Do Prime Brokers Induce Similarities in Hedge Funds Performance?*

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Abstract

Hedge fund performance is highly correlated across funds in complex ways. Using a sample of prime brokerage relationships, I document that the performance of hedge funds that deal with the same broker is 53% more correlated. The results are robust to different performance measures, different subperiods, and other possible determinants of performance similarity as the hedge funds' domicile and investment style. Overall, my results reveal prime brokers' lending activity and information sharing as important determinants of the cross-sectional correlation of hedge fund performance.

Keywords: Hedge Funds, Prime Brokers, Performance

JEL: G2, G23

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1 Introduction

Mallaby (2010) and the Alternative Investment Management Association (2011) argue that hedge funds are "small enough to fail", since most of them have relatively low levels of assets under management. Consequently, the potential harm to the financial 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.

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 intermediary of prime brokers. The prime broker service is very concentrated.[1] The links between hedge fund managers and brokers contribute to the increasing popularity of a single trading idea, which amplifies the impact of potential shocks on the market. The purpose of the paper is to estimate how the prime broker influences the investment strategies of hedge funds.

One advantage of hedge funds lies in the flexibility of their strategies and the secrecy of their trades. However, this does not prevent sharing of information to occur between groups of hedge fund managers or among selected managers and their prime brokers. 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 influence the amount of leverage employed by hedge funds. Consequently, diversifying behaviour by individual hedge funds does not prevent the convergence of several hedge funds to a similar set of positions.

One limitation in the investigation of this similarity channel is that prime brokers do not disclose their individual margin requirements. Therefore, the influence of the tightening of credit availability to hedge funds may only be discovered indirectly. I expect that the returns

[1] The top three (twelve) brokers service 41% (75%) of hedge funds (see Table 1).

of funds which deal with the same prime broker are more likely to be correlated.

Most of the time hedge funds choose a prime broker when they are founded and usually do not change the 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.

I begin the analysis of hedge fund correlations by evaluating idiosyncratic returns for the sample which lasts from January 2000 to December 2010 and several subperiods. As a benchmark model I use Fung and Hsieh (2004) eight-factor model. 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. Second, I use measures to quantify the similarities in idiosyncratic returns. Third, I regress the similarity measures on three dummy variables: 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. I find that dealing with the same broker increases performance correlation across funds of around 53%.

Extensive research has been done in exploring performance and risk exposures of hedge funds. Fung and Hsieh (1997) introduce a set of risk factors for the hedge fund analysis. Later, Fung and Hsieh (2001) and Agarwal and Naik (2004) add option-like payoffs to capture the nonlinearity in exposures. Fung and Hsieh (2004) and Bollen and Whaley (2009) use time-varying beta estimators. Patton and Ramadorai (2011) present a methodology to account for time series variation in hedge fund exposures to risk factors using high-frequency data.

The paper is also related to the strand of the literature which investigates similarities and contagion between hedge funds returns. Adrian (2007) uses hedge fund return correlations to proxy the degree of similarities of hedge fund styles. This measure significantly determines 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 is attenuated. 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 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.

The paper also contributes to the literature which explores the performance of hedge funds related to non-market factors. Klaus and Rzepkowski (2009) show that during financial distress of prime brokers 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. Mirabile (2015) finds 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 onshore and offshore hedge funds. They conclude that its magnitude depends on the subsample. Cumming et al. (2013) find that hedge funds domiciled in Delaware do not have higher returns than other funds.

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

2.1 Test Hypotheses

I develop a framework that could help to explain why idiosyncratic hedge fund returns are similar to each other. The framework provides a way of inspecting through which channels similarity propagates. I consider three main channels, unrelated to market factors, that may explain idiosyncratic hedge fund returns: style, domicile and prime broker.

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

Hypothesis 1. Hedge funds idiosyncratic returns are more similar if two hedge funds belong to the same style.

