Prime Broker Credit Supply and the Stock Market: Evidence on Hedge Fund Transmission*

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May 8, 2026

Abstract

Broker-dealers participate in the stock market predominantly through lending to hedge funds via their prime brokerage divisions. Using confidential data on hedge fund-by-broker borrowing, we document a conditional transmission mechanism from prime broker credit supply to stock prices: idiosyncratic broker distress is perfectly diversified by hedge funds substituting across prime brokers, while widespread shocks to the broker-dealer sector transmit to equity prices. In such widespread episodes, as in the Q1 2016 European broker-dealer distress episode, hedge funds cannot fully replace lost borrowing and sell off equities. This forced deleveraging has a price impact with a multiplier of at least three, meaning that if hedge funds, on net, sold off 1% of total shares outstanding, stock prices would fall by 3%. We find evidence of aggregate transmission: when broker-dealer health deteriorates, aggregate prime brokerage lending falls and high hedge fund-owned portfolios under perform low hedge fund-owned portfolios. These effects are amplified when substitution capacity is impaired. This conditional credit supply channel identifies an intermediary asset pricing mechanism in markets with limited direct intermediary participation.

*Paper previously circulated in November 2024 as "Does Broker-Dealer Health Matter for Stock Prices?" 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 Erik Heitfield (discussant), Yakov Amihud, Sirio Aramonte, Will Cassidy, Ricardo Correa, Xavier Gabaix, German Guttierez, Zhiguo He, Sebastian Hillenbrand, Franz Hinzen, Sebastian Infante, Dalida Kadyrzhanova, Pete Kyle, Jonathan Lewellan, Sai Ma, Quinn Maingi, Phil Monin, Nathan Foley-Fisher, Dino Palazzo, Lubomir Petrasek, Andreas Schrimpf, Julia Selgrad, Davide Tomio, Bruce Tuckman, Andrea Vedolin, Courtney Wiegand, and Ram Yamarthy for their comments and suggestions. We also want to thank seminar participants at New York University, Dartmouth University, Boston University, Cleveland Fed, the Federal Reserve Board, Fordham University, Texas Christian University, the University of Colorado, the University of Mississippi, the Treasury's Office of Financial Research, and University of Notre Dame for their insightful comments. Zarra thanks NYU Stern's Center for Global Economy and Business (CGEB) for generously providing funding for data purchases, and Irene Caracioni for excellent research assistance. The views and opinions are those of the authors and do not necessarily represent the views of the Board

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1 Introduction

Intermediary financial health is an important determinant for asset prices: factors constructed from aggregate broker-dealer balance sheets explain returns across a wide range of asset classes (Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)). Further, broker-dealers directly affect asset prices in markets where they invest (Siriwardane (2019), Haddad and Muir (2021), Eisfeldt, Herskovic, Rajan, and Siriwardane (2022)). However, broker-dealers do not only participate directly by investing, they also participate indirectly by supplying credit to other intermediaries, particularly hedge funds.

While broker-dealers participate indirectly across many asset markets, this indirect participation is the predominant form in equity markets: broker-dealers lend to hedge funds through their prime brokerage divisions rather than holding securities directly. Prime brokerage lending finances hedge funds' risky asset positioning and provides the principal source of leverage for their equity purchases. Prime brokerage lending is large: as of Q2 2024, total prime brokerage lending to hedge funds was $2.3 trillion.[1][2]

In this paper, we document a conditional transmission mechanism from prime broker credit supply to stock prices, operating during periods of systemic broker-dealer distress when hedge funds' capacity to substitute across counterparties becomes impaired. We substantiate this claim with three main results: (i) broker-dealer financial health shocks can causally affect equity prices through changes in lending to hedge funds, (ii) the strength of this transmission depends on hedge funds' capacity to substitute across broker-dealers, and (iii) when substitution is limited, forced sales lead to a high price impact multiplier.

To directly study the transmission mechanism, we exploit confidential regulatory data on hedge fund balance sheets assembled from the Securities and Exchange Commission's (SEC) Form PF filing. This dataset includes information on hedge fund total prime brokerage borrowing quantities and counterparty-level borrowing quantities from late 2012 through 2022 and allows us to directly study broker credit supply and the exposure of hedge funds to broker-dealer-level distress. To study the transmission of shocks from hedge funds to the equity markets, we merge this balance sheet information with adviser-level equity securities holdings data from FactSet Ownership.

This paper relies on three layers of evidence to establish that transmission from broker-dealer health to equity prices is conditional: (i) well-identified cross-sectional event studies, (ii) general tests of conditional substitution in panel, and (iii) novel aggregate time-series correlations. First, we use two cross-sectional event studies to isolate credit supply shocks and study their transmission to stock prices via hedge fund equity holdings. This approach

[1]Total prime brokerage loans include not only equity-related financing but also lending against other instruments, such as convertible bonds, as well as securities lending that facilitates short positions.

[2]For comparison, total broker-dealer equity holdings was only $343.7B from the Federal Reserves Financial Account in that quarter.

addresses key endogeneity concerns, namely that economic forces affecting broker-dealer credit supply may also drive hedge fund credit demand. In these episodes, we observe differential transmission patterns consistent with differences in how widespread the shock is. We call this phenomenon conditional substitution. Second, we turn to panel regressions using all quarters of data to test whether hedge funds can generally substitute away from idiosyncratic broker-dealer shocks. This allows us to establish that transmission is not unconditional. Third, we examine aggregate time-series correlations between broker-dealer health, prime brokerage lending, and stock returns. These correlations provide consistent evidence that, under the condition of widespread distress, shocks transmit to stock market prices.

In the first set of analyses, we trace event study shocks from broker-dealers to hedge funds to equity markets.[3] First, we study the distress among large European broker-dealers stemming from idiosyncratic write-downs and debt default concerns at Deutsche Bank and Credit Suisse in Q1 2016.[4] This distress spread to other European broker-dealers operating in American equity markets, disproportionately affecting those with lower profitability and weaker capital positions. We group together the most distressed brokers, as measured by credit default swap (CDS) spread changes, which we call the "Euro 5."[5][6] Second, we study the lending behavior of broker-dealers that suffered losses during the collapse of the family office Archegos in early 2021. When Archegos collapsed in March of 2021, it created over $10 billion in losses to six broker-dealers (Halftermeyer (2021b)). We consider these six broker-dealers suffering significant losses as the shocked broker-dealers in this second experiment.

Our first cross-sectional analysis documents that shocked broker-dealers indeed contracted prime brokerage credit relative to non-shocked broker-dealers. The economic magnitudes are material. Euro 5 lending in aggregate fell by 23% in Q1 2016, compared to 8% for U.S. G-SIBs and an increase of 17% for (non-shocked) non-U.S. G-SIBs. During the Archegos episode, shocked brokers reduced lending by 5% while (non-shocked) U.S. G-SIBs increased lending by 17% and (non-shocked) foreign G-SIBs increased lending by 23%. However, contractions in aggregate credit, while suggestive, are still subject to the

[3]To select these events, we conduct a narrative analysis of large losses, impairments, and fines from 2013-2022. These two broker-specific shocks are the largest in the sample in terms of losses, financial distress, and the set of broker-dealers affected.

[4]All discussions in this paper of specific broker-dealers come from publicly available sources, such as public regulatory balance sheets, parent company level financial health measures, or news reports. For example, discussions of events affecting specific broker-dealers that are hedge fund counterparties, or construction of counterparty-treatment groups, are based solely on publicly available information. Hence, no confidential data is used in the sections that discuss individual counterparties. Form PF data pertaining to hedge fund counterparties is analyzed and reported *only* using aggregated sets of counterparties.

[5]We will interchangeably use the term "Euro 5" event and European broker-dealer distress event.

[6]The Euro 5 broker-dealers are Barclays, Credit Agricole, Credit Suisse, Deutsche Bank, and Royal Bank of Scotland/Natwest Group.

possibility of conflating supply and demand effects. For instance, if hedge funds that borrow from shocked broker-dealers differ systematically from those that don't, credit contraction from shocked brokers may simply proxy for differences in credit demand that covary with hedge fund characteristics. To isolate the effect due to credit supply factors, we estimate Khwaja and Mian (2008) style regressions of changes in borrowing by fund f from broker b on an indicator for whether broker b is shocked, controlling for common borrowing demand via a fund-fixed effect. We find strong evidence of supply effects in both the Euro 5 and Archegos events.

Next, we investigate fund-level total borrowing. A priori, cross-sectional transmission of broker-dealer stress to a hedge fund's total borrowing is ambiguous given the market's structure. On the one hand, the market is highly concentrated, with the top five lenders accounting for 55% of lending, suggesting that even an idiosyncratic shock could have aggregate consequences.[7] On the other hand, large hedge funds maintain diversified counterparty networks, borrowing from an average of 4.3 lenders, which could mitigate exposure to any single counterparty shock. Which of these forces dominates is ultimately an empirical question.

We test these competing hypotheses by regressing total prime brokerage borrowing by fund f on an indicator for whether the fund borrows from any shocked broker. We find that in the Euro 5 episode, hedge funds that borrowed from at least one of the Euro 5 shocked brokers immediately prior to the shock were unable to perfectly replace the borrowing lost from Euro 5 lenders, and their total borrowing fell relative to funds with no Euro 5 counterparties. In contrast, during the Archegos stress, hedge funds were able to fully replace the borrowing lost from Archegos-affected brokers by borrowing more from non-shocked brokers, with no discernible impact on the hedge fund's total borrowing.

We trace these credit supply shocks through to equity prices. Hedge funds exposed to Euro 5 brokers reduced their equity holdings but did not reduce exposure to other asset classes such as corporate bonds or foreign exchange contracts. Changes in market value reflect both valuation effects and actual reductions in shares held. Since only the latter provides evidence of price impact due to forced deleveraging, we examine equity holdings directly via FactSet Ownership. Stocks held by Euro 5-connected managers experienced abnormal sell-offs during Q1 2016, leading to significant price distortions.

Stocks more heavily held by funds that borrowed from Euro 5 brokers had abnormally lower returns than other stocks, even controlling for standard factor exposure, and these observed negative returns did not fully revert until April 2016. We estimate a micro-price multiplier–the percentage point change in the price for a one percentage point sell-off of all shares outstanding–of between 2.9 and 4.72 for this shock, which is larger than the estimates

[7] These lending concentration figures are taken from the Office of Financial Research (OFR) Hedge Fund Monitor and includes both prime brokerage and repo lending.

from routine events such as index inclusions and dividend reinvestment.[8] To help explain this large multiplier, we find that the bulk of the sell-off was absorbed by non-levered investors, whose demand is typically more inelastic. This is in line with the prediction of many intermediary asset pricing models that suggest that the transfer of assets from more specialized, levered investors such as hedge funds to other less specialized investors yields increased risk premia and negative realized returns.[9]

Why is there a transmission from broker-dealer stress to hedge funds in the European broker distress episode but not in the Archegos episode? We argue that the key difference lies in the condition and response of non-shocked brokers. During Archegos, non-shocked brokers remained healthy and expanded their lending, fully offsetting the contraction of distressed brokers. By contrast, during the European broker distress period, the CDS spreads of non-shocked brokers also rose sharply, signaling impaired health and limiting their capacity to provide offsetting credit. In Q1 2016, we document that lending from the healthiest non-shocked broker-dealers to shocked hedge funds increased; however, these ex-ante lenders were smaller and likely unable to fully meet hedge funds lost borrowing. These results are consistent with a conditional transmission mechanism, where the key condition is the availability of healthy substitute lenders.

In the second set of analyses, we use the full panel to test whether hedge funds can substitute across broker-dealers outside systemic distress. Each quarter we group together the five broker-dealers with largest CDS spreads: when broker-dealers experience large cross-sectional increases in CDS spreads, they tend to reduce their credit supply to hedge funds. However, outside of Q1 2016, we find no evidence of impaired substitution identifiable in the cross-section; hedge funds fully replace lost borrowing from distressed brokers by increasing borrowing from healthier counterparties.

In the third set of analyses, we examine aggregate time-series correlations to assess whether they are consistent with transmission occurring under widespread distress and when substitution capacity is limited. First, consistent with adverse shocks common across broker-dealers transmitting to equity prices, we show that, when the He, Kelly, and Manela (2017) measure of aggregate broker-dealer financial health deteriorates, both aggregate prime brokerage lending volumes fall and the return spread between high and low hedge fund-crowded portfolios is low. The relationship between returns and aggregate broker-dealer factors is strongest during the bottom decile of broker-dealer health periods.

Second, we show that this aggregate transmission of broker-dealer health to stock prices strengthens when substitution capacity is limited. To proxy for the capacity of hedge funds to substitute to healthier broker-dealers, we compute the share of ex-ante lending by

[8]See Gabaix and Koijen (2021) for a review of these estimates.

[9]This also aligns with the findings of the demand system asset pricing literature (Koijen and Yogo (2019), Koijen, Richmond, and Yogo (2023)) that suggests that investor composition affects prices.

healthier broker-dealers (those in the top quartile of broker-level net worth changes) minus the share of ex-ante lending by less healthy broker-dealers (those in the bottom quartile of broker-level net worth changes). When this proxy identifies low substitution capacity, we find that deteriorating broker-dealer health predicts larger declines in aggregate prime brokerage lending, aggregate hedge fund equity exposures, and the return spread between high and low hedge fund-crowded stocks. This conditional relationship provides direct evidence that aggregate transmission depends on the availability of substitute credit.

We identify a conditional prime brokerage credit supply channel from broker-dealer health to equity prices. Transmission occurs when widespread distress impairs hedge funds' capacity to substitute across counterparties, forcing equity sales with substantial price impact. This mechanism reveals a channel for how intermediaries affect asset prices through indirect participation—the predominant form of broker-dealer participation in equity markets.

1.1 Relating to the literature

This paper's primary contribution is to the intermediary asset pricing literature. Using confidential regulatory data on hedge fund prime brokerage borrowing and fund-by-broker borrowing amounts, we provide *direct* evidence of a credit-supply transmission from broker-dealers to equity markets through hedge fund portfolios and identify the conditions under which this transmission operates. This mechanism helps elucidate why equity prices respond to intermediary asset-pricing factors and why intermediaries can matter in markets without direct holdings.

Motivated by the Global Financial Crisis, theoretical work (e.g., He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014)) argues that when the marginal investor is a representative intermediary, shocks to intermediary balance sheets can have an outsized effect on asset prices. Empirical tests of intermediary asset pricing focus on the broker-dealer sectora particularly active type of intermediary. First, Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) construct time-series measures of intermediary health using innovations to broker-dealer leverage and use their measures to explain returns across many asset classes, including equities.[10]

While factor models test whether a representative intermediary is *marginal*, the literature also asks whether intermediaries *cause* price movements, focusing on whether secu-

[10]More precisely, both use different measures of broker-dealer leverage. The Adrian, Etula, and Muir (2014) factor is constructed from time series innovations of flow of funds aggregate broker-dealer leverage. The He, Kelly, and Manela (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, Kelly, and Manela (2017) state that the primary dealer sector is a natural candidate for the representative financial intermediary," while Adrian, Etula, and Muir (2014) state that "we focus on measuring the SDF of a representative financial intermediary using the aggregate leverage of security broker-dealers."

rities or asset classes more held by intermediaries are responsive to these factors or direct shocks. Cross-asset class tests (Haddad and Muir (2021)) show that asset classes with greater broker-dealer ownership load more strongly on intermediary factors, while within-asset class studies examine intermediary ownership in debt securities (Timmer (2018)), CDS markets (Siriwardane (2019); Eisfeldt, Herskovic, Rajan, and Siriwardane (2022)), and equities (Seegmiller (2024)).[11] While these papers provide evidence that intermediaries' (and broker-dealers') direct participation affects prices, this paper substantiates the importance of transmission via broker-dealers' indirect participation in equity markets.

We provide the first estimate of a stock price multiplier for a shock to arbitrageur capital during a period of intermediary distress. This estimate contributes to the inelastic markets literature, including works by Koijen and Yogo (2019), Koijen, Richmond, and Yogo (2023), and Gabaix and Koijen (2021). The micro-elasticity literature, surveyed in Gabaix and Koijen (2021), finds lower average price multipliers for routine events such as dividend reinvestments and index inclusions than those estimated from the forced de-leveraging of hedge funds in this paper. By estimating a price multiplier for a broker-dealer health shock, we provide a bridge between the inelastic-markets literature and intermediary asset pricing, demonstrating how inelastic demand interacts with arbitrageur capital constraints to generate amplified price responses during periods of intermediary distress.

Our paper focuses on identifying a transmission mechanism between multiple layers of intermediaries (broker-dealers and hedge funds) in order to study asset prices. In doing so, we build on and extend related work on hedge fund leverage, broker-dealer relationships, and prime brokers.

We next connect our tests to the hedge-fund-crowding literature, particularly Brown, Howard, and Lundblad (2021), which documents that hedge funds concentrate in similar positions and that crowded equities earn higher average returns but share common downside tail risk. We ask whether broker-dealer shocks can cause this tail risk. First, we show that crowded portfolios systematically underperform when aggregate broker-dealer health deterioratesperiods that also feature declines in aggregate prime-brokerage lending.[12] Second, we test whether worsening broker conditions can trigger crashes in crowded portfolios. Third, in our time-series tests, we show that portfolios highly crowded with levered hedge funds perform particularly poorly in periods where both aggregate broker-dealer health and hedge fund substitution capacity is impaired. [13]

Several studies have examined individual shocks to prime brokers and the consequences for hedge funds' borrowing and investments. Aragon and Strahan (2012) demonstrate that stock liquidity deteriorated more sharply after the Lehman Brothers collapse for stocks with

[11] Timmer (2018) and Seegmiller (2024) do not directly test broker-dealer ownership. Seegmiller (2024) looks at aggregate institutional ownership of assets—in line with tests of a representative agent.

[12] To our knowledge, we are the first to document this fact.

[13] To our knowledge, we are the first to construct portfolio sorts on *levered* hedge funds.

greater exposure to hedge funds that had Lehman Brothers as a prime broker. They also find that, consistent with liquidity representing a priced risk factor, returns on these stocks were higher going forward. However, their interpretation is that costs associated with bankruptcy drive these results, evidenced by no such findings around the Bear Stearns failure. We show instead that shocks to prime brokers outside of bankruptcy can still transmit to stock prices through hedge fund clients. Further, we identify an alternative mechanism, specifically that shocks transmit only when substitution to other broker-dealers is impaired.

Relatedly, Kruttli, Monin, and Watugala (2022) analyze the effects of a large, prolonged shock to Deutsche Bank in 2015-2016 on hedge fund borrowing using confidential Form PF data. They find that hedge funds that borrowed from Deutsche Bank faced credit contractions and were unable to substitute to other brokers to offset this lost borrowing. They also show that hedge funds partially replaced this lost leverage through increasing the illiquidity of their holdings and increasing the synthetic leverage embedded in derivatives. We also study this episode, but focus on a set of five plausibly shocked prime brokers in Q1 2016 in particular, and similarly find that hedge funds borrowing from shocked prime brokers in Q1 2016 were unable to fully replace this lost borrowing. However, our contribution is to trace this contraction in prime brokerage borrowing through to equity prices.

While Kruttli, Monin, and Watugala (2022) do not explore the mechanisms driving imperfect substitution, Aragon and Strahan (2012) attribute the inability to substitute in Lehman's case to bankruptcy-specific factorsnamely, 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. We provide direct evidence that, under normal market conditions, hedge funds are capable of diversifying broker-dealer health shocks. In particular, we show that the diversifiability of a shock depends on the health and willingness of non-directly shocked broker-dealers to extend additional credit.

Dahlqvist, Sokolovski, and Sverdrup (2021) examine how "prime-broker risk" affects hedge-fund performance. They show that single-broker hedge funds experience lower returns following adverse broker-specific shocks, while multi-broker funds exhibit no such exposure. They also document that hedge-fund returns load on the He, Kelly, and Manela (2017) factor, which they interpret as capturing "shocks to the health of pivotal prime brokers," and conclude that systematic prime-brokerage risk helps explain hedge-fund returns. Although our paper shares their interest in how prime-broker events affect hedge funds and how hedge funds manage such risks, we differ in our question, methodology, and findings. As we study the impact of broker shocks on hedge fund by broker borrowing quantities and the total equity holdings of funds using Form PF, we can directly study credit supply and substitution across broker-dealers. Much of our analysis focuses on broker-specific shocks that arise during periods of broader distress. In these settings, we find that even multi-broker hedge funds fail to fully diversify the impact of broker-dealer deterioration on their equity holdings and on asset prices. More broadly, the two studies ask different questions: while Dahlqvist, Sokolovski, and Sverdrup (2021) focuses on how prime-broker risk affects hedge fund returns, we show how broker-dealer credit supply shocks directly transmit to equity markets via hedge funds.

Much of this paper explores the capacity of funds (borrowers) to substitute away from broker credit supply shocks (lenders) in concentrated credit markets. The high capacity of substitutability across brokers by hedge funds differs from findings in other markets such as Amiti and Weinstein (2018) and Galaasen, Jamilov, Juelsrud, and Rey (2023) who study idiosyncratic shocks in other concentrated markets.

