Hedge Funds and Financial Intermediaries*

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Abstract

Hedge funds and financial intermediaries are connected through their prime brokerage relationship. We find that systematic financial intermediary risk, as measured by the covariation between the fund return and the return of a portfolio of key prime brokers, captures cross-sectional differences in hedge fund returns. Once we control for the systematic risk, we find little evidence that idiosyncratic financial intermediary risk matters. We evaluate if large adverse shocks to individual prime brokers propagate to their hedge fund clients and find a significant impact only in the case of the Lehman Brothers' bankruptcy. However, that impact was mitigated for funds with multiple prime brokers, suggesting that even extreme prime broker shocks are diversifiable.

Keywords: Networks, prime brokers, systematic risk.

JEL codes: G12, G23, G24.

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1 Introduction

What is the effect of financial intermediaries on hedge fund returns? There are, at least, two non mutually exclusive channels through which financial intermediaries, such as commercial and investment banks, could impact hedge fund returns. The first channel is through financial intermediaries' effect on asset prices and risk premiums. The second channel manifests itself in a hedge fund's prime brokerage relationship with the financial intermediaries. In this paper, we examine both channels. We evaluate intermediary risk in the cross-section of hedge fund returns and analyze the effects of individual prime brokers on the returns of their hedge fund clients.

Recent research finds that factors proxying for shocks to the intermediaries' aggregate risk-bearing capacity can capture the cross-section of expected returns of multiple asset classes (Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)). Importantly, intermediary health seems to matter relatively more for exotic assets that households are unlikely to hold directly (Haddad and Muir (2018)). Given that hedge funds are dynamically-managed portfolios of such exotic assets, one would expect hedge funds to be exposed to the health of the intermediary sector. There is considerable suggestive evidence of intermediary risk being a driver of hedge fund returns, but, to the best of our knowledge, no formal, comprehensive evaluation have yet been undertaken.[1]

Prime brokers, typically large investment banks, provide their hedge fund clients with many services including clearing, custodial services, securities lending, research and financ-

[1]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 and find that banks play the most important role in transmitting shocks to hedge funds.

ing. An individual prime broker could have an effect on the returns of a hedge fund through its ability to influence a fund's leverage via margin and collateral requirements. Liu and Mello (2011) describe the capital structure of hedge funds as being fragile, while Dai and Sundaresan (2009) model the prime broker hedge fund relationship as a hedge fund holding a short "funding put option" with its prime broker. Hence, it seems possible that the financial distress of a prime broker is translated into funding pressure for the corresponding hedge fund who may be forced to rapidly de-leverage its positions. In turn, assuming that market liquidity is imperfect, this may result in fire-sale prices and poor returns for the fund (see, e.g., Mitchell and Pulvino (2012)). The best known example of this shock propagation from an individual prime broker to hedge funds is the bankruptcy of Lehman Brothers and the liquidation of nearly half of its hedge fund clients (Aragon and Strahan (2012)). The question of how this mechanism impacts hedge fund returns in less extreme situations and whether this risk is diversifiable remains open.

We begin by looking at the prime broker and hedge fund relationships as a network to identify the key financial intermediaries in the sector.[2] Using an extended dataset that allows us to identify prime broker and hedge fund affiliations over time, we find that 38 financial intermediaries, out of 370, emerge as central in the prime-broker-hedge-fund network, representing around 95% of the hedge funds over the period from 2000 to 2017. We then construct intermediary pricing factors as portfolios of these prime brokers. We consider a number of weighting schemes including a scheme where the weight of each intermediary is based on its dynamic network-centrality score, equal-weighting, and value-weighting. We find that these factors are highly correlated with each other and the intermediary factor of He et al. (2017). Given this finding, we simply use the value-weighted portfolio of prime brokers as our main intermediary factor.

[2]Recently, network tools have been used to explore the connectedness of venture capital funds (Hochberg, Ljungqvist, and Lu (2007)), individual stock traders (Ozsoylev, Walden, Yavuz, and Bildik (2013)), portfolio managers (Rossi, Blake, Timmermann, Tonks, and Wermers (2018)), and dealers (Li and Schürhoff (2019), Di Maggio, Kermani, and Song (2017)).

Given the typically limited success of models from other asset classes, it is not obvious whether an intermediary factor's pricing power would survive in the cross-section of hedge fund returns. We find that it does. Our results show that the covariation between the fund return and the return of the portfolio of prime brokers captures cross-sectional differences in hedge fund returns. A portfolio of hedge funds with high intermediary risk delivers an annual Fung and Hsieh (2004) alpha that is around 6.7% higher than a portfolio with low intermediary risk. Moreover, the price of financial intermediary risk estimated from the returns of individual hedge funds is similar to that reported by He et al. (2017) for other asset classes. They report a quarterly risk price estimate of 9.4%, while we find a risk price estimate of around 7.7%. These results are robust to controlling for an extensive set of fund characteristics and other factors that have been shown in the literature to affect the cross-section of returns. Moreover, our results indicate that the exposure to the intermediary risk is largely independent of individual fund characteristics, including a fund's use of leverage.

The question remains whether the idiosyncratic shocks to individual prime brokers affect their hedge fund clients? We first check whether being a client of a particular prime broker has an effect on the average risk-adjusted returns of a hedge fund. We find no significant evidence supporting a link between a particular prime broker and average hedge fund performance. Next, we investigate whether there is a contemporaneous relationship between hedge fund returns and the returns of its prime broker. We find that regressing hedge fund returns on returns of its prime broker yields a positive and significant slope coefficient. However, we find that this is driven entirely by systematic risk exposure. Once we control for market risk and aggregate financial-sector risk, there is no significant relationship between hedge fund returns and the returns of its prime broker.

It is possible, however, that the hypothesized mechanism of shock propagation from an individual prime broker to its hedge fund clients is only relevant in the case of large adverse shocks to the prime broker. To see if this is the case, we examine four events where a prime broker experienced a large, adverse idiosyncratic shock. Using a difference-in-difference methodology, we find that, with the exception of the Lehman bankruptcy, adverse individual prime broker shocks have negligible impact on the relative returns of their hedge fund clients. In the case of the Lehman bankruptcy, however, we find that only the hedge funds using Lehman as its sole prime broker were significantly negatively affected by its bankruptcy, while the hedge funds with multiple prime brokers were not. This result suggests that even extreme idiosyncratic prime broker shocks are diversifiable through the use of multiple prime brokers. In sum, our results indicate that the effect of prime brokers on hedge fund returns stems primarily from the systematic component.

Our work relates to three strands of the literature. First, we contribute to the growing literature on financial intermediary asset pricing (see He and Krishnamurthy (2018) for a survey). Adrian et al. (2014) show that a factor constructed from shocks to the leverage of US securities broker-dealers is able to price the cross-section of US bond and equity portfolios. He et al. (2017) find that a pricing factor (HKM factor hereafter) constructed from the equity ratios of a small group of key intermediaries (the New York Federal Reserve Primary Dealers) is able to price a wide cross-section of assets in many different markets. However, neither of these two studies consider hedge funds. We bridge this strand of the literature with the hedge fund literature. Our results emphasize the robustness and external validity of intermediary pricing as the intermediary factors work in the cross-section of basic assets and also affect the broader universe of hedge fund returns.

Second, we contribute to the literature on the determinants of hedge fund returns (see Agarwal, Mullally, and Naik (2015) for a survey). Hedge funds are dynamically-managed portfolios of, possibly illiquid, securities of multiple asset classes. Partly because of that, established factor models from other asset classes have struggled to explain hedge fund returns in both the time series and particularly in the cross-section. This spawned the development of hedge-fund-specific factor models, among which the Fung-Hsieh model is widely used and captures the time series of hedge fund returns (Fung and Hsieh (1997, 2001, 2004)). However, none of the Fung-Hsieh factor loadings generate a significant return spread in the cross-section (Sadka (2010)).

A number of additional factors have been proposed to explain the cross-section of hedge fund returns, among which the liquidity and market dislocation factors are particularly prevalent (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 (2016), Sadka (2010), and Teo (2011)). Importantly, Bali, Brown, and Caglayan (2012) find that the systematic risk, not residual risk, has the greatest role in explaining the cross section of hedge fund returns. The literature, however, has not converged on the relevant systematic factors. We show that accounting for other factors (namely, the liquidity factor of Sadka (2010), 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), and the tail risk factor of Agarwal et al. (2017)), preserves the cross-sectional spread in returns of the intermediary-factor-sorted hedge fund portfolios.

Lastly we add to the literature that examines the relationship between prime brokers and hedge funds. There are only a few studies that empirically analyze this issue. Aragon and Strahan (2012) show that Lehman prime brokerage clients were relatively more likely to fail following Lehman's bankruptcy. However, they focus on stock market liquidity rather than hedge fund returns. Klaus and Rzepkowski (2009) argue that adverse individual prime broker shocks are passed onto the clients, but their analysis is restricted to a limited sample period and they do not control for 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. While their results are suggestive of prime brokers' ability to affect their clients' returns, they neither directly examine prime broker returns nor control for systematic financial sector risk. Hence, their work is unable to answer the question of whether specific shocks to a prime broker are passed onto its hedge funds clients. We also relate to the studies examining the role of prime brokers in information transfer (see, e.g., Kumar, Mullally, Ray, and Tang (2019)) and capital introduction (see, e.g., Obizhaeva (2019)); however, we differ from them in that our focus is primarily on risk.

2 Data and descriptive statistics

2.1 Hedge fund data

We obtain hedge fund data from Eurekahedge. The database includes both dead and live funds, which mitigates survivorship bias. We consider the sample of monthly net-of-fees returns and assets under management (AUM) from January 2000 to June 2017.[3]

Taking the June 2017 snapshot Eurekahedge database as a starting point, we follow the literature and apply a number of filters to the data. First, we consider only the hedge funds that report monthly returns (17,006 unique funds in total). Second, we exclude all the funds with missing AUM and whose minimum AUM is below USD 15 million. Third, we require that each fund in the sample reports at least 24 monthly returns during our sample period (this filter helps address the multi-period sampling bias and helps to obtain sensible regression estimates). Finally, in the case that a hedge fund has multiple share classes, we only consider one share class per fund to ensure that each hedge fund is represented only once in our sample. After applying these filters, our final sample is a panel of 2697 unique hedge funds.[4]

In addition to reporting returns and AUM, Eurekahedge provides information on a

[3]Although Eurekahedge includes fund returns since inception, it only started collecting fund return data from year 2000. We follow Teo (2009) and exclude returns before 2000 to further reduce potential survivorship bias.

[4]Our data filter with respect to fund AUM is relatively strict; however, our main results are not sensitive to different samples of hedge funds.

number of fund characteristics including management and incentive fees, lock-up and redemption conditions, minimum investment amounts, whether a fund has a high water mark provision, whether a fund employs leverage and, most important for our analysis, its prime brokerage relationships. However, the static fund information reported in each version of the database contains only the most up-to-date prime brokerage affiliations for each fund. Hence, using a single download of the database does not allow one to identify any prime broker changes that may have taken place over the life of a given fund.

To overcome this limitation, we source 21 additional snapshots of the database. We have two snapshots per year, between 2006 and 2016, that are taken in June and December of each year (except for the year 2009 for which there is no June snapshot available).[5] We manually clean the reported prime broker names as Eurekahedge does not issue a company identifier to prime brokers and because the same broker is frequently coded differently by two different funds. Additionally, we roll subsidiaries up to their respective parent company. For example, during our sample period we regard Newedge Group as Société Générale and Pershing LLC as Bank of New York Mellon. Starting in January 2006, we carry forward the prime brokerage information from the most recently available version of the database. Given that the information on each fund's prime brokerage affiliation is at most six months dated, we mitigate any misclassification of prime brokerage affiliation during our sample period. Finally, in the cases of two prime brokers merging, starting in the month of the completion of the merger, we change the prime brokerage affiliation of the funds affiliated with the target prime broker to that of an acquirer. For example, Merrill Lynch becomes Bank of America Merrill Lynch from January 2009. After applying all the filters, we are left with 370 unique prime brokers in our sample.

[5]The average semi-annual prime broker turnover is around 2.25%, but there are many changes around the financial crisis. For example, between June 2007 and June 2009 around 18% of the funds changed their prime broker. Hence, it is important to reconstruct a panel of prime brokerage affiliations using historic versions of the database. The Internet Appendix plots prime broker turnover over time.

2.2 Hedge fund returns and characteristics

Panel A of Table 1 reports the summary statistics for the hedge fund monthly after-fee returns in our sample. All the returns are in USD and in excess of the risk-free rate.[6] We report the mean, median, standard deviation, skewness, minimum and maximum of the excess returns. Each of these statistics is the time-series average of monthly cross-sectional statistics. We report the summary statistics for the full sample and also by year and hedge fund style. Each of the funds in our sample is classified as one of the following nine styles: Event Driven, Global Macro, Long Only, Long Short, Long Short, Managed Futures, Market Neutral, Multi Strategy, Others, and Relative Value.[7]

Overall, the sample contains 2697 individual hedge funds, but the number of available funds fluctuates by year from the minimum of 440 in year 2000 to the maximum of 1778 in year 2012. Hedge funds of all of the nine styles are well represented in our sample, with the Long Short style making up 36% of our sample, which is slightly elevated but typical in hedge fund databases. The average monthly hedge fund excess return is 0.61% for the full sample period. Average returns vary substantially over time; for example, 2008 was the worst performance year with the average monthly return of -1.63%, while 2009 was a particularly good year with an average monthly return of 2.16%. There is substantial cross-sectional dispersion in hedge fund returns (the average monthly cross-sectional standard deviation is 3.96%). The large cross-sectional range of returns is well demonstrated by the minimum and maximum returns across the years. For example, the minimum and maximum monthly return for the full sample period is -24.52% and 34.21%, respectively.

[6]For funds that do not report returns in USD, we use the end of the month exchange rate to convert them into USD equivalents. For static characteristics like the minimum investment, we use the USD exchange rate on 30 June 2017 for the conversion in the cases where it is reported in currencies other than the USD.

[7]The investment style nomenclature in hedge fund databases varies across data provider. To facilitate a consistent classification, comparable to the existing literature, we remap the 15 self-reported Eurekahedge style classifications according to the nine category investment style mapping suggested by Kosowski, Joenväärä, and Tolonen (2016).

There is also reasonable variation in the average returns across hedge fund styles. For example, hedge funds classified as Market Neutral have slightly lower average monthly return and standard deviation (0.44% and 2.30%, respectively) than hedge funds of other styles.

Panel B of Table 1 reports summary statistics for fund AUM, fund age, and the number of reporting months. There is substantial size disparity among the hedge funds in our sample. Fund AUM ranges from the minimum of USD 15 million up to the maximum of USD 25,381 million. The average fund AUM is USD 397 million, while the median AUM is USD 120 million. Age is calculated, for each fund in each month t, as the difference in the number of month between month t and the fund's inception date. At each month the average age of a fund is around six and a half years; each fund reports on average 94 months of returns.

2.3 Prime broker and factor data

We collect return and market capitalization data on all the publicly listed prime brokers in our sample. US stock data are from the Center for Research in Security Prices, and the data for the foreign intermediaries are from Datastream or Bloomberg. Exchange rates data are obtained from Datastream. The seven Fung and Hsieh (2004) factors are from Datastream and David A. Hsieh's Hedge Fund Data Library. The traded and non-traded HKM factors are available from Asaf Manela's webpage. The Pástor and Stambaugh (2003) liquidity factor, Sadka (2010) liquidity factor, the Bali et al. (2014) uncertainty factor, and the Agarwal et al. (2017) tail risk factor are available from the authors' websites. The risk-free rate and Fama and French (1993, 2012) factor data are from Kenneth R. French's Data Library. Additional factor data are from AQR. The Internet Appendix provides links to these websites.

2.4 Prime broker and client network

To learn more about the market structure, we begin with a network representation of the prime broker and hedge fund relationship.[8] Figure 1 shows a network graph representing the client-dealer relationship between funds and prime brokers for the June 2017 snapshot of the database. Each node (vertex) is either a hedge fund (represented by circles) or a prime broker (represented by purple squares), and there is a link (edge) between two nodes if the former is a client of the latter. The graph presents a client-prime broker relationship and is bipartite in graph terminology.[9] Figure 1 is a simple way to get an overview of the prime brokerage market structure. Clearly, the industry is highly concentrated as a few big prime brokers service the majority of funds, with several funds spreading their business across multiple prime brokers.[10]

Next we look at the prime broker market structure over time. Panel A of Table 2 shows the share of the total number of hedge funds in our sample that are serviced by each of the top 10 prime brokers. Panel B of Table 2 shows, for the top 10 brokers, the sum of the AUM of their clients as the percentage of the total hedge fund AUM. We see that the top 5 prime brokers, ranked either on the number of clients or the sum of their clients' AUM, capture over 50% of the hedge fund market. 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 either first or second. This is consistent with Aragon and Strahan (2012) who report prime broker market shares for the years between

[8] For this analysis, we consider all the hedge funds in our database that report a prime broker affiliation (7976 funds in total).

