R^2 + \sigma^2 - \sigma_R^2)} - \frac{\lambda\sigma_R^2}{\lambda(N\sigma_R^2 + \sigma^2 - \sigma_R^2)} \cdot \frac{dL_A}{dD_A}$$

This system describes the relationship between L_A and L_b as a function of D_A.

We can solve:

The simplified expression for $\frac{dL_A}{dD_A}$ is:

$$\frac{dL_A}{dD_A} = \frac{-1 + \frac{(N-1)\rho\sigma_R^2}{N\sigma_R^2 + \sigma^2 - \sigma_R^2}}{\lambda(\sigma^2 + \sigma_R^2)\left(1 - \frac{(N-1)\sigma_R^2}{(\sigma^2 + \sigma_R^2)(N\sigma_R^2 + \sigma^2 - \sigma_R^2)}\right)}$$

The simplified expression for $\frac{dL_b}{dD_A}$ is:

$$\frac{dL_b}{dD_A} = -\frac{\rho}{\lambda(N\sigma_R^2 + \sigma^2 - \sigma_R^2)} - \frac{\sigma_R^2\left(N\sigma_R^2 - \rho\sigma_R^2(N-1) + \sigma^2 - \sigma_R^2\right)}{\lambda\left(\sigma_R^2(N-1) - (\sigma^2 + \sigma_R^2)(N\sigma_R^2 + \sigma^2 - \sigma_R^2)\right)(N\sigma_R^2 + \sigma^2 - \sigma_R^2)}$$

While not a perfect analog to the earlier case, we see that the direct health impact on D_a onto L_b via spillovers dampen the incentive as the second term is less than 0.

The full expression for $\frac{dL_{\text{tot}}}{dD_A}$ is:

$$\frac{1}{\lambda\left(\sigma_R^2(N-1)-(\sigma^2+\sigma_R^2)(N\sigma_R^2+\sigma^2-\sigma_R^2)\right)(N\sigma_R^2+\sigma^2-\sigma_R^2)}[\rho(\sigma_R^2(N-1)$$
$$-(\sigma^2+\sigma_R^2)(N\sigma_R^2+\sigma^2-\sigma_R^2))+$$
$$+\sigma_R^2(N\sigma_R^2-\rho\sigma_R^2(N-1)+\sigma^2-\sigma_R^2)]+(N\sigma_R^2+\sigma^2-\sigma_R^2)(N\sigma_R^2-\rho\sigma_R^2(N-1)+\sigma^2-\sigma_R^2)]$$

When N becomes large, the expression for $\frac{dL_{\text{tot}}}{dD_A}$ simplifies as follows:

B.4.1 Proof for $N \to \infty$

For large N, the dominant terms in the expression (the N^2 terms) simplify to:

$$\frac{dL_{\text{tot}}}{dD_A} \approx \frac{1}{\lambda}$$

This shows that as N becomes large, the sensitivity of total borrowing to changes in D_A tends towards a constant value, $\frac{1}{\lambda}$.

C Identifying Broker-Dealer Distress Events: A Narrative Approach

To test the importance of broker-dealer health on lending, we ideally need a shock to one or more large prime brokers that is plausibly exogenous to (a) the macroeconomic environment and (b) the health of other intermediaries. As we aim to identify the effect in cross-section, we can either identify (a) idiosyncratic shocks to specific broker-dealers or (b) systematic shocks with plausible cross-sectional variation. In this paper, as we are focusing on distress-based shocks, we choose the former approach since the latter often coincides with macroeconomic conditions.[61]

A key constraint in our project is the availability of full prime broker networks. Form ADV prime brokerage data is available only starting in late 2012, so we restrict our main analysis sample to 2013Q1 through 2022Q4.[62] Since we want shocks affecting large broker-dealers, we limit ourselves to the fifteen largest brokers associated with a bank or bank holding company, listed in Table18.

[61] In our sample period, two plausible shocks of the latter type are (a) COVID-19 distress and (b) Brexit. Both events likely impacted certain groups of broker-dealers more than others; however, they coincided with significant changes in macro fundamentals.

[62] Our data begins in 2012Q4, making 2013Q1 the first period in which we can study broker-specific differences. This period restricts several candidate shocks, such as the collapse of Lehman and the European banking crisis.

Table 18: **Large Broker-Dealers:** These broker-dealers are the most common Form ADV prime broker counterparties that bank holding companies or investment banks.

