Hedge Funds and Prime Broker Risk*

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Abstract

We show that large adverse shocks to an individual prime broker only impact the performance of hedge funds using the affected broker exclusively, highlighting the diversifiability of idiosyncratic shocks. Conversely, we find systematic financial intermediary risk a significant determinant in the cross-section of hedge fund returns. Moreover, the average hedge fund's exposure to this risk exceeds the aggregate risk of its holdings. This incremental exposure is asymmetric, driven solely by negative intermediary shocks. In contrast, mutual funds and other risk factors show no similar effect. Our findings underscore the unique risks of hedge funds due to their prime brokerage dependencies.

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1 Introduction

Prime brokers, typically large investment banks, offer their hedge fund clients a range of services, most notably financing. In fact, over 50% of hedge fund leverage originates from prime brokers (Figure 1a), and much of it is short-term and can be retracted rapidly (Figure 1b). Consequently, adverse shocks to prime brokers might transmit to hedge funds as funding pressure, compelling rapid de-leveraging (see, e.g., Brunnermeier and Pedersen, 2009; Liu and Mello, 2011; Adrian and Shin, 2013). This could lead to fire-sale pricing and diminished fund performance (see, e.g., Mitchell and Pulvino, 2012). Such shocks can be idiosyncratic, affecting a single prime broker, as exemplified by the detrimental impact of Lehman Brothers' bankruptcy on its hedge fund clients (Aragon and Strahan, 2012). Alternatively, shocks can be systematic, impacting the entire prime brokerage sector. We investigate the impact of both types of shocks on hedge fund risks and returns, emphasizing systematic shocks due to their notable impact and limited coverage in existing literature.

We begin by examining a panel of hedge funds around four events where a prime broker experienced a large, adverse idiosyncratic shock (including the Lehman bankruptcy). We find that these shocks significantly negatively impact the relative performance of their hedge fund clients. However, this negative effect is predominantly experienced by funds that rely solely on the affected prime broker. In contrast, hedge funds engaging multiple prime brokers do not show significant effects. This indicates that even the most severe idiosyncratic prime broker shocks can be diversified by using multiple brokers. In line with this finding, we observe a clear trend post-2008, with an increasing number of hedge funds affiliated with multiple prime brokers (Figure 2), suggesting a proactive stance by hedge fund managers in mitigating idiosyncratic prime broker risks.

Contrasting the diversifiable and typically economically modest effect of idiosyncratic prime broker shocks on hedge funds performance, we find a significant effect of systematic prime broker risk. To assess the impact of systematic prime broker shocks, we first analyze the relationships between prime brokers and hedge funds to pinpoint the key players in the sector. Using a dataset that tracks hedge funds' prime broker affiliations over time, we discover that a small group of prime brokers, those designated as New York Federal Reserve Primary Dealers, account for approximately 85% of hedge fund assets under management (AUM). Consequently, we employ the primary dealer factor developed by He, Kelly, and Manela (2017) as the systematic financial intermediary risk factor, thus capturing shocks to the health of these pivotal prime brokers and aligning with the existing intermediary asset pricing literature. Conducting standard asset pricing tests, we find that the covariation between the hedge fund return and the He et al. (2017) factor captures cross-sectional differences in hedge fund returns. Specifically, a portfolio of hedge funds with high intermediary risk significantly outperforms a portfolio with low intermediary risk by around 7% per year on a risk-adjusted basis. These results are robust to controlling for an extensive set of fund characteristics shown to relate to the cross-section of hedge fund returns.

Next, we ask whether hedge funds' systematic financial intermediary risk exposures are simply a reflection of the assets that funds hold, or whether this exposure is also driven by hedge funds' connection to prime brokers. In particular, we investigate whether hedge fund financial intermediary ex post beta is simply the weighted beta of their reported holdings, or if hedge funds are exposed to financial intermediary risk above and beyond their holdings. We posit that the excess financial intermediary beta arises due to the prime broker shock propagation channel. More specifically, if prime brokers compel hedge funds to adjust their positions during periods of prime broker distress via reductions in leverage financing, the hedge funds' ex post financial intermediary exposure will exceed what is implied by a simple buy-and-hold portfolio of their holdings.[1]

Essentially, we aim to identify the portion of a hedge fund's financial intermediary beta not reflected in the beta of its holdings, which we denote $\beta^{\text{PBCh.}}$, while accounting

[1]The mechanism is conceptually akin to Edelen (1999), who finds that compelled trades by mutual funds impact their returns.

for leverage and short sales. For example, if a hedge fund is levered two to one and the aggregate financial intermediary beta of its holdings portfolio is 0.2 and its short positions' beta is zero, then the implied aggregate beta of its holdings is 0.4. If we estimate this fund's financial intermediary beta to be 0.5, then the excess 0.1 would be attributed to $\beta^{\text{PBCh.}}$. In other words, $\beta^{\text{PBCh.}}$ is computed after appropriate adjustments for leverage and short sales. To this end, we model hedge fund returns to establish testable predictions for financial intermediary betas under assumptions about short selling and leverage. Specifically, we show that, with only a few tractable identifying assumptions, we can estimate the average $\beta^{\text{PBCh.}}$ without granular data on hedge fund leverage or short sales.[2]

Our empirical strategy, thus, seeks to identify the average excess financial intermediary beta in hedge funds. Due to the necessity of observing hedge fund holdings, we focus on the subset of funds that file Form 13F with the Securities and Exchange Commission (SEC), i.e., primarily equity hedge funds. Hence, we estimate the average excess financial intermediary beta among these hedge funds. Subsequently, we perform a similar estimation for a control group of active equity mutual funds. These mutual funds are similar to equity hedge funds in many respects but are devoid of prime broker affiliations and are thus not expected to show similar excess financial intermediary exposure. By contrasting the estimates derived from hedge funds with those from mutual funds, we aim to identify the distinctive impact of prime brokers on hedge funds.

We find that hedge funds display a positive and significant excess financial intermediary beta, a pattern not observed in mutual funds. Specifically, our estimated average $\beta^{\text{PBCh.}}$ is statistically significant and constitutes around 12% of the cross-sectional standard deviation of the financial intermediary hedge fund holdings-implied beta. Given that the average

[2]We require reliable estimates of the average hedge fund leverage and the average hedge fund long/short ratio, which are available from Barth, Hammond, and Monin (2020), who report comprehensive sets of descriptive statistics using regulatory hedge fund data. Moreover, our results are robust to alternative reasonable choices of these parameters. However, our empirical approach does not permit the estimation of heterogeneous effects within the prime broker channel. Given our primary objective to establish the existence of the prime broker channel, estimating the average excess financial intermediary beta suffices.

financial intermediary exposure of hedge fund holdings is typically low, this excess beta effectively doubles the average financial intermediary exposure already inherent in hedge funds' long positions. In stark contrast, we find no such excess exposure among mutual funds. Importantly, in line with economic intuition, we also find no excess exposure to other equity risk factors like the Fama and French (1993) HML factor for either hedge funds or mutual funds, highlighting the unique role of financial intermediary risk.

Furthermore, we find that this effect is strongly asymmetric, driven solely by adverse systematic prime broker shocks. Specifically, the average hedge fund's downside financial intermediary beta is both statistically significant and economically substantial, amounting to approximately 28% of the cross-sectional standard deviation downside financial intermediary hedge fund holdings-implied beta. In contrast, we do not detect any excess downside beta among mutual funds. This asymmetry is further highlighted by the absence of excess upside financial intermediary beta in both hedge funds and mutual funds. In essence, hedge funds experience a pronounced incremental negative impact during prime brokers' downturns, without corresponding benefits during their upswings. This aligns with the hypothesized mechanism of the prime broker channel, where only negative prime broker shocks propagate to hedge fund clients. Moreover, the pronounced asymmetry of this response mitigates concerns that our observations are primarily influenced by hedge funds' unobserved holdings, as these holdings would need to be highly specific on average to produce such a distinct asymmetric reaction to systematic prime broker shocks. In line with this, we do not observe significant asymmetric exposures to other risk factors. In total, our results provide compelling evidence in support of the prime broker shock propagation channel and underscore its significant and asymmetric impact on hedge funds.

Our findings shed light on the intricate relationship between hedge funds and their prime brokers, providing valuable insights for investors, fund managers, and regulators.

Related literature

Our work contributes to three strands of the literature. First, we contribute to the literature on financial intermediary asset pricing (see He and Krishnamurthy, 2018, for a survey). In particulaFr, Adrian, Etula, and Muir (2014) show that a factor constructed from shocks to the leverage of US securities broker-dealers can price the cross-section of US bond and equity portfolios. Subsequently, He et al. (2017) find that a pricing factor constructed from the equity ratios of a small group of key intermediaries, the primary dealers, can price a wide cross-section of assets in many different markets. However, neither of these studies consider hedge funds. Intermediary health should matter relatively more for exotic assets like hedge funds that households rarely hold directly (Haddad and Muir, 2021). There is also suggestive evidence that intermediary risk matters for hedge fund returns.[3] Our cross-sectional asset pricing results emphasize the external validity of intermediary pricing, as we find the intermediary factors shown to work in the cross-section of base assets also affect the broader universe of hedge fund returns. Importantly, our findings that hedge funds exhibit excess systematic financial intermediary beta (in line with the prime broker channel) offer a unique and novel perspective in the literature on how systematic financial intermediary risk propagates among hedge funds, highlighting the special nature of hedge funds and systematic financial intermediary risk.

Second, we contribute to the large literature on the drivers of hedge fund returns. Hedge funds are dynamically managed portfolios of securities of multiple asset classes. Partly because of this, established factor models from other asset classes have struggled to explain hedge fund returns in both the time series and in the cross-section. This spawned

[3] For example, Boyson, Stahel, and Stulz (2010) find that excess correlation of returns across hedge fund style indices increases significantly with large, adverse shocks to either a portfolio of prime broker firms or a portfolio of bank stocks. In line with this finding, Khandani and Lo (2007, 2011) show that many hedge funds experienced losses during the market-wide deleveraging in 2007. Additionally, Chen, Joslin, and Ni (2018) find that the tightening of the intermediary constraints predicts higher future excess returns for a number of financial assets, including an aggregate hedge fund portfolio. Similarly, Billio, Getmansky, Lo, and Pelizzon (2012) study the connectedness between hedge funds, banks, broker/dealers, and insurance companies, finding that banks play the most important role in transmitting shocks to hedge funds.

the development of hedge-fund-specific factor models (see, e.g., Agarwal and Naik, 2004; Fung and Hsieh, 1997, 2001, 2004), among which the Fung-Hsieh model is widely used and captures the time series of hedge fund returns. However, none of the Fung-Hsieh factor loadings generate a significant return spread in the cross-section (Sadka, 2010). Several additional factors have been proposed to explain the cross-section of hedge fund returns (see, e.g., Agarwal, Ruenzi, and Weigert, 2017; Bali, Brown, and Caglayan, 2014; Buraschi, Kosowski, and Trojani, 2013; Cao, Chen, Liang, and Lo, 2013; Hu, Pan, and Wang, 2013; Klingler, 2022; Sadka, 2010; Teo, 2011). The literature, however, has not converged on the relevant systematic factors. Our results show that systematic financial intermediary risk is a key driver of hedge fund returns. This aids in the reconciliation of hedge fund performance with a theoretically motivated factor found to be important in other asset classes. Given the typically limited success of models from other asset classes in explaining the cross-section of hedge fund returns, aligning hedge fund returns with a risk factor shown to be priced in other asset classes marks progress in determining the key systematic risks.[4] Moreover, our findings on the excess systematic financial intermediary beta in hedge funds identify a distinct characteristic of hedge funds that is absent in other asset classes. Our empirical approach of contrasting holdings-implied returns with reported returns relates to the literature on mutual funds (see, e.g., Kacperczyk, Sialm, and Zheng, 2008) and the recent work of Agarwal, Ruenzi, and Weigert (2023) studying hedge fund performance. We, however, are the first to apply this methodology to studying differences in risk exposures of hedge funds and their holdings.

