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

Daniel Barth[†] Nicholas Zarra[‡]

September 17, 2026

Abstract

The relationship between intermediary health and asset prices is typically shown to operate through direct participation. We document an alternative indirect channel through prime brokerage lending to hedge funds. During the widespread European broker-dealer distress in 2016, shocked intermediaries reduced lending to hedge funds who could not fully replace the lost borrowing and sold equities. More inelastic investors absorbed this flow, resulting in a price multiplier of about three. However, this pass-through does not exist for idiosyncratic shocks because hedge funds substitute to healthier broker-dealers. Nevertheless, when aggregate broker-dealer health deteriorates, hedge fund prime brokerage borrowing falls and stocks more exposed perform poorly.

*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 Jonathan Wallen (discussant), 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, Yiming Ma, Sai Ma, Quinn Maingi, Phil Monin, Tyler Muir, 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 participants at SFS Cavalcade, 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

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

‡Federal Reserve Board of Governors. Email: nick.zarra@frb.gov

1 Introduction

Factors constructed from broker-dealer balance sheets explain returns across a wide range of asset classes (Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)), suggesting intermediaries are marginal investors in those markets. It has been well-documented that one channel through which broker-dealers affect asset prices is direct participation; broker-dealers move prices in markets by trading securities (Siriwardane (2019), Haddad and Muir (2021), Eisfeldt, Herskovic, Rajan, and Siriwardane (2022)). However, broker-dealers also participate indirectly by lending to other intermediaries, namely hedge funds, and this indirect participation is large. As of Q4 2025, total lending to hedge funds exceeded $5.5 trillion.[1] In the stock market, indirect participation may be especially important. While broker-dealers hold minimal positions directly, they supply substantial prime brokerage credit that finances equity purchases. As of Q4 2025, total prime brokerage lending to hedge funds was $3.3 trillion.[2]

This paper provides evidence that indirect participation is a transmission channel from broker-dealer health to asset prices, via prime brokerage lending to hedge funds, by studying each step of the channel. We do so by providing evidence from an event study, panel analyses and time-series tests to make the following conclusions. First, when broker-dealers become distressed they contract credit; if the shock is sufficiently broad that hedge funds cannot fully substitute to healthier lenders, funds deleverage. Second, forced equity sales have an outsized impact on price with large estimated price multipliers between 2.65 to 4.7. Third, we show that these price impact multipliers are plausible because non-levered investors with more inelastic demand absorb the bulk of these sales.

To study this 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 fund-by-counterparty-level aggregate borrowing quantities from late 2012 through 2022, which allows us to directly study broker-dealer credit supply and the exposure of hedge funds to broker-dealer level distress. To study the transmission of shocks from hedge funds to equity markets, we merge this balance sheet information with adviser-level equity securities holdings data from FactSet Ownership.

We provide three complementary analyses. First, we use a cross-sectional event study to isolate credit supply shocks and study their transmission to stock prices via hedge fund equity holdings. This approach addresses key endogeneity concerns, namely that

[1] This estimate comes from the Office of Financial Research's Hedge Fund Monitor and includes lending to finance security positions across asset classes.

[2] Total prime brokerage loans included not only equity-related financing but also lending against other instruments, such as convertible bonds, as well as securities lending that facilitates short positions. By comparison, total broker-dealer equity holdings was only $384B from the Federal Reserves Financial Account in that quarter.

economic forces affecting broker-dealer credit supply may also drive hedge fund credit demand. In this episode, we provide evidence that suggests that the widespread nature of broker-dealer distress contributed to hedge funds not being able fully replace lost credit, leading to transmission. Second, we use panel regressions across all quarters to show that idiosyncratic broker-dealer shocks do not transmit, establishing that transmission depends on the breadth of distress. Third, we examine aggregate time-series correlations, showing that crowded portfolios underperform and aggregate prime brokerage lending falls when broker-dealer health deteriorates broadly. These correlations provide consistent evidence that, under the condition of widespread distress, shocks transmit to stock prices.

First, we study the distress among large European broker-dealers in Q1 2016. Beginning with idiosyncratic write-downs and debt default concerns at Deutsche Bank and Credit Suisse, a set of European broker-dealers all announced one-off charge-offs and experienced deterioration of their financial health based on market measures.[3] The European broker-dealers with deteriorating financial health all had 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."[4]

We first establish that Euro 5 broker-dealers contracted prime brokerage credit. Euro 5 prime brokerage lending in aggregate fell 23% in Q1 2016, compared to a decline of 8% for U.S. G-SIBs and an increase of 17% for non-shocked foreign G-SIBs. However, aggregate credit contractions could reflect either supply or demand effects. To isolate credit supply factors, we estimate Khwaja and Mian (2008) style regressions of changes in prime brokerage borrowing by fund f from broker b on an indicator for whether broker b is a Euro 5 broker, controlling for fund-level borrowing demand via fund fixed effects. We find strong evidence of a credit supply shock: conditional on a fund's total borrowing change, Euro 5 brokers reduced lending significantly more than non-Euro 5 brokers.

A crucial question is whether hedge funds could fully substitute to healthier lenders. If so, hedge funds' borrowing would be unaffected and there would be no transmission to holdings or asset prices. The market structure makes this ambiguous. Concentration is high, with the top five lenders accounting for 55% of lending[5], but large hedge funds maintain diversified networks of lenders, with 4.3 lenders on average. In the Euro 5 event

[3] 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.

[4] We will interchangeably use the term "Euro 5" event and European broker-dealer distress event. The Euro 5 broker-dealers are Barclays, Credit Agricole, Credit Suisse, Deutsche Bank, and Royal Bank of Scotland/Natwest Group.

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

study, we find evidence of imperfect substitution, consistent with the findings of Kruttli, Monin, and Watugala (2022). Regressing total prime brokerage borrowing by fund f on an indicator for Euro 5 exposure, we find that exposed funds' total borrowing fell relative to unexposed funds. While the healthiest non-shocked broker-dealers did increase lending to affected hedge funds, these lenders were ex-ante smaller and seemingly unable to fully offset the Euro 5 contraction. The inability to fully substitute seems to reflect the worsening health of the non-shocked broker-dealers — CDS spreads rose not only at Euro 5 brokers but also to a lesser extent at non-shocked broker-dealers, signaling broadly reduced capacity to extend additional credit. We describe additional tests of this mechanism below.

Next, we show that hedge funds exposed to Euro 5 brokers reduced equity holdings but did not reduce exposure to other asset classes, such as corporate bonds or foreign exchange derivatives. Examining actual share holdings through FactSet Ownership, we find that stocks more heavily held by Euro 5-exposed managers experienced abnormal sell-offs during Q1 2016, and had abnormally low returns, even controlling for standard factor exposures. Returns partially reverted by April 2016, consistent with temporary price pressure rather than fundamental repricing. Using these price effects, we estimate the first micro-level price multiplier, the percentage point change in price for a one percentage point sell-off of all shares outstanding, implied by the forced sales of Euro 5 exposed hedge funds. Our estimates range from 2.65 to 4.7, which are substantially larger than multipliers from routine market events such as index inclusions and dividend reinvestments.[6]

We provide evidence that this large multiplier is the result of exposed hedge funds' sales being absorbed by investors with inelastic demand, rather than by other levered arbitrageurs who would normally provide elastic liquidity. Instead, it was non-levered investors, namely investment advisers and households, that absorbed the bulk of the selling flow. This transfer from specialized levered investors (hedge funds) to less specialized investors with more inelastic demand is consistent with high price impact. This provides direct micro-level evidence for a core prediction of intermediary asset pricing theory: when constrained intermediaries are forced to transfer assets to other investors, substantial price adjustments are required to clear markets (He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014)).

While the Euro 5 episode provides causal evidence of an indirect participation channel, when transmission generally occurs is less clear. In this event study, transmission in this shock can be traced cross-sectionally because hedge funds were unable to fully substitute lost borrowing by increasing borrowing from healthier dealers. This suggests that transmission depends on the health of the non-shocked broker-dealers.[7] To test this hy-

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

[7] We distinguish between two definitions of *idiosyncratic* shock to broker-dealer health. The first relates to a shock in which stress originates outside of the prime brokerage business; this is consistent with the definition of idiosyncratic in the causal inference literature. The second definition, used here, relates to

pothesis, we turn to panel tests across over the full sample period and find no evidence of transmission occurring absent widespread distress. Each quarter, we identify the five broker-dealers with largest CDS spread changes. To validate this premise, we show that these broker-dealers reduce credit supply to hedge funds in the same quarter. However, we find that Q1 2016 is the only period in our sample where widespread distress occurred simultaneously with cross-sectional credit supply contraction. That is, in all other quarters with cross-sectional credit supply contraction, hedge funds were able to fully replace lost borrowing from distressed brokers by substituting to healthier counterparties.

