Hedge Funds and Financial Intermediary Risk *

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Abstract

Hedge funds and financial intermediaries are connected through their prime brokerage relationship. We find that systematic financial intermediary risk is important for understanding the cross-section of hedge fund returns. We show that systematic shocks propagate from prime brokers to hedge funds and not the reverse. There is little evidence that idiosyncratic financial intermediary risk matters. We evaluate if large adverse shocks to individual prime brokers propagate to their clients, finding a significant impact only in the Lehman bankruptcy case. This impact, however, was mitigated for funds with multiple prime brokers, suggesting that even extreme prime broker shocks are diversifiable.

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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 could impact hedge fund returns. The first is through financial intermediaries' systematic 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 (ascertaining that shocks propagate from prime brokers to hedge funds and not the reverse) and analyze individual prime brokers' effects on their hedge fund clients' returns.

Recent research finds that factors capturing shocks to the intermediaries' aggregate risk-bearing capacity are important determinants in the cross-section of multiple asset classes' expected returns (see He and Krishnamurthy (2018) for a survey). Moreover, intermediary health seems to matter relatively more for exotic assets that households rarely hold directly (Haddad and Muir (2021)). Given that hedge funds are essentially managed portfolios of such exotic assets, one would expect them to be exposed to financial intermediary risk. There is an extensive literature on the cross-section of hedge fund returns (see Agarwal, Mullally, and Naik (2015) for a survey), but no consensus has been reached. For example, Bali, Brown, and Caglayan (2012) find that systematic risk has the greatest role in explaining the cross-section of hedge fund returns, however the ultimate source of that risk is not clear. Our first contribution is bridging the gap between the intermediary asset pricing literature and the hedge fund literature, showing that intermediary risk is an important determinant in the cross-section of hedge-fund returns.

Prime brokers (typically large investment banks) provide their hedge fund clients with many services, including custodial services, securities lending, and financing. Prime brokers could affect hedge fund returns through their 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 is possible that a prime broker's financial distress is translated to the corresponding hedge fund as funding pressure, thereby forcing it to rapidly de-leverage its positions. In turn, 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 shock propagation from an individual prime broker to its hedge funds is the Lehman Brothers bankruptcy and the liquidation of nearly half of its hedge fund clients (Aragon and Strahan (2012)). Our second contribution is the evaluation of how individual prime brokers impact hedge fund returns, showing that, despite a close link between prime brokers and their clients, idiosyncratic financial intermediary risk is diversifiable.

We begin by looking at the prime broker and hedge fund relationships as a network to identify the key financial intermediaries in the sector. Using a dataset that allows us to identify hedge funds' prime broker affiliations over time, we find that out of 370 financial intermediaries, 38 emerge as central in the prime-broker-hedge-fund network. These prime brokers represent around 95% of the hedge funds over the 2000 to 2017 period and most are designated as New York Federal Reserve Primary Dealers. We then construct intermediary pricing factors as portfolios of these prime brokers. We consider several weighting schemes including one where the weight of each intermediary is based on its dynamic network-centrality score. We find, however, that these factors are highly correlated with each other and with the intermediary factors of He, Kelly, and Manela (2017), which are constructed from a set of primary dealers. Given this finding, we simply use the traded factor of He et al. (2017) as our main intermediary factor to better relate to the existing literature.

We find that the covariation between the hedge fund return and the return of the portfolio of key financial intermediaries captures cross-sectional differences in hedge fund returns. A portfolio of hedge funds with high intermediary risk significantly outperforms a portfolio with low intermediary risk by around 7.7% per year on a risk-adjusted basis.

Moreover, the price of financial intermediary risk of 3.1% estimated from the monthly returns of individual hedge funds is roughly equal to that reported by He et al. (2017) for other asset classes. These results are robust to controlling for an extensive set of fund characteristics and other factors that have been shown to affect the cross-section of returns. A placebo test repeating the same analysis using either an intermediary factor constructed from a large sample of US financial firms (but excluding all the prime brokers) or a proxy for aggregate hedge fund sector performance, does not produce a meaningful spread in hedge fund returns. This highlights that our results are driven by the financial intermediaries who are important prime brokers or primary dealers.

Hedge funds could themselves be categorized as financial intermediaries. Thus, a valid question is what effect do hedge funds have on the cross-section of hedge fund returns and their prime brokers? And what is their effect on asset prices in general? First, we verify that aggregate hedge fund performance neither explains the cross-section of hedge fund returns nor subsumes the explanatory power of the financial intermediary factor. Then, we formally investigate whether hedge fund shocks affect prime brokers. We use the granular instrumental variable (GIV) methodology of Gabaix and Koijen (2020) that exploits idiosyncratic shocks to large constituents as an identification strategy. We find no evidence to suggest that shocks to hedge fund clients systematically propagate to their prime brokers. In contrast, applying the GIV approach to estimate the causal elasticity between hedge fund portfolio returns and financial intermediary shocks (by exploiting idiosyncratic shocks to individual prime brokers), we find that the estimated elasticity is positive and statistically significant for hedge fund portfolios with high intermediary risk. These results imply that financial intermediary shocks indeed propagate to hedge fund returns, while the reverse direction does not appear relevant.

To aid the economic interpretation of our results we present some institutional details. We examine the absolute and relative size of the hedge fund industry, using a variety of data sources to ascertain if hedge funds are large enough to have an economically meaningful impact on asset prices. We find that the hedge fund sector has increased substantially since the early 2000s but has been small in absolute and relative terms before then, suggesting that any asset pricing effect could only be a fairly recent phenomenon. Moreover, total hedge fund assets remain around five times smaller than prime brokers' total assets and are less concentrated, suggesting that prime brokers are likely relatively more important in asset price determination. Importantly, we observe that, contractually, the prime broker–hedge fund relationship disproportionately favors the prime broker. Using aggregated regulatory data, we report that, on average, over 50% of hedge fund financing comes from its prime brokers, with around 35% of total financing extended on an overnight basis. We also find that hedge funds are typically overcollateralized, hence prime brokers are relatively protected from hedge fund shocks. Prime brokers can thus easily and quickly rescind the lion's share of hedge fund debt capital, which could lead to sudden unwinding of hedge fund positions. Such a shock would be particularly pertinent if multiple prime brokers are affected (i.e., a systematic prime broker shock), thus triggering broad unwinding of positions and likely impacting asset prices. In this setting, prime brokers trigger the unwinding, implying that it is the prime broker shocks, and not the hedge fund shocks, that should be priced. This is in line with our empirical results. In sum, our findings suggest that, from an asset pricing perspective, hedge funds act primarily as a veil for prime broker shocks.

The question remains whether idiosyncratic shocks to individual prime brokers affect their hedge fund clients. We investigate whether there is a contemporaneous relationship between hedge fund returns and its prime broker's returns. We find that regressing hedge fund returns on its prime broker's returns yields a positive and significant slope coefficient. However, this is driven entirely by systematic risk exposure. Once we control for market risks and financial-intermediary risk, there is no significant relationship between hedge fund returns and those 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 a panel of hedge funds around four events where a prime broker experienced a large, adverse idiosyncratic shock. We use a difference-in-difference methodology to control for market-wide effects. We find that, with the exception of the Lehman bankruptcy, adverse individual prime broker shocks have a negligible impact on their hedge fund clients' relative returns. 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 channel.

Related literature

Our work relates to three strands of the literature. First, we relate to the literature on financial intermediary asset pricing. Adrian, Etula, and Muir (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 constructed from the equity ratios of a small group of key intermediaries, the 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. There is suggestive evidence that intermediary risk matters for hedge fund returns, but no formal, comprehensive evaluation has yet been undertaken.[1] Our results emphasize the external validity of intermediary pricing, as the intermediary factors work in the cross-section of basic assets and also affect

[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.

the broader universe of hedge fund returns. Moreover, our analysis, showing that causal direction of shock propagation runs from prime brokers to hedge funds, suggests that hedge funds act primarily as conduits of systematic prime broker shocks. This finding indirectly implies that hedge fund leverage shocks are not structural, but stem mainly from the prime brokers, which helps interpret the puzzling result of Ang, Gorovyy, and Van Inwegen (2011), which shows that hedge fund leverage is counter cyclical to the leverage of listed financial intermediaries. In this dimension, our work also speaks to the small literature examining the effects of hedge funds on asset prices (see, e.g., Mitchell, Pedersen, and Pulvino (2007), Mitchell and Pulvino (2012), and Chen, Kelly, and Wu (2020)). Our conclusions are most in line with the earlier work of Fung and Hsieh (2000a), arguing that hedge funds do not have a systematic effect on returns.[2]

Second, we relate to the large literature on the drivers of hedge fund returns. Hedge funds are dynamically managed portfolios of (possibly illiquid) securities of multiple asset classes. Partly because of this, established factor models from other asset classes have struggled to explain hedge fund returns in both the time series and in the cross-section. This spawned the development of hedge-fund-specific factor models (e.g., Agarwal and Naik (2004), Fung and Hsieh (1997, 2001, 2004)), among which the Fung-Hsieh model is widely used and captures the time series of hedge fund returns. However, none of the Fung-Hsieh factor loadings generate a significant return spread in the cross-section (Sadka (2010)). Several additional factors have been proposed to explain the cross-section of hedge fund returns, particularly prevalent among which are the liquidity and market dislocation factors (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 (2019), Sadka (2010), and Teo (2011)). The literature, however, has not converged on the relevant systematic factors. Our results, that systematic financial

[2]Our focus is on returns and we do not examine other market outcomes such as liquidity. Exiting literature, however, finds that hedge funds may affect market liquidity (e.g., Cao, Liang, Lo, and Petrasek (2017), Chen et al. (2020), and Choi, Getmansky, and Tookes (2009)).

intermediary risk to be the key driver of hedge fund returns and that idiosyncratic shocks matter little, is in line with the findings of Bali et al. (2012) highlighting the important role of systematic risk (and not residual risk) in hedge fund return determination. We also show that, accounting for other factors (namely, the liquidity factor of Pástor and Stambaugh (2003), the macroeconomic uncertainty factor of Bali et al. (2014), the correlation factor of Buraschi et al. (2013), 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.

Third, we relate 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 on to the clients, but their analysis is restricted to a sample period from January 2004 to June 2008 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, but they neither directly examine prime broker returns nor control for systematic financial-sector and regional risk factors. Hence, their work is unable to answer the question of whether specific shocks to a prime broker are passed on to its hedge fund clients. A few papers study hedge fund funding flows. Franzoni and Giannetti (2019) find that hedge funds that are officially affiliated with financial conglomerates seem to have more stable access to capital. Kruttli, Monin, and Watugala (2019) show that Deutsche Bank's hedge fund clients experienced a reduction in their borrowing after an adverse shock to the bank in 2015–2016. Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel (2020) report that macro-prudential regulations adopted post-2014 led to regulated prime brokers' hedge fund clients reducing their leverage below the maximum permitted level and employing a larger number of prime brokers. These works are complementary to ours as they focus mainly on fund flows and hedge fund leverage, while we examine returns. We also indirectly relate to the studies examining other roles of prime brokers, such as information sharing (Kumar, Mullally, Ray, and Tang (2019)) and capital introduction (Obizhaeva (2019)). However, we differ from these studies in that our focus is on the systematic and idiosyncratic financial intermediary risk.

2 Data and descriptive statistics

2.1 Hedge fund data

We obtain hedge fund data from Eurekahedge.[3] 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.[4]

Taking the June 2017 snapshot of the Eurekahedge database as a starting point, we follow the literature, applying several filters to the data. First, we consider only the hedge funds that report monthly returns, excluding all funds-of-funds. Second, we exclude all 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 in which 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.

In addition to reporting returns and AUM, Eurekahedge provides information on several fund characteristics including management and incentive fees, lock-up and redemption

[3]We use the Eurekahedge database as it allows us to identify prime broker and hedge fund affiliations over time. The Eurekahedge database is also used by Hombert and Thesmar (2014) for their main analysis in which they show that the sample of hedge funds in the Eurekahedge database is similar to that in the Lipper/TASS database.

[4]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.

conditions, minimum investment amounts, whether a fund has a high watermark provision, whether a fund employs leverage and, most importantly, 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 a given fund's lifetime.

To overcome this limitation, we source 21 additional snapshots of the database. We use two snapshots per year, between 2006 and 2016, which are taken annually in June and December (except for 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 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 cases where two prime brokers merge, we change the prime brokerage affiliation to that of an acquirer for funds associated with the target prime broker beginning in the month of the merger's completion. For example, in our sample, Merrill Lynch becomes Bank of America Merrill Lynch in January 2009. After applying the filters, we are left with 370 unique prime brokers in our sample.

[5] The average annualized prime broker turnover is around 4.5%, 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 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 are for the time series of monthly cross-sectional averages of excess returns, which is essentially a time series of returns to an equal-weighted portfolio of hedge funds. To capture the variation between different funds' returns, we also report the cross-sectional standard deviation of the average excess returns. We report the summary statistics for the full sample and 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, 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 2000 to the maximum of 1778 in 2012. All nine hedge fund 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, but average returns vary substantially over time. For example, 2008 was the worst performing 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 0.68% and is highest in 2008 (3.12%). There is also reasonable variation in the average

[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 in cases reported in currencies other than the USD.

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

returns across hedge fund styles. For example, hedge funds classified as Market Neutral have slightly lower average monthly returns and standard deviations (0.44% and 1.35%, respectively) than hedge funds of other styles.

Panel B of Table 1 reports summary statistics for fund AUM and fund age (the Internet Appendix reports the summary statistics for additional characteristics). These statistics are the time-series average of monthly cross-sectional statistics that aim to convey the typical cross-sectional properties of the funds in our sample. There is substantial size disparity among the hedge funds. Each month, fund AUM can range from USD 15 million to USD 25,381 million. The average fund AUM is USD 397 million, while the median AUM is USD 120 million. Each fund reports, on average, 94 months of returns and we set the minimum at 24 months of returns. We calculate age for each fund in each month t as the difference in the number of months between month t and the fund's inception date. Each month, an average fund is around seven years and eight months old, with 50% of the funds typically being between four and 10 years old.

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 (CRSP), and the data for the foreign intermediaries are from Datastream or Bloomberg. Exchange rate 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 intermediary factors of He et al. (2017) are available from Asaf Manela's webpage. The Pástor and Stambaugh (2003) liquidity factor; Sadka (2010) liquidity factor; 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 database's June 2017 snapshot. Each node (vertex) is either a hedge fund (represented by circles) or a prime broker (represented by purple squares), and a link (edge) exists 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 (see the Internet Appendix for an example of the construction and encoding of the network as an adjacency matrix). Figure 1 gives a simple 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.[9]

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 their clients' AUM as the percentage of the total hedge fund AUM. We see that the top five prime brokers, ranked either on number of clients or sum of 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

[8]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)).

[9]Multiple prime broker affiliations were less common in 2007. Using multiple prime brokers is not costless because it increases operational complexity and thereby operational risks. For example, having multiple prime brokers forces hedge funds to duplicate many processes and makes it difficult for them to 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%. The Internet Appendix shows a network representation of the client-prime-broker relationships for the database's June 2007 snapshot and plots the fraction of funds with multiple prime brokers over time.

Morgan Stanley are almost always ranked first or second. This is consistent with Aragon and Strahan (2012) who report prime broker market shares between 2002 and 2008, and similar to Di Maggio et al. (2017) and Eisfeldt, Herskovic, Rajan, and Siriwardane (2018), who respectively find that the market structure in the credit default swap and bond dealer markets is highly persistent.

3 Financial intermediary risk factors

Intermediary asset pricing models emphasize the special role financial intermediaries play in asset price determination. In our analysis of systematic financial intermediary risk among hedge funds, we are guided by the theoretical framework of He et al. (2017) who posit that the pricing kernel is comprised of aggregate wealth and the intermediary's equity capital ratio (He and Krishnamurthy (2012, 2013) provide micro foundations). In this framework, negative shocks to the intermediary's equity capital ratio increase their marginal value of wealth, and thus these shocks should be priced in markets where intermediaries are "marginal" investors. Indeed, He et al. (2017) show that their empirical proxies for the intermediary's equity capital ratio shocks are priced in a large cross section of asset classes. However, the questions of how to identify "marginal" financial intermediaries and aggregate their individual pricing kernels to form a "representative intermediary" lack clear theoretical guidelines.

He et al. (2017) consider the primary dealers as a set of key financial intermediaries for their empirical analysis. Primary dealers are a natural group to consider as there is ample evidence suggesting that they account for the bulk of trading in many markets (see Cetorelli, Hirtle, Morgan, Peristiani, and Santos (2007)). They include several large foreign banks and represent a large fraction of the US broker-dealer and banking sectors' total value. Nevertheless, there is some degree of arbitrariness in choosing to focus only on the primary dealers. Moreover, it is unclear as to the correct weights to assign each intermediary in constructing an empirical pricing factor. Without detailed data on the relative specialization of individual intermediaries, greater precision in these choices is typically impossible. Our data, however, allow us to see the relative importance of different financial institutions in the prime brokerage business, and we let this guide our choices in constructing empirical intermediary pricing factors.

Data availability dictates the focus on the publicly listed prime brokers. We identify 38 listed prime brokers in our dataset and find that they capture the lion's share of the prime brokerage market. 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. Surprisingly, although our approach of identifying the most important financial intermediaries is different, we converge on a similar group of intermediaries as He et al. (2017). Our set of key intermediaries contains all, but one, of the primary dealers.[10]

We consider various weighting schemes based on the constituents' importance to hedge funds in their role as prime brokers. The network graph in Figure 1 serves as a guide to compute various reweightings based on rank. When each link is unweighted, a particular broker's number of clients 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). A popular ranking metric, which takes into account the importance of connections, is the eigenvalue centrality (also referred to as the prestige centrality; see, e.g., Jackson (2010)). The intuition for this measure 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 ap-

[10]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.

propriately scaled eigenvalues of the corresponding adjacency matrix, g (see the Internet Appendix). To obtain a network over time, we construct the adjacency matrix for each month in the Eurekahedge database. In other words, each month we take the 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.[11] We also consider equal and value weights.