2 Data and Institutional Details

2.1 Data

2.1.1 Form PF

The SEC's Form PF data collection spans from December 2012 through present. Our study uses data from January 2013 through December 2022. Adopted as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Form PF is filed by investment advisers registered with the SEC who manage at least $150 million in private fund assets. All SEC-registered investment advisers are required to file regardless of fund domicile, meaning that the collection includes foreign-domiciled hedge funds.[14] Advisers filing Form PF report information about each of the hedge funds they advise, including net assets (equity capital), gross assets (balance sheet assets, roughly equity capital plus borrowings), returns, investor composition, and more. *Large hedge fund advisers* — those with at least $1.5 billion in hedge fund assets under management – are required to report detailed balance sheet information quarterly for each of their *qualifying hedge funds* — those with at least $500 million in assets under management. Balance sheet data include asset class exposures, borrowings, and risk metrics, among other details.

This study makes use of two types of data on hedge fund liabilities. First, we use data on hedge fund borrowings, including the borrowing amount and the identity of any counterparty from which the hedge fund borrows at least 5% of the fund's net assets.[15] Since these key variables are reported on a quarterly basis, our Form PF analysis is exclusively conducted at this frequency.

[14] The SEC Private Fund Statistics report that only 34.2% of the total net asset value of reporting hedge funds is domiciled in the U.S.

[15] We describe the full set of variables used in Appendix Section A.2.

While the available data represent *total* borrowing across all borrowing types, our interest in this study is equity prime brokerage borrowing specifically. To construct a series of prime brokerage borrowing by counterparty, we assign prime brokerage borrowing amounts for fund i to counterparty j by assuming that the distribution of prime brokerage borrowing across all of fund i's counterparties is the same as the distribution of total borrowing. That is, if fund i borrows \$100 from counterparty A and \$200 from counterparty B, and borrows a total of \$150 via prime brokerage, we assume \$50 of prime brokerage borrowing comes from A and \$100 comes from B. We remove funds with zero reported prime brokerage borrowing or zero equity holdings. We also remove funds that do less than 1% of their total borrowing via the prime brokerage contract.

2.1.2 Additional Hedge Fund Data: Enhanced Financial Accounts, and SEC Private Fund Statistics

Aggregated information from Form PF are publicly available via a variety of sources, and we use this data when possible. The Federal Reserve's Enhanced Financial Accounts and the SEC Private Fund Statistics both report aggregated information about hedge fund balance sheets, investment exposures, and other information.

2.1.3 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 (BHCs) for the broker-dealers in the sample. For foreign BHCs, 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.[16] From FactSet Ownership's Security files, we collect the common market net worth for each bank holding company, which we call NW_t^b.[17]

2.1.4 Security Holdings Data

Based on the SEC's 13-F filings, FactSet's Ownership data provide adviser-level, quarterly information on institutional equity holdings, shares outstanding, and other relevant information from 2000 to present. FactSet also provides a proprietary classification of institutional investors into investor types.[18] We clean the data as described in Koijen,

[16] We use the senior five-year CDS spread as it has the most comprehensive set of matches.
[17] We use FactSet to provide measure market net worth as it provides the fullest coverage of global bank holding companies.
[18] We adopt Koijen, Richmond, and Yogo (2023)'s classification of FactSet entities into key institutional types such as hedge funds, investment advisers, and brokers.

Richmond, and Yogo (2023). As institutional holdings can exceed shares outstanding in certain periods, we scale institutional holdings proportionally to sum to shares outstanding.

Merge with Form PF: FactSet also provides a proprietary cross-walk between its manager-level (i.e. adviser-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 and merge the FactSet holdings data with Form PF using this cross-walk. We remove filings for funds held by bank holding companies and any manager where the reported long equity holdings from FactSet is at least 300% larger than the reported long equity holdings in Form PF.

2.1.5 Security- and Firm-Level Outcomes and Characteristics

We collect stock-level return information, trading volume, and volatility data from the CRSP U.S. Stock Database. From the CRSP-Compustat Merged database, we collect standard firm-level balance sheet information and stock-level exposure. From this dataset, we 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 data with the holdings data via CUSIP. In certain tests, we use security-level predicted exposures, collected from Chen and Zimmermann (2022).

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 SIC code. We also remove stocks in the bottom quintile of market capitalization in the last period and those with prices less than $3 in the prior quarter.

2.2 Institutional Details: Prime Brokers and Equity 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 Global Financial Crisis.

Prime brokers provide leverage to their clients through various contracts, including repurchase agreements, margin loans, and securities lending agreements to facilitate short sales, as well as synthetic financing. Lending for equity purchases primarily takes place through the latter three types of contracts. Margin loans are the primary method used to extend credit to clients for financing long equity positions. These loans are secured by the clients portfolio, with terms based on the clients 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 both the direct financing expense and potential opportunity costs if the brokers parent company needs to allocate additional funds to support margin lending activities.

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

2.3 Hedge Funds

Hedge funds are the primary institutional investors that employ leverage for equity investing in the U.S. 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 U.S., 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.

Hedge funds represent an important class of equity market investors. First, they are large in scale. According to the SEC's Private Fund statistics, hedge funds reported $10.8 trillion in gross assets under management in Q4 2022. Second, they hold a meaningful share of the equity market in aggregate. Using Form PF data merged with FactSet equity holdings, Panel A of Table 1 reports that leveraged hedge fund mangers identified in Form PF hold 3.7% of the stock market and 5.1% of the total aggregate institutional market share. Beyond their holdings, leveraged hedge funds make up even more of the overall turnover share, using two distinct measures Our first measure quantifies the share of investor-to-investor turnover attributable to hedge funds. We compute turnover as the sum of absolute changes in investor-level positions. By this metric, hedge funds account for about 13.8% of turnover, roughly 2.5 times their direct holdings share, indicating trading activity far in excess of their direct ownership. A second, distinct measure looks at changes in institutional shares across the aggregated classes of Koijen, Richmond, and Yogo (2023). Concretely, we sum absolute changes in each class's share of each stock, which captures cross-class reallocations (and is not inflated by within-class churn). By this measure, hedge funds account for about 19.2% of the total change, implying that a large fraction of the trading that moves assets across investor types involves hedge funds.

These facts are even more stark for the average security. Hedge funds own about 8.3% of the market share (and 12.2% of the institutional share) for the average stock. Stock-level exposures are also highly heterogeneous: at the 90th percentile, hedge funds hold 20.5% of the market share and 30.6% of the institutional share. Similar heterogeneity holds for turnover shares. The typical stock is held by about 17 leveraged hedge-fund advisers, that is, advisers than manage at least one leveraged hedge fund.

Together, these patterns highlight that hedge funds are not only large in aggregate but also systematically important for the trading and ownership structure of many individual securities.

Table 1: **Summary Statistics: Hedge Fund and Institutional Shares:** This table reports both aggregate- and stock-level measures of hedge fund equity market participation from FactSet Ownership. A FactSet manager is included in the sample if it is associated with at least one hedge fund in Form PF that has non-zero prime brokerage borrowing and non-zero equity holdings reported on Form PF. Stock-level measures are reported as pooled statistics across individual stocks, while aggregate measures are computed as quarterly averages of total market-wide values. Hedge funds' share of total market capitalization is reported as "HF Market Share" and hedge funds' share of total institutional holdings as "HF Inst. Share". Total institutional holdings are defined as all holdings identified in FactSet Ownership associated with an institutional investor. Two measures of hedge portfolio turnover are reported. HF Turnover Share (1) captures the fraction of investor-to-investor turnover among institutional investors attributable to hedge funds. HF Turnover Share (2) captures the fraction of investor-class-to-investor-class turnover attributable to hedge funds. Aggregate turnover shares are weighted by lagged prices. Number of Managers denotes the count of distinct managers holding each stock.

Panel A: Aggregate (market-wide):

Statistic	HF Market Share	HF Inst. Share	HF Turnover Share (1)	HF Turnover Share (2)
	3.7	5.06	13.78	19.24

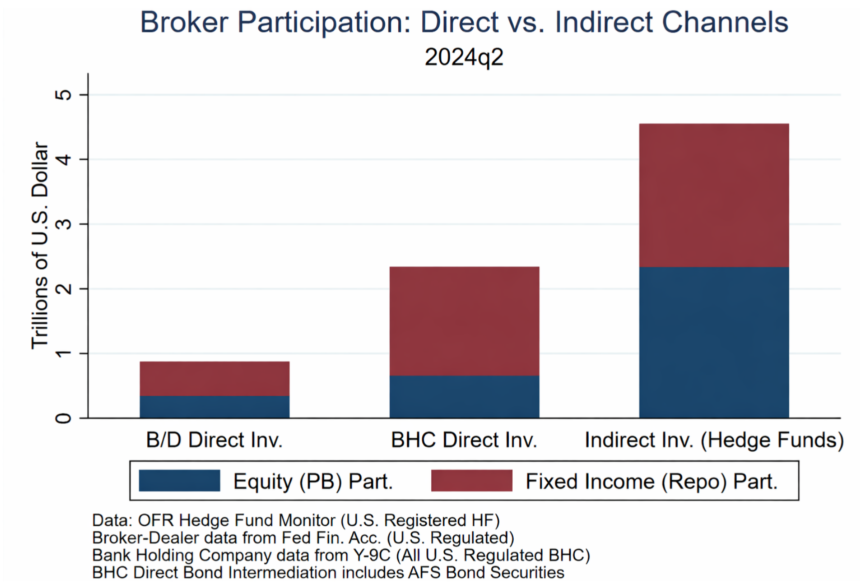
Panel B: Stock-level

Statistic	Mean	SD	P50	P10	P25	P75	P90
HF Market Share	8.27	10.53	4.50	0.69	1.83	10.15	20.49
HF Inst. Share	12.23	14.83	6.77	1.38	2.96	14.84	30.56
HF Turnover Share (1)	17.66	14.00	14.09	4.09	7.89	23.37	35.59
HF Turnover Share (2)	19.08	15.70	15.49	2.12	6.47	28.15	41.13
Number of Managers	16.46	11.18	14.00	4.00	8.00	22.00	31.00

2.4 Prime Brokerage Lending Patterns

In Figure 1, we compare total prime brokerage lending, as reported in the OFR Hedge Fund Monitor, with broker-dealer equity holdings from the Financial Accounts. The OFR aggregates reported prime brokerage lending across funds and intermediaries, providing a comprehensive measure of the scale of financing in this market.[19] As of Q2 2024, total prime brokerage lending to hedge funds was roughly \$2.3 trillion.[20] By contrast, the Flow of Funds indicates that broker-dealers' total equity holdings are about \$350 billion, highlighting the scale of prime brokerage intermediation relative to dealers' balance sheet equity positions.

Figure 1: **Broker-Dealer Securities Market Participation:** The figure reports broker-dealers' total direct equity and fixed income holdings and prime brokerage lending and repo lending to hedge funds. Data is from OFR Hedge Fund Monitor, which aggregates Form PF filings, and the Financial Accounts. Values are as of Q2 2024.



Moreover, the hedge fund lending market is highly concentrated, with a small number of institutions accounting for the vast majority of lending (Table 2). Lending to hedge funds predominantly comprises the largest global systemically important banks (G-SIBs). The OFR Hedge Fund Monitor reports the borrowing share by each institution, though the identities of counterparties are anonymized.[21] Table 2 reports the cumulative distribution of lending shares of the top-10 hedge fund lenders. On average, the top five lenders account for 55.7% of total loans, while the top ten provide about 80.2%. This degree of concentration is striking when compared with broader lending markets: Y-9C data indicate that the top five and top ten bank lenders account for 40.3% and 53.7% of total loans, respectively, in Q1

[19] We report the 2024 data as the OFR Hedge Fund Monitor first began reporting data that period.

[20] Prime brokerage loans include not only equity-related financing but also lending against other instruments, such as convertible bonds, as well as securities lending that facilitates short positions.

[21] The OFR notes that "Historically, the top 10 creditors include both U.S. Global Systemically Important Banks (G-SIBs) and foreign G-SIBs."

2024. The high level of concentration in hedge fund lending suggests that an idiosyncratic shock to a single large lender could have significant consequences for hedge fund financing.

Table 2: **Cumulative Borrowing Concentration:**: This first column reports cumulative borrowing concentration for the largest hedge fund counterparties from the OFR Hedge Fund Monitor. The OFR states "Historically, the top 10 creditors include both U.S. Global Systemically Important Banks (G-SIBs) and foreign G-SIBs." The second column reports the cumulative concentration for BHC Total Loans from Y-9C Filings. Both data are for Q1 2024.

	(1)	(2)
	Hedge Fund Credit Concentration	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

Additionally, while lenders are concentrated, hedge funds borrow from multiple counterparties. Table 3 reports the summary statistics for both large leverage users (funds with at least one billion dollars of prime brokerage borrowing) and any fund with prime brokerage borrowing. For a given fund, we classify a Form PF counterparty as a "prime broker" if the prime brokerage imputation method described above assigns non-zero prime brokerage lending to that counterparty. On average, funds with prime brokerage borrowing borrow from 3.09 lenders and large leverage users from 4.30 lenders, though there is some variation around these means. The 25th percentile of large hedge funds borrow from 2.00 lenders while the 75th percentile borrow from 5.00 lenders. A large hedge fund borrows about 50% of their total borrowing from their largest counterparty, which is about 16% more than would be expected if hedge funds borrowed equally from each counterparty. While hedge fund lending is concentrated and granular from lenders' perspectives, hedge funds, especially larger ones, appear to diversify their borrowing network by spreading borrowing across multiple lenders.

3 Cross-Sectional Event Study Evidence

In this section, we test whether there is a causal association between broker-dealer health and hedge fund leverage and equity holdings by exploiting cross-sectional variation in the hedge fund counterparty network. Cross-sectional event studies help alleviate concerns that

Table 3: **Prime Brokerage Network Characteristics:** This table provides summary statistics on borrowing network size and concentration for Form PF filing hedge funds. Column (1) provides summary statistics for the set of hedge funds that borrow at least $1 billion in prime brokerage borrowing. Column (2) provides summary statistics for the set of all hedge funds with non-zero prime brokerage borrowing. Both columns reflect data from 2013-2022. The first seven rows provide the distribution of the number of counterparties for each fund. Row eight refers to the borrowing share from the largest lender. As this can differ across the size distribution, we also provide in row nine the deviation share, which is defined as the borrowing share from the largest lender from the equally-weighted share. For a given fund, a Form PF counterparty is classified as a prime broker and included in this table if the prime brokerage imputation method described above assigns non-zero Form PF prime brokerage lending to that counterparty.

	(1) At least $1B in PBL	(2) Any PBL
Mean Number of PB	4.30	3.09
SD Number of PB	3.24	2.87
10th Pctile Number of PB	2.00	1.00
25th Pctile Number of PB	2.00	1.00
50th Pctile Number of PB	3.00	2.00
75h Pctile Number of PB	5.00	4.00
90th Pctile Number of PB	7.00	6.00
Mean of Max Borr Shr	0.52	0.65
Mean of Dev Borr Shr	0.16	0.12
Number of Fund by Q obs in Sample	7529	20911

broker-dealer lending may correlate with other determinants of hedge fund leverage and asset prices, including macroeconomic conditions or hedge fund balance sheet characteristics.

3.1 The Ideal Experiment

The ideal experiment would combine a randomly-assigned hedge fund counterparty network (i.e., a random set of prime brokerage lenders) and a shock to the health of one or a small set of broker-dealers that is unrelated to their prime brokerage activities and broader market conditions.

Then, the relative change in hedge fund borrowing from the set of shocked broker-dealers compared to the borrowing from non-shocked broker-dealers would causally identify the passthrough from broker-dealer health shocks to hedge fund leverage.

Importantly, cross-sectional tests allow for credibly identified causal effects but are not direct analogues to time-series analysis. While time-series estimates capture aggregate transmission, cross-sectional estimates rely on relative exposure, and periods with credible shocks to a subset of broker-dealers would not necessarily correspond to periods with aggregate health variation.

A key economic outcome in a cross-sectional shock to broker-dealer health is whether hedge funds can replace any lost borrowing. Because hedge funds typically maintain relationships with multiple counterparties, idiosyncratic broker-dealer distress may be mitigated through substitution of borrowing away from impaired broker-dealers to healthier ones. Conversely, the granularity of these markets implies that even idiosyncratic shocks may have meaningful transmission effects if the size of lost borrowing is large and not easily replaced. Thus, cross-sectional tests of the passthrough of broker-dealer health to hedge fund borrowing are effectively tests of hedge funds' abilities to replace the borrowing lost from shocked counterparties. We emphasize this feature of our cross-sectional analysis in our analyses below.

3.2 Near-Ideal Experiments

Motivated by the ideal experiment, we conduct a narrative analysis of potential episodes of broker-dealer shocks over the 2013–2022 period in Online Appendix F. We identify two possible historical events during our sample that come close to matching the features of the ideal experiment. We describe each below. *Note that the information reported in this paper on specific individual broker-dealers is derived solely from published sources.*

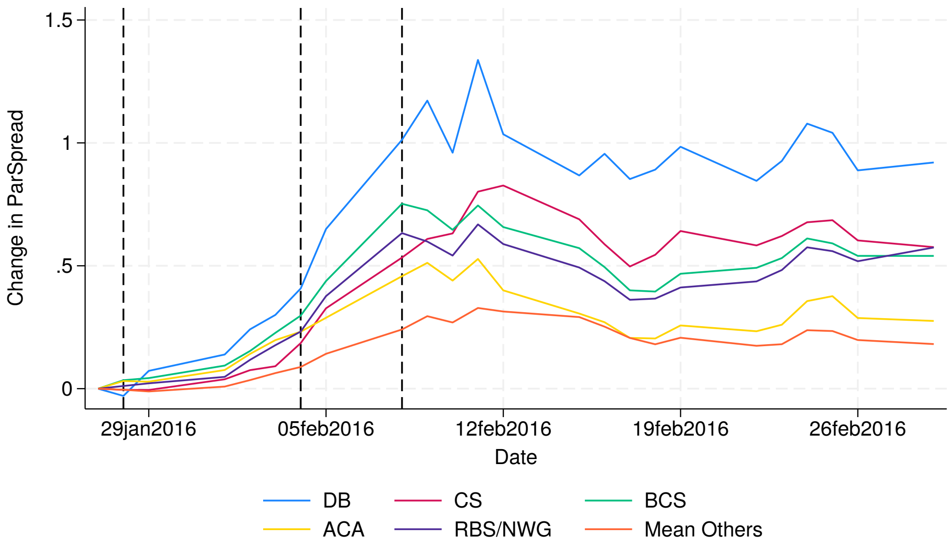
3.2.1 European Broker-Dealer Distress

The European Broker-Dealer Distress episode began with bank-specific losses at two large European broker-dealers but quickly broadened into a sector-wide shock as investors reassessed the stability of European broker-dealer sector.

Bank-Originated Losses: The immediate catalysts were large write-downs and restructuring charges at two global systemically important banks (G-SIBs): Deutsche Bank announced a record full-year loss of 6.7 billion euros in January 20, 2016, driven by its strategic restructuring and 5.8 euros billion in impairments tied to planned divestitures of German retail and Chinese commercial banking operation. Credit Suisse reported substantial impairments linked to legacy U.S. investment banking assets on February 4, 2016, resulting in write-downs equal to nearly 9% of its market capitalization, among the largest quarterly losses across broker-dealers at the time. Crucially, these write-downs were the result of past strategic and accounting decisions, not contemporaneous macroeconomic conditions.

Investor Liabilities Concerns and Sector-Wide Distress: Market attention quickly shifted from asset impairments to the liability side of European broker-dealers' balance sheets. In the first two months of 2016, CDS spreads of European banks increased substantially, with Additional Tier 1 (AT1) subordinated debt, a particularly important funding instrument for European brokers, experiencing significant price declines amidst concerns over debt repayment capacity by Deutsche Bank (see Gleason, Bright, Martinez, and Taylor 2017 and Bologna, Miglietta, and Segura 2020 for a broader discussion of AT1-induced

Figure 2: **CDS Spread Changes for Early 2016Q1:** This figure plots the individual cumulative CDS spread change for each of the Euro 5 broker-dealers and for “Other” broker-dealers, starting from January 27, 2016. A broker-dealer is classified as “Other” if it lends to at least one Form PF hedge fund with prime brokerage borrowing and the broker-dealer has a liquid CDS spread.



distress). To see the widespread distress for European broker-dealers, Figure 2 plots cumulative CDS spread changes during early Q1 2016. While banks with direct losses saw the largest increases, other European G-SIBs, namely Barclays and RBS, also experienced notable widening. For example, following Credit Suisse’s February 4 announcement, Barclays’ CDS spreads rose by 21 basis points and RBS’s by 19 basis points, nearly matching the broker-dealers with actual losses.[22]

In the analysis that follows, we translate this historical narrative of European broker-dealer distress into an empirical treatment definition, identifying which broker-dealers were most affected and using this classification to study the transmission of distress via a difference-in-differences framework.

