Do Prime Brokers Induce Similarities in Hedge Funds Performance?*

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Abstract

This paper investigates hedge fund idiosyncratic returns from January 2000 to December 2010. Even after filtering for the exposure to standard risk factors, idiosyncratic returns are still correlated across hedge funds. This raises the question about the potential channels of the similarities in the filtered returns. I conjecture that the presence of the same prime broker, the same domicile or the same style may induce these similarities. Exploiting these hypotheses, I find that dealing with the same prime broker is significantly related to the similarity of idiosyncratic returns. These results are robust to the use of alternative risk factors, subsamples, as well as to alternative similarity measures.

Keywords: Hedge Funds, Prime Brokers, Performance

1 Introduction

Many firms have formal links with other firms in their industry to collaborate on specific issues. On the contrary, hedge funds are not formally linked with each other, except via the

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intermediary of prime brokers. The prime broker service is very concentrated. Table 1 shows that the top three (twelve) brokers service 41.06% (75.03%) of hedge funds. The purpose of this paper is to estimate the influence of the prime broker on the investment strategies of hedge funds. The structural-informational links between hedge fund managers and brokers contribute to the increasing popularity of a single trading idea, which amplifies the impact of potential informational shocks on the market.

If the hedge fund is large enough, its failure may potentially pose systemic risk. This claim is widely disputed by the financial industry. Mallaby (2010) and the Alternative Investment Management Association (2011) argue that hedge funds are "small enough to fail", since most of them are relatively small in terms of value of assets under management. Consequently, the potential harm to the economic system if one of them fails is limited. Nonetheless, the similarity of positions in the hedge fund sector could impose a risk to financial markets.

Diversifying behaviour by individual hedge funds does not prevent the convergency of several hedge funds to the same set of positions. The advantage of hedge funds lies in the flexibility of their strategies. Hence, hedge funds could be expected to herd less than other institutions. The secrecy of hedge fund trades makes herding even more unlikely. However, this does not prevent sharing of information to occur between groups of hedge fund managers or among selected managers and their prime brokers. Consequently, some herding is possible. The securities lending service gives rise to another dependency of hedge funds towards their prime brokers. Through their margin requirements and collateral risk management, prime brokers determine the amount of leverage employed by hedge funds.

One limitation in the context of investigating this channel of similarity relies on the fact that prime brokers do not disclose the margins they require to individual hedge funds. Therefore, the influence of the tightening of credit availability to hedge funds may only
be discovered indirectly. I expect that the returns of funds which deal with the same prime broker are more likely to be correlated.

Most of the time a hedge fund chooses a prime broker when it is founded. Usually the fund does not change this decision afterwards. Moreover, their investment strategies are very dynamic. It means that any analysis of the relationship between hedge funds and prime brokers is unlikely to suffer from reverse causality, because the connectivity was known and set at the moment of the hedge fund formation.


As a benchmark model I use a Fung and Hsieh (2004) eight-factor model. I evaluate idiosyncratic returns for the sample which lasts from January 1994 to April 2012 and several subperiods. Further I add to the initial regression a set of proxies for market and funding liquidity and a proxy for panic to verify that the results are not driven by omitted variables issue. This paper contributes to the academic research which explores performance and risk exposures via the implementation of methods that allow for time-series variation in risk exposures. I use ordinary least squares with rolling windows method.

The paper belongs to the strand of the literature which analyzes similarities and contagion between hedge funds returns. Adrian (2007) uses hedge fund return correlations to proxy the degree of similarities of hedge fund strategies which is assumed to be a key determinant of the risk of the entire hedge fund industry. Boyson et al. (2010) and Reca et al.
(2013a) find evidence of hedge fund contagion, because of return clustering across hedge fund styles which cannot be explained by risk factors, i.e., fundamentals. They define hedge fund contagion as the correlation outside of the interval which is expected from economic fundamentals. Pericoli and Sbracia (2010) explore the dynamic correlation between idiosyncratic hedge fund returns over the period 1995-2009. They find that the correlations were low and stable for the first twelve years, but increased sharply by 2007. Further, they add additional factors such as returns on leveraged loans, a proxy for returns on distressed debt and a proxy for funding liquidity. After controlling for these factors, the rise in idiosyncratic return correlations during the crisis decreased. Sun et al. (2012) use return data to measure the distinctiveness of a fund’s investment strategy. Billio et al. (2011) explore connectedness of participants and systemic risk in the finance sector, particularly of hedge funds, using Granger-causal relations. They report evidence that hedge funds have become more interconnected over time, potentially increasing systemic risk. On the other hand, Reca et al. (2013b), analyzing 13F forms, argue that hedge funds herd less and have portfolios with less crowded trades than other institutions. I implement measures that allow to quantify the similarities in idiosyncratic returns.