Having identified a set of key intermediaries and potential weights, we form our candidate financial intermediary factors as the weighted sum of all the publicly listed prime brokers' monthly excess returns. We construct six financial intermediary factors: a value-weighted and equal-weighted portfolio of prime brokers and four alternative factors using the dynamic weighting procedure described above. We then examine these six factors together with the traded and non-traded factors of He et al. (2017) (results are reported in the Internet Appendix). We find that all the financial intermediary factors have similar statistical properties and are highly correlated. For example, the correlations between the traded factor of He et al. (2017) and the value-weighted portfolio and equal-weighted portfolio of prime brokers 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 0.87). To better relate to the existing literature, and given such high correlation among the factors and the potential for introducing a measurement error when using network-based factors, we simply perform our main analysis using the excess returns to a value-weighted portfolio of primary

[11]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 and a large AUM, and the ranking of the brokers based on the two methods will be very close.

dealers (that is, the traded financial intermediary factor (FI) of He et al. (2017)). We focus on the traded factor because it helps us exploit the time-series dimension of financial intermediary risk in our analysis of idiosyncratic shocks. Additionally, He et al. (2017) show that the pricing power of their capital ratio factor is predominantly driven by the equity component. Moreover, during our sample period, there is little difference between the He et al. (2017) traded and the non-traded factors, particularly at the monthly frequency as there is little variation in book debt, which is only available quarterly.[12] Nevertheless, we also show that our main results are similar when using the non-traded capital-ratio-based factor (see the Internet Appendix).

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 commonly used in the literature.[13] Specifically, every month we sort all the hedge funds in our sample into 10 portfolios based 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:

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

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 theoretically-motivated

[12] The correlation between the non-traded and the traded He et al. (2017) factors is 92.5% during our sample period.

[13] 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)).

two-factor model that He et al. (2017) consider. After having monthly beta estimates, $\hat{\beta}^{\mathrm{FI}}_{i,t}$, we form 10 equal-weighted portfolios of hedge funds based on them. Hedge funds with the lowest FI betas are allocated to Portfolio 1, while the funds with the highest FI betas are allocated to Portfolio 10. This procedure gives us 10 time series of monthly hedge fund portfolio returns. As a last step, we compute the post-ranking betas of each of the 10 portfolios by regressing the portfolio returns on the two factors in (1).

Table 3 reports the average monthly excess returns and Fung and Hsieh (2004) seven-factor alphas for our 10 hedge fund portfolios. It also reports the post-sort and pre-sort 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.[14] The hypothetical strategy of going long Portfolio 10 and going short Portfolio 1 yields an annualized excess return of 9.84% (t-stat = 4.0) or an annual alpha of 7.68% (t-stat = 2.7). This provides an intuitive measure of the economic significance and is also an asymptotically valid nonparametric test of monotonicity, ((Cattaneo, Crump, Farrell, and Schaumburg (2020)). Our results are robust to the choice of financial intermediary risk factor. We repeat the analysis using the He et al. (2017) non-traded financial intermediary factor and find that the annualized spread in alpha is equal to 8.28% (t-stat = 3.3) (reported in the Internet Appendix).

To interpret this positive spread in the average returns as compensation for risk, we show that the portfolios in Table 3 exhibit a positive spread in their loading on 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 0.17

[14] 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).

(t-stat = 2.6) 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). After the correction, the positive relative spread in post-ranking FI factor betas slightly increases and remains statistically significant, while the negative spread in market betas decreases in absolute terms and becomes statistically insignificant (reported in the Internet Appendix). Additionally, if the spread in average returns is driven by compensation for risk, we should observe the portfolio of hedge funds with high intermediary beta underperform the portfolio with intermediary beta when this risk is realized (i.e., during the times of large, adverse shocks to the FI factor and vice versa during the times of a large, positive shocks). We examine the twenty largest positive and negative realizations of the FI factor, orthogonalized with respect to the market return, and indeed find this pattern (reported in the Internet Appendix). These results are in line with the financial intermediary risk being a determinant of the cross-section of hedge fund returns.

It is worth noting that the results seem to be driven by the financial intermediaries who are important prime brokers or primary dealers. Similar to He et al. (2017), we perform a placebo test in which we redo the above analysis using a financial intermediary factor constructed from a sample of US broker-dealers (all public firms in CRSP with SIC codes 6211 and 6221) but exclude all the firms that we identify as prime brokers. Due to the significant overlap, this definition also excludes all the primary dealers. We find that using a financial intermediary factor without the largest prime brokers does not produce a statistically significant spread in either average excess returns or alphas (reported in the Internet Appendix), suggesting that the pricing power stems mainly from the key financial intermediaries.

One immediate concern could be that driving these results is a fund's individual relationship with its prime broker rather than its exposure to systematic financial intermediary risk. To alleviate this concern, we separately examine groups of hedge funds that are relatively more or less dependent on their prime brokers. Hedge funds that report using leverage may be more exposed to prime broker funding shocks than those that do not. Similarly, funds that are larger or have multiple prime brokers may have more bargaining power, face better funding conditions and be less dependent on their prime brokers. Hence, we perform the portfolio sorting procedure conditional on the fund's reported use of leverage, fund's AUM, and whether a fund has one or multiple prime brokers. We find that the positive spread in alpha between the high-beta portfolio and the low-beta portfolio is preserved among all the sub-groups and the difference between these high-minus-low portfolios of the different groups is not significant (Internet Appendix reports the results).

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 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:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{\mathrm{FI},t}\hat{\beta}^{\mathrm{FI}}_{i,t} + \lambda_{\mathrm{M},t}\hat{\beta}^{\mathrm{M}}_{i,t} + c_t' X_{i,t} + \varepsilon_{i,t+1}, \tag{2}$$

where $r_{i,t+1}$ are the month $t+1$ excess returns for fund i, $\lambda_{0,t}$ is the intercept, $\hat{\beta}^{\mathrm{FI}}_{i,t}$ is the month t FI factor beta of fund i, $\hat{\beta}^{\mathrm{M}}_{i,t}$ 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.[15] The controls are standard in the literature and includes the fund's excess return for month t, age, AUM, management fee, incentive fee, high watermark (a dummy variable that equals one if fund i has a high watermark provision and zero otherwise), lockup (a dummy variable that equals one if fund i has a lockup provision and zero otherwise), mandated redemption notice period, and minimal investment in the fund. Controls also include hedge fund style and geographical region dummies. The factor premiums are estimated as the time series averages of $\lambda_{\mathrm{FI},t}$ and $\lambda_{\mathrm{M},t}$.

Columns I–V of Table 4 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 (1987) (the lag length is selected automatically using the Newey and West (1994) procedure). The estimated FI risk premium is positive and significant in all the specifications. In the final specification with all the covariates, presented in column V, the point estimate of the monthly risk premium is 3.12% (significant at the 5% level). Our estimate of the financial intermediary risk premium is remarkably similar to the monthly financial intermediary risk premium of 3.10% 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. Importantly, our results remain essentially unaffected if we measure financial intermediary risk using the non-traded He et al. (2017) factor instead (reported in the Internet Appendix).

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

[15] We repeat the analysis using each hedge fund's individual rolling financial intermediary factor beta estimates and our results are similar (the Internet Appendix presents the results).

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 statistically significant, which is in line with the observation that smaller, younger funds tend to have higher average returns than larger, more established funds (see, e.g., Aggarwal and Jorion (2010)). The 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 coefficient on management fee is positive and marginally statistically significant as in Teo (2009) who examines a similar hedge fund database. The high watermark 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 with similar results (see the Internet Appendix).

In sum, we find that there is a significant, positive relationship between exposure to intermediary risk and individual hedge funds' average returns. Moreover, we find that the financial intermediary risk premium estimated using a cross-section of hedge funds are similar to the risk premium estimated in the cross-section of base asset classes. This result may seem intuitive if one thinks of hedge funds as just managed portfolios of multiple asset classes. However, given the typically limited success of models from other asset classes in explaining the cross section of hedge fund returns, the ability to reconcile hedge fund returns with a risk factor shown to be priced in other asset classes is a step toward identifying the most important systematic risks.

5 What kind of financial intermediaries are hedge funds?

Our previous section's results show that shocks to key financial intermediaries are priced in the cross-section of hedge-fund returns. Hedge funds, however, could themselves be categorized as financial intermediaries that are active in many asset markets. This begs the question: what effect, if any, do hedge funds have on asset prices? In our setting, there may be a concern that aggregate hedge fund health could also be a determinant of the cross-section of hedge-fund returns. In this section, we evaluate whether that is the case and analyze the causal mechanism of systematic prime broker shock propagation.

There are only a few studies examining the effects of hedge funds on asset prices. In an earlier study, Fung and Hsieh (2000a) argue that hedge fund exposures are often insignificant, either in absolute terms or relative to other market participants, and they do not have a systematic effect on asset prices. Subsequent works find that hedge funds can (i) have a temporary effect on asset prices during periods of market dislocation (e.g., Mitchell et al. (2007), who study convertible arbitrage in 2005, finding evidence of short-term deviations from fundamental values associated with hedge fund capital outflows), (ii) improve stock price information efficiency and liquidity (Cao et al. (2017), Chen et al. (2020), and Choi et al. (2009)), (iii) affect idiosyncratic volatility (Kang, Kondor, and Sadka (2014)), and even (iv) manipulate stock prices on critical reporting dates (Ben-David, Franzoni, Landier, and Moussawi (2013)). Additionally, Kruttli, Patton, and Ramadorai (2015) find that a measure of the aggregate illiquidity of hedge fund portfolios has predictive power for returns of some asset classes. Nonetheless, there is limited evidence of hedge funds affecting expected returns and there is no consensus in the extant literature on the role of hedge funds vis-à-vis prime brokers in expected return determination.

We begin by repeating our cross-sectional asset pricing analysis of the previous section, but substitute the financial intermediary factor for a measure of aggregate hedge fund sector performance. We posit that, if hedge funds systematically affect expected returns, shocks to the sector should at least be priced in the cross section of hedge funds. We approximate shocks to the hedge fund sector's health using the aggregate asset-weighted Credit Suisse hedge fund index return.[16] We find that exposure to aggregate hedge fund sector performance does not produce a statistically significant spread in either average excess returns or alphas in the cross section of hedge funds (reported in the Internet Appendix). We also find that aggregate hedge fund factor beta is not a significant predictor of average returns in a cross-sectional regression framework, with or without additional controls (we do not report these results). Lastly, we examine the pricing performance of the financial intermediary factor jointly with the aggregate hedge fund sector returns in a double-sort procedure. We find that inclusion of the aggregate hedge fund return does not affect the pricing power of the financial intermediary factor (we report these results in Table 8 and discuss further in Section 7). In sum, our results suggest that there is no evidence that the hedge fund sector has a consistent, systematic effect on expected returns.

The question remains as to why the intuitive plausibility that hedge funds systematically affect asset prices does not seem to be borne out empirically. To shed light on this question, we examine the relative size of the hedge fund sector, zooming in on hedge fund financing arrangements. Panel (a) of Figure 2 shows the time series of aggregate hedge fund AUM alongside total market equity and total assets (sourced from COMPUSTAT) of the 38 listed prime brokers during our sample period. In line with Fung and Hsieh (2000a), we observe that, in the early 2000s, aggregate hedge fund AUM, as reported by a commercial hedge fund database, was small in both absolute and relative terms (total hedge fund AUM was around 200 million USD in March 2000, while the market value of prime broker equity was close to 1.2 billion USD).[17] Following a period of rapid growth, aggregate hedge fund AUM

[16]The correlation between the Credit Suisse and Eurekahedge asset-weighted index returns is around 94%. We consider the Credit Suisse broad hedge fund index because it is available for longer and frequently analyzed in the literature (see, e.g., Boyson et al. (2010), and Jurek and Stafford (2015)). We also examine monthly changes in aggregate hedge fund AUM (as a proxy for aggregate hedge fund wealth), but the results are similar. For simplicity, we thus focus on index returns.

[17]We use aggregated AUM from Barclays Hedge database as it is publicly available, has broad coverage, is consistent calculated, and has been used in the literate (e.g., Ang et al. (2011)). Considering instead the

reached around two trillion USD in 2007, similar to the total market value of prime broker equity at the time. Subsequently, hedge fund sector AUM has been roughly equal to the market value of prime broker equity (in June 2017, hedge fund AUM and the market value of prime broker equity were around 2.6 and 2.4 trillion USD, respectively). However, it is a market player's total assets rather than just its equity that should matter for determining the potential effect on asset prices. Indeed, compared to total prime broker assets (around 32 trillion USD in June 2017), hedge fund AUM is still relatively small.

There may be three immediate concerns. First, whether a commercial database accurately captures the total hedge fund AUM as there is evidence that not all hedge funds report to commercial databases (Barth, Joenväärä, Kauppila, and Wermers (2020)). Second, whether our relative size ranking changes once we account for hedge fund leverage. Third, and most importantly, despite its relatively small size, hedge funds may still be marginal investors in some markets and thus could have a systematic effect on asset prices. We address these concerns by examining regulatory data from Form PF (an obligatory regulatory form filed by all hedge funds operating in the US with at least 150 million USD in AUM). Form PF data are only available from 2014 as the regulatory disclosure requirement was only introduced in late 2011 as part of the Dodd-Frank Act. These regulatory data show that total hedge fund AUM is approximately 38% larger than a commercial database estimate. This fact, however, does not materially alter our conclusions as total prime broker assets are still, on average, around nine times larger.

Examining the gross hedge fund AUM (hedge fund AUM plus total hedge fund borrowings), we observe that aggregate hedge fund leverage is moderate: gross AUM is, on average, 1.8 times larger than net AUM, which is in line with the findings of Ang et al. (2011), who use proprietary fund of funds data. Between 2014 and 2017, hedge funds controlled about 6.3 trillion USD in assets. Although this number is still around five times less than prime brokers' total assets, it is substantial in absolute terms. Moreover, hedge funds

total AUM of all the funds in the Eurekahedge database yields similar results.

seem to control enough capital to play a role in asset price formation in some markets.

We posit, however, that hedge funds are unlikely to have a systematic effect on asset prices due to the fragility of their financing. 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 leverage type 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. Panel (c) of Figure 2 demonstrates that, on average, over 50% of hedge fund borrowing is provided by their prime brokers. Importantly, on average, 40% percent of hedge fund financing is provided on an overnight basis (Panel (d) of Figure 2). These patterns highlight that a prime broker can easily and suddenly rescind a large portion of hedge fund debt capital. Hence, a systematic shock to prime brokers would almost mechanically propagate to hedge funds via margin calls and forced deleveraging and then, provided the shock is large enough, to the assets held by hedge funds. This mechanism is in line with the theory of Brunnermeier and Pedersen (2009), where speculators face leverage constraints (see, Mitchell and Pulvino (2012) for a discussion and empirical application in the context of hedge funds). Relatedly, Kang et al. (2014) find that the collapse of Lehman was associated with a idiosyncratic volatility shock to stocks held by Lehman-connected hedge funds (i.e., the direction of shock propagation is from the prime broker to stocks via hedge funds). In sum, the key insight from the evidence presented is that hedge fund leverage shocks are not structural; prime brokers' control of the bulk of hedge fund debt financing renders hedge funds' role in the market as primarily a veil of prime broker shocks.[18] We formally investigate this conjecture in the next subsection.

[18] It is worth noting that, on average, an additional 30% of hedge fund total debt financing comes from the repo market, a colossal market and the main source of funding for prime brokers (see, e.g., Adrian and Shin (2010)). Hence, a shock to the repo market, such as the dramatic increase in haircuts experienced during the 2008 financial crisis (see, Gorton and Metrick (2009)), would be another example of an exogenous shock to hedge fund leverage.

5.1 Granular instrumental variable (GIV) approach

In this subsection, we utilize GIV methodology of Gabaix and Koijen (2020) to first investigate whether there is empirical support for the reverse channel (i.e., from hedge fund returns to prime broker returns) and second, to empirically establish a causal link from prime broker shocks to the hedge fund sector.

5.1.1 Hedge funds to prime broker channel

We begin by examining a potential reverse causality concern, i.e., whether hedge fund shocks affect prime brokers. Specifically, we investigate whether shocks to particular prime broker's hedge fund clients impact its returns.

Preliminaries We hypothesize that the prime broker (financial intermediary) return, $r_{j,t}^{\mathrm{FI}}$, can be represented as

$$r_{j,t}^{\mathrm{FI}} = \gamma_j r_{S,t}^j + \beta_{j,t}^{\mathrm{FI}} r_t^{\mathrm{FI}} + \beta_{j,t}^{\mathrm{M}} r_t^{\mathrm{M}} + a_j + \eta_{j,t}^{\mathrm{FI}}, \tag{3}$$

where $r_{S,t}^j$ is the size-weighted (based on their AUM in the previous period) return of the hedge fund clients of prime broker j (the size weights, S_i^j, are normalized to add to one, $\sum_i S_i^j = 1$), r_t^{FI} and r_t^{M} are the month t excess returns for the prime brokers' value-weighted portfolio and the aggregate stock market portfolio, respectively. a_j is the intercept, and $\eta_{j,t}^{\mathrm{FI}}$ represents a catchall shock that contains both systematic (with the exception of the market and aggregate financial intermediary risk) and prime broker specific components.

The sensitivity of prime broker returns to its clients' returns, our coefficient of interest, is denoted as γ_j and may be non-zero. However, we cannot estimate γ_j using OLS as $\eta_{j,t}^{\mathrm{FI}}$ and $r_{S,t}^j$ are likely correlated, hence the estimate would be biased (e.g., a prime broker and its clients could be exposed to the same risk. For instance, a specific exchange rate).

However, by exploiting variation in idiosyncratic returns of large hedge funds, the GIV methodology allows us to estimate γ_j and test whether it is, in fact, non-zero, i.e., whether hedge fund clients' returns systematically affect their prime brokers. The GIV methodology is applicable when shocks to large players could affect aggregate outcomes. The distribution of hedge fund sizes is strongly positively skewed (the Internet Appendix plots the histogram of fund AUM), thus, GIV methodology seems relevant in our setting.

We model the return of hedge fund i as

$$r_{i,t} = \sum_f \beta_i^{\text{HF},f} F_t^{\text{HF},f} + c_i' X_{i,t-1} + a_i + u_{i,t}, \tag{4}$$

where each $F_{t,f}^{\text{HF}}$ is a factor and $\beta_i^{\text{HF},f}$ are factor loadings, $X_{i,t-1}$ is a vector of controls that includes all the fund-specific characteristics for each fund i, a_i is the intercept, and $u_{i,t}$ is an idiosyncratic hedge fund shock. Then, for each prime broker j, we estimate the GIV regression, using two-stage-least squares (2SLS). Closely following Gabaix and Koijen (2020), we instrument for $r_{S,t}^j$ in equation (3) using $z_t^j = r_{S,t}^j - r_{E,t}^j$ (where $r_{E,t}^j$ is an equal-weighed return of of prime broker j's hedge fund clients at time t), while controlling for common hedge fund variation, $F_t^{\text{HF},f}$ (which we extract using principal component analysis (PCA)) and fund characteristics.[19] The main identifying assumption is $E[u_{i,t}\eta_{j,t}^{\text{FI}}] = 0$, i.e., the exclusion restriction. In other words, we assume that we can isolate idiosyncratic hedge fund shocks and that they are independent of prime broker shocks.