JP Morgan	Morgan Stanley	Goldman Sach	Bank of America	Citi
Barclays	BNP Paribas	Credit Suisse	Deutsche Bank	UBS
BNY Mellon	Charles Schwab	Jefferies	Societe Generale	Wells Fargo

Guided by the markets we want to study, we seek shocks that disrupt the capacity of a broker-dealer to finance itself. We consider three main types of events: (1) Impairments/Unexpected Losses, (2) Debt Default Concerns or Runs, and (3) Large Fines and Impairments. Each of these events has the potential to disrupt a broker-dealer's funding. Using sources such as Compustat, annual reports, financial news, and government fine announcements, we assemble a list of these announcements.[63] For debt defaults or runs, we identify events from the literature. When possible, we group together brokers with similar losses.[64]

The two key datasets are (a) ViolationsTrackers' list of fines and (b) Compustat's Special Items ("SPIQ"). The former is publicly available and aggregates all fines issued to major corporations by the United States Government, including announcement dates, fine amounts, and fine types.[65] Compustat's Special Items dataset contains one-time items, often related to goodwill impairments or expected litigation expenses, which are likely exogenous. To our knowledge, no dataset describes special items specifically, so we manually analyze relevant corporate filings or financial news sources.

Defining Relevance of Losses: We include any debt concern event in our initial set of potential events. For fines, we require that a loss (defined as a fine or special item) either (a) amount to \$1B or more for the broker-dealer itself, or (b) average \$1B or more in losses per broker-dealer within a plausible grouping of brokers. This criterion allows us to identify only large events and to include regulatory announcements that affect multiple bank holding companies on the same date—a common occurrence. We present our list of possible events in Tables 20, 19, and 21.

Defining Market Health Impact and Surprise: Not all large announcements of losses are unexpected or relevant to the firm's financing ability. To test if a shock is a surprise, we regress the two-day CDS spread change on an indicator variable that takes the value of one if the broker

[63] We classify fines in the third category, even when they appear in the first category.

[64] This could be due to common exposure to a counterparty, such as Archegos for Credit Suisse and Morgan Stanley in 2021Q1-2, or similar types of losses—such as the write-downs for major European broker-dealers in 2015Q4-2016Q1.

[65] This data is available free of charge. A subscription service is offered to download data in spreadsheet form.

experienced a loss or fine on that date. We also compute the average CDS spread change for all broker-dealers on these dates. We retain only events significant at the 1% level.

After compiling this list, we exclude events where hedge fund demand or equity prices were likely influenced by other mechanisms. For example, Wells Fargo announced a large fraud settlement on February 21, 2020, with the Department of Justice. Although market measures of distress suggested financial health impairments, this event coincided with the onset of the COVID-19 pandemic, raising concerns about its exogeneity relative to macroeconomic conditions. We also remove prime brokers that are not significant in the quarter of the shock, based on Y-9C loan data or, if unavailable, on Form ADV hedge fund relationships for that quarter.[66]

This process yields a list of 10 possible broker-specific events. We then group broker events into plausible groupings, as described below.

Table 19: **Near Defaults**: This table presents a list of near defaults or defaults by broker-dealers in the regulatory data sample from 2013-2022.

Bank	Month	Event	News Source	Lit
DB	2016m1-2	CoCo Bond Default	Bloomberg	Bologna et al. [2020]
DB x2	2016m9	CoCo Bond Default	Bloomberg	Bologna et al. [2020]

[66] For instance, Credit Suisse was a significant prime broker until mid-2021; however, losses related to Archegos led it to exit American prime brokerage markets afterward. Thus, although outside our sample period, Credit Suisse's 2023Q1 collapse is a poor candidate for shock analysis.

Table 20: **Broker Special Items:** This table describes special item losses reported to Compustat for large American brokers and the corresponding two-day changes in CDS spreads around these announcements. The provisions are classified as arising from trading losses, impairments, or legal issues. ΔCDS^b (abnormal) refers to the difference in two-day CDS spread changes between the treated broker and other brokers on the announcement date. Dates are sourced from Compustat, except for the Deutsche Bank losses in 2016 Q1 and the Credit Suisse losses in 2021 Q1. The significance level indicates the statistical significance of a cross-sectional regression of ΔCDS^b on an indicator variable that takes the value of one if a broker had a fine announcement on that date. Standard errors are heteroskedasticity-robust.