[9] See the Appendix for an example of the construction and encoding of the network as an adjacency matrix.

[10] Multiple prime broker affiliations were less common in 2007. Using multiple prime brokers is not costless because of process duplication and inability to easily net collateral requirements across trades. However over the sample period the share of hedge funds with multiple prime brokers has been increasing from 14% to 24% of the funds. The Internet Appendix shows a network representation of the client-prime-broker relationships for the June 2007 snapshot of the database and plots the fraction of funds with multiple prime brokers over time.

2002 and 2008, and similar to Di Maggio et al. (2017) and Eisfeldt, Herskovic, Rajan, and Siriwardane (2018), who respetively find that the market structure in the credit default swap and bond dealer markets is highly persistent.

3 Financial intermediary risk factors

One of the central challenges in empirically testing the intermediary asset pricing theories is identifying a set of financial intermediaries that are the "marginal" investors. Another issue is the question of how to aggregate their individual pricing kernels to form a "representative intermediary"? If all the intermediaries considered are "marginal" investors, then a weighted sum of their individual pricing kernels is a valid pricing kernel for any weight even if intermediaries are heterogeneous (see He et al. (2017) for a discussion). However, that is not the case if some of the intermediaries are either not marginal in some markets or during certain periods.

Adrian et al. (2014) consider all the US broker-dealers, while He et al. (2017) focus on NY Fed primary dealers as a set of key financial intermediaries for their empirical analysis. Primary dealers are a natural group to consider as they represent a large fraction of the total value of the US broker-dealer and banking sectors, respectively. The primary dealers also include foreign banks and there is ample evidence suggesting that they account for the bulk of trading in many markets (see Cetorelli, Hirtle, Morgan, Peristiani, and Santos (2007)).[11] Nevertheless, there is some degree of arbitrariness in the choice of focusing on only the primary dealers. With respect to the weighs attached to each intermediary, He et al. (2017) consider both value-weighted and equal-weighted factors. The two factors yield similar cross-sectional pricing results, but with a few discrepancies of risk prices in some asset classes. However, without detailed data on the relative specialization of individual

[11] Primary dealers represent between 50% and 90% of value (measured by total assets, book equity or market equity) of all the US broker-dealers and banks respectively (see He et al. (2017)).

intermediaries greater precision in the weight assigned to a particular intermediary is not possible. Our data allow us to construct alternative intermediary pricing factors, exploiting the relative importance of different financial institutions in capturing the share of the prime brokerage business.

3.1 Financial intermediary factor choice and construction

We focus on only the listed prime brokers and identify 38 listed prime brokers in our dataset. They capture the lion's share of the prime brokerage market and around 95% of hedge funds in our sample are clients of one or several of these prime brokers. Moreover, these funds account for around 90% of total hedge fund AUM. Thus, we consider these prime brokers as the key financial intermediaries for the hedge fund industry. Interestingly, although our approach of identifying the most important financial intermediaries is different, we converge on a very similar group of intermediaries as He et al. (2017). Our group of intermediaries contains all, but one, of the primary dealers.[12] Our financial intermediary factor is the weighted sum of monthly returns of all the publicly listed prime brokers. We consider portfolio weights based on the constituents' importance to hedge funds in their role as primary brokers. Moreover, we consider value-weighed and equal-weighted portfolios of these firms.

The network graph in Figure 1 serves as a guide to compute various reweightings based on rank. When each link is unweighted, the number of clients for a particular broker is simply the degree of that node. When each link is weighted by the fund's AUM, a prime broker's total AUM is that node's strength (sum of ingoing edge weights). Another popular

[12] In total, 27 out of 38 listed prime brokers are or were at some point during the sample period designated as primary dealers. Only one primary dealer, Countrywide Financial, is not in our sample of prime brokers. Our sample of prime brokers also contains eleven additional US and international financial intermediaries that were not primary dealers, namely Archer Daniels Midland (ADM), Banco Bradesco, BNY Mellon, Credit Agricole, Fortis, Interactive Brokers, Itau Unibanco, National Bank of Canada, Natixis, Rand Merchant Bank (RMB), and SEB.

ranking metric, which takes into account the importance of connections, is the eigenvalue centrality (also referred to as prestige centrality; see, e.g., Jackson (2010)). The intuition is that a node's rank should be related to the importance of its connections, which in turn are ranked based on the importance of their connections. This self-referential measure is operationalized by computing the (appropriately scaled, see the Appendix for details) eigenvalues of the corresponding adjacency matrix, g.

To obtain a network over time, we construct the adjacency matrix for each month in the Eurekahedge database. In other words, each month we consider funds that report AUM and their prime broker, and construct the adjacency matrix with the appropriate edge weights. This adjacency matrix is the basis for that month's prime broker ranking metrics (eigenvector centrality based on number of clients, eigenvector centrality weighted by AUM, total number of clients, and total AUM). For example, in the case of reweighting based on AUM and total number of clients, the weights each year for the top 10 brokers are essentially equal to the weights reported in Table 2. It is worth noting that given the bipartite network any centrality measures will be correlated with the simple degree distribution of that node. For example, if a prime broker has a high eigenvector centrality, it will also have a large number of clients. Similarly, if a prime broker has a high eigenvector centrality in an AUM-weighted network, it will have a large AUM, and the ranking of the brokers based on the two methods will be very close.

3.2 Financial intermediary factor characteristics

We construct six financial intermediary factors: a value-weighted portfolio (FI) and equal-weighted portfolio (FI_{ew}) of prime brokers, and four alternative factors using the dynamic weighting procedure described above. Table 3 presents the descriptive statistics and the correlation matrix for all the factors, together with the traded HKM factor.

All the financial intermediary factors are highly correlated and have very similar statistical properties. For example, the correlations between the HKM factor and FI and FI_{ew} are 0.98 and 0.95, respectively. As predicted the structure of the broker-hedge-fund network makes the network-weighted factors highly correlated with the value-weighted and equal-weighted factors (the lowest correlation is 0.86).[13] This is perhaps surprising as a few large intermediaries (e.g., HSBC, with only a small prime brokerage business) are assigned negligible weights and some intermediaries that are central in the prime broker network (e.g., Goldman Sachs) are assigned high weights by our procedure. Hence, one could expect more pronounced differences using alternative weighting schemes. However, this is not the case, but it seems reasonable given the commonalities in the prime broker returns (the first principal component explains over 50% of the common variation in the prime broker returns). Additionally, it is clear from the correlation matrix that all the intermediary factors are extremely correlated with the first principal component of prime broker returns (the highest correlation is 0.99). Given such high correlation among the factors and the potential for introducing measurement error when using network-based factors, we simply perform our main analysis using the value-weighted portfolio of prime brokers.

4 Financial intermediary risk in the cross section of hedge funds

4.1 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 that is commonly used in the literature.[14] Specifically, every month we sort all the hedge funds in our sample into ten portfolios based

[13]The Internet Appendix plots FI, FI_{AUM} and FI_{N} over time. These series essentially mirror each other.

[14]Fama and French (1992) use this approach to estimate betas for individual stocks and the approach is subsequently adopted for hedge fund beta estimation (see, e.g., Sadka (2010), Teo (2011), Hu et al. (2013), Bali et al. (2014)).

on their 24-month rolling financial intermediary factor loadings. For each hedge fund i, we estimate the rolling FI factor loading in month t using the following regression:

$$r_{i,t} = a_{i,t} + \beta_i^{\mathrm{FI}} r_t^{\mathrm{FI}} + \beta_i^{\mathrm{M}} r_t^{\mathrm{M}} + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$, r_t^{FI} and r_t^{M} are the month t excess returns for fund i, the value-weighted portfolio of prime brokers and the aggregate stock market portfolio, proxied by the returns on the S&P 500 index, respectively. Regression (1) corresponds to the two-factor model used by He et al. (2017). After having monthly beta estimates, $\hat{\beta}_{i,t}^{\mathrm{FI}}$, we form ten 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 ten 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 (1).

Table 4 reports the average monthly excess returns and Fung and Hsieh (2004) seven-factor alphas for our ten hedge fund portfolios. It also reports the post-sort and pre-sort FI betas and market betas and the R^2 from the Fung and Hsieh (2004) seven-factor regression. The pre-ranking beta of a portfolio is its average fund level rolling beta. The high-FI-factor loading portfolio (Portfolio 10) has the highest average return or alpha, and the low-FI-loadings portfolio (Portfolio 1) has the lowest.[15] Gauging from the average returns of the other portfolios, the relationship appears monotonic. The hypothetical strategy of going long Portfolio 10 and going short Portfolio 1 yields an annualized excess return of 8.52% (t-stat = 4.0) or an annual alpha of 6.72% (t-stat = 2.1). This provides an intuitive measure

[15] We also consider an eight-factor model which augments the Fung and Hsieh (2004) seven-factor model with an emerging market index, and a global seven-factor model as in Kosowski, Kaupila, Joenväärä, and Tolonen (2019), which augments the global Fama and French (2012) model with cross-sectional momentum of Asness, Moskowitz, and Pedersen (2013), time-series momentum of Moskowitz, Ooi, and Pedersen (2012), betting-against-beta of Frazzini and Pedersen (2014) and tradable liquidity risk factor of Pástor and Stambaugh (2003). We find that these different risk adjustments do not change the results (see the Internet Appendix).

of the economic significance. Additionally, we find that the spread in portfolio returns is largely preserved over holding periods from one to six months (reported in the Internet Appendix). It is worth noting that this high-minus-low spread in returns and alphas is driven predominantly by the high returns in Portfolio 10 (its average annualized return and alpha are 12.96% and 4.68%, respectively).

To interpret this positive spread in the average returns as compensation for risk, we show that the portfolios in Table 4 exhibit a positive spread in their loading with intermediary risk over the same period used to compute the alpha. The post-ranking betas appear to increase monotonically from Portfolio 1 to Portfolio 10 and there is a significant difference of 0.19 (t-stat = 2.2) between the FI factor betas of Portfolio 10 and Portfolio 1. To improve the precision of the beta estimates in the presence of possible return smoothing, we estimate post-ranking portfolio betas by including both the contemporaneous and lagged FI and market excess returns in the regression as suggested by Asness, Krail, and Liew (2001). The relative spread in post-ranking betas slightly increases and remains marginally significant (reported in the Internet Appendix). These results are in line with the financial intermediary risk being a significant determinant of the cross-section of hedge fund returns.

While we do find that that there is a positive relationship between ex post exposure to intermediary risk and average returns, this does not rule out that this is simply due to known determinants of expected hedge fund returns in the cross-section. Next, we formally evaluate whether financial intermediary risk exposure is robust to controlling for various fund characteristics.

4.2 Cross-sectional regressions

In this subsection, 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:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{\text{FI},t}\hat{\beta}^{\text{FI}}_{i,t} + \lambda_{\text{M},t}\hat{\beta}^{\text{M}}_{i,t} + cX_{i,t} + \varepsilon_{i,t+1}, \tag{2}$$

where $r_{i,t+1}$ are the month $t+1$ excess returns for fund i, $\lambda_{0,t}$ is the intercept, $\hat{\beta}^{\text{FI}}_{i,t}$ is the month t FI factor beta of fund i, $\hat{\beta}^{\text{M}}_{i,t}$ 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. Each fund i at time t, is assigned the estimated post-ranking portfolio betas of the decile portfolio to which this fund belongs. This means that all funds in the same portfolio have the same beta, but a fund's beta will vary over time as it moves across deciles. The controls are standard in the literature and includes the fund's excess return for month t, age, AUM, management fee, incentive fee, lockup (a dummy variable that equals one if fund i has a lockup provision and zero otherwise), high water mark (a dummy variable that equals one if fund i has a high water mark provision and zero otherwise) mandated redemption notice period, and minimal investment in the fund. Controls also include hedge fund style and geographical region dummies. The factor premiums are estimated as the time series averages of $\lambda_{\text{FI},t}$ and $\lambda_{\text{Mkt},t}$.

Columns I–V of Table 5 report the average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regression in (2). The t-statistics in parenthesis use standard errors adjusted for autocorrelation and heteroskedasticity as in Newey and West (1994). The estimated FI risk premium is positive and significant in all the specifications. In the final specification with all the covariates, presented in column V, the point estimate of the monthly risk premium is 2.58% (t-statistic = 2.4). Expressed on a quarterly basis, the risk premium is 7.74%, which is similar to the quarterly financial intermediary risk premium of 9.35% in He et al. (2017), estimated in the cross-section of seven asset classes (equities, US bonds, sovereign bonds, options, credit default swaps, commodities, and currencies), but not hedge funds.

It is worth noting that the most significant reduction in the point estimate of the FI factor price of risk results from the addition of the previous month's hedge fund return in the regression. As hedge fund returns are known to be autocorrelated, possibly due to return smoothing, it seems important to control for past returns. Other controls do not appear to have much impact on the average effect of intermediary factor loading on factor returns. However, the coefficients on the controls are of the signs as reported by the existing literature. For example, the coefficients on a fund's AUM and age are negative and significant, which is in line with the observation that smaller and younger funds tend to have higher average returns than larger and more established funds (see, e.g., Aggarwal and Jorion (2010)). The 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 water mark dummy is positive as in Agarwal, Daniel, and Naik (2009), but not statistically significant. Given that we consider a global sample of hedge funds, we control for geographical differences using region dummies; however, this does not affect the results. As an additional robustness test, we estimate regression (2) on a subsample of hedge funds that report their returns in USD and get very similar results (see the Internet Appendix).

In sum, we find that there is a significant positive relationship between exposure to intermediary risk and average returns of individual hedge funds.

4.3 Intermediary risk exposure and fund characteristics

In this subsection we consider a potential channel through which hedge funds could be exposed to financial intermediary risk. There is a close link between each hedge fund and the intermediary sector through its prime brokerage relationships. The question is what role, if any, does this link play in explaining the relationship between hedge funds and financial intermediaries.

Prime brokers have many different functions, among which providing leverage to hedge funds is key for the question at hand. A large fraction of hedge funds use some leverage. Fund leverage can take the form of either outright short-term borrowing or synthetic leverage embedded in derivatives. Regardless of the type of leverage used, the amount employed by hedge funds is influenced by their prime broker either directly through adjustments to their credit lines or indirectly through margin and collateral requirements. Assuming a hedge fund's financing constraints bind, a tightening of its credit could impact its trading. Hence, a shock to the fund's prime broker could result in de-leveraging and a positive shock could lead to more leverage taken by the fund. If liquidity is imperfect, this process could impact prices and subsequent returns of the fund. This suggests that we may see a difference in the intermediary risk exposure between the funds that use leverage and the funds that do not. Thus, we examine whether funds that use leverage or that are in other ways highly dependent on their prime brokers are more exposed to financial intermediary risk.

We begin with the portfolio sorting procedure as in the previous section. We examine hedge funds that report their use of leverage and funds that report that they do not use leverage separately. Due to the reduced sample size we only consider five intermediary-beta-sorted portfolios for each group. Panel A of Table 6 reports the Fung and Hsieh (2004) seven-factor alphas for the five beta-sorted portfolios for each group and the difference between the alphas of the two groups. In each group the spread in alpha between the high-beta portfolio and the low-beta portfolio is positive and significant in both cases. However, the t-statistics are lower with the double sort than the single sort. Moreover, the difference between these high-minus-low portfolios is not significant. This suggests that the intermediary risk relationship is not affected by the funds' use of leverage.

To ensure that the potential effect is not being masked by omitted variables, we also evaluate the impact of leverage on hedge fund returns in the cross-sectional regression framework. We estimate regression (2), but also include an indicator for whether the fund uses leverage and an interaction between this leverage dummy variable and each fund's HKM beta. Column VI of Table 5 reports the results. We observe a positive but not statistically significant coefficient of the interaction between hedge fund intermediary beta and leverage, indicating that leveraged funds do not have a different exposure to financial intermediaries. This is in line with the result of Ang, Gorovyy, and Van Inwegen (2011), who find that changes in hedge fund leverage is more predictable by economy-wide factors than by fund-specific characteristics.

To check the robustness of our results, we further sort by fund AUM and by whether a fund has one or multiple prime brokers. Funds that are larger or have multiple prime brokers may have more bargaining power and face better funding conditions. They may then be less exposed to funding shocks coming from its prime broker. Hence, if individual prime broker exposure is driving the results, we would observe a lower spread in returns in the cases of larger funds and funds that have multiple prime broker relationships. We again form five intermediary-beta sorted portfolios for each of the groups. Panel B of Table 6 reports the Fung and Hsieh (2004) seven-factor alphas for portfolios sorted on AUM (the median fund AUM is used as a cut-off) and intermediary beta. Panel C of Table 6 reports the alphas for portfolios sorted on the number of prime brokers and intermediary beta. While we find that in each group the differences in alphas between the high-beta portfolio and the corresponding low-beta portfolio are always positive and marginally statistically significant, there are no significant differences in alphas of the high-minus-low portfolios between the groups in any of the cases.