Treatment Group Construction: We first define the set of treated broker-dealers most affected by the shock. Because distress extended beyond banks with reported losses, we base treatment assignment on CDS spread responses rather than firm identities. Specifically, we identify a set of high-salience announcements, centered around major disclosures by the banks with direct losses, listed in Appendix Table A2.[23] For each broker-dealer, we calculate

[22] These parallel movements are indicative of broader fragility among European broker-dealers. As Deutsche Bank’s 2015 annual report noted, “negative developments concerning other financial institutions perceived to be comparable to us... affected the prices at which we have accessed the capital markets.” Financial press reports similarly described widespread “anxiety about the health of Europe’s banks” and heavy CDS buying against junior debt instruments (Rennison and Jackson (2016)). Given European G-SIBs reliance on market-based funding such sentiment likely tightened funding conditions across the sector.

[23] Some of the events were first highlighted by Gleason, Bright, Martinez, and Taylor (2017).

one-day CDS spread changes around these announcements and cumulate the effects. As a robustness check, we also measure cumulative CDS spread changes from Deutsche Bank's subordinated debt disclosure on January 28 to its CDS peak on February 9.

Appendix Table A3 shows that both methods produce similar patterns. The following results stand out. First, the five brokers with the largest CDS spread increases are the same — Deutsche Bank, Credit Suisse, Barclays, RBS (NatWest), and Credit Agricole — all large European G-SIBs. Second, spread increases are not limited to these five: the median broker experienced a 12 basis point increase under the event-based method and 33 basis points under the start-to-peak window, consistent with broad market concern. To preserve confidentiality, we group the five most affected dealers, the top quintile of spread increases, as the "treated" group. We refer to this group of shocked broker-dealers as the "Euro 5", and refer to the 2016 European broker-dealer distress episode as the "Euro 5" experiment.

Plausibility of Euro 5 Treatment Grouping: This grouping is supported by an alternative grouping methodology, similar ex-ante characteristics across the five brokers, and large one-off losses realized by all five institutions. Appendix Table A3 shows that these five brokers consistently occupy the upper tail of CDS responses, regardless of measurement window. Second, Appendix Section C.2.3 shows that institutions experiencing moderate CDS spillovers tend to be affiliated with parent companies that were ex-ante less profitable (lower market-to-book ratios) and more reliant on lower-tier capital. This pattern is consistent with investors extrapolating distress to similar banks, making CDS-based treatment definitions economically meaningful.

Ex-post, all of these banks identified in the Euro 5 experienced or announced substantial one-off charge-offs in Q1 2016 similar to those of Credit Suisse and Deutsche Bank: Barclays incurred 1.878bn pounds in legal and retail write-downs; RBS faced 2.21bn pounds in unexpected legal and restructuring costs; and Credit Agricole absorbed 448mn euros in net restructuring losses.[24] Thus, all five brokers experienced unexpected loss realizations.

Plausible Exogeneity of the Shock: A central appeal of this episode is that its origins were idiosyncratic. The initial losses arose from legacy asset impairments and past strategic decisions at two banks, not contemporaneous macroeconomic conditions. The timing of these announcements is sharp and well-dated, and the effects were disproportionately concentrated among certain European G-SIBs, with limited immediate spillovers to U.S.

[24] On February 26, 2016, RBS announced over 2.21bn pounds were due to unexpected legal costs and additional restructuring costs. (Bray (2016)) In midst of a restructuring, on March 1, Barclays announced a major dividend cut as it faced an additional 1.61bn pounds of legal provisions and 261mn in impairments related to Italian retail banks. (Arnold (2016), Barclays PLC (2015)) On February 17, 2016, Credit Agricole announced a plan to simplify the Groups capital structure that raised concerns about its earnings prospects. In their released statement, they estimated a negative impact of 470mn euros. (Crdit Agricole S.A. (2016b)) In their Q1 results, total realized losses were 448mn euros.(Crdit Agricole S.A. (2016a))

broker-dealers. These features make the episode a plausibly exogenous shock to the financial health of a subset of intermediaries well-suited for studying cross-sectional transmission through counterparty relationships.

Despite these features, two identification concerns remain. First, treated and control broker-dealers may differ systematically in ways that would generate divergent outcomes even absent the shock, for example, U.S. versus non-U.S. broker-dealers may differ structurally in funding models, client bases, or regulation. Second, exposures to distressed European dealers may be correlated with exposures to contemporaneous euro-area macro risks, raising the possibility that our estimates capture broader regional risk rather than broker-specific distress.[25]

We address the first concern by restricting the sample to non-U.S. broker-dealers, ensuring comparisons within a more homogeneous group. We address concerns over regional exposure by directly measuring regional exposure at the fund and stock levels. At the fund level, we construct proxies for adviser exposure to the euro area. At the stock level, we control for a stock's European bank ownership and the share of foreign revenues for the company.

3.2.2 Archegos

In late March 2021, Archegos Capital Management, a large family office, collapsed following margin calls on its total return swaps. Nine major counterparties were exposed, and six broker-dealers ultimately reported losses exceeding \$10 billion (Table 4). For several institutions, including Nomura and Credit Suisse, losses amounted to approximately 15% of pre-shock net worth and prompted a withdrawal from the prime brokerage business (Arons, Hu, and Nakamichi (2021), Halftermeyer (2021a)). The majority of losses were realized in April 2021.

Table 4: **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 U.S. dollars. The net worth of the bank holding company associated with each broker is reported as of December 31, 2020, also in billions of U.S. dollars.

BHC	Reported Losses	BHC Market Net Worth	Losses to Net Worth	Loss Announcement
Credit Suisse	5.5	31.3	17.6%	8-Apr-21
Nomura	2.9	17.7	16.4%	27-Apr-21
UBS	0.774	54.5	1.4%	27-Apr-21
Morgan Stanley	0.911	123	0.7%	16-Apr-21
MUFG	0.27	111.1	0.2%	30-Mar-21
Mizuho	0.09	32	0.28%	N/A
Goldman Sachs	0	90.7	0.0%	N/A
Deutsche Bank	0	22.5	0.0%	N/A
Wells Fargo	0	124.7	0.0%	N/A

[25] Because our strategy relies on cross-sectional variation, the concern is not aggregate shocks that affect all funds uniformly, but rather differential exposures to European risks across the cross-section.

Treatment Group Construction Our treatment group consists of the six broker-dealers with reported losses to Archegos, which are listed in Table 4. Grouping together brokers with losses to a common counterparty provides a clear treatment group for the shock. With this in mind, we do not include brokers who had exposure to Archegos but avoided losses as they did not experience a direct balance sheet health shock.

Exogeneity and Interpretation We regard Archegos as a useful second setting for a couple reasons. First, the set of directly exposed broker-dealers is well-identified, and the financial health consequences are unambiguous. Second, the magnitude of losses is substantial and comparable to earlier broker distress episodes, including the European Broker-Dealer distress period in 2016 described above. In both the Euro 5 and Archegos episodes, roughly one-third of estimated prime brokerage lending came from treated banks at the onset of the stress.

Nevertheless, the Archegos case raises identification concerns. Although Archegos was a family office and not a hedge fund, it relied extensively on prime brokerage services through synthetic exposures, and the losses from the failure of Archegos originated in the prime brokerage function of affected banks. Nonetheless, the direction of this bias is likely toward an empirical association between lending contraction and Archegos-related losses. We expound on this point and the direction of the potential bias when discussing our empirical results below.

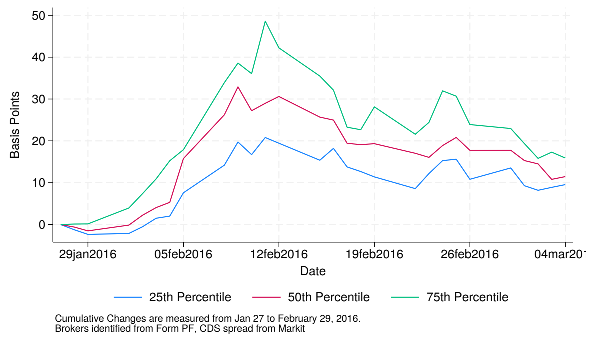
3.2.3 Differences in Aggregate Health

While these two experiments involve plausibly treated broker-dealers with similar scale, roughly one-third of prime brokerage lending came from treated banks in each episode, the aggregate state of the broker-dealer sector differed substantially. Figure 3 presents cumulative CDS spread changes for non-shocked broker-dealers during each episode. Panel (a) shows that during Euro 5, even broker-dealers not directly affected experienced substantial health deterioration: the 25th percentile of CDS spread changes exceeded 10 basis points and at times reached 20 basis points. In contrast, panel (b) shows that during Archegos, non-shocked broker-dealers' CDS spreads were stable or declining: the 25th percentile was negative, and the 75th percentile rarely exceeded two basis points.

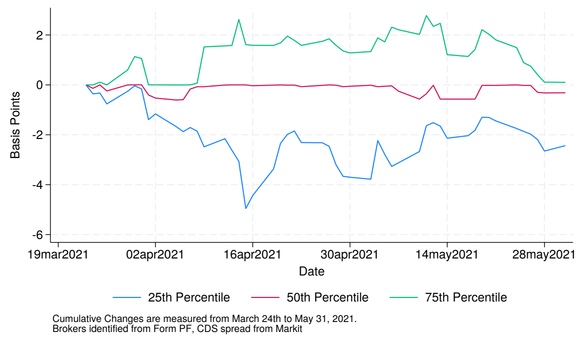
Standard measures of aggregate intermediary health confirm this pattern. The He, Kelly, and Manela (2017) intermediary capital ratio tightened from 6.2% to 5.1% between Q4 2015 and Q1 2016, but increased from 5.5% to 6.7% between Q4 2020 and Q2 2021. These differences in aggregate broker-dealer health provide context for understanding the divergent transmission outcomes documented in the sections that follow.

Figure 3: **Aggregate Broker-Dealer Health Across Episodes:** This figure presents cumulative CDS spread changes for broker-dealers not directly shocked in each episode. We report the 25th, 50th, and 75th percentile across broker-dealers. Panel (a) shows cumulative CDS spread changes for non-Euro 5 broker-dealers from January 27, 2016 onwards. Panel (b) shows cumulative CDS spread changes for broker-dealers without losses to Archegos from March 24, 2021 onwards.

(a) Euro 5



(b) Archegos



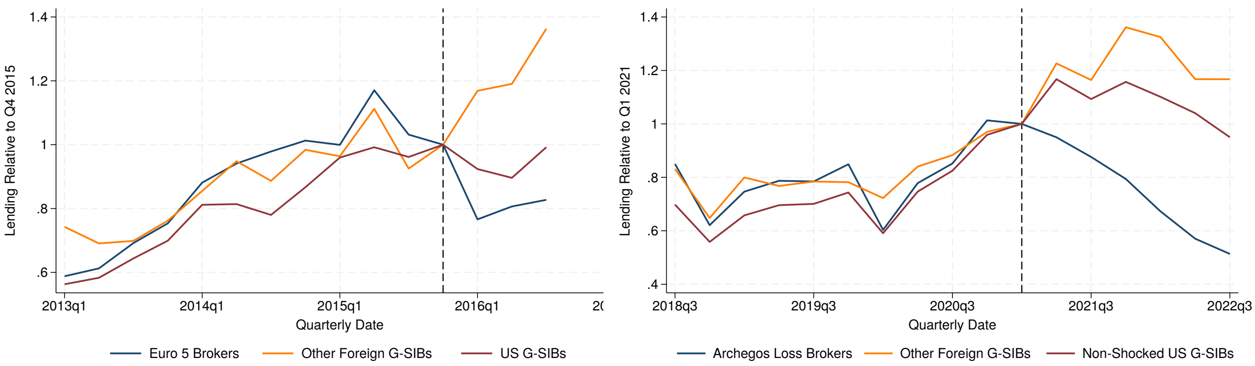
3.3 Hedge Fund Borrowing from Treated Banks

A necessary condition for broker-dealer health to transmit to equity prices through hedge fund borrowing is that shocked broker dealers need to retract credit provided to hedge funds as a result of the shock. In Figure 4, we plot total (imputed) prime brokerage lending to hedge funds for three sets of institutions: shocked institutions (Euro 5 and Archegos Loss banks), other foreign G-SIBS, and U.S. G-SIBs, of which the latter two represent control (non-treated) banks. We index the level of lending to the period prior to the shock: Q4 2015 for the Euro 5 episode and Q4 2020 for the Archegos episode. In Q1 2016, the Euro 5 banks provided \$278 billion in prime brokerage lending to hedge funds, other (non-shocked) G-SIBS provided \$57 billion, and U.S. G-SIBS provided \$554 billion. Panel (a) shows that in Q4 2015, when information about some of the shocked brokers began to emerge, there is a slight decline of lending by the Euro 5 brokers, while other foreign and U.S. G-SIBs slightly increased lending. In Q1 2016, total lending declined significantly for Euro 5 broker-dealers by about 23% compared to a 8% decline for U.S. G-SIBs and a 17% increase for foreign G-SIBs. This provides direct evidence that Euro 5 banks reduced their lending substantially in the immediate aftermath of the realization of the shock, whereas non-shocked banks on average either slightly cut or dramatically increased their borrowing.

Panel (b) shows similar dynamics during the Archegos episode. In Q4 2020, the Archegos-loss banks provided \$419 billion of prime brokerage loans to hedge funds, other (non-shocked) G-SIBs provided \$88 billion, and (non-shocked) U.S. G-SIBs provided \$710 billion. Shortly following the realizations of losses due to Archegos's failure, treated banks reduced lending to hedge funds while non-treated banks increased lending. These trends persisted for multiple quarters following the shock, again suggesting that balance sheet impairment had a direct association with a pullback in prime brokerage lending to hedge funds.

Figure 4: **Aggregate Total Lending by Broker Type:** This figure plots the time-series of total lending by the treated and non-treated sets of G-SIB brokers for both the European broker distress experiment and Archegos experiment. For non-treated banks, we decompose into lending by other foreign G-SIBs and U.S. G-SIBs. We normalize total lending to hedge funds to 100% in Q4 2015 for the European broker distress experiment and total lending to hedge funds to 100% in Q1 2021 for the Archegos experiment. We remove the observation for foreign G-SIBs in Q1 2014 due to an insufficient number of counter-parties for the Euro 5 experiment. The Q1 2014 value reported in this plot is interpolated from the Q4 2013 value and the Q2 2014 value of the foreign G-SIBs lending series.

(a) Euro 5 **(b) Archegos**



3.4 Within Fund Estimator

The aggregate lending trends provided in the previous section are strongly suggestive that balance sheet shocks to credit providers can have a direct and causal association with hedge fund borrowing. Nonetheless, total equilibrium borrowing quantities are determined by both demand and supply, and identification concerns remain. To control for unobserved confounding variables, in this section we estimate Khwaja and Mian (2008) style regressions in the broker-by-fund panel:

$$\Delta Y_{q+1} = \alpha_f + \beta Treated_q^{f,b} + \gamma X^{f,b} + \epsilon_{q+1}^{f,b} \qquad (1)$$

where ΔY_{q+1} is defined either as the change in log prime brokerage borrowing by fund f from bank b, $\Delta \log(PBL_q^{f,b})$ (as in Kruttli, Monin, and Watugala (2022)), or the change in prime brokerage borrowing scaled by prior-period net assets, $\frac{\Delta PBL_q^{f,b}}{NAV_q}$. The period q indexes the treatment period, Δ reflects the change between q and $q+1$, and $Treated_q^{f,b}$ is a dummy variable indicating whether bank b is a shocked bank (either a Euro 5 or Archegos-loss bank). The $X^{f,b}$ controls include the past two quarters' returns (accounting for concerns over past performance), the lagged log level of net asset value (for the log-change specification, accounting for concerns about fund size), and fund strategy fixed effects. We compute heteroskedastic robust standard errors.[26]

Table 5 reports the estimates for equation (1) for the Euro 5 experiment. In column (1) we include no controls or fixed effects, while columns (2)-(4) incrementally add strategy fixed effects and controls. In each specification, we find a statistically significant and negative estimate: for each shocked broker from which a fund borrows, their log-borrowing growth rate is between between -0.141 and -0.172 log-points lower. This provides evidence that funds borrowed less from the treated set of brokers. In column (5), we include a fund fixed-effect, which absorbs common demand effects. This addresses concerns that funds exposed to a common demand shock were matched to the distressed European broker-dealers, and the coefficient represents the change in the borrowing mix across counterparties within a given fund. Column (5) reports a negative and statistically robust coefficient of -0.158, suggesting that these declines are not driven by common demand or fund characteristics. Columns (6) subsets our analysis to funds reporting at least $100M in long equity holdings of listed firms, which restricts to funds more likely to matter for equity markets. We find near identical coefficients. In Column (7), we include an additional indicator variable for non-Euro 5 foreign broker-dealers. We find that these other broker-dealers are statistically indistinguishable from U.S brokers and that our point estimate for shocked European broker-dealers remains robust.

In Columns (8) and (9), we repeat the specifications in columns (6) and (7) but use $\frac{\Delta PBL_q^{f,b}}{NAV_q}$ as the dependent variable. Scaling by assets allows for easier comparisons across specifications and, in particular, will allow us to compare the size of the effect implied by the within-estimator to the total reduction of borrowing we will estimate in a subsequent section. We find qualitatively similar effects.

In Table 6, we re-estimate equation (1) for the Archegos experiment, with period q set as Q1 2021. As in Table 5, in all specifications we find a significant negative association

In both the Euro 5 and Archegos experiments, hedge funds borrowed less from shocked broker-dealers, even controlling for common demand. Are funds able to perfectly replace this decline in borrowing from shocked banks? To investigate this, we examine the impact on total fund-level prime brokerage borrowing by regressing it on a dummy variable indicating whether the fund borrows from *any* shocked bank. We estimate the following model:

$$\Delta Y_q^f = \alpha + \beta Treated_q^f + \gamma X^f + \epsilon^f \tag{2}$$

where variables are defined analogously to equation (1) but are measured at the fund level rather than the bank-by-fund level. The variable $Treated_q^f$ is equal to one if fund f borrows from at least one treated bank.

[26]We have also clustered standard errors by fund and the statistical significance is quantitatively similar.

Table 5: **Within Fund Estimation Strategy (Euro 5)**: This table reports the estimates for equation (1) for Q1 2016, which regresses changes in fund prime brokerage borrowing from a counter-party on $Treated^{f,b}_{2015q4}$. $Treated^{f,b}_{2015q4}$ is an indicator variable that takes the value of one if the fund-broker observation includes an Euro 5 broker as of December 31, 2015 and zero otherwise. $OtherForeignBroker^{f,b}_{2015q4}$ is an indicator variable that takes the value of one if the fund-broker observation includes an non-Euro 5 foreign broker as of December 31, 2015 and zero otherwise. Changes in fund prime brokerage borrowing from a counter-party are either log changes ($\Delta ln(PBL^{f,b}_t)$) or changes scaled by lagged net asset value ($\frac{\Delta PBL^{f,b}_t}{NAV^f_{t-1}}$). "Controls" refer to the past two quarters' returns, the lagged log level of net asset value, and fund strategy fixed effects. Outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. "Large Eq" funds report at least 100 million dollars of long equities in Q4 2015. Reported standard errors are heteroskedasticity robust.

	$\Delta Log(PBL^{f,b}_t)$							$\frac{\Delta PBL^{f,b}_t}{NAV^f_{t-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Treated^{f,b}_{2015q4}$	-0.141***	-0.164***	-0.156***	-0.172***	-0.158***	-0.155***	-0.163***	-0.022**	-0.024**
	(0.037)	(0.037)	(0.038)	(0.037)	(0.035)	(0.036)	(0.035)	(0.008)	(0.009)
$OtherForeignBroker^{f,b}_{2015q4}$							-0.027		
							(0.054)		
R^2	0.01	0.07	0.04	0.10	0.64	0.59	0.64	0.01	0.49
N	1,103	1,103	1,103	1,103	1,086	962	1,086	974	962
Controls		X		X					
StratFE			X	X					
KMFE					X	X	X		X
Sample						Large Eq		Large Eq	Large Eq

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

Table 6: **Within Fund Estimation Strategy (Archegos)**: This table reports the estimates for equation (1) for Q2 2021, which regresses changes in fund prime brokerage borrowing from a counter-party on $Treated^{f,b}_{2021q1}$. $Treated^{f,b}_{2021q1}$ is an indicator variable that takes the value of one if the fund-broker observation includes a broker with reported losses to Archegos as of March 31, 2021 and zero otherwise. $OtherForeignBroker^{f,b}_{2021q1}$ is an indicator variable that takes the value of one if the fund-broker observation includes an non-Archegos loss foreign broker as of March 31, 2021 and zero otherwise. Changes in fund prime brokerage borrowing from a counter-party are either log changes ($\Delta ln(PBL^{f,b}_t)$) or changes scaled by lagged net asset value ($\frac{\Delta PBL^{f,b}_t}{NAV^f_{t-1}}$). "Controls" refer to the past two quarters' returns, the lagged log level of net asset value, and fund strategy fixed effects. Outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. "Large Eq" funds report at least 100 million dollars of long equities in Q1 2021. Reported standard errors are heteroskedasticity robust.

