Hedge Fund Funding Risk

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Abstract

This paper shows theoretically and empirically that hedge funds with a strong loading on funding-risky positions can underperform hedge funds with a weak loading on the same positions. Standard theory would imply that a higher loading on a funding-risky strategy generates higher excess returns due to the additional risk taken. However, hedge funds are actively managed portfolios, facing a funding risk of their own. Hence, if there is a strong link between the funding-risky strategy and the hedge fund manager's own funding risk, a deterioration in funding conditions leads to severe losses for the manager because he is forced to delever exactly at a time when expected returns from providing liquidity are highest.

Keywords: Hedge Funds, Funding Liquidity Risk, Limits of Arbitrage

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1 Introduction

Hedge funds are typically considered as the investor class that most closely resembles textbook arbitrageurs. They are capable of profiting from small mispricings across different markets by taking leveraged long and short positions across different asset classes. However, there are several important differences between hedge fund managers and the wealth-maximizing textbook arbitrageur. Most importantly, hedge fund managers face severe funding risks through two channels. First, they face the risk of investor redemptions after poor performance. This risk can even cause a risk-neutral hedge fund manager to act as if he was risk-averse (Lan, Wang, and Yang, 2013; Drechsler, 2014). Second, hedge funds are dependent on the funding provided by their prime brokers. In contrast to investor redemptions, prime broker funding can even change overnight, for instance by increased margin requirements.[1]

In this paper, I investigate how the combination of investing in a funding-risky strategy and the manager's own funding risk affect hedge fund returns. In particular, I investigate the consequences of a relationship between returns from providing liquidity and the risk of a cut in hedge fund funding. Arbitrage spreads are commonly associated with a lack of "arbitrage capital" in the market. Hence, it is reasonable to assume that an increase in spreads between almost identical assets coincides with tighter funding conditions for hedge funds. I show theoretically and empirically that if arbitrage spread and hedge fund funding risk are positively correlated, it is optimal for the manager to avoid the arbitrage opportunity.

To study the effects of funding risk on the optimal investments of a hedge fund manager, I consider a partial equilibrium model with two investment opportunities. and funding risk. In the model, a constrained hedge fund manager can allocate his wealth between a position in a strategy with returns related to funding conditions in the market and an alpha-generating strategy, which is uncorrelated with his own funding risk. The manager's constraint is a collateral or margin constraint that requires him to use parts of his own wealth to fund his positions. Funding risk is incorporated in the model by assuming that margin requirements can increase when the expected returns of the funding-risky asset increase. By definition, this implies that the manager receives a funding shock exactly at the time when his position in the funding-risky asset moves against him. Only a manager who has the skill of generating alpha from a different source avoids loading on the liquidity asset, thereby avoiding the risk of major losses.

To test my theory in the data, I start by constructing a measure of a mispricing or market

[1] Leveraged positions are typically financed with overnight funding. One example of changing funding conditions are increases in margin requirements (see, for instance, Brunnermeier and Pedersen, 2009). Another source of leverage is the usage of derivatives which also relies on major derivatives-dealing banks.

dislocation that is plausibly related to the funding risk that hedge funds have with their prime brokers. I use mispricings in international money markets, captured by deviations from the covered interest rate parity (CIP) as a proxy. To avoid any currency or security-specific effects, I construct an index of CIP mispricings for 9 different currency pairs and contracts with 7 different maturities between 1 week and 1 year. I only focus on the following five liquid currencies: British Pound, Euro, Japanese Yen, Swiss Franc, and US Dollar. The constructed index is strongly correlated with funding liquidity, proxied by the TED spread (the difference between 3-month US Libor rate and 3-month US treasury bill yield) and market uncertainty, as proxied by the VIX index (the implied volatility of S&P 500). On the other hand, the CIP deviation measure is only weakly related to other previously studied factors, like the 7 Fung Hsieh risk factors.

To link these mispricings to hedge funds, I obtain hedge fund returns and other fund characteristics for the 1994-2014 sample period from the Lipper/TASS hedge fund database. To test my hypothesis, I form decile portfolios of these funds based on their sensitivity to CIP deviations over the past three years, rebalancing the portfolios on a monthly basis. I find that hedge funds whose past returns are weakly related to CIP deivations outperform hedge funds whose past returns are strongly related to CIP deviations by a large margin. In particular, the risk-adjusted return of a portfolio that is long the hedge fund portfolio with the weakest loading on CIP deviations and short the portfolio with the highest loading on CIP deviations has a risk-adjusted monthly excess return of 0.54% (t-stat of 2.46).

This result is the exact opposite of what is commonly expected of a priced risk factor: a *weaker* loading on CIP deviations gives *higher* excess returns. While this result would be puzzling for tradable assets like bonds or stocks it is less surprising for hedge funds. My finding suggests that it actually requires skill to avoid a loading on CIP deviations. In particular, hedge funds who are better capable of managing their funding risk, by having access to funding-unrelated alpha-generating strategies, show a lower return-sensitivity to CIP deviations and are therefore capable of earning higher excess returns. This result is in line with research by Titman and Tiu (2011) who find that hedge funds whose returns are only weakly related to common risk factors outperform hedge funds whose returns are strongly related to priced risk factors. Indeed, I find that hedge funds with a weak loading on CIP deviations also have a weaker loading other risk factors. In contrast to Titman and Tiu (2011), I find that avoiding one single risk, which is plausibly related to funding liquidity risk, improves hedge fund performance significantly.

In line with my theory, I also find that the difference portfolio which is long hedge funds with a weak loading on CIP deviations and short hedge funds with a strong loading on CIP deviations generates high excess returns and alphas during crisis periods and gives small and insignificant returns in normal times. My empirical finding is robust to a battery of robustness checks. First, considering different subsamples of the database, I obtain qualitatively similar results. Splitting the hedge fund sample into hedge funds that have currently suffered drawdawns and hedge funds that are currently performing at their high-water mark (HWM), I find that the effect is present in both subsamples, but more pronounced for funds that have recently suffered drawdowns. Splitting the sample into 3 different categories based on the hedge funds' investment style shows that the result holds across investment styles too. Finally, my result is also robust to several well-known biases in hedge fund return database, like backfilling bias, return-smoothing, and survivorship bias.

2 Related Literature

The theoretical part of my paper is related to two strands of literature. The first strand of literature focuses on the institutional frictions that (hedge)fund managers face. Managers can face withdraws precisely when they need cash the most (Shleifer and Vishny, 1997) and "the fragile nature of hedge fund equity" (Liu and Mello, 2011) makes them reluctant to invest in potentially profitable mispricings. I add to this literature by showing that the funding risk of the manager and his management thereof has important consequences for hedge fund returns. My model is closest to Lan et al. (2013), but other examples of incorporating the convex compensation and the manager's funding risk into manager's risk-return tradeoff are Goetzmann, Ingersoll, and Ross (2003), Basak, Pavlova, and Shapiro (2007), Pangeas and Westerfield (2009), Dai and Sundaresan (2011) ,Drechsler (2014), Christoffersen, Musto, and Yilmaz (2015), Sotes-Paladino and Zapatero (2015).

Second, my theory is also related to the literature on the limits of arbitrage and in particular to theories emphasizing that arbitrageurs need to collateralize their positions. These margin requirement limits their ability to profit from arbitrage opportunities (see Gromb and Vayanos, 2002; Liu and Longstaff, 2004; Brunnermeier and Pedersen, 2009; Gârleanu and Pedersen, 2011; Gromb and Vayanos, 2015, among many others). In my theory, this margin constraint is even more severe because margins can widen exactly when arbitrage spreads are highest.

The empirical part of my paper is related to the literature on the cross section of hedge fund returns. Hedge fund liquidity and hedge fund's loading on market liquidity has been studied by, among others, Aragon (2007), Sadka (2010), and Teo (2011). Aragon (2007) shows that hedge funds that impose stricter withdraw conditions for investors ("less liquid funds") outperform funds with more favorable investor redemptions. Sadka (2010) shows that hedge funds with a higher loading on market liquidity (proxied by the Sadka, 2006 liquidity factor) outperform hedge funds with a lower loading on market liquidity. Using a sub-sample of "liquid" hedge funds (funds that offer favorable redemption terms to their investors), Teo (2011) finds that a higher loading on market liquidity (as proxied by the Pastor and Stambaugh, 2003 liquidity factor) have higher risk-adjusted returns. Finally, Hu, Pan, and Wang (2013) construct a Noise measure, capturing mispricings in the US treasury market, and show that hedge funds with a higher loading on this Noise measure have higher excess returns than hedge funds with a lower loading on this noise measure.