Standard intermediary asset pricing factors are identified based on aggregate broker-dealer health fluctuations, so, finally, we test for evidence of transmission in those periods. First, we document that when the He, Kelly, and Manela (2017) measure of aggregate broker-dealer health deteriorates, both aggregate prime brokerage lending falls and stock portfolios more owned by hedge funds underperform. The relationship between broker-dealer health and return spreads on hedge fund sorted portfolios is concentrated in periods of severe distress. Second, to test the substitution mechanism more directly, we construct proxies for aggregate substitution capacity based on the distribution of broker-dealer health and ex-ante lending quantities, using the confidential data since 2013. We document an amplified relationship between aggregate broker-dealer health and stock market prices when substitution is likely to be more difficult, suggesting a role for substitution capacity in addition to broker-dealer health.

2 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

shock to a single or set of broker-dealers health that arises against the backdrop of largely stable aggregate health of non-shocked broker-dealers. We focus on the second definition because, as we argue, it is the relevant condition for substitution and more directly connects to the intermediary asset pricing literature. The Euro 5 shock would be idiosyncratic under the first definition but would be considered an aggregate shock under the second definition, which is why we now refer to it as "widespread" rather than idiosyncratic.

(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.[8]

While factor models test whether a representative intermediary is *marginal*, the literature also asks whether intermediaries *cause* price movements, focusing on whether securities 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)).[9] 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

[8] 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."

[9] 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.

that crowded portfolios systematically underperform when aggregate broker-dealer health deteriorates—periods that also feature declines in aggregate prime-brokerage lending.[10] Second, we find that 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.[11]

Several studies examine individual shocks to prime brokers and their consequences for hedge funds' borrowing and investments, each documenting that a broker-hedge fund relationship broke down in a single episode. Aragon and Strahan (2012) show that stock liquidity deteriorated more sharply after the Lehman Brothers collapse for stocks with greater exposure to hedge funds that had Lehman as a prime broker, and attribute the failure to substitute to bankruptcy-specific factorsnamely, the loss of client collateral that had been rehypothecated by Lehman.[12] Kruttli, Monin, and Watugala (2022) show, using confidential Form PF data, that hedge funds borrowing from Deutsche Bank during its 2015-2016 distress faced credit contractions they could not fully offset by substituting to other brokers.[13] 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.

To reconcile this mechanism with the results of the intermediary asset pricing literature, we make two contributions beyond these works. First, we identify the conditions under which transmission occurs and show that they align with the distress periods identified by that literature. Neither paper explores this margin: Aragon and Strahan (2012) attribute their finding to bankruptcy-specific mechanics, while Kruttli, Monin, and Watugala (2022) do not explore the general conditions that would drive imperfect substitution Using a standard factor for intermediary balance sheet health from the intermediary asset pricing literature (He, Kelly, and Manela (2017)), we instead document that transmission occurs when *aggregate* intermediary health is impaired. That is, the periods in which the intermediary asset pricing literature would imply price declines associated with worsening intermediary health are also the periods which we identify a plausible transmission mechanism to equity prices through hedge fund deleveraging.

Second, by focusing directly on asset-pricing quantities, prices, holdings, and changes in holdings, rather than credit quantities alone, we find direct evidence for predictions of standard intermediary asset pricing theory that these other papers cannot speak to. In our

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

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

[12] They also find that, consistent with liquidity representing a priced risk factor, returns on these stocks were higher going forward.

[13] We also study this episode, but focus on a set of five plausibly shocked prime brokers in Q12016 in particular, and similarly find that hedge funds borrowing from shocked prime brokers in Q1 2016 were unable to fully replace this lost borrowing.

event study, we estimate a price impact multiplier substantially larger than routine-event benchmarks in the literature. We then show that investment advisers and households are, in net, the buyers of the shares hedge funds sell off during this period. This pattern is consistent with the theoretical prediction that price impact is amplified when constrained, sophisticated intermediaries are forced to sell to less sophisticated, less specialized investors.

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 argue 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.

3 Data and Institutional Details

3.1 Data

3.1.1 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 more detailed information, quarterly, for each of their *qualifying hedge funds* — those with at least $500

[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.

million in net assets under management. This additional information includes 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 total borrowing amounts by borrowing type, specifically the reported amount of borrowing via prime brokerage. Second, we use data on the identity and total amount borrowed (across all borrowing types) for any counterparty from which the hedge fund borrows at least the equivalent of 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.

While the available fund-by-counterparty level 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 at the fund-by-counterparty level, 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.

3.1.2 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.

3.1.3 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.[16] From FactSet Ownership's Security

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

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

files, we collect the common market net worth for each bank holding company, which we call NW_t^b.[17]

3.1.4 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, 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.

3.1.5 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).

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 prior quarter and those with prices less than $3 in the prior quarter.

[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.

3.2 Institutional Details

3.2.1 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 and arranged financing agreements, 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 arranged financing agreements, 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. Historically, margin loans are the primary method used to extend credit to clients for financing long equity positions. These loans are secured by the client's portfolio, with terms based on the client's creditworthiness and the risk profile of the assets held as collateral. While hedge funds commonly obtain margin loans in the United States through Regulation T or portfolio margin accounts, prime brokers can also provide long equity financing via offshore arranged financing agreements. In these arrangements, the prime broker arranges financing through an affiliated offshore entity, allowing the hedge fund to maintain a single prime brokerage relationship while the offshore affiliate extends the credit. Because the financing is provided outside the U.S., it can support leverage beyond the limits imposed by Regulation T or portfolio margin.[19]

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,

[19] Public data on arranged financing are extremely limited, as these agreements are not identified in standard margin lending or regulatory datasets. While the legal structure of arranged financing is not observed directly, the resulting borrowing is reflected in hedge fund prime brokerage borrowing reported in Form PF.

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.

3.2.2 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 managers 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, based on 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

3.2.3 Prime Brokerage Lending Patterns

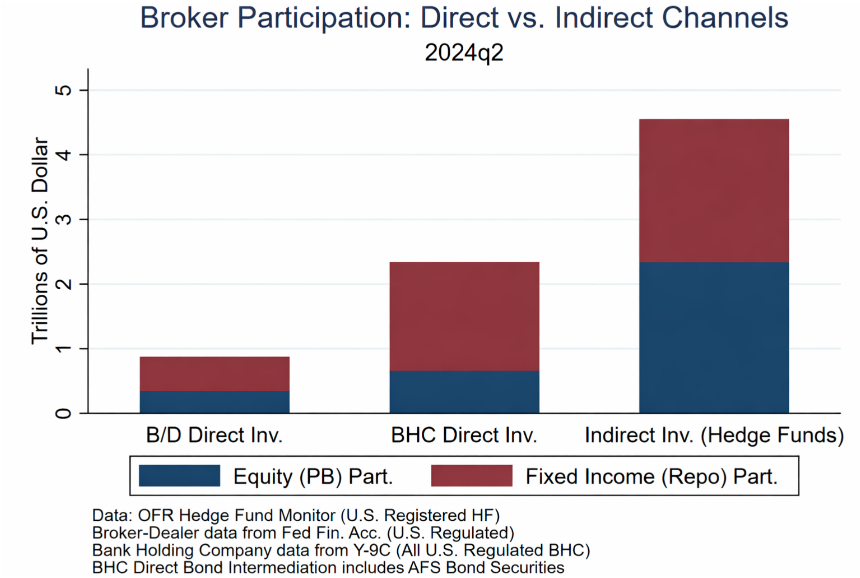
In Figure 1, we compare total prime brokerage lending, as reported in the OFR Hedge Fund Monitor, with broker-dealer equity holdings from the Financial Accounts. The OFR aggregates reported prime brokerage lending across funds and intermediaries, providing a comprehensive measure of the scale of financing in this market.[20] As of Q2 2024, total prime brokerage lending to hedge funds was roughly \$2.3 trillion.[21] 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.

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

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

[21]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.

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



identities of counterparties are anonymized.[22] 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 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.

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,

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

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

especially larger ones, appear to diversify their borrowing network by spreading borrowing across multiple lenders.