	$\Delta Log(PBL^{f,b}_t)$							$\frac{\Delta PBL^{f,b}_t}{NAV^f_{t-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Treated^{f,b}_{2021q1}$	-0.074**	-0.073**	-0.083***	-0.083***	-0.079***	-0.085***	-0.082***	-0.024**	-0.024***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)	(0.029)	(0.009)	(0.008)
$OtherForeignBroker^{f,b}_{2021q1}$							-0.015		
							(0.031)		
R^2	0.01	0.02	0.07	0.08	0.52	0.51	0.52	0.01	0.42
N	1,183	1,183	1,183	1,183	1,169	1,043	1,169	1,054	1,043
Controls		X		X					
StratFE			X	X					
KMFE					X	X	X		X
Sample						Large Eq		Large Eq	Large Eq

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

Table 7 reports results from estimating equation (2) for the Euro 5 experiment. In column (1), we find that borrowing from at least one Euro 5 bank results in an average decline in total borrowing of -0.19 log points. In columns (2) and (3), we restrict to funds with at least \$100 million in long cash-equity exposure and introduce controls, and we continue to find an economically large and statistically significant effect.

In the fund-by-broker cross-section, we directly controlled for a potential matching of broker-dealers and funds via the within-fund estimator. As such a control is not possible in the fund cross-section, we directly test for two major matching concerns. In column (4), we restrict out sample to funds that borrow from at least one non-U.S. broker-dealer. This helps ameliorate identification concerns that funds borrowing from Euro 5 brokers are different than other funds and that because the shock originates at European banks, such funds might be directly exposed to a European specific macro shock. In column (5), we control for the share of hedge fund assets, measured at the adviser level, invested in the European Economic Area (EEA).[27] Once again, we find an economically large and statistically significant effect. In column (6), we repeat specification (5) but with the change in fund-level prime brokerage borrowing scaled by net assets as the key independent variable. We find that funds borrowing from at least one distressed European broker borrow 0.067 less (roughly interpreted as prime brokerage leverage points) than other funds.

As a back of the envelope exercise, we can compare the size of lending reduction from our within-fund estimator. As the average fund borrows from 1.6 treated counterparties and borrows 0.024 less prime brokerage dollars scaled by lagged net assets from each treated broker (from Table 5), the average exposed fund would have a reduction of 0.038 prime brokerage scaled by net asset value. This is about 60% of our point estimate in column (6).[28] Jointly, this suggests that the cross-sectional credit supply shock makes up a large amount of the fund-level deleveraging.

Finally, as a placebo test, we re-estimate equation (2) for each quarter in 2015 and 2016, shown in Appendix Figure 5. We find that a negative and significant point estimate is only present in Q1 2016, in line with funds exposed to the European 5 broker-dealers only reducing lending more than other funds during the credit supply shock period.

Next, we estimate equation (2) for the Archegos experiment, repeating all the same specifications as in Table 7 (excluding column (5) because the EEA Holdings control is irrelevant for the Archegos episode). Results are reported in Table 8. In columns (1)-(4), we find no economic or statistically significant relationship between total fund borrowing

[27] This variable is constructed from Question 28 on Form PF, in which advisers report for all hedge funds that they advise the share of assets in the EEA. This variable is not available at the fund level.

[28] This estimate of a 0.038 decline is larger than the decline implied by the coefficients in column (6) of Table 7, which indicates an average decline in borrowing for exposed hedge funds of 0.029, suggesting that some of the association implied by the Khwaja and Mian (2008) estimate is due to an increase in borrowing from non-shocked banks.

Table 7: **Fund-Level Total Borrowing (Euro 5):** This table reports estimates for equation (2) for Q1 2016, which regresses changes in fund-level prime brokerage borrowing on $Treated^f_{2015q4}$. $Treated^f_{2015q4}$ is an indicator variable that takes the value of one if the fund borrows from at least one Euro 5 broker as of December 31, 2015 and zero otherwise. "EEA Holdings" is a continuous variable that controls for the share of a hedge fund *manager*'s assets invested in the European Economic Association (EEA). Changes in fund prime brokerage borrowing from a counter-party are either log changes ($\Delta ln(PBL^f_t)$) or changes scaled by lagged net asset value ($\frac{\Delta PBL^f_t}{NAV^f_{t-1}}$). "Controls" include the contemporaneous net asset value growth rate. The minimum equity cut-offs refer to a minimum fund-level equity threshold of \$100 million in the prior period. Outcome variables are winsorized at the 2.5% and 97.5% levels on a quarterly basis. Reported standard errors are heteroskedasticity robust.

	$\Delta Log(PBL^f_t)$					$\frac{\Delta PBL^f_t}{NAV^f_{t-1}}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated^f_{2015q4}$	-0.186***	-0.146***	-0.139***	-0.207***	-0.140***	-0.067***
	(0.041)	(0.035)	(0.032)	(0.045)	(0.033)	(0.025)
EEA Holdings					0.028	
					(0.159)	
Intercept	0.074**	0.046*	0.079***	0.162***	0.075**	0.038**
	(0.031)	(0.027)	(0.025)	(0.042)	(0.032)	(0.019)
R^2	0.058	0.048	0.155	0.205	0.155	0.227
N	493	415	415	252	415	415
StratFE	X	X	X	X	X	X
Controls			X	X	X	X
MinEquity		X	X	X	X	X
Sample	All	All	All	Foreign	All	All

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

and ex-ante borrowing from a shocked bank. Estimated coefficients are both imprecisely estimated and much smaller in magnitude than in the Euro 5 specifications.[29] In fact, in column (5), we find that funds borrowing from banks that suffered material Archegos-related losses actually *increased* their total prime brokerage borrowing when measured relative to prior period net assets.

Table 8: **Fund-Level Total Borrowing (Archegos):** This table reports estimates for equation (2) for Q2 2021, which regresses changes in fund-level prime brokerage borrowing on $Treated^f_{2021q1}$. $Treated^f_{2021q1}$ is an indicator variable that takes the value of one if the fund borrows from at least one broker with reported losses to Archegos as of March 31, 2021 and zero otherwise. Controls include the contemporaneous net asset value growth rate. Changes in fund prime brokerage borrowing from a counter-party are either log changes ($\Delta ln(PBL^f_t)$) or changes scaled by lagged net asset value ($\frac{\Delta PBL^f_t}{NAV^f_{t-1}}$). The minimum equity cut-offs refer to a minimum fund-level equity threshold of \$100 million in the prior period. Outcome variables are winsorized at the 2.5% and 97.5% levels on a quarterly basis. Reported standard errors are heteroskedasticity robust

	$\Delta Log(PBL^f_t)$				$\frac{\Delta PBL^f_t}{NAV^f_{t-1}}$
	(1)	(2)	(3)	(4)	(5)
$Treated^f_{2021q1}$	-0.005	-0.021	0.005	0.071	0.096***
	(0.034)	(0.032)	(0.031)	(0.071)	(0.030)
Intercept	0.061**	0.073***	0.026	-0.040	-0.024
	(0.028)	(0.027)	(0.029)	(0.068)	(0.024)
R^2	0.050	0.070	0.136	0.151	0.119
N	463	398	398	311	398
StratFE	X	X	X	X	X
Controls			X	X	X
MinEquity		X	X	X	X
Sample	All	All	All	Foreign	All

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

We quickly note that the identification concern associated with the Archegos episode, specifically that the losses originated from the prime brokerage function of affected banks rather than being an exogenous shock to balance sheet health, works against the results in Table 8. To the extent that losses are endogenous to the prime brokerage relationship, one would expect any resulting credit retrenchment to bias the analysis toward detecting transmission to hedge fund borrowing. The absence of such an effect therefore strengthens our interpretation that hedge funds were able to fully replace the borrowing lost from Archegos through alternative funding sources. In this section we provide evidence for this interpretation.

3.5 Imperfect Substitution and the Role of Intermediary Health

Tables 7 and 8 document a striking divergence: broker-dealer health shocks transmit to hedge fund total borrowing in Euro 5 but not in Archegos. One possible reason is differences

[29] We also varied the shock period to Q1 2021 or Q3 2021 and find no significant relationship between total prime brokerage borrowing and ex-ante borrowing from a bank with reported Archegos losses.

in substitution capacity. When hedge funds lose access to credit from shocked broker-dealers, transmission depends on whether healthier broker-dealers can absorb the displaced borrowing. This capacity, in turn, depends on two factors: the aggregate health of non-shocked broker-dealers (their willingness to lend) and the scale of lost borrowing relative to available capacity (their ability to lend). When aggregate health deteriorates or the scale of the shock is large relative to healthy capacity, substitution is impaired and transmission occurs. When healthy broker-dealers have ample spare capacity, hedge funds can fully replace lost borrowing and transmission is prevented. Appendix Figures 4 and 6 illustrate these divergent substitution patterns for exposed hedge funds.

Section 3.2.3 established that aggregate broker-dealer health differed substantially across the two episodes. In the cross-section, we cannot directly study these aggregate differences; however, we can exploit cross-sectional variation in broker health to examine whether hedge funds exhibit any substitution behavior and whether broker health matters for lending. Specifically, we test whether healthier non-shocked brokers were willing to expand lending during Euro 5, and whether hedge funds substituted toward these healthier counterparties.

We measure the health of non-shocked brokers using their CDS spread changes on Euro 5 announcement dates. For large equity hedge funds, we estimate fund-by-broker regressions relating borrowing changes to broker health:

$$\Delta \log(PBL^{f,b}_{2016q1}) = \alpha + \beta CumulativeEuroCDS^{b} + \epsilon^{f,b}_{2016q1} \tag{3}$$

$$\Delta \log(PBL^{f,b}_{2016q1}) = \alpha + \beta BelowMedian^{b} + \epsilon^{f,b}_{2016q1} \tag{4}$$

Table 9 shows that hedge funds substituted toward healthier (below-median CDS change) broker-dealers and away from less healthy (above-median CDS change) brokers. Within-fund specifications (column 4) confirm this pattern holds when controlling for common demand shocks. Figure 5 shows that exposed hedge funds increased borrowing from below-median brokers while reducing borrowing from above-median brokers. This demonstrates that the substitution mechanism was operative, hedge funds redirected borrowing toward healthier counterparties when possible.

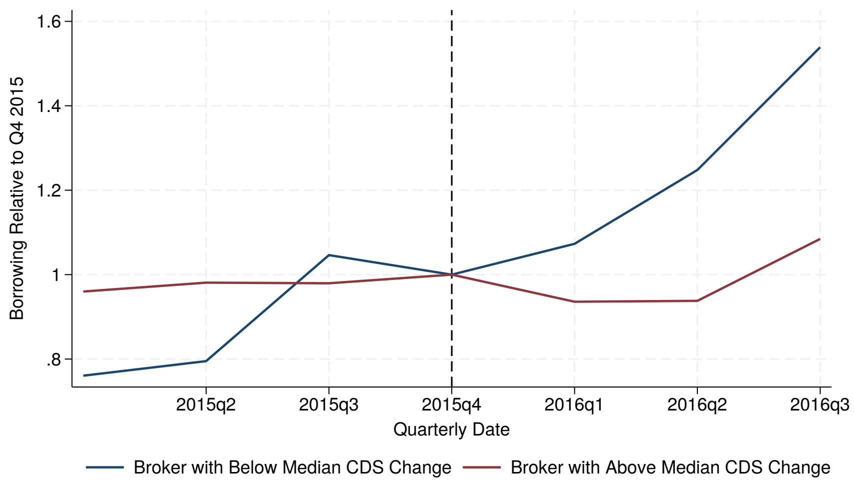
Capacity constraints. While hedge funds substituted toward healthier brokers, this substitution could not fully offset lost borrowing. The scale of the required reallocation exceeded available capacity at healthier institutions. A simple calculation illustrates the constraint: exposed hedge funds lost \$35 billion in borrowing from Euro 5 banks. In Q4 2015, below-median CDS brokers provided only \$19 billion in total prime brokerage lending to all hedge funds. To absorb the displaced borrowing, these healthier brokers would need to nearly triple their aggregate lending, an infeasible expansion. This capacity constraint explains why partial substitution occurred (funds shifted toward healthier brokers) but

Table 9: **Fund by Broker Borrowing: non-Euro 5 Brokers** This table reports estimates for equations (3) and (4), which regresses changes in fund prime brokerage borrowing from a counter-party on various broker exposure measures. "Cumulative Event CDS Spreads" is a continuous measure constructed from the cumulative CDS spread changes for each broker over a major announcement date. "Below Median CDS" is an indicator variable that takes a value of one if a non-Euro 5 broker has a below median CDS change. "Above Median CDS" is an indicator variable that takes a value of one if a non-Euro 5 broker has an above median CDS change. The sample "non-Euro 5" excludes fund-by-broker observations associated with the Euro 5 brokers. The intercept then estimates the effects for Euro 5 broker-dealers. Outcome variables are winsorized at the 2.5% and 97.5% levels. Standard errors are robust to heteroskedasticity.

	$\Delta Log(PB_{f,t,b})$			
	(1)	(2)	(3)	(4)
Cumulative Event CDS Spreads Chg	-1.069**			
	(0.458)			
Below Median CDS Chg		0.307***	0.392***	0.400***
		(0.116)	(0.117)	(0.101)
Above Median CDS Chg			0.084**	0.138***
			(0.038)	(0.033)
Intercept	0.155*	-0.073***	-0.157***	-0.186***
	(0.094)	(0.023)	(0.030)	(0.027)
R^2	0.01	0.02	0.02	0.59
N	498	498	756	751
Sample	non-Euro 5	non-Euro 5	All	All
KMFE				X
Outcome	Log	Log	Log	Log

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

Figure 5: **Broker Health and Exposed Funds' Substitution Patterns:** This figure plots aggregate borrowing from non-"Euro 5" brokers for funds that borrowed from at least one "Euro 5" broker in Q4 2015. We split non-"Euro 5" brokers into two groups based on the increase of their CDS spreads over "Euro 5" news-announcement dates, as shown in Table A2. In blue, we plot the aggregate borrowing from non-treated brokers with below median CDS spread changes over those event dates, normalized to 100% in Q4 2015. In red, we plot the aggregate borrowing from non-treated brokers with above median CDS spread changes over those event dates, normalized to 100% in Q4 2015.



transmission still resulted (total borrowing declined).

4 Transmission to Equity Prices

The previous section showed that hedge funds borrowing from Euro 5 banks had their aggregate prime brokerage borrowing contract. For this contraction to affect equity prices, de-leveraging hedge funds must reduce their equity holdings. We document this using two complementary data sources: Form PF balance sheet data on fund-level asset exposures and FactSet 13F data on manager-level equity holdings.

We begin with Form PF fund-level long equity exposures. For hedge funds with more than \$100 million in long equity holdings in December 2015, we estimate:

$$\Delta \ln(LongEq^{f}_{2016q1}) = \alpha + \beta Treated^{f}_{2015q4} + \gamma X^{f} + \epsilon^{f}_{2016q1} \tag{5}$$

where $\Delta \ln(LongEq^{f}_{2016q1})$ is the log change in fund f's long equity exposure and $Treated^{f}_{2015q4}$ indicates that fund f borrows from at least one Euro 5 broker in Q4 2015.

Table 10 reports results in Columns (1)-(3). All specifications show negative and statistically significant coefficients on Euro 5 exposure. Column (1) reports the baseline specification. Column (2) adds hedge fund strategy fixed effects. Column (3) adds net asset value controls. Across all specifications, funds exposed to Euro 5 brokers reduced long equity exposures by 5.5-6.8% more than non-exposed funds. In Column (3), the intercept becomes statistically insignificant, suggesting non-exposed hedge funds did not reduce equity positions on average beyond what their net asset value growth rate. In Appendix Table A4, we document that we do not find an abnormal reduction of Form PF asset-class exposures for Euro 5 hedge funds for other asset classes.

The fund-level evidence shows that hedge funds reduced equity exposures following the Euro 5 shock. However, declines in the market value of equity holdings conflate two effects: reductions in shares held versus valuation effects from price declines. To isolate actual sales, we turn to manager-level holdings data from FactSet 13F filings merged with Form PF.[30]

We construct two measures of equity portfolio size for manager m:

$$MarketPricePort^{m}_{t} = \sum_{s} Price^{s}_{t} * SharesHeld^{m,s}_{t} \tag{6}$$

$$StalePricePort^{m}_{t} = \sum_{s} Price^{s}_{2015q4} * SharesHeld^{m,s}_{t} \tag{7}$$

[30] Investor level variation is now at the FactSet manager level, equivalent to an investment adviser, and may comprise multiple hedge funds.

Table 10: **Hedge Fund De-leveraging and Equity Reductions:** This table reports estimates on equity exposures of hedge funds (managers) borrowing from Euro 5 brokers. Columns (1)-(3) report Form PF balance sheet data for fund-level long equity exposures (equation 5). Columns (4)-(8) report manager-level data from 13F holdings (equation 8). The dependent variables in Columns (1)-(3) are log changes in Form PF long equity exposure with progressive controls. Column (4) shows manager-level prime brokerage borrowing changes. Columns (5)-(8) show log changes in manager-level equity holdings. Column (5) measures holdings at market prices. Columns (6)-(8) use stale prices that fix stock prices at 2015Q4 levels, isolating changes due to share quantities rather than price movements. $Treated^f$ indicates fund exposure to Euro 5 brokers; $Treated^m$ indicates manager exposure (at least one fund borrowing from Euro 5). Column (7) includes an interaction with manager-level PB borrowing changes ($\Delta\ln(PBL^m)$). Column (8) includes controls for other investor types. All specifications include at least \$100 million in long equity exposure (Form PF) or equity holdings (13F) in Q4 2015. Outcome variables are winsorized at the 2.5% and 97.5% levels. Standard errors are heteroskedasticity-robust.

	Fund (Form PF)			Manager (13F)				
	Δ Log(Long Eq)			Δ Log (PBL)	Δ Log (Mkt)	Δ Log(Stale Price)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated^{f,m}$	-0.068***	-0.062***	-0.055***	-0.096*	-0.067**	-0.088***	-0.057*	-0.088***
	(0.023)	(0.022)	(0.018)	(0.052)	(0.034)	(0.034)	(0.032)	(0.034)
$\Delta ln(PBL^m)$							0.100	
							(0.089)	
$Treated^m \times \Delta ln(PBL^m)$							0.243**	
							(0.110)	
PrivBank								0.022
								(0.025)
IA								0.008
								(0.025)
FS HF								0.003
								(0.028)
BR								-0.157***
								(0.047)
Intercept	-0.050***	-0.054***	-0.019	0.008	-0.083***	-0.025	-0.026	-0.025
	(0.015)	(0.016)	(0.013)	(0.038)	(0.025)	(0.025)	(0.025)	(0.025)
R^2	0.021	0.053	0.338	0.017	0.020	0.034	0.195	0.024
N	415	415	415	196	196	196	196	2,831
StratFE		X	X					
Controls			X					X

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

The market price measure incorporates both share changes and price movements. The stale price measure fixes prices at 2015Q4 levels, isolating changes in share quantities. We estimate:

$$\Delta \ln(Port^{m}_{2016q1}) = \alpha + \beta Treated^{m}_{2015q4} + \gamma X^{m} + \epsilon^{m}_{2016q1} \tag{8}$$

where $Treated^{m}_{2015q4}$ indicates the manager advises at least one fund borrowing from a Euro 5 bank, for $Port \in \{MarketPricePort^{m}_{2016q1}, StalePricePort^{m}_{2016q1}\}$.

Columns (4)-(8) of Table 10 report results for managers with at least \$100 million in equity holdings in Q4 2015. Column (4) confirms that exposed managers de-levered: manager-level prime brokerage borrowing fell by 9.6% more for exposed managers.[31] Column (5) shows market-valued portfolios fell 6.7% more for exposed managers. Both specifications show negative intercepts, indicating that the market value of equity holdings declined for non-exposed funds. This suggests that market-wide price movements partially drove the observed changes in portfolio values.

Columns (6)-(8) use stale prices to isolate actual sales. Column (6) shows exposed managers reduced share holdings by 8.8% more than non-exposed managers. The intercept becomes statistically insignificant, confirming non-exposed managers did not reduce positions. Column (7) adds an interaction with manager-level de-leveraging intensity, showing managers who cut borrowing most also sold the most shares. Column (8) includes controls for other investor types from Koijen, Richmond, and Yogo (2023), showing that only Euro 5-exposed hedge funds and broker-dealers reduced equity positions during this period.[32] Full specifications are in Appendix Table A5.

The comparison between market-price and stale-price measures clarifies the role of price effects. In Column (5), the negative intercept for non-exposed managers reflects general price declines in stocks held by hedge funds during this period. In Column (6), fixing prices at Q4 2015 levels removes this intercept's significance, demonstrating that non-exposed managers did not actually sell sharesthe apparent portfolio decline was driven entirely by price movements. This pattern is consistent with the insignificant coefficient in Column (4), which shows non-exposed managers did not reduce prime brokerage borrowing. Together, these results indicate that stocks held by Euro 5-exposed managers experienced poor returns during this period, but only the exposed managers engaged in actual sell-offs.

[31] Manager-level prime brokerage borrowing aggregates all fund-level borrowing for funds filing Form PF in both Q4 2015 and Q1 2016. We exclude managers whose funds report PF equity exposure exceeding 300% of FactSet equity holdings.

[32] Broker-dealer 13F holdings may reflect risk management for prime brokerage activities. We control for broker-dealer holdings in Appendix Table A8 and find it does not affect our price results.