Sample selection We focus on the hedge funds that have at least a 24 month return history and report a prime-broker affiliation to a broker with at least five clients. This limits our sample to 1654 individual hedge funds and 43 prime brokers. These data are available from January 2006 as we do not have timely information on prime broker affiliation

[19]Our reduced form model is deliberately simple and parsimonious. In particular, we choose to study individual prime brokers separately. We do not introduce a feedbook loop. We also abstract from any additional factors driving prime broker returns as it is not required for identification. A few potential extensions are possible, but they go beyond the scope of our paper.

before that date.[20] For the GIV analysis, we restrict the sample to the period after the Great Financial Crisis (June 2009–June 2017). We do so for two reasons. First, the exclusion restriction is unlikely to hold during the crisis; there were a myriad of shocks simultaneously impacting many market players, thus disentangling idiosyncratic shocks, especially with only monthly data, is difficult. Second, early in our sample period, we have too few observations for some prime brokers' hedge fund clients.[21] As discussed previously, the prime brokerage industry is highly concentrated 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 accounts for the largest number of hedge fund AUM. Given that our estimation requires a rich panel of hedge funds for each prime broker, we focus our analysis on the five prime brokers with the most clients (Goldman Sachs, Morgan Stanley, UBS, JP Morgan, and Credit Suisse). Focusing solely on the largest prime brokers has the additional advantage of alleviating the potential concern that prime brokers differ significantly in the types of hedge funds they represent. The distributions of hedge fund sizes and styles are similar across these five prime brokers (the Internet Appendix plots the distributions).[22]

Results We report the GIV regression results in Panel A of Table 5. We separately estimate the sensitivity of prime broker returns to the returns of its clients, γ^{GIV}, for the five largest prime brokers. As additional controls, each 2SLS regression includes fund characteristics, the market return, the traded financial intermediary factor, and the first three principal components of hedge fund returns.[23] If hedge fund clients shocks systematically

[20]The Internet Appendix presents the descriptive statistics on the performance and AUM of each prime broker's clients, each broker's size in terms of clients, and, in the case of listed prime brokers, their market capitalization.

[21]For example, we observe only 56 JP Morgan hedge fund clients in December 2006, but the number increases to 133 by December 2010.

[22]Long Short is the predominant style for all prime brokers' hedge fund clients. However, one noteworthy pattern is that, relative to other large prime brokers, JP Morgan has fewer hedge fund clients following the Long Short style, and more clients following the Relative Value style.

[23]For ease of expositions, we consider the first three principal components in all our reported specification as the factor-choice criteria of Bai and Ng (2002), implying that the number of suggested factors in each of our specifications is typically between three and five. Our results are similar if we include the first five principal components instead.

affected the returns of its prime brokers, we would expect the sign of γ^{GIV} to be positive. In contrast, we find that for each prime broker the estimated γ^{GIV} is negative, but not statistically significant. Nevertheless, the magnitude of the coefficients appears to be similar across the four largest prime brokers, ranging from -0.432 for Morgan Stanley to -0.654 for JP Morgan (the estimated coefficient is larger for Credit Suisse, but that is likely driven by the smaller cross-section). In each case, the first-stage F-statistics, testing for weak instruments, are high (ranging from 28.4 to 157.9), which, based on typical thresholds used in the literature, implies that the instruments are strong (see, e.g., Stock, Wright, and Yogo (2002)). The estimates are also stable to the inclusion of additional principal components (not tabulated). Importantly, the negative sign of γ^{GIV} suggests that a hedge fund's positive returns may actually be associated with their respective prime broker's poor performance. This relation is economically intuitive if one considers that many hedge fund trades are conducted using bilateral OTC derivatives in which the fund's prime broker may inadvertently be the counterparty, as the OTC derivatives market is highly concentrated and the largest prime brokers are also the largest derivative dealers.[24] An illustrative example is provided by the April 2012 JP Morgan "London Whale" credit default swaps (CDS) trading loss,[25] as there is some anecdotal evidence that many hedge funds trading those instruments profited from it.[26] Indeed, we observe that hedge funds following a Fixed Income style performed very well around the event (Figure 5 plots the returns of JP Morgan hedge fund clients around the time of that event. We analyze this further in the next section).

[24]The New York Fed's OTC Derivatives Supervisors Group has around 15 participating dealers (including Goldman Sachs, Morgan Stanley, UBS, JP Morgan, and Credit Suisse) which are also the largest prime brokers (see, https://www.newyorkfed.org/markets/otc_derivatives_supervisors_group).

[25]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 CDS. 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.

[26]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.

Discussion Given the recent collapse of Archegos Capital Management (a family office) that led to around 10 billion USD in losses for a number of prime brokers, does it make sense that hedge funds do not have an average systematic effect on prime brokers?[27] We believe that it does. First, the Archegos case appears to be a unique example of extremely poor risk management by certain firms.[28] Second, most hedge funds are too small to have a meaningful effect on their prime brokers; a median hedge fund's AUM is only USD 120 million, while the market capitalization of a typical prime broker is around USD 35 billion. Third and most important, as we discuss earlier, contractually, the prime-broker-hedge-fund relationship strongly favors the prime broker. To reiterate this point, we provide some additional supportive evidence of this asymmetry. We collect data on OTC derivatives' net current credit exposure and total fair value of collateral for four US banks from the quarterly Consolidated Reports of Condition and Income (Call reports).[29] Since 2009, Schedule RC-L (Derivatives and Off-Balance Sheet Items) of the Call report provides a separate breakdown of credit exposure and collateral for OTC derivative positions for different counterparties, including banks and securities firms, hedge funds, sovereign governments, and corporations. Figure 3 plots the time series of the ratio of OTC derivatives net current credit exposure to the total fair value of posted collateral for the different counterparties. For all the banks and consistently across time, hedge funds are highly overcollateralized (the average collateral to exposure ratio is around four), consistent with the aggregate numbers presented in Figure 2. Importantly, this pattern strongly contrasts the undercollateralized corporate and sovereign counterparties. Although it is possible that certain hedge funds may be treated differently, the evidence suggests that, on average, prime brokers are relatively more protected from

[27] See, for example, "Total bank losses from Archegos implosion exceed $10bn" by Leo Lewis and Owen Walker, *Financial Times*, 27 April 2021.

[28] See, for example, "Credit Suisse made just $17.5m in Archegos fees in year before $5.4bn losses" by Owen Walker and Stephen Morris, *Financial Times*, 27 April 2021.

[29] All banks in the US file a quarterly Call report to the Federal Deposit Insurance Corporation (FDIC). However, we find that many banks, particularly foreign-domiciled banks (e.g., Barclays, Deutsche Bank, Credit Suisse, UBS, and HSBC), leave Schedule RC-L blank. Meaningful data are only provided by Citi, Goldman Sachs, JP Morgan, and Bank of America; hence we focus on those four banks. However, given their importance as prime brokers and primary dealers, we believe these banks to be representative.

hedge fund shocks than hedge funds are from prime broker shocks.

5.1.2 Prime broker to hedge fund sector channel

In this subsection, we apply the GIV methodology to establish a causal link between aggregate prime broker shocks and hedge fund returns.

Preliminaries We begin with the following representation of hedge fund portfolio return

$$r_t^{\mathrm{HF}} = a + \beta^{\mathrm{FI}} r_t^{\mathrm{FI}} + \beta^{\mathrm{M}} r_t^{\mathrm{M}} + \eta_{j,t}^{\mathrm{HF}}, \tag{5}$$

where r_t^{HF} is a return to a portfolio of hedge funds, a is the intercept, r_t^{FI} and r_t^{M} are as previously defined (equation (5) is similar to regression (1)), and $\eta_{j,t}^{\mathrm{HF}}$ represents a catchall shock that contains both additional systematic shocks and idiosyncratic ones.

In the previous section, we find that, for instance, Portfolio 10 has positive and significant financial intermediary beta, β^{FI}, and that it delivers relatively high average returns. Our goal here is to ascertain whether it is possible to attribute a causal link between aggregate financial intermediary shocks and hedge fund returns. Specifically, we estimate the causal elasticity between hedge fund portfolio returns and financial intermediary shocks. As in the previous subsection, we do this using the GIV methodology as we believe it may be applicable in this setting. The financial intermediary risk factor is comprised of returns of only around 30 individual financial institutions of varying sizes. The size distribution is positively skewed (the Internet Appendix plots the histogram of sizes), hence shocks to a few constituents could influence the aggregate performance, which is the exactly the requirement for GIV applicability.

We model the return of each financial intermediary (prime broker) j as

$$r_{j,t}^{\mathrm{FI}} = \sum_f \beta_j^{\mathrm{FI},f} F_t^{\mathrm{FI},f} + a_j + u_{j,t}, \tag{6}$$

where each $F_t^{\mathrm{FI,f}}$ is a factor and $\beta_i^{\mathrm{FI},f}$ are factor loadings, a_j is a constant, and $u_{j,t}$ is an idiosyncratic prime broker shock. It is important to note that the size-weighted sum of prime broker returns is the financial intermediary factor: $\sum_j S_j r_{j,t}^{\mathrm{FI}} = r_t^{\mathrm{FI}}$. It is also worth noting that we are agnostic, in this setting, about the exact factors driving individual prime broker returns (following Gabaix and Koijen (2020), we extract common variation using PCA to best isolate idiosyncratic prime broker shocks). Then, as in the previous subsection, we estimate the GIV regression using 2SLS. The exclusion restriction in this case is that individual prime broker shocks, $u_{j,t}$, are truly idiosyncratic and uncorrelated with other factors driving hedge fund portfolio returns.

Sample selection To be consistent with our analysis in the previous sections, we focus on the listed prime brokers that are also primary dealers (26 prime brokers in total).[30] We examine the same sample period as in the previous sections (January 2000 to June 2017). To dampen the effects of extreme outliers, following Gabaix and Koijen (2020), we winsorize the data at 1% and 99% across all prime brokers and periods (our results are similar for other winsorization thresholds).

Results We report the GIV regression results in Panel B of Table 5. We estimate the causal elasticity, $\beta^{\mathrm{FI,GIV}}$, for the high-FI-factor loading and the low-FI-factor loading portfolios of hedge funds (defined in Section 4). Each 2SLS regression includes the market return and the first three principal components of prime broker returns as additional controls. For the high-FI-factor loading portfolio, we find that the point estimate of $\beta^{\mathrm{FI,GIV}}$ is equal to 0.527 and is statistically significant (t-stat = 2.65). In contrast, for the low-FI-factor

[30] We exclude ABN AMRO as it only has 19 months of returns.

loading portfolio, the $\beta^{\text{FI,GIV}}$ estimate is substantially lower (0.213) and is statistically insignificant (t-stat = 1.17). These results suggest that shocks to financial intermediaries propagates to the returns of hedge funds that are exposed to financial intermediary risk. The first stage F-statistic, testing for weak instruments, is equal to 14.5, implying that the instrument is reasonable. Moreover, we find that our $\beta^{\text{FI,GIV}}$ estimates are stable and robust to the inclusion of additional principal components as controls (not tabulated).[31]

Discussion Earlier we show that financial intermediary risk is priced in the cross-section of hedge funds. In this section, we examine the time-series dimension using the GIV approach. Our results suggest that causal direction of shocks runs from prime brokers to hedge funds, but not the reverse. Given the institutional setting, and the fact that prime brokers control the bulk of hedge fund funding, it is economically intuitive that shocks propagate from prime brokers to hedge funds.

6 Individual prime broker effects

Despite an intuitive link between individual prime brokers and their hedge fund clients, our results thus far show that the exposure to the systematic component of financial intermediary shocks 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.

[31] It may be instructive to note that the largest absolute idiosyncratic shock (defined as the residual of our instrument on the principal components) occurs on March 2008 (i.e., the month of Bear Stearns' bankruptcy). In contrast, October 2008 (at the epicenter of the financial crisis) does not even qualify as a top 100 idiosyncratic financial intermediary shock, which makes economic sense as shocks during that period were likely primarily systematic. This example illustrates that GIV procedure appears to perform as expected.

6.1 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.[32] We are particularly interested in whether the prime broker specific shocks propagate 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 reverberate to its hedge fund clients. We explore to what extent this is the case by considering the following panel regression:

$$r_{i,t} = a_i + b\, r_{i,t}^{\mathrm{PB}} + c' X_{i,t-1} + \varepsilon_{i,t}, \tag{7}$$

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. A fund fixed effect is denoted by a_i and $X_{i,t-1}$ 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, $r_{i,t}^{\mathrm{PB}}$, 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:

$$r_{j,t}^{PB} = a_j + \beta_j^{\mathrm{M}} r_t^{\mathrm{M}} + \beta_j^{\mathrm{FI}} r_t^{\mathrm{FI}} + \beta_j^{\mathrm{CI}} r_{j,t}^{\mathrm{CI}} + \varepsilon_{j,t} \tag{8}$$

where r_t^{FI} and r_t^{M} 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

[32] We first check whether being a client of a particular prime broker has an effect on a hedge fund's average risk-adjusted returns. We find no significant evidence supporting a link between a particular prime broker and average hedge fund performance (see the Internet Appendix for details).

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 a 24 month return history (i.e., the sample described in subsection 5.1.1). We use standard errors clustered by hedge fund and time.

We report the results in Table 6 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 b coefficient of 0.12 (t-stat = 8.5). This is unsurprising as both the hedge funds 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 (7) with the residual 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 0.041 but remains statistically significant (t-stat = 2.2). 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 most of their business in their home countries (countries of their primary listing). In turn, many of their hedge fund clients 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 simply be correlated due to their common exposures to country-specific risk. 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 6, 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. This result is confirmed when we separately examine the US-domiciled hedge funds and find that the b coefficient is not significant after controlling for the market and FI factor (not tabulated). In sum, our results indicate that once we adequately control for market risk and systematic financial-sector risk, there is no significant relationship between hedge fund returns and the returns of its prime broker.

6.2 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 could be 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 temporarily reduce the quality of other services as its resources are redirected elsewhere. To evaluate this potential effect, we focus on four well-publicized 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.

6.2.1 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. We note that the Lehman event, and the other events we consider, likely capture both the systematic and idiosyncratic shocks. Indeed, any hedge fund operating at the time of the Lehman bankruptcy would have been exposed to the systematic shock that the event represented. However, Lehman's hedge fund clients would also have been exposed to the idiosyncratic component of the shock. Our analysis focuses on the differential impact of the shocks on the clients of the affected prime broker relative to other prime brokers' hedge fund clients. The top panel of Figure 4 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 epicenter of the financial crisis, it also clearly represents an extreme individual shock.

Next, we 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 a reason that they use a hazard model of reporting in their analysis, instead of 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 or termination.

The middle panel of Figure 4 presents the total number of Lehman hedge fund clients that report to the database each month. From September 2008 to the beginning of 2009, we observe a pronounced decrease in the number of Lehman hedge fund clients that report to the database. The middle panel of Figure 4 also presents the total number of hedge funds in a matched group of hedge funds that were clients of other prime brokers.

Each Lehman hedge fund client that reported to the database in August 2008 is matched to another hedge fund based on fund style, average AUM (decile), average return (decile), return standard deviation (decile), and average financial intermediary beta (decile).[33] Thus, in August 2008 we have a sample of Lehman hedge fund clients and a group of similar hedge funds that are other prime brokers' clients. Although our sample contains fewer Lehman hedge funds clients, we confirm the conclusions of Aragon and Strahan (2012), which are that only around 60% of the Lehman's clients survive past January 2009 and that Lehman hedge fund clients left the database at a higher rate than other, similar funds.

Thus, given that many Lehman funds stopped reporting around the event, we adjust their delisting returns. In the spirit of adjusting for equity delisting returns bias (Shumway (1997)), for each fund that stops reporting we add a delisting return of −30% for the month following the last report return. We view this as a conservative adjustment as, particularly in the case of Lehman clients, such losses are well supported by anecdotal evidence (see, e.g., Aikman (2010)). Using instead −10%, −50%, or −70% as a delisting return does not alter the general conclusion.[34] The bottom panel of Figure 4 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. Although we see poor performance across the sector at the time of the event, the imputed delisting returns suggest that Lehman funds

[33]For the matching procedure, we estimate each fund's average return, standard deviation, and average financial intermediary beta over the 12 months prior to the event month.

[34]There is little consensus in the literature on the appropriate delisting return adjustment. For example, Titman and Tiu (2010) use −100% , Ang and Bollen (2010) use −25%, and Sun and Teo (2019) use −10% as their delisting return base cases. Hodder, Jackwerth, and Kolokolova (2014) estimate an unconditional delisting return of −6%. However, they note that a large negative delisting return is possible under adverse circumstances, as in during the financial crisis.

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[35], and the April 2012 JP Morgan trading loss (discussed previously). The Lehman and Bear Stearns events are both extreme events in the sense that in each case both prime brokers ceased to exist after the event. However, the Bear Stearns failure and subsequent sale to 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 large, individual, adverse shocks to each prime broker.

The top three panels of Figure 5 show the monthly excess returns of Bear Stearns, UBS, and JP Morgan around the events, representing large adverse idiosyncratic shocks for prime brokers. The bottom panels of Figure 5 show the cumulative return indexes of the respective prime brokers' hedge fund clients' portfolios 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 CDS and, as we discuss earlier, there is some evidence to suggest that many hedge funds trading those instruments profited from it. 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 delisting 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 affected prime brokers' hedge fund clients and those of the matched groups. It appears that the Lehman event may have been unique, and the implications for hedge fund performance are not generalizable to other large prime broker shocks.