This paper also contributes to the literature which explores performance of hedge funds related to non-market factors. Klaus and Rzepkowski (2009) show that during financial distress of a prime broker there is a decline in hedge fund performance and that the hedge funds which rely on multiple prime brokers have higher returns. Li et al. (2011) provide evidence that managers from higher-SAT (Scholastic Aptitude Test) undergraduate institutions have higher returns, more inflows and take less risk. Baden-Fuller et al. (2011) conclude that an increase in network centrality of a hedge fund has a negative effect on performance and increases risk-taking. Mirable and Gottesman (2012) find that funds which have chosen the most popular domicile and leading service providers have lower performance than
those who made other choices. Aragon et al. (2013) explore the difference in performance of the onshore and offshore hedge funds. They conclude that its magnitude depends on the subsample. Cumming et al. (2013) explore hedge funds which domicile is Delaware. They conclude that hedge funds domiciled there do not outrun or perform more poorly than other funds in terms of returns. I regress similarity measures on three dummy variables, such as hedge funds are registered in the same legal domicile, the funds claim that they have the same style and the funds deal with the same prime broker.

The remainder of the paper is organized as follows. Section 2 describes the hypotheses and the framework. Section 3 describes the data. Section 4 presents and analyzes the results. Section 5 draws conclusions.

2 Empirical Methodology

I develop a framework that could help to explain why idiosyncratic hedge fund returns are similar to each other. This framework provides a way of inspecting through which channels similarity propagates.

The domicile is the location where the fund is legally organized. Fund domiciles differ in tax system and regulatory climates. Their laws and regulations constrain the investment strategies of the funds. Liang and Park (2008) document that the presence of share restrictions affects the fund performance. This leads to the first hypothesis:

Hypothesis 1. Hedge funds idiosyncratic returns are more similar if two hedge funds are registered in the same domicile.

It is common for hedge funds with similar investment strategies to have similar positions. This argument provides the second hypothesis:

Hypothesis 2. Hedge funds idiosyncratic returns are more similar if two hedge funds belong to the same strategy.
Prime brokerage is a service provided by banks to hedge funds. The core services provided by a prime broker include financing, securities lending, custody, clearing, settlement, reporting and on-going asset servicing. Therefore, prime brokers have some knowledge of a hedge fund’s positions. According to Baden-Fuller et al. (2011), prime brokers sometimes inform some of their hedge fund clients about selective trades made by others. According to Simon et al. (2013), they also share and distribute information about the conditions surrounding a possible investment action, whether there is more demand than supply for certain assets, the type of institutions that would like to buy or sell and the size of specific orders. Hence, the hedge funds may combine the brokers’ flow of information with their initial trading ideas. The herding refers to the phenomenon by which funds mimic other funds, despite the fact that their own private information or model suggests different strategies. The prime broker may also organize meetings between hedge fund managers and executives from companies or institutional investors.

The securities lending service gives rise to another dependency of hedge funds towards their prime brokers. Through their margin requirements and collateral risk management, prime brokers determine the amount of instrument leverage employed by hedge funds. When a security is borrowed from a broker and sold short, a hedge fund receives cash proceeds from the sale, on which it is paid interest at prevailing rates. Certain prime brokerage arrangements allow the borrower to reinvest these proceeds to purchase additional securities long. Prime brokerage is limited in terms of the level of leverage it can provide. Thus, banks and hedge funds have over the years developed creative structures to provide higher levels of borrowing.

Financing terms can be changed on short notice. Prime brokers tend to increase hedge fund collateral requirements and mandate haircuts in the event of extended stressful market conditions, thus inducing forced deleveraging of risky positions. Hedge funds relying on the
service of the most affected brokers during the last crisis such as Bear Stearns or Lehman Brothers were as a result more likely to face higher funding liquidity risk and therefore to obtain lower returns. Aragon and Strahan (2012) find that hedge funds who used Lehman Brothers as their prime broker could not trade after the bankruptcy, and the probability of failure for these funds was twice higher than for similar funds who used other prime brokers.

The interconnection of a hedge fund with its prime broker through information and suggestions about trades and through lending service yields the third hypothesis:

Hypothesis 3. Hedge funds idiosyncratic returns are more similar if two hedge funds deal with the same prime broker.

The prime broker has information about the financial health of hedge fund \( i \), however, this is incomplete information. Hence, the broker may take into account, poor returns of another fund \( j \), when making a decision about financial conditions to fund \( i \). Another possibility that poor returns of hedge fund \( j \) hurt the prime broker. Both issues could lead to tighter financial conditions to hedge fund \( i \), thereby propagating initial stress of hedge fund \( j \) to hedge fund \( i \). This yields the additional hypothesis:

Hypothesis 3’. The additional risk of hedge fund \( i \) caused by hedge fund \( j \) being in distress is higher if two hedge funds have the same prime broker.