4.1 Stock-Level Treatment and Sell-Offs

To study whether the equity sold by Euro 5 connected hedge fund managers have implications for equity prices, we propose the following proxy for stock-level de-leveraging pressure, defined for stock s as of Q4 2015:

$$Euro5MktShare_t^s = \sum_{m \in M(s)} MktShareHFs_t^{s,m} * Treated_{2015q4}^m \tag{9}$$

where $Treated_{2015q4}^m$ is defined as in the previous sections, $M(s)$ is the set of managers that own shares in stock s, and $MktShareHFs_t^{s,m}$ denotes the percentage of total shares outstanding in stock s held by manager m at time t. In the tables, we refer to $Euro5MktShare_t^s$ as "% Held Euro5 HFs". Under this definition, a stock is more exposed to Euro 5-connected hedge funds if a larger share of its outstanding equity is held by hedge fund managers with at least one Euro 5 relationship. For our baseline analysis, we restrict the sample to non-financial stocks priced above \$3 at the end of 2015 and exclude stocks in the bottom two deciles of market capitalization. We further require that each stock has positive exposure to both Euro 5 and non-Euro 5 hedge fund managers.[33]

We test whether exposure to the Euro 5 predicts abnormal equity sales by exposed managers by estimating the following stock-level panel regression:

$$\begin{aligned} \Delta Euro5MktShare_t^s = \alpha_t + \alpha_{sic} + \beta_1 Euro5MktShare_{t-1}^s \\ + \beta_2 Euro5MktShare_{t-1}^s \times \mathbf{1}_{1=2016q1} + \epsilon_t^s \end{aligned} \tag{10}$$

where $\Delta Euro5MktShare_t^s$ is the quarterly change in the market share of the stock held by Euro 5 managers, α_{sic} is a two-digit SIC industry code fixed effect, and $Euro5MktShare_{t-1}^s$ is its lagged exposure. $\mathbf{1}_{1=2016q1}$ is an indicator variable if the quarter is Q1 2016. Because hedge fund portfolios are frequently rebalanced, we control for mean reversion at the security level via the β_1 coefficient, which captures average portfolio turnover each quarter. With this control in place, the coefficient β_2 identifies the abnormal sell-off intensity associated with exposure to Euro 5 broker-dealers during the European broker-dealer distress period.

In Column (1) of Table 11 we estimate that in Q1 2016, for a one-percentage-point increase in the ownership stake of the treated managers for a given stock, there is a corresponding 0.124 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 fund managers with credit supply-induced sell-offs. To address this, we calculate abnormal sales in Columns (2)-(5), incorporating industry- and time-fixed effects. In Column

[33] Our findings are robust to alternative thresholds for these filters.

(5), we find that a one percentage point larger ownership by managers connected to the Euro 5 (in Q4 2015) associates with a 0.052 percentage point larger reduction in holdings in the following period. However, in Q1 2016, we find that a one percentage point larger ownership of Euro 5 managers associates with an *additional* .076 percentage point reduction in the percentage of the stock held by these managers, suggesting position liquidations by Euro 5 managers that are correlated with the extent of Euro 5 manager ownership in Q4 2015.

Table 11: **Stock-Level Sell-Offs by Euro 5 Adviser** This table reports estimates for equation (10). Equation (10) regresses the change in security-level market share held by Euro 5 advisers ($\Delta Euro5MktShare_t^s$) on the market share held by those same advisers ($Euro5MktShare_t^s$). 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 by quarter.

	$\Delta\%HeldEuro5HFs$				
	(1)	(2)	(3)	(4)	(5)
Lag % Held Euro5 HFs	-0.124***	-0.048***	-0.049***	-0.050***	-0.052***
	(0.016)	(0.005)	(0.005)	(0.006)	(0.006)
Lag % Held Euro5 HFs × I{Q12016}		-0.076***	-0.075***	-0.077***	-0.076***
		(0.005)	(0.005)	(0.005)	(0.005)
Intercept	0.004***	0.003***	0.003***	0.003***	0.004***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.10	0.02	0.03	0.03	0.03
N	1,537	19,548	19,548	19,548	19,548
Q12016	X				
QtrxYearFE			X		X
IndustryFE				X	X

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

4.2 Evidence of Equity Price Impact

We test for price pressure using two complementary measures: ex-ante exposure to Euro 5-connected managers and realized sell-offs. For ex-ante exposure, we estimate:

$$ret^s_{2016q1} = \alpha + \beta Euro5MktShare^s_{2015q4} + X^f + \epsilon^s_{2016q1} \tag{11}$$

For realized sell-offs, we estimate:

$$ret^s_{2016q1} = \alpha + \beta \Delta MktShareE5HFs^s_{2016q1} + X^f + \epsilon^s_{2016q1} \tag{12}$$

where ret^s_{2016q1} is the stock's return (raw or residualized against factor models), $Euro5MktShare^s_{2015q4}$ is the pre-shock ownership share by Euro 5-connected managers, and $\Delta MktShareE5HFs^s_{2016q1}$ is the change in their ownership. Standard errors are clustered at the two-digit SIC industry-code level.

Table 12: **Price Impact: Ex-Ante Exposure and Realized Sell-Offs:** This table reports estimates for equations (11) and (12). Columns (1)-(3) test whether ex-ante exposure to Euro 5-connected managers predicts lower returns. Columns (4)-(7) test whether realized sell-offs by these managers predict lower returns. Returns are raw (Ret_s) or residualized against the Fama-French 4-factor model ($\varepsilon_{FF4,s}$). Column (2) controls for non-Euro 5 hedge fund exposure and includes industry fixed effects. Column (3) uses FF4 residuals. Columns (5)-(7) progressively add controls for non-Euro 5 hedge fund sell-offs and restrict to stocks with Euro 5 sell-offs (E5SellOff = X) or above-median sell-offs. Exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the two-digit SIC industry code level.

	Ex-ante Exposure			Realized Sell-offs			
	Ret_s	Ret_s	$\varepsilon_{FF4,s}$	Ret_s	Ret_s	Ret_s	$\varepsilon_{FF4,s}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Held Euro5 HFs_{2015q4}	-0.687***	-0.359***	-0.552***				
	(0.152)	(0.129)	(0.174)				
% Held non-Euro5 HFs_{2015q4}		-0.604***	-0.678***				
		(0.136)	(0.189)				
Δ % Held Euro5 HFs				1.022***	1.014***	2.629***	4.075***
				(0.347)	(0.357)	(0.603)	(0.717)
Δ % Held non-Euro5 HFs					-0.653	-0.204	-0.718
					(1.044)	(1.610)	(1.791)
Intercept	0.040**	0.037***	0.045***	0.011	0.011	0.036**	0.044***
	(0.018)	(0.007)	(0.009)	(0.017)	(0.017)	(0.018)	(0.015)
R^2	0.02	0.21	0.20	0.01	0.01	0.02	0.05
N	1,537	1,537	1,537	1,537	1,537	828	828
IndustryFE		X	X				
E5SellOff						X	X

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

Table 12 reports results. Columns (1)-(3) show that ex-ante exposure predicts lower returns. In Column (1), a one percentage point higher ownership by Euro 5-connected managers associates with 69 basis points lower returns. Column (2) adds industry fixed effects and controls for non-Euro 5 hedge fund exposure, yielding a 36 basis point effect. Column (3) finds similar results for residualized returns to the Fama-French 4 models. These results indicate that stocks more exposed to Euro 5-connected managers underperformed, consistent with selling pressure.

Notably, in Column (2), the coefficient on non-Euro 5 hedge fund exposure is also negative and significant, suggesting stocks held by hedge funds generally performed poorly during this period. However, this does not necessarily imply price pressure from non-Euro 5 managers. The ex-ante exposure measure may capture common hedge fund stock selection or factor exposures rather than causal sell-off effects. To distinguish correlation from causation, we turn to realized sell-offs.

Columns (4)-(7) test whether realized sell-offs predict returns. Column (4) shows a positive coefficient (sell-offs associate with lower returns for Euro 5 managers. In Column (5), we find that controlling for non-Euro 5 hedge fund sell-offs does not affect the point estimate. Crucially, the coefficient on non-Euro 5 sell-offs in Column (5) is statistically insignificant and negative, indicating that sales by non-Euro 5 managers did not generate price pressure. This contrasts sharply with the negative ex-ante exposure coefficient for non-Euro 5 managers in Column (2). This suggests that the negative point estimate from the non-Euro 5 ex-ante measure captures common hedge fund stock characteristics rather than causal price impact from selling. This finding is consistent with Table 10, which showed that non-Euro 5 managers did not reduce their equity positions during this period. Columns (6)-(7) restrict to stocks with Euro 5 sell-offs. Column (6) shows that a one percentage point increase in Euro 5 sell-offs, that is a -1% change in Δ % Held Euro5 HFs, associates with 263 basis points lower returns. Full specifications including additional factor model controls appear in Appendix Tables A6 and A7.

In Appendix Table A8, we show that our results are robust to controlling for other types of intermediary exposures (including other hedge fund managers, investment advisers, and broker-dealers). While we earlier saw that broker-dealers decreased their equity holdings in Table A5, we do not find a relationship between stock returns and broker-dealer holdings. We additionally find that our results are robust to controlling for the direct exposure of E5 banks to stocks via equity ownership and lending.

Lastly, in Appendix Table A10, we perform as a placebo test the same specifications as in columns (1)-(3) of Table 12 for the Archegos experiment. As expected, we find no relationship between stock returns and the percentage of the stock held by managers that borrow from Archegos-affected banks. This is consistent with the absence of a passthrough from Archegos distress to fund-level prime brokerage borrowing.

4.2.1 Reversion

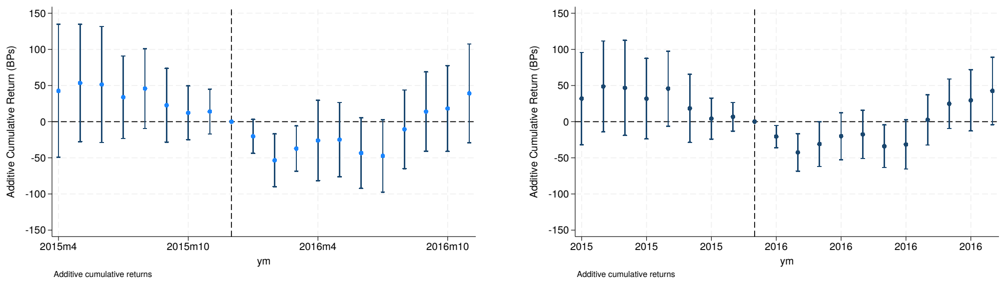
Without the release of any fundamental news or a permanent shock to intermediary capital, other investors should ultimately step in to arbitrage away any temporary mispricings. To test this, we study the impact on abnormal cumulative arithmetic returns. Since we are interested in reversions, we move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

$$\begin{aligned} cumret^s_{2015m12+\tau} = {} & \alpha + \beta_1 Euro5MktShare^s_{2015q4} \\ & + \beta_2 NotEuro5MktShare^s_{2015q4} + \epsilon^s_{2015m12+\tau} \end{aligned} \tag{13}$$

We estimate equation (13) separately for each month between April 2015 and November 2016.

The coefficient of interest is β_1, which measures the change in the cumulative return for stock s (which we normalize to 0 as of Dec 31st, 2015) for a one percentage point higher ownership of Euro 5-connected managers. Figure 6 plots β_1 both unconditionally (panel (a)) and controlling for industry fixed effects (panel (b)). In both panels, β_1 is statistically indistinguishable from zero in each of eight months prior to the shock date, which we define here as December 2015. In January 2016, β_1 falls below zero and is marginally statistically significant, reaches a low in February 2016, and recovers by April 2016. In panel (b), we estimate a β_1 coefficient just above -50 basis points.

Figure 6: **Cumulative Returns and Reversals:** This figure presents estimates β_1 in equation (13) for the period from April 2015 to December 2016. Each point represents the regression estimate of arithmetic cumulative returns, $CumRet_t^s$, on the percentage of shares outstanding held by Euro 5-connected managers as of Q4 2015.



(a) Without industry controls **(b) With industry controls**

4.3 Price Multiplier

How large is the impact of sales on stock prices? To quantify the impact, we compute the price multiplier both directly and as implied by our reduced-form estimates. The price multiplier is defined as:

$$M = \frac{\frac{\Delta P}{P}}{\frac{\Delta Q}{Q}} = \frac{\beta_2}{\beta_1}$$

A price multiplier has the interpretation of the expected percentage point price decline for a one percentage point decline in the total shares outstanding held by affected managers. We have already computed estimates for β_1 and β_2. Equation (11), with estimates provided in Table 12, provides an estimate of $\frac{\Delta P}{P}$ because quarterly returns approximate stock price changes, while equation (10), with estimates reported in Table 11, provides an estimate of $\frac{\Delta Q}{Q}$.

A back-of-the-envelope calculation estimates a price multiplier of $\frac{-0.359}{-0.124} = 2.9$ (Table 12, Column (2) and Table 11, Column (1)) based on the total sell-off and $\frac{-0.359}{-0.076} = 4.72$ for the abnormal sell-offs.

In Table 12, we directly estimate a price multiplier of 2.63 from Column (6) for raw returns and 4.075 for Fama-French-Carhart four-factor residuals from Column (7). The price multiplier appears to be large when looking at stocks with large sell-off pressure, suggesting possible non-linear effects.

To contextualize the size of the price multiplier, we briefly review the literature.[34] Gabaix and Koijen (2021) considers a price multiplier of one to be reasonable, offering a range of literature-based estimates from 0.7 to 2.5. The estimates surveyed represent average price multipliers from routine events such as index inclusions and dividend reinvestments in normal times.

This paper estimates a price multiplier under very different conditions; we estimate the multiplier in the context of a direct, prolonged shock to arbitrage capital, where institutions typically thought to be liquidity providers liquidity demanders. These conditions appear to associate with a higher price impact.[35] In the next section, we provide additional evidence to explain why a high multiplier is both reasonable and perhaps expected.

4.4 Non-Levered Investors Absorb the Shock

Most intermediary asset pricing theory models suggest that "intermediaries" hold assets primarily due to some form of specialization or lower risk aversion. These models predict that when intermediaries become distressed, risk premia increase significantly, causing realized returns to turn negative if the asset is transferred to less specialized or sophisticated investors. We test this prediction by analyzing which investors absorb the sell-off.

In order to determine who buys the stocks the de-leveraging hedge fund managers sell, we study which of the following investor groups increase their positions: hedge funds without a relationship with the Euro 5 (nonEuro5 HFs), other hedge funds (Other HFs), FactSet-classified broker-dealers (Brokers), FactSet-classified investment advisers that are not Form PF-identified hedge funds (Inv Adv), or the FactSet household sector (Households).[36] We estimate:

$$\Delta MktShare^{i,s}_{2016q1} = \alpha + \beta \Delta Euro5MktShare^{s}_{2016q1} + \epsilon^{s}_{i} \tag{14}$$

where i refers to the institutional types described above.

We present the coefficient estimates for equation (14) in Table 13. In Columns (1)

[34] We thank Pete Kyle for feedback and discussion here.

[35] The market microstructure invariance literature, see Kyle and Obizhaeva (2016) and Kyle and Obizhaeva (2023), also suggests an outsized impact for shocks such as these, where some investors might be forced to sell rapidly, resulting in large price impacts.

[36] We classify hedge fund manager sets as follows: nonEuro5 HFs refers to a manager with at least one Form PF hedge fund with positive prime brokerage borrowing in Form PF's Question 43, with at least one counter-party identified in Form PF's Question 47, and without a Euro 5 counterparty. Other HFs includes all other hedge fund managers identified via FactSet or Form PF. This set includes FactSet identified hedge fund managers without a Form PF fund, managers with Form PF filing funds that do not report counter-parties on Q47, and managers where their reported long equity holdings from FactSet is at least 300% larger than their reported equity in Form PF. 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, Richmond, and Yogo (2023). This means that the household sector includes retail investors and institutional investors who do not file 13-F filings.

Table 13: **Other Institutional Shares and Euro 5 Sell-offs:** For the set of stocks that Euro 5 managers collectively sold off in 2016Q1, this table estimates equation (14), which regresses the change in market share of other institutional investor classes on the change in market share of Euro 5-affiliated managers. The other institutional investor classes include PF hedge funds that do not borrow from Euro 5 brokers but do report counterparty borrowing information ($\Delta\%HeldnonEuro5HFs$), all other hedge fund managers ($\Delta\%HeldOtherHFs$), broker-dealers ($\Delta\%HeldBrokers$), the Household sector ($\Delta\%HeldHouseholds$), and investment advisers identified in FactSet excluding advisers with Form PF filing hedge funds ($\Delta\%\%HeldInvAdv$). All institutional classes are identified using Koijen, Richmond, and Yogo (2023)'s taxonomy of FactSet classifications. The Household sector is defined as the residual of total institutional filers holding shares. Standard errors are clustered at the two-digit SIC industry code level.

	$\Delta\%HeldnonEuro5HFs$	$\Delta\%HeldOtherHFs$	$\Delta\%HeldBrokers$	$\Delta\%HeldHouseholds$	$\Delta\%HeldInvAdv$
	(1)	(2)	(3)	(4)	(5)
$\Delta\%HeldEuro5HFs$	-0.021	-0.024	0.006	-0.486***	-0.397***
	(0.036)	(0.058)	(0.022)	(0.101)	(0.110)
Intercept	-0.000	-0.001	-0.001***	-0.002*	0.003**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
R^2	0.00	0.00	0.00	0.04	0.02
N	828	828	828	828	828

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

through (4), we report estimates of the portfolio changes of other hedge fund managers and the broker-dealer sector, the other main levered investor classes. Neither broker-dealers nor any other hedge fund classes absorb the shock. Instead, in Columns (4) and (5), we find that over 87% of the sell-off appears to be absorbed by the FactSet household sector and other non-levered investment advisers, with the bulk absorbed by the investment adviser sector.

These results are both interesting and in line with theory. 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 quantity patterns, it is unsurprising that we estimate 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, Richmond, and Yogo (2023)), both of which predict substantial price effects when less elastic, non-levered investors absorb the sell-off.

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

5 Perfect Substitution in the Cross-Section Outside Systemic Distress

Sections 3 and 4 provide suggestive evidence for two patterns: broker-dealer health shocks transmit to equity prices during a systemic distress episode (Euro 5), but hedge funds substitute effectively during an episode where healthier broker-dealers have spare capacity (Archegos). However, these patterns are based on two case studies with identification limitations. Is Archegos representative of how hedge funds respond to idiosyncratic broker-dealer shocks, or does cross-sectional broker-dealer distress routinely transmit outside systemic episodes? To answer this, we test whether cross-sectional variation in broker-dealer health predicts hedge fund borrowing outcomes across all quarters in our sample.

We measure broker-dealer distress each quarter using changes in CDS spreads. Define $Distress_t^b = CDS_{t,max}^b - CDS_{t-1,eoq}^b$ as the maximum CDS spread for broker b in quarter t minus the end-of-prior-quarter level. We demean this measure to isolate cross-sectional variation: $AbnormalDistress_t^b = Distress_t^b - \overline{Distress}_t$. Each quarter, we classify the five broker-dealers with the highest $AbnormalDistress_t^b$ as distressed (Distressed $\text{Broker}_t^{b,1} = 1$), mirroring our event study approach.

Figure 7 plots the distribution of $AbnormalDistress_t^b$ for non-distressed brokers (those with Distressed $\text{Broker}_t^{b,1} = 0$). In Q1 2016, we see that non-distressed broker-dealers' financial health deteriorates for all aspects of the distribution. Apart from Q1 2020 (Covid onset, discussed in Appendix E.1) and modest increases in 2022, broker-dealer health shocks are predominantly idiosyncratic rather than systemic.

Figure 7: **Distribution of Broker-Dealer Distress:** This figure plots the quarterly median, 25th percentile, and 75th percentile of $AbnormalDistress_t^b$ for brokers not classified as distressed (Distressed $\text{Broker}_t^{b,1} = 0$). The measure captures cross-sectional variation in CDS spread changes.