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. Aragon et al. (2013) document that the presence of share restrictions affects the fund performance. This leads to the second hypothesis:

Hypothesis 2. Hedge funds idiosyncratic returns are more similar if two hedge funds

are registered in the same domicile.

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 hedge funds' 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 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 the proceeds to purchase additional securities long. Prime brokerage is limited in 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 information is incomplete. Hence, the prime broker may take into account poor returns of another fund j, when making a decision about financial conditions to fund i. Another possibility is 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.

2.2 Methodology

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 the issue, I conduct the analysis using the unsmoothed returns. Getmansky et al. provide the following relationship between observed and actual returns:

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + ... + \theta_k R_{t-k}, \tag{1}$$

where $1 = \theta_0 + \theta_1 + ... + \theta_k$.

A monthly observed return R_t^o is a weighted average of the fund's true economic unsmoothed 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 θ_0, θ_1 and θ_2 for each hedge fund by maximum likelihood method.[2] 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 unsmoothed hedge fund returns on a set of market factors and then take the residuals which are the idiosyncratic components of hedge fund returns. To take the dynamic nature of the hedge fund strategies into account I use 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 time-varying changes in a multi-factor model:

$$R_{jt}^{hf} - R_t^f = \sum_k \beta_{jt}^k F_t^k + \varepsilon_{jt}, \tag{2}$$

where R_{jt}^{hf} is the return of the hedge fund j, R_t^f is the risk-free return, β_{jt}^k is the coefficient corresponding to the factor F_t^k, ε_{jt} is the idiosyncratic return.

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 less the risk free rate, 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 mar-

[2] I estimate this MA(2) model using the "innovations algorithm" of Brockwell and Davis (2009).

ket 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)).

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 hedge 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) and the TED spread which is the difference between LIBOR and the 3 month Treasury bill rate (TED). 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 volatility 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.

Once I have obtained idiosyncratic returns, I explore 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. I estimate these measures 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 dependence.

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 bellow the same quantile.

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

As the correlation measures vary from minus one to one, I use the inverse hyperbolic tangent transformation in the OLS regression:

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

where S_{ij} is the inverse hyperbolic tangent of the similarity measure, α is the intercept, the γs are coefficients, $D_{1ij} = 1$ if two funds execute the same style (and zero else),, $D_{2ij} = 1$ if two funds i and j are legally domiciled in one country (and zero else), $D_{3ij} = 1$ 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 use 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. $\text{CoVaR}_q^{j|i}$ denotes the q%-VaR of hedge fund j conditional on hedge fund i being at its q%-VaR level. The CoVaR measure allows to explore the risk spillovers from hedge fund i to hedge fund j. $\Delta\text{CoVaR}_q^{j|i}$ captures the increase in risk of hedge fund j when hedge fund i falls into distress:

$$\Delta\text{CoVaR}_q^{j|i} = \text{CoVaR}_q^{j|X^i=VaR_q^i} - \text{CoVaR}_q^{j|X^i=Median^i}. \tag{4}$$

To estimate VaR and CoVaR measures, I use quantile regressions (see Koenker and Basset (1978) for the methodology). Further, I also apply the cross-sectional linear regression model with the same explanatory variables as in Equation 3. 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 16,979 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 styles. 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 style 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 funds to focus attention on the hedge funds. Liang (2003) finds that managed futures funds differ from hedge funds in trading strategies. The second filter is that I include only funds which base currency is USD. Moreover, the information about the fund should include its style, domicile 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 234 unique hedge funds.

To investigate the temporal stability of the results I use four other samples of funds. I apply the same data filters as before. One sample is the whole period from 1994 to 2012. Three subsamples are obtained by dividing the whole period in three sub periods, 1994-1999, 2000-2005 and 2006-2012.