My results are opposite to these findings. I find that a lower loading on my CIP mispricing measure provides higher excess returns. While this finding would be difficult to rationalize in the cross-section of stock returns (or other tradable assets) it is not that surprising for hedge funds, where a lower factor loading indicates managerial skill. It is important to note that I do not challenge the results by Sadka (2010), Teo (2011), and Hu et al. (2013). My theory suggests that if the risk factor is not strongly correlated with hedge fund funding risk, hedge funds with a higher loading on the risk factor are providing higher returns. It is only the link between the risk factor and the hedge funds' funding risk that requires hedge fund risk management skill. Empirically, it is important to note that my CIP deviation measure is almost uncorrelated to market liquidity and the Noise measure.

Finally, my project is also related to the literature examining hedge fund trading activity and risk taking. Abreu and Brunnermeier (2003) develop a theoretical model to rationalize that riding an asset pricing bubble instead of trading against it could be optimal. Brunnermeier and Nagel (2004) provide evidence that hedge funds did not trade against over-priced stocks during the dotcom bubble. My findings point in a similar direction, avoiding a mispricing instead of trading on it can be optimal. Mitchell and Pulvino (2012) emphasize that short-term financing through prime brokers was an issue for hedge funds during the financial crisis. Ang, Gorovyy, and Van Inwegen (2011) examine hedge fund leverage and show that it is counter-cyclical to the leverage of major dealer-brokers and decreased significantly during the financial crisis. Ben-David, Franzoni, and Moussawi (2012) provide empirical evidence that hedge funds significantly reduced their equity holdings during the crisis.

The remainder of this paper is organized as follows. In Section 3, I develop a theoretical model showing that avoiding an arbitrage opportunity could be optimal if it is related to funding risk. I describe the data and the construction of the CIP deviation measure in Section 4 and provide the empirical results in Section 5. Section 6 concludes.

3 An Illustrative Model

In this section, I develop a stylized model of a risk-averse hedge fund manager who can invest in a "true" alpha-generating strategy and a strategy that generates excess returns proportional to the state of funding liquidity in the market. The purpose of the model is to illustrate that if the expected excess returns of the second asset are related to the fund manager's funding risk, we obtain qualitatively different results than for static portfolios and lower loading on the funding-risky asset is associated with higher fund returns.

3.1 Model Setup

The Manager

A risk-averse hedge fund manager with logarithmic utility is maximizing his incomes from managing a fund. For simplicity, the income is just modelled as a constant fraction of fund wealth cW which is continuously paid to the manager, which implies that his utility function is given as $u(W) = \log(cW)$. To keep the focus on the manager's investment decisions and in order to obtain tractable, I do not incorporate other institutional details such as wealth outflows after poor performance and incentive-based compensation in the manager's decision.[2]

The Assets

The market consists of three different assets. First, a "true" α-generating strategy with

$$\frac{dS}{S} = (r + \alpha)dt + \xi dz_1. \tag{1}$$

This asset can be interpreted as a manger-specific skill. As argued by Rajan (2008), such a skill of generating α is rare and can be attributed to a managerial skill of identifying undervalued financial assets, engaging in shareholder activism, or being capable of employing financial entrepreneurship or engineering to outperform the market.The second asset is generating excess returns only in situations when funding conditions are tight. For instance, the expected return from this asset increases when there is a temporary deviation from the law

[2]As shown by Pangeas and Westerfield (2009), a high-water-mark compensation combined with the risk that the fund gets liquidated after poor performance leads a risk-neutral hedge fund manager to act as if he was risk-averse. Hence, assuming risk-aversion can be seen as reduced-form way to incorporate these institutional details.

of one price, which results in a spread between two almost identical assets.

$$\frac{dP}{P} = (r + \mu(L))dt + \sigma(L)dz_2. \tag{2}$$

The interpretation behind this asset is not that the manager directly engages in an arbitrage opportunity but rather that he takes advantage of a temporary market dislocation by providing scarce liquidity.

The variable L is a state variable capturing funding illiquidity in the market and following the process:

$$dL = \kappa(L)dt + \nu(L)dz_2,$$

where both processes are driven by the same source of uncertainty to ensure market completeness. The functions $\mu(.)$, $\sigma(.)$, $\kappa(.)$, and $\nu(.)$ are affine functions of L which will be specified later. For simplicity, I assume zero correlation between the two Brownian motions z_1 and z_2. This assumption is in line with the interpretation that returns from the $\alpha-$generating strategy are unrelated to liquidity conditions.

Finally, the manager can also invest in a risk-free asset with dynamics:

$$\frac{dB}{B} = rdt,$$

where r denotes the risk-free interest rate, which I assume to be a constant.

Constraints

The manager faces a margin constraint for investing in the risky assets, which depends on the state of funding illiquidity:

$$m|a| + n|b| \leq \rho(L), \tag{3}$$

where a and b are the fractions of wealth that the manager allocates to the two different assets, m and n are the margin requirements for investing in the first and second asset respectively, and $\rho(L)$ is function of L with $\rho(.) \in (0, 1]$, $\rho(0) = 1$. Note that the absolute values of a and b incorporate the intuition that both, long and short positions, in the risky assets require margin. The absolute value is necessary for two reasons. First, if $r + \mu(L)$ becomes negative, the manager optimally takes a short position in the second asset. Second, even though I assume α to be a positive constant, the absolute value of a is necessary to rule out situations in which the expected return of the second asset is so large that the manager would be willing to short the first asset in order to free margin capital. Allowing this way of freeing margin would be counter factual since both, long and short positions, require margin.

The key ingredient to my model is $\rho(L)$ which can change over time. If $\rho(L) \equiv 1$ the interpretation of Equation (3) is straightforward: The maximal position that the manager can take in the first (second) asset is $\frac{1}{m}$ $\left(\frac{1}{n}\right)$, assuming that he does not invest in the second (first) asset. If $\rho(L) = m$, the manager can only take an unlevered position in the first asset. For $\rho(L) < m$, the manager is not even able to sustain an unlevered position in the asset. One possible reason for allowing this situation is that the alpha-generating strategy could rely on derivatives positions and complex trades which might not be readily available when funding conditions deteriorate.

The point of the model is to illustrate that when $\rho(L)$ changes at exactly the same time when $|L|$ increases, a manager who is heavily invested in the second asset underperforms a manager who is only taking a small position the second asset. The underperformance occurs for two reasons. First, as $|L|$ increases, the trade went against the manager. Second, as funding conditions deteriorate, it might not be possible to earn the losses back again once $|L|$ converges back to its long-term average. This is because the manager needs to de-lever his portfolio. This aspect of the portfolio being actively managed is what distinguishes funding risk factors for hedge funds from risk factors for static portfolios.

3.2 Results

The manager's optimization problem can be characterized as:

$$\max_{a,b,\psi} \mathbb{E}_t \left[\int_t^{\infty} \left(e^{-\rho(s-t)} u(W_s) - \psi(m|a| + n|b| - \rho(L)) \right) ds \right],$$

where the dynamics of wealth are given as:

$$\begin{aligned} dW &= \left(a\frac{dS}{S} + b\frac{dP}{P} + (1-a-b)\frac{dB}{B} - c \right) W \\ &= \left(a\alpha + b\mu(L) + r - c \right) W dt + a\xi W dz_1 + b\sigma(L) W dz_2 \end{aligned}$$

and ψ is chosen such that the manager behaves as if he was unconstrained. I next derive the manager's Hamilton-Jacobi Bellman equation as:

$$0 = \max_{a,b,\psi} \Bigg[u(W) - \psi(m|a| + n|b| - f(L)) - \rho J + \left(a\alpha + b\mu(L) + r - c \right) W J_W + \\ \left(\frac{1}{2}\xi^2 a^2 + \frac{1}{2}\sigma(L)^2 b^2 \right) W^2 J_{WW} + \kappa(L) J_L + \frac{1}{2}\nu(L)^2 J_{LL} + J_{LW} b\sigma(L)\nu(L) W \Bigg],$$

where I guess (and verify in the appendix) that the indirect utility function takes the form

$$J = \frac{1}{\rho} \log(cW) + H(L), \tag{4}$$

where $H(L)$ is a quadratic function of L, specified in the appendix. Under this guess, the manager's optimal allocation to the two risky assets is given as the solution to a myopic mean-variance optimization problem.