These results suggest that a fund's individual relationship with its prime broker or brokers does not have an effect on its exposure to the aggregate financial intermediary risk.

5 Individual prime broker effect

Despite an intuitive link between individual prime brokers and their hedge fund clients, our results thus far suggest that it is the exposure to the health of the aggregate financial intermediary sector that is the key driver of hedge fund returns. In this section, we investigate the effects an individual prime broker may have on the returns of its hedge fund clients.

5.1 Prime broker fixed effect

We begin by asking the question of whether the individual prime broker has an average effect on hedge fund risk-adjusted returns. For example, does a hedge fund client of JP Morgan deliver different risk-adjusted returns than a hedge fund client of Goldman Sachs? However, as hedge funds and their prime brokers may choose their trading relationships strategically (Eren (2015)), we would need exogenous variation in prime broker assignment to make causal claims. Nevertheless, as a first pass, we simply explore if there is a meaningful variation in hedge fund risk-adjusted returns across the different prime brokers without making any claims of causality. We run the following panel regression:

$$\hat{\alpha}_{i,t} = a_{PB} + b'X_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where $\hat{\alpha}_{i,t}$ is the risk-adjusted return (the sum of the intercept and the residual from a regression of excess fund returns on the seven Fung and Hsieh (2004) factors) of fund i in month t, a_{PB} is the fixed effect for the prime broker of fund i and $X_{i,t}$ is a vector of controls that includes all the fund-specific characteristics and style dummies as in regression (2) and an indicator that takes a value of one if fund i has multiple prime brokers and zero otherwise. We use standard errors that are clustered at individual hedge fund and month levels.

For this analysis we focus on the funds that have at least 24 month return history and report a prime-broker affiliation with a broker that has at least five clients. This restricts our sample to 1654 individual hedge funds and 43 prime brokers. We begin the sample period in January 2006 as we do not have timely information on prime broker affiliation before that date. Table 7 presents the descriptive statistics on the performance and AUM of each prime broker's clients, and each broker's size in terms of clients and, in the case of listed prime brokers, market capitalization. It appears that there is some variation in hedge fund performance across prime brokers. Table 7 also highlights the high concentration of the industry as the bulk of the clients are affiliated with just a few prime brokers. In our sample, Goldman Sachs has, on average, the most clients and is responsible for the largest number of hedge fund AUM.

The top panel of Figure 2 displays the estimated fixed effect coefficients for all the prime brokers. Goldman Sachs is used as a base prime broker. Only the coefficients that are significantly different from zero at the 5% level are shown. In total, four prime brokers out of 43 have significant coefficients. An F-test (not tabulated) for equality of all the fixed effects rejects that null of equality of all the coefficients at the 5% significance level. It is, however, important to consider the large disparity in prime broker importance as measured by the number of their hedge funds clients and their respective AUM.

The bottom panel of Figure 2 displays the average share of the total hedge fund client AUM that each prime broker represents during our sample period. The hedge fund clients of Interactive Brokers seem to deliver higher alpha than the clients of Goldman Sachs. However, the AUM of those funds is small and accounts for less than 0.15% of the total hedge fund AUM, whereas the total AUM of the hedge fund clients of Goldman Sachs represents close to 17% of the total hedge fund AUM. Hence, a comparison across such different funds and prime brokers is not particularly meaningful, which is in line with the argument of Berk and van Binsbergen (2015) who emphasize the importance of accounting for fund AUM when measuring mutual fund performance and skill. Nevertheless, our analysis yields some noteworthy results. Clients of the two large prime brokers (JP Morgan and Credit Suisse) seem to earn, on average, significantly higher alpha. The positive performance of JP Morgan affiliated funds may have been impacted by the aggressive growth of its prime brokerage business. More likely, however, is that the observed difference in alpha is driven primarily by the migration during the 2008 financial crisis of many successful funds to prime brokers with more secure capital bases, such as JP Morgan and Credit Suisse. Notwithstanding these cases, our results suggest that prime broker affiliation does not have an important effect on hedge fund alphas.

5.2 Hedge funds and prime broker returns

In this subsection we investigate whether there is a relationship between hedge fund returns and the returns of its prime broker. In particular, we are interested whether the prime broker specific shocks are propagated onto its clients. The motivation is intuitive. Given the close business relationship between hedge funds and its prime brokers, a shock to an individual prime broker, especially a negative one, could be passed onto its hedge fund clients. We explore to what extent it is the case by considering the following panel regression:

$$r_{i,t} = a_i + br_{i,t}^{\mathrm{PB}} + cX_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $r_{i,t}$ and $r_{i,t}^{\mathrm{PB}}$ are the month t excess returns for fund i and the month t excess returns for the prime broker of fund i, respectively. In the cases where a fund has multiple prime brokers $r_{i,t}^{\mathrm{PB}}$ is the average excess return of the prime brokers of fund i. Considering only the funds that have a single prime broker does not change our results. Fund fixed effect is denoted by a_i and $X_{i,t}$ is a vector of controls that includes all the fund-specific characteristics. Due to the inclusion of fund specific fixed effects, only the hedge fund characteristics that vary with time are identified in our regressions.

Note that the prime broker return, $r^{\mathrm{PB}}_{i,t}$, is comprised of both the systematic and idiosyncratic components. To isolate the prime broker specific shocks, we assume that the return of each prime broker j can be represented by:

$$r^{PB}_{j,t} = a_j + \beta^{\mathrm{M}}_j r^{\mathrm{M}}_t + \beta^{\mathrm{FI}}_j r^{\mathrm{FI}}_t + \beta^{\mathrm{CI}}_j r^{\mathrm{CI}}_{j,t} + \varepsilon_{j,t} \tag{5}$$

where r^{FI}_t and r^{M}_t are the month t excess returns to the value-weighted portfolio of prime brokers and the aggregate stock market portfolio, respectively. Given that we consider a diverse group of international prime brokers, we also add a proxy for country-specific systematic risk in the form of the excess return to each country's stock market index, $r^{\mathrm{CI}}_{j,t}$. We interpret the error term, $\varepsilon_{j,t}$, as a prime broker specific shock. For this analysis, we focus only on the hedge funds that are affiliated with a listed prime broker and have at least 24 month return history. We use standard errors clustered by hedge fund and time.

We report the results in Table 8 with column I as our baseline specification. We find that regressing excess hedge fund returns on excess returns of its prime broker yields a positive and highly significant coefficient b coefficient of 0.12 (t-statistic = 8.5). This is not surprising as both the hedge fund and their brokers are exposed to the aggregate market. Next, we orthogonalize the returns of each prime broker to the market return and re-estimate the regression. In other words, we replace $r^{\mathrm{PB}}_{j,t}$ in regression (4) with the error term from the regression of $r^{\mathrm{PB}}_{j,t}$ on r^{M}_t for each prime broker j. This reduces the coefficient from 0.12 to 0.05; however, it remains strongly significant (t-stat = 3.5). Given our earlier results, we know that both the hedge funds and prime brokers are also exposed to the aggregate financial sector risk. We, therefore, orthogonalize the returns of each prime broker to both the market return and the return of the FI factor, and then repeat the analysis. The coefficient further decreases to 0.035, but remains weakly statistically significant (t-stat = 1.9). Adding fund specific controls, namely fund age and fund AUM, does not affect the results.

Our final correction relates to the origin of the prime broker. The prime brokers come from eleven different countries (Brazil, Canada, France, Germany, Japan, the Netherlands, South Africa, Sweden, Switzerland, the UK and the US). Although many are large global banks, a few of them conduct the bulk of their business in their home countries (countries of their primary listing). In turn, many of their hedge fund clients specialize and invest mainly in those countries. For example, the two Brazilian prime brokers (Banco Bradesco and Itau Unibanco) have predominantly Brazilian hedge fund clients. Hence, in those cases, the prime broker returns and the returns of their clients may simple be correlated due to their common exposures to country-specific risk. In order to account for this effect, we orthogonalize the returns of each prime broker to the excess return to the stock market index of its home country, CI, in addition to the market and FI returns. The regression results reported in column V of Table 8, show that there is no longer a correlation between the idiosyncratic prime broker returns and the returns of its hedge fund clients after we account for home country aggregate market exposure.

In sum, our results indicate that once we adequately control for market risk and aggregate financial-sector risk, there is no significant relationship between hedge fund returns and the returns of its prime broker.

5.3 Event studies of adverse, individual prime broker shocks

The results of the previous subsection suggest that individual prime broker's returns affect the returns of its hedge fund clients only through its contribution to aggregate financial-sector risk. However, it is possible that the mechanism of idiosyncratic shock propagation from prime broker to hedge fund client is highly nonlinear. In other words, it is possible that only the extreme adverse individual prime broker shocks are propagated to the hedge fund clients. Following an extreme adverse shock a prime broker may be forced to tighten the liquidity it offers to its clients and possibly also temporary reduce the quality of other services as its resources are redirected elsewhere. To evaluate this potential effect, we focus on four well-publicised events that represent large adverse shocks to specific prime brokers and examine the relative performance of each of the affected prime brokers' hedge fund clients around these events.

5.3.1 Prime broker events

We begin by looking at the Lehman bankruptcy that took place on 15 September 2008. It is an important event to consider as Aragon and Strahan (2012) show that Lehman hedge fund clients failed at a significantly higher rate in 2008 than similar hedge funds that were affiliated with other prime brokers. Moreover, Fernando, May, and Megginson (2012) find that the Lehman bankruptcy also negatively affected its equity underwriting clients. The top panel of Figure 3 shows the monthly returns of Lehman and the return to a value-weighted portfolio of prime brokers (FI) around the time of the bankruptcy. Although the Lehman event was at the epicentre of the financial crisis, it is clear that it represents an extreme individual shock as well.

We next consider the performance of Lehman hedge fund clients. Prime broker clients are identified as those that report using a particular prime broker at the time of the event. It is important to recognize that as reporting to a hedge fund database is voluntarily when a hedge fund experiences poor returns and begins to liquidate it often simply stops reporting its results. This point is stressed by Aragon and Strahan (2012) and it is one of the reason that they use a hazard model of reporting, or not, in their analysis rather than looking at hedge fund returns directly. Although there are multiple reasons to stop reporting, it seems reasonable to assume that during a crisis many hedge funds exit the database due to significantly bad performance and/or termination. The middle panel of Figure 3 presents the total number of Lehman hedge fund clients that report to the database each month. Starting in September 2008 and continuing into the beginning of 2009, we observe a pronounced decrease in the number of Lehman hedge fund clients that report to the database. Thus, in the spirit of adjusting for equity delisting returns bias (Shumway (1997)), we replace the last reported return of each fund in the database by -30%. We view this as a conservative adjustment, but, particularly in the case of Lehman clients, such losses are well supported by anecdotal evidence (see, e.g., Aikman (2010)). Using instead -10%, -50% or -70% as a termination return does not alter the general conclusion.

The bottom panel of Figure 3 presents the cumulative return index of a portfolio of Lehman's hedge fund clients along with the return index of a matched portfolio of similar funds that use a different prime broker. The indexes are set to unity during the month prior to the event month. As there is some heterogeneity across hedge fund clients of different prime brokers, we use a matching procedure to enhance visual comparison. Each Lehman's hedge fund client is matched to another hedge fund based on fund style, average AUM (decile), return of the fund over the 12 months prior to the event month (decile), standard deviation of the fund's return over the 12 months prior to the event month (decile) and each fund's average financial intermediary beta during the 12 months prior to the event month (decile).

Although our sample contains fewer Lehman hedge funds clients, we are able to confirm the conclusions of Aragon and Strahan (2012) as only around 60% of the Lehman's clients survives past January 2009. The imputed termination returns suggest that Lehman funds were more severely affected by the Lehman bankruptcy than other comparable funds.

Next, we examine the Bear Stearns failure in March 2008, the September 2011 UBS rogue trader trading loss[16], and the April 2012 JP Morgan "London Whale" trading loss.[17]. The Lehman and Bear Stearns events are both extreme events in the sense that in each case both prime brokers seized to exist after the event. However, the Bear Stearns failure and subsequent sale to JP Morgan was a controlled termination in contrast to that of Lehman (see Brunnermeier (2009) for a discussion). The other two events that we consider are less severe, but still represent very large individual adverse shocks to each prime broker.

The top three panels of Figure 4 show the monthly excess returns of Bear Stearns, UBS and JP Morgan around the events. It is clear that the events represent large adverse idiosyncratic shocks for prime brokers. The bottom panels of Figure 4 show the cumulative return indexes of portfolios of hedge fund clients of the respective prime brokers together with the cumulative return indexes of the matched hedge funds. In the case of JP Morgan hedge fund clients, we examine separately the returns of the funds following the Fixed Income style as the JP Morgan loss was caused by trading credit default swaps and there is some anecdotal evidence that many hedge funds trading those instruments profited from it.[18] Our sample contains 58 Bear Stearns clients, 136 UBS clients and 150 JP Morgan clients at the time of the respective events. Our treatment of the termination returns and the matching procedure are the same as before.

In contrast to the Lehman funds, we see no stark differences between the returns of the hedge fund clients of the affected prime brokers and those of the matched groups. It appears that the Lehman event may have been unique and the implications for hedge fund

[16] 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 lead to the resignation of the company's CEO.

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

[18] See, for example, "The Hunch, the Pounce and the Kill: How Boaz Weinstein and Hedge Funds Outsmarted JP Morgan" by Azam Ahmed, *New York Times*, 26 May 2012.

performance are not generalizable to other large prime broker shocks.

5.3.2 Difference-in-difference regression

To formally evaluate whether or not the returns of the clients of the affected prime brokers are relatively more severely impacted by a very large adverse shock to their prime broker, we estimate the following panel regression:

$$\begin{aligned} r_{i,t} = a_i &+ b_1 \text{PB Events}_t + b_2 \text{PB Client}_i + b_3 \text{PB Events}_t \times \text{PB Client}_i \\ &+ b_4 \text{Lehman Event}_t + b_5 \text{Lehman Client}_t + b_6 \text{Lehman Event}_t \times \text{Lehman Client}_i \\ &+ cX_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where $r_{i,t}$ is the month t excess returns for fund i, PB Events$_t$ is an indicator variable that is equal to one during the event window surrounding the Bear Stearns, UBS or JP Morgan events, and zero otherwise, PB Client$_i$ is an indicator variable that is equal to one if a hedge fund i was a client of the affected prime broker one month prior to the event, and zero otherwise, PB Events$_t \times$PB Client$_i$ is the interaction of the two indicator variables, Lehman Event$_t$ is an indicator variable equal to one during the event window surrounding the Lehman Brother bankruptcy, Lehman Client$_i$ is an indicator variable that is equal to one if a hedge fund was a client of Lehman one month prior to the bankruptcy, and Lehman Event$_t \times$Lehman Client$_i$ is the interaction of the two terms. The event window is 4 months, including the month of the start of the event. Fund fixed effect is denoted by a_i and $X_{i,t}$ is a vector of controls that includes all the fund-specific characteristics for each fund i. We use standard errors clustered by hedge fund and time.

Given that the visual analysis suggests that the Lehman event may be special, we consider the Lehman event and the other prime broker shocks separately. Hence, the differential effect of a large prime broker shock on its hedge fund clients is captured by the b_3 coefficient and the differential effect of the Lehman bankruptcy on its clients is captured by the b_6 coefficient. If the returns of a prime broker's hedge fund clients are disproportionally, negatively impacted by large idiosyncratic shocks to their prime broker, we would expect the two coefficients to be negative and significant.

We report the results of regression (6) in Table 9. The coefficients on PB Events$_t$ and Lehman Event$_t$, in our baseline specification reported in column I, are equal to -1.30% and -4.36%, respectively and are marginally statistically significant (t-stats $= 1.9$ and 2.2), indicating that the events considered indeed represent adverse shocks for the hedge fund sector. However, the results of the baseline specification suggest that during the event window the returns of the clients of the affected prime brokers are not significantly different than those of the other funds. The coefficient b_3 is positive, but very small and statistically insignificant, which indicates that the returns of the Bear Stearns, UBS and JP Morgan's hedge funds clients were not relatively worse during the times when each of these prime brokers experienced a large shock. This result is in line with the visual analysis in the previous subsection. The lack of evidence of adverse idiosyncratic shock propagation from prime brokers to hedge fund clients suggests that hedge funds are not particularly dependent on their prime brokers. This would be the case, for example, if hedge funds used little leverage, which is in line with the theoretical result of Panageas and Westerfield (2009) who show that even risk-neutral hedge fund managers use leverage conservatively. Perhaps surprisingly, the baseline regression is unable to statistically show that the returns of Lehman's hedge fund clients were relatively worse at the time of the Lehman bankruptcy: the coefficient b_6, although negative, is statistically insignificant.