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

4.1 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 or 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 credi-

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

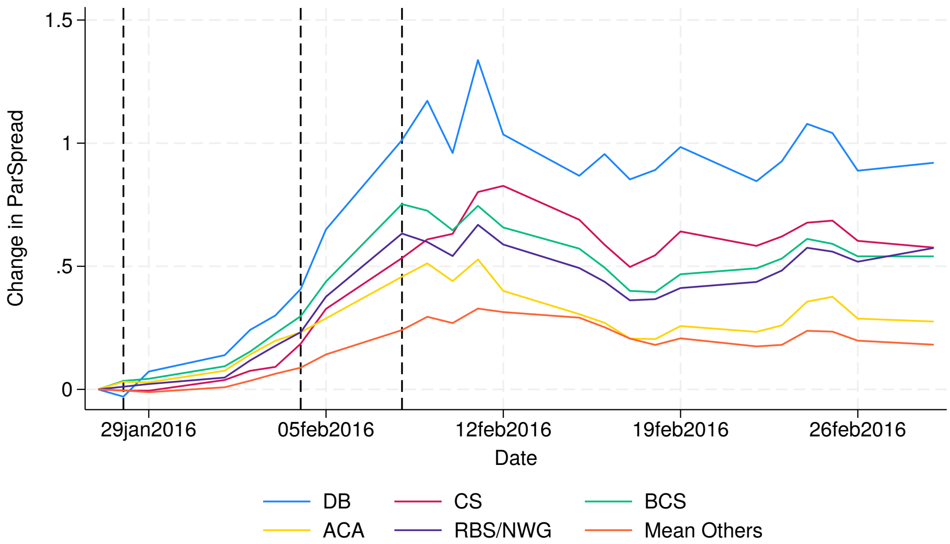
ble shocks to a subset of broker-dealers would not necessarily correspond to periods with aggregate health variation.

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.

4.2 The European Broker-Dealer Distress Episode

We focus on the European broker-dealer distress episode in early 2016, which closely matches the features of the ideal experiment. *Note that the information reported in this paper on specific individual broker-dealers is derived solely from published sources.*

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.



4.2.1 Event Description

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 billion euros in impairments tied to planned divestitures of German retail and Chinese commercial banking operations. 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 historical 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 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.[23]

Treatment Group Construction: 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. 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.[24] For each broker-dealer, we calculate 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 spread peak on February 9.

Appendix Table A3 shows that both methods produce similar patterns. 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 measure-

[23] 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.

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

ment window. And, Appendix Section B.2.3 shows that institutions experiencing moderate CDS spread increases tend to be affiliated with parent companies that were ex-ante less profitable (lower market-to-book ratios) and 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 grouping 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.[25] 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. 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.[26]

We address these concerns by conducting various robustness exercises. We address the concern over differences between U.S. and non-U.S. broker-dealers 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

[25] 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))

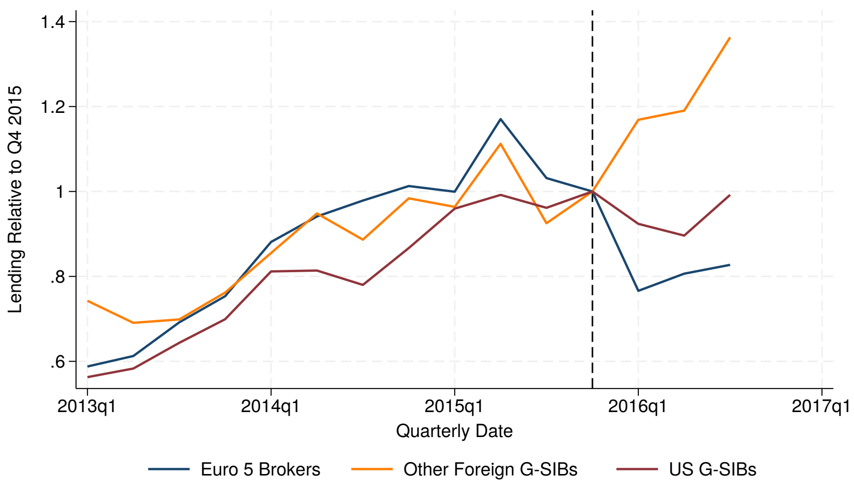
[26] Because our strategy relies on cross-sectional variation, the concern is not aggregate shocks that affect all funds uniformly, but rather differential exposures to European risks across the cross-section.

euro area. At the stock level, we control for a stock's European bank ownership and the share of foreign revenues for the company.

4.3 Broker-Dealer Credit Supply

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 3, we plot total (imputed) prime brokerage lending to hedge funds for three sets of institutions: Euro 5 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 Q4 2015, the period prior to the shock. 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. Figure 3 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 an 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 materially increased their lending.

Figure 3: **Aggregate Total Lending by Broker Type (Euro 5):** This figure plots the time-series of total lending by the Euro 5 and non-treated sets of G-SIB banks. For non-treated banks, we decompose into other foreign G-SIBs and U.S. G-SIBs. We normalize total lending to hedge funds to 100% in Q4 2015 for each group of lenders. 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.



The aggregate lending trends provided in the previous section are 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:

$$\Delta Y_t^{f,b} = \alpha_f + \beta Treated_t^{f,b} + \gamma X^{f,b} + \epsilon_{t+1}^{f,b}, \tag{1}$$

where $\Delta Y_t^{f,b}$ is defined either as the change in log prime brokerage borrowing by fund f from bank b, $\Delta \log(PBL_t^{f,b})$ (as in Kruttli, Monin, and Watugala (2022)), or the change in prime brokerage borrowing scaled by prior-period net assets, $\frac{\Delta PBL_t^{f,b}}{NAV_t}$. The period t indexes the treatment period, Δ reflects the change between t and $t+1$, and $Treated_t^{f,b}$ is a dummy variable indicating whether f borrows from a Euro 5 bank b in period t. 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.[27]

Table 4 reports the estimates for equation (1). 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 $\frac{\Delta PBL_t^{f,b}}{NAV_{t-1}}$ 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

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

section. We find qualitatively similar effects.

Table 4: **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 broker is a 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 and the lagged log level of net asset value. StratFE are strategy fixed effects. KMFE are fund fixed effects."Large Eq" funds report at least 100 million dollars of long equities in Q4 2015. Outcome variables are winsorized at the 2.5% and 97.5% levels quarterly. Reported standard errors are heteroskedasticity robust.

	$\Delta \log(PBL^{f,b}_t)$							$\frac{\Delta PBL^{f,b}_t}{NAV^f_t}$	
	(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
* $p < 0.10$, ** $p < 0.05$, * $p < 0.01$

4.4 Imperfect Substitution of Hedge Funds across Broker-Dealers

In the Euro 5 experiment, 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:

$$\Delta Y^f_t = \alpha + \beta Treated^f_t + \gamma X^f + \epsilon^f \tag{2}$$

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

Table 5 reports results from estimating equation (2). 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.

Table 5: **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 ($\frac{\Delta PBL^f_t}{NAV^f_t}$). "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)	(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)	
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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 our 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).[28] 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 4), the average exposed fund would have a reduction of 0.038 prime

[28]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.

brokerage scaled by net asset value. This is about 60% of our point estimate in column (6). 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 3. 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 borrowing less than other funds only during the credit supply shock period.

The above results demonstrate that hedge funds were unable to fully replace the borrowing lost from Euro 5 broker dealers. What could rationalize this inability to substitute? One possibility is that there is limited additional broker-dealer capacity from which hedge funds funds can borrow. In Q1 2016, the Euro 5 shock occurred against the backdrop of declining broker dealer health for non-treated broker-dealers (see Figure 2). If financial health is associated with a willingness to extent credit, then the broadly declining financial health of non-shocked broker-dealers would imply limited capacity to increase lending to exposed hedge funds.

We test this hypothesis by examining how the health of non-shocked broker dealers affected their lending decisions in Q1 2016. Specifically, we test whether hedge funds borrow more from healthier non-shocked brokers than less healthy non-shocked brokers. If the financial health of non-shocked broker-dealers associates with their willingness to extend additional credit, we should expect relatively healthier broker-dealers to increase lending relative to less healthy broker-dealers. We measure the health of non-shocked brokers using their CDS spread changes on Euro 5 announcement dates. We include two measures: the level of the cumulative CDS spread change and an indicator for whether the broker's CDS spread change is below the median (among non-shocked brokers). 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 6 shows that hedge funds substituted toward healthier (below-median CDS change) broker-dealers instead of less healthy (above-median CDS change) brokers. Within-fund specifications (column 4) confirm this pattern holds when controlling for common demand shocks and thus suggests the observed patterns are related to the relative health of those broker-dealers. This is consistent with hedge funds substituting to broker-dealers that have the capacity, based on their financial health, to supply credit.