Getmansky et al. (2004) show that the true serially uncorrelated returns are not observable. The observed returns are returns reported by managers. These two returns do not coincide because of illiquidity of some assets and manipulation of returns by manager. To address this issue, I conduct the analysis using the unsmoothed returns. Getmansky et al. provide the following relationship between observed and actual returns:

\[
R_t' = \theta_0 R_t + \theta_1 R_{t-1} + \ldots + \theta_k R_{t-k}, \tag{1}
\]

where \( 1 = \theta_0 + \theta_1 + \ldots + \theta_k \).
A monthly observed return $R^o_t$ is a weighted average of the fund’s true economic returns $R_t$ over the most recent $k + 1$ months. Following Ammann et al. (2010) and Cassar and Gerakos (2012), I set $k$ equal to two and estimate $\theta_0, \theta_1$ and $\theta_2$ for each hedge fund strategy by estimating this MA(2) model with maximum likelihood. I use the “innovations algorithm” of Brockwell and Davis (1991). Then I normalize the resulting estimates by dividing each theta by $1 + \theta_1 + \theta_2$ to satisfy the constraint of equation (1).

In the initial stage I regress hedge fund returns on a set of market factors and then take the residuals which are the idiosyncratic components of hedge fund returns:

$$R^h_{jt} - R^f_t = \sum_k \beta^k_j F^k_t + \epsilon_{jt},$$

where $R^h_{jt}$ is the return of the hedge fund $j$, $R^f_t$ is the risk-free return, $\beta^k_j$ is the coefficient corresponding to the factor $F^k_t$, $\epsilon_{jt}$ is the error term.

The benchmark model is the eight-factor model proposed by Fung and Hsieh (2004), which includes three trend-following risk factors on bonds, currencies and commodities capturing a non-linear exposure, three equity-oriented risk factors (the S&P 500 monthly return (S&PCOMP) less the risk free rate and a size spread factor, the Russel 2000 return (FRUSS2L) less S&P 500 return and the return on the MSCI emerging market stock index (MSEMKF) less the risk free rate) and two bond-oriented risk factors (the monthly change in the 10-year treasury constant maturity yield (D10YR) and the monthly change in spread between the yield on 10-year BAA corporate bonds less the 10-year treasury constant maturity yield (DSPRD)). The changes in spreads are both first differences of the levels.

According to the literature, liquidity has a substantial impact on returns, even after controlling for systematic hedge fund risk factors. Following Brunnermeier and Pedersen (2009), I distinguish between market and funding liquidity. The former is low when it is difficult to sell an asset, the latter when it is costly to obtain funding. Sadka (2010) shows that funds
that are highly sensitive to an aggregate market liquidity factor carry on average a 6% annual return premium over those funds that exhibit less sensitivity. Teo (2011) shows that even liquid hedge funds have significant exposures to liquidity risk. During the last crisis, prime brokers suffered from a maturity mismatch as they were not able to roll over their short-term liabilities. Most hedge funds rely on short-term financing from prime brokers to pursue leveraged investment strategies, therefore, a funding liquidity risk arises because prime brokers transfer their funding pressure to hedge funds via stricter credit conditions.

To account for hedge fund exposure to distress risk, stock momentum, and market and funding illiquidity, I augment the Fung and Hsieh model with the Fama and French (1993) high-minus-low (HML) book-to-market factor, the Carhart momentum factor (MOM), the Pastor and Stambaugh (2003) liquidity factor (PSLIQ), the TED spread which is the difference between LIBOR and the 3 month Treasury bill rate (TED), respectively. Moreover, I include the change in the CBOE’s volatility index (DVIX). According to Chen and Liang (2007) and Billio et al. (2012), the impact of it on hedge fund returns is significant, because fund managers act as volatility buyers or sellers, depending on the expectation they formulate on future market returns.

I also redo the analysis using the Fama-French four-factor model to ensure that the results are not artifacts of the risk model I use. This set of factors is based on the size (SMB), value (HML) and market factor (MKTXS) identified in Fama and French (1993). I also add the momentum factor (MOM).

Another specification which I use includes sector indices returns to adjust returns for sector effects.

To take the dynamic nature of the hedge fund strategies into account I implement OLS with rolling windows. The need for time-varying betas is documented in the literature. Mitchell and Pulvino (2001), Asness et al. (2001), Agarwal and Naik (2004) argue that there
is an asymmetry of hedge fund factor loadings in up-market versus down-market conditions. Patton and Ramadorai (2011) find that hedge fund risk exposures vary significantly across months. Since hedge funds do not have a constant exposure over time, it is necessary to incorporate these time-varying changes in a multi-factor model:

\[ R^h_{jt} - R^f_t = \sum_k \beta^k_{jt} F^k_t + \epsilon_{jt}, \]  

(3)

where \( R^h_{jt} \) is the return of the hedge fund \( j \), \( R^f_t \) is the risk-free return, \( \beta^k_{jt} \) is the coefficient corresponding to the factor \( F^k_t \), \( \epsilon_{jt} \) is the error term.