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

6.2.2 Difference-in-difference regression

To formally evaluate whether the affected prime brokers' clients' returns are relatively more severely impacted by a large adverse shock to their prime broker, we estimate the following panel regression:

$$
\begin{aligned}
r_{i,t} = a_i &+ b_1 \text{PB Events}_t + b_2 \text{PB Client}_i + b_3 \text{PB Events}_t \times \text{PB Client}_i \\
&+ b_4 \text{Lehman Event}_t + b_5 \text{Lehman Client}_t + b_6 \text{Lehman Event}_t \times \text{Lehman Client}_i \\
&+ c' X_{i,t-1} + \varepsilon_{i,t}, \qquad (9)
\end{aligned}
$$

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 $\text{Events}_t \times$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 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. Finally, Lehman $\text{Event}_t \times$Lehman Client_i is the interaction of the two terms. The event window is four months, including the month of the start of the event. A fund fixed effect is denoted by a_i, and $X_{i,t-1}$ 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 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 (9) in Table 7. We note that our methodology controls for the systematic shocks coinciding with the prime broker events. The coefficients on PB Events_t and Lehman Event_t capture the systematic effects. In our baseline specification, reported in column I, these coefficients 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 affected prime brokers' clients' returns are not significantly different than those of the other funds. The coefficient b_3 is positive, but 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 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. This result is also in line with Aragon, Ergun, Getmansky, and Girardi (2017) who show, using regulatory data, that over 80% of the hedge funds in their sample maintain a liquidity cushion which can act as a buffer against funding liquidity shocks. Perhaps surprisingly, the baseline regression is unable to statistically show that Lehman's hedge fund clients' returns 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 differently affect the hedge funds that 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 and those who use several could help understand 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 (9). 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 the 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 7, paint a stark picture. The coefficients on the interaction terms, PB Events$_t$ × PB Unique Client$_i$ and Lehman Event$_t$ × 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). The coefficients b_3 and b_6, which in the auxiliary specification reflect the relative return difference of the affected prime broker's clients with multiple prime brokers, are around zero and 2%, respectively. The results remain unaltered with the inclusion of hedge fund fixed effect and controls. Moreover, the results are robust to event windows from two to six months and to different delisting return adjustments. The results are also similar if we instead consider risk-adjusted hedge fund returns (reported in the Internet Appendix).[36] These results are unlikely to be driven by fund size; first, we control for size in our regressions, and second the correlation between hedge fund AUM and an indicator of whether a fund has multiple prime brokers is 0.20 unconditionally and 0.14 for the Lehman clients. Hence, our results

[36]One noteworthy difference when using the risk-adjusted hedge fund returns is that the coefficient b_6, which reflects the relative return difference of the Lehmans's clients with multiple prime brokers, is no longer statistically significant. Our finding that the coefficient b_6 is positive and significant may suggest that Lehman hedge fund clients using Lehman as one of their multiple prime brokers fared relatively better during the bankruptcy. However, the regression using the risk-adjusted returns shows that this seemingly counterintuitive result is simply driven by different factor loadings among the funds.

indicate that, in the case of the Lehman bankruptcy, hedge funds who used Lehman as its only prime broker experienced a significantly larger loss than other funds, while those that used Lehman as just one of several did not.

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. It also suggests that a prime broker shock has led to its hedge fund clients' significant under-performance only in the case of the 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 shock 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 the Dai and Sundaresan (2009) conjecture that hedge funds have relations with multiple prime brokers for better risk management.

7 Robustness

7.1 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 Pástor and Stambaugh (2003), the macroeconomic uncertainty factor of Bali et al. (2014), the correlation factor of Buraschi et al. (2013), the tail risk factor of Agarwal et al. (2017), and aggregate hedge fund index return.

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 Pástor and Stambaugh (2003), we first sort funds into five quintiles based on their historical Pástor and Stambaugh (2003) liquidity betas. Within each quintile, we then sort each fund into five portfolios sorted on their historical FI betas (all portfolios are equal-weighted and rebalanced monthly). The five FI beta-sorted portfolios are finally averaged over each of the Pástor and Stambaugh (2003) liquidity sorted portfolios. The same procedure is performed for the other factors.

Table 8 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 (9.24% and 8.88%, respectively) and statistically significant (t-stats = 4.9 and 3.3) when controlling for the correlation factor.

Controlling for the liquidity factor reduces the spreads.[37] The annualized spread in returns and alphas is 6.72% and 4.08%, respectively (t-stats = 4.7 and 2.5). 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 4.32% and 3.72%, respectively, but remains statistically significant (t-stats = 2.8 and 2.3). This suggests that a portion of intermediary risk may be related to macroeconomic uncertainty, particularly given our sample period.

We also 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 5.40% and 4.68%, respectively. Both spreads remain statistically significant (t-stats = 3.3 and 2.8). 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.

[37]We consider the Pástor and Stambaugh (2003) measure, as in Teo (2011), instead of the Sadka (2010) liquidity measure as it is only available for the shorter period between January 2000 and December 2012. Nevertheless, we verify that the results are similar using alternative liquidity measures (not tabulated).

Lastly, we evaluate whether accounting for aggregate hedge fund performance (using the aggregate asset-weighted Credit Suisse hedge fund index return) affects the cross-section of the FI sorted portfolios. The annualized spread in returns and alphas decreases to 4.68% and 4.44%, respectively. Both spreads remain statistically significant (t-stats = 3.5 and 2.9). Given that aggregate hedge fund performance is not an established risk factor and we find the exposure to broad hedge fund performance has no cross-sectional explanatory power by itself, the reduction in the spread most likely arises due to the hedge fund index returns being correlated with other factors like liquidity. That notwithstanding, aggregate hedge fund performance does not subsume the importance of FI for the cross-section of hedge fund returns.

7.2 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 all the hedge funds' first twelve months of returns in our sample. We then repeat our main analysis pertaining to systematic financial intermediary risk. The Internet Appendix presents the results of intermediary-beta-sorted portfolios and the cross-section regressions. There is no noticeable effect on our results.

7.3 Delisting return adjustment

As we have discussed in subsection 6.2, reporting to a hedge fund database is voluntary and funds that terminate their operations could stop reporting returns prematurely, which could bias performance measurements. In line with our analysis in subsection 6.2 we assume that, for the month after a fund stops reporting, its return is −30%. We then repeat our main analysis pertaining to systematic financial intermediary risk. The Internet Appendix presents the results of intermediary-beta-sorted portfolios and the cross-section regressions. There is no noticeable effect on our results.

8 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. 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 other services. The global financial crisis, which led to the demise of multiple US investment banks, highlighted the importance of shock propagation from prime brokers to hedge funds. We study the effect of prime broker shocks on hedge fund returns. We find that the financial intermediary risk captures cross-sectional differences in hedge fund returns. We also establish a causal effect of aggregate prime broker shocks propagating to hedge funds exposed to financial intermediary risk, but we find no evidence of the reverse. To provide economic intuition for these results, we illustrate that the prime broker–hedge fund relationship disproportionately favors the prime broker and that prime brokers tightly control the bulk of hedge fund financing. Taken together, our analysis suggests that hedge funds act primarily as a veil to aggregate prime broker shocks. However, we find that individual prime brokers influence their hedge funds' clients only in the event of extreme adverse shocks and even those shocks appear diversifiable by using multiple prime brokers. 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 a limited effect.

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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 runs from January 2000 to June 2017. N is the number of unique hedge funds for each year or for each investment style. The statistics in Panel A (Mean, SD, Min, and Max) are based on the time-series of monthly cross-sectional averages of excess returns (in %, and converted to USD for funds denominated in another currency). SD is the standard deviation of the time series of monthly excess returns. SD^{CS} is the cross-sectional standard deviation of the average excess returns. The statistics in Panel B are for fund characteristics AUM (in USD million) and Age (in months). The statistics are time-series averages of monthly cross-sectional statistics and represent a typical distribution of hedge fund characteristics available in a given month in the sample.

Panel A: Monthly returns

	N	Mean	SD	Min	Max	SD^{CS}
Full sample	2697	0.61	2.07	−9.17	7.64	0.68
Year						
2000	440	0.74	2.21	−2.73	4.66	1.92
2001	510	0.51	1.45	−2.35	2.54	1.61
2002	614	0.53	1.35	−2.40	2.09	1.59
2003	764	2.09	1.35	0.02	4.36	1.98
2004	918	1.06	1.59	−2.02	4.04	1.37
2005	1082	0.63	1.51	−1.82	2.39	1.23
2006	1274	1.01	1.77	−2.21	4.03	1.34
2007	1447	0.89	1.67	−2.05	3.54	1.63
2008	1569	−1.63	3.56	−9.17	2.91	3.12
2009	1635	2.16	2.74	−1.63	7.64	2.38
2010	1716	0.90	2.74	−4.53	5.12	1.45
2011	1776	−0.35	2.56	−5.53	3.75	1.22
2012	1778	0.73	1.92	−4.12	3.14	1.12
2013	1750	0.76	1.43	−1.77	2.73	1.41
2014	1703	0.03	1.17	−1.90	2.51	1.24
2015	1629	−0.13	1.44	−2.15	2.79	1.26
2016	1488	0.25	1.73	−2.89	3.89	1.38
2017	1340	1.03	0.51	0.52	1.93	1.56
Style						
Event Driven	141	0.65	2.11	−11.13	8.46	0.55
Global Macro	203	0.52	1.54	−3.34	5.71	0.50
Long Only	328	0.71	3.81	−20.23	12.79	0.59
Long Short	960	0.63	2.46	−8.91	8.80	0.66
Managed Futures	181	0.51	2.66	−6.57	10.84	0.52
Market Neutral	114	0.44	1.35	−9.38	4.55	0.55
Multi Strategy	266	0.72	1.94	−8.83	6.82	0.78
Others	78	0.54	2.35	−6.37	7.98	1.62
Relative Value	426	0.59	1.64	−9.44	5.58	0.59

Panel B: Characteristics

	N	Mean	Median	25 percentile	75 percentile	Min	Max
AUM	2697	396.8	119.9	52.2	322.5	15.0	25381.1
Age	2697	92.5	74.5	46.1	120.3	24.3	497.5

Table 2: Top prime brokers over time

The table presents the market share of each prime broker (name abbreviated), recorded in the June snapshot every year in the universe of funds reporting prime broker affiliation and AUM (7976 funds). The prime brokers are ranked by their number of clients (Panel A) and the total AUM their clients manage (Panel B). The statistic (as a percentage of the total) is showed in parentheses next to the prime broker's 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: Merrill Lynch, MS: Morgan Stanley, and SocGen: Societe Generale.

Panel A: Clients

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
MS (17.0)	MS (18.4)	MS (17.9)	GS (15.6)	GS (15.0)	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 (11.0)	MS (12.0)	GS (11.6)
UBS (10.3)	UBS (11.3)	UBS (13)	UBS (11.7)	UBS (10.9)	UBS (10.9)	UBS (10.3)	UBS (11.0)	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 (6.0)	BAML (6.9)	DB (6.7)	JPM (7.2)	JPM (7.4)	DB (7.4)	CS (7.0)	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 (4.0)	CS (5.5)	CS (6.0)	CS (6.0)	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 (21.0)	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 (18.0)	GS (16.0)	MS (15.7)	GS (13.6)	GS (14.8)	JPM (15.8)	JPM (15.4)	JPM (13.0)	MS (12.5)	MS (14.8)
BS (9.9)	BS (11.0)	JPM (14.3)	GS (13.5)	MS (11.5)	UBS (12.0)	UBS (11.2)	UBS (11.0)	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 (10.0)	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 (9.0)	DB (9.0)	CS (9.7)	CS (9.3)	UBS (8.4)	JPM (8.1)
Nomura (4.8)	ML (4.0)	BAML (5.1)	CS (8.0)	CS (8.3)	CS (6.7)	CS (7.7)	DB (8.2)	UBS (9.3)	CS (8.0)	CS (8.0)
CS (3.9)	CS (4.0)	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 (3.0)	LB (3.4)	AIG (2.8)	BNP P (2.8)	SEB (2.8)	Citi (4.1)	BAML (4.0)	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: Risk-adjusted returns and other characteristics for beta-sorted portfolios

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the traded financial intermediary factor of He et al. (2017), FI, (controlling for the market return) and rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return, α_{FH8} refers to Fung and Hsieh (2004) seven-factor alpha, and R^2_{FH8} to the corresponding R-squared. $\bar{r}$ and α_{FH8} are reported in % per month. The post betas are the betas from a single time series regression of factors against each of the 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH8}	R^2_{FH8}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.24	−0.30	0.61	0.03	0.45	−0.37	0.81
	(0.32)	(0.23)		(0.06)	(0.13)	(0.05)	(0.12)
2	0.25	−0.14	0.64	0.05	0.33	−0.14	0.50
	(0.20)	(0.13)		(0.05)	(0.08)	(0.03)	(0.11)
3	0.40	0.02	0.65	0.06	0.28	−0.06	0.38
	(0.18)	(0.14)		(0.04)	(0.07)	(0.03)	(0.08)
4	0.46	0.08	0.70	0.07	0.24	0.00	0.31
	(0.18)	(0.09)		(0.03)	(0.07)	(0.07)	(0.05)
5	0.53	0.18	0.64	0.07	0.22	0.05	0.26
	(0.16)	(0.09)		(0.04)	(0.06)	(0.04)	(0.03)
6	0.51	0.15	0.58	0.07	0.19	0.11	0.22
	(0.16)	(0.11)		(0.03)	(0.06)	(0.06)	(0.03)
7	0.53	0.13	0.57	0.08	0.21	0.17	0.19
	(0.17)	(0.11)		(0.04)	(0.06)	(0.08)	(0.04)
8	0.70	0.31	0.51	0.09	0.20	0.24	0.15
	(0.17)	(0.13)		(0.04)	(0.06)	(0.12)	(0.06)
9	0.75	0.24	0.48	0.12	0.21	0.34	0.10
	(0.20)	(0.15)		(0.06)	(0.09)	(0.14)	(0.09)
10 (high)	1.06	0.34	0.48	0.20	0.20	0.65	−0.13
	(0.29)	(0.21)		(0.06)	(0.12)	(0.17)	(0.12)
10−1	0.82	0.64	0.08	0.17	−0.25	1.02	−0.94
	[3.96]	[2.71]		[2.57]	[−2.18]	[9.21]	[−6.94]

Table 4: Hedge fund financial 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. 10 portfolios are formed by 24-month rolling regressions of hedge fund returns on the traded financial intermediary factor of He et al. (2017), FI,(controlling for the market return) and are rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the 10 portfolios. These post-ranking betas are then assigned to each fund according to which decile portfolio they belonged to in 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), management fee (in %), incentive fee (in %), a dummy indicating if the fund has a high watermark, a dummy indicating if the fund has a lockup provision, the redemption notice (in days), and the minimum fund investment amount (USD million). β^{M} is the time t post-ranking beta with respect to the market. r_t is the time t excess fund return (in %). 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). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). N is the number of observations. The sample runs from January 2000 to June 2017.

	I	II	III	IV	V
β^{FI}	4.522***	4.167***	4.526***	3.493***	3.124**
	(1.133)	(1.031)	(1.530)	(1.316)	(1.285)
β^{M}			0.270	0.256	0.272
			(0.505)	(0.380)	(0.363)
r_t				0.104***	0.110***
				(0.015)	(0.014)
Age				−0.001*	−0.001**
				(0.001)	(0.000)
log(AUM)				−0.030**	−0.023**
				(0.012)	(0.010)
Management fee				0.033*	0.034**
				(0.018)	(0.017)
Incentive fee				0.001	−0.000
				(0.004)	(0.004)
High water mark				0.043	0.045
				(0.052)	(0.044)
Lockup				0.061	0.057
				(0.041)	(0.030)
Redemption notice				0.001**	0.001***
				(0.000)	(0.000)
Minimum investment				0.001	0.003
				(0.005)	(0.003)
Constant	0.165				
	(0.185)				
Style fixed effects	No	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	Yes
N	193,366	193,366	193,366	178,282	178,282
R^2	0.248	0.319	0.391	0.434	0.469

Table 5: Granular instrumental variable regressions

The table presents 2SLS GIV regression estimates. Panel A shows elasticity estimates, γ^{GIV}, for five large prime brokers from regressions of monthly prime broker returns on the value weighted return of its hedge fund clients (instrumented by a GIV as explained in Section 5.1.1), controlling for the financial intermediary (FI) and market (M) factors, the principal components (PCs) extracted from a panel of hedge fund returns, and fund age and AUM. The sample period for the regressions in Panel A runs from June 2009 to June 2017. Panel B shows elasticity estimates, $\beta^{\text{FI,GIV}}$, from regressions of monthly hedge fund portfolio returns on the value weighted return of 26 prime brokers (instrumented by a GIV as explained in Section 5.1.2), controlling for the market factor, and the principal components extracted from a panel of prime brokers. High-FI-risk and low-FI risk HF portfolios are portfolios of hedge funds with the highest and lowest relative loading on the FI factor (as defined in Table 3). The sample period for the regressions in Panel B runs from January 2000 to June 2017. All the specifications include a constant (not reported). 2SLS standard errors are reported in parenthesis. N is the number of observations, N_{panel} is the size of the full panel of hedge funds (Panel A) or prime brokers (Panel B) used for the construction of the respective GIVs, F-stat is the "first-stage" F-statistic to test for weak instruments.

Panel A: Hedge funds to individual prime broker GIV

	γ^{GIV}	R^2	N	Factors	PCs	N_{panel}	F-stat
Goldman Sachs	−0.492	0.706	95	M, FI	1-3	20633	50.236
	(1.069)						
Morgan Stanley	−0.432	0.703	95	M, FI	1-3	16321	95.641
	(1.063)						
UBS	−0.618	0.638	95	M, FI	1-3	11631	79.726
	(1.250)						
JP Morgan	−0.654	0.813	95	M, FI	1-3	12318	157.907
	(0.477)						
Credit Suisse	−1.540	0.600	95	M, FI	1-3	9724	28.367
	(2.485)						

Panel B: Prime brokers to hedge fund sector GIV

	$\beta^{\text{FI,GIV}}$	R^2	N	Factors	PCs	N_{panel}	F-stat
High-FI-risk HF portfolio	0.527***	0.478	209	M	1-3	4976	14.499
	(0.199)						
Low-FI-risk HF portfolio	0.213	0.484	209	M	1-3	4976	14.499
	(0.182)						

Table 6: 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, $\perp$, sequentially 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. The standard errors in parentheses are 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
$r_{i,t}^{\mathrm{PB}}$	0.119***				
	(0.014)				
$r_{i,t}^{\mathrm{PB}} \perp$ M		0.052***			
		(0.015)			
$r_{i,t}^{\mathrm{PB}} \perp$ M, FI			0.041**	0.040**	
			(0.017)	(0.018)	
$r_{i,t}^{\mathrm{PB}} \perp$ M, FI, CI					0.008
					(0.017)
N	120,105	120,105	120,105	120,105	120,105
Adjusted R^2	0.086	0.010	0.005	0.008	0.004
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes

Table 7: Event study

This table presents 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 four 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 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. Standard errors in parentheses are 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^{**}
	(0.683)	(0.683)	(0.697)	(0.695)
PB Client	0.124^{**}	0.135^{*}		
	(0.050)	(0.075)		
PB Events × PB Client	0.015	0.057	0.096	0.072
	(0.123)	(0.304)	(0.317)	(0.326)
PB Unique Client		-0.016		
		(0.077)		
PB Events × PB Unique Client		-0.066	-0.037	-0.030
		(0.350)	(0.357)	(0.356)
Lehman Event	-4.360^{**}	-4.360^{**}	-4.322^{**}	-4.718^{**}
	(2.011)	(2.011)	(2.030)	(2.037)
Lehman Client	0.057	-0.121		
	(0.150)	(0.118)		
Lehman Event × Lehman Client	-0.296	1.894^{**}	2.043^{**}	2.188^{**}
	(1.218)	(0.958)	(0.948)	(0.921)
Lehman Unique Client		0.641^{**}		
		(0.303)		
Lehman Event × Lehman Unique Client		-7.164^{***}	-7.192^{***}	-7.092^{***}
		(2.440)	(2.587)	(2.437)
Constant	0.475^{***}	0.474^{***}		
	(0.172)	(0.172)		
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 8: Double sorts with controls

This table presents results for portfolios sorted on the financial intermediary factor, FI, controlling separately for the correlation factor of Buraschi et al. (2013) (available up to June 2012), the liquidity factor of Pástor and Stambaugh (2003), the macroeconomic uncertainty factor of Bali et al. (2014), the tail risk factor of Agarwal et al. (2017) (available up to December 2012), and the aggregate asset-weighted Credit Suisse hedge fund index return. 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). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

	Correlation 1/2000−6/2012		Liquidity 1/2000−6/2017		Uncertainty 1/2000−6/2017		Tail 1/2000−12/2012		HF Index 1/2000−6/2017	
	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}	$\bar{r}$	α_{FH}
1 (low)	0.32	−0.20	0.32	−0.07	0.42	−0.10	0.51	0.03	0.40	−0.11
	(0.33)	(0.25)	(0.21)	(0.14)	(0.23)	(0.14)	(0.27)	(0.20)	(0.2)	(0.13)
2	0.38	0.02	0.44	0.00	0.42	0.02	0.42	0.07	0.44	0.03
	(0.23)	(0.14)	(0.19)	(0.11)	(0.18)	(0.11)	(0.25)	(0.15)	(0.18)	(0.11)
3	0.57	0.27	0.47	0.11	0.49	0.13	0.59	0.25	0.52	0.14
	(0.22)	(0.12)	(0.16)	(0.09)	(0.17)	(0.10)	(0.22)	(0.13)	(0.16)	(0.1)
4	0.71	0.40	0.61	0.19	0.61	0.24	0.67	0.35	0.58	0.19
	(0.23)	(0.15)	(0.18)	(0.11)	(0.17)	(0.10)	(0.23)	(0.14)	(0.18)	(0.11)
5 (high)	1.09	0.54	0.89	0.27	0.78	0.21	0.96	0.42	0.79	0.26
	(0.32)	(0.21)	(0.24)	(0.16)	(0.23)	(0.15)	(0.28)	(0.19)	(0.24)	(0.16)
5−1	0.77	0.74	0.56	0.34	0.36	0.31	0.45	0.39	0.39	0.37
	[4.91]	[3.34]	[4.68]	[2.50]	[2.81]	[2.34]	[3.32]	[2.83]	[3.47]	[2.86]

Figure 1: Static network of hedge funds and prime brokers

The figure shows the network obtained by examining all the alive hedge funds in the Eurekahedge database reporting a prime broker affiliation 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.