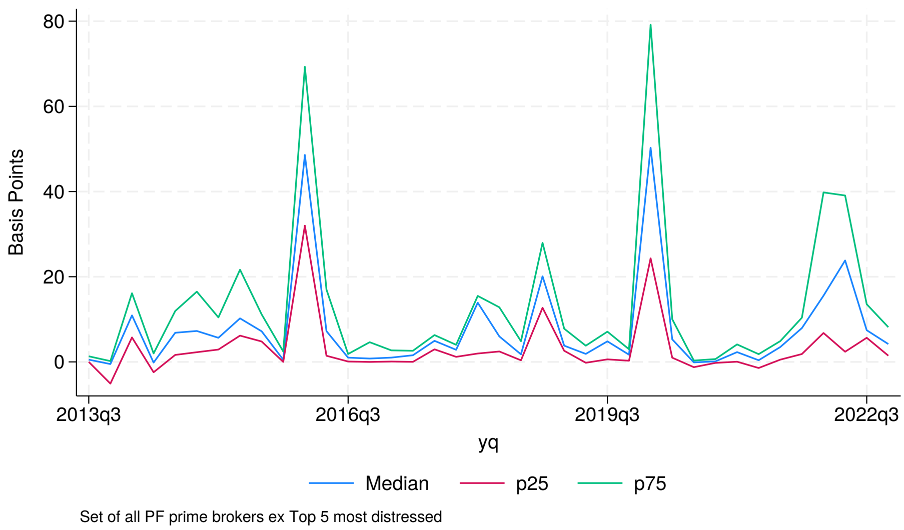
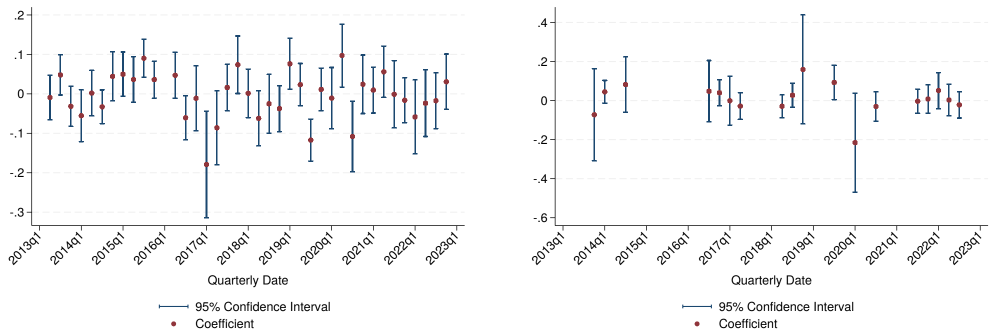


Figure 8 tests whether exposure to distressed brokers predicts credit supply contractions or total borrowing declines. Each quarter, we estimate equations (1) and (2) using the top-five distressed broker indicator. The left panel shows that several quarters exhibit negative relationships between distressed broker exposure and fund-by-broker borrowing, indicating credit supply contractions. However, the right panel reports estimates for Equation 2 for each quarter where we estimate a negative point estimate for the distressed broker-dealers dummy variable in Equation 1. We find no quarter where exposure to distressed brokers associates with statistically significant declines in total hedge fund borrowing.

Interestingly, while broker-dealers show evidence of aggregate distress and cross-section dispersion in Q1 2020, we do not document cross-sectional credit supply contraction in that quarter. Further tests in Appendix E.1 support this.[38]

Figure 8: **Repeated Cross-Sections:** The right panel plots quarterly coefficients from fund-by-broker regressions of borrowing changes on distressed broker indicators. The left panel plots quarterly coefficients from fund-level regressions of total borrowing changes on distressed broker exposure. Error bars represent 95% confidence intervals.



Fund by broker **Fund**

Throughout our sample, we find no evidence that cross-sectional broker-dealer health shocks transmit to hedge fund total borrowing or equity prices. Distressed brokers contract credit supply, but hedge funds substitute to healthier brokers, preventing transmission. Panel tests pooling across quarters (Appendix E.0.1) confirm this pattern: on average, distressed brokers reduce lending, but hedge funds replace lost borrowing. This evidence suggests that Archegos appears consistent with this broader pattern: when broker-dealer distress is idiosyncratic and healthier brokers have spare capacity, hedge funds substitute effectively and transmission does not occur.

6 Testing the Role of Systemic Distress on Transmission

The cross-sectional tests in the Archegos event study and Section 5 provide empirical evidence that idiosyncratic broker-dealer shocks do not transmit to equity prices when

[38]Note that this does not rule out Covid being an aggregate credit supply shock.

hedge funds can substitute effectively. However, the Euro 5 episode suggests a different pattern emerges during systemic distress as substitution breaks down. In this section, we test *generally* whether transmission occurs during periods of systemic distress as there might be limited spare lending capacity.

Studying systemic distress in the cross-section is challenging: first, cross-sectional tests require meaningful variation in broker-dealer health across institutions that coincide with deteriorating aggregate health, which are empirically rare. Second, cross-sectional tests cannot study common shocks where all broker-dealers become distressed as there is no meaningful variation.

We turn to aggregate time-series tests and test two hypotheses: If the transmission mechanism occurs during systemic distress, we expect first to see a relationship in aggregate data between broker-dealer health, prime brokerage lending growth, and returns on stock portfolios sorted by hedge fund ownership. Second, in periods when substitution capacity is impaired, we expect to see a stronger empirical aggregate relationship.

6.1 Testing the Role of Aggregate Broker-Dealer Health

We extend the FactSet hedge fund ownership data used in Section 3 to construct a longer monthly time series from 2002m1 to 2022m12.[39] Each month, we merge this ownership data with stock returns from CRSP, sort stocks into quintiles based on the most recent hedge fund ownership shares, compute equally-weighted returns for each quintile, and construct a high-minus-low return spread.[40]

As our proxy for aggregate broker-dealer health, we use the He, Kelly, and Manela (2017) intermediary capital ratio of the primary dealer sector.[41] This measure of aggregate health would commingle two distinct cases. In the first case, broker-dealer financial health deteriorates on average (value-weighted) but with cross-sectional heterogeneity, as in the Euro 5 episode. In the second case, all broker-dealers become distressed equally, so on average (value-weighted) broker-dealer financial health deteriorates but in a way not identifiable in the cross-section.

Figure 9 provides initial evidence consistent with this mechanism operating in aggregate. Panel (a) plots total hedge fund prime brokerage borrowing, measured from the SEC's Private Funds Statistics, against broker-dealer health. The series comove tightly: when intermediary balance sheets are strong, aggregate prime brokerage lending is elevated. While this relationship reflects an equilibrium outcome shaped by both supply and demand,

[39]We start in 2002m1, the first year when median hedge fund ownership in FactSet reaches at least 2%; from 1999-2001, hedge fund ownership shares were too low to construct reliable portfolio sorts.

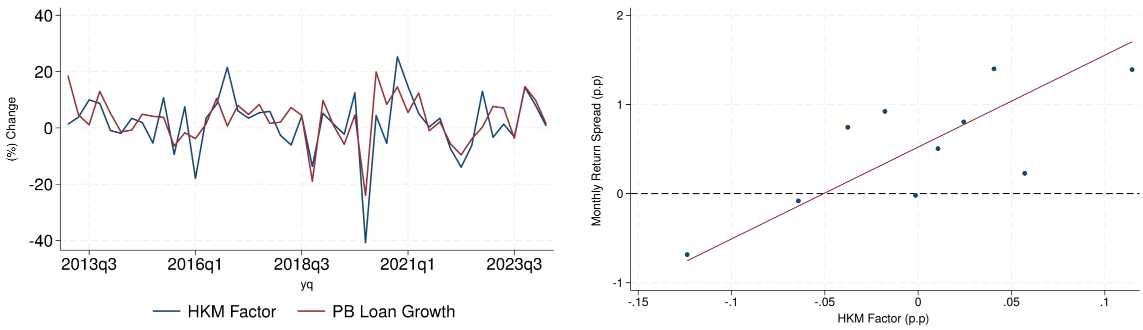
[40]The literature often refers to portfolios with substantial hedge fund presence as "hedge fund crowded" portfolios. This approach follows Brown, Howard, and Lundblad (2021), who document that hedge fund-sorted portfolios share common tail risk, though they do not link this to broker-dealer health.

[41]From Form ADV, we know that most large prime brokers are subsidiaries of bank holding companies that also operate as primary dealers.

it demonstrates that aggregate credit quantities respond to broker-dealer health. Panel (b) shows that hedge fund-crowded stocks perform poorly when aggregate broker-dealer health deteriorates.

Visual inspection of Panel (b) reveals that large negative return spreads concentrate in the bottom decile of broker-dealer health. While the overall trend line is positive, it is noisy, and the relationship appears strongest during periods of severe distress, precisely the periods when credit supply could contract and substitution capacity should matter.

Figure 9: **Prime Brokerage Lending, Stock Returns, and Intermediary Health:** Panel (a) shows prime brokerage lending tracks broker-dealer health (HKM Factor). Panel (b) presents binscatters of returns on long-minus-short portfolios, sorted by hedge fund exposure, constructed from FactSet's hedge fund database, against the He, Kelly, and Manela (2017) intermediary net-worth factor ("HKM Factor"), without market controls.



(a) Prime Brokerage Lending and Intermediary Health

(b) HF-Crowded Returns and Intermediary Health

Asymmetric transmission. Our event studies focused on adverse events to sets of broker-dealers, suggesting an asymmetry. In Panel (b), we see a strong relationship between the HKM factor and hedge fund sorted returns in periods where there is aggregate broker-dealer distress (i.e. a negative value for HKM). We test this formally by estimating regressions of the monthly return spread on the He, Kelly, and Manela (2017) intermediary capital factor, interacting it with an indicator for the bottom decile of the HKM factor. Because the HKM factor is constructed using broker-dealer market net worth, we control for the market excess return to isolate the broker-dealer health channel. If the mechanism operates asymmetrically, we should observe a positive interaction coefficient.

Table 14 presents the results. Columns (1)-(3) test for a linear relationship between broker-dealer health and return spreads. Column (1) shows a positive coefficient, but Columns (2)-(3) show no statistically significant linear relationship when controlling for the contemporaneous market return. The unconditional time-series relationship is weak and noisy once controlling for the market

Columns (4)-(7) test for asymmetry by interacting broker-dealer health with the bottom decile indicator. The results reveal a striking pattern: the relationship only emerges when we condition on periods of severe distress. In Column (4), the interaction coefficient of 0.260 is large and statistically significant. As a more negative value of HKM indicates distress, we see that greater intermediary distress in the lowest decile associates with lower portfolio returns. The main effect of the HKM factor remains statistically insignificant, indicating that the relationship operates predominantly during episodes of widespread distress. This pattern persists when controlling for the market return (Column 5), when restricting the sample period to the Form PF period (Column 6), and when additionally interacting the bottom decile with the market return (Column 7). This pattern parallels our event study findings: Euro 5 (which was in the bottom decile of quarters), which occurred during a period of broader broker-dealer weakness when substitution was constrained, transmitted to equity prices.

Table 14: **Asymmetric Effects of Intermediary Health on Return Spreads:** This table presents regression estimates examining the relationship between the He, Kelly, and Manela (2017) intermediary capital factor and the return spread between high and low hedge fund ownership portfolios. The dependent variable is the monthly return spread (in decimals). Columns (1)-(3) report baseline specifications with and without market return controls. Columns (4)-(7) include an interaction between the HKM factor and an indicator for the bottom decile of broker-dealer health (Bottom Decile of HKM). Column (7) additionally interacts the bottom decile indicator with the market excess return. Columns (3) and (6) restrict the sample to 2013m4 onwards. The sample includes 252 monthly observations from 2002m1 to 2022m12 (117 observations for restricted sample). Robust standard errors are reported in parentheses.

	$spread_t^{hf}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HKM Factor	0.096***	0.042	0.093	0.077**	0.025	0.039	0.002
	(0.028)	(0.044)	(0.075)	(0.032)	(0.040)	(0.066)	(0.042)
Market Excess Return		0.001	-0.001		0.001	-0.001	0.002*
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Bottom Decile of HKM				0.030***	0.033***	0.047***	0.029***
				(0.011)	(0.011)	(0.018)	(0.010)
HKM × Bottom Decile				0.260***	0.264***	0.434***	0.414***
				(0.064)	(0.066)	(0.081)	(0.107)
Bottom Decile × Market							-0.004**
							(0.002)
Observations	252	252	117	252	252	117	252
R-squared	0.064	0.078	0.023	0.089	0.105	0.090	0.125

To test the substitution mechanism more directly, we now construct a proxy for substitution capacity independent of aggregate health and test for it.

6.2 Testing the Role of Aggregate Substitution Capacity

To test whether transmission depends on the distribution of broker-dealer health, we exploit information on the relative size of prime-brokerage lending for each broker-dealer using Form PF. We then construct measures of aggregate (average) broker-dealer health and the distribution of lending across broker-dealers based on their relative health. As counterparty information information is reported quarterly in Form PF, we conduct these tests on a quarterly frequency.

We measure aggregate broker-dealer health as the lending-share-weighted log growth of broker-dealer net worth:[42]

$$AggregateHealth_t = \sum_b \Delta \ln(MarketEquity_t^b) \cdot LendingShare_{t-1}^b \tag{15}$$

where $MarketEquity_t^b$ is the FactSet market equity of broker-dealer b, and $LendingShare_{t-1}^b$ is the broker-dealers ex-ante share of total prime brokerage lending.

In Q1 2016, we previously documented in Section 3.5 that there was some substitution to healthier broker-dealer, but those broker-dealers were ex-ante relatively smaller. Generalizing this result, we proxy for substitution capacity as the relative amount of lending from healthier broker-dealers (those in the top quartile of net worth changes) minus less healthy broker-dealers (those in the bottom quartile of net worth changes). Formally, each quarter we rank broker-dealers by their log market equity changes, sort them into quartiles, and compute the total ex-ante lending share of brokers in each quartile:

$$LendingShr_{t-1}^q = \sum_{b \in B_q} LendingShr_{t-1}^b \tag{16}$$

where B_q denotes broker-dealers in health quartile q, with $q = 4$ being the healthiest and $q = 1$ the least healthy.

We define $ShareSpread_t$ as the difference between the ex-ante lending shares of the healthiest and least healthy broker-dealers:

$$ShareSpread_t = LendingShr_{t-1}^4 - LendingShr_{t-1}^1 \tag{17}$$

When $ShareSpread_t$ is high, healthy broker-dealers account for a larger share of ex-ante lending capacity, facilitating substitution. When $ShareSpread_t$ is low or negative, distressed broker-dealers dominate lending activity, limiting substitution because there is little

[42] This approach is similar to He, Kelly, and Manela (2017), who construct their intermediary capital factor from broker-dealer market equity. Unlike our cross-sectional analysis, which identified discrete distress events using book equity ratios, market equity is more appropriate here because it captures continuous variation in health. We do not use capital ratios (equity scaled by assets) because differences in accounting standards across countries complicate broker-level variation in balance sheet ratios.

spare capacity at healthier institutions.

We estimate:

$$\Delta Outcome_t = \alpha + \beta_1 AggHealth_t + \beta_2 ShareSpread_t + \beta_3 (AggHealth_t \times ShareSpread_t) + \epsilon_t \tag{18}$$

where $Outcome_t$ includes the log change in aggregate prime brokerage lending, the log change in aggregate hedge fund equity exposures (from Form PF), or the equally weighted return spread between high and low hedge-fund-holding portfolios.

Our coefficient of interest is β_3. The mechanism predicts that deteriorating broker-dealer health ($AggHealth_t < 0$) should have larger negative effects on outcomes when substitution capacity is poor ($ShareSpread_t < 0$), implying $\beta_3 < 0$. We complement this continuous specification with a 2×2 classification based on median splits, testing whether outcomes in the "doubly bad" state (below-median health and substitution) are disproportionately worse than predicted by either factor alone.

Table 15 reports estimates of equation (18).[43] Column (1) examines aggregate prime brokerage lending, controlling for the aggregate market return. The interaction term is negative, indicating that lending declines more sharply when both aggregate health and substitution capacity deteriorate. Column (2) shows similar patterns for aggregate hedge fund equity exposures.

Columns (3)-(4) examine stock market returns. Column (3) uses raw returns, while Column (4) uses returns residualized against the Fama-French four factors. Both specifications yield negative interaction terms, indicating that the amplification effect is distinct from exposure to standard risk factors.

The quantitative magnitudes are economically substantial. Consider a ten percent decline in broker-dealer log net worth. When substitution capacity is high ($ShareSpread_t = +0.20$), the decline in quarterly return spread is only 0.2 percentage points. When substitution capacity is low ($ShareSpread_t = -0.20$), the same health shock produces a 3.3 percentage point decline, more than fifteen times larger. In states with easy substitution, we observe almost no transmission to stock market returns; when substitution is impaired, the amplification effect is large.

Column (5) examines extreme outcomes, defined as quarters in the worst 10% of return spread realizations. The interaction term confirms that transmission events concentrate when both aggregate health and substitution capacity are impaired. Column (6) uses the 2×2 classification. The interaction term indicates that neither below-median health nor below-median substitution alone predicts worse returns; only their joint occurrence matters. The point estimate suggests the quarterly return spread is 4.5 percentage points lower in

[43] Appendix Table A13 reports the complete set of specifications including models without market return controls.

the doubly-bad state.

Column (7) replaces our aggregate health measure with the He, Kelly, and Manela (2017) intermediary capital ratio. The negative interaction term persists, indicating that the documented relationship between intermediary health and equity returns is substantially stronger during periods of poor substitution capacity.

Table 15: **Aggregate Health and Substitution Capacity:** This table reports regression estimates for equation (18). $AggHealth_t$ is the lending-share-weighted average log market equity change defined in equation (15). $ShareSpread_t$ is the difference in lending shares between the healthiest and least healthy quartiles of broker-dealers. Outcome variables include: log changes in aggregate prime brokerage lending ($\Delta \ln(PBL_t)$, Column 1), log changes in aggregate hedge fund equity exposures ($\Delta \ln(Eq_t)$, Column 2), the raw equally weighted return spread ($spread_t^{raw}$, Columns 3-4, 6), the return spread residualized against Fama-French four factors ($\varepsilon_{FF4,t}$, Column 4), and an indicator for whether the quarter is among the worst 10% of return spread realizations (Column 5). Column (6) uses a 2×2 classification based on median splits of $AggHealth_t$ and $ShareSpread_t$. Column (7) uses the He, Kelly, and Manela (2017) intermediary capital ratio instead of $AggHealth_t$. Columns (1)-(2) control for the aggregate market return. The sample includes 39 quarters from 2013 Q2 to 2022 Q4. Robust standard errors are reported in parentheses.

	$\Delta \ln(PBL_t)$	$\Delta \ln(Eq_t)$	$spread_t^{raw}$		Top 10%	$spread_t^{raw}$	$spread_t^{raw}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$AggHealth_t$	0.112*	0.160**	0.176**	0.0138	-1.180***		
	(1.73)	(2.40)	(2.65)	(0.38)	(-5.34)		
$ShareSpread_t$	0.0668	0.0533	0.0505	0.0456	-0.140		0.0806*
	(1.54)	(1.35)	(1.04)	(1.17)	(-0.91)		(1.73)
$AggHealth_t \times ShareSpread_t$	-1.050***	-1.080***	-0.786*	-0.562*	7.570***		
	(-3.45)	(-3.55)	(-1.72)	(-1.87)	(4.38)		
Mktrf Ret	0.734***	0.833***					0.349***
	(7.60)	(8.43)					(2.76)
Lo Agg, Hi Sub						-0.00101	
						(-0.06)	
Hi Agg, Lo Sub						0.0197	
						(0.92)	
Lo Agg, Lo Sub						-0.0449**	
						(-2.09)	
HKM							-0.0172
							(-0.18)
$HKM \times ShareSpread_t$							-0.836*
							(-1.76)
Intercept	0.00535	-0.00338	0.0183**	0.00409	0.0154	0.0247*	0.00692
	(0.66)	(-0.50)	(2.36)	(0.64)	(0.72)	(1.82)	(0.94)
R^2	0.835	0.879	0.380	0.124	0.684	0.227	0.454
N	39	39	39	39	39	39	39

t statistics in parentheses

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

6.3 Interpreting the Aggregate Evidence

These time-series tests complement the cross-sectional evidence that provide complementary evidence of a conditional transmission mechanism. While the aggregate evidence is not causal and some of our tests rely only on 39 quarters data, we present two layers of aggregate evidence. First, we document an aggregate relationship between broker-dealer health, prime brokerage lending, and the returns of high-minus-low hedge fund exposed stock portfolios. In line with the importance of widespread distress, the relationship between our proxy of aggregate broker-dealer health and stock returns is strongest when aggregate broker-dealer health deteriorates the most. This is consistent with aggregate transmission. Second, we find evidence that in periods where broker-dealer substitution capacity deteriorates, the relationship between aggregate broker-dealer health and our outcome variables strengthens.

7 Conclusion

This paper provides direct evidence that this prime broker credit supply matters for equity prices, but the transmission mechanism is conditional on the aggregate health of the broker-dealer sector. When broker-dealer distress is idiosyncratic and healthier brokers have spare capacity to expand credit, hedge funds substitute effectively and transmission does not occur. Transmission emerges only when the broker-dealer sector's aggregate health is sufficiently impaired that substitution becomes constrained. This credit supply channel is especially important for understanding how broker-dealers affect equity markets as broker-dealers hold few direct positions yet their balance sheet health strongly predicts returns

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A Data Appendix

A.1 Key Form PF Variables

Table A1 describes the key variables from Form PF used in our analysis.

Question Number	Description	Frequency
Q09	Fund-Level NAV	Quarterly
Q17	Fund-Level Returns	Monthly/Quarterly
Q28	HF Manager-Level Regional Exposure	Quarterly
Q30	Fund-Level Asset Class Exposure (Long/Short)	Monthly
Q43(b)(i)	Fund-Level Prime Brokerage Borrowings	Monthly
Q47	Total Borrowings by Counter-Party	Quarterly

Table A1: **Key Variables from Form PF:** This table describes the key variables from Form PF in the analysis.