Third, we contribute to the relatively small but growing literature that examines the relationship between prime brokers and hedge funds. Aragon and Strahan (2012) show that Lehman prime brokerage clients were more likely to fail following Lehman's bankruptcy. However, they focus on stock market liquidity rather than hedge fund returns. In contrast

[4]Our results show that systematic financial intermediary risk is important and that idiosyncratic shocks are largely diversifiable. This is in line with the findings of Bali, Brown, and Caglayan (2012), highlighting the key role of systematic risk (and not residual risk) in hedge fund return determination.

to their work, we distinguish between hedge funds with a single prime broker and those with multiple, revealing that idiosyncratic prime broker shocks, even extreme ones like the Lehman bankruptcy, are primarily diversifiable. Relatedly, Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel (2020) find that macro-prudential regulations implemented post-2014 resulted in clients of regulated prime brokers reducing their prime broker leverage levels and engaging more prime brokers. These patterns suggest a proactive stance by hedge funds towards potential prime broker funding shocks. This aligns well with our findings, which indicate the diversifiable and economically modest impact of individual prime broker shocks on hedge funds. Klaus and Rzepkowski (2009) argue that adverse prime broker shocks are passed on to their clients, but their analysis is restricted to a short sample period, from January 2004 to June 2008, and they do not differentiate between systematic and idiosyncratic financial intermediary risk. Chung and Kang (2016) find that individual hedge fund returns are correlated with the returns of a portfolio of hedge funds sharing the same prime broker. Our findings align with theirs in that we find that prime broker shocks can affect hedge fund clients. However, we differ substantially from their work by highlighting that 1. the effects are driven by large adverse prime broker shocks, 2. the individual shocks are diversifiable, and 3. that the first order effect stems from systematic shocks. Our work is complementary and closely related to Kruttli, Monin, and Watugala (2022), who show that Deutsche Bank's hedge fund clients experienced a reduction in their borrowing after an adverse shock to the bank in 2015–2016. We draw upon their empirical findings that prime brokers in distress limit hedge fund clients' leverage, to aid the interpretation of our hypothesized mechanism behind the prime broker shock propagation channel. Moreover, our findings that individual prime broker shocks affect their clients' returns contrast those of Kruttli et al. (2022) as, despite showing a significant reduction in leverage, they do not find an effect on hedge fund returns.

We also indirectly relate to the studies examining prime brokers' other roles, such as information sharing (Kumar, Mullally, Ray, and Tang, 2020), capital introduction (Obizhaeva, 2019), and studies of the economic effects of additional affiliations like Franzoni and Giannetti (2019), who find that hedge funds that are officially affiliated with financial conglomerates have more stable access to capital. We differ from these studies in that our focus is on the systematic and idiosyncratic financial intermediary risk.

2 Data

2.1 Hedge fund data

We obtain monthly returns, AUM, and characteristics data on hedge funds from five leading commercial databases: BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS. We combine these data sources to create a comprehensive union database, capturing all hedge funds, both dead and alive, available in any of these five databases.[5] Our sample period runs from January 2000 to June 2021.[6]

In line with the literature, we apply several basic filters to the data. We consider only the hedge funds that report monthly net-of-fees returns and exclude all fund-of-funds. Following the procedure detailed in Almeida, Ardison, and Garcia (2020), we exclude funds with unusual return patterns, such as large amounts of consecutive equal returns and repeated "blocks" of returns (see, e.g., Straumann, 2009; Bollen and Pool, 2012, for further details on these data issues). We exclude funds that never report their currency, style, or AUM, and we also exclude funds with an AUM below $1 million. When a hedge fund has multiple share classes, we consider only a single share class for each fund and aggregate their AUMs. Lastly, we require that each fund in the sample reports at least 24 monthly returns during our sample period. After applying these filters, our final sample is a panel of 16,160 unique hedge funds that are associated with 7,103 unique hedge fund managing companies (managers, hereafter).

[5] The specifics of this merging process are detailed in the Internet Appendix.
[6] Due to inconsistent coverage, we exclude data from before 2000, in line with Teo (2009).

Table 1 reports the summary statistics for the hedge fund excess returns and AUMs in our sample. All returns and AUMs are in USD. We report summary statistics for the full sample, various sub-periods, and hedge fund styles. Each of the funds in our sample is classified as one of the following 12 styles: CTA, Emerging Markets, Event Driven, Global Macro, Long Only, Long Short, Market Neutral, Multi Strategy, Others, Relative Value, Sector, and Short Bias.[7] We report cross-sectional averages of each fund's average monthly excess returns and each fund's standard deviation of its monthly excess returns, which illustrates the typical performance of a hedge fund in our sample. Similarly, the AUM statistics (mean, median, 25 and 75 percentiles) are the time-series average of monthly cross-sectional statistics that aim to convey the typical cross-sectional AUM distribution of the funds in our sample. We also report the cross-sectional standard deviation of the average excess returns.

A typical hedge fund in our sample has an average annualized return (standard deviation) of 5.06% (15.04%), but the average performance varies across funds with the cross-sectional standard deviation of 10.91%. There is also substantial variation across time: the best average return (standard deviation) of 9.02% (12.72%) is recorded during the 2000–2007 period. The Great Financial Crisis period (2008–2009) is associated with the poorest performance, with an average return (standard deviation) of 2.43% (21.22%). There is also a meaningful variation in average performance across hedge fund styles. For example, hedge funds classified as Market Neutral have slightly lower average monthly returns and standard deviations (2.71% and 11.04%, respectively) than hedge funds of other styles. Significant size disparities exist among hedge funds in our sample, with the majority being relatively small. The median fund AUM is $47 million with the interquartile range spanning from $12 and $181 million and only a moderate variation observed across time and styles. However, the presence of several large hedge funds inflates the average AUM

[7]Different hedge fund databases use varied investment style nomenclatures. For a unified classification that aligns with existing literature, we adjust these native database style classifications to fit the 12 investment style categories proposed by Kosowski, Joenväärä, and Tolonen (2016).

to $348 million.

In addition to reporting returns and AUM, hedge fund databases provide details on various static fund characteristics, including geographic focus, investment style, management and incentive fees, lock-up and redemption terms, minimum investment thresholds, and the presence of a high watermark provision. We incorporate these characteristics as control variables in our tests and utilize them for further filtering in certain analyses. Importantly, the databases provide information on hedge fund prime brokerage affiliations. However, each database version only reflects the most recent prime broker affiliations for each fund, preventing us from detecting historical shifts in affiliations. To address this, we prioritize a sub-sample of hedge funds from the Eurekahedge database for analyses requiring timely prime broker data. This database enables tracking of affiliations over time. Specifically, we obtain additional database snapshots biannually (in June and December) from 2006 to 2017. Since the data on each fund's prime brokerage affiliation is updated at least every six months, we minimize misclassification of prime brokerage affiliations throughout our sample period. The Eurekahedge database is regarded as representative and is solely employed by Hombert and Thesmar (2014) for its empirical investigations. Table 1 additionally presents summary statistics for our Eurekahedge sample. We note that the performance and AUM metrics closely align with the full union database, with only the mean AUM being smaller, as our union database contains a few more of the mega hedge funds.

2.2 Hedge fund equity holdings data

For our analysis of the systematic prime-broker shock propagation channel in Section 5, we obtain quarterly hedge fund US equity holdings from Thomson Reuters' 13F holdings database. Since Form 13F is filed at the manager level rather than for individual funds, we aggregate the hedge fund returns and AUM, as previously described, to the manager level. The Internet Appendix provides details on merging 13F managers with manager-level data from our union hedge fund database.

2.3 Mutual fund data

We source data on mutual funds returns, characteristics, and holdings from the Center for Research in Security Prices (CRSP) spanning July 2006 to June 2021. Share classes are consolidated following Berk and Van Binsbergen (2015). We adjust for reported fees to compute gross returns. Additionally, we exclude funds not categorized under CRSP objective codes: sector, growth, income, or income & growth. We also omit passive funds and those with an absolute value of the log of the market-value-to-AUM ratio larger than log(2). We ensure each fund has at least 24 valid observations with both reported and holdings-based returns.

2.4 Stocks and factor data

Data on stock returns and prices are from CRSP. We integrate these with hedge fund 13F holdings using CUSIPs. Similarly, using the provided PERMNOs, we merge the stock data with mutual fund holdings. The intermediary factor of He et al. (2017) is from Asaf Manela's webpage. The seven Fung and Hsieh (2004) factors are from Datastream and David A. Hsieh's Hedge Fund Data Library. The risk-free rate and Fama and French (1993, 2015) factor data are from Kenneth R. French's Data Library.

3 Event studies of individual prime broker shocks

In this section, we investigate how shocks to individual prime brokers impact the performance of their hedge fund clients. We seek to determine whether shocks from an individual prime broker are transmitted to its hedge fund clients. We posit that it is predominantly the largest adverse shocks to an individual prime broker that are likely to affect its clients. In other words, following a large adverse shock, a prime broker may need to limit the liquidity available to its clients and possibly temporarily reduce the quality of other services as it reallocates its constrained resources. This can adversely affect its clients' operations and performance. To evaluate this potential effect, we focus on four well-publicized events that represent large adverse shocks to specific prime brokers and examine how these events influenced the performance of their hedge fund clients.

3.1 Prime broker events

We begin by looking at the Lehman bankruptcy that took place on 15 September 2008. Figure 3 presents the proportion of Lehman's hedge fund clients that reported returns to the Eurekahedge database in July 2008 and continued to do so in subsequent months. By January 2009, 28% of the Lehman-affiliated funds from July 2008 no longer reported returns to the database. In stark contrast, during the same period, only 4% of the matched group of hedge funds stopped reporting.[8] This finding is in line with Aragon and Strahan (2012), who also find that Lehman-affiliated funds disappeared from the database at a higher rate than other hedge funds.[9] While there are multiple reasons for discontinuing performance reporting, it is reasonable to assume that, during a crisis, numerous hedge funds exit the database due to markedly poor performance or liquidation. Lo, Getmansky, and Mei (2004) contend that over 90% of non-reporting funds are ultimately liquidated. Hence, we interpret these results as a higher failure rate of Lehman clients.

In contrast to previous studies, we categorize Lehman-affiliated hedge funds into two groups: those who used Lehman as their sole prime broker at the time of its bankruptcy, and those who used it alongside other brokers. We hypothesize that prime broker shocks could differently affect hedge funds that are its sole clients. Specifically, funds with multiple

[8]The matched group comprises hedge funds that had affiliations with prime brokers other than Lehman. Each Lehman hedge fund client that reported to the database in July 2008 is matched to another hedge fund (without replacement) based on the number of prime brokers, style, AUM, and returns over the last 12 months leading up to July 2008.

[9]Our sample contains 47 hedge funds that were affiliated with Lehman Brothers, which is smaller than the 77 Lehman-affiliated hedge funds considered in Aragon and Strahan (2012), however, our findings align closely with theirs.

prime brokers might be less susceptible to an adverse shock from a single prime broker, given their ability to diversify their funding and operational needs across prime brokers. Figure 3 shows that a staggering 40% of Lehman clients that used Lehman as their sole prime broker were liquidated, compared to just 4% of the matched group. Notably, 21% of Lehman clients with a single prime broker ceased operations in September 2008. In contrast, none of Lehman clients with multiple prime brokers were affected in September and only 12% had subsequently disappeared by January 2009, with zero exits observed in the matched group. Thus, while Lehman clients with multiple prime brokers experienced disruptions following the bankruptcy, their resilience was markedly higher than that of funds affiliated solely with Lehman.

Next, we examine other large, but less extreme, adverse shocks to individual prime brokers, in contrast to the extreme case of Lehman's bankruptcy. Specifically, we consider the March 2008 Bear Stearns failure.[10], the September 2011 UBS rogue trader trading loss[11], and the April 2012 J.P. Morgan trading loss[12]. Our sample provides reasonable coverage of the affected hedge funds: it comprises 169 Bear Stearn clients, 260 UBS clients, and 201 J.P. Morgan clients during the respective events. Examining the affected brokers' clients' risk adjusted returns around the time of the event, we observe trends that align with our analysis of hedge fund performance during the Lehman bankruptcy. Specifically, hedge funds using an affected prime broker as their sole prime broker underperformed relative to their peers, whereas funds with multiple prime brokers showed no distinct performance

[10]The Lehman and Bear Stearns events are both extreme events in the sense that, in each case, both prime brokers ceased to exist after the event. However, the Bear Stearns failure and subsequent sale to J.P. Morgan was a more controlled termination than that of Lehman (see, e.g., Brunnermeier, 2009).