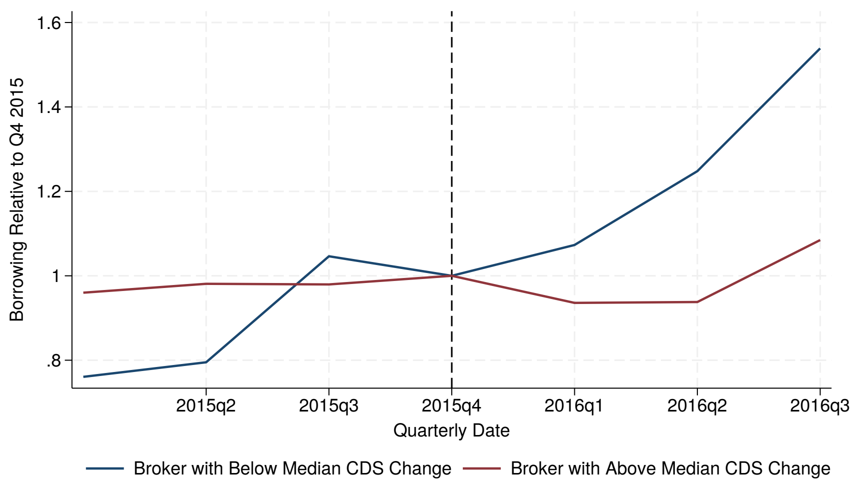
While the regressions test for cross-sectional differences, Figure 4 shows that exposed hedge funds increased borrowing from below-median brokers while reducing borrowing from above-median brokers in aggregates.

Table 6: **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 4: **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.



While these results indicate that hedge funds did redirect borrowing toward healthier counterparties to some degree, they were unable to fully offset lost borrowing. Why did hedge funds not replace all of their lost borrowing? One likely explanation is that the scale of lost borrowing exceeded available capacity at healthier institutions: 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, which is likely infeasible. More broadly, this pattern suggests that imperfect substitution is a consequence of the breadth of the shock itself, which we will test more generally in Sections 6 and 7.1.

5 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 7 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 would be explained by 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

Table 7: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

PF.[29]

We construct two measures of equity portfolio size for manager m, summing over each stock s the manager holds:

$$MarketPricePort_t^m = \sum_s Price_t^s * SharesHeld_t^{m,s}, \tag{6}$$

$$StalePricePort_t^m = \sum_s Price_{2015q4}^s * SharesHeld_t^{m,s}, \tag{7}$$

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:

$$\Delta \ln(Port_{2016q1}^m) = \alpha + \beta Treated_{2015q4}^m + \gamma X^m + \epsilon_{2016q1}^m \tag{8}$$

where $Treated_{2015q4}^m$ indicates the manager advises at least one fund borrowing from a Euro 5 bank, and $Port_{2016q1}^m \in \{MarketPricePort_{2016q1}^m, StalePricePort_{2016q1}^m\}$.

Columns (4)-(8) of Table 7 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, defined as the sum across all fund-level prime brokerage borrowing for a given manager m, fell by 9.6% more for exposed managers.[30] 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, indicating we cannot reject the null that non-exposed managers did not reduce positions. Column (7) adds an interaction with manager-level de-leveraging intensity, showing managers who cut borrowing more also sold more 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.[31] Full specifications are in Appendix Table A5.

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

[30] We exclude managers whose funds report PF equity exposure exceeding 300% of FactSet equity holdings.

[31] 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.

5.1 Stock-Level Treatment and Sell-Offs

To study whether the equities 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 as:

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

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.[32]

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 8 we estimate that in Q1 2016, for a one-percentage-point increase in the ex-ante ownership stake of the treated managers for a given stock, there is a corresponding 0.124 percentage point larger decline in the market share of that stock held by these funds on average. However, this effect conflates the normal rebalancing behavior of hedge fund managers with credit supply-induced sell-offs. We address this in Columns (2)-(5) by staggering in a Q1 2016 indicator and time and industry fixed effects. In each

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

specification, 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. This provides compelling evidence that stocks more exposed to Euro 5 managers faced abnormal sales pressure.

Table 8: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 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), and $Euro5MktShare^s_{2015q4}$ and $\Delta MktShareE5HFs^s_{2016q1}$ are defined as above. Standard errors are clustered at the two-digit SIC industry-code level.

Table 9 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.

Table 9: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (3) finds similar results for residualized returns to the Fama-French 4-factor model. 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 these competing interpretations, we turn to realized sell-offs.

Columns (4)-(7) test whether realized sell-offs predict returns. Column (4) shows a positive coefficient (position changes associate with returns for Euro 5 managers). In Column (5), we find that controlling for non-Euro 5 hedge fund position changes does not affect the point estimate. Crucially, the coefficient on non-Euro 5 position changes in Column (5) is statistically insignificant and negative, indicating that position changes by non-Euro 5 managers did not generate price effects. 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. This finding is consistent with Table

7, 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 a 263 basis point lower return, and 408 basis point lower return in column (7). 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 ex-ante broker-dealer holdings. We additionally find that our results are robust to controlling for the direct exposure of Euro 5 broker-dealers to stocks via equity ownership and lending.

5.2.1 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:

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

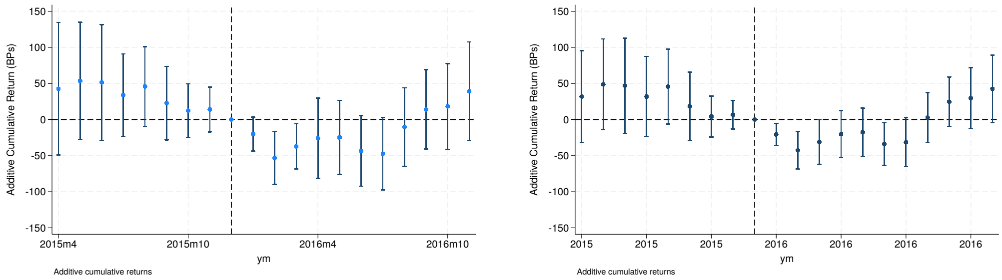
We estimate equation (13) separately for each month between April 2015 and November 2016.

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 5 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.

5.3 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

Figure 5: **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**

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 9, provides an estimate of $\frac{\Delta P}{P}$ because quarterly returns approximate stock price changes, while equation (10), with estimates reported in Table 8, 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 9, Column (2) and Table 8, Column (1)) based on the total sell-off and $\frac{-0.359}{-0.076} = 4.72$ for the abnormal sell-offs. In Table 9, 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).

To contextualize the size of the price multiplier, we briefly review the literature.[33] 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 become liquidity demanders. These conditions appear to associate with a higher price impact.[34] In the next section, we provide additional

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

[34]The market microstructure invariance literature, see Kyle and Obizhaeva (2016) and Kyle and

evidence to explain why a high multiplier is both reasonable and perhaps expected.

5.4 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).[35] 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 10. In Columns (1) through (3), 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

---

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.

[35] 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 10: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

find a quantitatively large absorption effect among these groups.[36] 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.

6 Perfect Substitution in the Cross-Section Outside Systemic Distress

In Q1 2016, we document transmission from broker-dealer health to the stock market. A key feature of the Euro 5 episode was that distress was widespread: even non-shocked broker-dealers experienced financial health deterioration and hedge funds attempted to substitute to healthier broker-dealers, but were unable to fully do so. We now test whether imperfect substitution characterizes all cross-sectional health shocks.

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. Each quarter, we classify the five broker-dealers with the highest $Distress_t^b$ as distressed (Distressed Broker$_t^{b,1}$ = 1), mirroring our event study

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

approach.

Figure 6 plots the distribution of $Distress_t^b$ for non-distressed brokers (those with Distressed Broker$_t^{b,1} = 0$). In Q1 2016, we see that non-distressed broker-dealers' financial health deteriorates across all aspects of the distribution. In contrast, apart from Q1 2020 (Covid onset, discussed in Appendix C.2) and modest increases in 2022, broker-dealer health shocks are predominantly idiosyncratic: distress concentrates among a subset of brokers while others remain healthy.

Figure 6: **Distribution of Broker-Dealer Distress:** This figure plots the quarterly median, 25th percentile, and 75th percentile of $Distress_t^b$ for brokers not classified as distressed (Distressed Broker$_t^{b,1} = 0$). The measure captures cross-sectional variation in CDS spread changes.