It is important to note that we consider hedge funds with both a single prime broker and multiple ones. Hence, the client indicator variables capture 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 hypothesize that prime broker shocks could affect differently the hedge funds who are its sole clients because a hedge fund with multiple prime brokers could be less susceptible to an adverse individual prime broker shock than a manager with only one prime broker. This difference between funds that use only one prime broker or several could help understanding the baseline results. To this end, we add two additional indicator variables, PB Unique Client$_i$ and Lehman Unique Client$_i$, and their respective interactions with the relevant event indicators to regression (6). The two indicators are equal to one if a hedge fund i used the affected prime broker as its only prime broker at the time of that prime broker event, and zero otherwise. For example, Lehman Unique Client$_i$ captures the hedge fund clients of Lehman who used Lehman as their only prime broker at the time of its bankruptcy.

The results of the auxiliary specification, reported in columns II−IV of Table 9, paint a stark picture. The coefficients on the interaction terms, PB Events$_t$ $\times$ PB Unique Client$_i$ and Lehman Event$_t$ $\times$ Lehman Unique Client$_i$ are negative, and, in the case of Lehman the coefficient is large, around -7% and statistically significant (t-stats around 2.8). This indicates that in the case of Lehman bankruptcy, hedge funds who used Lehman as its only prime broker experienced a significantly larger loss than other funds. The coefficients b_3 and b_6 reflect the relative return difference of the affected prime broker's clients with multiple prime brokers, are around zero and 2%, respectively. It may seem counterintuitive that Lehman hedge fund clients that used Lehman as one of their multiple prime brokers fared relatively better at the time of the bankruptcy. However, it is important to note that using multiple prime brokers at the time of the bankruptcy was relatively uncommon and the Lehman hedge fund clients with multiple prime brokers were much larger and more established funds.[19] Additionally, it is possible that the exposure of these hedge funds with multiple prime brokers to Lehman was minimal as Aikman (2010) reports that during the

[19]The average AUM in August 2008 of the hedge funds that used Lehman as its sole prime broker and one of several was USD 171 million and USD 1.668 billion, respectively.

financial crisis many hedge funds removed significant assets from the prime brokers that were considered least financially sound. The results remain unaltered with the inclusion of hedge fund fixed effect and controls. Moreover, the results are robust to event windows from 2 to 6 months, and to different termination return adjustments. Finally, the results are similar if we instead consider risk-adjusted hedge fund returns (see the Internet Appendix).

In sum, the analysis of hedge fund events suggests that large individual prime broker shocks only affect the returns of its hedge fund clients who use the affected prime broker as its only prime broker, and that a prime broker shock has lead to significant under-performance of its hedge fund clients only in the case of Lehman bankruptcy. We draw two implications from this result. First, to have an economically significant impact on the returns of its hedge fund clients, a prime broker shocks needs to be extreme as was the case with Lehman's bankruptcy. Second, the propagation of extreme negative prime broker shocks to its clients represents diversifiable counterparty risk that is mitigated by using multiple prime brokers, which is in line with Dai and Sundaresan (2009) suggestion that hedge funds have relations with multiple prime brokers for better risk management.

6 Robustness

6.1 Double sorts on correlation, liquidity, uncertainty and tail risk

In this subsection we check whether the cross-sectional spread in returns and alphas of the FI-factor-sorted hedge fund portfolios is preserved in the presence of factors considered in the literature, namely, the liquidity factor of Sadka (2010), 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) and the tail risk factor of Agarwal et al. (2017).

We follow the procedure outlined in Ang, Hodrick, Xing, and Zhang (2006) to account for alternative factors. For example, to control for liquidity factor of Sadka (2010), we first sort funds into five quintiles based on their historical Sadka (2010) liquidity betas. Within each quintile, we then sort each fund into five portfolios sorted on their historical FI betas (all porfolios are equal-weighted and rebalanced monthly). The five FI beta-sorted portfolios are finally averaged over each of the Sadka (2010) liquidity sorted portfolios. The same procedure is performed for the other factors.

Table 10 presents the Fung and Hsieh (2004) alphas and average monthly returns for the five portfolios obtained from controlling for the various factors. The difference in the average annualized returns and alphas between the high intermediary and the low intermediary beta remains high (9.12% and 8.04%, respectively) and significant (t-stats = 3.2 and 2.7) when controlling for the correlation factor.

Controlling for the two liquidity factors reduces the spreads. In the case of the Pástor and Stambaugh (2003) liquidity factor, the annualized spread in returns and alphas is 5.40% and 3.24%, respectively (t-stats = 3.8 and 1.9). In the case of the Sadka (2010) measure, the spread in returns remains statistically significant but the spread in alphas does not. This decrease in significance is likely driven by the availability of the Sadka (2010) liquidity measure for the shorter period between January 2000 and December 2012. However, the results imply that the FI factor is related to liquidity risk. This seems natural given that financial intermediaries are the key suppliers of liquidity in the economy.

Next we look at the cross-section of the FI sorted portfolios after accounting for aggregate macroeconomic uncertainty. The annualized spread in returns and alphas decreases to around 3% in both cases, but remains statistically significant (t-stat = 2.0). This suggests that a portion of intermediary risk may be related to macroeconomic uncertainty, particularly given our sample period.

Lastly we examine the cross-section of the FI sorted portfolios after accounting for the tail risk factor of Agarwal et al. (2017). The annualized spread in returns and alphas decreases to 3.00% and 4.68%, respectively. The spread in alpha remains statistically significant (t-stat = 2.9). This result suggests that tail risk and financial intermediary risk may be related. Nevertheless, our results still show that FI has incremental power in explaining the cross section of hedge fund returns.

6.2 Backfill bias

Backfill bias is usually a concern in hedge fund research. We concentrate mainly on estimating cross-sectional differences in performance where backfilling should be less of an issue. Nevertheless, to ameliorate back-fill bias, we follow Fung and Hsieh (2000b) and disregard the first 12 months of return of all the hedge funds in our sample and then repeat our main analysis. The Internet Appendix presents the results of intermediary-beta-sorted portfolios and the cross-section regressions. There is no noticeable effect on our results.

6.3 Hedge fund portfolio returns during extreme factor realizations

Our results thus far indicate that exposure to financial intermediary risk is highly predictive of future hedge fund returns. On average, hedge funds that have a high beta on the FI factor earn higher risk-adjusted returns than those with a low beta. We want to ensure that this relationship is preserved in the tails. If this difference in returns is truly a compensation for risk, we should observe the portfolio of hedge funds with low intermediary beta to act as a hedge during the times when this risk is realized (i.e., in periods of large negative shocks to the financial sector). Vice versa, the high-beta portfolios should strongly outperform the portfolio with low beta in periods with large positive shocks to the intermediaries.

We offer some informal evidence in support of this. We examine the twenty largest positive and negative realizations of the FI factor (orthogonalized with respect to the market return) and calculate the return on the two decile portfolios with the highest and lowest loading (portfolios 1 and 10, respectively). The Internet Appendix shows the average returns for the two portfolios (also orthogonalized with respect to the market return) during the extreme negative and positive realizations of the FI factor. The portfolio with low intermediary beta yields a very small negative market-risk-adjusted return during extreme negative shocks to the FI factor, while the portfolio with high beta earns a relatively large negative risk-adjusted return during these periods. The direction is reversed in the periods experiencing large positive shocks to the FI factor. This provides further evidence that the spread in average hedge fund returns of the intermediary-beta-sorted portfolios is likely driven by the exposure to intermediary risk.

6.4 Network-based factors

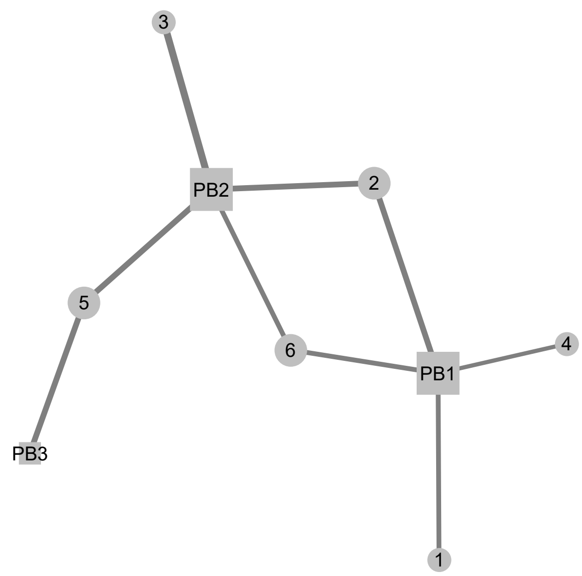
We evaluate the pricing power of the network-constructed factors in the cross-section of hedge fund returns. We proceed by running Fama and MacBeth (1973) regressions, for each reweighted factor, of hedge fund excess returns on the reweighted factor beta and additional controls as in regression (2). The Internet Appendix contains the results. For all four reweighted factors the price of risk is positive and significant (t-statistics are all above 2.1) in the specification without controls. The point estimates of the risk premium are similar to the one reported in Table 5 for our main specification. However, the addition of controls decreases the risk premium estimates in all the cases (ranging from 1.66% to 2.31% depending on the reweighting scheme) and it loses significance in the the specification using the network-centrality-based factor $\mathrm{FI}_{\mathrm{N}}^{eigen}$ (t-stat = 1.6). The network weighting scheme may introduce additional noise into the estimation. These results have two implications. First, it reiterates the importance of financial intermediary risk in the cross-section of hedge fund results. Although the results are not as strong as our benchmark case, the estimated effects using alternative factors are qualitatively similar to our benchmark specification. Second, the slight deterioration in pricing performance suggests that in constructing an empirical intermediary pricing factor over-weighting intermediaries dominant in the prime brokerage sector does not better capture the "marginal" intermediaries.

7 Concluding remarks

Apart from a contraction during the global financial crisis 2007–2009, the growth of the hedge fund industry has been robust over the last decade. According to Hedge Fund Research, hedge fund AUM reached a record high of USD 3.2 trillion in the first quarter of 2018. Taking hedge funds' leverage into account, the total amount of invested capital is likely double that amount. In their task of managing these assets, hedge funds work with one or more large investment banks who act as their prime brokers and provide them with leverage, among many other services. Following the collapse of the hedge fund Long Term Capital Management, much attention has focused on the possibility that hedge fund trading could distort market prices or that large losses in one or several hedge funds get transmitted to one or several systemically important banks. However, there is little evidence that hedge funds systematically distort prices (Fung and Hsieh (2000a)). Moreover, the global financial crisis, which lead to the demise of multiple US investment banks, showed that the reverse direction of shock propagation (from prime brokers to hedge funds) is, perhaps, more important. In line with this, we find that the financial intermediary risk captures cross-sectional differences in hedge fund returns. However, we do not find evidence of individual prime brokers having an effect on their hedge funds clients, which may be surprising given their close connectedness. In sum, our findings suggest that the health of the aggregate financial sector, i.e., the systematic risk, seems to be the key driver of hedge fund returns and the idiosyncratic shocks to individual prime brokers have only limited effect.

Appendix: A simple network example

This appendix shows an example of how the empirical prime broker-fund network is constructed each month. Letting g denote the network and λ denote the proportionality factor, the requirement that the centrality of a node should be proportional to the centrality of its network is equivalent to requiring that the centrality measure satisfies $\lambda \text{Cent}(g) = g\text{Cent}(g)$. That is, the centrality vector, $\text{Cent}(g)$, is an eigenvector of g. The graph shows the network in the adjacency matrix, g. The rows and columns of the matrix corresponds to the fund and prime broker, $\{\text{Fund}_{1:6}, \text{PrimeBroker}_{1:3}\}$. Each edge entry is equal to a number indicating the AUM. As there is no directional annotation in this case, the graph is undirected and g is symmetric, and since it is constructed from a broker-client relationship, it is bipartite (meaning its nodes can be partitioned into two disjoint subsets where no two nodes are adjacent). The squares are prime brokers and the circles are funds, and the width of an edge signifies the amount of AUM (the size of each node is set to the degree of each node, or the total number of clients). The eigenvector corresponding to the largest eigenvalue (scaled by the largest entry) for this adjacency matrix is e, where the largest element by construction is 1, which would rank prime broker number 2 as the most central. By convention, this is the centrality ranking based on the eigenvector (which by the Perron-Frobenius theorem will always be non-negative).



$$g = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.20 & 1.20 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.50 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.90 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.20 & 1.20 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.00 & 1.00 & 0.00 \\ 1.00 & 1.20 & 0.00 & 0.90 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.20 & 1.50 & 0.00 & 1.20 & 1.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.20 & 0.00 & 0.00 & 0.00 & 0.00 \end{bmatrix}$$

$$e = \begin{bmatrix} 0.23 & 0.70 & 0.53 & 0.21 & 0.52 & 0.58 & 0.65 & 1.00 & 0.22 \end{bmatrix}$$

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Table 1: Summary statistics

The table presents summary statistics for the sample of hedge funds in the Eurekahedge database. The sample period is from January 2000 to June 2017. N is the number of unique funds for each year or for each investment style. SD is the standard deviation of monthly returns. The statistics in Panel A are based on the time-series averages of monthly cross-sectional averages of excess returns (in %, and converted to USD for funds denominated in another currency). The statistics in Panel B are for fund characteristics: AUM (based on the time-series average of monthly cross-sectional averages of AUM, in USD million), Age (the age distribution for dead and alive funds each month), and Reporting (the cross-sectional average of the total number of monthly observations for each fund).

Panel A: Monthly returns

	N	Mean	Median	SD	Skewness	Min	Max
Full sample	2697	0.61	0.50	3.96	0.93	−24.52	34.21
Year							
2000	440	0.74	0.41	5.76	1.01	−18.37	34.46
2001	510	0.51	0.46	4.65	0.27	−21.16	23.24
2002	614	0.53	0.38	4.64	0.51	−19.08	24.95
2003	764	2.09	1.59	3.78	1.20	−12.18	25.96
2004	918	1.06	0.86	3.18	1.97	−11.84	31.44
2005	1082	0.63	0.41	3.01	0.56	−12.07	17.30
2006	1274	1.01	0.83	3.16	1.39	−13.44	26.68
2007	1447	0.89	0.61	3.53	1.28	−19.72	34.88
2008	1569	−1.63	−1.32	6.41	1.59	−47.87	67.77
2009	1635	2.16	1.83	4.90	0.93	−26.01	44.65
2010	1716	0.90	0.79	4.28	3.10	−30.27	55.44
2011	1776	−0.35	−0.24	3.81	0.50	−34.06	42.14
2012	1778	0.73	0.66	3.19	−0.24	−31.71	27.93
2013	1750	0.76	0.81	2.95	−1.00	−32.71	21.28
2014	1703	0.03	0.03	3.17	0.03	−34.72	30.53
2015	1629	−0.13	−0.02	3.90	1.59	−28.01	43.82
2016	1488	0.25	0.26	3.55	1.93	−19.86	33.21
2017	1340	1.03	0.93	2.70	−0.51	−32.08	25.85
Style							
Event Driven	141	0.65	0.51	3.08	0.72	−7.54	11.78
Global Macro	203	0.52	0.47	3.59	0.19	−9.86	12.00
Long Only	328	0.71	0.55	4.16	0.34	−12.41	16.97
Long Short	960	0.63	0.50	4.01	0.56	−17.56	23.72
Managed Futures	181	0.51	0.43	3.94	0.16	−11.26	13.42
Market Neutral	114	0.44	0.40	2.30	0.33	−6.28	7.67
Multi Strategy	266	0.72	0.56	3.55	0.51	−10.28	15.57
Others	78	0.54	0.56	4.37	−0.48	−11.61	10.25
Relative Value	426	0.59	0.55	2.68	0.40	−8.69	11.34

Panel B: Characteristics

	N	Mean	Median	25 percentile	75 percentile	Min	Max
AUM	2697	396.80	119.86	52.19	322.02	15.00	25381.14
Age	2697	78.31	74.02	65.46	87.50	54.75	118.99
Reporting	2697	93.99	83.00	49.00	127.00	24.00	210.00

Table 2: Top prime brokers over time

The table presents the market share of each prime broker (name abbreviated), recorded on the June snapshot every year in the universe of funds that reports prime broker affiliation and AUM (7976 funds). The prime brokers are ranked by their number of clients (Panel A) and total AUM their clients manage (Panel B). The statistic (as a percentage of the total) is showed in parentheses next to the prime broker name. The abbreviation mapping is BA: Bank of America; 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: JP Morgan; LB: Lehman Brothers; ML: Merril Lynch; MS: Morgan Stanley; and SocGen: Societe Generale.