The most basic technique to assess the constancy of a model’s parameters is to compute parameter estimates over a rolling window which size is determined ad-hoc and fixed through the entire sample. If the parameters change at some point during the sample, then the rolling estimates should capture this instability. Following Roncalli and Teiletche (2007), I implement the rolling OLS with window lengths of 24 months.

Once I have obtained idiosyncratic returns, I analyze similarities between hedge fund strategies. It is the second step of the framework. I verify the existence of comovements (similarities) among hedge fund returns by analyzing pairwise correlations between the returns on hedge fund strategies that are unaffected by common market factors.

Pearson’s, Spearman’s and Kendall’s correlation coefficients are the most commonly used measures of monotone association, with the latter two usually suggested for non-normally distributed data. The first measure is Pearson’s correlation. I estimate it between each hedge fund return and all other ones. Pearson’s correlation is affected by outliers, unequal variances, non-normality and nonlinearity. Also, I use Kendall’s tau and Spearman’s rho to generate more refined estimates of hedge fund independence.

Moreover, following Boyson et al. (2010), I estimate the conditional probability that a return of hedge fund \( i \) is below a given quantile conditional on a return of hedge fund \( j \) also
being below the same quantile.

In the third step, I implement the cross-sectional linear regression model. I consider the following binary explanatory variables. If two funds are registered in the same domicile (different domiciles) the variable domicile is one (zero). If two funds follow the same strategy (different strategies) the variable strategy is one (zero). If two hedge funds operate with the same prime broker (different prime brokers) then the prime broker variable is one (zero).

The correlation measures vary from minus one to one. To implement OLS I use the inverse hyperbolic tangent transformation:

\[ S_{ij} = \alpha + \gamma_1 D_{1ij} + \gamma_2 D_{2ij} + \gamma_3 D_{3ij} + u_{ij}, \]  

(4)

where \( S_{ij} \) is the inverse hyperbolic tangent of the similarity measure, \( \alpha \) is the intercept, the \( \gamma \)s are coefficients, \( D_{1ij} \) is one if two funds \( i \) and \( j \) are legally domiciled in one country (and zero else), \( D_{2ij} \) is one if two funds execute the same strategy (and zero else), \( D_{3ij} \) is one if two funds use the service of the same prime broker (and zero else). I expect to find positive coefficients for all explanatory variables.

To test Hypothesis 3' I implement a CoVaR measure, which was introduced by Adrian and Brunnermeier (2011). The common measure of risk is the value at risk (VaR) which focuses on the risk of an individual institution in isolation. CoVaR\(_{ij}^{q\%}\) denotes the q%-VaR of hedge fund \( j \) conditional on hedge fund \( i \) being at its q%-VaR level. The CoVaR measure allows to analyze the risk spillovers from hedge fund to hedge fund. \( \Delta \text{CoVaR}_{ij}^{q\%} \) captures the increase in risk of hedge fund \( j \) when hedge fund \( i \) falls into distress:

\[ \Delta \text{CoVaR}_{ij}^{q\%} = \text{CoVaR}_{ij}^{q\%|X_i=\text{VaR}_{ij}^{q\%}} - \text{CoVaR}_{ij}^{q\%|X_i=\text{Median}_i} \]  

(5)

To find VaR and CoVaR measures I use quantile regressions (see Adrian and Brunnermeier
Further, I also implement the cross-sectional linear regression model with the same explanatory variables as in Equation 4. The dependent variable is the normalized ΔCoVaR measure.

3 Data

The source of the hedge fund dataset is the Center for International Securities and Derivatives Markets (CISDM). The original database contains 16979 unique hedge funds from January 1994 to April 2012. It includes active and defunct hedge funds (graveyard), managed futures funds and fund of funds. The funds in the graveyard were once included in the active fund database. The hedge funds are broadly representative of the sector and contain funds managed in a variety of different strategies. The data include both U.S. and international hedge funds. All returns are in base currencies. Returns are net of all management and performance-based fees, including the fees charged by funds of funds managers. In addition to hedge fund monthly returns, the data include information on the strategy employed by the hedge funds, the value of assets under management (AUM), the inception date, the domicile and the name of the prime brokers.

Since inclusion in a database is at the discretion of a hedge fund manager, the CISDM dataset may suffer from selection bias. A poor performing hedge fund has no reason to report to commercial database, and a hedge fund with superior performance may not disclose their returns because either they are closed for new investors and there is no reason for advertisement or they are afraid of competitors. Edelman et al. (2011) show that self-selection bias is negligible for commercial hedge fund databases, since the impact of these two opposite biases is roughly of the same magnitude. Agarwal et al. (2010) find that the performance of self-reporting and non-reporting funds does not differ significantly.