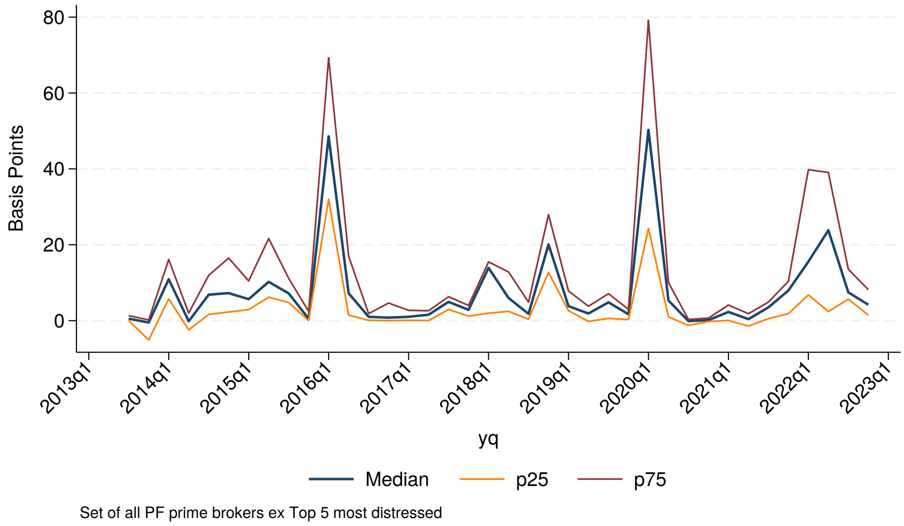
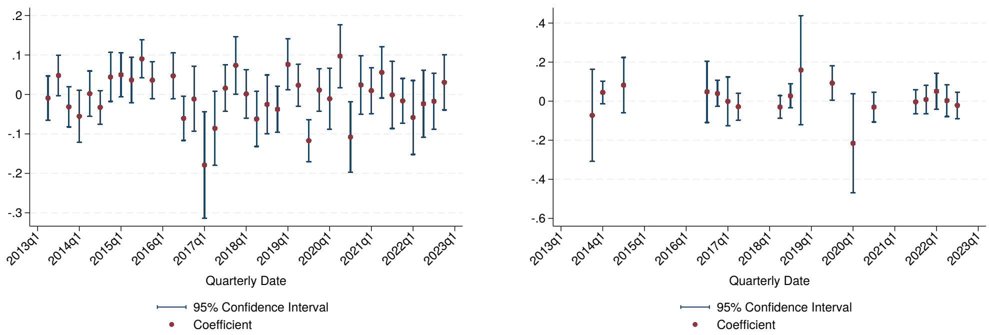


Figure 7 tests whether exposure to distressed brokers predicts credit supply contractions or total borrowing declines. Each quarter, we estimate equations (1) and (2) using the top-five distressed broker indicator. The left panel shows that several quarters exhibit negative relationships between distressed broker exposure and fund-by-broker borrowing, indicating credit supply contractions. As these quarters are not those with the highest levels of median broker-dealer distress in Figure 6, these results suggests that even idiosyncratic broker-dealer shocks can contract credit as Kruttli, Monin, and Watugala (2022) argues.

However, the right panel reports estimates for Equation 2 for each quarter in which we estimate a negative coefficient on the distressed broker-dealer indicator in Equation 1. We find no quarter where exposure to distressed brokers associates with statistically significant declines in total hedge fund borrowing. Given the distribution of broker-dealer health, we interpret this as, in quarters with idiosyncratic broker distress, hedge funds fully substituting away from troubled lenders to healthier counterparties.

Interestingly, while broker-dealers exhibit aggregate distress and cross-sectional dispersion in Q1 2020 equal to or surpassing the Q1 2016 period, we do not document cross-sectional credit supply contraction in that quarter.[37] Q1 2016 remains the only quarter in our sample exhibiting both cross-sectional credit supply contraction and imperfect substitution.

Figure 7: **Repeated Cross-Sections:** The left panel plots quarterly coefficients from fund-by-broker regressions of borrowing changes on distressed broker indicators. The right 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**

The exercise shown in Figure 7 is susceptible to a multi-hypothesis testing problem and does not cleanly identify "idiosyncratic shocks." Just by randomness, some of the cross-sectional results shown in the left-panel of Figure 7 may demonstrate a negative and significant coefficient because it shows 40 independent, cross-sectional regressions. To address the former concern, we provide panel evidence in the Appendix C.1. We estimate pooled regressions of an indicator for whether the broker is "distressed relative to the historical distribution, and find that in a similar specification similar to that estimated in Figure 7(a), that distressed brokers contracted credit on average. However, like the results reported in Figure 7(b), we find that hedge fund exposure to these distressed brokers is not associated with a decline in total prime brokerage borrowing.

To identify idiosyncratic variation, in Appendix Section D, we exploit plausibly exogenous variation in broker-dealer health based on broker losses from the Archegos bankruptcy in 2021. While this shock caused substantial distress to shocked broker-dealers, market measures of the financial health of non-shocked broker-dealers show that non-shocked broker-dealers were undistressed and aggregate measures of financial health were unchanged. Identically to the panel results, we find that shocked broker-dealers contracted credit and hedge funds perfectly substituted away.

[37]We explore the Covid episode in more detail in Appendix C.2. Note that this does not rule out Covid being an aggregate credit supply shock.

7 Testing Aggregate Transmission

In Q1 2016, broker-dealer distress transmitted to equity prices through prime brokerage credit supply contraction which promoted forced hedge fund deleveraging. During this episode, hedge funds' attempts to substitute toward healthier broker-dealers were seemingly constrained by insufficient capacity, forcing widespread sell-offs. This suggests that aggregate deterioration in broker-dealer health could trigger forced sales that transmit to equity prices system-wide.

We test two versions of this hypothesis in the time-series. First, we examine whether aggregate correlations are consistent with this transmission mechanism using publicly available data. Specifically, we test whether broker-dealer health associates with both prime brokerage lending growth and returns on stock portfolios sorted by hedge fund ownership. Second, we test the substitution capacity mechanism more directly: if substitution constraints drive the transmission, the relationship between broker-dealer health and equity returns should be stronger when hedge funds are less able to substitute lost borrowing.

7.1 Testing the Role of Aggregate Broker-Dealer Health

We extend the FactSet hedge fund ownership data used in Section 4 to construct a longer monthly time series from January 2002 to December 2022.[38] Each month, we merge this ownership data with stock returns from CRSP, sort stocks into quintiles based on the the previous quarter's hedge fund ownership shares, compute equally-weighted returns for each quintile, and construct a high-minus-low return spread.[39]

As our proxy for aggregate broker-dealer health, we use the He, Kelly, and Manela (2017) intermediary capital ratio of the primary dealer sector.[40] 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 equally impaired, so average (value-weighted) broker-dealer financial health deteriorates but with no cross-sectional dispersion.

Figure 8 provides initial evidence consistent with this mechanism. 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

[38]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.

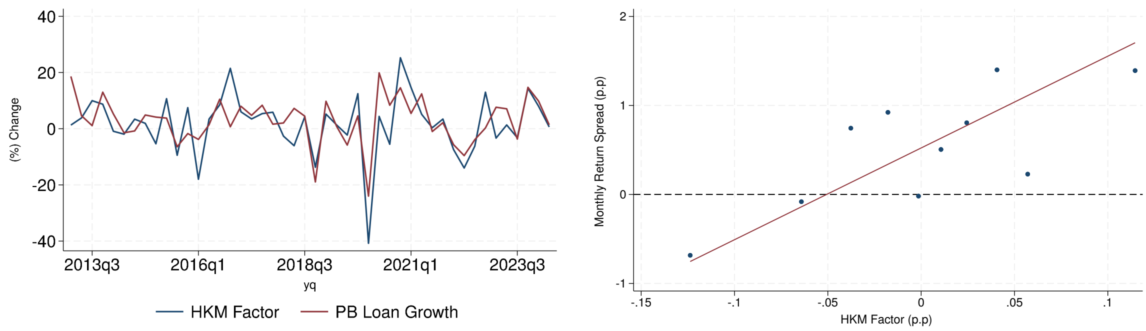
[39]The literature often refers to portfolios with substantial hedge fund presence as "hedge fund crowded" portfolios. This approach follows Brown, Howard, and Lundblad (2021), who document that hedge fund-sorted portfolios share common tail risk, though they do not link this to broker-dealer health.

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

an equilibrium outcome shaped by both supply and demand, it demonstrates that aggregate credit quantities respond to broker-dealer health.

Visual inspection of Panel (b) shows that hedge fund crowded stocks, measured by the high-minus-low portfolio sorted on hedge fund ownership, perform poorly when aggregate broker-dealer health deteriorates. This panel also 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, so we test this formally by estimating regressions of the monthly return spread on the He, Kelly, and Manela (2017) intermediary capital factor.

Figure 8: **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

Table 11 presents the results. Columns (1)-(3) test for a linear relationship between broker-dealer health and return spreads. Column (1) estimates a positive coefficient without controls, suggesting that hedge fund crowded stocks perform worse when broker-dealer health deteriorates. However, in Columns (2) and (3), estimated on the full sample and the Form PF period (April 2013 onward) respectively, this linear relationship becomes statistically insignificant when controlling for the contemporaneous market return.

It is not obvious whether the relationship between broker-dealer health and the return spread on hedge fund sorted portfolios should be uniform across broker-dealer health. In particular, we only find evidence of credit supply contraction and forced de-leveraging in periods of acute distress. To test whether the sensitivity between broker-dealer health and return spreads on hedge fund sorted portfolios is stronger during periods of severe distress, in Columns (4)-(7) we interact the HKM factor with an indicator for whether the HKM factor is in its bottom two deciles. If the mechanism operates asymmetrically, with increased sensitivity during severe distress, we should observe a positive interaction coefficient.