Date Announced	Broker Parent	Ticker	Losses B$USD	Type	ΔCDS^b (abnormal)	$\overline{\Delta CDS}$	Significance
4/17/2013	BANK OF AMERICA CORP	BAC	-2.2	Provisions (Legal)	3.63	3.59	1% level
7/30/2013	BARCLAYS PLC	BCS	-3.0	Provisions (Legal)	-3.43	-3.84	Not/Neg
10/11/2013	JPMORGAN CHASE & CO	JPM	-9.3	Provisions (Legal)	-0.64	-1.32	Not/Neg
1/17/2014	MORGAN STANLEY	MS	-1.3	Provisions (Legal)	0.06	-1.82	Not/Neg
2/6/2014	CREDIT SUISSE GROUP	CS	-1.7	Provisions (Legal)	-0.24	-0.83	Not/Neg
4/16/2014	BANK OF AMERICA CORP	BAC	-6.0	Provisions (Legal)	-0.46	-1.23	Not/Neg
7/14/2014	CITIGROUP INC	C	-4.2	Provisions (Legal)	-0.85	0.49	Not/Neg
7/16/2014	BANK OF AMERICA CORP	BAC	-4.0	Provisions (Legal)	0.83	-0.42	1% level
7/22/2014	CREDIT SUISSE GROUP	CS	-2.1	Provisions (Legal)	-1.13	-1.86	Not/Neg
7/30/2014	BARCLAYS PLC	BCS	-1.5	Provisions (Legal)	0.96	4.03	Not/Neg
7/31/2014	BNP PARIBAS	BNPQY	-8.1	Provisions (AML)	3.30	5.63	1% level
10/14/2014	JPMORGAN CHASE & CO	JPM	-1.1	Provisions (Legal)	3.52	1.18	5% level
1/14/2015	JPMORGAN CHASE & CO	JPM	-1.1	Provisions (Legal)	5.36	1.13	1% level
1/20/2015	MORGAN STANLEY	MS	-3.9	Provisions (Legal)	-0.97	-2.45	Not/Neg
3/3/2015	BARCLAYS PLC	BCS	-2.1	Provisions (Legal)	0.30	0.82	Not/Neg
7/29/2015	BARCLAYS PLC	BCS	-1.6	Provisions (Legal)	0.08	-0.41	Not/Neg
1/28/2016	DEUTSCHE BANK AG	DB	-6.4	Impairments (Retail Banking)	6.91	0.33	1% level
2/4/2016	CREDIT SUISSE GROUP	CS	-4.1	Impairments (Restructuring)	13.81	9.76	1% level
2/5/2016	BNP PARIBAS	BNPQY	-1.2	Provisions (Legal)	-1.95	6.80	Not/Neg
3/1/2016	BARCLAYS PLC	BCS	-3.1	Impairments (Restructuring)	-6.09	-7.73	Not/Neg
2/2/2017	DEUTSCHE BANK AG	DB	-1.1	Provisions (Legal)	-4.69	-2.09	Not/Neg
2/14/2017	CREDIT SUISSE GROUP	CS	-2.6	Provisions (Legal)	-0.82	-1.04	Not/Neg
1/17/2018	BANK OF AMERICA CORP	BAC	-1.1	Impairments (Taxes)	0.55	0.43	Not/Neg
7/24/2019	DEUTSCHE BANK AG	DB	-1.2	Provisions (Legal)	-0.24	-0.89	Not/Neg
2/18/2021	CREDIT SUISSE GROUP	CS	-1.4	Provisions (Legal)/Loan Write-Offs	1.09	-0.72	Not/Neg
03/27/2021	CREDIT SUISSE GROUP	CS	-4.7	Trading Losses	6.41	0.51	1% level
2/10/2022	CREDIT SUISSE GROUP	CS	-2.3	Provisions (Retail)	4.75	1.92	1% level
10/14/2022	WELLS FARGO & CO	WFC	-2.0	Provisions (Legal)	4.40	-2.23	1% level

Table 21: **Broker Fines and Litigation:** This table describes large fines imposed by American regulatory agencies from 2013-2022 from ViolationsTrackers and the the two-day changes in CDS spreads around the announcements. ViolationsTrackers classifies fines into several groups including toxic securities abuse related fines (*toxic sec*), consumer protection violation fines (*consumer*), Foreign Corrupt Practices Act violations (*FCPA*), economic sanction violation (*sanctions*), mortgage related misconduct (*mortgage*), AML (*AML*), and False Claims Act and related (*false*). Agency refers to which agency imposes the fine. ΔCDS^b (abnormal) refers to the difference in two-day CDS spreads changes between the treated broker and other brokers on announcement date. Inclusion refers to whether a broker-event meets the inclusion threshold due to individual fine size ("I") or the average fine size ("A"). Significance refers level of statistical significance for a cross-sectional regression of ΔCDS^b on a indicator variable that takes the value of one for whether a broker had a fine announcement on that date. Standard errors are heteroskedasticity robust.