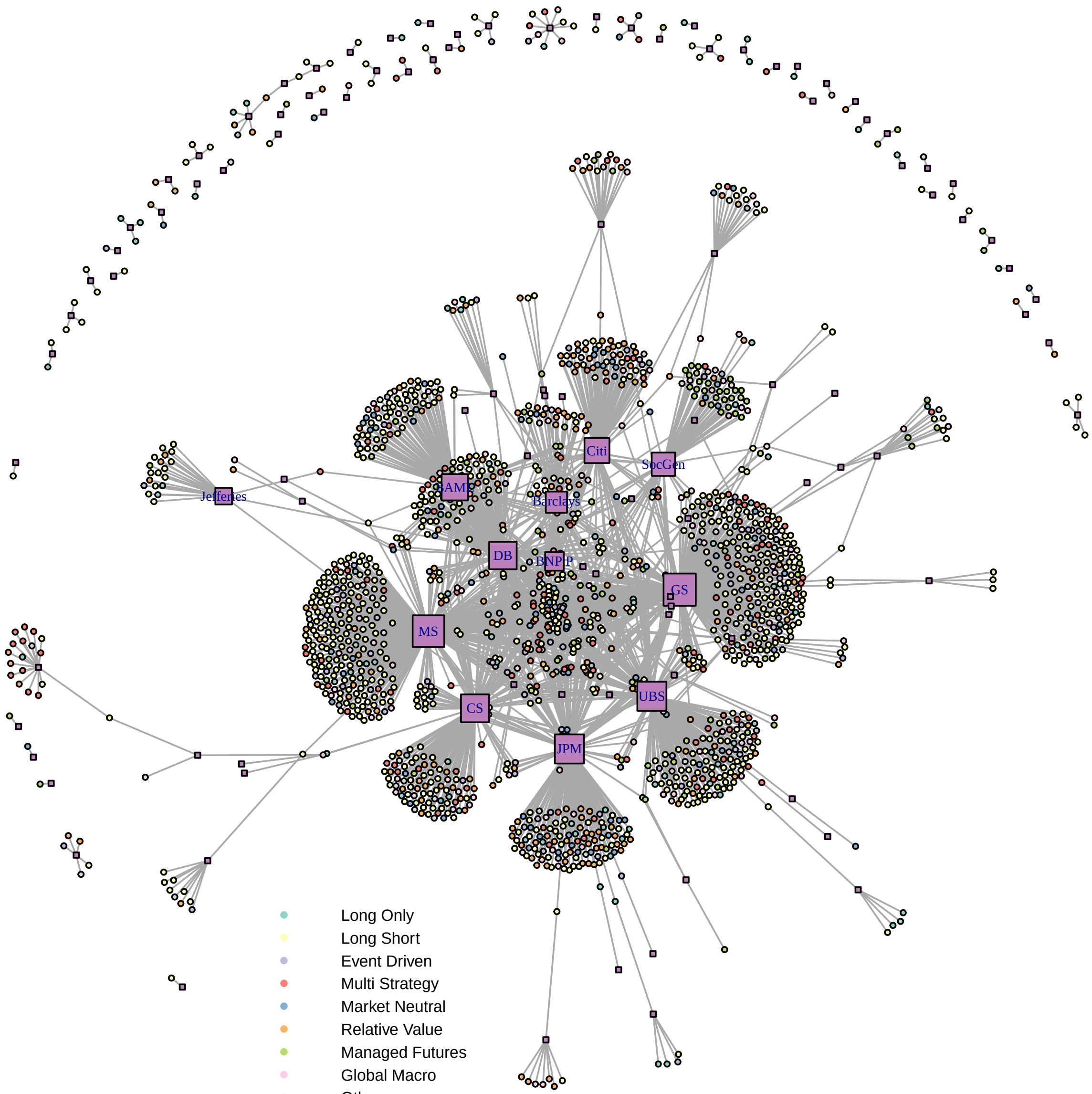


Figure 2: Aggregate hedge fund and prime broker sizes and hedge fund borrowings

Panel (a) of the figure shows the aggregate hedge fund (HF) AUM and aggregate prime broker (PB) market equity and total assets. AUM_{COM} is the aggregate HF AUM reported by a commercial database, BarclayHedge. AUM_{SEC} and Gross AUM_{SEC} are the aggregate net and gross HF AUM reported by the US Securities and Exchange Commission (SEC) in its annual reports on Form PF data (available from 2014). Gross HF AUM is defined as AUM plus total HF borrowings. Form PF is an obligatory regulatory form filed by hedge funds operating in the US with at least 150 million USD in AUM. PB equity is the total market value of 38 listed prime brokers. PB assets are the sum of the total assets (from COMPUSTAT) of the 38 prime brokers. All the values are in trillion USD. Panel (b) shows the percentage share of each source of aggregate hedge fund borrowings. Panel (c) shows the ratio of aggregate hedge fund collateral to total borrowing for different funding sources. Panel (d) shows hedge fund financing of different duration as an average share of total borrowings. The duration categories refer to the maximum available duration (e.g., up to one day, up to seven days, etc.). Data in panels (a), (b), and (c) are from SEC annual reports on Form PF data. The data are quarterly and range from 2000 Q1 to 2017 Q2.

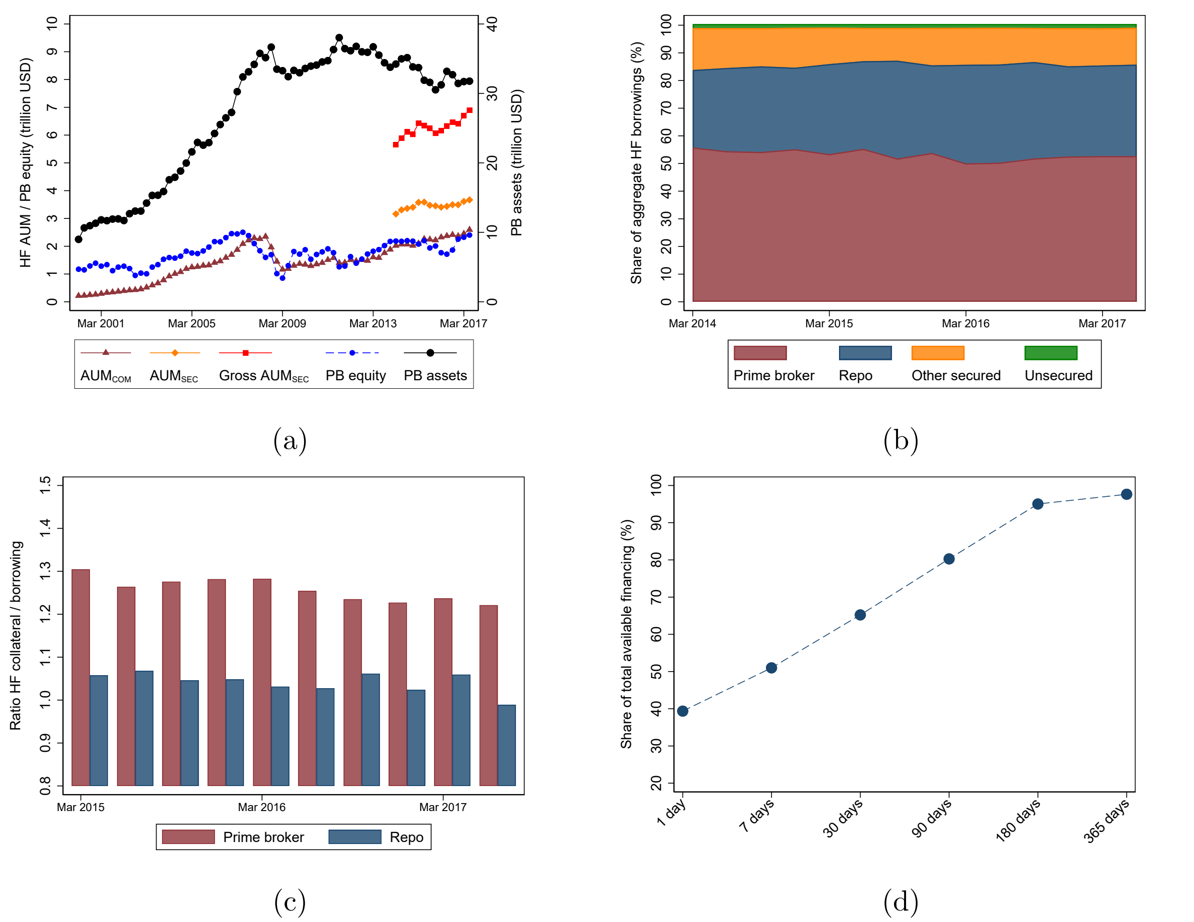


Figure 3: Call Reports

This figures below show the quarterly time series of the ratio of OTC derivatives' net current credit exposure to the total fair value of posted collateral for four different counterparties: hedge funds, banks and securities firms, sovereigns, and corporations. The data are from the Call reports of Bank of America, Citi, Goldman Sachs, and JP Morgan. The data are quarterly and are from 2009 Q1 to 2018 Q4.

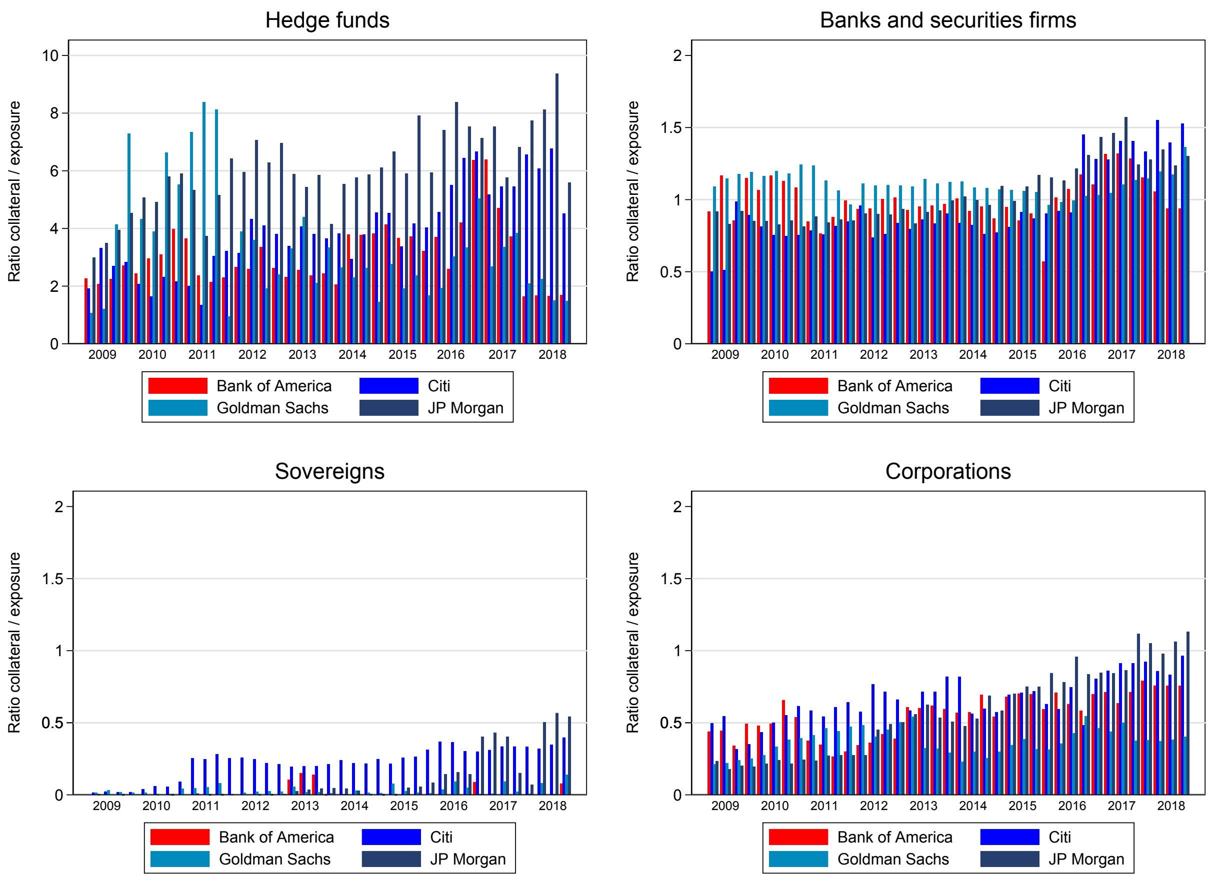
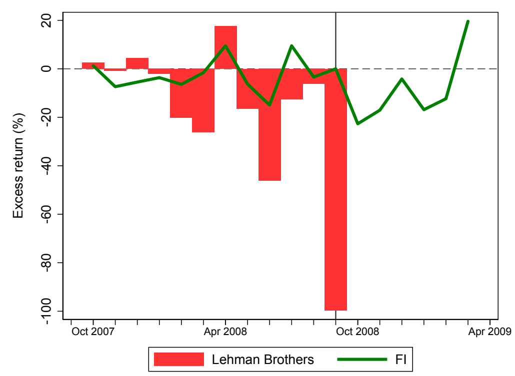
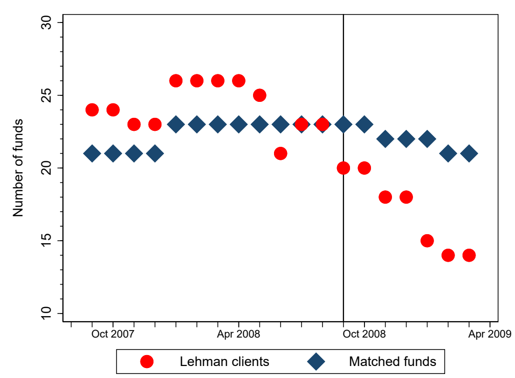


Figure 4: Event study of Lehman bankruptcy

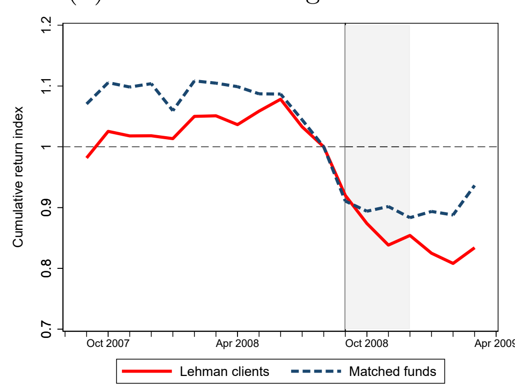
The top panel of the figure shows the monthly returns of Lehman Brothers and the return to a value-weighted portfolio of prime brokers (FI) around the time of Lehman's bankruptcy (September 2008). The vertical line indicates the time of the event. The middle panel shows the number of Lehman's hedge fund clients reporting to the database each month along with number of hedge fund clients of a matched group of hedge funds using a different prime broker. 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 twelve months before the event, and each fund's financial intermediary beta. The shaded region indicates a four-month event window.