Panel A: Clients

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
MS (17)	MS (18.4)	MS (17.9)	GS (15.6)	GS (15)	GS (14.3)	GS (13.4)	GS (12.7)	GS (12.7)	GS (12.5)	MS (13.2)
GS (15.9)	GS (16.5)	GS (15.6)	MS (14.5)	MS (12.6)	MS (12.7)	MS (11.3)	MS (11.6)	MS (11)	MS (12)	GS (11.6)
UBS (10.3)	UBS (11.3)	UBS (13)	UBS (11.7)	UBS (10.9)	UBS (10.9)	UBS (10.3)	UBS (11)	UBS (10.3)	UBS (9.9)	UBS (10.3)
BS (9.3)	BS (7.5)	JPM (7.3)	JPM (7.3)	BAML (7.4)	DB (7.4)	JPM (8.3)	JPM (8.5)	JPM (7.7)	JPM (7.5)	SocGen (7.9)
DB (5.8)	DB (6)	BAML (6.9)	DB (6.7)	JPM (7.2)	JPM (7.4)	DB (7.4)	CS (7)	DB (7.3)	DB (6.8)	CS (6.8)
ML (4.1)	CS (4.3)	DB (5.8)	SocGen (6.3)	SocGen (6.7)	SocGen (6.7)	SocGen (7.2)	DB (6.9)	CS (6.9)	CS (6.7)	DB (6.8)
BA (3.9)	ML (4.1)	SocGen (5.1)	BAML (6.1)	DB (6.6)	BAML (6.4)	CS (6.6)	SocGen (6.3)	BAML (6.3)	SocGen (6.6)	BAML (5.8)
CS (3.7)	BA (3.4)	Citi (4)	CS (5.5)	CS (6)	CS (6)	BAML (6.1)	BAML (5.8)	SocGen (6.2)	BAML (6.1)	JPM (5.3)
Nomura (3.7)	Citi (3.2)	CS (3.8)	Citi (4.4)	Citi (3.9)	Citi (4.1)	Citi (3.5)	Citi (3.6)	Citi (3.4)	Citi (3.7)	Citi (4.1)
SocGen (3.1)	SocGen (3.2)	MAN (2.4)	MAN (2.2)	MAN (2.4)	Barclays (1.8)	Barclays (2.2)	Barclays (2.2)	Barclays (2.4)	IB (2.8)	Barclays (2.9)

Panel B: AUM

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
MS (21)	MS (19.7)	MS (22.2)	JPM (17.4)	JPM (16.3)	JPM (16.2)	GS (17.6)	GS (16.9)	GS (20.4)	GS (21.3)	GS (21.6)
GS (17.7)	GS (18)	GS (16)	MS (15.7)	GS (13.6)	GS (14.8)	JPM (15.8)	JPM (15.4)	JPM (13)	MS (12.5)	MS (14.8)
BS (9.9)	BS (11)	JPM (14.3)	GS (13.5)	MS (11.5)	UBS (12)	UBS (11.2)	UBS (11)	MS (10.2)	JPM (11.7)	DB (9.7)
DB (8.3)	UBS (8.7)	UBS (9.5)	UBS (11.2)	UBS (10.5)	MS (10.7)	MS (9.7)	MS (10)	DB (10.2)	DB (10.2)	UBS (8.7)
UBS (7.9)	DB (8.5)	DB (6.5)	DB (8.1)	DB (8.4)	DB (9)	DB (9)	CS (9.7)	CS (9.3)	UBS (8.4)	JPM (8.1)
Nomura (4.8)	ML (4)	BAML (5.1)	CS (8)	CS (8.3)	CS (6.7)	CS (7.7)	DB (8.2)	UBS (9.3)	CS (8)	CS (8)
CS (3.9)	CS (4)	SocGen (4.9)	SocGen (4.4)	BAML (5.3)	BAML (4.9)	Barclays (5.1)	Citi (5.8)	BAML (5.3)	BAML (5.7)	BAML (5.7)
BA (3.3)	SocGen (3.6)	CS (3.5)	BAML (3.4)	SocGen (5.2)	SocGen (4.6)	SocGen (4.6)	BAML (4.7)	Citi (4.4)	Barclays (4.5)	Citi (4.3)
SocGen (3)	LB (3.4)	AIG (2.8)	BNP P (2.8)	SEB (2.8)	Citi (4.1)	BAML (4)	Barclays (3.2)	Barclays (4.2)	Citi (3.7)	SocGen (4.3)
LB (2.8)	BA (2.6)	Citi (1.9)	Citi (2.5)	Barclays (2.7)	Barclays (3.5)	Citi (3.8)	BNP P (2.8)	SocGen (2.6)	SocGen (3.1)	Barclays (3.2)

Table 3: Intermediary factors summary statistics and correlation matrix

The table presents summary statistics and the correlation matrix of the financial intermediary factors constructed using different weighting schemes. FI is the value-weighted portfolio of 38 listed financial intermediaries; $\mathrm{FI}_{\mathrm{ew}}$ is an equal-weighted portfolio; FI_{N} and $\mathrm{FI}_{\mathrm{AUM}}$ are portfolios of financial intermediaries where the weights are based on the number of hedge fund clients and the total client AUM, respectively; $\mathrm{FI}_{\mathrm{N}}^{eigen}$ and $\mathrm{FI}_{\mathrm{AUM}}^{eigen}$ are portfolios of financial intermediaries where the weights are based on the eigenvector centrality with client connections and AUM connections, respectively; HKM is the traded factor of primary dealers of He et al. (2017); PC1 is the first principal component extracted from a panel of returns of 29 financial intermediaries with continuous return series during the sample period. The reported statistics are in %. The means and standard deviations are annualized. The data are monthly and the sample period runs from January 2000 to June 2017.

Panel A: Summary statistics

	FI	$\mathrm{FI}_{\mathrm{ew}}$	FI_{N}	$\mathrm{FI}_{\mathrm{AUM}}$	$\mathrm{FI}_{\mathrm{N}}^{eigen}$	$\mathrm{FI}_{\mathrm{AUM}}^{eigen}$	HKM
Mean	9.49	8.12	6.17	5.4	6.56	5.79	7.9
SD	23.25	23.12	27.83	28.59	29.71	28.48	23.34
Min	−22.67	−25.55	−23.67	−24.97	−24.64	−33.28	−23.43
Max	29.12	26.21	26.09	26.93	24.84	24.67	30.55

Panel B: Correlation matrix

	FI	$\mathrm{FI}_{\mathrm{ew}}$	FI_{N}	$\mathrm{FI}_{\mathrm{AUM}}$	$\mathrm{FI}_{\mathrm{N}}^{eigen}$	$\mathrm{FI}_{\mathrm{AUM}}^{eigen}$	HKM	PC1
FI	1.000							
$\mathrm{FI}_{\mathrm{ew}}$	0.967	1.000						
FI_{N}	0.941	0.947	1.000					
$\mathrm{FI}_{\mathrm{AUM}}$	0.938	0.939	0.999	1.000				
$\mathrm{FI}_{\mathrm{N}}^{eigen}$	0.867	0.874	0.974	0.977	1.000			
$\mathrm{FI}_{\mathrm{AUM}}^{eigen}$	0.902	0.913	0.981	0.984	0.969	1.000		
HKM	0.982	0.951	0.932	0.930	0.863	0.900	1.000	
PC1	0.976	0.988	0.930	0.923	0.854	0.892	0.963	1.000

Table 4: Risk-adjusted returns and other characteristics for beta-sorted portfolios

The table presents mean excess return, alphas and betas of hedge fund portfolios. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return; α_{FH} refers to Fung and Hsieh (2004) seven-factor alpha and R^2_{FH} to the corresponding R-squared. $\bar{r}$ and α_{FH} are reported in % per month. The post betas are the betas from a single time series regression of factors against each of the ten portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH}	R^2_{FH}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.37	−0.18	0.57	0.05	0.40	−0.37	0.80
	(1.16)	(−0.69)		(0.63)	(2.65)	(−6.48)	(5.33)
2	0.38	−0.08	0.63	0.08	0.26	−0.12	0.46
	(1.75)	(−0.57)		(1.44)	(2.31)	(−4.45)	(5.47)
3	0.39	0.01	0.66	0.06	0.26	−0.04	0.34
	(2.13)	(0.05)		(1.55)	(3.09)	(−1.58)	(4.59)
4	0.37	−0.01	0.69	0.09	0.20	0.01	0.28
	(2.16)	(−0.07)		(2.08)	(2.14)	(0.40)	(5.71)
5	0.49	0.15	0.68	0.08	0.20	0.06	0.25
	(3.26)	(1.71)		(2.42)	(2.98)	(1.68)	(6.69)
6	0.50	0.12	0.63	0.08	0.21	0.12	0.22
	(3.12)	(1.30)		(2.81)	(3.69)	(2.30)	(8.02)
7	0.58	0.24	0.58	0.09	0.23	0.18	0.18
	(3.38)	(1.92)		(2.52)	(4.87)	(2.88)	(6.14)
8	0.66	0.19	0.50	0.13	0.16	0.26	0.14
	(3.63)	(1.32)		(2.46)	(2.07)	(3.16)	(2.81)
9	0.61	0.17	0.48	0.13	0.18	0.37	0.09
	(3.17)	(1.09)		(2.16)	(2.28)	(4.02)	(1.39)
10 (high)	1.08	0.39	0.49	0.24	0.18	0.68	−0.10
	(3.82)	(1.96)		(3.64)	(1.50)	(5.18)	(−1.09)
10−1	0.71	0.56	0.08	0.19	−0.22	1.05	−0.90
	(3.97)	(2.14)		(2.16)	(−1.89)	(11.94)	(−7.14)

Table 5: Hedge fund intermediary risk premium

The table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on post-ranking intermediary betas. Ten portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary, FI traded factor (controlling for the market return) and rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the ten portfolios. These post-ranking betas are then assigned to each fund according to which decile portfolio they belonged to at a given month. Time $t+1$ monthly excess fund returns (%) are regressed on the time t post-ranking betas as well as fund age (in months), AUM (in USD million), a dummy indicating if the fund has a lockup provision, management fee (in %), incentive fee (in %), the redemption notice (in days), the minimum fund investment amount (USD million) and a dummy indicating if the fund has a high water mark. β^{M} is the time t post-ranking beta with respect to the market. r_t is time t excess fund return (in %). Leverage is a dummy indicating whether the fund is levered or not. Fixed effects are style dummies, following the Kosowski et al. (2016) mapping, and geographical region dummies (Asia ex-Japan, Australia, Canada, EMEA, Japan, South America, US). t-statistics with Newey and West (1994) standard errors are reported in parentheses. N is the number of observations. The sample runs from January 2000 to June 2017.

	I	II	III	IV	V	VI
β^{FI}	3.683	3.202	3.490	2.753	2.579	2.450
	(3.711)	(3.549)	(2.728)	(2.510)	(2.425)	(2.214)
β^{M}			0.306	0.303	0.335	0.331
			(0.590)	(0.782)	(0.906)	(0.877)
r_t				0.106	0.111	0.113
				(7.068)	(7.939)	(7.928)
Age				−0.001	−0.001	−0.001
				(−1.833)	(−2.409)	(−2.189)
log(AUM)				−0.032	−0.025	−0.028
				(−2.779)	(−2.365)	(−2.494)
Lockup				0.061	0.056	0.054
				(1.455)	(1.794)	(1.718)
Management fee				0.035	0.035	0.029
				(1.918)	(2.108)	(1.780)
Incentive fee				0.001	−0.000	−0.001
				(0.302)	(−0.057)	(−0.256)
Redemption notice				0.001	0.001	0.001
				(2.123)	(2.646)	(2.536)
Minimum investment				0.000	0.002	0.002
				(0.107)	(0.666)	(0.542)
High water mark				0.039	0.039	0.040
				(0.766)	(0.895)	(0.896)
Leverage						−0.003
						(−0.061)
$\beta^{\mathrm{FI}}\times$Leverage						0.418
						(0.797)
Constant	0.166					
	(0.891)					
Style fixed effects	No	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	Yes	Yes
N	193,366	193,366	193,366	178,282	178,282	172,239
R^2	0.248	0.318	0.386	0.430	0.467	0.468

Table 6: Intermediary factor portfolios by leverage, AUM, and number of prime brokers

The table presents the FI factor sorted portfolios in the cross-section of hedge fund returns by leverage, number of prime brokers, and AUM. Five portfolios are constructed every month, for each of the binary partitions (on leverage, AUM, and prime brokers). Reported are Fung and Hsieh (2004) alphas (monthly, in %). The AUM cutoff between Small and Big is USD 120 million. The sample runs from January 2000 to June 2017.

Panel A: Leverage

	1 (low)	2	3	4	5 (high)	5−1
Yes	−0.02	0.05	0.18	0.22	0.33	0.35
	(−0.09)	(0.44)	(2.29)	(1.90)	(1.94)	(1.86)
No	−0.25	−0.02	0.06	0.22	0.23	0.49
	(−1.26)	(−0.15)	(0.56)	(1.46)	(1.26)	(1.96)
Yes−No	0.24	0.07	0.12	0.00	0.09	−0.14
	(3.33)	(1.32)	(2.27)	(0.06)	(0.78)	(−1.17)

Panel B: AUM

	1 (low)	2	3	4	5 (high)	5−1
Small	−0.06	−0.00	0.14	0.18	0.22	0.28
	(−0.35)	(−0.01)	(1.39)	(1.21)	(1.19)	(1.52)
Big	−0.12	−0.01	0.15	0.22	0.26	0.38
	(−0.66)	(−0.06)	(1.81)	(1.77)	(1.54)	(2.01)
Small−Big	0.05	0.01	−0.02	−0.03	−0.04	−0.09
	(0.65)	(0.08)	(−0.28)	(−0.40)	(−0.51)	(−0.89)

Panel C: Number of prime brokers

	1 (low)	2	3	4	5 (high)	5−1
One	−0.11	−0.01	0.19	0.32	0.37	0.48
	(−0.59)	(−0.12)	(2.42)	(2.60)	(2.02)	(2.13)
Multiple	0.01	0.27	0.26	0.44	0.44	0.43
	(0.05)	(2.83)	(3.15)	(3.98)	(2.89)	(2.32)
One−Multiple	−0.12	−0.28	−0.07	−0.11	−0.08	0.04
	(−1.30)	(−4.51)	(−1.19)	(−1.40)	(−0.69)	(0.37)

Table 7: Prime broker and fund statistics

The table presents summary statistics for prime brokers and their hedge fund clients. Size is the average market capitalization during our sample period of the publicly listed prime brokers (in USD billion). Return (Fund) statistics are based on the time series of monthly average excess returns for each fund belonging to a given prime broker (monthly, in %). AUM (fund) is based on the time series of average AUM for each fund, and AUM (prime broker) on the time series of the sum of the AUM managed by each prime broker (divided evenly in the cases when a fund uses multiple prime brokers). The AUM statistics are in million USD. Clients is the time series count average. The sample contains 1654 funds that report a prime brokerage affiliation, and where the prime broker has at least five clients (43 brokers). The sample period runs from January 2006 to June 2017.