Date Announced	**Broker Parent**	**Ticker**	**Fine B$USD**	**Type**	**Agency**	**Avg. Fine in Q**	ΔCDS^b **(abnormal)**	$\overline{\Delta CDS}$	**Inclusion**	**Significance**
19nov2013	JPMorgan Chase	JPM	13.0	toxic sec.	DOJ	4.0	0.17	-3.08	I	Not/Neg
02dec2013	Bank of America	BAC	0.4	toxic sec.	FHLMC	4.0	-1.30	1.40	A	Not/Neg
20dec2013	Deutsche Bank	DB	1.9	toxic sec.	FHFA	4.0	4.25	-1.48	I	10% level
30dec2013	Wells Fargo	WFC	0.6	toxic sec.	FNMA	4.0	0.58	-0.65	A	Not/Neg
07jan2014	JPMorgan Chase	JPM	1.7	AML	NYS	1.1	0.86	-0.25	I	Not/Neg
07jan2014	JPMorgan Chase	JPM	0.5	AML	Treas	1.1	0.86	-0.25	A	Not/Neg
07feb2014	Morgan Stanley	MS	1.3	toxic sec.	FHFA	3.8	-2.50	-0.89	I	Not/Neg
21mar2014	Credit Suisse	CS	0.9	toxic sec.	FHFA	3.8	0.11	-0.86	A	Not/Neg
26mar2014	Bank of America	BAC	9.3	toxic sec.	FHFA	3.8	4.03	-0.91	I	1% level
14jul2014	Citigroup	C	7.0	toxic sec.	DOJ	3.5	-0.85	0.49	I	Not/Neg
24jul2014	Morgan Stanley	MS	0.3	toxic sec.	SEC	3.5	-0.02	0.15	A	Not/Neg
21aug2014	Bank of America	BAC	16.7	mortgage	DOJ	16.7	1.05	-1.41	I	5% level
22aug2014	Goldman Sachs	GS	3.2	toxic sec.	FHFA	3.5	0.65	-0.60	I	Not/Neg
21nov2014	Credit Suisse	CS	1.8	tax violations	DOJ	1.8	-1.80	-1.90	I	Not/Neg
01may2015	BNP Paribas	BNPQY	9.0	sanctions	DOJ	9.0	0.14	-0.57	I	Not/Neg
11feb2016	Morgan Stanley	MS	2.6	toxic sec.	DOJ	2.6	2.39	6.24	I	Not/Neg
08apr2016	Wells Fargo	WFC	1.2	false	DOJ	1.2	1.12	-1.68	I	1% level
11apr2016	Goldman Sachs	GS	5.1	toxic sec.	DOJ	5.1	-0.81	-1.39	I	Not/Neg
17jan2017	Deutsche Bank	DB	7.2	toxic sec.	DOJ	6.2	-0.81	0.17	I	Not/Neg
18jan2017	Credit Suisse	CS	5.3	toxic sec.	DOJ	6.2	-0.44	-0.42	I	Not/Neg
21mar2018	UBS	UBS	0.2	toxic sec.	NYS	1.1	-0.01	2.65	A	Not/Neg
29mar2018	Barclays	BCS	2.0	toxic sec.	NYS	1.1	-1.36	-0.73	I	Not/Neg
01aug2018	Wells Fargo	WFC	2.1	toxic sec.	DOJ	2.1	-1.56	1.69	I	Not/Neg
21feb2020	Wells Fargo	WFC	3.0	fraud	DOJ	3.0	0.55	0.53	I	1% level
22oct2020	Goldman Sachs	GS	2.9	FCPA	DOJ	2.9	0.04	-0.05	I	Not/Neg
20dec2022	Wells Fargo	WFC	3.7	consumer	CFPB	3.7	-0.29	0.76	I	Not/Neg

C.1 Grouping

After identifying the set of plausible events, we organize them into groups. The key grouping that emerges is the set of contemporaneous market distress write-downs. We augmented this set by incorporating documented shocks from existing literature and scanning broker or banking events highlighted in BIS Quarterly Reports. These reports provide insight into market turmoil associated with certain announcements, assisting in understanding potential groupings implied by market activities.

An example of this process is the European broker-dealer distress period. The "special items" database, supplemented by manual research, identifies several large write-downs for European broker-dealers in 2016Q1. In Table 19, one broker-dealer exhibits a default concern. Although these events do not imply a connection on their own, Bank for International Settlements [2016] explicitly suggests a link, so we group the asset and liability concerns into a single experiment. We combine the Deutsche Bank impairments in Q4 2015 and Q1 2016, Deutsche Bank Coco Bond default concerns, and Credit Suisse impairments in Q1 2015.

Similarly, for individual events like Credit Suisse's Archegos-related write-downs, common losses sometimes emerge among brokers outside our set or without large special items. In such cases, we group events together within the experiment. total losses exceeded \$10B.

C.2 Ranking the Plausible Events

We consider three dimensions when choosing experiments. First, we evaluate the size of the losses, both in raw terms and relative to the size of the balance sheets. Second, we examine the degree of market distress.

Table 22 depicts the final set of candidate broker shocks. We define two new variables to help compare across experiments. First, we scale losses by the broker-dealer's market net worth to measure their impact on broker capital. We also aggregate brokers as described in Section C.1 and compute total losses for the group.