Survival bias is reduced because the defunct hedge funds are included in the analysis.
Backfill is not monitored by CISDM. A common method to control for backfill bias is to drop the first 12 or 24 observations of each return series. However, I do not drop observations given the relatively high number of explanatory variables. Unreported analysis indicates that the estimates are mostly unaffected when the first 12 observations for each fund are dropped.

Another potential bias can arise when hedge funds stop reporting returns to the databases prior to liquidation, typically due to poor performance. Following Fung and Hsieh (2011) in the assessment of the impact of liquidation, I assume that the last return of a liquidated fund, which is typically not included in the sample is -50% in the month following the last reported return of the liquidated fund. The results remain qualitatively unchanged.

I clean the raw data from CISDM and impose several filters. First, I do not include funds-of-funds to avoid double counting and exclude managed futures to focus attention on the hedge funds. Liang (2003) finds that managed futures differ from hedge funds in terms of trading strategies. The second filter is that I include only funds which base currency is USD. The third filter is that I require funds to have the whole history of return observations. Moreover, the information about the fund should include its domicile, strategy and prime broker.

In order to have more unique hedge funds I reduce the period of the sample. The final sample spans the period from January 2000 to December 2010 and thus, it includes the collapse of the dot-com bubble in 2000-2001, the poor returns of quantitative funds during the summer 2007 and the financial crisis in 2008. If there is a missing return I take the return of the last available month. If several hedge funds belong to the same management company, I keep only one of them. After the filtering procedure, there is a total number of 246 unique hedge funds.

To support the results I use four other samples of funds. I implement the same data filters as before. One sample is the whole period from 1994 to 2012. Three subsamples are obtained

Table 2 presents the number of hedge funds broken down by strategy. Around half of the funds in the sample run the equity long-short strategy. The next two largest styles are multistrategy and event driven. Table 3 lists how many pairs of funds deal with the same prime broker, registered in the same domicile or belonging to the same style.

The CISDM database also provides indices. The equal weighted hedge fund index, the seven individual hedge fund strategy indices, the fund of fund index and the CTA equal weighted index reflect the median performance of funds reported to CISDM.

I collect a set of fifteen explanatory factors. Three trend-following risk factors on bonds (BD), currencies (FX) and commodities (COM) are obtained from David Hsieh’s website.  

The S&P 500 monthly total return (S&PCOMP), the Russell 2000 total return (FRUSS2L), the MSCI emerging market stock index (MSEMKF) and the change in CBOE Volatility Index (DVIX) are obtained from Datastream. The change in yield of a 10-year Treasury note (D10YR), the change in yield on 10-year BAA corporate bonds less the change in yield of a 10-year Treasury note (DSPRD) and the TED spread (TED) are obtained from the U.S. Federal Reserve’s website.  

Four Fama-French and Carhart factor returns are obtained from Ken French’s website. The Pastor and Stambaugh liquidity (PSLIQ) factor is obtained from Lubos Pastor’s website. All factors are denominated in USD. To estimate the excess returns of the trend-following factors, the S&P 500 and MSCI indices as a risk-free rate I use 3-month T-bill.

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1 https://faculty.fuqua.duke.edu/~dah7/HFRFDData.htm
2 http://www.federalreserve.gov/econresdata/default.htm
3 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
4 http://faculty.chicagobooth.edu/lubos.pastor/research/
4 Results

In this section, I empirically test the hypotheses described in Section 2. All results in this paper are reported using a second-order moving average, MA(2), model for the fund returns introduced by Getmansky et al. (2004).

For each fund, I calculate idiosyncratic returns using six specifications: 1) the eight-factor Fung and Hsieh model, 2) the four-factor Carhart model, 3) the eight-factor model augmented by HML and MOM factors, 4) the eight-factor model augmented by MOM, DVIX, TED and PSLIQ factors, 5) the eight-factor model augmented by HML, MOM, DVIX and TED factors 6) the one-factor model in which the factor is a style-based index.

The consequent analysis is based on the eight-factor Fung-Hsieh model and the eight-factor model augmented by HML, MOM, DVIX and TED factors. As the second step, I compute several measures of correlation between the residuals from equation (3). I also consider the $\Delta$CoVaR measure and the probability $p$ that at time $t$ the return of the hedge fund $j$ will fall below its 10th quantile, conditional on the same event occurring for the hedge fund $i$.

Table 4 lists the mean of the similarity measures of the obtained idiosyncratic returns of the hedge funds for the period which lasts from January 2000 to December 2010 for both specifications. Panel A presents the results for the residuals obtained from the benchmark model using OLS. Panel B lists the results for the augmented model. According to Panel A, the highest value of the average Pearson’s correlation is for the pairs of funds which have the same prime broker (0.077). The lowest value is for the pairs of funds working with different prime brokers (0.051). The same pattern is observed for the other two measures of correlation, the probability of the cooccurrence of low returns and normalized $\Delta$CoVaR.