[11]In September 2011 UBS reported a USD 2.3 billion loss caused by a rogue trader who was subsequently jailed. The loss amounted to approximately 4% of UBS's equity capital, was widely scrutinized by the press, and led to the resignation of the company's CEO. UBS's stock return was −20% in September 2011.

[12]On 27 April 2012 J.P. Morgan delayed the filing of the quarterly SEC form 10-Q. On 10 May 2012, during an investor conference call, J.P. Morgan management announced a $2 billion trading loss. The loss was reportedly caused by a London-based trader's position in CDS. The total size of the loss was subsequently updated to be around $7.5 billion and accounted for around 4% of J.P. Morgan's equity capital. The loss attracted substantial media attention and triggered an investigation by the Federal Bureau of Investigation. J.P. Morgan's stock return was −23% in May 2012.

deviation from the matched group.[13]

3.2 Difference-in-difference regression

To formally assess whether clients of the affected prime brokers experience more pronounced impacts from a large adverse shock to their prime broker, we employ the following panel regression:

$$
\begin{aligned}
\hat{\alpha}_{i,t} = {} & b_1 \text{Lehman Event}_t + b_2 \text{Lehman Event}_t \times \text{Lehman Client}_i \\
& + b_3 \text{Lehman Event}_t \times \text{Lehman Unique Client}_i \\
& + b_4 \text{PB Events}_t + b_5 \text{PB Events}_t \times \text{PB Client}_i \\
& + b_6 \text{PB Events}_t \times \text{PB Unique Client}_i \\
& + c' X_{i,t-1} + a_i + \varepsilon_{i,t},
\end{aligned} \tag{1}
$$

where $\hat{\alpha}_{i,t}$ is the month t risk-adjusted returns for fund i. Specifically, $\hat{\alpha}_{i,t}$ is a constant plus residuals from an individual regression of hedge fund excess returns on the Fung and Hsieh (2004) seven factors.[14] Lehman Event_t is an indicator variable equal to one during the event window surrounding the Lehman bankruptcy and zero otherwise. Lehman Client_i is an indicator variable that is equal to one if a hedge fund was a client of Lehman two months prior to the bankruptcy. Lehman Unique Client_i is equal to one if a hedge fund i used Lehman as their only prime broker at the time of its bankruptcy. PB Events_t, PB Client_i, and PB Unique Client_i are indicator variables analogous to those defined for the Lehman event, but they apply to the Bear Stearns, UBS, and JP Morgan events. PB $\text{Events}_t \times$PB Unique Client_i, Lehman $\text{Event}_t \times$Lehman Client_i, PB $\text{Events}_t \times$PB Client_i and PB $\text{Events}_t \times$PB Unique Client_i are the interaction terms. A fund fixed effect is de-

[13]The Internet Appendix shows, in event time, cumulative equal-weighted hedge fund risk-adjusted return indexes for the clients of the affected prime brokers and those from a matched group of hedge funds.

[14]We consider risk-adjusted returns for a more straightforward comparison across hedge funds of varying styles, however our findings remain consistent when simply using excess returns.

noted by a_i, and $X_{i,t-1}$ is a vector of controls that includes the fund-specific, time-varying characteristics for each fund i (specifically, we consider past returns, size, and age). We use standard errors clustered by hedge fund and time. Our results are estimated on the full Eurekahedge sample.[15]

We treat the Lehman event separately due to its extreme nature. The other three prime broker events are grouped together for enhanced statistical power and clarity of presentation. As discussed in the previous subsection, hedge funds can stop reporting after experiencing adverse shocks, hence we adjust their delisting returns. In the spirit of adjusting for equity delisting returns bias (Shumway, 1997), for each fund that stops reporting we add a delisting return of -30% for the month following the last reported return. We view this as a conservative adjustment as, particularly in the case of Lehman clients, such losses are well supported by anecdotal evidence (see, e.g., Aikman, 2010).[16] We consider a three-month event window (the month before, the event month, and the month after) as a benchmark specification, but also consider four and five month event windows. Our coefficients of interest, b_3 and b_6, on the interaction terms Lehman Event$_t \times$Lehman Unique Client$_i$ and PB Events$_t \times$PB Unique Client$_i$ capture the differential effects of the Lehman bankruptcy and the other three major prime broker shocks on their respective hedge fund clients that exclusively used the affected prime brokers. If large idiosyncratic shocks to a prime broker disproportionately and negatively affect the returns of its hedge fund clients, we would expect both coefficients to be negative and significant.

We report the results of regression (1) in Table 2. The coefficients on Lehman Event$_t$ and PB Events$_t$ capture the systematic effects (i.e., the average effect of these prime brokers

[15]We also replicate our analysis using the matched sample of hedge funds, as referenced in Figure 3 and the Internet Appendix. The outcomes from this matched sample align closely with our baseline results, which we report in the Internet Appendix.

[16]Using instead -10%, -50%, or -70% as a delisting return does not alter the general conclusion. There is little consensus in the literature on the appropriate delisting return adjustment. For example, Titman and Tiu (2010) use -100% , Ang and Bollen (2010) use -25%, and Sun and Teo (2019) use -10% as their delisting return base cases. Hodder, Jackwerth, and Kolokolova (2014) estimate an unconditional delisting return of -6%. However, they note that a large negative delisting return is possible under adverse circumstances, such as during the financial crisis.

shocks on hedge funds). These coefficients are large and negative in all specifications, however not statistically significant except for the coefficient on PB Events_t that is marginally statistically significant in the last specification that considers a longer event window. The economically large point estimates suggests that adverse financial sector shocks could impair average hedge fund performance, however weak statistical significance of these coefficients likely underscores cross-sectional differences. We formally investigate the impact of systematic financial intermediary risk on hedge fund performance in the next section. Specification I omits the indicator for the sole prime brokers. Hence, Lehman $\text{Event}_t \times$Lehman Client_i and PB $\text{Events}_t \times$PB Client_i capture the effect on all the funds that are connected to a particular affected prime broker, irrespective of whether it is a hedge fund's only prime broker or one of several. We find that the coefficients on Lehman $\text{Event}_t \times$Lehman Client_i and PB $\text{Events}_t \times$PB Client_i are both negative (-0.92 and -0.23, respectively) but only the coefficient on PB $\text{Events}_t \times$PB Client_i is statistically significant. The results of this specification suggest that, during the event window, the affected prime brokers' clients' risk-adjusted returns are worse than those of the other funds.

The lack of statistical significance for Lehman $\text{Event}_t \times$Lehman Client_i aligns with Figure 3, which indicates that primarily hedge funds using Lehman as their sole prime broker were adversely affected by its bankruptcy. This intuition is confirmed when we include the indicators Lehman $\text{Event}_t \times$Lehman Unique Client_i and PB $\text{Events}_t \times$PB Unique Client_i in specification II. Consistent with our hypothesis, the estimates of b_3 and b_6 are negative, -3.07% and -0.53% respectively, and both are statistically significant at the 1% level. In contrast, the estimates of b_2 and b_5, which, in this specification, only capture the effect of prime broker events on their hedge fund clients with multiple prime brokers, are no longer negative or statistically significant.[17] In other words, hedge funds exclusively using an affected prime broker faced significantly greater performance declines than other funds,

[17]The estimates of b_2 on Lehman $\text{Event}_t \times$Lehman Client_i is positive and substantial, reaching statistical significance in specification III. This appears to be a consequence of the short event-window in our benchmark specification. The initial positive value observed is temporary; upon extending the event window, the positive point estimate diminishes, aligning more with our expectations.

whereas funds with multiple prime brokers remained largely unaffected by such shocks. Although the absolute size of the estimates decreases slightly, the results remain essentially unaltered with the inclusion of hedge fund controls in specification III.

Hedge funds with only one prime broker might be more sensitive to financial intermediary shocks, regardless of whether their specific prime broker is directly impacted. To rule out this potential effect driving our results, we introduce an additional indicator variable, One Broker_i, and its interactions with the relevant event indicators to regression (1). In line with our conjecture, we find that the estimates of Lehman $\text{Event}_t \times$ One Broker_i and PB $\text{Events}_t \times$ One Broker_i coefficients are both negative but statistically insignificant and economically small. However, we do observe a noticeable reduction in the point estimate of b_6 from -0.46 to -0.35. Nevertheless, the estimate of b_6 remains statistically significant at the 5% level. In contrast, the estimate of b_3 exhibits only a minor decrease from -2.96 to -2.68, highlighting the profound impact of the Lehman bankruptcy on its clients.

Lastly, specifications V and VI, verify that the results are robust to different event windows. The magnitude and statistical significance of b_3 remain largely unchanged when expanding the event window from three to four or five months, suggesting that its economic significance actually increases with a longer event window. This pattern is also observed for b_6, with the economic significance also slightly increasing at longer event windows. These findings highlight that the adverse impact of prime broker shocks on their clients does not appear temporary, as we do not observe an obvious reversal. The average economic impact of the Lehman bankruptcy on clients who used it exclusively as their sole prime broker amounted to approximately a 10.80% (-2.16×5 months) loss in risk-adjusted return. Similarly, the average economic effect of the other three adverse prime broker shocks on their specific exclusive clients amounted to a 1.50% (-0.30×5 months) loss. Although notably smaller, this is still an economically meaningful effect.

In sum, the analysis of prime broker events shows that large individual prime broker shocks affect the performance of hedge fund clients who use the affected broker as their sole prime broker, with the impact being especially pronounced in the case of the Lehman bankruptcy. An important implication of this result is that the propagation of large (even extreme) negative individual prime broker shocks to their clients represents diversifiable counterparty risk that is mitigated by using multiple prime brokers. This observation aligns with the conjecture by Dai and Sundaresan (2009) that hedge funds establish relations with several prime brokers for improved risk management. Indeed, this trend is evident post Lehman bankruptcy. Figure 2 depicts the increasing fraction of funds with multiple prime brokers over time (while only about 10% of hedge funds had multiple prime brokers in 2006, by 2021, around 45% reported multiple prime broker affiliations).[18] Additionally, a question arises: even if individual prime broker shocks are diversifiable by using multiple prime brokers, what is the effect on a hedge fund if all of its prime brokers simultaneously face adverse shocks? We will investigate this further in the next sections.

4 Financial intermediary risk in the cross-section of hedge funds

Intermediary asset pricing models emphasize the special role financial intermediaries play in asset pricing. Our analysis in the previous section suggests that aggregate prime broker shocks influence hedge fund returns. Hence, in this section, we formally investigate the effect of systematic financial intermediary risk on the cross-section of hedge funds.

4.1 Measuring systematic financial intermediary risk

In measuring systematic financial intermediary risk, we are guided by the theoretical framework of He et al. (2017), which posits that the pricing kernel consists of aggregate wealth and the intermediary's equity capital ratio (He and Krishnamurthy, 2012, 2013, provide

[18] Using multiple prime brokers is not costless, as it increases operational complexity and thereby operational risks. For example, having multiple prime brokers forces hedge funds to duplicate many processes and makes it difficult for them, for example, to net collateral requirements across trades.

micro foundations). In their framework, shocks to the intermediary's equity capital ratio affect their marginal value of wealth, thus these shocks should be priced in markets where intermediaries are "marginal" investors.

However, when taking the model to the data, one must identify the "marginal" financial intermediaries. He et al. (2017) consider the primary dealers as a set of key financial intermediaries for their empirical analysis, finding that their empirical intermediary's equity capital ratio factor is priced in a large cross section of asset classes. Primary dealers are a natural group to consider as there is ample evidence suggesting that they account for the bulk of trading in many markets (see, e.g., Cetorelli, Hirtle, Morgan, Peristiani, and Santos, 2007). In our context, prime brokers are the most natural marginal players, leading us to analyze the prime broker market structure to identify the key entities.