		Returns (fund)		AUM (fund)		AUM (prime broker)		
Prime broker	Size	Average	Median	Average	Median	Average	Median	Clients
Goldman Sachs	63	0.43	0.56	254	237	56434	55032	228.3
Morgan Stanley	38	0.38	0.58	230	216	44573	38605	192.7
UBS	42	0.53	0.68	231	236	28473	29840	123.8
JP Morgan	66	0.50	0.59	428	436	49758	52272	115.8
Credit Suisse	30	0.53	0.63	245	248	23076	24802	92.8
Deutsche Bank	32	0.54	0.55	248	220	20603	19364	85.7
BAML	69	0.43	0.55	182	158	11154	10032	61.6
Citi	111	0.44	0.63	211	223	10353	10593	50.6
Bear Stearns	5	0.02	0.34	484	475	24456	30350	48.1
Societe Generale	27	0.33	0.28	257	286	10544	11295	41.2
Barclays	36	0.45	0.51	237	229	7038	7054	29.4
Merrill Lynch	16	0.17	0.79	158	177	3775	3930	23.8
Lehman Brothers	16	0.37	0.59	193	155	4298	3572	22.4
BNP Paribas	55	0.75	0.90	277	276	5492	6490	18.6
Itau Unibanco	20	0.84	1.04	187	187	2967	3243	15.4
Man Financial	1	0.82	0.60	196	196	2689	2759	13.9
SEB	10	0.42	0.37	486	491	6511	6325	13.3
Jefferies	5	0.63	0.90	112	117	1262	1057	11.7
RBC	38	0.43	0.63	198	205	2134	2053	10.7
Fidelity	NA	0.53	0.54	257	228	2067	1730	8.1
Banco Bradesco	16	0.91	1.13	213	212	1643	1630	7.8
Conifer	NA	1.25	1.04	376	55	5929	55	6.5
RMB	5	0.46	0.72	41	43	250	256	6.0
HSBC	125	0.45	0.46	151	154	901	874	5.9
Nomura	28	0.35	0.13	447	355	2587	931	5.4
TD	32	0.71	0.69	234	207	1351	1162	5.3
Interactive Brokers	2	1.32	1.27	97	94	536	615	5.3
National Bank of Canada	6	0.46	0.70	63	52	307	350	5.1
Peregrine	NA	0.58	0.54	125	130	601	549	4.9
BTIG	NA	0.51	0.81	62	47	364	255	4.8
BNY Mellon	16	1.13	0.90	87	88	388	382	4.3
Fortis	20	0.94	1.32	104	96	407	434	4.2
RBS	33	0.38	0.29	161	161	673	723	4.1
Scotiabank	28	0.49	0.69	151	128	638	645	4.1
ING	NA	0.57	0.65	128	116	443	454	3.3
Credit Agricole	36	0.68	0.89	170	174	684	644	3.3
ADM	8	0.82	1.28	62	51	217	158	3.2
Brown Brothers Harriman & Co	NA	0.86	1.10	187	163	609	404	3.2
ABN AMRO	24	1.10	1.11	171	154	536	486	3.1
Wells Fargo	55	0.71	0.77	66	32	323	32	3.1
Natixis	9	0.33	0.35	205	200	613	571	2.8
Dredsner Bank	NA	1.26	0.65	462	419	804	753	2.5
Merlin Securities	NA	1.40	1.33	57	37	113	112	2.4

Table 8: Hedge funds and prime broker returns

The table presents OLS panel regressions of monthly (time t) hedge fund returns in % on the return of each fund's prime broker (orthogonalized, $\perp$, with respect to the market return, M, the financial intermediary factor, FI, and each prime broker's home country stock market index, CI). CI is only included in the cases where a prime broker is listed outside of the US. Controls include: fund age and AUM. Hedge fund fixed effects are included in all specifications. t-statistics in parentheses are based on standard errors clustered by fund and time. N is the number of observations. The sample period runs from January 2006 to June 2017 and the sample contains 35 unique listed prime brokers.

	I	II	III	IV	V
$r_{i,t}^{PB}$	0.119				
	(8.453)				
$r_{i,t}^{PB} \perp M$		0.052			
		(3.491)			
$r_{i,t}^{PB} \perp M \perp FI$			0.036	0.035	
			(1.877)	(1.814)	
$r_{i,t}^{PB} \perp M \perp FI \perp CI$					0.005
					(0.237)
N	120,105	120,105	120,105	120,105	120,105
Adjusted R^2	0.086	0.010	0.004	0.007	0.004
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes

Table 9: Event study

This table shows OLS panel regressions of monthly hedge fund excess returns in % on a set of indicator variables and their interactions. PB Events is an indicator variable that is equal to one during the event window and zero otherwise. The event window is 4 months, including the event month. 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 at the time of the event, and zero otherwise. Lehman Event is an indicator variable equal to one during the event window around the Lehman Brother bankruptcy (September 2008), and zero otherwise. Lehman Client is an indicator variable that is equal to one if a hedge fund was a client of Lehman at the time of the event. PB Unique Client and Lehman 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, and zero otherwise. Hedge fund fixed effects are included in specifications displayed in columns III and IV. Controls include: fund age and AUM. t-statistics in parentheses are based on standard errors clustered by fund and time. N is the number of observations. The sample period runs from January 2006 to June 2017.

	I	II	III	IV
PB Events	−1.299	−1.299	−1.305	−1.426
	(−1.901)	(−1.902)	(−1.871)	(−2.053)
PB Client	0.124	0.135		
	(2.458)	(1.806)		
PB Events × PB Client	0.015	0.057	0.096	0.072
	(0.123)	(0.187)	(0.303)	(0.223)
PB Unique Client		−0.016		
		(−0.213)		
PB Events × PB Unique Client		−0.066	−0.037	−0.030
		(−0.188)	(−0.102)	(−0.086)
Lehman Event	−4.360	−4.360	−4.322	−4.718
	(−2.168)	(−2.168)	(−2.129)	(−2.316)
Lehman Client	0.057	−0.121		
	(0.382)	(−1.025)		
Lehman Event × Lehman Client	−0.296	1.894	2.043	2.188
	(−0.243)	(1.976)	(2.154)	(2.376)
Lehman Unique Client		0.641		
		(2.114)		
Lehman Event × Lehman Unique Client		−7.164	−7.192	−7.092
		(−2.936)	(−2.780)	(−2.910)
Constant	0.475	0.474		
	(2.765)	(2.764)		
N	131,073	131,073	131,073	130,216
Adjusted R^2	0.025	0.026	0.029	0.041
Fund fixed effects	No	No	Yes	Yes
Controls	No	No	No	Yes

Table 10: Double sorts with controls

This table presents results for portfolios sorted on the intermediary factor, FI, controlling separately for the correlation factor of Buraschi et al. (2013) (available up to June 2012), the liquidity factor of Sadka (2010) (available up to December 2012), the liquidity factor of Pástor and Stambaugh (2003), PS, the macroeconomic uncertainty factor of Bali et al. (2014), and the tail risk factor of Agarwal et al. (2017). Quintiles based on the controlling factor are determined monthly. Each of these portfolios are then subdivided into five quintiles based on their past FI beta loading (formed monthly and equal weighted). We obtain five FI portfolios controlling for the given factor by averaging each FI quintile over the five control portfolios, as in Ang et al. (2006). The excess market return is included as a control in all regressions. Reported are: mean excess returns $\bar{r}$ (in % per month) and Fung and Hsieh (2004) seven-factor alphas α_{FH} (in % per month). t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017.

	Correlation		Liquidity (Sadka)		Liquidity (PS)		Uncertainty		Tail Risk	
	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}
1	0.38	−0.18	0.53	0.16	−0.02	0.40	0.48	−0.05	0.48	0.05
	(1.11)	(−0.65)	(1.83)	(0.81)	(−0.12)	(1.82)	(2.02)	(−0.35)	(1.71)	(0.23)
2	0.40	−0.00	0.45	0.12	0.05	0.43	0.43	0.05	0.43	0.06
	(1.67)	(−0.01)	(1.91)	(0.77)	(0.45)	(2.47)	(2.43)	(0.51)	(1.82)	(0.42)
3	0.54	0.27	0.59	0.24	0.04	0.45	0.47	0.11	0.47	0.28
	(2.55)	(2.20)	(2.86)	(1.72)	(0.40)	(2.58)	(2.77)	(1.12)	(2.13)	(2.18)
4	0.69	0.38	0.65	0.24	0.12	0.51	0.61	0.20	0.61	0.29
	(3.02)	(2.60)	(2.87)	(1.80)	(1.03)	(2.84)	(3.62)	(1.81)	(2.62)	(2.14)
5	1.05	0.58	0.93	0.34	0.25	0.85	0.73	0.20	0.73	0.43
	(3.49)	(2.61)	(3.08)	(1.70)	(1.57)	(3.47)	(3.25)	(1.32)	(2.59)	(2.37)
5-1	0.67	0.76	0.40	0.17	0.27	0.45	0.25	0.26	0.25	0.39
	(3.71)	(2.91)	(3.92)	(1.07)	(1.91)	(3.80)	(2.03)	(2.03)	(1.78)	(2.93)

Figure 1: Simple static network of hedge funds and prime brokers

The figure shows the network obtained by looking at the hedge funds in June 2017 and assigning an edge between two vertices if there is a prime broker relationship between these entities (a fund and a prime broker). Circles are funds and square vertices are prime brokers. The circle color denotes the investment style of the fund. Node labels are printed for the largest prime brokers with names abbreviated. The abbreviation mapping is BAML: Bank of America Merrill Lynch; BNP P: BNP Paribas; CS: Credit Suisse; DB: Deutsche Bank; GS: Goldman Sachs; JPM: JP Morgan; MS: Morgan Stanley; and SocGen: Societe Generale. The graphical layout is obtained with the Fruchterman-Reingold algorithm, which indicates a core-periphery structure with central prime brokers ending up in the middle.

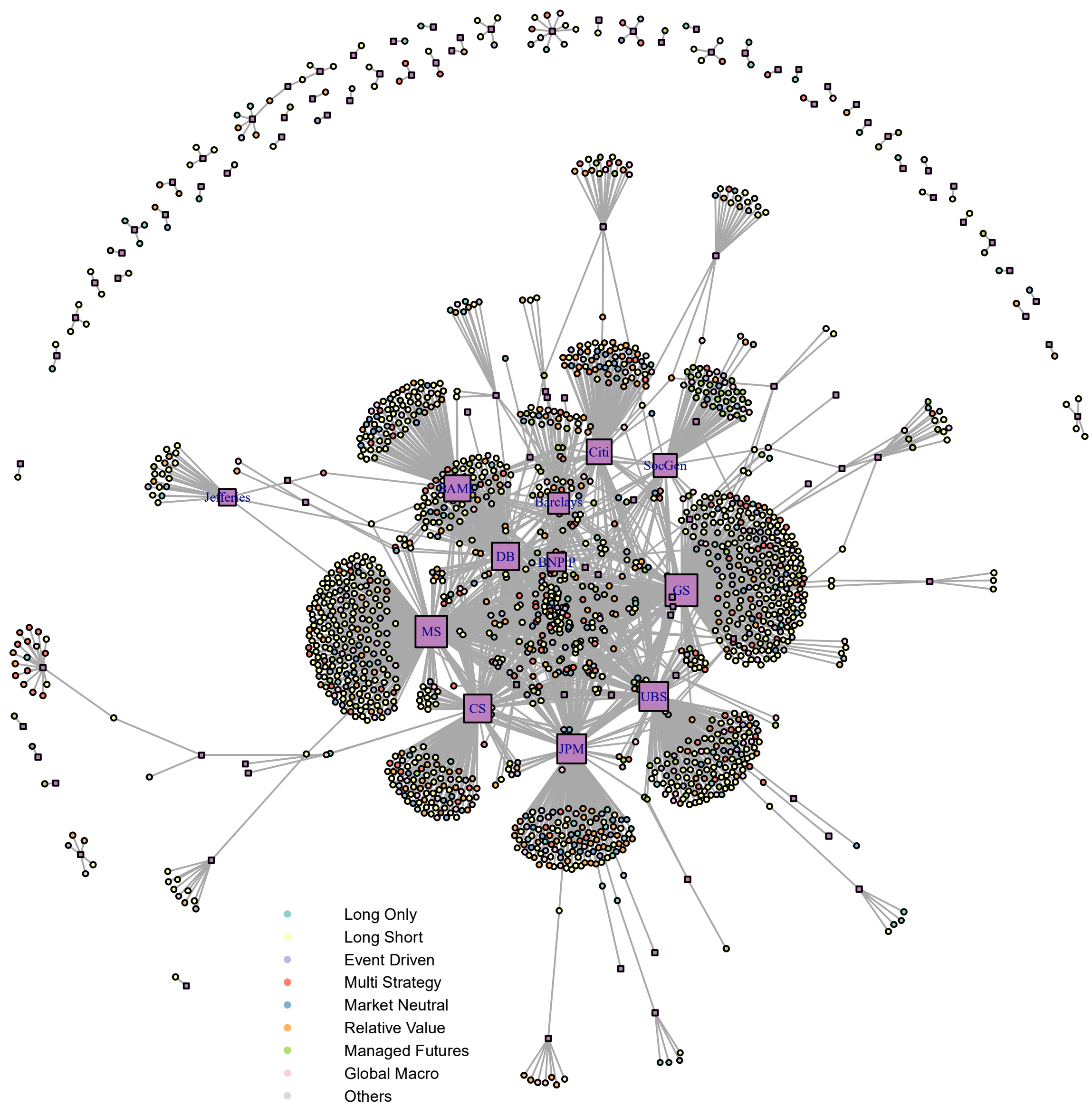


Figure 2: Prime broker fixed effect

The top panel of the figure shows the estimated coefficients of individual prime broker fixed effect on hedge fund alpha. The estimates are from regression (3). Only the coefficients that are found to be statistically significant at 10% level are shown. Goldman Sachs is used as a base prime broker. The sample contains 1645 funds that report a prime brokerage affiliation, and where the prime broker has at least five clients. The bottom panel displays the average share of the total hedge fund client AUM (in %) that each prime broker represents during our sample period. In both panels the prime broker names are displayed in a descending order based on their share of the total hedge fund sector AUM. The prime broker fixed effect is expressed in % per month. The sample period runs from January 2006 to June 2017.

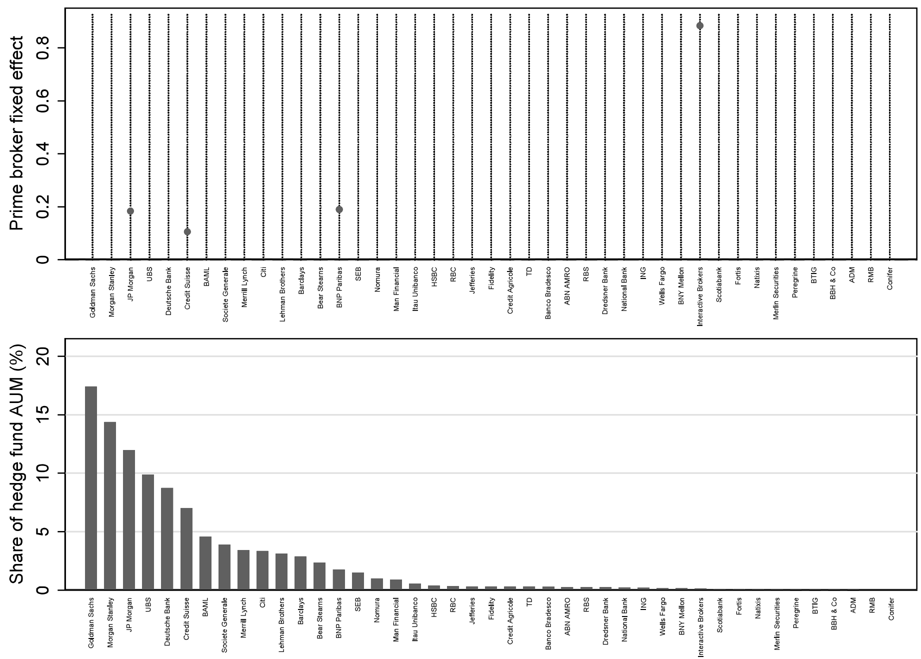
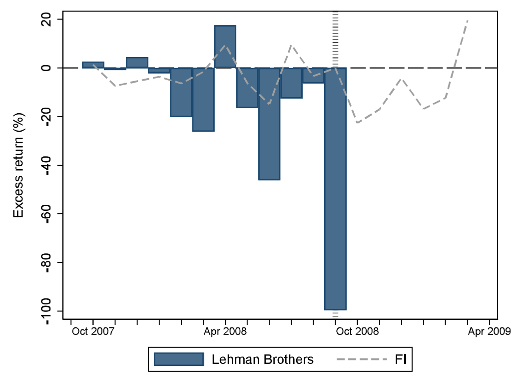
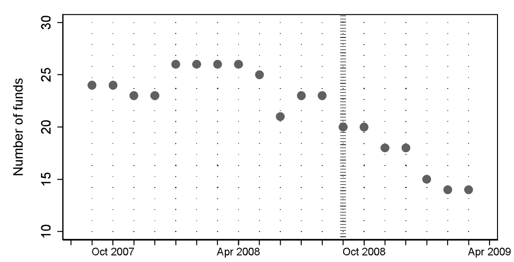


Figure 3: Event study of Lehman Brothers bankruptcy

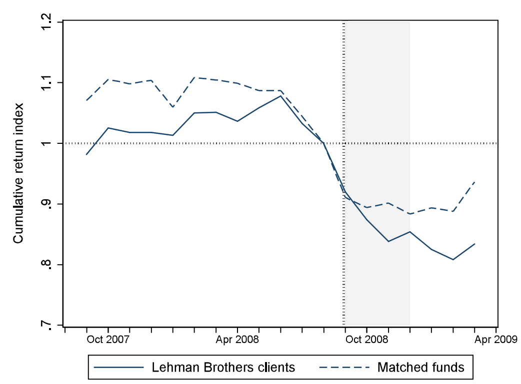
The top panel of the figure shows the monthly returns of Lehman Brothers and the return to a value-weighted portfolio of prime brokers (FI) around the time of Lehman's bankruptcy (September 2008). The dashed vertical line indicates the time of the event. The middle panel shows the number of Lehman's hedge fund clients reporting to the database each month. The bottom panel shows the cumulative return index of an equal-weighted portfolio of Lehman's hedge fund clients along with the return index of a matched portfolio of similar funds that use a different prime broker. The indexes are set to unity during the month prior to the event month. Hedge funds are matched on style, AUM, average returns and volatility over the 12 months before the event, and each fund's financial intermediary beta. The shaded region indicates a 4-months event window.