I check if the correlation of two funds which belong to one group according to prime broker is significantly greater compared to the hedge funds that do not belong to one group. The
difference is statistically significant. The results are qualitatively the same for the augmented model specification and the other two correlation measures. The gap in means of normalized $\Delta$CoVaR is also significant if two funds deal with the same prime broker for both specifications. The same holds true for the difference in average probabilities of coocurrence of low returns.

Table 5 presents the regression results for equation (4). The sample lasts from January 2000 to December 2010. N represents the number of pairs in the sample. Panel A of Table 5 shows five regression models which are different in their dependent variables. Models (1)–(3) use correlation measures. Model (4) uses normalized $\Delta$CoVaR. Model (5) uses the probability of the coocurrence of low returns. The measures are obtained using filtered returns from the benchmark model with dynamic coefficients.

Panel B uses the same sample of the funds but idiosyncratic returns are taken from the augmented Fung-Hsieh model. The results are not significantly altered in terms of both magnitude and statistical significance of the coefficient estimates. The results of Models (1)–(3) and (5) of Panels A and B provide strong statistical support for Hypotheses 2 and 3 for a positive association between similarity of idiosyncratic returns and that they follow the same strategy or have the same prime broker. All coefficients of the dummies that the funds employ the same strategy and have the same prime broker are positive and statistically significant at the 1% level. The data shows mixed evidence for Hypothesis 1. For the normalized $\Delta$CoVaR the coefficient on the prime broker dummy is significant for both specifications. It supports Hypothesis 3’.

I carry out a number of other robustness checks and briefly discuss the results, but do not explicitly present the regressions for reasons of conciseness. I consider other shorter time periods. The coefficients and measures of statistical significance are comparable to the values in the previous set of regressions for the whole period. I consider a two-step
model for fund returns. First, I find the idiosyncratic residuals obtained from the augmented Fung-Hsieh model. Then I compute the first principal component of the residuals. Further, I regress the residuals on this component to obtain new residuals. I replace initial residuals by newly obtained ones and redo the second and the third steps of the framework. The results remain qualitatively unchanged. Moreover, I consider the other two control variables that are available in the hedge fund dataset, age and assets under management. The findings are still robust to the inclusion of these two characteristics. Also, to address the issue that hedge funds could influence asset prices and induce a potential reverse causality problem at the first step, I redo the analysis only for the funds which average value of AUM was less than $500 million. In line with the second and the third hypotheses, I find a significant positive relationship between the second and the third dummies and the measures of similarity.

5 Conclusion

One of the key determinants of hedge fund risk is the degree of similarity among the trades of different funds. This paper presents the analysis of the similarity between idiosyncratic hedge fund returns using the CISDM dataset over the period from January 2000 to December 2010.

Idiosyncratic returns are identified by regressing unsmoothed monthly hedge fund returns on a set of factors introduced by Fung and Hsieh (2001, 2004) augmented by VIX, TED spread, HML and MOM factors, and taking the residuals. The modified model has a total of twelve factors.

When measuring the correlation of idiosyncratic returns, I find that the returns are still correlated. This raises the question about the potential channels of similarities in the filtered returns. This paper proposes the idea that similarity of returns can be enhanced by prime brokers.
I present new evidence about the channels of similarities in hedge fund idiosyncratic returns. The analysis shows that a strategy and a prime broker impose similarities to hedge fund performance. The effect is significantly stronger for the hedge funds that deal with the same prime broker than for the ones that employ the same strategy. In contrast, two hedge funds having the same domicile does not significantly affect the similarities of the performance. These empirical results are robust to the choice of an alternative performance evaluation model, the choice of an alternative similarity proxy and the choice of a time period.

I analyze whether the contagion measure among hedge fund returns, defined by Boyson et al. (2010), is linked to the prime broker, the domicile or the strategy. For the augmented specification, the domicile influences the conditional probability of low returns. Employing the same strategy is found to exhibit a positive (and significant for both specifications) relation to this probability. Also, I find evidence in line with the hypothesis that prime brokers matter.

Furthermore, I measure the risk which fund $i$ added to find $j$ using $\Delta$CoVaR. I show that for both specifications the coefficient of the dummy that two funds work with the same prime broker is positive and significant. Turning to the other two dummies, I find that the same domicile is not significant. However, the coefficient of the dummy that two funds exhibit the same strategy is significant for both specifications.

A promising direction for future work is to analyze the obtained similarity estimators taking different investment clienteles into account. Also, the paper raises the question how effects of the prime broker information channel and the prime broker financial constraints channel on hedge fund returns can be distinguished.
References


Alternative Investment Management Association (AIMA), 2011, No Hedge Fund Today Should Be Deemed Systemically Important.