Table 3 presents the market share of leading prime brokers over time. While our database contains around 480 unique prime broker names, the top 10 and 20 prime brokers, on average, account for around 86% and 95% of total hedge fund AUM, respectively. Moreover, we find a high degree of persistence in the relative importance of specific prime brokers. For example, Goldman Sachs and Morgan Stanley are almost always ranked first or second.[19] Notably, despite using a different approach to identify the most important financial intermediaries, we converge on a very similar group of intermediaries as He et al. (2017). The primary dealers capture, on average, around 87% of total hedge fund AUM, and, throughout the years, nearly all the top 10 prime brokers are consistently designated as primary dealers. Given this finding, and to better align with the existing literature (especially given the factor's availability at higher frequencies), we adopt He et al. (2017)'s financial intermediary factor (FI, thereafter) as our measure of the systematic financial intermediary risk.[20]

[19]This pattern is consistent with Aragon and Strahan (2012), who report prime broker market shares between 2002 and 2008, and similar to Di Maggio, Kermani, and Song (2017) and Eisfeldt, Herskovic, Rajan, and Siriwardane (2023), who respectively find that the market structure in the credit default swap and bond dealer markets is highly persistent.

[20]He et al. (2017)'s financial intermediary factor is defined as intermediary capital ratio innovations

4.2 Intermediary-beta-sorted portfolios

To evaluate the effect of financial intermediary risk on the cross-section of hedge fund returns, we begin with the portfolio-based approach commonly used in the literature (see, e.g., Sadka, 2010; Teo, 2011; Hu et al., 2013; Bali et al., 2014). Specifically, every month we sort all the hedge funds in our sample into 10 portfolios based on their 24-month rolling financial intermediary factor betas. For each hedge fund i, we estimate the rolling FI beta in month t using the following regression:

$$r_{i,t} = a_{i,t} + \beta_{i,t}^{\mathrm{FI}}\,\mathrm{FI}_t + \beta_{i,t}^{\mathrm{M}} r_t^{\mathrm{M}} + \varepsilon_{i,t}, \tag{2}$$

where $r_{i,t}$ is the month t excess returns for fund i, and FI_t and r_t^{M} are the month t realizations of FI and the aggregate stock market portfolio, respectively. Regression (2) corresponds to the theoretically-motivated two-factor model that He et al. (2017) consider. After having monthly beta estimates, $\hat{\beta}_{i,t}^{\mathrm{FI}}$, we form 10 equal-weighted portfolios of hedge funds based on them. Hedge funds with the lowest FI betas are allocated to Portfolio 1, while the funds with the highest FI betas are allocated to Portfolio 10. This procedure gives us 10 time series of monthly hedge fund portfolio returns. As a last step, we compute the post-ranking betas of each of the ten portfolios by regressing the portfolio returns on the two factors in regression (2).

Table 4 reports the average monthly excess returns, CAPM alphas and Fung and Hsieh (2004) seven-factor alphas for our 10 hedge fund portfolios. It also reports the post-sort and pre-sort betas. The pre-ranking beta of a portfolio is its average fund level rolling beta. The high-FI-beta portfolio (Portfolio 10) has the highest average return or alpha, and the low-FI-beta portfolio (Portfolio 1) has the lowest. The hypothetical strategy of going long Portfolio 10 and going short Portfolio 1 yields an annualized excess return of 5.76% (t-stat

(first differences in intermediary capital ratio). The intermediary capital ratio is constructed as the total primary dealer market equity divided by total assets (total market equity plus total book debt of the primary dealers).

= 2.26) or an annual CAPM and Fung and Hsieh (2004) alpha of 6.36% (t-stat = 2.13) and 6.96% (t-stat = 2.23), respectively.[21] To interpret this positive spread in the average returns as compensation for risk, we show that these portfolios exhibit a positive spread in their betas on the intermediary risk factor over the same period used to compute the alpha. The post-ranking betas increase monotonically from Portfolio 1 to Portfolio 10, and there is a significant difference of 0.27 (t-stat = 4.22) between the FI betas of Portfolio 10 and Portfolio 1. In the Internet Appendix, we confirm that the cross-sectional spread in returns and alphas is preserved in the presence of other factors considered in the literature, namely the liquidity factor of Pástor and Stambaugh (2003), the macroeconomic uncertainty factor of Bali et al. (2014), the correlation factor of Buraschi et al. (2013), the jump risk factor of Cremers, Halling, and Weinbaum (2015), the tail risk factor of Agarwal et al. (2017), the noise factor of Hu et al. (2013), and the option-based constraint measure of Chen, Joslin, and Ni (2019). These results are in line with the financial intermediary risk being a determinant of the cross-section of hedge fund returns.

4.3 Cross-sectional regressions

While we do find that that there is a positive relationship between exposure to intermediary risk and average returns, this does not rule out the influence of known determinants of expected hedge fund returns in the cross-section. In this subsection, we evaluate whether financial intermediary risk exposure is robust to controlling for various fund characteristics. To this end, we estimate Fama and MacBeth (1973) regressions of hedge fund excess returns on FI beta and additional controls by running the following cross-sectional regression for every month t:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{\mathrm{FI},t}\hat{\beta}^{\mathrm{FI}}_{i,t} + \lambda_{\mathrm{M},t}\hat{\beta}^{\mathrm{M}}_{i,t} + c'_t X_{i,t} + \varepsilon_{i,t+1}, \tag{3}$$

[21] We replicate this analysis for hedge fund styles with enough monthly data to form portfolios. We observe a spread in returns similar to the full sample for all styles except CTA and Global Macro. It is likely that the dynamic strategies employed by funds of those styles do not maintain exposure to any single factor long enough to produce a meaningful spread in returns. The Internet Appendix reports the results.

where $r_{i,t+1}$ are the month $t+1$ excess returns for fund i, $\lambda_{0,t}$ is the intercept, $\hat{\beta}_{i,t}^{\mathrm{FI}}$ is the month t FI beta of fund i, $\hat{\beta}_{i,t}^{\mathrm{M}}$ is the month t market beta of fund i, $X_{i,t}$ is a vector of controls, and $\varepsilon_{i,t+1}$ is an error term. The betas are estimated rolling betas, as in the previous subsection. The controls are standard in the literature and include the fund's excess return for month t, age, AUM, management fee, incentive fee, high watermark (an indicator variable that equals one if fund i has a high watermark provision and zero otherwise), lockup (an indicator variable that equals one if fund i has a lockup provision and zero otherwise), mandated redemption notice period, and minimal investment in the fund. Controls also include hedge fund style dummies. The factor premiums are estimated as the time series averages of $\hat{\lambda}_{\mathrm{FI},t}$ and $\hat{\lambda}_{\mathrm{M},t}$.

Specifications I–IV of Table 5 report the average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regression in (3). The standard errors in parenthesis are adjusted for autocorrelation and heteroskedasticity as in Newey and West (1987) (the lag length is selected automatically using the Newey and West (1994) procedure). The estimated FI risk premium is positive and significant in all the specifications. In specification IV, with all the covariates, the point estimate of the risk premium is 0.48% (5.76% annualized), significant at the 5% level. Moreover, the estimated premiums appear stable over time (see the Internet Appendix). The coefficients on the controls are of the signs as reported by the existing literature, and most are statistically significant.[22] In sum, we find that there is a significant, positive relationship between exposure to intermediary risk and individual hedge funds' average returns, even after controlling for a large set of hedge fund characteristics known to predict returns.

[22]For example, the estimated coefficients on a fund's AUM and age are both negative, with the one on age being statistically significant, which is in line with the observation that smaller, younger funds tend to have higher average returns than larger, more established funds (see, e.g., Aggarwal and Jorion, 2010). The estimated coefficients on management and incentive fee are positive and statistically significant, as in Teo (2009). The estimated coefficient on the redemption notice period is positive and significant, which is in line with Aragon (2007), who finds that proxies for share restrictions (such as lockup restrictions, redemption notice periods, and minimum investment amounts) are positively related to average hedge fund returns. The high watermark indicator is positive and statistically significant, as in Agarwal, Daniel, and Naik (2009).

5 Systematic prime-broker shock propagation channel

Our results in the previous sections show that systematic financial intermediary risk is a key driver of hedge fund returns and that individual prime broker shocks can impact their hedge fund clients. In this section, we examine whether hedge funds' financial intermediary systematic risk exposures are simply a mechanical reflection of the assets that funds hold, or whether this risk is also partially driven by hedge funds' relationships with prime brokers.

In particular, we analyze hedge fund ex post financial intermediary betas, asking whether the observed betas are in excess of what is implied by hedge fund holdings. Our hypothesis is that during periods of prime broker distress, if prime brokers force hedge funds to modify their positions, the resulting financial intermediary exposure for these hedge funds could surpass that implied by a passive buy-and-hold strategy of their holdings. To illustrate the proposed mechanism, consider a scenario where, at the start of the month, Hedge Fund X holds shares of Stock A. Assume that Stock A is not influenced by financial intermediary shocks, yet it undergoes a temporary, firm-specific downturn mid-month, which fully recovers by month's end. Ideally, as a long-term investor, the hedge fund manager would not alter her position in A. However, if during this period the prime brokers are hit by a systematic shock, prime brokers may, via margin calls, compel the manager to liquidate her position in A at a loss. Observing Hedge Fund X's realized returns for the month would lead us to conclude that it incurred financial intermediary risk exposure, contradicting the expected buy-and-hold returns of Stock A. This example suggests that hedge fund intra-month trading could be systematically influenced by prime broker shocks.

Our goal is to identify the portion of a hedge fund's financial intermediary beta not reflected in the beta of its holdings. We model hedge fund returns, taking into account short selling and leverage, to establish testable predictions for financial intermediary betas. Due to the necessity of observing hedge fund holdings, we concentrate on the subset of funds that file Form 13F (i.e., those for which we observe equity holdings).[23] Our empirical strategy seeks to identify the excess financial intermediary beta among equity hedge funds and compare it with a control group of active equity mutual funds. Lacking prime broker affiliations, these mutual funds are expected not to exhibit comparable excess financial intermediary exposure. Our analysis reveals that hedge funds display a significant excess financial intermediary beta, particularly during adverse prime broker shocks, a pattern not observed in mutual funds. Additionally, we find no excess exposure to other equity factors like HML for either group, underscoring the unique role of financial intermediary risk. The detailed methodology and comprehensive results are delineated below.

5.1 Model of hedge fund returns

We introduce a model of hedge funds returns to help guide our empirical tests and their economic interpretations. We model fund i's monthly observed realized excess return in month t, $r_{i,t}$, as follows:

$$r_{i,t} = c_i + \ell_i \left[(1 - \omega_i) r^{\mathrm{O}}_{i,t} + \omega_i r^{\mathrm{U}}_{i,t} - \ell^{\mathrm{S}}_i r^{\mathrm{S}}_{i,t} \right] + r^{\mathrm{I}}_{i,t}, \tag{4}$$

where c_i represents fund i's fixed costs, $r^{\mathrm{O}}_{i,t}$, $r^{\mathrm{U}}_{i,t}$, $r^{\mathrm{S}}_{i,t}$ are fund i's excess returns on its observed long, unobserved long, and unobserved short positions, respectively, and $r^{\mathrm{I}}_{i,t}$ is the component of fund i's return stemming from the hedge fund's intra-month trading. We regard $r^{\mathrm{O}}_{i,t}$, $r^{\mathrm{U}}_{i,t}$, and $r^{\mathrm{S}}_{i,t}$ as returns on portfolios that are rebalanced only at the beginning of each month t. Hence, if a fund does not trade between rebalancing dates, $r^{\mathrm{I}}_{i,t}$ is equal to zero. ω_i denotes the share of fund's capital invested in unobserved long positions (ω_i lies between zero and one), $\ell^{\mathrm{S}}_i \geq 0$ denotes the fund's short exposure (e.g., if $\ell^S_i = 1$ the fund is short \$1 for every \$1 it has invested in long positions), and $\ell_i \geq 1$ denotes fund leverage, which we assume is applied uniformly at the fund level to all its positions.