(a) Prime broker returns



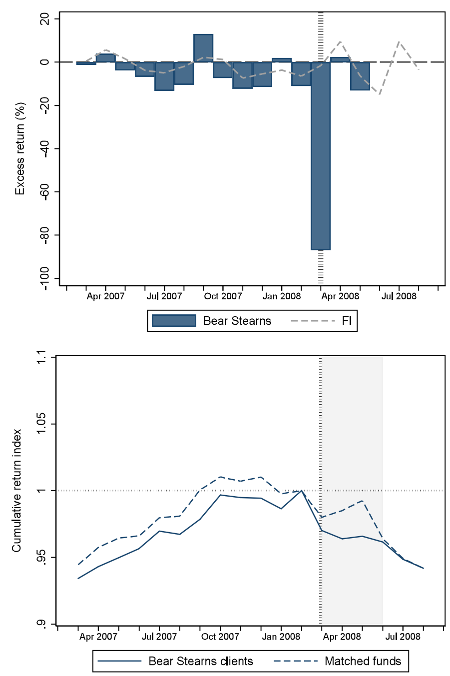
(b) Number of hedge funds



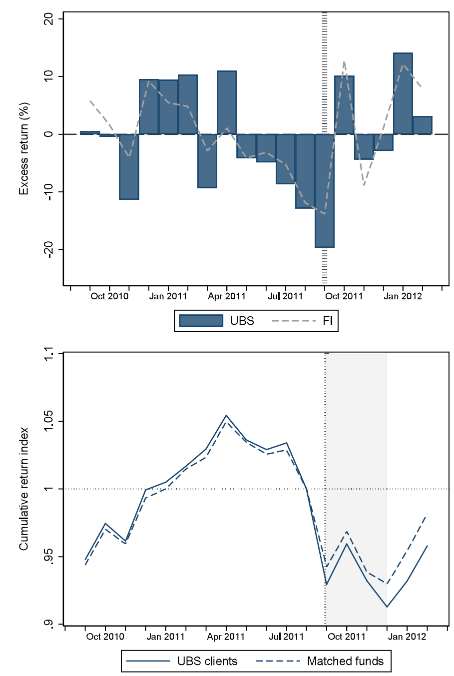
(c) Hedge fund returns

Figure 4: Event study of other prime broker shocks

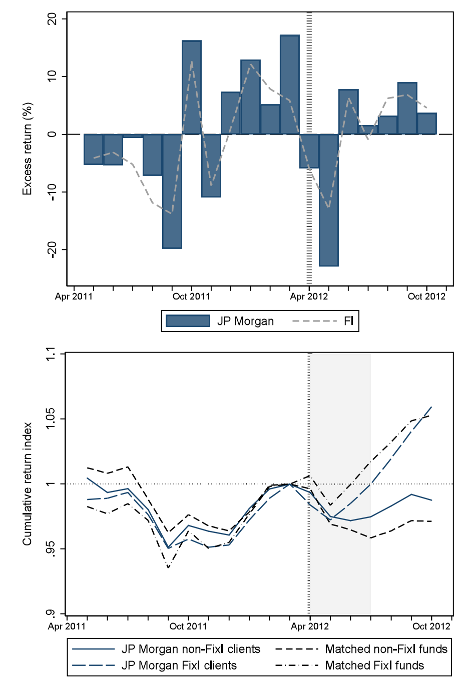
The top three panels of the figure show the monthly returns of Bear Stearns, UBS and JP Morgan around the time of a large negative shock to each prime broker. The three events considered are the failure of Bear Stearns (March 2008), the trading loss scandal of UBS (September 2011) and the trading loss scandal of JP Morgan (April 2012). In each sub-plot the return to a value-weighted portfolio of prime brokers (FI) is also plotted. The dashed vertical line indicates the time of each event. The bottom three panels show the cumulative return indexes of equal-weighted portfolios each prime broker's hedge fund clients together with the cumulative return indexes of the matched hedge funds. The indexes are set to unity during the month prior to the event month. Hedge funds are matched on style, AUM, average returns and volatility over the 12 months before the event, and each fund's financial intermediary beta. The shaded region indicates a 4-months event window. In the case of JP Morgan, the returns to a portfolio of hedge funds following a Fixed Income (FixI) style and hedge funds of other styles (Non-FixI) are displayed separately, along with the relevant matched funds.



(a) Bear Stearns



(b) UBS



(c) JP Morgan

Internet Appendix

Hedge Funds and Financial Intermediaries*

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List of tables

List of figures

Table IA.1: Data sources

Factors	Source
Agarwal, Ruenzi, and Weigert (2017)	http://www2.gsu.edu/~fncvaa/
Asness, Moskowitz, and Pedersen (2013)	https://www.aqr.com/Insights/Datasets
Bali, Brown, and Caglayan (2014)	http://faculty.msb.edu/tgb27/
Fama and French (1993, 2012)	http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
Frazzini and Pedersen (2014)	https://www.aqr.com/Insights/Datasets
Fung and Hsieh (2004)	https://faculty.fuqua.duke.edu/~dah7/HFData.htm
He, Kelly, and Manela (2017)	http://apps.olin.wustl.edu/faculty/manela/data.html
Moskowitz, Ooi, and Pedersen (2012)	https://www.aqr.com/Insights/Datasets
Pástor and Stambaugh (2003)	http://faculty.chicagobooth.edu/lubos.pastor/research/
Sadka (2010)	https://www2.bc.edu/ronnie-sadka/

Table IA.2: Risk-adjusted returns for beta-sorted portfolios (8-factor model)

The table presents mean excess return, alphas and betas of hedge fund portfolios. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return; α_{FH8} refers to Fung and Hsieh (2004) eight-factor alpha and R^2_{FH8} to the corresponding R-squared. $\bar{r}$ and α_{FH8} are reported in % per month. The eight factors are the seven original Fung and Hsieh (2004) factors plus the MSCI Emerging Market index. The post betas are the betas from a single time series regression of factors against each of the ten portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH8}	R^2_{FH8}	β^{FI}	β^{Mkt}	β^{FI}	β^{Mkt}
1 (low)	0.37	−0.09	0.70	0.05	0.40	−0.37	0.80
	(1.16)	(−0.46)		(0.63)	(2.65)	(−6.48)	(5.33)
2	0.38	−0.02	0.74	0.08	0.26	−0.12	0.46
	(1.75)	(−0.18)		(1.44)	(2.31)	(−4.45)	(5.47)
3	0.39	0.06	0.79	0.06	0.26	−0.04	0.34
	(2.13)	(0.68)		(1.55)	(3.09)	(−1.58)	(4.59)
4	0.37	0.03	0.78	0.09	0.20	0.01	0.28
	(2.16)	(0.33)		(2.08)	(2.14)	(0.40)	(5.71)
5	0.49	0.19	0.79	0.08	0.20	0.06	0.25
	(3.26)	(2.81)		(2.42)	(2.98)	(1.68)	(6.69)
6	0.50	0.17	0.75	0.08	0.21	0.12	0.22
	(3.12)	(2.45)		(2.81)	(3.69)	(2.30)	(8.02)
7	0.58	0.30	0.71	0.09	0.23	0.18	0.18
	(3.38)	(3.38)		(2.52)	(4.87)	(2.88)	(6.14)
8	0.66	0.25	0.63	0.13	0.16	0.26	0.14
	(3.63)	(2.30)		(2.46)	(2.07)	(3.16)	(2.81)
9	0.61	0.25	0.64	0.13	0.18	0.37	0.09
	(3.17)	(2.00)		(2.16)	(2.28)	(4.02)	(1.39)
10 (high)	1.08	0.49	0.65	0.24	0.18	0.68	−0.10
	(3.82)	(3.06)		(3.64)	(1.50)	(5.18)	(−1.09)
10−1	0.71	0.59	0.09	0.19	−0.22	1.05	−0.90
	(3.97)	(2.22)		(2.16)	(−1.89)	(11.94)	(−7.14)

Table IA.3: Risk-adjusted returns for beta-sorted portfolios (global factor model)

The table presents mean excess return, alphas and betas of hedge fund portfolios. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return; α_{G} refers to global seven-factor alpha as in Kosowski, Kaupila, Joenväärä, and Tolonen (2019) and R^2_{G} to the corresponding R-squared. The global seven-factor model consists of: global equity market excess return, size factor, and value factor of Fama and French (2012), global cross-sectional momentum of Asness et al. (2013), global time-series momentum of Moskowitz et al. (2012), global betting-against-beta of Frazzini and Pedersen (2014), and tradable liquidity risk factor of Pástor and Stambaugh (2003). $\bar{r}$ and α_{G} are reported in % per month. The post betas are the betas from a single time series regression of factors against each of the ten portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_G	R^2_G	β^{FI}	β^{Mkt}	β^{FI}	β^{Mkt}
1 (low)	0.37	−0.18	0.78	−0.16	0.80	−0.56	1.22
	(1.21)	(−0.91)		(−2.51)	(8.46)	(−10.86)	(9.56)
2	0.47	−0.01	0.82	−0.08	0.61	−0.27	0.83
	(1.96)	(−0.12)		(−1.83)	(7.66)	(−8.45)	(14.64)
3	0.53	0.11	0.81	−0.02	0.48	−0.16	0.65
	(2.71)	(1.22)		(−0.69)	(8.03)	(−5.67)	(15.24)
4	0.46	0.09	0.79	−0.01	0.40	−0.10	0.51
	(2.46)	(0.90)		(−0.27)	(5.48)	(−3.71)	(9.64)
5	0.52	0.20	0.82	−0.02	0.38	−0.05	0.41
	(3.13)	(2.54)		(−0.73)	(6.22)	(−2.21)	(11.05)
6	0.45	0.20	0.83	−0.03	0.37	−0.00	0.34
	(2.89)	(2.70)		(−1.41)	(9.65)	(−0.08)	(13.40)
7	0.44	0.15	0.81	−0.02	0.35	0.05	0.30
	(2.84)	(2.12)		(−0.82)	(6.92)	(1.60)	(11.47)
8	0.57	0.29	0.72	0.01	0.28	0.11	0.27
	(4.31)	(3.69)		(0.30)	(6.08)	(2.90)	(7.14)
9	0.60	0.24	0.73	0.03	0.31	0.20	0.21
	(3.59)	(3.16)		(1.01)	(5.78)	(4.13)	(2.98)
10 (high)	1.02	0.39	0.71	0.10	0.36	0.50	0.04
	(3.96)	(3.20)		(2.74)	(4.41)	(7.19)	(0.25)
10−1	0.65	0.57	0.29	0.26	−0.44	1.06	−1.18
	(3.66)	(2.78)		(5.20)	(−5.58)	(16.93)	(−8.45)

Table IA.4: Risk-adjusted returns for different holding periods

The table presents monthly Fung and Hsieh (2004) seven-factor alphas in % of hedge fund portfolios over for 1 to 12 month holding periods. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. The portfolio returns are computed using overlapping holding periods, as in Jegadeesh and Titman (1993). Every month, for each of the decile portfolios a new tranche is formed and held for the holding period (1, 3, 6, 9 or 12 months). For every month, each portfolio's return is the average returns over the tranches for that month. t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017.

	1 month	3 month	6 month	9 month	12 month
1 (low)	−0.18	−0.11	−0.06	0.03	0.12
	(−0.69)	(−0.45)	(−0.29)	(0.15)	(0.62)
2	−0.08	−0.02	0.02	0.01	0.05
	(−0.57)	(−0.14)	(0.15)	(0.12)	(0.43)
3	0.01	0.03	0.05	0.07	0.10
	(0.05)	(0.30)	(0.53)	(0.76)	(1.11)
4	−0.01	0.06	0.10	0.14	0.15
	(−0.07)	(0.56)	(1.08)	(1.56)	(1.66)
5	0.15	0.15	0.13	0.14	0.14
	(1.71)	(1.80)	(1.59)	(1.62)	(1.65)
6	0.12	0.14	0.12	0.10	0.13
	(1.30)	(1.45)	(1.22)	(1.06)	(1.30)
7	0.24	0.18	0.13	0.09	0.10
	(1.92)	(1.53)	(1.09)	(0.80)	(0.88)
8	0.19	0.14	0.13	0.11	0.07
	(1.32)	(1.06)	(0.97)	(0.81)	(0.56)
9	0.17	0.16	0.15	0.14	0.11
	(1.09)	(1.14)	(1.07)	(0.98)	(0.73)
10 (high)	0.39	0.31	0.34	0.33	0.24
	(1.96)	(1.53)	(1.68)	(1.63)	(1.18)
10−1	0.56	0.41	0.40	0.30	0.12
	(2.14)	(1.68)	(1.73)	(1.35)	(0.57)

Table IA.5: Financial intermediary post-ranking betas estimated with lags

This table presents the post-ranking betas of the ten hedge fund portfolios estimated with lags as in Hu, Pan, and Wang (2013), to take persistence in hedge fund returns into account. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary, FI traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. The betas are from a single time series regression of factors against each of the ten portfolios. Reported are the contemporaneous post-ranking coefficients, and the sum of the contemporaneous and lagged coefficient. t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017.

	β^{FI}	β^{FI} + lag	β^{M}	β^{M} + lag
1 (low)	0.04	0.07	0.40	0.08
	(0.57)	(0.73)	(2.93)	(0.24)
2	0.07	0.10	0.26	0.01
	(1.39)	(1.52)	(2.53)	(0.05)
3	0.05	0.09	0.27	−0.01
	(1.58)	(1.72)	(3.40)	(−0.03)
4	0.08	0.09	0.20	0.05
	(2.06)	(1.75)	(2.13)	(0.22)
5	0.07	0.08	0.20	0.02
	(2.49)	(2.13)	(3.06)	(0.11)
6	0.08	0.07	0.21	0.03
	(2.48)	(1.82)	(3.27)	(0.13)
7	0.09	0.09	0.23	−0.01
	(2.88)	(2.43)	(5.18)	(−0.06)
8	0.12	0.16	0.17	−0.05
	(2.79)	(3.01)	(2.51)	(−0.22)
9	0.12	0.15	0.19	−0.04
	(2.31)	(2.44)	(2.53)	(−0.17)
10 (high)	0.22	0.30	0.19	−0.09
	(4.10)	(4.49)	(1.85)	(−0.33)
10−1	0.18	0.23	−0.20	−0.17
	(2.22)	(2.25)	(−1.85)	(−0.49)

Table IA.6: Hedge fund intermediary risk premium (only the USD funds)

This table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on post-ranking intermediary betas. Ten portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary, FI traded factor (controlling for the market return) and rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the ten portfolios. These post-ranking betas are then assigned to each fund according to which decile portfolio they belonged to at a given month. Time $t+1$ monthly excess fund returns (%) are regressed on the time t post-ranking betas as well as fund age (in months), AUM (in USD million), a dummy indicating if the fund has a lockup provision, management fee (in %), incentive fee (in %), the redemption notice (in days), the minimum fund investment amount (USD million) and a dummy indicating if the fund has a high water mark. β^{Mkt} is the time t post-ranking beta with respect to the market. r_t is time t excess fund return (in %). Leverage is a dummy indicating whether the fund is levered or not. Fixed effects are style dummies following the Kosowski, Joenväärä, and Tolonen (2016) mapping. t-statistics with Newey and West (1994) standard errors are reported in parentheses. The sample period runs from January 2000 to June 2017 and contains only the hedge funds that report their returns in USD.

	I	II	III	IV	V
β^{FI}	3.395	2.990	3.187	2.395	2.443
	(5.035)	(4.638)	(2.755)	(2.367)	(2.178)
β^{M}			0.304	0.299	0.289
			(0.602)	(0.809)	(0.769)
r_t				0.120	0.120
				(8.488)	(8.454)
Age				−0.001	−0.001
				(−2.418)	(−2.081)
log(AUM)				−0.029	−0.029
				(−2.508)	(−2.342)
Lockup				0.061	0.061
				(1.445)	(1.455)
Management fee				0.019	0.016
				(1.068)	(0.863)
Incentive fee				−0.000	−0.000
				(−0.035)	(−0.091)
Redemption notice				0.001	0.001
				(1.878)	(1.829)
Minimum investment				0.005	0.005
				(1.373)	(1.193)
High water mark				0.049	0.056
				(0.823)	(0.979)
Leverage					0.038
					(0.787)
$\beta^{\text{FI}}\times$Leverage					−0.058
					(−0.091)
Constant	0.311				
	(2.019)				
Style fixed effects	No	Yes	Yes	Yes	Yes
N	133,287	133,287	133,287	125,639	121,921
R^2	0.183	0.270	0.336	0.387	0.390

Table IA.7: Event study: risk-adjusted returns

This table shows OLS panel regressions of monthly Fung and Hsieh (2004) risk adjusted hedge fund returns in % on a set of indicator variables and their interactions. PB Events is an indicator variable that is equal to one during the event window and zero otherwise. The event window is 4 months, including the event month. 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 at the time of the event, and zero otherwise. Lehman Event is an indicator variable equal to one during the event window around the Lehman Brother bankruptcy (September 2008). Lehman Client is an indicator variable that is equal to one if a hedge fund was a client of Lehman at the time of the event. PB Unique Client and Lehman 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. Hedge fund fixed effects are included in specifications displayed in columns III and IV. Controls include: fund age and AUM. t-statistics in parentheses are based on standard errors clustered by fund and time. N is the number of observations. The sample period runs from January 2006 to June 2017.