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

The hedge fund excess returns are summarized in the Table 1 of the Appendix. The CISDM database also provides indices. The equal weighted hedge fund index, the seven individual hedge fund style indices, the fund of fund index and the CTA equal weighted index reflect the median performance of funds reported to CISDM. Table 2 in the Appendix shows descriptive statistics of the returns of indices. All means and medians are positive.

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.[3] 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 term spread, i.e., yield of a 10-year Treasury note (D10YR), the change in credit spread, i.e., 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[4] and the website of the Federal Reserve Bank of St. Louis.[5] Four Fama-French and Carhart factor returns are obtained from Ken French's website.[6] The Pastor and Stambaugh liquidity (PSLIQ) factor is obtained from Lubos Pastor's website.[7] All factors are denominated in USD. Table 3 of the Appendix provides descriptive statistics of monthly factor returns.

4 Results

In this section, I empirically test the hypotheses described in Section 2. All results in the paper are reported using a second-order moving average, MA(2), model for unsmoothing 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,

[3]https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm
[4]http://www.federalreserve.gov/econresdata/default.htm
[5]http://research.stlouisfed.org
[6]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[7]http://faculty.chicagobooth.edu/lubos.pastor/research/

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 the style-based index.

The subsequent 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 2. I also consider the ΔCoVaR 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 the rolling OLS with window lengths of 24 months. 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 (0.074). The lowest value is for the pairs of funds working with different prime brokers (0.051). The same pattern is observed for two other measures of similarity, the normalized ΔCoVaR and the probability of the coocurrence of low returns.

I check if the average 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 highly statistically significant. The results are qualitatively the same for the augmented model specification and the other two correlation measures. The average correlation for pairs of funds which deal with the same prime broker is 53% higher than the average correlation for pairs of funds with different prime brokers. The gap in means of normalized ΔCoVaR 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.

The average correlation for pairs of funds which are registered at the same domicile is not statistically different from the average correlation for pairs of funds which are registered at different domiciles for both specifications. However, the gap in means of normalized ΔCoVaR is significant for both specifications. The difference in average probabilities of coocurrence of low returns is significant only for the augmented model. Moreover, if two funds execute the same style the mean of the similarity measure is significantly higher than the mean of the similarity measure for two funds with different styles for all types of measures and both specifications.

Table 5 presents the results for the cross-section regression (Equation 3). The sample lasts from January 2000 to December 2010, with more than 30,000 pairwise correlations. Panel A shows five regression models which are different in their dependent variables. Models (1)–(3) use correlation measures, Model (4) uses normalized ΔCoVaR and Model (5) uses the probability of the coocurence 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 1 and 3 for a positive association between similarity of idiosyncratic returns when hedge funds follow the same style or have the same prime broker. All coefficients of the dummies that the funds employ the same style and have the same prime broker are positive and statistically significant at the 1% level. For the normalized ΔCoVaR the coefficient on the prime broker dummy is significant for both specifications. It supports Hypothesis 3'. The data shows mixed evidence for Hypothesis 2.

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. I investigate the similarity between idiosyncratic hedge fund returns using the CISDM dataset over the period from January 2000 to December 2012. 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 correlation raises the question about the potential channels of similarities in the filtered returns. The 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 style 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 style. In contrast, two hedge funds having the same domicile does not significantly affect the similarities of the performance. The 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 explore whether the contagion measure among hedge fund returns, defined by Boyson et al. (2010), is linked to the prime broker, the domicile or the style. For the augmented specification, the domicile influences the conditional probability of low returns. Employing the same style 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 ΔCoVaR. 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 their coefficients are also significant for both specifications.

A promising direction for future work is to investigate 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.

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

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

Table 2: **Number of Unique Funds**

This table presents the number of the unique hedge funds for each strategy for the main sample and the subsamples.