(a) Prime broker returns



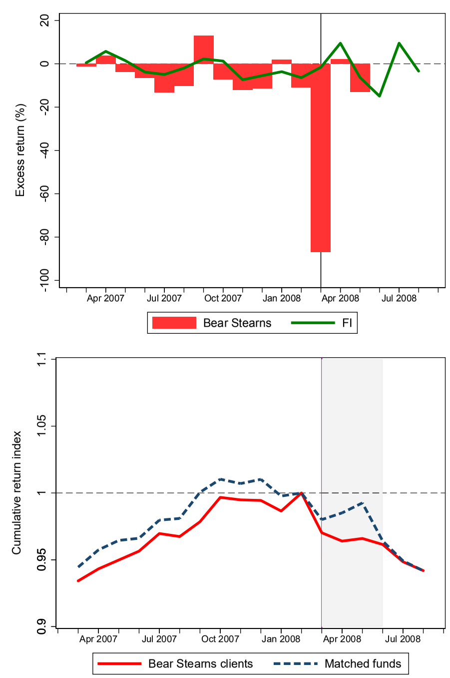
(b) Number of hedge funds



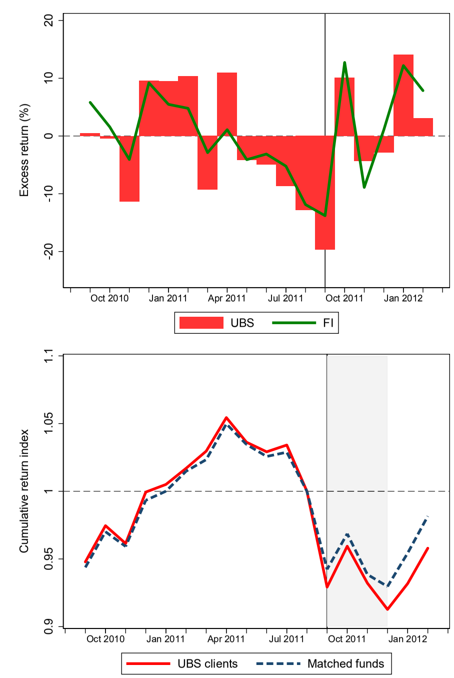
(c) Hedge fund returns

Figure 5: Event study of other prime broker shocks

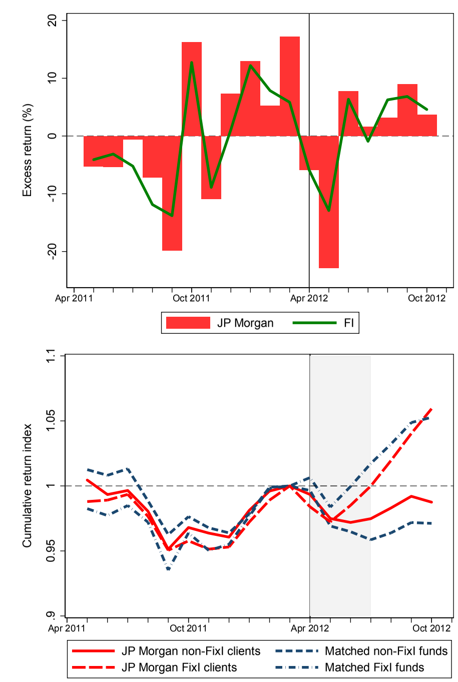
The top three panels of the figure show the monthly returns of Bear Stearns, UBS, and JP Morgan around the time of a large negative shock to each prime broker. The three events considered are the failure of Bear Stearns (March 2008), the trading loss scandal of UBS (September 2011) and the trading loss 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 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 twelve months before the event, and each fund's financial intermediary beta. The shaded region indicates a four-month 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

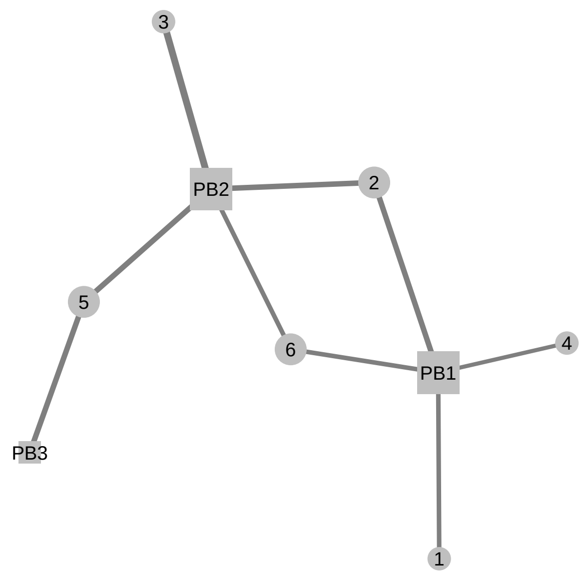
July 2, 2021

List of tables

List of figures

IA-.A Simple network example

Here we show 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).



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

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

IA-.B Prime broker fixed effect

Here we ask 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:

$$\hat{\alpha}_{i,t} = a_{PB} + c' X_{i,t} + \varepsilon_{i,t}, \tag{IA-2}$$

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 the Fama–MacBeth regressions in the main text, 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.

The top panel of Figure IA.5 displays the estimated fixed effect coefficients and the 95% confidence intervals for all the prime brokers. Goldman Sachs is used as a base prime broker. In total, only two prime brokers out of 43, Interactive Brokers and JP Morgan, have significant coefficients. It is also 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 IA.5 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 tiny 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. However, the clients of JP Morgan, a large prime broker, seem to earn, on average, significantly higher alpha. This observed difference in alpha should not be interpreted causally as it is likely 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.[*] Therefore, our results suggest that prime broker affiliation does not have an important effect on hedge fund alphas.

[*]See, for example, "Lehman collapse puts prime broker model in question" by James Mackintosh, *Financial Times*, 24 September 2008.

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: Summary statistics of hedge fund characteristics

The table presents summary statistics of hedge fund characteristics for the sample of hedge funds in the Eurekahedge database. The sample period runs from January 2000 to June 2017. N is the number of unique hedge funds for which data on a particular characteristic are available. The statistics are for management fee (in %), incentive fee (in %), a dummy indicating if the fund has a high watermark, a dummy indicating if the fund has a lockup provision, the redemption notice (in days), the minimum fund investment amount (in USD million), and the number of prime brokers that a fund uses. The statistics are time-series averages of monthly cross-sectional statistics and represent a typical distribution of hedge fund characteristics available in a given month in the sample.

	N	Mean	Median	25 percentile	75 percentile	Min	Max
Management fee	2686	1.48	1.50	1.00	1.99	0.00	12.50
Incentive fee	2683	17.24	20.00	17.32	20.00	0.00	40.49
High water mark	2647	0.84	1.00	1.00	1.00	0.00	1.00
Lockup	2673	0.21	0.00	0.00	0.00	0.00	1.00
Redemption notice	2664	33.65	29.50	8.13	46.16	0.00	284.00
Minimum investment	2575	1.41	0.59	0.11	1.00	0.00	49.31
Number of prime brokers	1667	1.34	1.00	1.00	1.11	1.00	8.08

Table IA.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. $\mathrm{FI_T}$ and $\mathrm{FI_{NT}}$ are the traded and the non-traded primary dealer factors of He et al. (2017), respectively. $\mathrm{PB_{VW}}$ is the value-weighted portfolio of 38 listed prime brokers; $\mathrm{PB_{EV}}$ is an equal-weighted portfolio; $\mathrm{PB_N}$ and $\mathrm{PB_{AUM}}$ are portfolios of prime brokers where the weights are based on the number of hedge fund clients and the total client AUM, respectively; $\mathrm{PB_N^{\mathit{eigen}}}$ and $\mathrm{PB_{AUM}^{\mathit{eigen}}}$ are portfolios of prime brokers where the weights are based on the eigenvector centrality with client connections and AUM connections, respectively; PC1 is the first principal component extracted from a panel of returns of 29 prime brokers with continuous return series during the sample period. The reported summary 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

	$\mathrm{FI_T}$	$\mathrm{PB_{VW}}$	$\mathrm{PB_{EW}}$	$\mathrm{PB_N}$	$\mathrm{PB_{AUM}}$	$\mathrm{PB_N^{\mathit{eigen}}}$	$\mathrm{PB_{AUM}^{\mathit{eigen}}}$
Mean	7.90	9.49	8.12	6.17	5.40	6.56	5.79
SD	23.34	23.25	23.12	27.83	28.59	29.71	28.48
Min	−23.43	−22.67	−25.55	−23.67	−24.97	−24.64	−33.28
Max	30.55	29.12	26.21	26.09	26.93	24.84	24.67

Panel B: Correlation matrix

Variables	$\mathrm{FI_T}$	$\mathrm{FI_{NT}}$	$\mathrm{PB_{VW}}$	$\mathrm{PB_{EW}}$	$\mathrm{PB_N}$	$\mathrm{PB_{AUM}}$	$\mathrm{PB_N^{\mathit{eigen}}}$	$\mathrm{PB_{AUM}^{\mathit{eigen}}}$	PC1
$\mathrm{FI_T}$	1.000								
$\mathrm{FI_{NT}}$	0.925	1.000							
$\mathrm{PB_{VW}}$	0.982	0.913	1.000						
$\mathrm{PB_{EW}}$	0.951	0.883	0.967	1.000					
$\mathrm{PB_N}$	0.932	0.861	0.941	0.947	1.000				
$\mathrm{PB_{AUM}}$	0.930	0.858	0.938	0.939	0.999	1.000			
$\mathrm{PB_N^{\mathit{eigen}}}$	0.863	0.789	0.867	0.874	0.974	0.977	1.000		
$\mathrm{PB_{AUM}^{\mathit{eigen}}}$	0.900	0.819	0.902	0.913	0.981	0.984	0.969	1.000	
PC1	0.962	0.897	0.975	0.988	0.930	0.923	0.853	0.892	1.000

Table IA.4: Risk-adjusted returns for beta-sorted portfolios (8-factor model)

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 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 are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and 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 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH8}	R^2_{FH8}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.24	−0.22	0.73	0.03	0.45	−0.37	0.81
	(0.32)	(0.19)		(0.07)	(0.13)	(0.05)	(0.12)
2	0.25	−0.07	0.79	0.05	0.33	−0.14	0.50
	(0.21)	(0.10)		(0.05)	(0.08)	(0.03)	(0.11)
3	0.40	0.07	0.76	0.06	0.28	−0.06	0.38
	(0.18)	(0.09)		(0.04)	(0.07)	(0.03)	(0.08)
4	0.46	0.13	0.79	0.07	0.24	0.00	0.31
	(0.18)	(0.07)		(0.03)	(0.07)	(0.02)	(0.05)
5	0.53	0.23	0.78	0.07	0.22	0.05	0.26
	(0.16)	(0.07)		(0.04)	(0.06)	(0.04)	(0.03)
6	0.51	0.20	0.73	0.08	0.19	0.11	0.22
	(0.16)	(0.08)		(0.03)	(0.06)	(0.06)	(0.03)
7	0.53	0.18	0.70	0.08	0.21	0.17	0.19
	(0.17)	(0.08)		(0.04)	(0.06)	(0.08)	(0.04)
8	0.70	0.37	0.65	0.09	0.20	0.24	0.15
	(0.17)	(0.11)		(0.04)	(0.06)	(0.12)	(0.06)
9	0.75	0.31	0.61	0.12	0.21	0.34	0.10
	(0.20)	(0.12)		(0.05)	(0.09)	(0.14)	(0.08)
10 (high)	1.06	0.44	0.62	0.20	0.20	0.65	−0.13
	(0.29)	(0.17)		(0.06)	(0.12)	(0.17)	(0.12)
10−1	0.82	0.66	0.08	0.17	−0.25	1.02	−0.94
	[3.96]	[2.72]		[2.57]	[−2.18]	[9.21]	[−6.94]

Table IA.5: Risk-adjusted returns for beta-sorted portfolios (global factor model)

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 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 are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and 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 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_G	R^2_G	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.24	−0.20	0.73	0.03	0.45	−0.37	0.81
	(0.32)	(0.24)		(0.07)	(0.13)	(0.05)	(0.12)
2	0.25	−0.09	0.76	0.05	0.33	−0.14	0.50
	(0.21)	(0.12)		(0.05)	(0.08)	(0.03)	(0.11)
3	0.40	0.11	0.77	0.06	0.28	−0.06	0.38
	(0.18)	(0.11)		(0.04)	(0.07)	(0.03)	(0.08)
4	0.46	0.14	0.81	0.07	0.24	0.00	0.31
	(0.18)	(0.09)		(0.03)	(0.07)	(0.02)	(0.05)
5	0.53	0.25	0.83	0.07	0.22	0.05	0.26
	(0.16)	(0.07)		(0.04)	(0.06)	(0.04)	(0.03)
6	0.51	0.15	0.80	0.08	0.19	0.11	0.22
	(0.16)	(0.07)		(0.03)	(0.06)	(0.06)	(0.03)
7	0.53	0.19	0.78	0.08	0.21	0.17	0.19
	(0.17)	(0.08)		(0.04)	(0.06)	(0.08)	(0.04)
8	0.70	0.31	0.78	0.09	0.20	0.24	0.15
	(0.17)	(0.09)		(0.04)	(0.06)	(0.12)	(0.06)
9	0.75	0.25	0.73	0.12	0.21	0.34	0.10
	(0.20)	(0.11)		(0.05)	(0.09)	(0.14)	(0.08)
10 (high)	1.06	0.44	0.67	0.20	0.20	0.65	−0.13
	(0.29)	(0.15)		(0.06)	(0.12)	(0.17)	(0.12)
10−1	0.82	0.64	0.18	0.17	−0.25	1.02	−0.94
	[3.96]	[2.38]		[2.57]	[−2.18]	[9.21]	[−6.94]

Table IA.6: Risk-adjusted returns for beta-sorted portfolios (non-traded factor)

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the non-traded financial intermediary factor of He et al. (2017), $\mathrm{FI_{NT}}$, (controlling for the market return) and are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and funds in Portfolio 10 have the highest. $\bar{r}$ refers to the mean excess return, α_{FH8} refers to Fung and Hsieh (2004) seven-factor alpha, and R^2_{FH8} to the corresponding R-squared. $\bar{r}$ and α_{FH8} are reported in % per month. The post betas are the betas from a single time series regression of factors against each of the 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH8}	R^2_{FH8}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.34	−0.29	0.60	−0.01	0.57	−0.36	0.81
	(0.32)	(0.22)		(0.07)	(0.10)	(0.06)	(0.12)
2	0.45	−0.10	0.62	−0.01	0.42	−0.16	0.56
	(0.22)	(0.14)		(0.04)	(0.07)	(0.04)	(0.11)
3	0.47	0.03	0.64	0.02	0.35	−0.09	0.45
	(0.20)	(0.12)		(0.03)	(0.07)	(0.03)	(0.09)
4	0.48	0.13	0.66	0.02	0.31	−0.04	0.36
	(0.16)	(0.09)		(0.03)	(0.06)	(0.03)	(0.06)
5	0.48	0.09	0.65	0.03	0.27	0.00	0.32
	(0.17)	(0.10)		(0.03)	(0.07)	(0.05)	(0.04)
6	0.51	0.13	0.67	0.02	0.26	0.03	0.28
	(0.14)	(0.09)		(0.02)	(0.05)	(0.03)	(0.03)
7	0.49	0.14	0.58	0.04	0.24	0.08	0.27
	(0.15)	(0.11)		(0.02)	(0.04)	(0.04)	(0.03)
8	0.59	0.23	0.50	0.04	0.23	0.13	0.25
	(0.17)	(0.12)		(0.04)	(0.06)	(0.04)	(0.04)
9	0.63	0.25	0.46	0.05	0.26	0.20	0.24
	(0.20)	(0.15)		(0.04)	(0.07)	(0.05)	(0.05)
10 (high)	0.99	0.39	0.51	0.12	0.31	0.41	0.16
	(0.27)	(0.18)		(0.06)	(0.10)	(0.05)	(0.09)
10−1	0.66	0.69	0.08	0.12	−0.26	0.77	−0.65
	[3.17]	[3.31]		[2.46]	[−2.27]	[16.02]	[−4.57]

Table IA.7: Financial intermediary post-ranking betas estimated with lags

This table presents the 10 hedge fund portfolios' post-ranking betas estimated with lags as in Hu, Pan, and Wang (2013), to take persistence in hedge fund returns into account. 10 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 are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and funds in Portfolio 10 have the highest. The betas are from a single time series regression of factors against each of the 10 portfolios. Reported are the contemporaneous post-ranking coefficients, and the sum of the contemporaneous and lagged coefficient. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

	β^{FI}	$\beta^{\mathrm{FI}} + \mathrm{lag}$	β^{M}	$\beta^{\mathrm{M}} + \mathrm{lag}$
1 (low)	0.02	0.05	0.46	0.06
	(0.06)	(0.08)	(0.11)	(0.33)
2	0.03	0.07	0.34	0.00
	(0.04)	(0.05)	(0.07)	(0.25)
3	0.05	0.08	0.29	−0.01
	(0.03)	(0.05)	(0.07)	(0.24)
4	0.06	0.07	0.25	0.03
	(0.03)	(0.04)	(0.07)	(0.23)
5	0.06	0.09	0.23	−0.03
	(0.03)	(0.04)	(0.06)	(0.19)
6	0.07	0.07	0.19	0.02
	(0.03)	(0.04)	(0.06)	(0.2)
7	0.07	0.09	0.21	−0.02
	(0.03)	(0.04)	(0.06)	(0.21)
8	0.08	0.12	0.21	−0.04
	(0.04)	(0.05)	(0.05)	(0.21)
9	0.11	0.14	0.22	−0.05
	(0.05)	(0.06)	(0.08)	(0.24)
10 (high)	0.19	0.28	0.22	−0.11
	(0.05)	(0.07)	(0.11)	(0.28)
10−1	0.17	0.22	−0.24	−0.16
	[2.51]	[2.79]	[−2.05]	[0.53]

Table IA.8: Placebo test: beta-sorted portfolios for non-prime-broker intermediary factor

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the non-prime-broker financial intermediary factor (controlling for the market return) and are rebalanced monthly. The financial intermediary factor is the return to a value-weighted portfolio of non-prime brokers. Non-prime brokers are defined as public US firms in the broker–dealer SIC groups (6211, 6221) that are not major prime brokers or NY Fed primary dealers. Funds in Portfolio 1 have the lowest loading on the factor and 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. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

				Post betas		Pre betas	
	$\bar{r}$	α_{FH}	R^2_{FH}	β^{FI}	β^{M}	β^{FI}	β^{M}
1 (low)	0.65	−0.21	0.46	0.12	0.19	−0.42	0.97
	(0.31)	(0.31)		(0.08)	(0.19)	(0.10)	(0.18)
2	0.49	−0.11	0.52	0.04	0.28	−0.19	0.61
	(0.23)	(0.19)		(0.05)	(0.11)	(0.06)	(0.19)
3	0.47	−0.01	0.59	0.04	0.26	−0.11	0.47
	(0.20)	(0.13)		(0.03)	(0.09)	(0.05)	(0.14)
4	0.45	0.02	0.65	0.05	0.22	−0.04	0.37
	(0.17)	(0.10)		(0.03)	(0.07)	(0.04)	(0.10)
5	0.45	0.04	0.67	0.05	0.23	0.01	0.28
	(0.17)	(0.09)		(0.03)	(0.06)	(0.03)	(0.07)
6	0.49	0.17	0.64	0.04	0.22	0.06	0.23
	(0.15)	(0.1)		(0.03)	(0.05)	(0.02)	(0.04)
7	0.57	0.23	0.61	0.06	0.22	0.12	0.19
	(0.16)	(0.11)		(0.03)	(0.06)	(0.03)	(0.03)
8	0.56	0.30	0.62	0.05	0.31	0.19	0.16
	(0.18)	(0.13)		(0.03)	(0.04)	(0.03)	(0.03)
9	0.60	0.26	0.63	0.10	0.31	0.30	0.09
	(0.21)	(0.15)		(0.04)	(0.06)	(0.03)	(0.03)
10 (high)	0.70	0.30	0.66	0.15	0.37	0.60	−0.19
	(0.27)	(0.19)		(0.04)	(0.07)	(0.04)	(0.06)
10−1	0.06	0.50	0.25	0.03	0.18	1.02	−1.16
	[0.22]	[1.52]		[0.32]	[0.88]	[11.43]	[−8.16]

Table IA.9: 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 the sample median AUM (USD 120 million). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample runs from January 2000 to June 2017.