Proposition 1. *Define the following variable:*

$$\Psi = \frac{ma^u + n|b^u| - f(L)}{\frac{m^2}{\xi^2} + \frac{n^2}{\sigma^2}} \tag{5}$$

1. *If $\Psi \leq 0$, the manager's margin constraint is not binding and he takes the following positions a^u and b^u in the first and second asset respectively:*

$$a^u = \frac{\alpha}{\xi^2} \text{ and } b^u = \frac{\mu(L)}{\sigma^2} \tag{6}$$

2. *If $\Psi > 0$ and $b^u > 0$, the manager takes the following positions a and b in the first and second asset respectively:*

$$a = \max\left(a^u - m\frac{\Psi}{\xi^2}, 0\right) \text{ and } b = b^u - n\frac{\Psi}{\sigma^2}, \tag{7}$$

3. *If $\Psi > 0$ and $b^u < 0$, the manager takes the following positions a and b in the first and second asset respectively:*

$$a = \max\left(a^u - m\frac{\Psi}{\xi^2}, 0\right) \text{ and } b = b^u + n\frac{\Psi}{\sigma^2}, \tag{8}$$

4. *If $\Psi > 0$ and $b^u = 0$, the manager takes the manager does not invest in the second asset and invests the maximal position of $\frac{\rho(L)}{m}$ in the first asset.*

The results of Proposition 1 can be interpreted as follows. First, without binding margin constraints, the alpha of the first asset has no effect on the manager's optimal holding of the funding-risky asset. When margin constraints are binding, the amount invested in the funding risky asset decreases as the alpha of the first asset increases. Finally, it is worth noting that the manager would under no circumstances short the first asses since this would lower his expected returns and would not alleviate the binding margin constraint.

3.3 Illustration of the Main Result

To illustrate the properties of the optimal trading strategy, I choose the following baseline parameters. I use a time horizon T of one year, a risk-free rate $r = 2\%$, which I set equal to the manager's compensation c. Furthermore, I assume that the alpha-generating strategy has a standard deviation of 0.2 and a good manager can extract $\alpha = 0.05$ from the strategy while a bad manager can extract 0.01. Both assets have a margin requirement of $m = n = 0.25$. The state variable follows a Vasicek process with mean-reversion speed $\kappa(L) = -L$, long-term mean-reversion level zero, and drift $\nu(L) = L$. The second asset has a drift $\mu(L) = -\lambda L$ with $\lambda = 0.1$ and volatility $\sigma(L) = 0.5$. The funding function is given as $\rho(L) = e^{-L^2}$.

Figure 1 illustrates the optimal asset holdings of the two managers. As we can see from the figure, there are three different regions. First, as long as the managers are unconstrained they take identical positions in the funding-risky asset. Second, once margin constraints become binding, the good manager invests less in the liquidity asset than the bad manager. The intuition behind this observation is that the good manager allocates more of his wealth to the alpha-generating strategy than the bad manager. Third, as L increases even further, such that the expected returns of the liquidity asset increase above a certain threshold, both managers, again, take a similar position in the liquidity asset. Note, however, that due to the poor market conditions the investment in the liquidity asset is relatively small.

Turning next to the returns of hedge fund investors over the one-year horizon, I simulate the returns generated by the two different managers. To do so, I discretize the one-year period into 10.000 time steps and simulate 10.000 sample paths of returns. Figure 2 compares the returns generated by the two managers. As we can see from Panel (a), the returns of the bad manager are left-skewed with a small positive mean. This result is in line with the common wisdom that liquidity provision can be seen as "picking up nickels in front of a steamroller." In contrast to that, the returns of the good manager exhibit a higher standard deviation, but also a higher mean and Sharpe ratio. In particular the returns generated by the good manager are right-skewed, indicating that there are situations where the manager can generate significant excess returns for his investors.

4 The Data

4.1 Hedge Fund Data

The data for my analysis comes from the May 2016 version of the Lipper TASS hedge fund database. Hedge funds report voluntarily to this database and one concern with these self-reported returns is survivorship bias because poorly performing funds drop out of the database. To mitigate this concern, I use both, live hedge funds (which are still reporting to TASS as of the latest download) and graveyard funds (which stopped reporting). Since the graveyard database was only established in 1994, I focus my analysis on the 1994-2014 period. Following the literature on hedge funds (see, for instance, Cao, Chen, Liang, and Lo, 2013, Hu et al., 2013, among others), I apply three filters to the database. First, I require funds to report returns net of fees on a monthly basis. Second, I drop hedge funds with average AUM below 10 Mio USD. For funds that do not report in USD, I use the appropriate exchange rate to convert AUM into USD equivalents.[3] Third, I require that each fund in my sample reports at least 24 monthly returns during my sample period.

Table 1 provides summary statistics for all hedge funds in my sample. For variables that change over time, I first compute the time-series average and then report cross-sectional summary statistics in the table. As we can see from the first two rows of the table, the average fund in the database reports a positive return of 0.51% per month with a standard deviation of 3.27. On average, funds have 147.46 million US dollar in AUM, ranging from the minimum of 10 million up to 7797.83 million. The average fund in the database reports 90 monthly returns and is 47 months old. TASS also provides information on when a hedge fund started reporting to the database, which enables me to compute the percentage of backfilled returns, which is on average 43.48% with a high standard deviation of 31.35% across funds. In my main analysis I include backfilled return observation, but I show in a robustness check that my results are robust to excluding these observations.

The next two variables give an indication of funds' risk of withdraws. First, the average lockup provision of hedge funds in my sample is 2.8 months. It is worth noting that more than half of the funds in the database do not have any lockup provision and that the high median is driven by few outliers with extreme lockup provisions. Second, the funds' redemption notice period varies across funds from 0 to 365 days, with an average of 36.1 days. Finally, median management and incentive fee of funds in my sample are 1.5% and 20%, which is in line with the often-mentioned 2/20 rule, stating that hedge-fund managers earn a 2% base compensation and a 20% incentive-based compensation. Furthermore, 61.49% of the funds in my sample have a HWM provision and 22.55% of the managers invest their personal capital in the fund.

Table 2 summarizes average hedge fund returns for the different styles and years in my sample. As we can see from Panel A, average returns range from 0.79% per month for long-short equity to 0.23 for funds of funds. In total, there are 3.029 funds of funds in my sample. I run my main analysis using all 8.384 funds and show later that my results are

[3]Following, Cao et al. (2013), I use the returns reported in the original currency in my analysis. Adjusting returns into USD leaves the inference unchanged.

robust to splitting the sample into hedge funds and funds of funds. The second-largest style in my sample are hedge funds using long/short equity strategies with 1958 funds, followed the event-driven style with 536 funds and multi-strategy with 524 funds.

Panel B of Table 2 shows average hedge fund returns per year. As we can see from the table, 2008 and 2011 have been bad years for the average hedge fund in the sample with negative average monthly returns of -1.50% in 2008 and -0.44% in 2011. It is important to note that, although the total number of hedge funds is 8.384, the amount of hedge funds varies significantly over time from a minimum of 711 in 1994 to 5.720 in 2009. Hence, splitting the overall sample of hedge funds into different subcategories can result in a relatively small sample during some years. Later, in my analysis, I account for this observation by sorting hedge funds into quintiles instead of deciles to insure a sufficient amount of funds per portfolio.

4.2 Deviations from the Covered Interest Rate Parity

In this section, I construct a measure of mispricings in international money markets which can be linked to major derivatives-dealing banks' funding constraints.

The first criterion for constructing my measure is that the data should go back until January 1994, which is the start date of my hedge fund panel data. This criterion rules out several potentially interesting mispricings, such as the CDS-bond basis (Bai and Collin-Dufresne, 2013), the CDS-index basis (Junge and Trolle, 2014), or the TIPS-treasury arbitrage (Fleckenstein, Longstaff, and Lustig, 2014). A second criterion is that it should be a broad mispricing which is not specific to a particular security and instutional frictions, like the on-the-run off-the-run spread (Krishnamurthy, 2002). Instead, the idea is to capture similar mispricings across a variety of different assets and quantify a systemic component.