Style	2000-2010		1994-1999		2000-2005		2006-2012		1994-2012	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Equity Long-Short	117	50.00%	50	58.82%	213	49.08%	244	49.29%	27	56.25%
Emerging Markets	11	4.70%	2	2.35%	18	4.15%	30	6.06%	2	4.17%
Multistrategy	16	6.84%	4	4.71%	30	6.91%	26	5.25%	3	6.25%
Fixed Income	4	1.71%	0	0.00%	6	1.38%	13	2.63%	0	0.00%
Global Macro	15	6.41%	5	5.88%	24	5.53%	36	7.27%	4	8.33%
Equity Market Neutral	6	2.56%	1	1.18%	15	3.46%	19	3.84%	0	0.00%
Event Driven	16	6.84%	7	8.24%	32	7.37%	24	4.85%	3	6.25%
Debt Arbitrage	12	5.13%	5	5.88%	12	2.76%	10	2.02%	4	8.33%
Distressed Securities	5	2.14%	2	2.35%	18	4.15%	12	2.42%	0	0.00%
Equity Long-Only	13	5.56%	2	2.35%	13	3.00%	25	5.05%	2	4.17%
Convertible Arbitrage	2	0.85%	4	4.71%	18	4.15%	9	1.82%	1	2.08%
Other	17	7.26%	3	3.53%	35	8.06%	47	9.50%	2	4.17%
Overall	234	100.00%	85	100.00%	434	100.00%	495	100.00%	48	100.00%

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 and the subsamples.

	2000-2010		1994-1999		2000-2005		2006-2012		1994-2012	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Same Style	7498	19763	1284	2886	25103	68858	33089	89176	372	756
Same Domicile	10505	16756	1759	1811	34680	59281	45444	76721	562	566
Same Prime Broker	3894	23367	673	2897	11892	82069	16392	105873	258	870

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 bellow the same quantile. $\Delta \mathrm{CoVaR}_q^{j|i} = \mathrm{CoVaR}_q^{j|X^i=VaR_q^i} - \mathrm{CoVaR}_q^{j|X^i=Median^i}$

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

Measure	Same Domicile			Same Style			Same Prime Broker		
	Yes	No	t-stat of Diff	Yes	No	t-stat of Diff	Yes	No	t-stat of Diff
Pearson's correlation	0.055	0.054	0.942	0.061	0.052	4.727***	0.074	0.051	9.258***
Kendall's tau	0.037	0.036	0.931	0.040	0.034	5.108***	0.049	0.034	9.824***
Spearman's rho	0.053	0.052	0.806	0.059	0.050	5.023***	0.071	0.049	9.429***
$\frac{\Delta \mathrm{CoVaR}_q^{j\|i}}{\mathrm{CoVaR}_q^{j\|X^i=Median^i}}$	0.079	0.073	2.033**	0.081	0.072	2.798***	0.092	0.072	4.901***
Conditional proba	0.150	0.148	1.433	0.157	0.146	7.677***	0.164	0.146	9.019***

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

Measure	Same Domicile			Same Style			Same Prime Broker		
	Yes	No	t-stat of Diff	Yes	No	t-stat of Diff	Yes	No	t-stat of Diff
Pearson's correlation	0.060	0.058	0.991	0.066	0.056	5.258***	0.084	0.055	11.779***
Kendall's tau	0.037	0.036	1.214	0.041	0.034	5.130***	0.051	0.034	10.912***
Spearman's rho	0.054	0.052	1.204	0.059	0.050	4.902***	0.073	0.049	10.534***
$\frac{\Delta \mathrm{CoVaR}_q^{j\|i}}{\mathrm{CoVaR}_q^{j\|X^i=Median^i}}$	0.074	0.067	2.523***	0.076	0.067	2.990***	0.089	0.066	6.446***
Conditional proba	0.152	0.147	3.160***	0.156	0.146	6.191***	0.163	0.147	8.608***