[23] In the Internet Appendix, we confirm that systematic financial intermediary risk continues to significantly influence average hedge fund returns within the cross-section of hedge funds that file Form 13F.

We hypothesize that $r^{\mathrm{I}}_{i,t}$ is driven by systematic prime broker shocks and noise:

$$r^{\mathrm{I}}_{i,t} = \beta^{\mathrm{PBCh.}}_i r^{\mathrm{FI}}_t + \nu_{i,t}, \tag{5}$$

where r^{FI}_t is the excess return of the financial intermediary factor, and $\nu_{i,t}$ is a random shock, which could also potentially include idiosyncratic prime broker shocks. Intuitively, one can think of $\beta^{\mathrm{PBCh.}}_i r^{\mathrm{FI}}_t$ arising due to intra-month trading resulting from margin financing adjustments. For example, an adverse shock to the prime broker sector could result in a hedge fund being forced to unwind some of its positions at potentially unfavorable prices, affecting returns. Notably, this forced intra-month trading arises due to systematic financial intermediary shocks and cannot be easily diversified away by having multiple prime brokers as was discussed in Section 3.[24]

Combining equations (4) and (5) yields:

$$r_{i,t} = c_i + \ell_i \left[(1-\omega_i) r^{\mathrm{O}}_{i,t} + \omega_i r^{\mathrm{U}}_{i,t} - \ell^S_i r^{\mathrm{S}}_{i,t}\right] + \beta^{\mathrm{PBCh.}}_i r^{\mathrm{FI}}_t + \nu_{i,t}. \tag{6}$$

We further let portfolio components' excess returns follow a reduced-form model:

$$r^{\mathrm{O}}_{i,t} = \beta^{\mathrm{O}}_i r^{\mathrm{FI}}_t + \epsilon^{\mathrm{O}}_{i,t}, \tag{7a}$$

$$r^{\mathrm{U}}_{i,t} = \beta^{\mathrm{U}}_i r^{\mathrm{FI}}_t + \epsilon^{\mathrm{U}}_{i,t}, \tag{7b}$$

$$r^{\mathrm{S}}_{i,t} = \beta^{\mathrm{S}}_i r^{\mathrm{FI}}_t + \epsilon^{\mathrm{S}}_{i,t}, \tag{7c}$$

where all the random shocks, $\epsilon^{\mathrm{O}}_{i,t}$, $\epsilon^{\mathrm{U}}_{i,t}$, and $\epsilon^{\mathrm{S}}_{i,t}$ are orthogonal to r^{FI}_t. In our baseline implementation, we consider a two-factor representation with the market factor, r^{M}_t, and

[24]Barth et al. (2020) find approximately 94% of total borrowing by equity hedge funds, which are the focus of our empirical analysis, originates from their prime brokers. Therefore, in the face of an adverse systemic prime broker shock, these hedge funds are unlikely to easily substitute prime broker funding with an alternative source.

r_t^{FI}, but in the formulation above, we omit r_t^{M} to simplify the exposition. Then each fund's ex post beta on the financial intermediary factor, β_i, is given by:

$$\beta_i = \frac{\mathrm{Cov}\left(r_{i,t}, r_t^{\mathrm{FI}}\right)}{\mathrm{Var}\left(r_t^{\mathrm{FI}}\right)} = \ell_i\left[(1-\omega_i)\beta_i^{\mathrm{O}} + \omega_i\beta_i^{\mathrm{U}} - \ell_i^S\beta_i^{\mathrm{S}}\right] + \beta_i^{\mathrm{PBCh.}}. \tag{8}$$

5.2 Identification strategy

Our main object of interest is $\beta_i^{\mathrm{PBCh.}}$, that is the incremental financial intermediary beta, which we hypothesize is positive and arises due to prime broker-hedge fund connections. In other words, our null hypothesis is that $\beta_i^{\mathrm{PBCh.}} = 0$ and our alternative hypothesis is that $\beta_i^{\mathrm{PBCh.}} > 0$. Our approach is to measure the average $\beta_i^{\mathrm{PBCh.}}$ in the cross-section of hedge funds. To this end, we estimate the following cross-sectional regression:

$$\widehat{\beta}_i = a + b\widehat{\beta}_i^{\mathrm{O}} + \varepsilon_i, \tag{9}$$

where $\widehat{\beta}_i$ ($\widehat{\beta}_i^{\mathrm{O}}$) is financial intermediary beta estimate from time-series OLS regressions of $r_{i,t}$ ($r_{i,t}^{\mathrm{O}}$) on r_t^{M} and r_t^{FI}.

The OLS estimator of the slope is

$$\widehat{b} = \frac{\mathrm{Cov}\left(\widehat{\beta}_i, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)} = \frac{\mathrm{Cov}\left(\ell_i\left[(1-\omega_i)\widehat{\beta}_i^{\mathrm{O}} + \omega_i\widehat{\beta}_i^{\mathrm{U}} - \ell_i^S\widehat{\beta}_i^{\mathrm{S}}\right] + \widehat{\beta}_i^{\mathrm{PBCh.}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)}. \tag{10}$$

In order to identify $\beta_i^{\mathrm{PBCh.}}$ we make the following assumptions:

$$\beta_i^S = s_i\left[(1-\omega_i)\beta_i^{\mathrm{O}} + \omega_i\beta_i^{\mathrm{U}}\right] + \zeta_i, \tag{11a}$$

$$\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right) = 0, \tag{11b}$$

$$\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{PBCh.}}, \widehat{\beta}_i^{\mathrm{O}}\right) = 0, \tag{11c}$$

where s_i represents the proportion of long positions' beta that is hedged with short positions (e.g., if a fund aims to hedge all its long beta exposure, s_i would be equal to one), and ζ_i is the residual financial intermediary beta of fund i's short positions that is independent of its long positions. We assume that $\mathrm{E}(\zeta_i) = 0$, which implies that hedge funds, on average, hold no incremental short exposure to financial intermediary risk that is independent of their long positions. Assumption (11a) is motivated by two considerations. First, hedge funds, particularly equity hedge funds, are known to match their long and short positions based on firm characteristics to offset systematic risk. The "pairs trading" strategy that is implemented by simultaneously going long and short in two similar firms is a clear example of this approach (see, e.g., Gatev, Goetzmann, and Rouwenhorst, 2006). Second, an assumption commonly made in empirical asset pricing, which is supported by empirical evidence, is that factor betas depend on characteristics (see, e.g., Koijen and Yogo, 2019; Daniel, Mota, Rottke, and Santos, 2020). Therefore, if we assume that hedge funds short stocks resembling those they hold long, and that betas are driven by stock characteristics, then the betas of funds' short positions would correlate with those of their long positions, regardless of whether fund managers explicitly consider these betas when selecting their shorts. Assumption (11b) posits that the financial intermediary betas of the observed long positions are, on average, independent of the betas of the unobserved long positions. A plausible alternative posits a positive correlation between the two betas, stemming from the potential specialization of hedge funds in certain types of firms, holding, for example, both equity and debt of the same firm. Our assumption, however, is conservative. We show in the Internet Appendix that a positive covariance would bias our estimates towards zero, making it more challenging to detect a significant prime broker propagation effect. Assumption (11c) posits that the financial intermediary betas of the observed long positions are, on average, independent of the incremental beta from the hedge-fund-prime-broker channel. This condition is consistent with the null hypothesis of no prime broker propagation effect. In sum, even though we cannot observe some of the hedge funds' positions, our identification strategy, under reasonable assumptions, enables us to estimate the average excess financial intermediary beta of hedge funds effectively.

We then have that

$$\widehat{b} = \bar{\ell}(1-\bar{\omega}) - \bar{\ell}(1-\bar{\omega})\bar{s}\bar{\ell}^{\mathrm{S}} \times \mathrm{AF}, \tag{12}$$

where the bar denotes a cross-sectional mean (e.g., $\bar{\ell}$ is the cross-sectional average fund leverage), and $\mathrm{AF} = \mathrm{Var}(\beta_i^{\mathrm{O}})/\mathrm{Var}(\widehat{\beta}_i^{\mathrm{O}}) \leq 1$ is the attenuation bias factor arising as the result of the regressor being estimated.

The intercept estimator is given as

$$\widehat{a} = \bar{\beta} - \widehat{b} \times \bar{\beta}^{\mathrm{O}} = \left(1 - \bar{\ell}^{\mathrm{S}}\bar{s}\right)\bar{\ell}\bar{\omega}\bar{\beta}^{\mathrm{U}} - (1-\mathrm{AF})\bar{\ell}(1-\bar{\omega})\bar{s}\bar{\ell}^{\mathrm{S}}\bar{\beta}^{\mathrm{O}} + \bar{\beta}^{\mathrm{PBCh.}}. \tag{13}$$

From equation (13), we observe that the attenuation bias factor reduces the probability of detecting a positive $\widehat{a}$. Consequently, being as conservative as possible, we assume $\mathrm{AF} = 1$ when interpreting our main results. Given $\widehat{a}$ and our assumptions, the average incremental financial intermediary beta (prime-broker-channel beta) can be approximated by:

$$\bar{\beta}^{\mathrm{PBCh.}} = \widehat{a} - \left(1 - \bar{\ell}^{\mathrm{S}}\bar{s}\right)\bar{\ell}\bar{\omega}\bar{\beta}^{\mathrm{U}}. \tag{14}$$

5.3 Variable construction

The two key variables necessarily for our empirical strategy are $r_{i,t}$ and $r_{i,t}^{\mathrm{O}}$. For $r_{i,t}$, we use each fund's reported net returns in excess of the risk-free rate, $r_{f,t}$. Given that hedge fund holdings are reported at the manager level, in the event that a manager has multiple funds, $r_{i,t}$ is computed as an asset-weighted portfolio excess return of each manager's individual funds. For $r_{i,t}^{O}$, following Kacperczyk et al. (2008), we define it as the total excess return on a hypothetical buy-and-hold portfolio based on the most recently disclosed stock positions.

$$r_{i,t}^{O} = \sum_{j=1}^{n} \tilde{w}_{j,t-1} r_{j,t} - r_{f,t}, \tag{15}$$

where $r_{j,t}$ is a monthly return for stock j, and $\tilde{w}_{j,t-1}$ is the weight of stock j in a fund's portfolio. The weights depend on the number of shares held by the fund at the most recent disclosure data at time $t-\tau$, $N_{j,t-\tau}$, and the stock price at the end of the previous month, $P_{j,t-1}$ (adjusted for stock splits and other share adjustments when necessary):

$$\tilde{w}_{j,t-1} = \frac{N_{j,t-\tau} P_{j,t-1}}{\sum_{j}^{n} N_{j,t-\tau} P_{j,t-1}}. \tag{16}$$

5.4 Sample selection and descriptive statistics

Our approach to estimating $\beta_i^{\text{PBCh.}}$ involves comparing hedge funds with mutual funds (our control group), under the expectation that mutual funds' financial intermediary risk is entirely determined by their holdings, unaffected by the prime broker channel. To facilitate comparison to mutual funds and ease of interpretation, we concentrate on a uniform group of independent hedge fund managers where we can observe most of their long positions. In particular, we consider only the managers with, at most, five individual hedge funds, all of which must have a global or North American investment focus and predominantly invest in equities (as identified by their style, such as "Long-Short Equities" or "Equity Market Neutral"). Moreover, we require the median of the absolute value of the logarithm of the ratio of holdings market value to reported fund AUM to be less than log(5).[25] After implementing these filters, we arrive at our final sample of 523 hedge fund managers.[26]

Table 6 presents the descriptive statistics for our sample of hedge funds (Panel A), and our sample of US mutual funds (Panel B) that we use as a control group. We observe,

[25] The Internet Appendix provides details on the hedge fund sample selection.
[26] In robustness tests, we confirm that our empirical results are similar if we instead consider all the 1,305 matched managers with 13F filings.

on average, around eight years of returns for each hedge fund, and around seven years of returns for each mutual fund. The average (median) hedge fund size is around $409 ($216) million. The average mutual fund size is larger ($984 million) due to the presence of a few mega funds, but the median mutual fund is of similar size to that of hedge funds ($206 million). The average (median) number of stocks held by hedge funds is 74 (40), while mutual funds typically hold slightly more stocks in their portfolios, with the average (median) holdings being 90 (61) stocks. The average (median) ratio of holdings market value to reported AUM (TNA Ratio) is 1.41 (1.00) for hedge funds, implying that hedge funds typically use some leverage. In contrast, the average (median) TNA Ratio of mutual funds is 0.94 (0.96), implying that equity mutual funds do not use leverage and remain fully invested except for a small liquidity cushion of around 6% of AUM. We find that the average (median) stock turnover in hedge funds is around 22% (20%) per quarter and is only 11% (9%) in mutual funds, which is consistent with economic intuition as hedge funds are considered more active traders.