The mispricing that I use in my analysis are deviations from the covered interest rate parity (CIP). The idea behind CIP is that investing one unit of currency A at time t in a money-market account with interest rate $r^A(t,T)$ should yield the same return as exchanging this one unit of currency A into currency B, putting that money into a money-market account with interest rate $r^B(t,T)$, and entering a forward agreement to exchange the cashflow back into currency A, which hedges the currency risk of the transaction. Let $fwd_{A/B}(t,T)$ denote the forward exchange rate from currency A to currency B at time t with maturity T. The CIP then implies that the theoretical forward rate is given as:

$$fwd^*_{A/B}(t,T) := FX_{A/B}(t)\left(\frac{1+r^A(t,T)}{1+r^B(t,T)}\right), \qquad (9)$$

where $FX_{A/B}(t)$ denotes the spot exchange rate from currency A to currency B and $r^A(t,T)$ and $r^B(t,T)$ denote the interest rate received from time t to time T in currency A and B respectively.

The advantage of using CIP deviations is that they provide a simple and model-free proxy of market dislocations. Furthermore, as noted by Pasquariello (2014), CIP deviations capture a dislocation in international money markets. These dislocations are likely to be linked to hedge fund funding conditions, since deviations typically occur when major banks experience funding constraints.[4] These funding constraints are typically passed on to customers, either directly in form of higher margin requirements or indirectly in the form of more adverse derivatives prices, if customers obtain leverage indirectly through derivatives.

There are a large number of possible ways to aggregate CIP deviations across different currencies and maturities into one measure. To mitigate data-mining concerns, I choose to construct an index of international money market "dislocations", closely following the procedure outlined in Pasquariello (2014). In particular, I measure CIP deviations for the following nine currency pairs: CHF/USD, GBP/USD, EUR/USD, JPY/USD, CHF/EUR, GBP/EUR, JPY/EUR, CHF/GBP, JPY/GBP, using spot rates and forward rates with 7, 30, 60, 90, 180, 270, and 360 days to maturity. I use Libor rates with the same maturity as the forward rates as a proxy for the risk-free rate in the respective currency. All data for constructing CIP deviations are obtained from the Bloomberg system. As in Pasquariello (2014), for each currency and each maturity, I then compute the deviation from the CIP as:

$$CIP_{i,t}^{D} = \left|\ln(Fwd_{A/B}(t,T)) - \ln(Fwd_{A/B}^{*}(t,T))\right| \times 10^4. \tag{10}$$

This procedure gives 7 different proxies for mispricings in each of the 9 different currency pairs studied, resulting in 63 different mispricings, which are aggregated into one index:

$$CIP_t^D = \frac{1}{n_t}\sum_{i=1}^{n_t} CIP_{i,t}, \tag{11}$$

where n_t is the number of available mispricings at time t.[5]

While measuring CIP deviations is relatively straight-forward, there are several issues with actually implementing the strategy. As noted by Pasquariello (2014) two issues are trading costs and funding costs. Trading costs occur because the CIP deviation measure

[4]For instance, Bottazzi, Luque, Pascoa, and Sundaresan (2012) and Ivashina, Scharfstein, and Stein (2015) argue that deviations from CIP can be driven by a dollar shortage of banks with international borrowing and lending.

[5]Note that the index becomes richer as time passes. Most notably, exchange rates involving the Euro are only available from 1999 onwards.

is not adjusted for bid-ask spreads. Funding costs occur, because the rate at which an arbitrageur can fund a position is likely above the Libor rate, which is the interest rate at which a bank with good credit quality can obtain funding. Furthermore, using Libor as a proxy for the risk-free rate leads to several problems. Libor is an unfunded lending rate, possibly containing a credit-risk component. To avoid picking up a large credit risk component, the index is constructed focusing on five of the safest and most liquid currencies.[6] An additional issue with Libor is that the rates are potentially downward-biased due to misreporting.

Overall, my measure of CIP deviations is likely to overestimate the tradable dislocations in international money markets. Nevertheless, given that I use a large panel of 63 currency-maturity pairs in the most liquid currencies, an increase in my index of CIP deviations captures a market-wide dislocation that should not exist in a frictionless world. Hence, an increase in CIP^D indicates a situation where hedge funds can earn a premium for providing liquidity. However, since increases in CIP^D are also related to major banks' funding constraints, providing liquidity is risky because CIP^D can increase even further and, additionally to that, hedge funds can face a cut in their funding exactly when premiums are highest.

Properties of CIP^D

Figure 3 shows the time series of monthly month-end CIP_t^D, illustrating that the measure spikes during crisis episodes.[7] The first spike of the measure occurs in September 1998, the month when Long-Term Capital Management (LTCM) was bailed out. Afterwards, the measure starts spiking again at the onset of the financial crisis, showing a small increase during the Quant crisis in August 2007 and a larger spike during the bailout of Bear Stearns in March 2008. Not surprisingly, the measure peaks in September 2008, the month when Lehman brothers went bankrupt. Another major spike of the measure occurs during the European debt crisis in Autumn 2011. The measure increases sharply in August 2011, when the discussion about the US debt ceiling escalated. Shortly after this event, France and the United States lost their tiple-A rating by the rating agency Standard and Poors. These events mark the onset of the European debt crisis. The measure converges back to a lower level after Mario Draghi's speech in July 2012 where he declared that "within our mandate,

[6]Note that Libor rates in all five currencies are determined by the same mechanism, using a similar panel of banks. All Libor rates are reported at the same time of day (11:45 am, London time). An alternative would be using overnight swap (OIS) rates instead of Libor rates. The drawback with this approach is that OIS rates do not go back until 1994.

[7]One difference between my analysis and the analysis in Pasquariello (2014) is that my goal is to relate CIP deviations to hedge fund returns. Hence, I construct my measure using month-end data only.

the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough."[8]

I study the relationship between ΔCIP_t^D and other commonly used proxies of market uncertainty and funding illiquidity in Table 3. Changes in CIP_t^D are strongly related to changes in the TED spread, which is the difference between the 3-month US Libor rate and the 3-month US treasury yield and a common proxy for market liquidity, as well as to changes in the VIX index, which is the implied volatility of the S&P 500 and a common measure of market uncertainty.

4.3 Hedge Fund Risk Factors and their Relation to CIP^D

I now describe the seven most commonly used hedge fund risk factors, which were proposed by Fung and Hsieh (2004) and investigate their relationship to ΔCIP_t afterwards. The first two factors are related to stock markets, capturing US stock market excess returns (MKT) and the returns from a small-minus big portfolio (SMB). I use the first two Fama-French factors, obtained from Kenneth French's website, to proxy for these two factors. Furthermore, Fung and Hsieh (2001) suggest the monthly change in the ten-year US treasury constant maturity yield (YLD) and the monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAA) as risk factors capturing interest-rate risk and credit risk. I obtain data for these two factors from the Bloomberg system. Finally, Fung and Hsieh also propose three trend-following factors one for bonds (BD), one for currencies (FX), and one commodities (COM), which are obtained from David Hsiesh's website.[9]

Table 3 shows the correlation between changes in CIP deviations and the seven hedge fund risk factors. As we can see, the correlation is generally low. Only the correlation between YLD and BAA, as well as the correlation between FX and COM is above 30%. The correlation between ΔCIP_t^D and the other seven factors is weaker than 15%, indicating that CIP deviations are not captured by the other factors.

Sadka (2010) points out that YLD and BAA are not capturing excess returns and are therefore not suitable to compute risk-adjusted hedge fund returns. I therefore follow Sadka (2010) and replace these two factors with tradable factors in my performance analysis in the following section. In particular, I obtain the Merril Lynch treasury bond index with 7-10 years to maturity and the a corporate bond index of BBB-rated bonds with 7-10 years to maturity from the Bloomberg system. I compute the returns on both indices and use excess return of the treasury bond index over the one-month treasury bill rate as a tradable

[8] See `https://www.ecb.europa.eu/press/key/date/2012/html/sp120726.en.html` for a verbatim of the speech.

[9] These factors are available under: `https://faculty.fuqua.duke.edu/~dah7/HFData.htm`

proxy for the YLD factor. The two variables have a correlation of -69%. Similarly, I use the difference between the returns from the BBB-rated corporate bond index and the treasury bond index as a proxy for the BAA factor. The correlation between these two variables is -76%. In the following I replace YLD and BAA with the two tradable factors to compute risk-adjusted returns.