Columns (4)-(7) reveal a striking asymmetric pattern. In Column (4), the interaction coefficient of 0.260 is large and statistically significant. Since more negative HKM values indicate distress, this positive interaction coefficient implies that in the bottom two deciles of broker-dealer health, return spreads are significantly more sensitive to further deterioration in intermediary health. The main effect of the HKM factor remains statistically insignificant, indicating that sensitivity operates predominantly during episodes of widespread distress. This asymmetric pattern persists when controlling for the market return (Column 5), when restricting the sample to the Form PF period (Column 6), and when additionally interacting the bottom two deciles indicator with the market return (Column 7).

Increased sensitivity does not necessarily imply transmission nor whether more exposed stocks performed worse. To assess this, we examine the economic magnitudes implied by Column (5), where only the interaction term is statistically significant. At the 20th percentile of aggregate broker-dealer health (HKM = -0.0535), the threshold for entering the bottom two deciles, the predicted monthly return spread is -0.19%. As broker-dealer health deteriorates from the 20th percentile to the 10th percentile (HKM = -0.0789), the predicted spread falls by an additional 38 basis points monthly to -0.57%. At extreme distress at the 1st percentile (HKM = -0.2066), the predicted hedge fund return spread reaches -2.46%. Taken together, a negative return spread indicates that hedge fund-crowded stocks underperform in periods of more severe broker-dealer distress, consistent with forced sales.

7.2 Testing the Role of Aggregate Substitution Capacity

To test the substitution mechanism more directly, we now construct a proxy for substitution capacity independent of aggregate health. We exploit information on the relative size of prime-brokerage lending for each broker-dealer using Form PF to construct measures of aggregate (average) broker-dealer health and the distribution of lending across broker-dealers weighted by their relative health. As counter-party 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:[41]

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

[41] 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.

Table 11: **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 two deciles of broker-dealer health (Bottom Two 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	0.068*	0.026	0.026	-0.030
	(0.028)	(0.044)	(0.075)	(0.036)	(0.045)	(0.077)	(0.045)
Market Excess Return		0.001	-0.001		0.001	-0.001	0.002**
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Bottom Two Decile of HKM				0.012	0.013	0.018	0.016**
				(0.008)	(0.008)	(0.012)	(0.008)
HKM × Two Bottom Decile				0.161**	0.148*	0.301**	0.406***
				(0.075)	(0.084)	(0.115)	(0.113)
Bottom Two Decile × Market							-0.005***
							(0.002)
Constant	0.006***	0.005***	0.008***	0.007***	0.006***	0.010***	0.004*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	252	252	117	252	252	117	252
R-squared	0.064	0.078	0.023	0.078	0.090	0.066	0.151
Sample	Full	Full	2013m4-	Full	Full	2013m4-	2013m4-

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

We previously documented in Section **??** that in 2016 Q1 there was some substitution to healthier broker-dealers, but those broker-dealers were ex-ante providing less prime brokerage. Generalizing this result, we proxy for substitution capacity as the relative amount of pre-period lending from healthier broker-dealers minus the amount provided by less healthy broker-dealers. 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, suggesting greater capacity for these broker-dealers to supply credit or less potential lending under threat from worsening broker-dealer health.. When $ShareSpread_t$ is low or negative, broker-dealers with poor financial health make up more lending activity, limiting substitution because there is less 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 $\Delta Outcome_t$ 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 12 reports estimates of equation (18).[42] 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 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 is large and positive, meaning that the possibility of a tail hedge fund return spread event is higher when both aggregate health and substitution capacity are impaired.

So far, we have interpreted the interaction coefficient for the doubly-bad state of low substitutability and low aggregate health. Column (6) uses the 2×2 classification to confirm the negative return spread occurs in this doubly-bad state. 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 the doubly-bad state than the doubly-good state.

Column (7) replaces our aggregate health measure with the He, Kelly, and Manela (2017) intermediary capital ratio used earlier. 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.

These time-series tests complement the cross-sectional evidence that provide 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

[42] Appendix Table A12 reports the complete set of specifications including models without market return controls.

Table 12: **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.

	$\Delta \ln(PBL_t)$	$\Delta \ln(Eq_t)$	$spread_t^{raw}$	$\varepsilon_{FF4,t}$	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

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

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.

8 Conclusion

We provide direct evidence that intermediaries affect asset prices via their lending to hedge funds. This alternative indirect participation mechanism complements the more standard direct ownership mechanism documented in the intermediary asset pricing literature. In our event study, when broker-dealers become impaired and contract credit, hedge funds are unable to fully replace the lost borrowing, de-lever, and sell equities. Furthermore, we find evidence consistent with transmission occurring in periods of aggregate broker-dealer distress, as indexed by standard intermediary asset pricing factors such as He, Kelly, and Manela (2017).

Our results demonstrate that intermediary asset pricing can operate through both direct holdings and indirect credit provision. The stock market is a particularly striking case because broker-dealers hold minimal equity positions directly, yet their prime brokerage lending finances substantial hedge fund equity holdings. Nevertheless, these findings suggest room for further studies. It seems natural to expect that indirect participation matters in other markets and could amplify the effects in markets where intermediaries also meaningfully directly participate. More broadly, our findings suggest that understanding which investor types serve as marginal investors requires examining not just who holds assets, but also who finances those holdings.

References

Acharya, V. V., R. Engle, M. Jager, and S. Steffen (2024): "Why Did Bank Stocks Crash During COVID-19?," *The Review of Financial Studies*, 37(9), 2627–2684.

Adrian, T., E. Etula, and T. Muir (2014): "Financial Intermediaries and the Cross-Section of Asset Returns," *The Journal of Finance*, 69(6), 2557–2596.

Amihud, Y. (2002): "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets*, 5(1), 31–56.

Aragon, G. O., and P. E. Strahan (2012): "Hedge Funds as Liquidity Providers: Evidence from the Lehman Bankruptcy," *Journal of Financial Economics*, 103(3), 570–587.

Arnold, M. (2016): "Barclays shares tumble 8% after dividend cut," .

Arons, S., B. Hu, and T. Nakamichi (2021): "Nomuras Prime Brokerage Pullback Deals Blow to Global Goals," *Bloomberg*, Firm to stop offering prime-brokerage services in U.S., Europe. Brokerage has lost top-level bankers in wake of Archegos saga.

Barclays PLC (2015): "Barclays PLC Results Announcement," .

Bologna, P., A. Miglietta, and A. Segura (2020): "Contagion in the CoCos Market? A Case Study of Two Stress Events," *The International Journal of Central Banking.*

Bray, C. (2016): "R.B.S. Reports Multibillion Dollar Loss in 4th Quarter," .

Brown, G. W., P. Howard, and C. T. Lundblad (2021): "Crowded Trades and Tail Risk," *The Review of Financial Studies*, 35(7), 3231–3271.

Brunnermeier, M. K., and Y. Sannikov (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104(2), 379–421.

Chen, A. Y., and T. Zimmermann (2022): "Open Source Cross-Sectional Asset Pricing," *Critical Finance Review*, 27(2), 207–264.

Crdit Agricole S.A. (2016a): "First quarter 2016 results," .

——— (2016b): "Results for the fourth quarter and full year 2015," .

Dahlqvist, M., V. Sokolovski, and E. Sverdrup (2021): "Hedge Funds and Financial Intermediaries," *Working Paper.*

Eisfeldt, A. L., B. Herskovic, S. Rajan, and E. Siriwardane (2022): "OTC Intermediaries," *The Review of Financial Studies*, 36(2), 615–677.

Gabaix, X., and R. S. J. Koijen (2021): "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis," Working Paper 28967, National Bureau of Economic Research.

Gleason, K., S. Bright, F. Martinez, and C. Taylor (2017): "Europes CoCos Provide a Lesson on Uncertainty," *OFR Working Paper.*

Haddad, V., and T. Muir (2021): "Do Intermediaries Matter for Aggregate Asset Prices?," *The Journal of Finance*, 76(6), 2719–2761.

Halftermeyer, M. (2021): "Credit Suisse to Exit Prime Services in Sharper Wealth Pivot," *Bloomberg*, Bank to exit most of prime services business after Archegos. Will restructure wealth management businesses into single unit.

He, Z., B. Kelly, and A. Manela (2017): "Intermediary asset pricing: New evidence from many asset classes," *Journal of Financial Economics*, 126(1), 1–35.

He, Z., and A. Krishnamurthy (2013): "Intermediary Asset Pricing," *American Economic Review*, 103(2), 732–70.