	I	II	III	IV
PB Events	−0.775	−0.776	−0.750	−0.856
	(−2.257)	(−2.261)	(−2.081)	(−2.484)
PB Client	0.173	0.244		
	(3.505)	(3.476)		
PB Events × PB Client	−0.039	−0.037	−0.019	−0.039
	(−0.333)	(−0.182)	(−0.084)	(−0.166)
PB Unique Client		−0.114		
		(−1.571)		
PB Events × PB Unique Client		0.000	0.014	0.028
		(0.001)	(0.059)	(0.119)
Lehman Event	−0.147	−0.147	−0.074	−0.418
	(−0.210)	(−0.210)	(−0.104)	(−0.579)
Lehman Client	0.169	−0.056		
	(0.969)	(−0.339)		
Lehman Event × Lehman Client	−1.761	0.393	0.467	0.587
	(−2.175)	(0.773)	(0.966)	(1.271)
Lehman Unique Client		0.772		
		(2.308)		
Lehman Event × Lehman Unique Client		−7.059	−6.979	−6.831
		(−2.877)	(−2.819)	(−2.854)
Constant	−0.057	−0.057		
	(−0.560)	(−0.563)		
N	131,073	131,073	131,073	130,216
Adjusted R^2	0.003	0.003	0.018	0.029
Fund fixed effects	No	No	Yes	Yes
Controls	No	No	No	Yes

Table IA.8: Risk-adjusted returns for beta-sorted portfolios (backfill bias adjusted)

The table presents mean excess return, alphas and betas of hedge fund portfolios. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return; α_{FH} refers to Fung and Hsieh (2004) seven-factor alpha and R^2_{FH} to the corresponding R-squared. $\bar{r}$ and α_{FH} are reported in % per month. The post betas are the betas from a single time series regression of factors against each of the ten portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. t-statistics with Newey and West (1994) standard errors are reported in parentheses. For each hedge fund in the sample the first 12 months of returns are discarded to ameliorate backfill bias. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH}	R^2_{FH}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.48	−0.16	0.51	−0.02	0.46	−0.38	0.80
	(1.62)	(−0.59)		(−0.28)	(3.73)	(−9.87)	(6.19)
2	0.45	−0.04	0.58	0.02	0.31	−0.13	0.45
	(2.33)	(−0.27)		(0.45)	(3.45)	(−6.49)	(7.11)
3	0.43	−0.04	0.65	0.06	0.27	−0.05	0.34
	(2.47)	(−0.32)		(1.74)	(3.64)	(−2.47)	(7.15)
4	0.39	0.00	0.63	0.06	0.19	0.01	0.26
	(2.44)	(0.02)		(1.97)	(2.78)	(0.31)	(7.64)
5	0.51	0.18	0.65	0.06	0.19	0.05	0.24
	(3.68)	(1.96)		(2.59)	(3.27)	(2.13)	(8.09)
6	0.54	0.16	0.62	0.07	0.22	0.11	0.21
	(3.69)	(1.73)		(3.24)	(5.24)	(3.05)	(7.99)
7	0.60	0.23	0.54	0.06	0.24	0.18	0.18
	(3.73)	(2.04)		(2.20)	(5.65)	(3.33)	(7.58)
8	0.69	0.21	0.49	0.12	0.17	0.26	0.14
	(3.79)	(1.51)		(3.40)	(2.99)	(3.83)	(2.96)
9	0.68	0.21	0.46	0.12	0.20	0.37	0.08
	(3.69)	(1.29)		(2.65)	(3.14)	(4.93)	(1.42)
10 (high)	1.07	0.39	0.41	0.23	0.16	0.70	−0.13
	(3.59)	(1.89)		(4.34)	(1.43)	(6.74)	(−1.27)
10−1	0.59	0.55	0.05	0.25	−0.30	1.08	−0.93
	(2.33)	(1.95)		(2.85)	(−2.42)	(14.63)	(−6.19)

Table IA.9: Hedge fund intermediary risk premium (backfill bias adjustment)

This table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on post-ranking intermediary betas. Ten portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary, FI traded factor (controlling for the market return) and rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the ten portfolios. These post-ranking betas are then assigned to each fund according to which decile portfolio they belonged to at a given month. Time $t+1$ monthly excess fund returns (%) are regressed on the time t post-ranking betas as well as fund age (in months), AUM (in USD million), a dummy indicating if the fund has a lockup provision, management fee (in %), incentive fee (in %), the redemption notice (in days), the minimum fund investment amount (USD million) and a dummy indicating if the fund has a high water mark. β^{Mkt} is the time t post-ranking beta with respect to the market. r_t is time t excess fund return (in %). Leverage is a dummy indicating whether the fund is levered or not. Fixed effects are style dummies following the Kosowski et al. (2016) mapping. t-statistics with Newey and West (1994) standard errors are reported in parentheses. For each hedge fund in the sample the first 12 months of returns are discarded to ameliorate backfill bias. The sample period runs from January 2000 to June 2017.

	I	II	III	IV	V
β^{FI}	3.605	3.150	3.377	2.549	2.398
	(3.599)	(3.566)	(2.688)	(2.349)	(2.109)
β^{M}			0.296	0.294	0.294
			(0.599)	(0.791)	(0.786)
r_t				0.099	0.098
				(6.648)	(6.582)
Age				−0.000	−0.000
				(−1.663)	(−1.468)
log(AUM)				−0.027	−0.030
				(−2.429)	(−2.528)
Lockup				0.084	0.084
				(1.963)	(2.008)
Management fee				0.028	0.022
				(1.528)	(1.146)
Incentive fee				−0.001	−0.002
				(−0.425)	(−0.482)
Redemption notice				0.001	0.001
				(1.188)	(1.132)
Minimum investment				0.001	0.001
				(0.219)	(0.155)
High water mark				0.072	0.063
				(1.727)	(1.468)
Leverage					−0.001
					(−0.013)
$\beta^{\text{FI}}\times$Leverage					0.386
					(0.741)
Constant	0.174				
	(0.928)				
Style fixed effects	No	Yes	Yes	Yes	Yes
N	165,882	165,882	165,882	152,909	147,946
R^2	0.249	0.323	0.392	0.435	0.435

Table IA.10: Hedge fund intermediary risk premium – alternative weightings

This table presents factor premiums estimated by Fama and MacBeth (1973) regressions (see Table IA.9 for further details), with the FI factor replaced by the weighted version based on: prime broker number of clients (N), their AUM, their eigenvector centrality with client connections, and their eigenvector centrality with AUM connections (based on the 2017 Eureka database extended with snapshots registering each fund's prime broker every six months, calculated monthly). t-statistics with Newey and West (1994) standard errors are reported in parentheses. N is the number of observations. The sample period runs from January 2000 to June 2017.

	N		AUM		N (eigen)		AUM (eigen)	
	I	II	III	IV	V	VI	VII	VIII
β^{FI}	2.91	1.75	3.02	1.75	3.27	1.66	4.34	2.31
	(2.72)	(1.94)	(2.52)	(1.80)	(2.16)	(1.59)	(2.82)	(1.93)
β^{M}		0.13		0.12		0.04		0.07
		(0.38)		(0.37)		(0.12)		(0.21)
r_t		0.11		0.11		0.11		0.11
		(7.09)		(7.13)		(7.01)		(7.06)
Age		−0.00		−0.00		−0.00		−0.00
		(−2.10)		(−2.00)		(−1.91)		(−1.96)
log(AUM)		−0.04		−0.04		−0.04		−0.04
		(−3.00)		(−2.89)		(−3.09)		(−2.94)
Lockup		0.06		0.06		0.06		0.06
		(1.53)		(1.50)		(1.47)		(1.53)
Management fee		0.03		0.03		0.03		0.03
		(1.62)		(1.74)		(1.60)		(1.65)
Incentive fee		−0.00		−0.00		−0.00		−0.00
		(−0.06)		(−0.09)		(−0.10)		(−0.16)
Redemption notice		0.00		0.00		0.00		0.00
		(1.86)		(1.85)		(1.53)		(1.82)
Minimum investment		−0.00		−0.00		−0.00		−0.00
		(−0.06)		(−0.12)		(−0.21)		(−0.11)
High water mark		0.03		0.03		0.02		0.03
		(0.59)		(0.55)		(0.48)		(0.58)
Constant	0.22		0.24		0.25		0.10	
	(1.42)		(1.46)		(1.44)		(0.60)	
Style fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
N	193,366	178,282	193,366	178,282	193,366	178,282	193,366	178,282
R^2	0.25	0.43	0.25	0.43	0.26	0.43	0.25	0.42

Figure IA.1: Prime broker turnover

This figure shows the proportion of hedge funds that change prime brokers between two subsequent database snapshots (typically six months apart). The sample runs from June 2006 to July 2017.

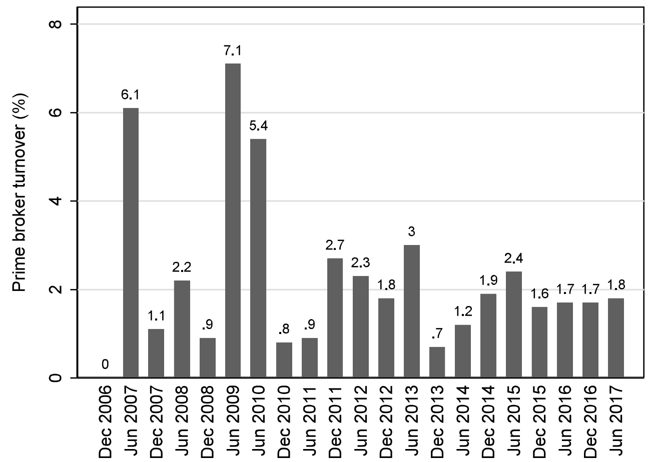


Figure IA.2: 2007 network of hedge funds and prime brokers

The figure shows the network obtained by looking at the sample of hedge funds in June 2007 and assigning an edge between two vertices if there is a prime broker relationship between these entities (a fund and a prime broker). Circles are funds and square vertices are prime brokers. The circle color denotes the investment style of the fund. Node labels are printed for the largest prime brokers. The graphical layout is obtained with the Fruchterman-Reingold algorithm, which indicates a core-periphery structure with central prime brokers ending up in the middle.

Figure IA.3: Fraction of funds that employ more than one prime broker

This figure shows the fraction of funds that employ more than one prime broker (based on information from 1667 funds that report their prime broker).

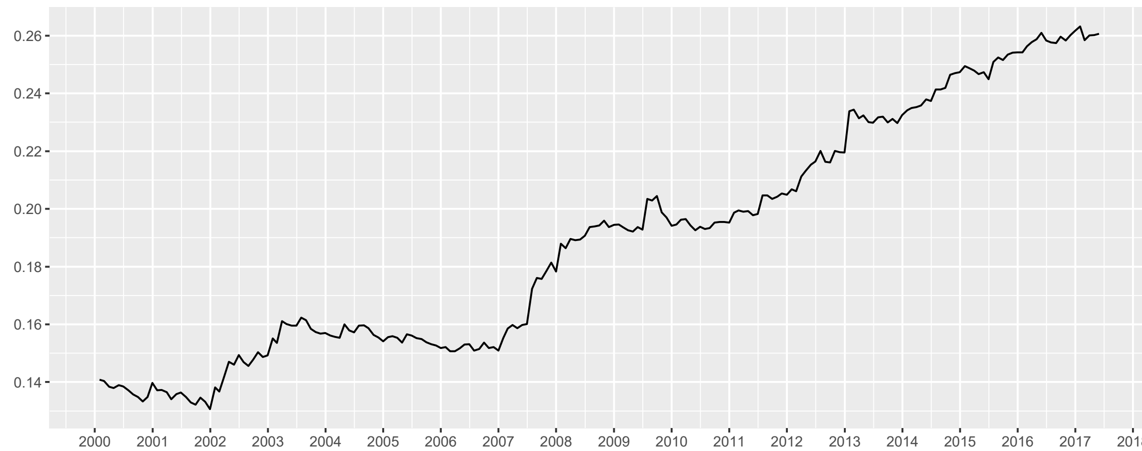


Figure IA.4: Time series of the financial intermediary factor

This figure shows the financial intermediary traded factor (FI) over the sample period. The factor is constructed as the excess return to a value-weighted portfolio of the publicly listed prime brokers. FI_N and FI_{AUM} are portfolios of financial intermediaries where the weights are based on the number of hedge fund clients and the total client assets under management. The sample period runs from January 2000 to June 2017. The shaded areas indicate NBER recessions.

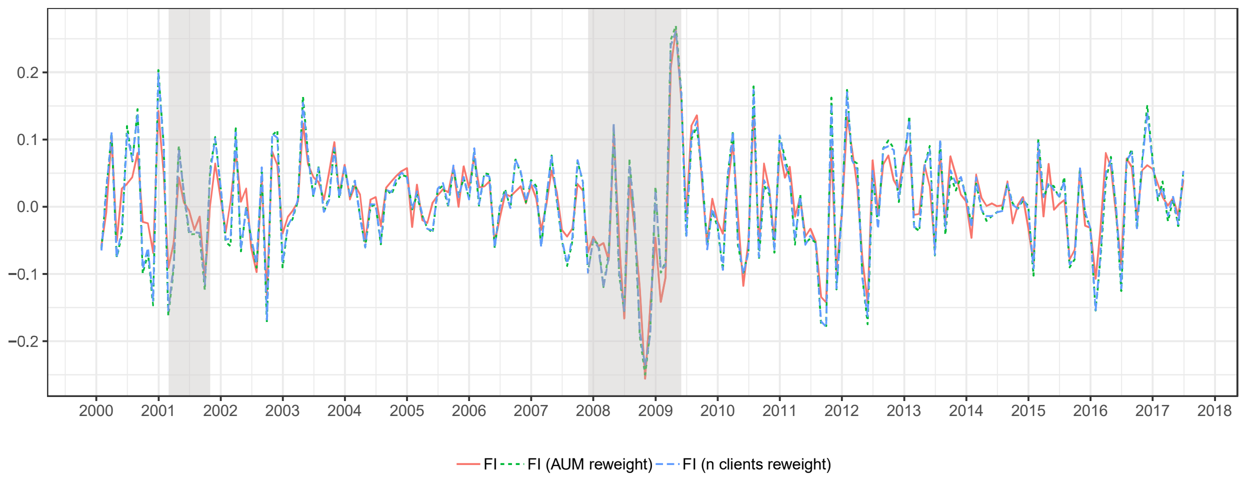
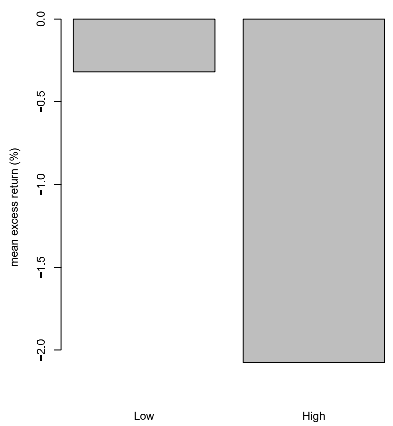
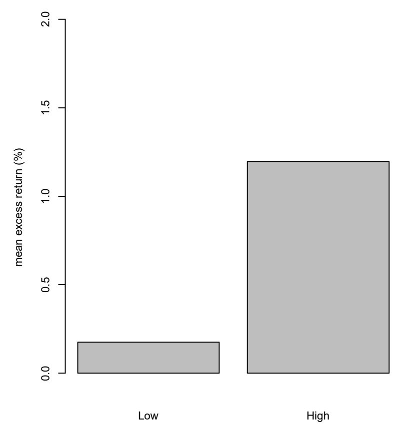


Figure IA.5: High/low FI sorted portfolio averages

This figure shows the average excess returns (monthly, in %) for two FI beta sorted portfolios (deciles one and ten, orthogonalized with respect to the market return) in the twenty months the FI factor (orthogonalized with respect to the market return) is at its lowest, and highest, respectively. Ten equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the financial intermediary traded factor (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor; funds in Portfolio 10 have the highest. The sample runs from January 2000 to June 2017.



(a) Lowest FI



(b) Highest FI

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