In the text, we define certain fund-level exposure measures that aggregate across different Q30 variables. Long and short listed equity positions as well as FX exposure are directly reported. "Bonds" refers to (long) bonds positions that might be financed via prime brokerage and is computed as the sum of total long convertible bond and corporate bond holdings. Risk-free assets refers to the sum of long cash and Treasury assets reported.

A.2 Form PF Data Cleaning

We construct our sample of prime brokers and banks from Question 47. Counter-parties are reported in two ways: First, for 31 "Major Financial Institutions", funds can select from a drop-down list. Second, funds can manually report their counter-parties. We assign each of the 31 Major Financial Institutions to the relevant bank holding company or parent company. Thereafter, we textually match write-in names to the relevant major financial institutions that our identified as prime brokers for Form ADV. In doing so, we match on both correct names, alternative names, and major misspellings.

We want to compute total prime brokerage between each hedge fund and broker. Form PF does not provide prime brokerage borrowing by counter-party, so we impute as follows:

$$PBL_t^{f,b} = \frac{TotalBorrowing_t^{f,b}}{\sum_b TotalBorrowing_t^{f,b}} * PBLoans_t^f$$

where $TotalBorrowing_t^{f,b}$ is the Q47 total borrowing quantity for fund f from broker b and $PBLoans_t^f$ is Question 43 total prime brokerage borrowing for fund f.

B Institutional Details Appendix

[placeholder for non-PF section]

B.1 Primer on (Prime) Brokers

Non-PF Appendix

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.[44]

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 1: Stylized Broker-Dealer Balance Sheets

Figure 1 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

[44]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.

could also rely on long-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.[45]

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. [46] 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.

B.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 2. The 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

[45] 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.

[46] See Correa, Du, and Liao (2022) for a detail explanation for the internal capital markets of banks and a discussion for how binding Reg W is.

Q4. In this paper, our focus is on traditional long leverage, as we only observe security-level long equity holding positions.

Figure 2: **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.[47]

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.[48] 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.[49] 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,

[47] 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.

[48] 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."

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

typically earning interest and subject to withdrawal on demand.[50] 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, Weiss, Rifkind, Wharton & Garrison LLP (2021). Second, funds borrow from a wider-range of counter-parties than before the market

B.3 Aggregate Investor Borrowing and Market Returns

We examine the relationship between aggregate investor borrowing and equity market performance using publicly available FINRA data. Figure 3 plots the year-over-year change in the equity market against aggregate margin loan growth rates calculated from investor loan data provided by FINRA, an important component of prime broker lending to equity investors. Total margin credit provision — aggregated across all investors — has displayed a strong procyclical relationship with equity market returns extending back to the 1960s.[51]

C E5 Appendix

This appendix provides additional results and information for the European Broker-Dealer Distress episode.

C.1 Exposed Funds' Substitution Patterns

Figure 4 examines borrowing patterns of hedge funds that borrowed from at least one Euro 5 broker in Q4 2015. The figure plots aggregate borrowing from non-shocked brokers by these exposed funds, alongside their borrowing from shocked brokers for reference. During Euro 5, exposed hedge funds could not replace their lost borrowing: lending from non-shocked banks to these funds actually declined slightly rather than increasing, despite exposed funds experiencing large borrowing losses from shocked brokers.

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

[51]Similar patterns are evident for hedge fund specific borrowing in the Enhanced Financial Accounts since 2012. A pervasive issue with both margin and prime brokerage loan data — including FINRA and the SEC's Private Funds Statistics — is that they co-mingle loans used to finance long positions with those facilitating short positions, the latter of which are frequently marked to market.

Figure 3: **FINRA Margin Loan Growth and the Market:** This figure plots the total margin lending reported by FINRA against the market return.

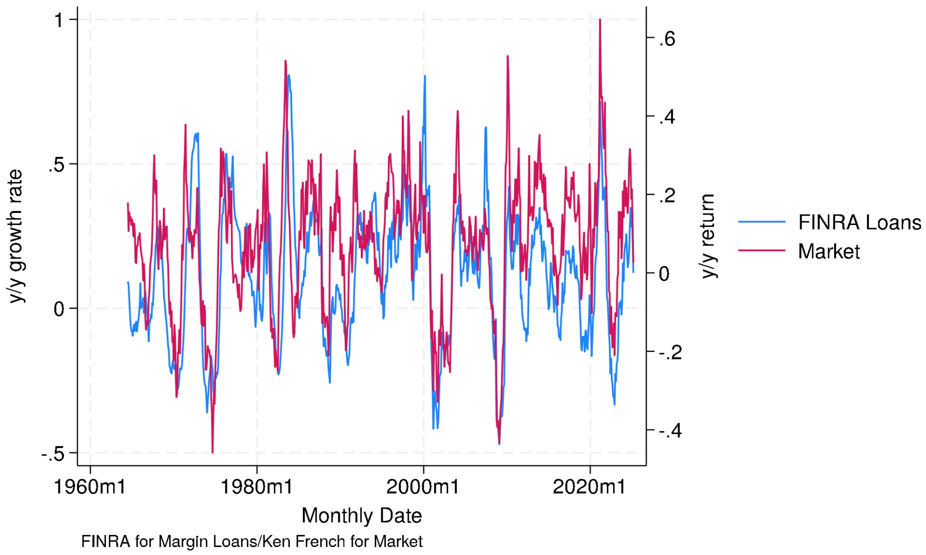
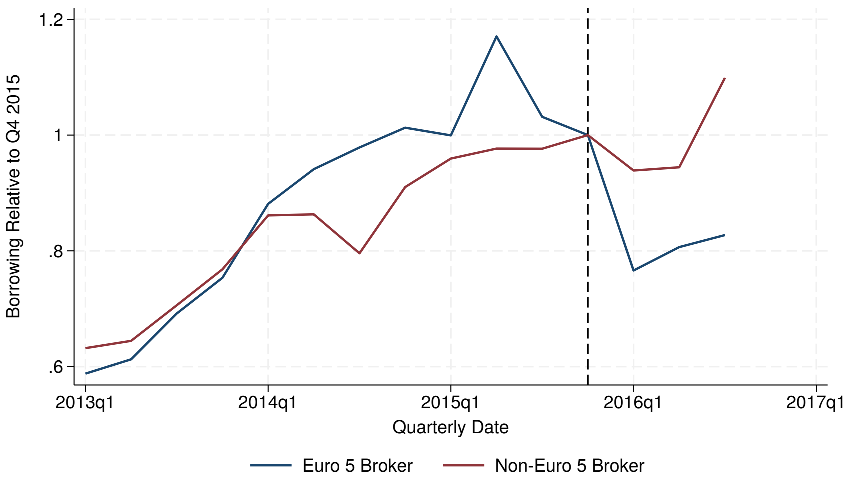


Figure 4: **Exposed Funds' Borrowing (Euro 5):** This figure plots aggregate borrowing from non-Euro 5 brokers by funds that borrowed from at least one Euro 5 broker in Q4 2015. For reference, total lending by the Euro 5 brokers to these same funds is also plotted. We normalize total lending to 100% in Q4 2015. The sample is restricted to funds that exist in both the pre-period and shock period.



C.2 Treatment Group Methodology

C.2.1 Euro 5 Announcements

Table A2: **News Events concerning European Broker Distress:** This table reports and describes the four major events for Deutsche Bank and Credit Suisse used in this paper. Deutsche Bank related events are assembled assembled from Gleason, Bright, Martinez, and Taylor (2017). This paper introduces the Credit Suisse announcement.

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

C.2.2 Euro 5 CDS Spreads

Here, we provide an illustrative list of broker-level CDS spread changes over the announcement windows. As the full list of PF counterparties is confidential, we construct a list of broker-dealers active in the United States for illustrative purposes from public data. Specifically, we construct a list of potentially important broker-dealers defined as the union of primary dealers and G-SIBs as of 2015Q4 that had a traded CDS spread. To insure these companies have large broker business we further require each institution to have a U.S.-registered broker-dealer with at least one billion dollars in assets, based on their most recent public FOCUS reports as of December 31, 2015.

Table A3: **CDS Spread Changes and Spillovers:** This table presents the cumulative CDS spread changes (in basis points) for large prime broker identified in public data. The Peak1 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 A2. We provide the respective quintile sorts for each measurement.

tic	CDS Change (Start to Peak1)	CDS Change (over Events)	Peak Quintiles	Event Quintiles
DB	117.2	52.2	5	5
BCS	72.6	45.9	5	5
CS	60.9	33.4	5	5
NWG	59.9	36.9	5	5
ACAEN	51.2	26.1	5	5
SCGLY	48.5	22.1	4	4
BNPQY	45.2	23.1	4	4
MFG	40.1	.6	4	1
BAC	39.5	24.1	4	4
SMFG	39.5	-2.4	4	1
GS	38.6	23.6	3	4
UBS	37.8	19.7	3	3
MS	37.4	22	3	4
MUFG	36.9	-3	3	1
C	35.7	20.1	3	3
HSBC	33.5	6.1	2	2
NXTFF	32.9	7.6	2	2
ING	27	12	2	3
JPM	21.7	12.4	2	3
NMR	19.7	2.5	2	2
WFC	17.4	9.3	1	3
ICBC	9.1	-1	1	1
BNS	6.7	4.4	1	2
BMO	6.5	2	1	2
BK	0	-.1	1	1

C.2.3 What characteristics explain our groupings?

What characteristics explain 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 as a proxy for liabilities.[52]

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 want to understand how the non-directly shocked grouped banks (Barclays, Credit Agricole, and NatWest/RBS), $TreatedNonShocked$, differed systematically for other non-treated banks. Using the set of publicly identified broker-dealers from Section C.2.2, we estimate the following regressions for those banks for common asset quality:

$$\frac{MarketCap_{2015q3}}{BookEquity_{2015q3}} = \alpha + \underbrace{\beta}_{-.3(t=-3.85)} TreatedNonShocked + \epsilon \tag{19}$$

We can study lower tier capital by:

$$\frac{AT1_{2015q3} + Tier2Capital_{2015q3}}{TotalCapital_{2015q3}} = \alpha + \underbrace{\beta}_{11\%(t=2.99)} TreatedNonShocked + \epsilon \tag{20}$$

$$AT1_{2015q3} + Tier2Capital_{2015q3} = \alpha + \underbrace{\beta}_{3\%(t=3.70)} TreatedNonShocked + \epsilon \tag{21}$$

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. These results are consistent with investors extrapolating solvency concerns to other brokers with similar asset and liability structures to Deutsche Bank and Credit Suisse.

[52] The main default concerns for Deutsche Bank were over their lower-tier AT1 instruments.

C.3 Appendix Credit Supply Results

C.3.1 Full Specifications for De-leveraging Evidence

Table A4 tests for the impact of de-leveraging on other asset class exposures (short equity, corporate bonds, foreign exchange, and risk-free assets) beyond the long equity exposures reported in the main text. We find no statistically significant evidence of reductions in these other asset classes, suggesting that hedge funds exposed to the Euro 5 banks predominantly reduced their long equity exposure.

Table A4: **Fund-Level Investment Class Exposures (Full Specifications):** This table reports the full specifications for equation (5). Outcome variables include changes in Form PF long equity exposure ($\Delta Log(LongEq_{f,t})$), short equity exposure ($\Delta Log(ShortEq_{f,t})$), the sum of Form PF convertible bond holdings and corporate bond holdings ($\Delta Log(Bonds_{f,t})$), risk-free assets, defined as the sum of U.S. Treasuries and cash ($\Delta Log(RF_{f,t})$), and long FX exposure ($\Delta Log(FX_{f,t})$). Controls include the contemporaneous net asset value growth rate. All funds have at least \$100 million in long equity exposure in the prior period. Outcome variables are winsorized at the 2.5% and 97.5% levels on a quarterly basis. Reported standard errors are heteroskedasticity robust. Columns (1)-(3) appear in the main text Table 10.

	$\Delta Log(LongEq_{f,t})$			$\Delta Log(ShortEq_{f,t})$	$\Delta Log(Bonds_{f,t})$	$\Delta Log(FX_{f,t})$	$\Delta Log(RF_{f,t})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Treated^{f}_{2015q4}$	-0.068***	-0.062***	-0.055***	-0.043	-0.119	0.195*	0.029
	(0.023)	(0.022)	(0.018)	(0.030)	(0.085)	(0.108)	(0.055)
Intercept	-0.050***	-0.054***	-0.019	0.037	0.217***	-0.077	0.071
	(0.015)	(0.016)	(0.013)	(0.023)	(0.064)	(0.085)	(0.046)
R^2	0.021	0.053	0.338	0.145	0.037	0.030	0.099
N	415	415	415	408	216	313	373
StratFE		X	X	X	X	X	X
Controls			X	X	X	X	X

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

Table A5 reports the full specifications for manager-level portfolio changes including all control variables and specifications.

Figure 5 reports the coefficient from equation (2) estimated each quarter from 2015q1 to 2016q4.

C.4 Euro 5 Asset Pricing

C.4.1 Ex-Ante Exposure

Table A6 reports the full specifications for ex-ante exposure regressions (equation 11). These results appear in condensed form in Columns (1)-(3) of the main text Table 12. Standard factor models (CAPM, FF3+UMD, betting-against-beta) do not account for the negative relationship between Euro 5 exposure and returns, suggesting the effect is not driven by standard risk factor exposures.

Table A5: **Manager-Level Portfolio Changes (Full Specifications):** This table reports full specifications for manager-level regressions of changes in prime brokerage borrowing and equity holdings on Euro 5 exposure. The dependent variables include log changes in manager-level prime brokerage borrowing ($\Delta Log(PBL_{m,t})$), market-price equity portfolios ($\Delta Log(Equity^{mkt}_{m,t})$), and stale-price equity portfolios ($\Delta Log(Equity^{stale}_{m,t})$). The stale price measure fixes stock prices at 2015Q4 levels. Some specifications include an interaction with manager-level PB borrowing changes and controls for other investor types. All managers have at least \$100 million in equity holdings in Q4 2015. Outcome variables are winsorized at the 2.5% and 97.5% levels. Standard errors are heteroskedasticity-robust. Columns (1), (2), and (5)-(7) appear in condensed form in main text Table 10.

	$\Delta Log(PBL_{m,2016q1})$	$\Delta Log(Equity^{mkt}_{m,2016q1})$			$\Delta Log(Equity^{stale}_{m,2016q1})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Treated^m_{2015q4}$	-0.096*	-0.067**	-0.038	-0.067**	-0.088***	-0.057*	-0.088***
	(0.052)	(0.034)	(0.032)	(0.033)	(0.034)	(0.032)	(0.034)
$\Delta ln(PBL^m)$			0.146			0.100	
			(0.095)			(0.089)	
$Treated^m_{2015q4} \times \Delta ln(PBL^m)$			0.174			0.243**	
			(0.118)			(0.110)	
PrivBank				0.065**			0.022
				(0.025)			(0.025)
IA				0.069***			0.008
				(0.025)			(0.025)
FS HF				0.018			0.003
				(0.028)			(0.028)
BR				-0.113**			-0.157***
				(0.048)			(0.047)
Intercept	0.008	-0.083***	-0.084***	-0.083***	-0.025	-0.026	-0.025
	(0.038)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
R^2	0.017	0.020	0.177	0.038	0.034	0.195	0.024
N	196	196	196	2,831	196	196	2,831

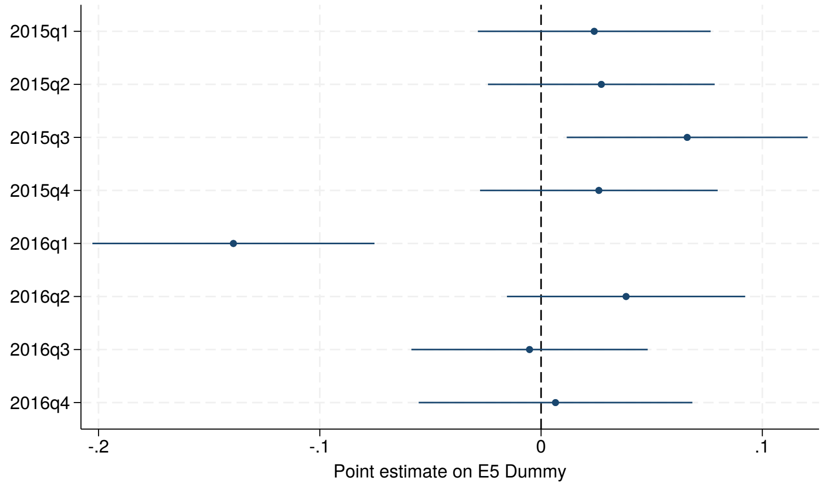
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: **Realized Returns and Ex-Ante Exposure to Euro 5 Advisers (Full Specifications):** This table reports full specifications for equation (11), which regresses realized returns on Euro 5 exposure share measures (% Held Euro5 HFs). Returns are raw (Ret^s_t), residualized against the CAPM model, Fama-French 3 + Momentum model ($\varepsilon^s_{FF4,t}$), or betting-against-beta factor. In some specifications, we include controls for non-Euro 5 hedge fund exposure (% Held non-Euro5 HFs), foreign sales share, 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 two-digit SIC industry code level. Columns (1)-(2) and (4) appear in condensed form in main text Table 12.

	$Ret_{s,t}$					$\varepsilon_{CAPM,s,t}$	$\varepsilon_{FF4,s,t}$	$\varepsilon_{BAB,s,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Held Euro5 HFs	-0.687***	-0.501***	-0.439***	-0.359***	-0.359***	-0.380***	-0.552***	-0.357***
	(0.152)	(0.139)	(0.136)	(0.129)	(0.129)	(0.129)	(0.174)	(0.129)
% Held non-Euro5 HFs			-1.043***	-0.604***	-0.603***	-0.623***	-0.678***	-0.607***
			(0.243)	(0.136)	(0.135)	(0.140)	(0.189)	(0.136)
Foreign Sales Share					0.001			
					(0.009)			
Intercept	0.040**	0.032***	0.049***	0.037***	0.037***	0.032***	0.045***	0.041***
	(0.018)	(0.006)	(0.017)	(0.007)	(0.007)	(0.007)	(0.009)	(0.006)
R^2	0.02	0.20	0.04	0.21	0.21	0.22	0.20	0.21
N	1,537	1,537	1,537	1,537	1,537	1,537	1,537	1,537
IndustryFE		X		X	X	X	X	X

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

Figure 5: **Imperfect Substitution Placebo Test:** This figure plots the regression coefficient from equation (2) estimated each quarter from 2015q1 to 2016q4.



C.4.2 Sell-Off

Table A7 reports the full specifications for realized sell-off regressions. These results appear in condensed form in Columns (4)-(7) of the main text Table 12. The key finding is that stocks sold off by Euro 5-connected managers experienced significantly lower returns.

Table A7: **Realized Returns and Change in Euro 5 Exposure (Full Specifications):** This table reports full specifications for regressions of realized returns on changes in the Euro 5 exposure share measures ($\Delta\%HeldEuro5HFs$). Returns are raw (Ret^s_t), residualized against the CAPM model ($\varepsilon^s_{CAPM,t}$) or residualized against the Fama-French 3 + Momentum model ($\varepsilon^s_{FF4,t}$). In some specifications, we include controls for non-Euro 5 hedge fund exposure change ($\Delta\%HeldnonEuro5HFs$) and fixed effects based on industry codes (IndustryFE). E5SellOff is "X" if a stock is sold-off by Euro 5 hedge funds in aggregates, and "above p50" if a stock has above median sell-offs, conditional on being sold. Exposure measures are winsorized at the 2.5% and 97.5% levels. Standard errors are clustered at the two-digit SIC industry code level. Columns (1)-(2) and (5)-(8) appear in condensed form in main text Table 12.

	$Ret_{s,t}$						$\varepsilon_{CAPM,s,t}$	$\varepsilon_{FF4,s,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\%HeldEuro5HFs$	1.022***	2.633***	1.014***	2.629***	4.083***	4.058***	2.617***	4.075***
	(0.347)	(0.596)	(0.357)	(0.603)	(0.953)	(0.963)	(0.586)	(0.717)
$\Delta\%HeldnonEuro5HFs$			-0.653	-0.204		-1.242	-0.555	-0.718
			(1.044)	(1.610)		(1.779)	(1.632)	(1.791)
Intercept	0.011	0.036**	0.011	0.036**	0.075***	0.075***	0.029	0.044***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.024)	(0.025)	(0.018)	(0.015)
R^2	0.01	0.02	0.01	0.02	0.04	0.05	0.02	0.05
N	1,537	828	1,537	828	414	414	828	828
E5SellOff		X		X	Above p50	Above p50	X	X

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

C.4.3 Other Investors and Return Relationship

While standard factor exposures fail to account for our findings, several identification threats remain. Primarily, we are concerned that other intermediaries or intermediary channels could affect asset prices in a way that is correlated with Euro 5 exposure. 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 these concerns, we construct stock-level exposures to institutional investors associated with these institutional classes as well as proxies for direct Euro 5 exposures and run the following regression:

$$ret^s_{2016q1} = \alpha + \beta_1 Euro5MktShare^s_{2015q4} + \beta_2 StockExposure^{s,i}_{2015q4} + \epsilon^s_{2016q1} \tag{22}$$

where $StockExposure^{s,i}_{2015q4}$ is either a stock-level ownership measure for a particular investor type or an indicator variable.