Khwaja, A. I., and A. Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98(4), 1413–42.

Koijen, R., R. Richmond, and M. Yogo (2023): "Which Investors Matter for Equity Valuations and Expected Returns?," *Review of Economic Studies*.

Koijen, R. S. J., and M. Yogo (2019): "A Demand System Approach to Asset Pricing," *Journal of Political Economy*, 127(4), 1475–1515.

Kruttli, M. S., P. J. Monin, L. Petrasek, and S. Watugala (2023): "LTCM Redux? Hedge Fund Treasury Trading and Funding Fragility," *Working Paper*.

Kruttli, M. S., P. J. Monin, and S. W. Watugala (2022): "The Life of the Counterparty: Shock Propagation in Hedge Fund-Prime Broker Credit Networks," *Journal of Financial Economics*.

Kyle, A. S., and A. A. Obizhaeva (2016): "Market Microstructure Invariance: Empirical Hypotheses," *Econometrica*, 84(4), 1345–1404.

Kyle, A. S., and A. A. Obizhaeva (2023): "Large Bets and Stock Market Crashes," *Review of Finance*, 27(6), 2163–2203.

Rennison, J., and G. Jackson (2016): "Investors Flock to CDS Amid Fear Over Banks Bonds," *Financial Times*.

Seegmiller, B. (2024): "Intermediation Frictions in Equity Markets," *SSRN*.

Siriwardane, E. N. (2019): "Limited Investment Capital and Credit Spreads," *The Journal of Finance*, 74(5), 2303–2347.

Timmer, Y. (2018): "Cyclical investment behavior across financial institutions," *Journal of Financial Economics*, 129(2), 268–286.

A Data Appendix

A.1 Key Form PF Variables

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

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.

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:

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

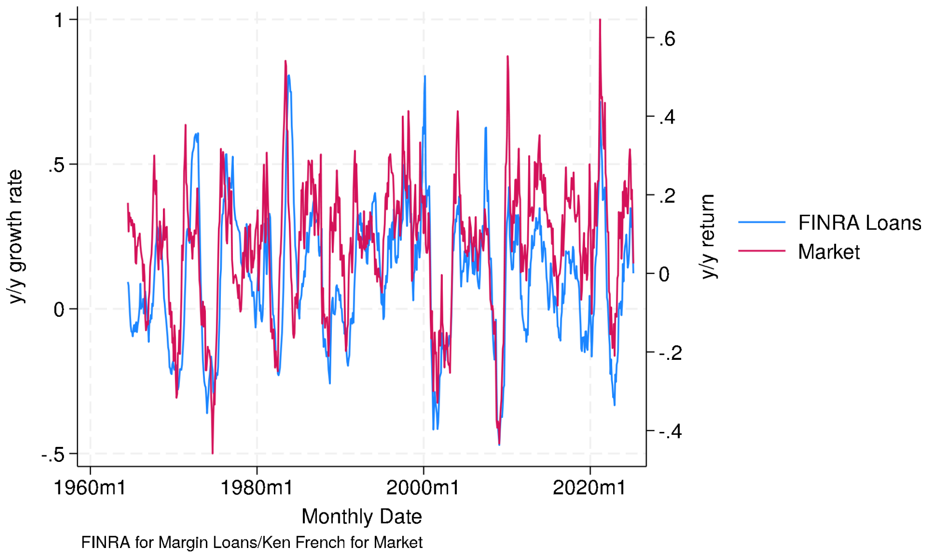
where $TotalBorrowing_t^{f,b}$ is the Q47 total borrowing quantity for fund f from broker b and $PBLoans_t^f$ is Question 43 total prime brokerage borrowing for fund f.

A.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 1 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.[43]

[43] 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 1: **FINRA Margin Loan Growth and the Market:** This figure plots the total margin lending reported by FINRA against the market return.



B E5 Appendix

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

B.1 Exposed Funds' Substitution Patterns

Figure 2 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.

B.2 Treatment Group Methodology

B.2.1 Euro 5 Announcements

Figure 2: **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.

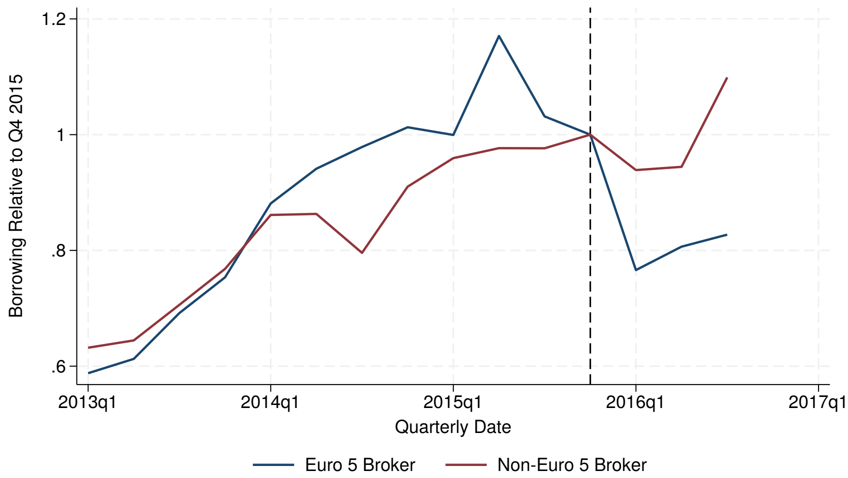


Table A2: **News Events concerning European Broker Distress:** This table reports and describes the four major events for Deutsche Bank and Credit Suisse used in this paper. Deutsche Bank related events are assembled from Gleason, Bright, Martinez, and Taylor (2017). This paper introduces the Credit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

B.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

B.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.[44]

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 from other non-treated banks. Using the set of publicly identified broker-dealers from Section B.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.

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

B.3 Appendix Credit Supply Results

B.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 7.

	$\Delta Log(LongEq_{f,t})$			$\Delta Log(ShortEq_{f,t})$	$\Delta Log(Bonds_{f,t})$	$\Delta Log(FX_{f,t})$	$\Delta Log(RF_{f,t})$
	(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 3 reports the coefficient from equation (2) estimated each quarter from 2015q1 to 2016q4.

B.4 Euro 5 Asset Pricing

B.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 9. 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 7.

	$\Delta Log(PBL_{m,2016q1})$	$\Delta Log(Equity^{mkt}_{m,2016q1})$			$\Delta Log(Equity^{stale}_{m,2016q1})$		
	(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

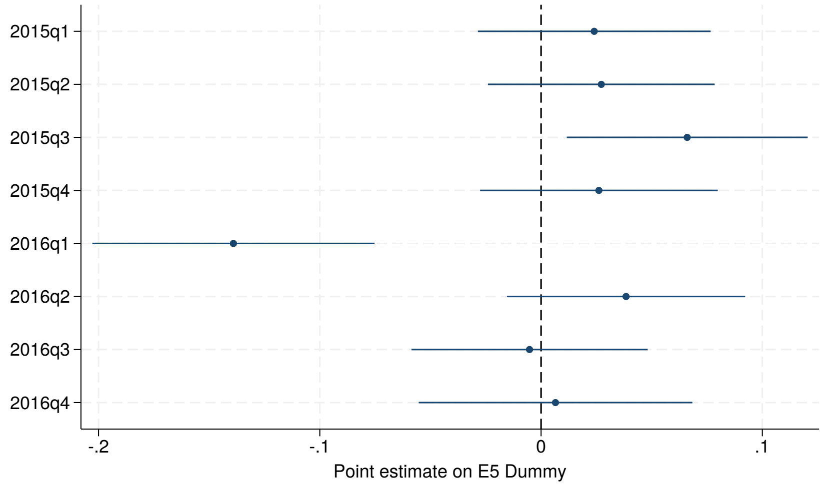
Standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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 9.

	$Ret_{s,t}$					$\varepsilon_{CAPM,s,t}$	$\varepsilon_{FF4,s,t}$	$\varepsilon_{BAB,s,t}$
	(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 3: **Imperfect Substitution Placebo Test:** This figure plots the regression coefficient from equation (2) estimated each quarter from 2015q1 to 2016q4.



B.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 9. 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_t^s), 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 9.

	$Ret_{s,t}$						$\varepsilon_{CAPM,s,t}$	$\varepsilon_{FF4,s,t}$
	(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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.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.

B.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.[45]

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:

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

[45] 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.

C Testing the role of aggregate health

C.1 Panel Analysis

We now study average credit supply and substitution effects in order to address multi-hypothesis test concerns in the main paper. First, we demean $Distress_t^b$ to isolate cross-sectional variation: $AbnormalDistress_t^b = Distress_t^b - \overline{Distress_t}$. To study credit supply using a difference-in-difference framework as in our experiments, we construct indicator variables based on $AbnormalDistress_t^b$ that allow for treatment assignment relative to the historical distribution. Specific, we construct the following indicator variable.