5 Results

Methodology

To test my hypothesis that hedge funds following funding-risky strategies can severely underperform hedge funds who do not rely on funding-risky strategies to generate their returns, I sort hedge funds into deciles based on their loading on CIP_t^D. Every month, for each fund i, I run a regression of hedge fund excess returns over the past 36 months on ΔCIP^D, controlling for excess returns of the (stock) market portfolio:[10]

$$R_{t,i}^{Exc} = \alpha + \beta^{CIP} \Delta CIP_t^D + \beta^{Mkt} R_t^{Mkt} + \varepsilon_t. \tag{12}$$

Based on β^{CIP}, I then put each hedge fund in one decile portfolio, where funds in the first portfolio have the most negative β^{CIP} while funds in the last portfolio have the highest β^{CIP}. The decile portfolios are rebalanced every month, repeating the sorting procedure. The first portfolio has the strongest loading on ΔCIP_t^D, while portfolio 10 has the weakest loading. Note that a strong loading on ΔCIP_t^D corresponds to a significant negative beta since increases in deviations from the CIP correspond lower returns for hedge funds following these strategies while a weak loading corresponds to an insignificant beta close to zero.

Main Results

I illustrate the results from this sorting procedure graphically in Figure 4, where I plot the monthly risk-adjusted returns of the 10 portfolios, controlling for the risk factors proposed by Fung and Hsieh (2004). As we can see, funds in portfolio 10, which have the weakest loading on CIP deviations have a monthly risk-adjusted return of 0.46%, which corresponds to an annual alpha of 5.52%. Strikingly, funds with a weak loading are outperforming funds with a strong loading on ΔCIP_t^D by more than 0.46% per month. Furthermore, the red

[10] Controlling only for returns of the market portfolio in the first step has been common practice in the literature (see Sadka, 2010, Hu et al., 2013 for hedge funds, or Ang, Hodrick, Xing, and Zhang, 2006, among many others, for stocks). In unreported robustness checks, I also experimented with controlling for the other six Fung Hsieh risk factors as well as with only using the past 24 months of observations, which both led to qualitatively similar results.

dots in the figure show Newey-West t-statistics of the respective portfolios and indicate that the results are not only economically but also statistically significant. The risk-adjusted return of the low-loading portfolio is significant at a 1% level with a t-statistic of 3.5 and the risk-adjusted return of the difference portfolio that is long the low-loading decile and short the high-loading decile is significant at a 5% level with a t-statistic of 2.18%.

More detailed results with the exact parameter estimates are reported in Table 5. I emphasize the following three observations from Table 5. First, excess returns of the hedge funds in the different deciles increase almost monotonically as the loading on ΔCIP^D weakens. However, the difference between top and bottom decile is not statistically significant. Second, the post-ranking betas of the 10 portfolios are increasing almost monotonically, even after controlling for the 7 Fung-Hsieh risk factors. The difference portfolio also has a statistically significant loading on ΔCIP^D (t-statistic of 1.95). This relatively small difference in post-sorting betas can be attributed to controlling for the 7 other risk factors. In an unreported robustness check, I also computed the post-sorting betas only controlling for the return on the market portfolio, which gave a β^{CIP} of 0.16 for the difference portfolio (t-statistic of 3.29). Third, the explanatory power of CIP_t^D and the other risk factors decreases almost monotonically from top to bottom portfolio as well. One possible explanation for this observation is that fund managers who are able to avoid loading on CIP_t^D are also better in avoiding other common risk factors. In that sense, my finding is related to Titman and Tiu (2011) who show that hedge funds with low loading on known risk factors outperform funds with high loadings.

A Closer Look at the Time Series

To get a better understanding of the decile excess returns, Figure 5 plots the time series of cumulative excess returns of the top and bottom decile. As we can see, the returns from the top decile (strong loading on CIP_t^D) are more volatile and generally lower than those of the low loading decile. More specifically, the high-loading portfolio suffers large losses around the LTCM crisis in 1998, around the default of Lehman brothers in 2008, and during the European debt crisis in 2011/2012. In contrast to that, the low-loading portfolio provides stable returns during crisis periods, with moderate losses during the 2008 crisis. Hence, Figure 5 indicates that the high risk-adjusted returns from funds with a weak loading on CIP deviations are mainly earned during crisis periods and that the high difference between funds with a strong and a weak loading mainly come from episodes of financial distress.

To provide some more formal evidence for this results, I split my sample into periods of crisis and normal times. First, I simply use anecdotal evidence about crisis periods, thereby identifying 18 months which are plausibly periods with severe funding constraints for hedge fund managers. The crisis periods are are August-September 1998 (the period of the Russian debt crisis and the LTCM bailout), August-October 2007 (the months of the quant crisis), August 2008 - January 2009 (the time around the default of Lehman brothers), August - December 2011 (the first part of the European debt crisis), and April - May 2012 (the second part of the European debt crisis). As we can see from Panel (I) of Table 6, monthly excess returns of the difference portfolio that is long hedge funds with a weak loading on ΔCIP_t^D (bottom decile) and short hedge funds with a strong loading on ΔCIP_t^D (top decile) during crisis periods are 3.23% which are statistically significant at a 1% level. Similarly risk-adjusted returns of the difference portfolio are 1.89% and also highly statistically significant. In contrast, the returns and risk-adjusted returns of the difference portfolio are insignificant during normal periods.

To test the difference between crisis and non-crisis episodes more formally, I follow Teo (2011) and split the sample period based on the level of the TED spread and define crisis periods as episodes where the TED spread is above its 80% quantile and non-crisis periods as episodes where the TED spread is below its 20% quantile. The results are qualitatively similar to (I), indicating that the difference portfolio is delivering statistically significant returns during times of financial distress, but insignificant returns during quiet times. Similarly, I split the sample period into times where average stock returns of the 16 largest dealer banks are below their 20% quantile (crisis episodes) and episodes where returns are above their 80% quantile. For this split, the results are qualitatively similar but less significant.[11]

Finally, I provide an overview of the characteristics of the funds in the different decile portfolios in Table 7. As we can see from the table, funds in the top and bottom decile have very similar characteristics, while there is a tendency for funds in portfolios 4-6 to have slightly different characteristics and a different allocation between styles. Most notably, portfolios 3-7 consist of almost 50% funds of funds while top and bottom portfolio only consist of 11% funds of funds. I formally test whether different characteristics can be responsible for my finding in Section 5.2, where I run Fama and MacBeth (1973) regressions, controlling for fund characteristics like lockup provision and assets under management as well as hedge fund style.

5.1 Results For Different Subsamples

To shed further light on my findings, I now split the entire hedge fund sample that I have used so far into various different subsamples and repeat my analysis. To ensure a sufficient number of funds in each quantile, I follow Teo (2011) and only form quintile portfolios.

[11] One possible explanation is that stock returns do not capture dealer-banks constraints appropriately. In the next version of this paper I plan on using EDF data to quantify periods of financial distress.

Fund-Specific Funding Risk

To investigate the role of hedge fund specific funding risk, I perform the following three tests. First, I split the sample into hedge funds that are currently performing at their HWM and funds that are currently under water. The idea behind this split is that hedge funds that have suffered drawdowns are facing an additional risk of getting their funding cut by their prime broker. To approximate drawdowns from the HWM, I use the ratio X between current NAV of the fund and maximium NAV over the history of the fund. Every month t, I then split the sample into one part that is currently at its HWM, where $X_{t-1} = 1$, and one part that has suffered drawdowns $X_{t-1} < 1$. I rebalance the two portfolios on a monthly basis. Panels (a) and (b) of Figure 6 illustrate the results. As we can see from the figure, hedge funds that are currently at their HWM generally outperform hedge funds that suffered drawdowns by a large margin.In both sub-samples, hedge funds with a high loading on CIP^D underperform funds with a low loading. However, the difference is smaller and less significant for funds that did not suffer drawdowns. In particular the difference portfolio that is long hedge funds with a weak loading and short hedge funds with a strong loading generates a monthly alpha of 0.3% for funds that did not suffer drawdowns while it generates a monthly alpha of 0.4% for funds that did suffer drawdowns.