The results show that two events stand out. The first is the European broker-dealer event (involving Deutsche Bank and Credit Suisse), which has the highest total loss across brokers and includes two of the three largest losses relative to broker net worth. This event also records the largest abnormal two-day CDS spread changes. Additionally, as noted, this event involved significant default concerns. The second notable event is the cumulative losses from Archegos. By total losses, this event ranks second, with Credit Suisse suffering major losses in both net worth and CDS spread changes.

Table 22: **Relevant Shocks:** This table reports the set of broker events that are plausible shocks. All variables defined like above. "Losses to Net Worth " denotes the total losses to the broker in the event scaled by last quarter's common market equity value. "Others Exposed" refers to the set of other broker-dealers identified as having common exposure to the specific broker discussed. Total Losses (B) is the sum of reported total losses for these broker-dealers.

Date **Announced** **Total Losses (B)**	**Broker** **Parent**	**Ticker**	**Ticker**	Losses (B)	ΔCDS^b **(abnormal)**	**Losses to Net Worth**	**Others Exposed**
4/17/2013	BANK OF AMERICA CORP	BAC	-2.2	3.63	-1.76%	N/A	3.630
3/26/2014	BANK OF AMERICA CORP	BAC	-9.3	4.03	-5.60%	N/A	-9.300
7/16/2014	BANK OF AMERICA CORP	BAC	-4.0	0.83	-2.20%	N/A	-4.000
1/14/2015	JPMORGAN CHASE & CO	JPM	-1.1	3.6	-0.54%	N/A	-1.100
1/28/2016	DEUTSCHE BANK AG	DB	-6.4	6.91	-15.49%	CS, RBS, BCS	-10.577
2/4/2016	CREDIT SUISSE GROUP	CS	-4.1	13.81	-10.50%	DB, RBS, BCS	-10.577
4/8/2016	WELLS FARGO & CO	WFC	-1.2	1.12	-0.49%	N/A	-1.200
03/27/2021	CREDIT SUISSE GROUP	CS	-4.7	6.41	-15.10%	NMR, UBS, MS MFG, MUFG	-10.445
2/10/2022	CREDIT SUISSE GROUP	CS	-2.3	4.75	-8.82%	N/A	-2.306
10/14/2022	WELLS FARGO & CO	WFC	-2.0	4.4	-1.35%	N/A	-2.000

D Appendix Results

D.1 Euro 5 Grouping Appendix

D.1.1 CDS Spreads surrounding Euro 5 news

Table 23: **CDS Spread Changes and Spillovers:** This table presents the cumulative CDS spread changes for large Form ADV prime brokers. All CDS quantities are in percentage points. The Peak CDS spread changes refers to the change of CDS changes from January 27th to February 9th. The Event CDS spread changes refer to the cumulative 1 day CDS spread changes in Table 4. We provide the respective quintile sorts for each measurement.

tic	CDS Change (over Events)	CDS Change (Start to Peak)	Peak Quintiles	Event Quintiles
DB	0.522	1.172	5	5
BCS	0.459	0.726	5	5
NWG	0.369	0.599	5	5
CS	0.334	0.609	5	5
ACA:EN	0.261	0.512	5	5
BAC	0.241	0.395	4	4
GS	0.236	0.386	4	4
BNPQY	0.231	0.452	4	4
SCGLY	0.221	0.485	4	4
MS	0.220	0.374	4	4
C	0.201	0.357	3	3
UBS	0.197	0.378	3	3
MQG	0.127	0.125	3	3
JPM	0.124	0.217	3	3
RY	0.123	0.133	3	3
ING	0.120	0.270	3	3
WFC	0.093	0.174	2	2
NTXFF	0.076	0.329	2	2
TD	0.067	0.132	2	2
HSBC	0.061	0.335	2	2
NMR	0.025	0.197	2	2
PNC	0.023	0.058	1	1
USB	0.009	0.031	1	1
MFG	0.006	0.401	1	1
SCHW	0.001	0.003	1	1
BK	-0.001	0.000	1	1
MUFG	-0.030	0.369	1	1

D.1.2 What characteristics explain our groupings?

What characteristics determine which European brokers are classified into the treatment group? Specifically, are there characteristics that could explain why some European banks, such as UBS, seem to exhibit limited distress? To investigate this, we construct measures of ex-ante unprofitability as a proxy for asset quality and reliance on lower-tier capital, which aligns with the funding market stress observed at Deutsche Bank.

Our measure of ex-ante unprofitability is the bank-level market-to-book ratio: a lower ratio indicates that the market values future profits below the historical book value. This metric is particularly advantageous as it avoids discrepancies due to differing accounting practices across countries. We derive this measure using Compustat accounting data and FactSet market prices.