We also report descriptive statistics for the holdings and fund (reported) return betas. The betas are estimated using a two-factor model, with the market as the first factor and either financial intermediary factor or Fama and French (1993) HML as the second factor. We use the HML factor as a placebo in our main analysis. As anticipated, the average holdings-implied market beta is approximately 1, aligning precisely for mutual funds, which typically mirror the market portfolio. The average market beta for hedge fund holdings is slightly higher at 1.12, indicating a propensity for selecting stocks with higher betas. The average fund market beta for mutual funds is essentially identical to their average holdings beta (0.96). In contrast, the average fund market beta for hedge funds is only 0.48, demonstrating the effect of short positions. For mutual funds, the FI holdings and fund betas are 0.013 and 0.010, respectively. Lastly, hedge funds show slightly larger FI holdings betas at 0.016 and notably higher fund betas at 0.026.

5.5 Prime broker channel empirical results

Equation (14) implies that, to establish evidence of the prime broker shock propagation channel, the hypothesis to be tested is as follows:

$$H_0 : \widehat{\beta}^{\text{PBCh.}} \equiv \widehat{a} - \left(1 - \bar{\ell}^{\text{S}} \bar{s}\right) \bar{\ell} \bar{\omega} \bar{\beta}^{\text{U}} = 0$$

$$H_1 : \widehat{\beta}^{\text{PBCh.}} \equiv \widehat{a} - \left(1 - \bar{\ell}^{\text{S}} \bar{s}\right) \bar{\ell} \bar{\omega} \bar{\beta}^{\text{U}} > 0.$$

In other words, the estimated intercept, $\widehat{a}$, needs to be both positive and sufficiently large. To test this hypothesis, we require values for the different parameters. For our benchmark results, we choose economically reasonable parameters based on existing literature and descriptive statistics, but verify that our results are robust to different choices for the values of these parameters.[27]

Panel A of Table 7 reports the benchmark empirical results from regression (9). We report the results for all the test variations separately for hedge funds and mutual funds. We find that, for hedge funds, $\widehat{\beta}^{\text{PBCh.}}$ is positive, equal to 0.021, and statistically significant at the 1% level (i.e., the estimated $\widehat{a}$ exceeds the parameterized model implied intercept). This indicates that hedge funds, on average, possess additional exposure to financial intermediary risk above and beyond their holdings. In contrast, mutual funds exhibit no such extra

[27] We use the findings of Barth et al. (2020), who study leverage dynamics of hedge funds utilizing comprehensive regulatory data, to guide our choice of $\bar{\ell}$ and $\bar{\ell}^{\text{S}}$. They find that an average equity hedge fund's gross leverage is 1.57, and it has around \$0.57 (=0.89/1.57) of short positions for every \$1 in long positions. We therefore choose $\bar{\ell}$ and $\bar{\ell}^{\text{S}}$ to be 1.57 and 0.57, respectively. We choose $\bar{s} = 1$, assuming that hedge funds, on average, aim to perfectly match the risk exposures of their long and short positions (we verify that our results are robust to smaller values of $\bar{s}$). Guided by our summary statistics we choose $\bar{\omega} = 0.23$. Our choice is based on monthly turnover of around 11% (i.e., rebalancing) and an assumption that, on average, around 12% of hedge fund assets remain unobserved. In particular, using 13F holdings, we find that on average, 6% of mutual fund positions remain unobserved, likely due to them being held in cash or short-term risk-free debt to manage liquidity and to take advantage of short-term market timing opportunities. We assume that this unobserved portion is twice as high for hedge funds, i.e., around 12% of AUM. Lastly, we choose $\bar{\beta}^{\text{U}} = 0.016$, which is equal to the average hedge fund holdings beta (we assume that the unobserved positions stem from the same universe as the observed, which is reasonable given that a large fraction of unobserved position is due to portfolio rebalancing). For mutual funds the choice is simpler, as they neither short nor use leverage i.e., $\bar{\ell}$ and $\bar{\ell}^{\text{S}}$ are one and zero, respectively. Hence, we only need to choose the values of $\bar{\beta}^{\text{U}}$ and $\bar{\omega}$. We set $\bar{\beta}^{\text{U}}$ as 0.013 (average mutual fund holdings FI beta) and set $\bar{\omega}$ to 0.125 (the sum of expected monthly turnover, 5.5%, and unobserved positions, 6%).

exposure. To assess the economic significance, we contrast $\widehat{\beta}^{\text{PBCh.}}$ with both the standard deviation of the holdings' FI betas and the standard deviation of Fama-French industry portfolios' FI beta. The latter is advantageous as it facilitates comparability between hedge funds and mutual funds and is independent of the data used in the estimation. For hedge funds, $\widehat{\beta}^{\text{PBCh.}}$ constitutes approximately 11.6% of the standard deviation of hedge fund holdings' FI beta and 13.3% of the standard deviation of Fama-French industry portfolios' FI beta, respectively. This indicates an economically meaningful excess FI beta, which is consistent with a prime broker shock propagation channel.

We posit that the prime broker shock propagation channel, if present, would mainly manifest through negative shocks to financial intermediaries, indicating an asymmetric effect. Specifically, prime brokers, during periods of adverse shocks, could induce hedge funds to adjust their positions via margin calls and other funding pressures. It is, however, unlikely that prime brokers could as seamlessly induce hedge funds to trade during good periods by extending them additional credit and services. To investigate this, we partition the analysis, estimating downside betas from months with negative FI factor returns and upside betas from those with positive returns. Considering first the downside FI betas, we observe for hedge funds positive and economically large $\widehat{a}$ (0.083), which is around four times greater than the model implied intercept. The difference, i.e., downside $\widehat{\beta}^{\text{PBCh.}}$, is statistically significant at the 1% level and constitutes 26.1% of the standard deviation of Fama-French industry portfolios' downside FI beta. In contrast, mutual funds show an $\widehat{a}$ that is also positive but over eight times smaller than that of hedge funds, and it is not statistically greater than the model implied intercept (p-value = 0.698). However, when analyzing upside FI betas, we identify negligible and negative $\widehat{a}$ that are consistent across both mutual funds and hedge funds. These asymmetrical outcomes support our hypothesis that hedge funds' additional exposure to financial intermediary risk occurs exclusively via negative shocks to financial intermediaries. Hedge funds notably incur negative impacts during periods of prime brokers' distress, yet do not equally benefit from positive shocks in prime broker performance. This is in line with the prime broker shock propagation channel.

We conduct a placebo test, repeating our entire analysis by replacing the FI factor with HML (Panel B of Table 7). Our expectations are that neither hedge funds nor mutual funds should have systematically larger exposure to HML above and beyond their holdings.[28] In line with our intuition, we find that $\widehat{a}$ is never greater than the model implied intercept for hedge funds or mutual funds. Our empirical model also makes predictions about the estimated slope coefficient, as outlined in equation (12). To verify the consistency of our estimates given our chosen parameter values, we compare the estimated slope $\widehat{b}$ with the parameterized model's implied slope, which is derived independently of the factor model. For hedge funds, the parameterized model-implied slope is 0.570, closely matched by the estimated $\widehat{b}$, which ranges from 0.506 to 0.574 across different specifications. This suggests that our chosen parameter values are reasonable.

Nevertheless, we conduct some sensitivity analysis of our estimates using different parameter values. In particular, we vary $\bar{\omega}$ and $\bar{s}$, as we do not have precise estimates for these parameters. Although we have reliable estimates from Barth et al. (2020) for $\bar{\ell}$ and $\bar{\ell}^{\mathrm{S}}$ (the average hedge fund leverage and the average long/short ratio, respectively), we also vary these parameters in our sensitivity analysis. We ascertain that our principal conclusions remain essentially unaffected by all reasonable selections of the model's parameters (the Internet Appendix provides sensitivity analysis results).

Lastly, we confirm that our results are robust across different models for estimating financial intermediary betas. Although our primary analysis uses a two-factor model with market and FI factors, we also examine the Fama and French (1993, 2015) three and five-factor models augmented with the FI factor. Our findings remain consistent across these models, as detailed in the Internet Appendix, which reports these alternative specifications.

[28] As previously mentioned, our tests necessitate assumptions about certain parameters, including $\bar{\beta}^{\mathrm{U}}$, the average exposure of unobserved positions. We posit that the average HML holdings beta serves as a reasonable proxy for $\bar{\beta}^{\mathrm{U}}$. It is unlikely that the HML exposures of hedge funds' unobserved positions would systematically deviate from those of their observed positions.

In summary, the empirical evidence presented confirms the impact of the prime broker shock propagation channel on hedge funds. The significant positive $\widehat{\beta}^{\mathrm{PBCh.}}$ for hedge funds indicates an additional exposure to financial intermediary risk, which extends beyond what their holdings alone can explain, and is particularly evident during negative financial intermediary shocks. In contrast, mutual funds do not exhibit similar excess exposure. The asymmetry in this risk exposure is highlighted by the distinct downside FI betas for hedge funds compared to those for mutual funds. Placebo tests using the HML factor further validate the unique nature of hedge funds' financial intermediary risk exposure.

6 Conclusion

Our paper presents comprehensive evidence of prime brokers' significant impact on hedge fund performance. We find that hedge funds are adversely affected by large, negative shocks to their individual prime brokers, with the impact predominantly confined to funds exclusively reliant on the affected broker. This suggests that the risks associated with idiosyncratic prime broker shocks are diversifiable. However, systematic financial intermediary risk appears to be less easily mitigated. We establish systematic financial intermediary risk as a crucial determinant in the cross-section of hedge fund returns. Given that the lion's share of hedge fund borrowing is short-term and stems from prime brokers, hedge funds can be compelled to adjust their positions via leverage adjustments in times of prime broker distress, thus propagating prime broker shocks. This leads to hedge funds' ex post financial intermediary exposure exceeding that implied by a portfolio of their holdings. In line with this, we find that the average hedge fund's exposure to systematic intermediary risk exceeds what their holdings imply. This additional risk exposure is asymmetric, manifesting during adverse systematic intermediary shocks. This is in stark contrast to mutual funds, which do not exhibit such effects, highlighting the unique vulnerability of hedge funds to the prime brokerage shock propagation channel.

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Table 1: Hedge fund summary statistics

The table presents summary statistics for hedge funds from the union database (BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS), segmented by different time periods and styles and for hedge funds from the Eurekahedge database that report prime broker affiliations. N_{Funds} and N_{Mgrs} represent the total number of unique hedge funds and management companies, respectively. μ_{TS} and σ_{TS} are cross-sectional averages of each fund's average monthly excess returns and each fund's standard deviation of its monthly excess returns. σ_{XS} is the time-series average of monthly cross-sectional standard deviation of excess returns. μ_{TS}, σ_{TS}, and σ_{XS} are expressed in % and are annualized. The AUM statistics are time-series averages of monthly cross-sectional statistics (USD million), reflecting a typical distribution of hedge fund sizes available in a specific month within the sample. The sample period runs from January 2000 to June 2021.