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

where τ is a percentile cut-off. We choose $\tau = 95\%$.[46]. This variable classified a broker-dealer as distressed if its abnormal distress measure is high compared to all other across all observations in the sample.[47]

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 A10 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 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 6, these results are consistent with idiosyncratic

[46]Other measures show similar values.

[47]Due to this inter-temporal comparison, we construct the indicator from $\textit{AbnormalDistress}_t^b$ as it would remove the effect of periods with large increases in aggregate distress.

Table A10: **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)
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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

shocks being diversified away.

C.2 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.[48] We then test whether fund-level borrowing from each broker is responsive to these broker health measures by estimating the following equation:

$$\Delta lnPBL_{2020q1}^{b,f} = \alpha_f + \beta Health_{2020q1}^b + \epsilon^{b,f} \tag{28}$$

In particular, we consider two specifications, as shown in Table A11. 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

[48] Measures (2) and (3) proxy for whether a broker's distress is better measured at the point it is most distressed during the quarter or at the end of the quarter.

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 A11: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Archegos Appendix

This appendix presents a robustness analysis using the Archegos Capital Management episode in Q2 2021. Unlike the Euro 5 episode, which occurred during a period of widespread broker-dealer distress, the Archegos shock was isolated and occurred when the aggregate broker-dealer sector was healthy. This contrast allows us to validate that transmission to equity markets depends on specific conditionsnamely, impaired substitution capacityrather than occurring following any broker-dealer shock.

D.1 Event Description

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 A13). 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 (2021)). The majority of losses were realized in April 2021.

Table A13: **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

Treatment Group Construction Our treatment group consists of the six broker-dealers with reported losses to Archegos, which are listed in Table A13. Grouping together brokers with losses to a common counterparty provides a clear treatment group for the shock. We do not include brokers who had exposure to Archegos but avoided losses as they did not experience a direct balance sheet health shock.

Differences from Euro 5: Aggregate Health Context While the Archegos and Euro 5 episodes involve comparable shock sizesroughly one-third of prime brokerage lending came from treated banks in each episodethe aggregate state of the broker-dealer sector differed substantially. Figure 4 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.

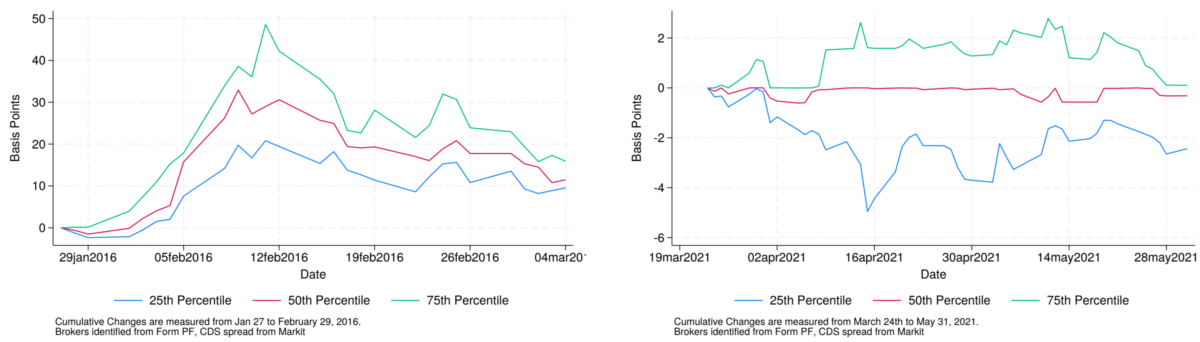
Standard measures of aggregate intermediary health confirm this pattern. The He, Kelly, and Manela (2017) intermediary capital ratio tightened from 6.2% to 5.1% between Q4 2015 and Q1 2016, but increased from 5.5% to 6.7% between Q4 2020 and Q2 2021. These differences in aggregate broker-dealer health provide context for understanding why transmission occurred in Euro 5 but not in Archegos.

D.2 Aggregate Lending Patterns

Figure 5 shows aggregate prime brokerage lending 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.

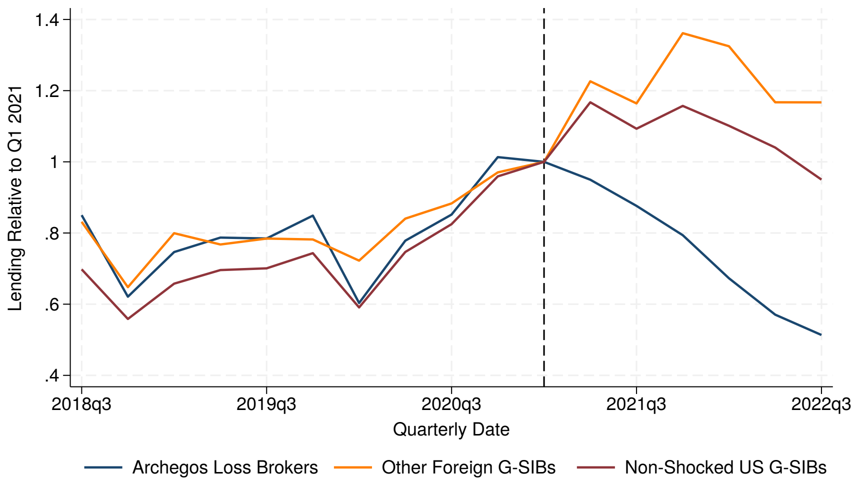
Figure 4: **Aggregate Broker-Dealer Health Across Episodes:** This figure presents cumulative CDS spread changes for broker-dealers not directly shocked in each episode. We report the 25th, 50th, and 75th percentile across broker-dealers. Panel (a) shows cumulative CDS spread changes for non-Euro 5 broker-dealers 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**



These trends persisted for multiple quarters following the shock.

Figure 5: **Aggregate Total Lending by Broker Type (Archegos):** This figure plots the time-series of total lending by the Archegos-loss and non-treated sets of G-SIB brokers. 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 2020.



D.3 Within Fund Estimator

We estimate the same within-fund specification as for Euro 5, using equation (1) for Q2 2021. Table A14 reports the results. As in the Euro 5 analysis, we find that hedge funds borrowed less from shocked broker-dealers, even controlling for common demand via fund fixed effects. The within-fund estimator shows a statistically significant negative association between borrowing from Archegos-loss banks and fund-by-broker borrowing changes.

Table A14: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.4 Fund-Level Total Borrowing: Perfect Substitution

The key difference emerges when examining fund-level total borrowing. We estimate equation (2) for the Archegos experiment, repeating the specifications from the Euro 5 analysis. Results are reported in Table A15. In columns (1)-(4), we find no economic or statistically significant relationship between total fund borrowing 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. 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.

This stark contrast with Euro 5 indicates that hedge funds were able to fully replace the borrowing lost from Archegos-loss banks through alternative funding sources. The healthy aggregate broker-dealer sector provided ample substitution capacity.

D.5 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

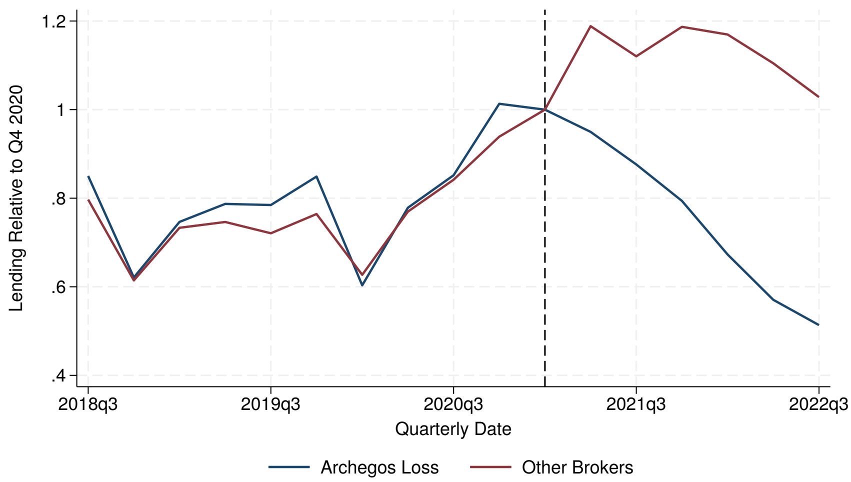
Table A15: **Fund-Level Total Borrowing (Archegos):** This table reports estimates for equation (2) for Q2 2021, which regresses changes in fund-level prime brokerage borrowing on $Treated^f_{2021q1}$. $Treated^f_{2021q1}$ is an indicator variable that takes the value of one if the fund borrows from 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.6 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.

Table A16: **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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$