To proxy for reliance on lower-tier capital, we measure the ex-ante dependence of a bank holding company on non-Tier 1 capital, expressed both as a share of total risk-weighted assets and as a share of total capital.

We estimate the following regressions for the banks in our spillover set:

$$\frac{MarketCap_{2015q3}}{BookEquity_{2015q3}} = \alpha + \underbrace{\beta}_{-.5} Spillover + \varepsilon \tag{73}$$

We can study lower tier capital by:

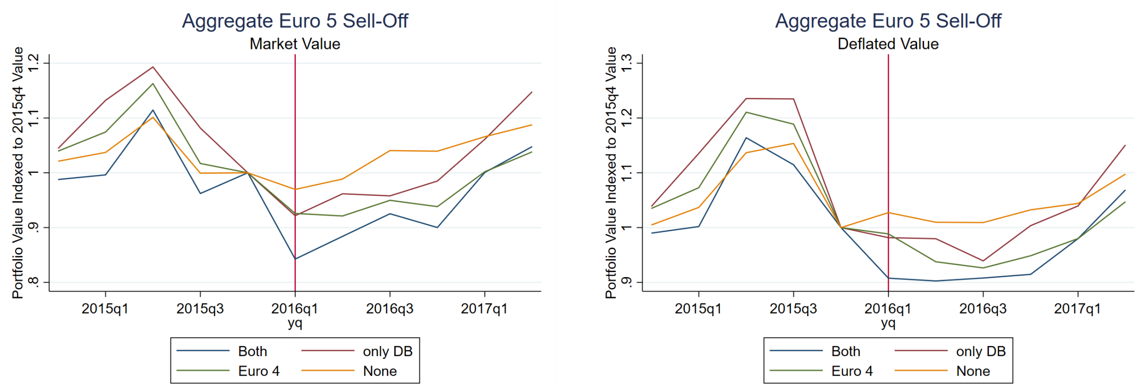
$$\frac{AT1_{2015q3} + Tier2Capital_{2015q3}}{TotalCapital_{2015q3}} = \alpha + \underbrace{\beta}_{12\%} Spillover + \varepsilon \tag{74}$$

$$AT1_{2015q3} + Tier2Capital_{2015q3} = \alpha + \underbrace{\beta}_{3\%} Spillover + \varepsilon \tag{75}$$

We can similarly show in the panel that, on average, banks with lower tier capital and that are ex-ante less profitable have higher CDS spread increases on event dates.

D.2 Is this just a shock to Deutsche Bank?

We choose to group together the most distressed banks over announcement dates into the treatment group; however, the direct evidence of a credit supply shock comes from Kruttli et al. [2022] and only provide evidence for Deutsche Bank. To test the importance of the non-Euro 5 brokers, we will study the equity market holdings behavior of four groups: managers that only have Deutsche Bank relationships (only DB), managers with relationships with at least one of the four other Euro 5 brokers but not Deutsche Bank (Euro 4), managers with relationships with at least one of the four other Euro 5 brokers and also Deutsche Bank (Both), and managers with no Euro relationships to an Euro 5 broker. (None)



(a) Market Value **(b) Deflated Value**

Figure 17: **Aggregate Sell-Off by Euro 5 Types:** We plot the time-series of the total value of holdings for hedge fund managers based on exposure type. We provide four groups: managers that only have Deutsche Bank relationships (only DB), managers with relationships with at least one of the four other Euro 5 brokers but not Deutsche Bank (Euro 4), managers with relationships with at least one of the four other Euro 5 brokers and also Deutsche Bank (Both). The left panel deflates aggregate holdings by the aggregate value-weighted returns each quarter.

First we replicate our aggregate results from before. In the left panel 17, we plot the time series of aggregate holdings at market value. We observe that both Euro 4 and DB-only managers experience similar declines in holdings. Interestingly, the decrease is greatest for managers who borrow from both a Euro 4 bank and DB, suggesting a compounding effect. In the right panel, we observe similar patterns. Somewhat unexpectedly, we find that the aggregate sell-off is now concentrated among managers that broker with both a Euro 5 bank and DB.

Next, we replicate Equation (24) for this grouping in Table 24. We find identical patterns to the aggregate results, with sell-off pressure being strongest among managers exposed to both Euro 4 banks and DB.

Table 24: **Euro 5 Manager Sell-Offs (Break-down):** This table presents estimates from Equation 24. We provide estimates for stale price portfolio changes. "Size" refers to the minimum equity cut-off last period to be included in this regression. The outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. Standard errors are heteroskedasticity-robust.