	N_{Funds}	N_{Mgrs}	μ_{TS}	σ_{TS}	σ_{XS}	AUM_{Mean}	AUM_{Q25}	AUM_{Q50}	AUM_{Q75}
Full sample	16,160	7,103	5.06	15.04	10.91	348	12	47	181
Sub-sample									
2000/01 – 2007/12	6,052	3,324	9.02	12.72	12.09	177	11	37	132
2008/01 – 2009/12	4,650	2,645	2.43	21.22	14.03	248	12	43	156
2010/01 – 2017/06	9,616	4,463	3.73	13.52	9.18	397	12	45	178
2017/07 – 2021/06	6,288	2,998	5.99	16.01	12.42	647	17	69	299
Style									
CTA	1,093	699	4.77	15.71	11.40	454	5	20	92
Emerging Markets	567	343	6.51	18.47	10.42	230	15	51	157
Event Driven	1,031	702	6.14	11.99	9.30	374	27	87	285
Global Macro	1,943	1,256	4.18	14.27	12.10	370	10	40	177
Long Only	992	573	7.41	18.91	8.84	329	15	54	176
Long Short	5,931	3,441	5.15	15.69	9.67	241	13	43	153
Market Neutral	278	227	2.71	11.04	6.47	172	15	51	165
Multi Strategy	1,228	774	2.98	14.60	10.35	468	12	41	174
Other	818	319	6.89	21.53	21.42	131	10	31	100
Relative Value	2,113	1,168	4.14	10.33	8.58	602	25	92	373
Sector	144	83	12.02	18.45	8.37	687	35	90	305
Short Bias	22	18	-1.86	16.70	8.81	36	13	23	40
Database									
Eurekahedge	5,397	3,046	5.92	15.06	8.82	219	14	50	178

Table 2: Event studies

This table presents panel regressions of monthly hedge fund risk-adjusted returns (in %) on various indicator variables and their interactions. The risk-adjusted returns equal the constant plus the residuals from individual regressions of hedge fund excess returns on the Fung and Hsieh (2004) seven factors. Lehman Event is an indicator variable equal to one during the event window around the Lehman bankruptcy (September 2008) and zero otherwise. Lehman Client is an indicator variable that is equal to one if a hedge fund was a Lehman client during the bankruptcy event. PB Events is an indicator variable that is equal to one during the prime broker event window. The three prime broker events considered are the failure of Bear Stearns (March 2008), the trading loss scandal of UBS (September 2011), and the trading loss scandal of JP Morgan (April 2012). PB Client is an indicator variable that is equal to one if a hedge fund was a client of the affected prime broker during its respective event. Lehman Unique Client and PB Unique Client are indicator variables equal to one if a hedge fund uses one of the affected prime brokers as the sole prime broker during the event window. One Broker is an indicator variable equal to one if a hedge fund is affiliated with only a single prime broker. In specifications I−IV, the event window is three months: the month before, the event month, and the month after (referred to as 1 & 1). Specifications V and VI consider a four month (1 & 2) and five month (1 & 3) event window, respectively. Hedge fund fixed effects are included in all specifications. Controls include lagged hedge fund AUM, age, and return. Standard errors in parentheses are clustered by fund and time. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample period runs from January 2000 to June 2021.

	I	II	III	IV	V	VI
Lehman Event	−1.842	−1.842	−1.838	−1.600	−1.032	−0.952
	(1.326)	(1.326)	(1.340)	(1.089)	(0.955)	(0.769)
Lehman Event × Lehman Client	−0.921	0.760	0.845**	0.610	−0.066	0.197
	(0.675)	(0.471)	(0.397)	(0.419)	(0.606)	(0.530)
Lehman Event × Lehman Unique Client		−3.067***	−2.958***	−2.681***	−2.653***	−2.160***
		(0.797)	(0.670)	(0.614)	(0.614)	(0.774)
Lehman Event × One Broker				−0.282	−0.177	−0.070
				(0.320)	(0.260)	(0.230)
PB Events	−0.708	−0.708	−0.709	−0.588	−0.506	−0.508*
	(0.610)	(0.610)	(0.601)	(0.394)	(0.317)	(0.259)
PB Events × PB Client	−0.230***	0.122	0.185	0.092	0.094	0.090
	(0.086)	(0.128)	(0.156)	(0.139)	(0.124)	(0.117)
PB Events × PB Unique Client		−0.533***	−0.463**	−0.348**	−0.274*	−0.300**
		(0.199)	(0.195)	(0.153)	(0.141)	(0.142)
PB Events × One Broker				−0.149	−0.125	−0.020
				(0.308)	(0.251)	(0.219)
Observations	561,841	561,841	556,444	556,444	556,444	556,444
Adjusted R^2	0.017	0.017	0.029	0.029	0.028	0.028
Hedge fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Event window	1 & 1	1 & 1	1 & 1	1 & 1	1 & 2	1 & 3

Table 3: Top prime brokers over time

The table presents the market share of leading prime brokers based on hedge funds that report their prime broker affiliation and AUM to Eurekahedge (captured in snapshots from 2008, 2010, 2014, 2017, and 2021). Prime brokers are ranked by their hedge fund clients' total AUM. Market share percentages for the top 10 prime brokers are shown in parentheses next to their names. The table also reports the market shares (in %) of the top 10 and top 20 prime brokers, and the market share of prime brokers that are Fed Primary Dealers (Fed PD). Abbreviations are as follows: BAML: Bank of America Merrill Lynch, BNP P: BNP Paribas, BS: Bear Stearns, CS: Credit Suisse, DB: Deutsche Bank, GS: Goldman Sachs, IB: Interactive Brokers, JPM: J.P. Morgan, LB: Lehman Brothers, MF G: MF Global, ML: Merrill Lynch, MS: Morgan Stanley, and SocGen: Societe Generale.

	2008	2010	2014	2017	2021
1	MS (22.1)	MS (18.0)	GS (15.9)	GS (19.3)	MS (12.9)
2	GS (18.8)	GS (15.3)	CS (12.9)	MS (13.6)	GS (11.5)
3	BS (13.1)	JPM (14.3)	MS (10.4)	CS (11.9)	Barclays (10.3)
4	DB (8.4)	UBS (10.8)	UBS (10.3)	JPM (10.5)	UBS (9.7)
5	UBS (8.0)	CS (8.4)	JPM (10.1)	UBS (8.1)	JPM (9.3)
6	ML (3.6)	DB (6.5)	BAML (6.9)	DB (7.1)	BAML (6.5)
7	CS (3.6)	SocGen (4.5)	DB (6.0)	BAML (5.9)	CS (5.5)
8	LB (3.0)	BAML (3.7)	Citi (5.5)	Barclays (4.2)	DB (4.3)
9	SocGen (3.0)	Citi (3.1)	Barclays (5.1)	SocGen (3.5)	SocGen (4.0)
10	Citi (2.6)	BNP P (2.6)	SocGen (3.2)	Citi (3.3)	SEB (3.3)
Top 10	86.2	87.3	86.2	87.3	77.4
Top 20	94.8	94.9	95.2	95.8	91.2
Fed PD	88.3	86.5	91.7	92.4	83.6

Table 4: Risk-adjusted returns for financial intermediary beta-sorted portfolios

The table presents hedge fund portfolios' mean excess returns, alphas and betas. These equal-weight portfolios are formed by sorting on betas from 24-month rolling regressions of hedge fund excess returns on the financial intermediary factor of He et al. (2017), FI, controlling for the market excess return and rebalanced monthly. Hedge funds in Portfolio 1 have the lowest beta on the FI factor and funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return, and α_{CAPM} and α_{FH7} refer to CAPM and Fung and Hsieh (2004) seven-factor alpha, respectively. $\bar{r}$, α_{CAPM} and α_{FH7} are expressed in % per month. The post-formation betas are the betas from time-series regression of the 10 portfolios' excess returns on the FI and market factors. The pre-formation betas are the monthly means of hedge funds' rolling factor betas in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2021.

				Post betas		Pre betas	
	$\bar{r}$	α_{CAPM}	α_{FH7}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.26	−0.09	−0.39	−0.04	0.66	−0.46	1.00
	(0.30)	(0.20)	(0.21)	(0.07)	(0.12)	(0.03)	(0.07)
2	0.35	0.08	−0.16	0.02	0.42	−0.19	0.61
	(0.20)	(0.12)	(0.12)	(0.04)	(0.07)	(0.02)	(0.04)
3	0.34	0.11	−0.09	0.04	0.34	−0.10	0.47
	(0.18)	(0.11)	(0.10)	(0.03)	(0.05)	(0.01)	(0.03)
4	0.35	0.14	−0.04	0.03	0.31	−0.05	0.37
	(0.15)	(0.08)	(0.08)	(0.03)	(0.05)	(0.01)	(0.02)
5	0.39	0.20	0.03	0.04	0.28	−0.00	0.31
	(0.14)	(0.09)	(0.07)	(0.03)	(0.05)	(0.01)	(0.02)
6	0.42	0.23	0.09	0.06	0.25	0.04	0.29
	(0.14)	(0.09)	(0.08)	(0.02)	(0.04)	(0.01)	(0.02)
7	0.41	0.21	0.05	0.07	0.25	0.08	0.27
	(0.14)	(0.10)	(0.10)	(0.03)	(0.05)	(0.02)	(0.02)
8	0.44	0.22	0.05	0.09	0.27	0.13	0.27
	(0.16)	(0.13)	(0.13)	(0.04)	(0.06)	(0.02)	(0.03)
9	0.51	0.25	0.10	0.13	0.28	0.22	0.24
	(0.18)	(0.15)	(0.14)	(0.04)	(0.07)	(0.03)	(0.03)
10 (high)	0.75	0.44	0.19	0.23	0.24	0.52	0.12
	(0.24)	(0.20)	(0.17)	(0.05)	(0.08)	(0.05)	(0.10)
10–1	0.48	0.53	0.58	0.27	−0.41	0.98	−0.88
	[2.26]	[2.13]	[2.23]	[4.22]	[−3.76]	[14.74]	[−7.92]

Table 5: Hedge fund financial intermediary risk premium

The table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly hedge fund excess returns on rolling financial intermediary betas. Betas are estimated by 24-month rolling regressions of hedge fund excess returns on the financial intermediary factor, FI, and the market excess return. Time $t+1$ monthly hedge fund excess returns (in %) are regressed on the time t rolling FI and market betas as well as fund's previous month's return (r_t, in %), age (in months), log of AUM, management fee (in %), incentive fee (in %), a high watermark indicator for the fund, a lockup provision indicator for the fund, the redemption notice (in days), and the minimum fund investment amount (USD million). Style fixed effects are dummies following the Kosowski et al. (2016) mapping. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). The total number of observations, the number of time-series (TS) observations, the mean number of cross-sectional (XS) observations as well as the mean R^2 of the cross-sectional regressions are also reported. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample runs from January 2000 to June 2021.

	I	II	III	IV
β^{FI}	0.303**	0.272**	0.693***	0.477**
	(0.126)	(0.117)	(0.244)	(0.219)
β^{M}			0.355*	0.314*
			(0.193)	(0.169)
r_t				0.059***
				(0.010)
Age				−0.006***
				(0.002)
log(AUM)				−0.009
				(0.013)
Managment fee				0.047***
				(0.014)
Incentive fee				0.004**
				(0.002)
High water mark				0.065**
				(0.027)
Lockup				0.060**
				(0.024)
Redemption notice				0.001***
				(0.000)
Minimum investment				0.001
				(0.000)
Constant	0.422***			
	(0.125)			
Style fixed effects	No	Yes	Yes	Yes
Total observations	1,167,620	1,167,620	1,167,620	999,564
TS observations	258	258	258	258
Mean XS observations	4,526	4,526	4,526	3,874
Mean R^2	0.014	0.051	0.094	0.112

Table 6: Hedge fund and mutual fund holdings data

This table presents cross-sectional summary statistics (mean, standard deviation, Q25, Q50 and Q75) of the sample of hedge funds (Panel A) and mutual funds (Panel B) described in Section 2. The first row reports statistics on the number of time-series observations per fund. The next four rows report the statistics of the time-series medians of fund AUM (in USD billion), the ratio of holdings market value to reported AUM (TNA Ratio), the number of stocks held and the quarterly turnover (the minimum of dollar value of buys and sales divided by the average AUM across the two adjacent quarters). Market and FI betas are the coefficients from regressing monthly reported/holdings-implied excess returns on the market and the FI factor. Similarly, HML betas are derived from regressing monthly reported/holdings-implied excess returns on the market and the Fama and French (1993) HML factor. The sample period runs from January 2000 to June 2021.