Appendix

Table 1: **Prime brokers**
This table presents the number of the hedge funds for each prime broker for the total CISDM sample.

<table>
<thead>
<tr>
<th>Prime Broker</th>
<th>Number of HF</th>
<th>Percent of HF</th>
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<tbody>
<tr>
<td>Morgan Stanley</td>
<td>1020</td>
<td>17.06%</td>
</tr>
<tr>
<td>Goldman Sachs</td>
<td>981</td>
<td>16.41%</td>
</tr>
<tr>
<td>UBS</td>
<td>454</td>
<td>7.59%</td>
</tr>
<tr>
<td>Deutsche Bank</td>
<td>396</td>
<td>6.62%</td>
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<tr>
<td>JP Morgan</td>
<td>319</td>
<td>5.34%</td>
</tr>
<tr>
<td>Credit Suisse</td>
<td>317</td>
<td>5.30%</td>
</tr>
<tr>
<td>Bank of America Securities LLC</td>
<td>242</td>
<td>4.05%</td>
</tr>
<tr>
<td>Merrill Lynch</td>
<td>197</td>
<td>3.29%</td>
</tr>
<tr>
<td>Bear Sterns</td>
<td>181</td>
<td>3.03%</td>
</tr>
<tr>
<td>Newedge</td>
<td>147</td>
<td>2.46%</td>
</tr>
<tr>
<td>BNP Paribas</td>
<td>118</td>
<td>1.97%</td>
</tr>
<tr>
<td>Citigroup</td>
<td>114</td>
<td>1.91%</td>
</tr>
<tr>
<td>Other</td>
<td>1493</td>
<td>24.97%</td>
</tr>
</tbody>
</table>

Table 2: **Number of Unique Funds**
This table presents the number of the unique hedge funds for each strategy for the main sample.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>2000-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number</td>
</tr>
<tr>
<td>Equity Long-Short</td>
<td>125</td>
</tr>
<tr>
<td>Emerging Markets</td>
<td>12</td>
</tr>
<tr>
<td>Multistrategy</td>
<td>17</td>
</tr>
<tr>
<td>Fixed Income</td>
<td>4</td>
</tr>
<tr>
<td>Global Macro</td>
<td>15</td>
</tr>
<tr>
<td>Equity Market Neutral</td>
<td>6</td>
</tr>
<tr>
<td>Event Driven</td>
<td>17</td>
</tr>
<tr>
<td>Debt Arbitrage</td>
<td>12</td>
</tr>
<tr>
<td>Distressed Securities</td>
<td>5</td>
</tr>
<tr>
<td>Equity Long-Only</td>
<td>13</td>
</tr>
<tr>
<td>Convertible Arbitrage</td>
<td>3</td>
</tr>
<tr>
<td>Other</td>
<td>17</td>
</tr>
<tr>
<td>Overall</td>
<td>246</td>
</tr>
</tbody>
</table>
Table 3: **Number of Pairs**
This table reports the number of pairs of the hedge funds registered in the same domicile, following the same strategy, having the same prime broker for the main sample.

<table>
<thead>
<tr>
<th></th>
<th>2000-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Same Domicile</td>
<td>11587</td>
</tr>
<tr>
<td>Same Strategy</td>
<td>8507</td>
</tr>
<tr>
<td>Same Prime Broker</td>
<td>4365</td>
</tr>
</tbody>
</table>
Table 4: **Means of Similarity Measures.**

The means of similarity measures are estimated over the period going from January 2000 to December 2010. The similarity measures are estimated using two different specifications. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Conditional proba is the conditional probability that a return of hedge fund $i$ is below 10th quantile conditional on a return of hedge fund $j$ also being below the same quantile.

\[
\Delta \text{CoVaR}^j_{i q} = \text{CoVaR}^j_{X = \text{VaR}^q_i} - \text{CoVaR}^j_{X = \text{Median}^i}
\]

**Panel A: OLS with rolling windows; Fung-Hsieh 8-factor Model**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Same Domicile</th>
<th>Same Strategy</th>
<th>Same Prime Broker</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
<td>t-stat of Diff</td>
</tr>
<tr>
<td>Pearson’s correlation</td>
<td>0.056</td>
<td>0.053</td>
<td>1.961**</td>
</tr>
<tr>
<td>Kendall’s tau</td>
<td>0.037</td>
<td>0.036</td>
<td>1.327</td>
</tr>
<tr>
<td>Spearman’s rho</td>
<td>0.054</td>
<td>0.052</td>
<td>1.283</td>
</tr>
<tr>
<td>$\Delta \text{CoVaR}^j_{X = \text{Median}^i}$</td>
<td>0.077</td>
<td>0.073</td>
<td>1.035</td>
</tr>
<tr>
<td>Conditional proba</td>
<td>0.151</td>
<td>0.148</td>
<td>2.394**</td>
</tr>
</tbody>
</table>