Panel A: Leverage

	1 (low)	2	3	4	5 (high)	5−1
Yes	−0.06	0.03	0.19	0.27	0.33	0.39
	(0.17)	(0.10)	(0.09)	(0.10)	(0.18)	[2.21]
No	−0.35	0.03	0.16	0.16	0.24	0.59
	(0.18)	(0.12)	(0.11)	(0.13)	(0.18)	[2.79]
Yes−No						−0.20
						[1.63]

Panel B: AUM

	1 (low)	2	3	4	5 (high)	5−1
Small	−0.14	0.09	0.12	0.20	0.22	0.36
	(0.17)	(0.11)	(0.09)	(0.13)	(0.19)	[2.01]
Big	−0.21	0.04	0.17	0.20	0.31	0.52
	(0.17)	(0.10)	(0.10)	(0.11)	(0.17)	[2.81]
Small−Big						−0.16
						[1.34]

Panel C: Number of prime brokers

	1 (low)	2	3	4	5 (high)	5−1
One	−0.20	0.09	0.21	0.27	0.38	0.58
	(0.17)	(0.11)	(0.08)	(0.11)	(0.17)	[2.95]
Multiple	0.02	0.16	0.33	0.48	0.41	0.39
	(0.18)	(0.09)	(0.10)	(0.10)	(0.16)	[1.81]
One−Multiple						0.19
						[1.53]

Table IA.10: Hedge fund intermediary risk premium (individual rolling beta)

The table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on rolling intermediary betas. Individual hedge fund betas are estimated by 24-month rolling regressions of hedge fund returns on the financial intermediary, FI traded factor (controlling for the market return). Time $t+1$ monthly excess fund returns (%) are regressed on the time t rolling betas as well as fund age (in months), AUM (in USD million), management fee (in %), incentive fee (in %), a dummy indicating if the fund has a high watermark, a dummy indicating if the fund has a lockup provision, the redemption notice (in days), and the minimum fund investment amount (USD million). β^{M} is the time t post-ranking beta with respect to the market. r_t is the time t excess fund return (in %). Fixed effects are style dummies, following the Kosowski, Joenväärä, and Tolonen (2016) mapping, and geographical region dummies (Asia ex-Japan, Australia, Canada, EMEA, Japan, South America, US). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). N is the number of observations. The sample runs from January 2000 to June 2017.

	I	II	III	IV	V
β^{FI}	0.880***	0.759***	0.962***	0.714***	0.659***
	(0.189)	(0.200)	(0.271)	(0.235)	(0.231)
β^{M}			0.438	0.384	0.375
			(0.490)	(0.381)	(0.372)
r_t				0.103***	0.108***
				(0.015)	(0.014)
Age				−0.001**	−0.001***
				(0.001)	(0.000)
log(AUM)				−0.029***	−0.022**
				(0.012)	(0.010)
Management fee				0.037**	0.037**
				(0.019)	(0.017)
Incentive fee				0.002	0.000
				(0.004)	(0.000)
High water mark				0.033	0.034
				(0.050)	(0.043)
Lockup				0.062	0.054*
				(0.041)	(0.030)
Redemption notice				0.001**	0.002***
				(0.000)	(0.001)
Minimum investment				0.000	0.002
				(0.000)	(0.003)
Constant	0.475				
	(0.171)				
Style fixed effects	No	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	Yes
N	193,366	193,366	193,366	178,282	178,282
R^2	0.256	0.326	0.396	0.437	0.472

Table IA.11: Hedge fund intermediary risk premium (non-traded factor)

The table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on post-ranking intermediary betas. 10 portfolios are formed by 24-month rolling regressions of hedge fund returns on the non-traded financial intermediary factor of He et al. (2017), $\mathrm{FI}_{\mathrm{NT}}$ (controlling for the market return) and are 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 in 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), management fee (in %), incentive fee (in %), a dummy indicating if the fund has a high watermark, a dummy indicating if the fund has a lockup provision, the redemption notice (in days), and the minimum fund investment amount (USD million). β^{M} is the time t post-ranking beta with respect to the market. r_t is the time t excess fund return (in %). 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). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). N is the number of observations. The sample runs from January 2000 to June 2017.

	I	II	III	IV	V
β^{FI}	4.225***	3.757***	4.762***	3.273**	2.874*
	(1.438)	(1.248)	(1.746)	(1.536)	(1.529)
β^{M}			0.454	0.408	0.409
			(0.461)	(0.345)	(0.341)
r_t				0.106***	0.111***
				(0.015)	(0.014)
Age				−0.001**	−0.001***
				(0.001)	(0.000)
log(AUM)				−0.024**	−0.018*
				(0.012)	(0.011)
Management fee				0.034*	0.035**
				(0.019)	(0.017)
Incentive fee				0.001	−0.000
				(0.003)	(0.004)
High water mark				0.039	0.038
				(0.052)	(0.045)
Lockup				0.054	0.055
				(0.042)	(0.030)
Redemption notice				0.001	0.001**
				(0.001)	(0.000)
Minimum investment				0.000	0.003
				(0.005)	(0.003)
Constant	0.403**				
	(0.184)				
Style fixed effects	No	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	Yes
N	193,366	193,366	193,366	178,282	178,282
R^2	0.241	0.314	0.392	0.435	0.471

Table IA.12: 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. 10 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 are rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the 10 portfolios. These post-ranking betas are then assigned to each fund according to which decile portfolio they belonged to in 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), management fee (in %), incentive fee (in %), a dummy indicating if the fund has a high watermark, a dummy indicating if the fund has a lockup provision, the redemption notice (in days), and the minimum fund investment amount (USD million). β^{M} is the time t post-ranking beta with respect to the market. r_t is the time t excess fund return (in %). Fixed effects are style dummies following the Kosowski et al. (2016) mapping. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). The 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
β^{FI}	4.138***	3.774***	3.898***	2.976***
	(0.896)	(0.86)	(1.328)	(1.121)
β^{M}			0.252	0.240
			(0.496)	(0.357)
r_t				0.117***
				(0.014)
Age				−0.001***
				(0.000)
log(AUM)				−0.026**
				(0.011)
Management fee				0.018
				(0.018)
Incentive fee				0.000
				(0.003)
High water mark				0.045
				(0.056)
Lockup				0.055
				(0.043)
Redemption notice				0.001**
				(0.001)
Minimum investment				0.006*
				(0.004)
Constant	0.281**			
	(0.145)			
Style fixed effects	No	Yes	Yes	Yes
N	133,287	133,287	133,287	125,639
R^2	0.183	0.270	0.337	0.387

Table IA.13: Placebo test: beta-sorted portfolios for aggregate hedge fund sector factor

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 equal-weighted portfolios are formed by 24-month rolling regressions of hedge fund returns on the return of the Credit Suisse broad asset-weighted hedge fund index (controlling for the market return) and are rebalanced monthly. The financial intermediary factor is the return to a value-weighted portfolio of non-prime brokers. Funds in Portfolio 1 have the lowest loading on the factor and 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 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. The sample period runs from January 2000 to June 2017.

	$\bar{r}$	α_{FH}	R^2_{FH}	β_{FI}	β_{mkt}	β_{FI}	β_{mkt}
1	0.55	0.29	0.27	0.24	0.10	−0.67	0.34
	(4.13)	(2.58)		(1.98)	(2.58)	(−2.20)	(4.49)
2	0.41	0.22	0.42	0.26	0.13	−0.08	0.21
	(4.15)	(2.32)		(2.72)	(4.65)	(−0.22)	(3.51)
3	0.35	0.07	0.50	0.50	0.11	0.19	0.18
	(2.74)	(0.81)		(5.19)	(4.14)	(0.73)	(3.55)
4	0.38	0.02	0.60	0.52	0.17	0.43	0.18
	(2.64)	(0.24)		(3.68)	(3.92)	(2.13)	(4.77)
5	0.46	0.02	0.60	0.71	0.15	0.65	0.16
	(2.66)	(0.23)		(4.40)	(2.89)	(2.76)	(6.72)
6	0.59	0.12	0.59	0.89	0.16	0.88	0.16
	(2.98)	(0.88)		(5.65)	(2.86)	(4.34)	(4.70)
7	0.58	0.03	0.64	1.00	0.19	1.14	0.17
	(2.60)	(0.22)		(7.77)	(4.07)	(6.08)	(6.94)
8	0.65	0.14	0.64	1.15	0.20	1.50	0.15
	(2.80)	(0.93)		(11.08)	(6.51)	(5.88)	(5.50)
9	0.71	0.12	0.63	1.52	0.22	2.01	0.11
	(2.39)	(0.63)		(13.19)	(5.57)	(7.53)	(2.96)
10	0.75	−0.05	0.58	2.22	0.24	3.36	−0.13
	(1.78)	(−0.17)		(19.29)	(4.38)	(13.06)	(−1.35)
10−1	0.20	−0.34	0.40	1.97	0.14	4.03	−0.47
	(0.52)	(−1.10)		(11.68)	(1.91)	(23.64)	(−3.43)

Table IA.14: 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 IA.15: Event study: risk-adjusted returns

This table shows 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 four 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 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. Standard errors in parentheses are 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^{**}
	(0.343)	(0.343)	(0.360)	(0.344)
PB Client	0.173^{***}	0.244^{***}		
	(0.049)	(0.070)		
PB Events × PB Client	−0.039	−0.037	−0.019	−0.039
	(0.118)	(0.205)	(0.220)	(0.232)
PB Unique Client		−0.114		
		(0.072)		
PB Events × PB Unique Client		0.000	0.014	0.028
		(0.227)	(0.232)	(0.233)
Lehman Event	−0.147	−0.147	−0.074	−0.418
	(0.700)	(0.700)	(0.711)	(0.722)
Lehman Client	0.169	−0.056		
	(0.174)	(0.166)		
Lehman Event × Lehman Client	-1.761^{**}	0.393	0.467	0.587
	(0.810)	(0.508)	(0.484)	(0.462)
Lehman Unique Client		0.772^{**}		
		(0.335)		
Lehman Event × Lehman Unique Client		-7.059^{***}	-6.979^{***}	-6.831^{***}
		(2.454)	(2.476)	(2.394)
Constant	−0.057	−0.057		
	(0.102)	(0.102)	(0.102)	(0.352)
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.16: Risk-adjusted returns for beta-sorted portfolios (backfill bias adjusted)

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 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 are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and 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 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. For each hedge fund in the sample the first twelve 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)	0.24	−0.30	0.61	0.03	0.48	−0.37	0.83
	(0.33)	(0.22)		(0.06)	(0.13)	(0.05)	(0.12)
2	0.22	−0.14	0.63	0.05	0.33	−0.14	0.50
	(0.21)	(0.13)		(0.05)	(0.09)	(0.03)	(0.10)
3	0.37	−0.01	0.65	0.06	0.28	−0.06	0.38
	(0.19)	(0.11)		(0.04)	(0.07)	(0.03)	(0.07)
4	0.42	0.05	0.69	0.06	0.25	0.00	0.31
	(0.18)	(0.10)		(0.03)	(0.08)	(0.03)	(0.04)
5	0.52	0.18	0.63	0.07	0.22	0.05	0.26
	(0.17)	(0.09)		(0.04)	(0.07)	(0.03)	(0.02)
6	0.52	0.17	0.55	0.08	0.18	0.11	0.22
	(0.16)	(0.11)		(0.03)	(0.06)	(0.06)	(0.03)
7	0.55	0.13	0.57	0.08	0.20	0.17	0.19
	(0.17)	(0.11)		(0.03)	(0.06)	(0.08)	(0.04)
8	0.69	0.30	0.51	0.09	0.21	0.24	0.15
	(0.17)	(0.13)		(0.04)	(0.06)	(0.12)	(0.07)
9	0.78	0.27	0.47	0.12	0.20	0.35	0.10
	(0.21)	(0.15)		(0.05)	(0.09)	(0.14)	(0.08)
10 (high)	1.04	0.34	0.46	0.20	0.20	0.65	−0.13
	(0.29)	(0.21)		(0.06)	(0.13)	(0.17)	(0.14)
10−1	0.80	0.64	0.07	0.17	−0.28	1.02	−0.96
	[3.76]	[2.60]		[2.54]	[−2.32]	[8.92]	[−6.30]

Table IA.17: Hedge fund intermediary risk premium (backfill bias adjustment)

The table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on post-ranking intermediary betas. 10 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 are rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the 10 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), management fee (in %), incentive fee (in %), a dummy indicating if the fund has a high watermark, a dummy indicating if the fund has a lockup provision, the redemption notice (in days), and the minimum fund investment amount (USD million). β^{M} is the time t post-ranking beta with respect to the market. r_t is the time t excess fund return (in %). 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). Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). N is the number of observations. For each hedge fund in the sample the first twelve 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}	4.629***	4.247***	4.576***	3.517***	3.069**
	(1.191)	(1.067)	(1.514)	(1.346)	(1.322)
β^{M}			0.260	0.240	0.233
			(0.487)	(0.365)	(0.357)
r_t				0.099***	0.104***
				(0.014)	(0.014)
Age				−0.001**	−0.001**
				(0.000)	(0.000)
log(AUM)				−0.025**	−0.020**
				(0.011)	(0.010)
Management fee				0.027	0.026
				(0.018)	(0.016)
Incentive fee				−0.001	−0.002
				(0.003)	(0.003)
High water mark				0.069	0.077**
				(0.043)	(0.039)
Lockup				0.082**	0.083***
				(0.043)	(0.033)
Redemption notice				0.001	0.001**
				(0.001)	(0.001)
Minimum investment				0.001	0.004
				(0.005)	(0.004)
Constant	0.153				
	(0.191)				
Style fixed effects	No	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	Yes
N	165,882	165,882	165,882	152,909	152,909
R^2	0.250	0.324	0.397	0.438	0.474

Table IA.18: Risk-adjusted returns for beta-sorted portfolios (delisting return adjusted)

The table presents mean excess returns and hedge fund portfolios' alphas and betas. 10 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 are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and 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 10 portfolios. The pre-sort betas are the monthly averages of each fund's rolling factor beta in their respective decile. Newey and West (1987) standard errors are reported in parentheses (lag length is selected automatically using the Newey and West (1994) procedure). t-statistics are reported in brackets. For every hedge fund that stops reporting to the database, the monthly return following the last reported return is imputed as −30%. 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)	0.08	−0.50	0.61	0.03	0.45	−0.37	0.81
	(0.32)	(0.24)		(0.07)	(0.13)	(0.05)	(0.13)
2	0.06	−0.36	0.63	0.06	0.32	−0.14	0.50
	(0.21)	(0.13)		(0.05)	(0.08)	(0.03)	(0.11)
3	0.24	−0.18	0.65	0.06	0.27	−0.06	0.38
	(0.19)	(0.12)		(0.04)	(0.08)	(0.03)	(0.08)
4	0.31	−0.10	0.69	0.07	0.24	0.00	0.31
	(0.18)	(0.1)		(0.03)	(0.07)	(0.00)	(0.05)
5	0.36	−0.01	0.64	0.07	0.20	0.05	0.26
	(0.16)	(0.10)		(0.04)	(0.06)	(0.04)	(0.03)
6	0.36	−0.04	0.57	0.08	0.18	0.11	0.22
	(0.17)	(0.11)		(0.03)	(0.06)	(0.05)	(0.03)
7	0.37	−0.05	0.55	0.08	0.21	0.17	0.19
	(0.17)	(0.12)		(0.04)	(0.06)	(0.08)	(0.04)
8	0.53	0.12	0.51	0.10	0.18	0.24	0.15
	(0.17)	(0.13)		(0.04)	(0.06)	(0.12)	(0.07)
9	0.57	0.03	0.48	0.13	0.19	0.34	0.10
	(0.21)	(0.15)		(0.05)	(0.09)	(0.13)	(0.08)
10 (high)	0.88	0.13	0.49	0.21	0.20	0.66	−0.13
	(0.30)	(0.21)		(0.06)	(0.12)	(0.17)	(0.12)
10−1	0.81	0.62	0.08	0.18	−0.25	1.02	−0.94
	[3.80]	[2.63]		[2.76]	[−2.19]	[9.37]	[−6.92]

Table IA.19: Hedge fund intermediary risk premium (delisting return adjustment)

This table presents factor premiums estimated by Fama and MacBeth (1973) regressions of monthly excess hedge fund returns on post-ranking intermediary betas. 10 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 are rebalanced monthly. The post-ranking betas are the betas from time series regressions of factors against each of the 10 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 watermark. β^{M} is the time t post-ranking beta with respect to the market. r_t is the time t excess fund return (in %). 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 every hedge fund that stops reporting to the database, the monthly return following the last reported return is imputed as −30%. The sample period runs from January 2000 to June 2017.

	I	II	III	IV	V
β^{FI}	4.371***	3.903***	4.426***	3.465***	3.074**
	(1.135)	(1.032)	(1.523)	(1.314)	(1.292)
β^{M}			0.366	0.353	0.365
			(0.510)	(0.384)	(0.370)
r_t				0.122***	0.129***
				(0.015)	(0.014)
Age				−0.000	−0.000
				(0.000)	(0.000)
log(AUM)				0.053***	0.060***
				(0.016)	(0.017)
Management fee				0.015	0.010
				(0.021)	(0.020)
Incentive fee				−0.001	−0.002
				(0.003)	(0.003)
High water mark				0.044	0.046
				(0.054)	(0.047)
Lockup				0.076**	0.079***
				(0.043)	(0.031)
Redemption notice				0.001	0.001
				(0.001)	(0.001)
Minimum investment				−0.002	0.001
				(0.004)	(0.004)
Constant	−0.019				
	0.190				
Style fixed effects	No	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	Yes
Num. obs.	194,748	194,748	194,748	179,575	179,575
R^2	0.193	0.248	0.305	0.340	0.368

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.