Panel A: Hedge Funds

Statistic	Mean	Std.Dev.	Q25	Q50	Q75
Number of TS Observations	90.351	57.316	42.000	75.000	126.000
AUM	0.409	0.478	0.106	0.216	0.478
TNA Ratio	1.406	1.062	0.684	1.005	1.834
Number of Holdings	73.889	88.051	22.000	40.000	81.000
Turnover	0.218	0.125	0.110	0.198	0.318
Beta Market					
Reported	0.475	0.377	0.158	0.429	0.726
Holdings-implied	1.122	0.327	0.905	1.097	1.300
Beta FI					
Reported	0.023	0.140	−0.064	0.018	0.108
Holdings-implied	0.016	0.176	−0.090	0.009	0.103
Beta HML					
Reported	−0.006	0.291	−0.156	−0.000	0.158
Holdings-implied	0.019	0.352	−0.207	0.010	0.252

Panel B: Mutual Funds

Statistic	Mean	Std.Dev.	Q25	Q50	Q75
Number of TS Observations	82.177	37.198	45.000	86.000	116.750
AUM	0.984	1.713	0.050	0.206	0.978
TNA Ratio	0.936	0.075	0.922	0.959	0.983
Number of Holdings	90.057	79.686	41.000	60.500	100.500
Turnover	0.107	0.068	0.055	0.091	0.141
Beta Market					
Reported	0.958	0.177	0.840	0.962	1.086
Holdings-implied	1.004	0.162	0.878	0.995	1.121
Beta FI					
Reported	0.010	0.105	−0.068	0.004	0.085
Holdings-implied	0.013	0.110	−0.069	0.006	0.089
Beta HML					
Reported	0.003	0.247	−0.185	0.021	0.197
Holdings-implied	0.015	0.260	−0.184	0.026	0.216

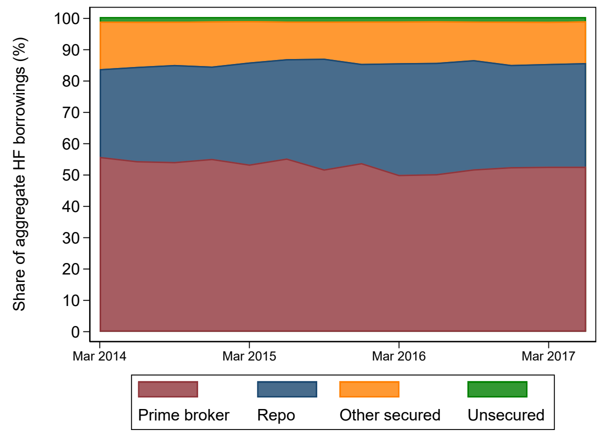
Table 7: Prime broker channel

This table presents the results from a test for excess systematic financial intermediary risk exposure, $\beta^{\text{PBCh.}}$, described in Section 5. Panel A presents the main specification considering a two-factor model comprised of market and FI factors, while Panel B presents the placebo specification considering a two-factor model of market and Fama and French (1993) HML factors. $\widehat{a}$ is the intercept and is $\widehat{b}$ the slope coefficient from a cross-sectional regression of factor betas estimated from reported returns on the factor betas estimated from the holdings-based returns. Downside factor betas, β_{down}, are estimated using the months with negative factor returns, and upside betas, β_{up}, are estimated using the months with positive factor returns. White (1980) standard errors are reported in parentheses. a_{model} is the regression intercept implied by the parameterized model of fund returns (see equation (14) and Subsection 5.5 for discussion on parameter choice). $\widehat{\beta}^{\text{PBCh.}}$ is the estimate of the prime broker channel beta, calculated as the difference between $\widehat{a}$ and a_{model}. The p-value of a one-sided test is reported in brackets. The last two columns report measures of the economic effect of the estimates. $\widehat{\beta}^{\text{PBCh.}}/\sigma(\beta_{Ind})$ is $\widehat{\beta}^{\text{PBCh.}}$ divided by the standard deviation of corresponding holdings betas. $\widehat{\beta}^{\text{PBCh.}}/\sigma(\beta_{Ind})$ is $\widehat{\beta}^{\text{PBCh.}}$ divided by the standard deviation of corresponding betas within the 49 Fama-French industry portfolios. The sample period runs from January 2000 to June 2021.

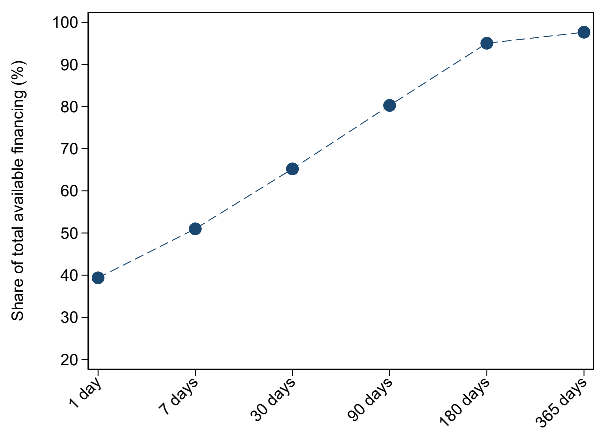
	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Ind})}$
Panel A: Financial intermediary factor								
Hedge funds								
β^{FI}	0.023	0.547	0.385	523	0.002	0.020	11.62%	13.27%
	(0.005)	(0.052)				[0.000]		
β^{FI}_{down}	0.083	0.512	0.272	357	0.018	0.065	27.68%	26.06%
	(0.014)	(0.068)				[0.000]		
β^{FI}_{up}	−0.003	0.574	0.360	382	0.011	−0.015	−6.50%	−7.53%
	(0.008)	(0.062)				[0.961]		
Mutual funds								
β^{FI}	−0.001	0.926	0.936	1,834	0.001	−0.003	−2.27%	−1.62%
	(0.001)	(0.007)				[1.000]		
β^{FI}_{down}	0.007	0.929	0.888	1,251	0.008	−0.001	−0.45%	−0.23%
	(0.002)	(0.012)				[0.630]		
β^{FI}_{up}	−0.003	0.945	0.945	1,410	0.001	−0.004	−2.22%	−1.83%
	(0.001)	(0.008)				[1.000]		
Panel B: HML (placebo)								
Hedge funds								
β^{HML}	0.003	0.513	0.383	523	0.003	0.000	0.08%	0.09%
	(0.010)	(0.039)				[0.489]		
β^{HML}_{down}	0.030	0.535	0.365	389	0.009	0.020	4.32%	4.98%
	(0.017)	(0.050)				[0.121]		
β^{HML}_{up}	0.014	0.506	0.366	338	0.010	0.004	1.09%	1.29%
	(0.015)	(0.048)				[0.387]		
Mutual funds								
β^{HML}	−0.008	0.943	0.971	1,834	0.002	−0.010	−3.77%	−3.12%
	(0.001)	(0.005)				[1.000]		
β^{HML}_{down}	0.001	0.921	0.933	1,499	0.008	−0.007	−2.29%	−1.70%
	(0.002)	(0.017)				[1.000]		
β^{HML}_{up}	−0.010	0.947	0.959	1,189	0.002	−0.012	−4.09%	−3.73%
	(0.002)	(0.008)				[1.000]		

Figure 1: Aggregate hedge fund borrowings

Panel (a) shows the percentage share of each source of aggregate hedge fund borrowings. Panel (b) shows hedge fund financing of different duration as an average share of total borrowings. The duration categories refer to the maximum available duration (e.g., up to one day, up to seven days, etc.). Data are from US Securities and Exchange Commission (SEC) annual reports on Form PF data. The data are quarterly and range from 2000:Q1 to 2017:Q2.



(a)



(b)

Figure 2: Hedge funds with multiple prime brokers

The figure shows the temporal evolution of the proportion of hedge funds using multiple prime brokers, based on semi-annual snapshots from the Eurekahedge database, spanning from June 2006 to January 2021.

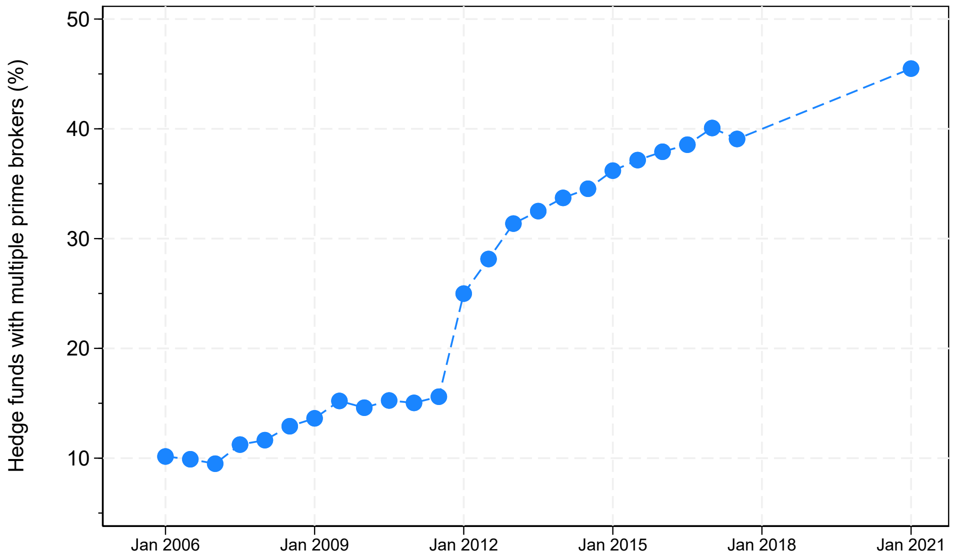
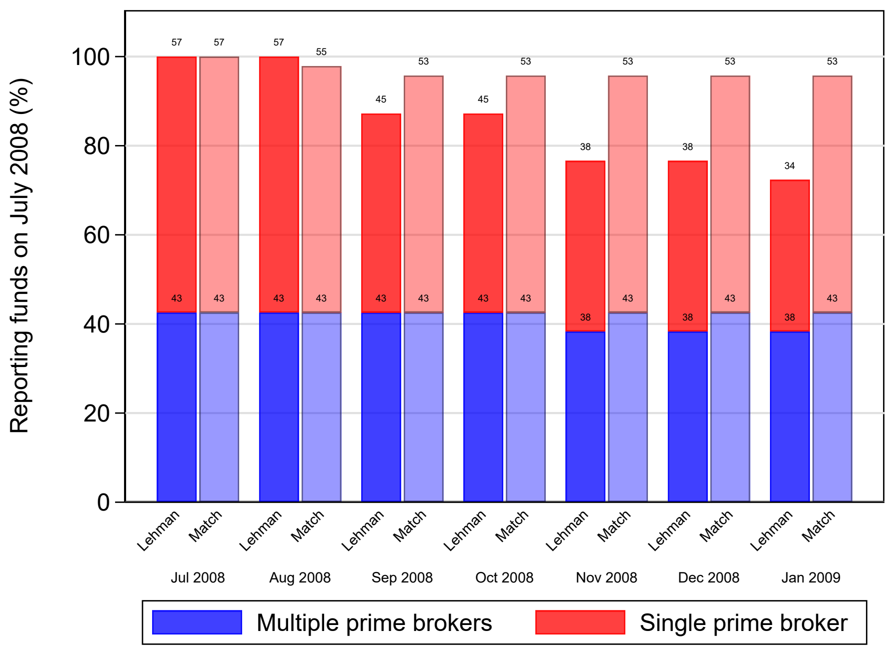


Figure 3: Event study of Lehman bankruptcy

The figure presents the proportion of Lehman's hedge fund clients that reported returns to the Eurekahedge database in July 2008 and continued to do so between August 2008 and January 2009. Taking the number of reporting clients in July 2008 as 100%, the figure illustrates how many of them also reported to the database in the subsequent months. The figure also shows reporting proportions for a matched group of hedge funds using a different prime broker. Hedge funds are matched based on the number of prime brokers, style, AUM, and past returns. The figure differentiates between hedge funds with multiple prime brokers (blue shades) and those with only one prime broker (red shades).



The Internet Appendix with supplemental material can be downloaded here:

https://www.valerisokolovski.com/research/#working-papers