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 style (different styles). The third dummy (D_{pb}) equals one (zero) if two funds have the same prime broker (different prime brokers). The t-statistics are computed using White heteroskedasticity robust standard errors. 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. $\Delta \text{CoVaR}_q^{j|i} = \text{CoVaR}_q^{j|X^i=VaR_q^i} - \text{CoVaR}_q^{j|X^i=Median^i}$

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

Variable	Correlation		Kendall's tau		Spearman's rho		$\frac{\Delta \text{CoVaR}_q^{j\|i}}{\text{CoVaR}_q^{j\|X^i=Median^i}}$		Conditional proba	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.049***	(37.992)	0.032***	(39.591)	0.047 ***	(39.415)	0.036***	(4.976)	-5.698***	(-28.266)
D_{style}	0.010***	(4.893)	0.006***	(5.047)	0.010***	(5.227)	0.008**	(2.528)	0.350***	(3.972)
D_{dom}	0.001	(0.780)	0.001	(0.066)	0.001	(0.559)	0.005*	(1.863)	0.032	(0.400)
D_{pb}	0.026***	(10.043)	0.016***	(10.140)	0.024***	(10.118)	0.019***	(4.824)	0.487***	(4.342)
Adjusted-R^2	0.47%		0.48%		0.49%		0.06%		0.13%	
N	27261		27261		27261		27261		27261	

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

Variable	Correlation		Kendall's tau		Spearman's rho		$\frac{\Delta \text{CoVaR}_q^{j\|i}}{\text{CoVaR}_q^{j\|X^i=Median^i}}$		Conditional proba	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.052***	(39.828)	0.032***	(38.758)	0.047 ***	(38.711)	0.026***	(4.000)	-5.885***	(-29.299)
D_{style}	0.011 ***	(5.281)	0.006***	(4.985)	0.009***	(4.970)	0.074***	(2.644)	0.389***	(4.429)
D_{dom}	0.001	(0.750)	0.001	(0.930)	0.002	(0.958)	0.006***	(2.345)	0.145*	(1.799)
D_{pb}	0.032***	(12.392)	0.018***	(11.175)	0.027***	(11.128)	0.023***	(6.365)	0.493***	(4.414)
Adjusted-R^2	0.68%		0.56%		0.56%		0.10%		0.16%	
N	27261		27261		27261		27261		27261	

Appendix

Table 1: **Summary Statistics of Average Monthly Excess Returns of Funds**

Descriptive statistics on the monthly return of the hedge funds within each subsample. The funds are equally-weighted within each category. The returns and standard deviations are expressed on a monthly basis.

Period	Mean			Med.			0.25			0.75		
	Mean	Med.	Std. Dev.	Mean	Med.	Std. Dev.	Mean	Med.	Std. Dev.	Mean	Med.	Std. Dev.
2000-2010	0.749	0.712	0.599	0.794	0.744	0.557	-1.917	-1.469	1.836	3.441	3.111	1.914
1994-1999	1.285	1.233	0.744	1.144	1.076	0.823	-1.608	-1.155	1.550	4.005	3.871	2.051
2000-2005	0.859	0.747	0.663	0.764	0.709	0.681	-1.545	-1.025	1.882	3.076	2.599	1.949
2006-2012	0.562	0.508	0.570	0.692	0.659	0.632	-2.030	-1.704	1.699	3.324	3.011	1.801
1994-2012	0.746	0.766	0.274	0.720	0.777	0.445	-1.922	-1.532	1.628	3.476	3.470	1.578

Table 1 (cont'd): **Summary Statistics of Average Monthly Excess Returns of Funds**

Period	Std. Dev.			Skewness			Kurtosis		
	Mean	Med.	St. Dev.	Mean	Med.	St. Dev.	Mean	Med.	St. Dev.
2000-2010	5.298	4.778	3.291	0.134	-0.078	1.207	8.005	5.842	7.282
1994-1999	5.090	4.351	3.325	-0.023	-0.028	0.880	5.554	4.552	3.313
2000-2005	4.331	3.514	3.151	0.403	0.224	1.110	6.323	4.511	5.257
2006-2012	5.086	4.416	3.103	-0.284	-0.281	0.927	5.841	4.422	4.167
1994-2012	5.077	5.000	2.851	-0.109	-0.206	0.647	6.539	5.513	3.588

Table 2: **Summary Statistics of Excess Returns of Indices**

This table lists summary statistics of the indices constructed by CISDM between January 2000 and December 2010.