Table A8 shows that across all institution types, the point estimate on Euro 5 connected manager exposure remains significant and remarkably stable. Second, in Columns (1)-(4), we find no other institutional exposure measure that is both negative and significant. Third, while Table A5 shows that broker-dealer equity balance sheets contracted, we see in both Column (2) and (5) that B/D exposure does not quantitatively affect our estimated sensitivity.

C.4.4 Amihud Illiquidity

A distinct but related concept to price impact from a sell-off is illiquidity. We measure illiquidity using the Amihud (2002) measure. First, we define:

$$AL^s_t = \log(1 + AmihudIlliquidity^s_t), \tag{23}$$

where *AmihudIlliquidity* is the stock-level measure introduced in their paper. We then test several common hypotheses related to illiquidity and hedge fund capital.[53]

Table A9 reports estimates for various tests relating stock-level exposure to the sell-off with illiquidity. In Columns (1) and (2), we test whether ex-ante stock-level illiquidity affects hedge fund managers decisions to sell off by using the following regression for 2016 Q1:

$$\begin{aligned}\Delta Euro5MktShare^s_{2016q1} = \alpha + \beta_1 Euro5MktShare^s_{2015q4} + \beta_2 AL_{2015q4} \\ + \beta_3 \left(Euro5MktShare^s_{2015q4} \times AL_{2015q4}\right) + \epsilon \end{aligned} \tag{24}$$

[53] These tests are similar to tests from Aragon and Strahan (2012).

Table A8: **Realized Returns and Other Investors** This table reports estimates for equation (22), controlling for direct Euro 5 exposure measures and institutional classes. Columns (1)-(4) incorporate controls for the ownership share of other institutional investor classes. These classes include all other hedge fund managers (% Held Other HFs), the broker-dealer sector (% Held Brokers), investment advisers identified in FactSet excluding advisers with Form PF filing hedge funds (% Held InvAdv), and the total institutional filers holding shares (% Held Inst.). Columns (5)-(6) incorporate controls for stock-level exposures to Euro 5 banks via those banks' direct ownership. These controls include the direct ownership shares of Euro 5-affiliated broker-dealers (Euro5 B/D) and of all institutional investors owned by Euro 5 banks (E5 Affiliate), both identified via FactSet. Columns (7)-(8) 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 bank 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 bank led a loan syndicate for the firm during that period.

	$Ret_{s,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Held Euro5 HFs	-0.447***	-0.455***	-0.444***	-0.559***	-0.458***	-0.474***	-0.501***	-0.499***
	(0.140)	(0.145)	(0.133)	(0.153)	(0.135)	(0.136)	(0.139)	(0.141)
% Held Other HF	-0.162							
	(0.109)							
% Held Brokers		-0.515						
		(0.756)						
% Held InvAdv			0.100***					
			(0.033)					
% Held Inst.				0.045				
				(0.030)				
% Held E5 B/D					-2.133*			
					(1.172)			
% Held E5 Affiliate						-1.428		
						(1.158)		
E5 Bank in Syndicate							-0.003	
							(0.036)	
E5 Bank Lead								-0.080**
								(0.036)
Intercept	0.048***	0.036***	-0.025	-0.003	0.037***	0.036***	0.032***	0.032***
	(0.013)	(0.010)	(0.018)	(0.022)	(0.007)	(0.008)	(0.006)	(0.006)
R^2	0.21	0.21	0.21	0.21	0.21	0.21	0.20	0.20
N	1,537	1,537	1,537	1,537	1,537	1,537	1,537	1,537
IndustryFE	X	X	X	X	X	X	X	X

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

Table A9: **Illiquidity and Sell-Off Pressure:** This table reports estimates for equation (24), which regresses various stock-level outcome variables on Euro 5 exposure share measures (% Held Euro5 HFs), log Amihud Illiquidity $AL(2015q4)$), and an interaction term. Stock-level outcomes are changes to stock-level Euro 5 exposure ($\Delta\%HeldEuro5HFs$), changes to log Amihud Illiquidity (ΔAL_t^s) and raw returns (Ret_t^s). Exposure measures are winsorized at the 2.5% and 97.5% levels. Amihud Illiquidity measures are standardized for comparability. All specifications include industry fixed effects. Standard errors are clustered at the two-digit SIC industry-code level.

	$\Delta\%HeldEuro5HFs$		ΔAL		$Ret_{s,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
% Held Euro5 HFs	-0.143***	-0.138***	1.762**	1.806**	-0.607***	-0.600***
	(0.015)	(0.013)	(0.749)	(0.820)	(0.172)	(0.174)
Lagged Illiq	0.002***	-0.001	0.560***	0.540***	-0.018**	-0.021**
	(0.000)	(0.000)	(0.065)	(0.082)	(0.007)	(0.010)
Interaction		0.055***		0.502		0.086
		(0.009)		(1.199)		(0.130)
Intercept	0.004***	0.004***	-0.066*	-0.067*	0.038***	0.038***
	(0.001)	(0.001)	(0.033)	(0.036)	(0.008)	(0.008)
R^2	0.17	0.18	0.28	0.28	0.22	0.22
N	1,352	1,352	1,352	1,352	1,352	1,352

Standard errors in parentheses

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

where all variables are defined as above. As we use the sample inclusion criteria from Amihud (2002), the number of observations is slightly lower than in previous regressions.

In Columns (2), we observe that β_3 is positive, suggesting that hedge fund managers sell off fewer illiquid stocks. In Columns (3) and (4), we find that Amihud illiquidity deteriorates for stocks more exposed to the hedge fund managers sell-off as β_2 is positive.

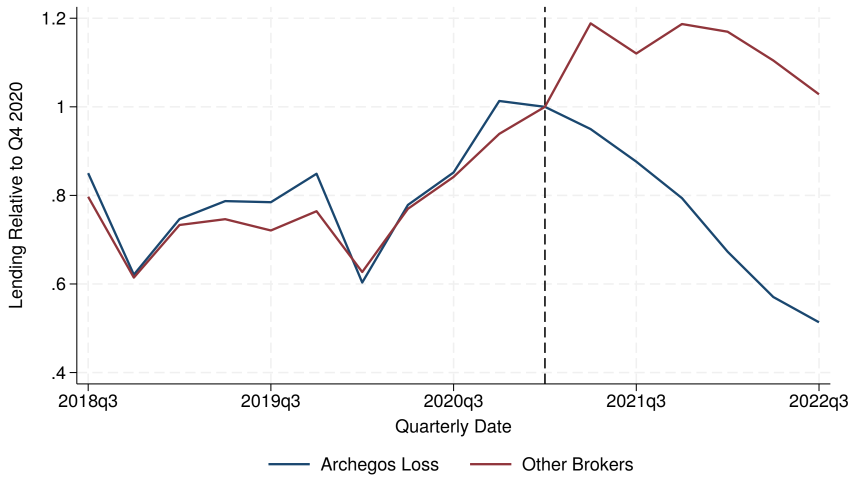
In Column (6), while both ex-ante illiquidity and distressed HF exposure are related to returns, we find that the interaction term is both economically and statistically insignificant. Overall, Columns (2) and (6) suggest that hedge fund managers actively manage liquidity when facing financing constraints.

D Archegos Appendix

D.1 Exposed Funds' Substitution Patterns

Figure 6 examines borrowing patterns of hedge funds that borrowed from at least one Archegos-loss broker in Q4 2020. The figure plots aggregate borrowing from non-shocked brokers by these exposed funds, alongside their borrowing from shocked brokers for reference. During Archegos, exposed hedge funds fully replaced their lost borrowing: lending from non-shocked broker-dealers increased sharply, almost perfectly offsetting the decline from Archegos-loss banks.

Figure 6: **Exposed Funds' Borrowing (Archegos):** This figure plots aggregate borrowing from non-Archegos-loss brokers by funds that borrowed from at least one Archegos-loss broker in Q4 2020. For reference, total lending by the Archegos-loss brokers to these same funds is also plotted. We normalize total lending to 100% in Q4 2020. The sample is restricted to funds that exist in both the pre-period and shock period.



D.2 Asset Pricing Placebo Test

We estimate our baseline regressions for raw realized returns in 2021q2 in Table A6, using 2021q1 exposures. We do not find a relationship between realized returns and our measure. Without controls, we find an economic and statistical zero relationship in Column (1). The zero statistical relationship holds in Columns (2)-(4), staggering in industry and other hedge fund exposures. Moreover, the point estimate flips signs in Column (3) as compared to Column (2) and Column (4). This placebo test reassures that there was no transmission to equity markets.

E Testing the role of aggregate health

E.0.1 Panel Analysis

To study credit supply using a difference-in-difference framework as in our experiments, we construct another indicator variables based on $AbnormalDistress^b_t$.

This indicator variable is:

$$\text{DistressedBroker}^{b,2}_t = D_i = \begin{cases} 1 & \text{if } AbnormalDistress^b_t \geq \mathrm{P}_\tau(AbnormalDistress), \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

where τ is a percentile cut-off. We choose $\tau = 95\%$.[54]. This variable classified a broker-dealer as distressed if its abnormal distress measure is high compared to all other across

[54] Other measures show similar values.

Table A10: **Realized Returns and Ex-Ante Exposure to Distressed Brokers (Archegos)** This table reports estimates for equation (11), which regresses realized returns on Archegos exposure share measures (% Held Euro5 HFs).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 two-digit SIC industry code level.

	$Ret_{s,t}$			
	(1)	(2)	(3)	(4)
% Held Arch HFs	-0.001	-0.055	0.026	-0.055
	(0.222)	(0.191)	(0.192)	(0.186)
% Held non-Arch HFs			-0.221	0.002
			(0.436)	(0.336)
Intercept	0.071***	0.073***	0.072***	0.073***
	(0.011)	(0.009)	(0.012)	(0.010)
R^2	0.00	0.19	0.00	0.19
N	1,355	1,355	1,355	1,355
IndustryFE		X		X
Outcome	Raw	Raw	Raw	Raw

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

all observations in the sample.

We study credit supply and fund substitution using panel methods. Using $\text{DistressedBroker}_t^{b,2}$, e test for whether distressed broker-dealers contracted credit and exposed hedge funds can perfectly substitute away from these broker-dealers. Akin to our event studies, we first test whether funds borrow less from shocked brokers while controlling for common demand in the fund-by-broker panel:

$$\Delta ln(PBL_t^{b,f}) = \alpha_{f,t} + \beta \text{Distressed}_t^{f,b,2} + \epsilon_t^b \tag{26}$$

where $\text{Distressed}_t^{f,b,2}$ is an indicator variable that takes the value of one if a fund borrows from brokers b with $\text{DistressedBroker}_t^{b,2} = 1$.

Next, we test whether funds exposed to distressed brokers borrow differently than non-exposed funds by estimating the following regression:

$$\Delta PBL_t^f = \alpha_t + \alpha_f + \beta Distressed_t^{f,2} + \epsilon_t^b \tag{27}$$

where $Distressed_t^{f,2}$ is a dummy that takes the value of one if a fund borrows from any distressed broker based on the $\text{DistressedBroker}_t^{b,2}$ measure.

Table A11 reports estimates for equation (26) and (27). As we have observed a large health effect in 2016q1 previously, we remove this quarter to avoid our results being driven by this previously-documented shock. Columns (1) and (2) report results for fund-by-broker borrowing specifications. We observe a negative and significant point estimate in Column (2), which is in line with poor broker-dealer financial health affecting credit supply. These

Table A11: **Panel Regressions:** This table reports estimates for equations 26 and 27. $Distressed_t^{f,b,2}$ is an indicator variable equal to one if a broker is in the top 5% of time-by-broker observations for the $AbnormalDistress_t^b$ measure. In Columns (3) and (4), we regress the log change in fund-level borrowing on an indicator variable ($Distressed_t^{f,2}$) equal to one if a fund borrows from any distressed broker in that quarter. $AbnormalDistress_t^b$ variable is defined as the demeaned change in the CDS spread from the last day of the previous quarter to its maximum value within the current quarter. Outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. Standard errors are clustered by fund.

	$\Delta ln(PB_{f,b,t})$		$\Delta ln(PB_{f,t})$	
	(1)	(2)	(3)	(4)
$Distressed_t^{f,b,2}$	-0.031	-0.045**		
	(0.020)	(0.021)		
$Distressed_t^{f,2}$			0.026	0.024
			(0.019)	(0.020)
Intercept	-0.015***	-0.014***	-0.025***	-0.023***
	(0.001)	(0.001)	(0.002)	(0.002)
R^2	0.10	0.55	0.08	0.17
N	41,696	41,696	10,785	10,690
Sample	All ex Q1 2016	All ex Q1 2016	All ex Q1 2016	All ex Q1 2016
FE	Fund+Q	KM	Q	Fund+Q
Data	Fund by Broker	Fund by Broker	Fund	Fund

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

results are similar to those for both the Euro 5 event and the Archegos event. In Column (3)-(4), we find that funds with ex-ante exposure to distressed broker-dealers appear to be able to substitute borrowing from those brokers. In Column (3) and (4), we estimate a positive point estimate between borrowing and ex-ante exposure to distressed broker-dealers. This estimate is significant when including additional fund fixed effects in Column (4). Given the patterns shown in Section 5, these results are consistent with idiosyncratic shocks being diversified away.

E.1 Aggregate Shocks and Covid

One prominent aggregate shock with potential broker-level exposure is the banking distress experienced during 2020Q1 as a result of Covid-19. Acharya, Engle, Jager, and Steffen (2024) documents that different bank holding companies– the ultimate parent companies of many of the brokers we study—exhibited heterogeneous market financial health outcomes during this period, suggesting variation in the health treatment. We now test whether cross-sectional supply differences can be observed.

To test this, we consider four distinct proxies for broker health: (1) the change in the brokers net worth, denoted as $\Delta \ln(NW_t^b)$, (2) the end-of-quarter CDS spread ΔCDS_t^b, (3) the maximum increase in the CDS spread during this period, denoted as $\Delta CDS_t^{\max,b}$, from the end-of-quarter value last quarter, and the top five distressed CDS spread change indicator from above.[55] We then test whether fund-level borrowing from each broker is

[55]Measures (2) and (3) proxy for whether a broker's distress is better measured at the point it is most

responsive to these broker health measures by estimating the following equation:

$$\Delta lnPBL^{b,f}_{2020q1} = \alpha_f + \beta Health^{b}_{2020q1} + \epsilon^{b,f} \tag{28}$$

In particular, we consider two specifications, as shown in Table A12. In Columns (1)-(4), we study the fund-broker borrowing response without a fund fixed effect. We find an insignificant, but consistently negative relationship between our broker-dealer financial health proxies and fund-by-broker borrowing quantities. In Columns (5)-(8), we control for common demand via a fund fixed effect. We do not find any evidence in Columns (5)-(8) that hedge funds exposed to more financially distressed broker-dealers experienced credit supply shocks. These results align with the findings on hedge fund fixed income borrowing from dealers by Kruttli, Monin, Petrasek, and Watugala (2023) who argue, in fixed income markets, hedge funds faced fund-specific risk limits.

Table A12: **Within Fund Estimator (2020q1)**: This table reports the estimates for equation (28). Columns (1)-(4) show the responsiveness of fund-by-bank borrowing to various exposure measures without controlling for fund fixed effects, while Columns (5)-(8) incorporate fund fixed effects. The variable $\Delta CDS^{b}_{coeq,t}$ represents the change in CDS spread from the last day of the previous quarter to the last day of the current quarter. $\Delta MktNetWorth^{b}_{t}$ is the log change in market net worth over the same period. $AbnormalDistress^{b}_{t}$ captures the change in CDS spread from the last day of the previous quarter to its maximum value within the current quarter, demeaned each quarter. "Top 5 Broker" is a dummy variable for banks ranked in the top five by $AbnormalDistress^{b}_{t}$ for the quarter. All outcome variables are winsorized at the 2.5% and 97.5% levels on a quarterly basis. Standard errors reported are robust to heteroskedasticity.

	$\Delta ln(PB_{f,b,t})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta CDS^{b}_{eoq,t}$	-0.024				-0.021			
	(0.112)				(0.098)			
$\Delta MktNetWorth^{b}_{t}$		-0.141				-0.077		
		(0.168)				(0.140)		
$\Delta CDS^{b}_{max,t}$			-0.044				-0.038	
			(0.053)				(0.050)	
Top 5 Bank				-0.004				-0.011
				(0.043)				(0.039)
Intercept	-0.311***	-0.395***	-0.271***	-0.325***	-0.313***	-0.364***	-0.280***	-0.322***
	(0.077)	(0.084)	(0.071)	(0.031)	(0.065)	(0.070)	(0.063)	(0.024)
R^2	0.00	0.00	0.00	0.00	0.59	0.59	0.59	0.59
N	1,037	1,037	1,037	1,037 Ple	1,037	1,037	1,037	1,037
FE	None	None	None	None	KM	KM	KM	KM

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

distressed during the quarter or at the end of the quarter.

Table A13: **Aggregate Health and Substitutability Analysis:** This table reports regression estimates for equation (18). $AggHealth_t$ is lending-share weighted average log market equity value change defined in equation (15). $ShareSpread_t$ is the proxy for ease of aggregate substitution. Outcome variables include log changes in aggregate prime brokerage lending ($\Delta \ln(PBL_t)$), changes in aggregate hedge fund equity exposures ($\Delta \ln(Eq_t)$), changes in the raw hedge fund equity return spread ($spread_t^{raw}$), changes in the hedge fund equity return spread residualized to the Fama-French 4 factors ($\varepsilon_{FF4,t}$), and binary indicator variables for if a quarter is among the 10% worst (Top 10 %) or 25% worst (Top 25 %) realizations of the realized return spread. Robust standard errors are reported.

	$\Delta \ln(PBL_t)$		$\Delta \ln(Eq_t)$		$spread_t^{raw}$	$\varepsilon_{FF4,t}$	Top 10 %	Top 25 %	$spread_t^{raw}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AggHealth_t$	0.460***	0.112*	0.555***	0.160**	0.176**	0.0138	-1.180***	-1.185**			
	(6.39)	(1.73)	(7.34)	(2.40)	(2.65)	(0.38)	(-5.34)	(-2.10)			
$ShareSpread_t$	0.0348	0.0668	0.0170	0.0533	0.0505	0.0456	-0.140	-0.703		0.0798*	0.0806*
	(0.68)	(1.54)	(0.33)	(1.35)	(1.04)	(1.17)	(-0.91)	(-1.46)		(1.74)	(1.73)
$AggHealth_t \times ShareSpread_t$	-1.310**	-1.050***	-1.376**	-1.080***	-0.786*	-0.562*	7.570***	10.51**			
	(-2.51)	(-3.45)	(-2.39)	(-3.55)	(-1.72)	(-1.87)	(4.38)	(2.52)			
Mktrf Ret		0.734***		0.833***							0.349***
		(7.60)		(8.43)							(2.76)
Lo Agg, Hi Sub									-0.00101		
									(-0.06)		
Hi Agg, Lo Sub									0.0197		
									(0.92)		
Lo Agg, Lo Sub									-0.0449**		
									(-2.09)		
HKM										0.166**	-0.0172
										(2.21)	(-0.18)
$HKM \times ShareSpread_t$										-1.036**	-0.836*
										(-2.04)	(-1.76)
Intercept	0.0280***	0.00535	0.0224**	-0.00338	0.0183**	0.00409	0.0154	0.181***	0.0247*	0.0159*	0.00692
	(2.79)	(0.66)	(2.25)	(-0.50)	(2.36)	(0.64)	(0.72)	(2.84)	(1.82)	(1.98)	(0.94)
R^2	0.669	0.835	0.712	0.879	0.380	0.124	0.684	0.448	0.227	0.322	0.454
N	39	39	39	39	39	39	39	39	39	39	39

t statistics in parentheses

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

ONLINE APPENDIX

F 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.[56]

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.[57] 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 TableA14.

Table A14: **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-dealers funding. Using sources such as Compustat, annual reports, financial news, and government fine announcements, we assemble a list of these announcements.[58] For debt defaults or runs, we identify events from the literature. When possible, we group together brokers with similar losses.[59]

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

[56]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.

[57]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.

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

[59]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 lossessuch as the write-downs for major European broker-dealers in 2015Q4-2016Q1.

major corporations by the United States Government, including announcement dates, fine amounts, and fine types.[60] 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 datea common occurrence. We present our list of possible events in Tables A16, A15, and A17.

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 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.[61]

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

Table A15: **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, Miglietta, and Segura (2020)
DB x2	2016m9	CoCo Bond Default	Bloomberg	Bologna, Miglietta, and Segura (2020)

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

[61]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 Suisses 2023Q1 collapse is a poor candidate for shock analysis.

Table A16: **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 A17: **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

F.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 A15, 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 2016.

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.

F.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 A18 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-dealers market net worth to measure their impact on broker capital. We also aggregate brokers as described in Section F.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 A18: **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	**Broker Parent**	**Ticker**	**Losses (B)**	ΔCDS^b **(abnormal)**	**Losses to Net Worth**	**Others Exposed**	**Total Losses (B)**
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