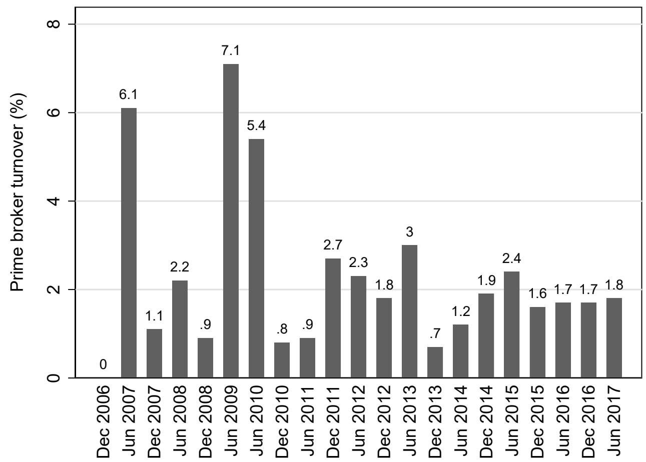


Figure IA.2: 2007 network of hedge funds and prime brokers

The figure shows the network obtained by examining all the alive hedge funds in the Eurekahedge database reporting a prime broker affiliation 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). 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.

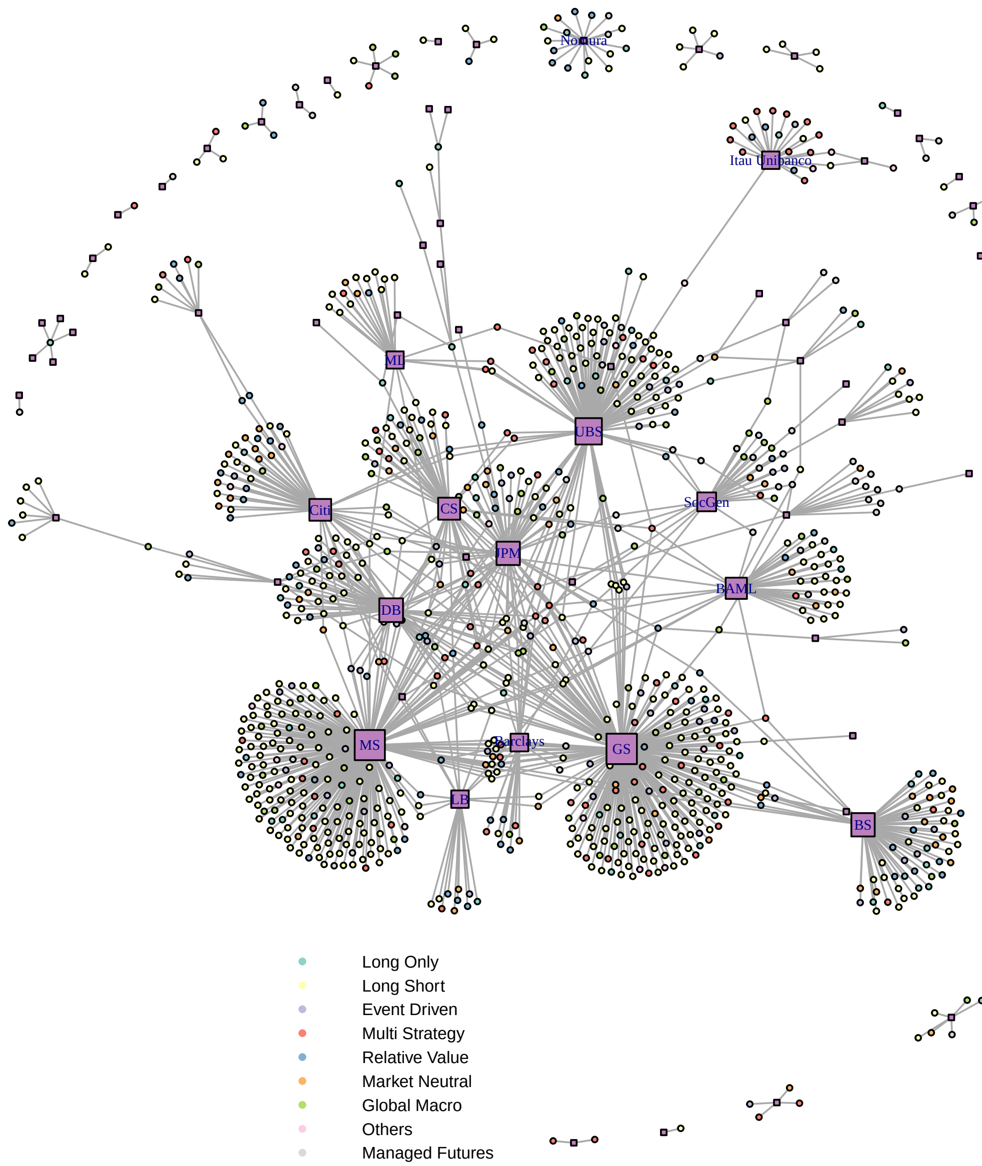


Figure IA.3: Fraction of funds that employ more than one prime broker

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

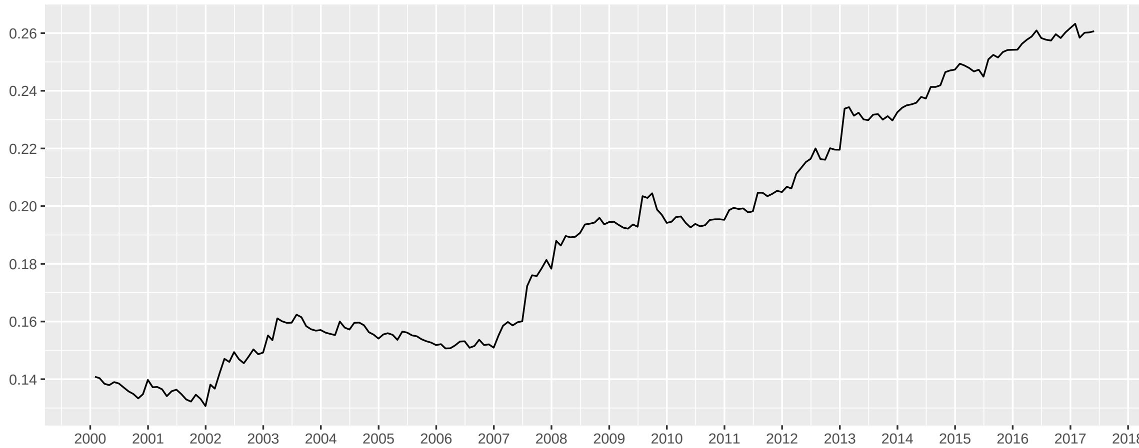
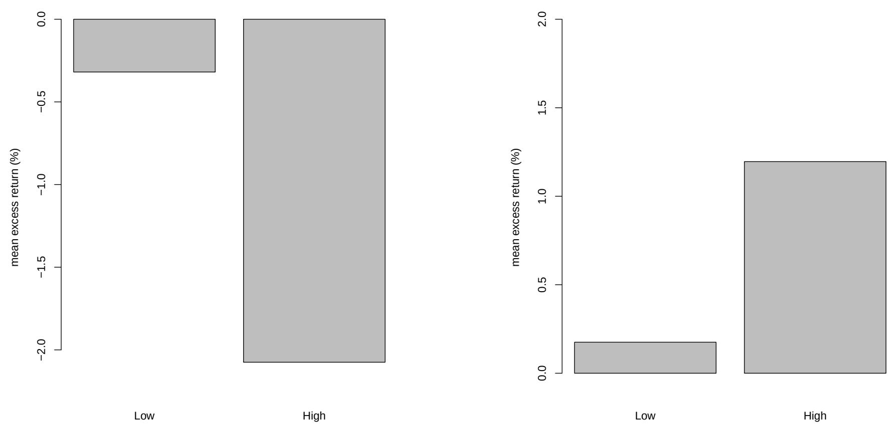


Figure IA.4: High/low FI sorted portfolio averages

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 20 months the FI factor (orthogonalized with respect to the market return) is at its lowest, and highest, respectively. 10 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 are rebalanced monthly. Funds in Portfolio 1 have the lowest loading on the factor and funds in Portfolio 10 have the highest. The sample runs from January 2000 to June 2017.



(a) Lowest FI (b) Highest FI

Figure IA.5: 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 (IA-2). The 95% confidence intervals that are based on standard errors clustered by fund and time are also displayed. 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 the case of a fund having multiple prime brokers, the fund's AUM is divided equally among the prime brokers). 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.

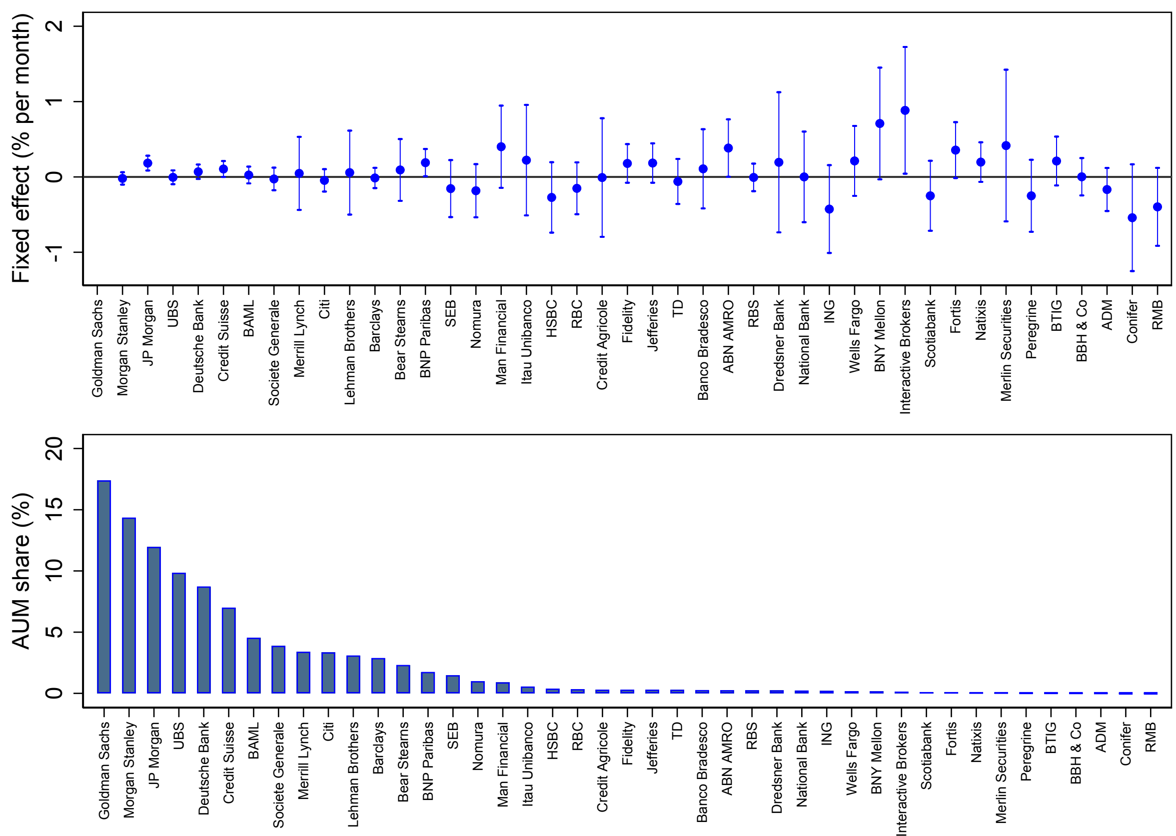


Figure IA.6: Hedge fund and prime broker size distributions

The top panel of the figure shows the histogram of hedge fund AUM (in USD billion) for funds that report a prime broker during the period from June 2009 to June 2017. The bottom panel of the figure shows the histogram of market capitalizations (in USD billion) of 26 primary dealers during the period from January 2000 to June 2017. The red lines in both panels represent fitted density functions.

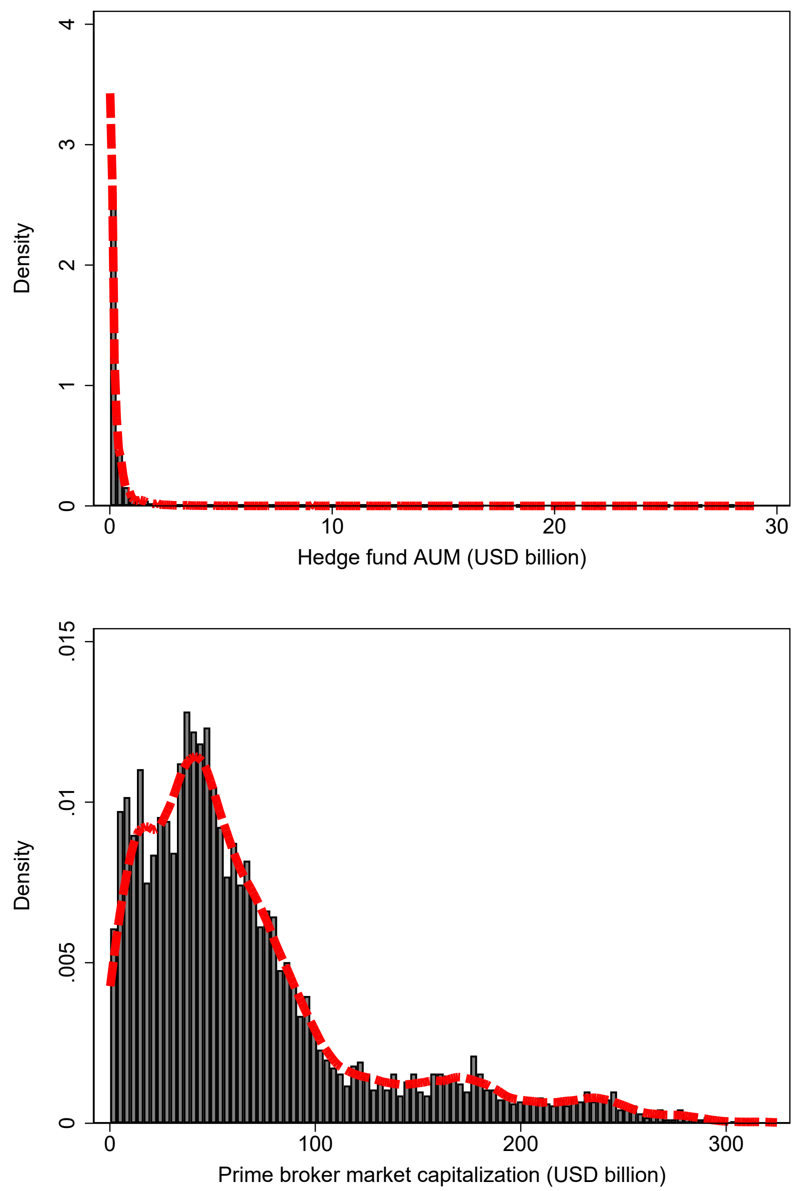
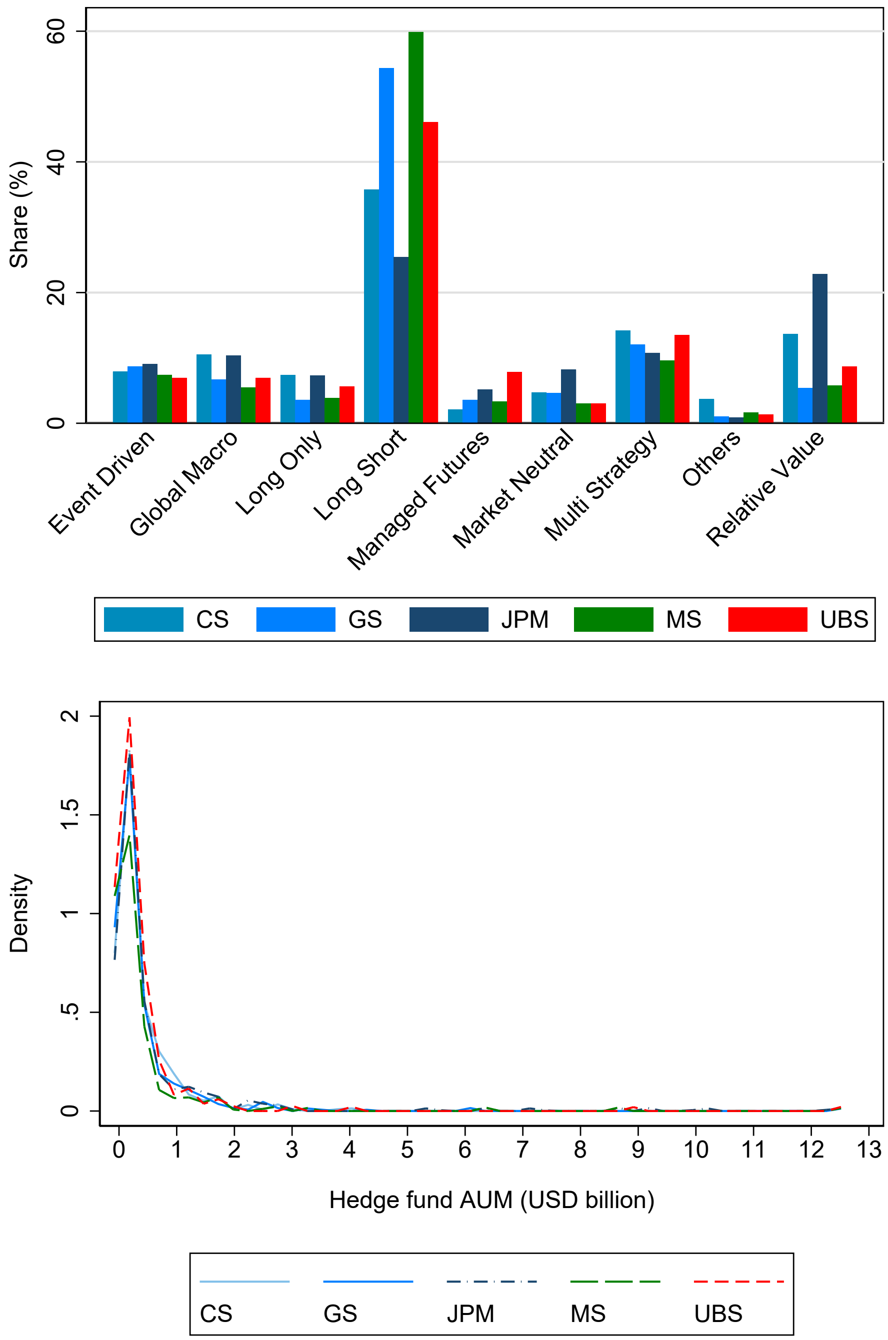


Figure IA.7: Hedge fund style distributions

The top panel of the figure shows the shares (in %) of each hedge fund style among the hedge fund clients of five large prime brokers. The bottom panel of the figure shows the distributions of hedge fund clients' average AUM for the five prime brokers. The prime brokers are Credit Suisse (CS), Goldman Sachs (GS), JP Morgan (JPM), Morgan Stanley (MS), and UBS. Hedge fund style definitions follow the Kosowski et al. (2016) mapping. The sample period runs from June 2009 to June 2017.



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