Non DB Euro 5 Relationship	-0.0493*	-0.0339	-0.0165	0.000310
	(0.0251)	(0.0268)	(0.0295)	(0.0317)
only DB Relationship	-0.0566	-0.0517	-0.0707	-0.0222
	(0.0362)	(0.0392)	(0.0429)	(0.0436)
DB+ at least one other Euro 5 Relationship	-0.0774**	-0.0623*	-0.0673*	-0.114***
	(0.0319)	(0.0336)	(0.0349)	(0.0354)
No Euro 5 Relationship	-0.00789	-0.0203	-0.0255	-0.0282
	(0.0122)	(0.0144)	(0.0175)	(0.0191)
R-squared	0.021	0.015	0.023	0.067
N	450	332	230	168
Size	All	At Least 0.2B	At Least 0.5B	At Least 1B
Port	Stale	Stale	Stale	Stale

Standard errors in parentheses

Robust standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.3 Euro 5 Asset Pricing Appendix

D.3.1 Asset returns and Changes in Euro 5 Exposure

The following specification is a necessary condition: do we observe that stocks sold off by our treatment group have lower returns? We study this via the following regression:

$$ret^s_{t\to t+1} = \alpha + \beta \Delta MktShareE5HFs^s_{t\to t+1} + \varepsilon^s_{t\to t+1} \tag{76}$$

where we regress the change in the total market share held by the treatment group on stock returns. The key point we want to validate is that the stocks sold off by the treatment group indeed have lower returns. Table 25 reports the estimates for these specifications.

In Column (1), we report a large and positive coefficient for our specification: this means if $\Delta MktShareE5HFs^s_{t\to t+1}$ increases, the stock is expected to have a higher realized return return. In Column (2), we subset on stocks sold-off by the Euro 5 in aggregate and find a substantially larger effect.. In Columns (3) and (4), we show that our point estimate remains large even when we control for the change in holdings associated with our control group. This pattern is robust for alternative return measures, including CAPM residuals, Fama-French 3+Momentum residual, and betting against beta. Note that, in all specifications, the point estimate for the change in non Euro 5 holdings is negative $\Delta MktShareE5HFs^{s}_{t\rightarrow t+1}$, implying that stocks in which non Euro 5 exposure increases is associated with higher returns. This is line with these investors purchasing the sold-off Euro 5 assets.

Table 25: **Realized Returns and Change in Euro 5 Exposure** This table reports estimates for a regression of realized returns on changes in the Euro 5 exposure share measures (Δ MktShareE5HFs). Returns are raw (Ret_t^s), residualized against the CAPM model, residualized against the Fama-French 3 + Momentum model ($\varepsilon^s_{FF4,t}$), or residualized against the Betting-against-Beta model ($BABRet_t$). In some specifications, we include controls for non-Euro 5 hedge fund exposure change (Δ MktSharenonE5HFs) and fixed effects based on industry codes (IndustryFE). Exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the three-digit SIC industry code level.

	$Rets_{s,q}$				$\varepsilon_{CAPM,s,q}$		$\varepsilon_{FF4,s,q}$		$BABRet_t^s$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta MktShareE5HFs$	1.442***	2.852***	1.149**	2.970***	1.362**	2.894***	1.681***	3.104***	1.322**	2.866***
	(0.517)	(0.786)	(0.470)	(0.741)	(0.545)	(0.772)	(0.479)	(0.757)	(0.552)	(0.729)
$\Delta MktSharenonE5HFs$			-0.323	-0.553	-0.559	-0.630	-0.408	-0.437	-0.557	-0.553
			(0.366)	(0.492)	(0.580)	(0.494)	(0.496)	(0.406)	(0.562)	(0.492)
Intercept	0.0142	0.0321**	0.0128***	0.0320***	0.00731	0.0254***	0.0156	0.0321***	0.0257	0.0444***
	(0.0171)	(0.0128)	(0.00102)	(0.00622)	(0.0180)	(0.00648)	(0.0127)	(0.00636)	(0.0174)	(0.00612)
R-squared	0.008	0.026	0.304	0.328	0.011	0.333	0.018	0.303	0.011	0.325
N	1659	902	1621	846	1653	845	1652	844	1654	846
selloff		X		X		X		X		X

D.4 Null Real Effects

We test for possible real effects by looking at changes in equity issuance, buyback, or debt issuance. We test on an indicator variable for whether the level of issuance changed over the next year or if the growth rate changes over the next-years. For each of this measurements, we then regress:

$$RealEffects^s_{2016q1\rightarrow 2017q1} = \alpha + \beta MktShareE5HF^s_{2015q4} + \varepsilon^s \tag{77}$$

Table 26 reports the point estimates for this specification.

We only observe significant point estimates for (1) which then become insignificant and economically zero when we control for the lagged level.