**Panel B: OLS with rolling windows; Augmented Fung-Hsieh Factor Model**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Same Domicile</th>
<th>Same Strategy</th>
<th>Same Prime Broker</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
<td>t-stat of Diff</td>
</tr>
<tr>
<td>Pearson’s correlation</td>
<td>0.058</td>
<td>0.055</td>
<td>1.466</td>
</tr>
<tr>
<td>Kendall’s tau</td>
<td>0.038</td>
<td>0.035</td>
<td>2.666***</td>
</tr>
<tr>
<td>Spearman’s rho</td>
<td>0.054</td>
<td>0.050</td>
<td>2.665***</td>
</tr>
<tr>
<td>$\Delta \text{CoVaR}^j_{X = \text{Median}^i}$</td>
<td>0.068</td>
<td>0.066</td>
<td>0.982</td>
</tr>
<tr>
<td>Conditional proba</td>
<td>0.155</td>
<td>0.146</td>
<td>7.187***</td>
</tr>
</tbody>
</table>
Table 5: Cross-sectional Regressions

This table presents regression estimates of the return similarities on dummies. The estimation period lasts from January 2000 to December 2010. The first dummy ($D_{dom}$) equals one (zero) if two funds registered in the same country (different countries). The second dummy ($D_{str}$) equals one (zero) if two funds follow the same strategy (different strategies). The third dummy ($D_{pb}$) equals one (zero) if two funds have the same prime broker (different prime brokers). The t-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. N is the number of fund pairs. Conditional proba is the conditional probability that a return of hedge fund $i$ is below 10th quantile conditional on a return of hedge fund $j$ also being bellow the same quantile. $\Delta CoVaR_{q}^{ij} = CoVaR_{q}^{i\mid X=X_{i}^{\text{Median}}} - CoVaR_{q}^{j\mid X=X_{j}^{\text{Median}}}$

### Panel A: OLS with rolling windows; Fung-Hsieh 8-factor Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation</th>
<th>Kendall’s tau</th>
<th>Spearman’s rho</th>
<th>$\Delta CoVaR_{q}^{ij} / CoVaR_{q}^{j\mid X^i=X_{i}^{\text{Median}}}$</th>
<th>Conditional proba</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.049***</td>
<td>0.032***</td>
<td>0.047***</td>
<td>0.022***</td>
<td>-5.854***</td>
</tr>
<tr>
<td>$D_{dom}$</td>
<td>0.003</td>
<td>0.001</td>
<td>0.001</td>
<td>0.003</td>
<td>0.098</td>
</tr>
<tr>
<td>$D_{str}$</td>
<td>0.008***</td>
<td>0.006***</td>
<td>0.009***</td>
<td>0.007**</td>
<td>0.340***</td>
</tr>
<tr>
<td>$D_{pb}$</td>
<td>0.031***</td>
<td>0.019***</td>
<td>0.029***</td>
<td>0.004**</td>
<td>0.561***</td>
</tr>
<tr>
<td>Adjusted-$R^2$</td>
<td>0.59%</td>
<td>0.60%</td>
<td>0.61%</td>
<td>0.11%</td>
<td>0.16%</td>
</tr>
<tr>
<td>N</td>
<td>30135</td>
<td>30135</td>
<td>30135</td>
<td>30135</td>
<td>30135</td>
</tr>
</tbody>
</table>

### Panel B: OLS with rolling windows; Augmented Fung-Hsieh Factor Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation</th>
<th>Kendall’s tau</th>
<th>Spearman’s rho</th>
<th>$\Delta CoVaR_{q}^{ij} / CoVaR_{q}^{j\mid X^i=X_{i}^{\text{Median}}}$</th>
<th>Conditional proba</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.050***</td>
<td>0.030***</td>
<td>0.045***</td>
<td>0.006</td>
<td>-5.997***</td>
</tr>
<tr>
<td>$D_{dom}$</td>
<td>0.002</td>
<td>0.002**</td>
<td>0.004**</td>
<td>0.002</td>
<td>0.305***</td>
</tr>
<tr>
<td>$D_{str}$</td>
<td>0.009***</td>
<td>0.005***</td>
<td>0.008***</td>
<td>0.010**</td>
<td>0.443***</td>
</tr>
<tr>
<td>$D_{pb}$</td>
<td>0.037***</td>
<td>0.023***</td>
<td>0.034***</td>
<td>0.040**</td>
<td>0.376***</td>
</tr>
<tr>
<td>Adjusted-$R^2$</td>
<td>0.77%</td>
<td>0.79%</td>
<td>0.79%</td>
<td>0.17%</td>
<td>0.21%</td>
</tr>
<tr>
<td>N</td>
<td>30135</td>
<td>30135</td>
<td>30135</td>
<td>30135</td>
<td>30135</td>
</tr>
</tbody>
</table>