Second, I use the hedge fund redemption notice period as a fund-specific proxy for funding liquidity. Hedge funds with longer redemption notice periods are less susceptible for equity withdraws in times of financial distress than funds with shorter redemption notice periods. Even thought this is a proxy for the equity part of the balance sheet, funding obtained from prime brokers can be related to equity withdraws. In line with Aragon (2007), Panels (c) and (d) of Figure 6 show that hedge funds with longer redemption notice periods tend to outperform funds with shorter redemption notice periods. Additional to that, we can see from the two figures that the effect is less pronounced for funds with longer redemption notice periods. In particular, the difference portfolio that is long hedge funds a weak loading on CIP deviations and short funds with a strong loading on CIP deviations generates a monthly alpha of 0.3% for funds with longer redemption notice periods and an alpha of 0.4% for funds with shorter redemption notice periods.

Third, I divide the sample into funds with lockup provision and funds without lockup provision. Again, this is a proxy for the equity side of funding risk. The results of this split are exhibited in panels (e) and (f) of Figure 6. As before, funds with longer lockup periods are generally performing better than funds with shorter lockup periods and the effect is more pronounced for funds without lockup provision. The difference portfolio for funds with lockup provision generates a monthly alpha of 0.22% while the difference portfolio for funds without lockup provision generates a monthly alpha of 0.38%.

Different Hedge Fund Styles

I next address the question of whether my results hold for funds with different investment styles. To that end, I split my sample into three different style categories, funds of funds (total of 3017 funds), long/short equity (total of 1953 funds), and funds from the remaining categories (total of 3395 funds). Panels (a), (b), and (c) of Figure 7 illustrate the results and show that the results are qualitatively similar for different styles. Panel (a) shows that funds of funds with a high loading on CIP^D are doing exceptionally poor compared to funds with a high loading on CIP^D in the other categories. One possible explanation for this observation is that funds of funds load indirectly on CIP^D by investing in hedge funds who load on it. When funding becomes scarce, their investments underperform and they face funding constraints of their own which amplifies the mechanism. For long/short equity funds the results is weakest.

5.2 Robustness Checks

In this section, I present the results from running Fama and MacBeth (1973) regressions, where I control for several fund characteristics. I repeat this analysis for three modifications of the database to address common issues with hedge fund data. First, to run Fama-MacBeth regressions, I compute the alpha of each hedge fund, using the following equation:

$$\begin{aligned}\alpha_{i,t} = R_{i,t}^{Exc} - (&\beta_i^{Mkt} R_t^{Mkt} + \beta_i^{SMB} R_t^{SMB} + \beta_i^{YLD} R_t^{YLD} + \beta_i^{BAA} R_t^{BAA} \\ &+ \beta_i^{BD} R_t^{BD} + \beta_i^{FX} R_t^{FX} + \beta_i^{COM} R_t^{COM}),\end{aligned} \tag{13}$$

where fund-specific betas are computed using the entire time series of hedge fund returns. I then follow the common practice (see, e.g. Klebanov (2008) or Hu et al. (2013)) and assign portfolio β^{CIP} for the regression. In particular, a fund that is in portfolio i at time t and in portfolio j at time $t+1$ gets β^{CIP} of portfolio i at time t and β^{CIP} of portfolio j at time $t+1$. I then run the following regression:

$$\alpha_{i,t} = \gamma_0 + \gamma_1 \beta_{i,t-1}^{CIP} + \gamma_2 Controls_i + \varepsilon \tag{14}$$

The results of this regression without control variables are exhibited in the first row of Table 8. As we can see, the loading on CIP deviations is statistically significant in explaining the cross-section of hedge fund returns. As a second step I control for the hedge fund's age, size (proxied by the logarithm of its assets under management), its redemption frequency, the redemption notice period, the lockup period, and its style (by adding style dummies). The effect of β^{CIP} is still statistically significant at a 5% level after adding these control variables.

Biases in Reported Hedge Fund Data

As a next step, I address the most common biases in hedge fund data. As mentioned in Section 4.1, hedge funds report their returns voluntarily to the Tass database. Fung and Hsieh (2000) explain that there are several biases in these self-reported data. The first concern, which is survivorship bias, can be mitigated by using both, hedge funds that are currently reporting to the database and funds that have stopped reporting to the database (which I do in my analysis). The second concern is selection bias, meaning that funds only report to the database if their returns are high. This concern is more difficult to address, but Fung and Hsieh (2001) argue that this concern is least relevant for funds of funds. Hence, Panel (c) of Figure 7 mitigates this concern. Another concern described by Fung and Hsieh (2001) is backfilling bias. A fund that starts reporting to the database can also report historical returns. Clearly, only funds with high past returns would do that which biases returns upwards.

Hence, the first main issue with the data is a selection bias. As explained in Section 4.1, the Tass database provides the date at which a fund started reporting to the database. To check if my results are robust to backfilled bias, I drop all backfilled observations. As illustrated in Table 1, on average 43% of hedge fund returns are backfilled. Repeating the analysis without backfilled returns leads to significantly lower alphas but qualitatively similar results. For brevity, I only report the results from a Fama-MacBeth regression where I drop backfilled observations.[12] The results of this analysis are presented in the third row of Table 8. While the size of the intercept drops sharply, the coefficient for β^{CIP} decreases from 4.2 to 3.8 and is still statistically significant at a 5% level.

Another concern about hedge fund data is return smoothing. Hedge funds holding illiquid securities might report returns with a lag (see Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004)). Getmansky et al. (2004) propose an econometric technique to un-smooth hedge fund returns. I use their technique to obtain un-smoothed returns R_t by estimating the following model:

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}, \tag{15}$$

where R_t^0 is the observed hedge fund return at time t and $\sum_{i=0}^{2} \theta_i = 1$. I then repeat my analysis using un-smoothed returns and report the results in the fourth row of Table 8. As we can see from the table, β^{CIP} is still statistically significant at a 5% level for this specification.

Finally, the voluntary nature of reporting hedge fund returns can also cause hedge funds with poor past performance to stop reporting to the database. To address this concern, I

[12] Regression results for top, bottom, and difference portfolio will be reported in an online appendix...

replace the last reported return of each hedge fund in the database with -20%.[13] The results of this robustness check are reported in the final row of Table 8. As we can see from this row, β^{CIP} is still significant at a 5% level and the size of the coefficient is almost unchanged, compared to the base case.

6 Conclusion

I develop a theory in which a hedge fund manager can invest in an arbitrage position and an alpha-generating strategy. If the arbitrage spread is strongly correlated with the manager's own funding risk, it is optimal to avoid loading on the arbitrage mispricing. To confirm this theory, I construct a measure of mispricings in international money markets and show that this measure is highly correlated to other proxies of funding liquidity. In line with my theory, I find that hedge funds with a *lower* loading on these mispricings outperform funds with a higher loading.

[13] The inference for β^{CIP} remains unchanged if I use more negative numbers like -50%.

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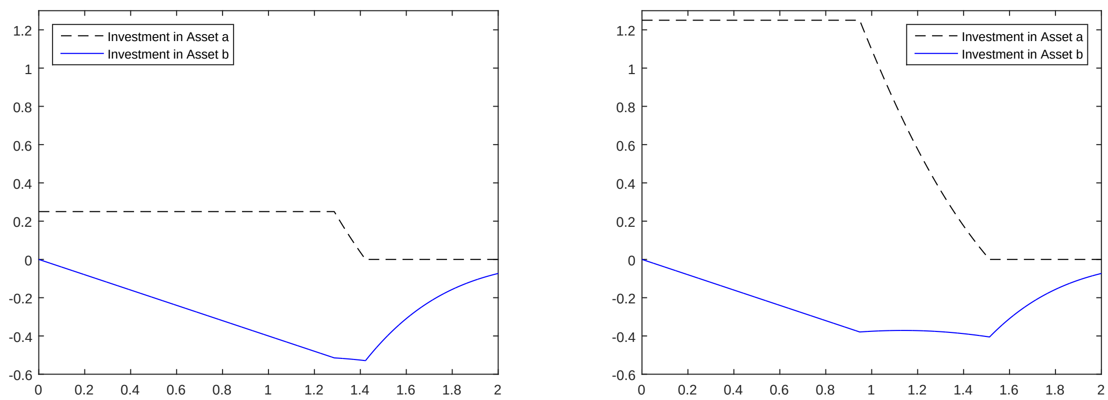
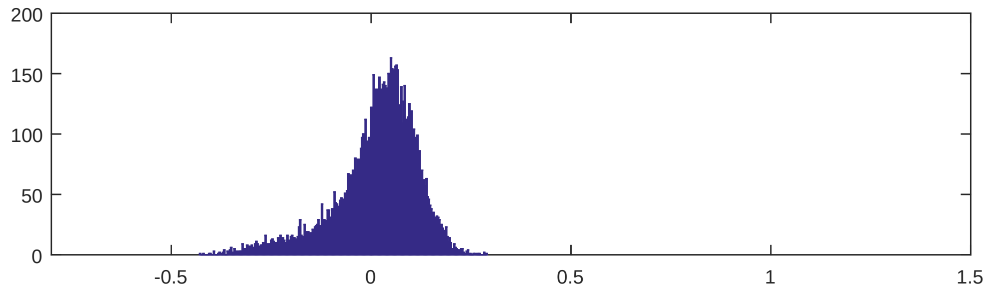
Figures and Tables