Style	Mean	Median	0.25	0.75	Std. Dev.	Skewness	Kurtosis
Equal Weighted HF Index	0.677	0.911	-0.450	1.898	2.097	-0.541	5.707
Convertible Arbitrage Index	0.629	0.750	0.068	1.300	1.770	-3.198	22.713
Distressed Securities Index	0.752	0.850	0.160	1.593	1.679	-2.431	17.664
Equity Long/Short Index	0.524	0.795	-0.563	1.800	1.898	-0.295	3.648
Equity Market Neutral Index	0.522	0.540	0.198	0.853	0.604	-0.335	6.613
Event Driven Multistrategy Index	0.637	0.955	0.005	1.705	1.683	-1.797	9.072
Fixed Income Arbitrage Index	0.559	0.605	0.320	0.870	1.434	-2.752	22.294
Global Macro Index	0.543	0.465	-0.165	1.195	1.064	0.891	6.009
Fund of Funds Diversified Index	0.375	0.520	-0.165	1.240	1.354	-1.248	7.430
CTA Equal Weighted Index	0.747	0.668	-1.081	2.480	2.526	0.418	2.909

Table 3: **Summary Statistics of Explanatory Variables**

This table lists summary statistics of the explanatory variables between January 2000 and December 2010. BD, FX, COM are excess returns on trend following factors constructed of look-back straddles on futures contracts of bonds, currencies and commodities, respectively. S&PCOMP denotes S&P 500 Composite, FRUSS2L denotes RUSSELL 2000, MSEMKF denotes MSCI Emerging Markets. D10YR is the change in yield of a 10-year Treasury note, and DSPRD is the change in yield on 10-year BAA corporate bonds less the change in yield of a 10-year Treasury note. MKTXS is the excess market return. SMB and HML are the returns of the size and value portfolios, respectively. MOM is the Carhart momentum factor. DVIX is the first-difference of the end-of-month value of the CBOE Volatility Index. TED is the TED spread, PSLIQ is the Pastor and Stambaugh liquidity factor.

Factor	Mean	Median	0.25	0.75	Std. Dev.	Skewness	Kurtosis
BD	-3.085	-5.039	-13.682	3.220	14.084	1.083	4.292
FX	0.885	-3.087	-11.662	8.279	18.928	1.256	4.750
COM	-0.902	-3.292	-9.685	5.278	13.334	1.000	3.931
S&PCOMP	0.053	0.734	-2.171	3.094	4.724	-0.490	3.537
FRUSS2L-S&PCOMP	0.494	0.410	-1.471	2.533	3.625	0.169	9.248
MSEMKF	1.027	1.197	-2.774	6.156	7.053	-0.623	4.169
D10YR	-0.023	-0.045	-0.160	0.115	0.240	-0.189	5.489
DSPRD	0.007	-0.010	-0.090	0.110	0.242	1.037	13.535
MKTXS	0.002	0.800	-2.600	3.235	4.876	-0.533	3.369
SMB	0.522	0.195	-1.540	2.635	3.882	0.904	11.657
HML	0.634	0.440	-1.150	2.640	3.725	-0.008	5.538
MOM	0.121	0.530	-2.030	3.190	6.550	-1.416	9.693
DVIX	-0.041	-0.350	-2.425	2.140	4.544	0.818	7.742
TED	0.517	0.380	0.193	0.614	0.467	2.303	9.644
PSLIQ	0.010	0.009	-0.012	0.036	0.043	0.528	5.918