	EqIssDum		BuyBackDum		DebtDum		EqIssG		BuyBackG		DebtIssG	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
% Held Euro5 HFs	0.178*	0.0409	-0.157	-0.0745	-0.161	-0.0692	-0.000129	-0.0000635	-0.00625	0.0226	0.265	0.170
	(0.101)	(0.0271)	(0.136)	(0.140)	(0.221)	(0.175)	(0.0000946)	(0.0000619)	(0.0269)	(0.0193)	(0.166)	(0.140)
EquityIssueDummy t-4		0.841***										
		(0.0936)										
BuybackDummy t-4				0.490***								
				(0.0369)								
DebtIssueDummy t-4						0.521***						
						(0.0219)						
EqIssG (y/y) (t-4)								0.153**				
								(0.0744)				
BuyBackG (y/y) (t-4)										0.537***		
										(0.0315)		
DebtIssG (y/y) (t-4)												0.442***
												(0.0487)
R-squared	0.003	0.692	0.001	0.184	0.000	0.283	0.002	0.253	0.000	0.354	0.002	0.208
N	1835	1821	1835	1821	1835	1821	1835	1821	1835	1821	1835	1821

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: **Firm-Level Issuance:** This table reports point estimates for Equation 77. Exposure measures are winsorized at 2.5% and 97.5%. Standard errors are clustered at the three-digit SIC code level.

D.5 Credit Supply during the Pandemic

The market turbulence induced by the COVID-19 pandemic offers possible cross-section health variation. Several studies, such as Acharya et al. [2024], highlight cross-sectional distress experienced by the bank holding companies of large broker-dealers during the pandemic. These studies show that bank holding companies faced varying degrees of distress in different markets; for instance, Acharya et al. [2024] attributes distress to credit line drawdowns by their ex-ante lenders.[67]

We provide additional analysis here to augment the null equity holdings results in Section 7. We test whether broker health affects lending growth in this quarter by:

$$\Delta ln(PBL_t^b) = \alpha_t + \alpha_b + \beta Health_t^b + \varepsilon_t^b \tag{78}$$

where $\Delta ln(PBL_t^b)$ is the log change in investor loans and $Health_t^b$ is the continuous measurement ($AbnormalDistress_t^b$) or the discrete measurement ($BigShock_t^b$) as described in the paper.

Table 27 reports the estimates of Equations 78. In Columns (1) and (2), we analyze the sample of Form ADV broker-dealers, finding a negative relationship between broker-level distress and credit provision for both distress proxies. However, not all Form ADV broker-dealers are large. Thus, in Columns (3) and (4), we limit the sample to broker-dealers above the median for investor loans in Q4 2019. In Column (3), we observe a small, positive, and insignificant relationship between log investor loan growth and the continuous measure of distress. In Column (4), we find a similarly weak relationship between log investor loan growth and the indicator variable. Together, Columns (3) and (4) suggest that cross-sectional health measures do not explain lending growth for large broker-dealers during these periods. These results indicate that the cross-sectional differences in health observed did not produce a dispersion in lending growth for large broker-dealers.

These findings differ from the Lehman Brothers and "Euro 5" experiments but are not necessarily contradictory. They do not rule out a weak cross-sectional credit supply shock that might be overshadowed by demand-side factors. Financial distress in this period was countered by significant fiscal and monetary stimulus. Most notably, the Federal Reserve established a "Primary Dealer Credit Facility" to provide collateralized loans to these institutions, aiming to prevent the funding runs experienced during the Global Financial Crisis. As most large prime brokers are also

[67] Exogeneity concerns precluded this event as possible narrative shock for the following reasons. First, the underlying macroeconomic distress may directly impact stocks and other securities. Second, the underling shock may also influence hedge funds outside of a credit supply mechanism. In related work, Kruttli et al. [2023] documents a decrease in leverage demand among fixed-income hedge funds during this period due to risk management practices by hedge funds.

primary dealers, this facility could curtail the transmission of broker distress to hedge fund balance sheets during this period.

Table 27: **Investor Loans during the Pandemic**: This table reports estimates for Equation 78 for Q1 2020. The dependent variable is the log-growth rate of investor loans. The independent variable is either the continuous abnormal CDS spread change $AbnormalDistress_t^b$ or $BigShock_t^b$. $BigShock_t^b$ is an variable indicating whether $AbnormalDistress_t^b$ is in its top 5% of broker observations. Standard errors are heteroskedasticity-robust.

	(1)	(2)	(3)	(4)
$AbnormalDistress_t^b$	-0.124*		0.0203	
	(0.0662)		(0.0562)	
$BigShock_t^b$		-0.181**		-0.0354
		(0.0759)		(0.0841)
R-squared	0.197	0.256	0.005	0.011
N	19	19	9	9
brokers	All ADV	All ADV	Top 50%	Top 50%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$