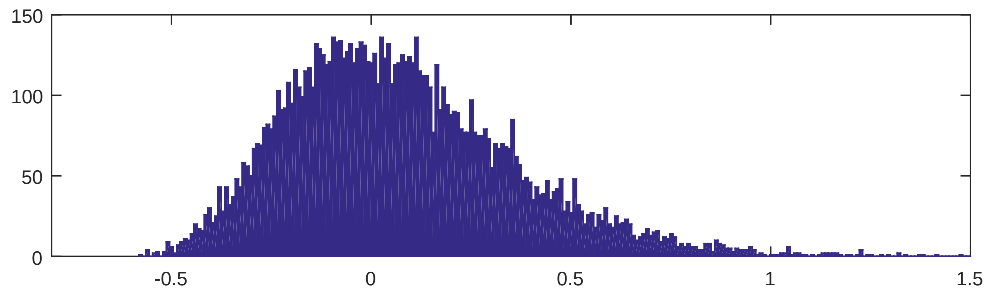


(a) Low-skill manager (b) High-skill manager

Figure 1: **Optimal risky asset holdings of different managers.** This figure shows the optimal investments in the alpha-generating strategy (asset a) and the funding-risky strategy (asset b) of a manager with low skill and high skill. The model parameters are $r = 0.02$, $c = 0.02$, $L_0 = 0$, $\kappa(L) = -L$, $\nu(L) = 1$, $m = n = 0.25$, $\mu(L) = -0.1L$, $\sigma(L) = 0.5$, and $\rho(L) = e^{-L^2}$.



(a) Low-skill manager



(b) High-skill manager

Figure 2: **Distribution of returns from following the optimal strategy.** This figure shows the distribution of returns that a hedge fund manager, following the optimal strategy, can generate. The model parameters are $r = 0.02$, $c = 0.02$, $L_0 = 0$, $\kappa(L) = -L$, $\nu(L) = 1$, $m = n = 0.25$, $\mu(L) = -0.1L$, $\sigma(L) = 0.5$, and $\rho(L) = e^{-L^2}$. Return distributions are obtained using 10.000 simulations, discretizing the one-year horizon using 10.000 points in time.

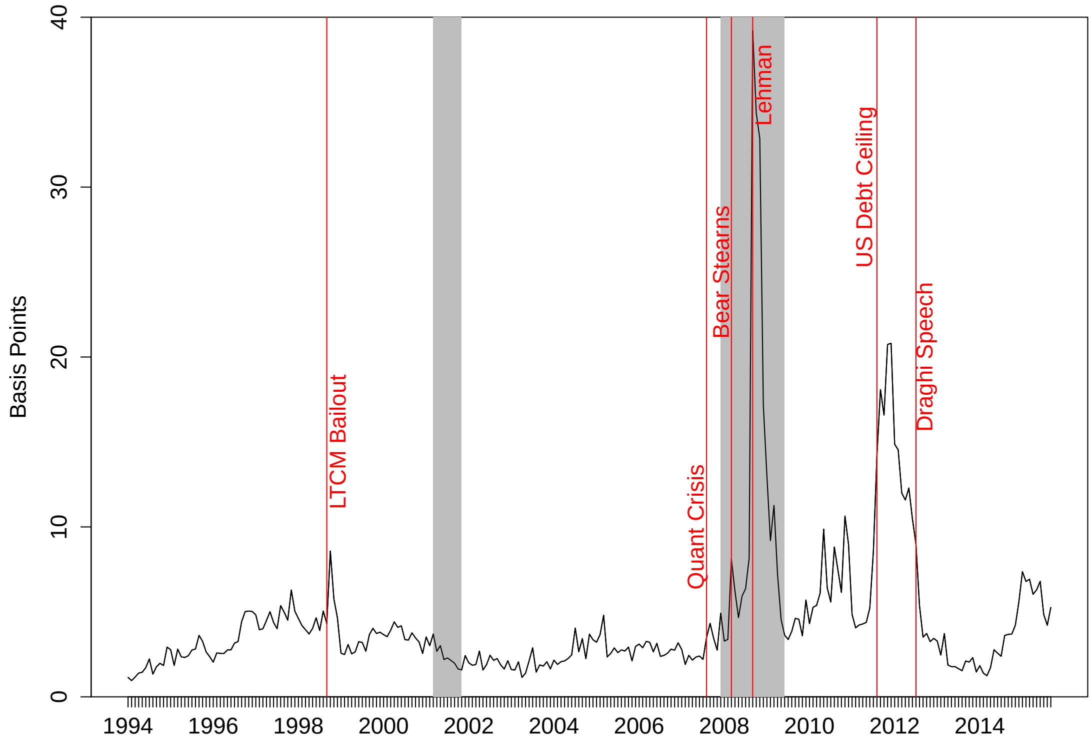


Figure 3: **Time Series of the Covered-Interest Rate Parity (CIP) Deviation Index.** This figure shows the time series of the CIP deviation index. The index is constructed as equal-weighted average of 9 different currency pairs of developed economies with 7 different maturities, ranging from one week to one year. The index construction is based on Equations (9)–(11), all observations are month-end. The highlighted events (red vertical lines) are the bailout of Long-Term Capital Management in September 1998, the quant crisis in August 2007, the bailout of Bear Stearns in March 2008, the default of Lehman Brothers in September 2008, the issue with the US debt ceiling in August 2011 (which resulted in a downgrade of US debt by Standard and Poors and coincided with the European debt crisis), and the date of Mario Draghi's speech in July 2012, declaring that the ECB will do whatever it can to preserve the Euro. The two shaded areas are US recession periods.

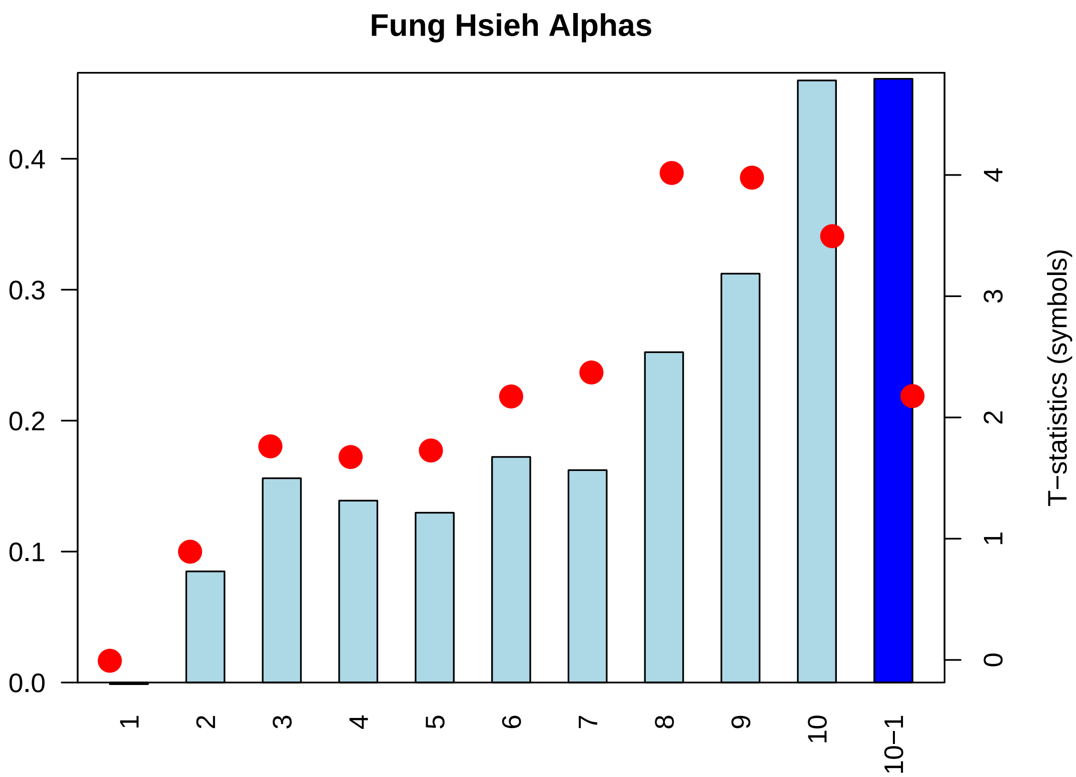


Figure 4: **Risk-adjusted returns of CIP-beta sorted hedge fund portfolios.** Each month hedge funds are sorted into 10 equally weighted portfolios according to their historical beta to changes in the covered interest rate parity (CIP) deviation index, constructed in Section 4.2. Funds in portfolio 1 have the strongest loading on changes in the CIP deviation index (the most negative beta), funds in portfolio 10 have the weakest loading (beta close to zero). The CIP beta is calculated using a regression of monthly portfolio returns on the market portfolio and changes in the CIP deviation index, using the 36 months prior to portfolio formation. Portfolio returns begin January 1997. The bars represent monthly portfolio alphas calculated using the 7 Fung-Hsieh factors, where credit and term factors are replaced by factor-mimicking tradable portfolios. The red dots are Newey-West t-statistics of the respective alphas. The blue bar displays the alpha of a portfolio that is long hedge funds in portfolio 10 and short hedge funds in portfolio 1. The sample period is January 1994 to December 2014, including all 8384 hedge funds from the Tass database.

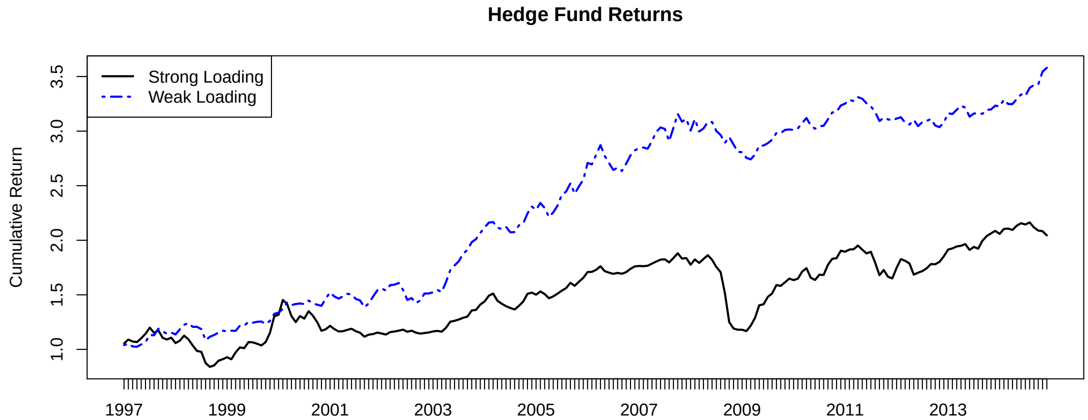
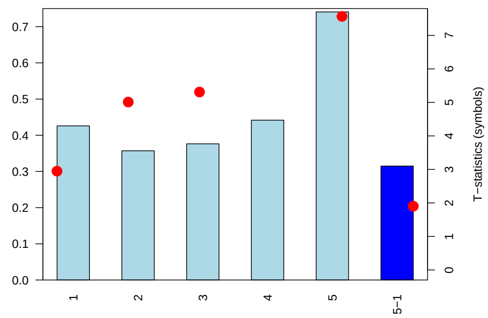
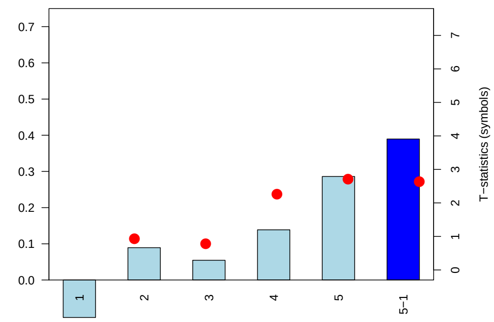


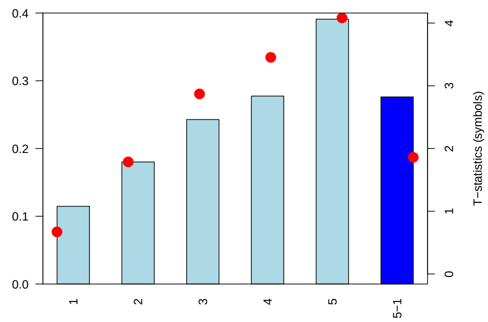
Figure 5: **Cumulative excess returns from investing in high and low loading funds.** This figure shows the cumulative excess returns of hedge funds with a strong loading (solid line) and low weak loading (dashed line) on the covered interest rate parity (CIP) deviation index, constructed in Section4.2. See the caption of Figure 4 for a description of the sorting procedure. The high (low) loading portfolio is the first (tenth) decile portfolio.



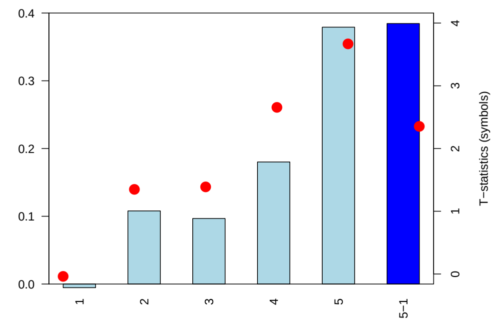
(a) No Drawdown ($X = 1$)



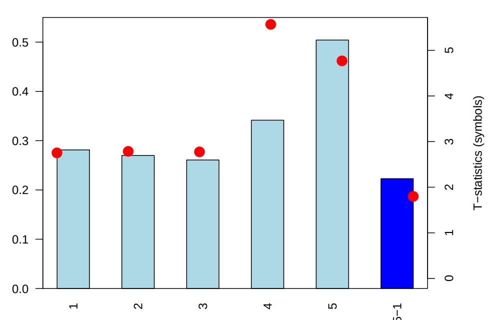
(b) Drawdown ($X < 1$)



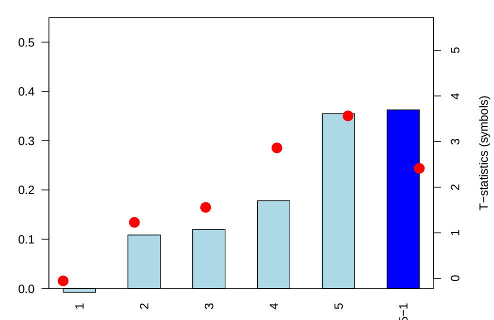
(c) Longer than median redemption



(d) Median or below redemption

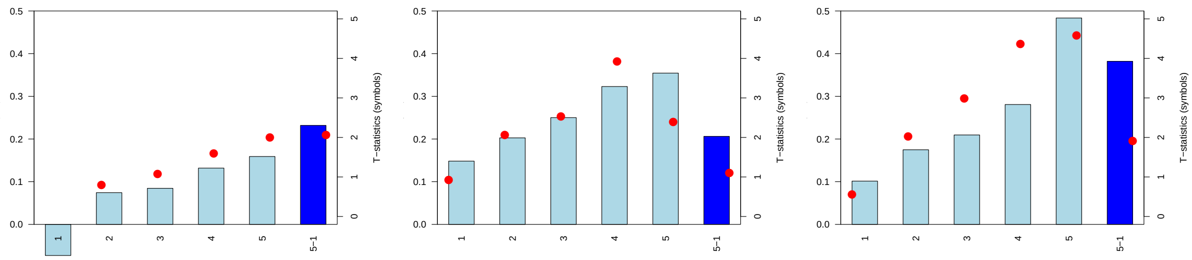


(e) Above median Lockup



(f) Median or below Lockup

Figure 6: **Risk-adjusted returns of different subgroups of CIP-beta sorted hedge fund portfolios.** Different subgroups of hedge funds are sorted into quintiles based on the sorting procedure described in the caption of Figure 4. Panels (a) and (b) compare hedge funds that have not suffered any drawdowns in the previous month ($HWM/NAV = 1$) with hedge funds that have suffered drawdowns in the previous month ($HWM/NAV = 1$). Panels (c) and (d) compare hedge funds which offer redemption terms for their equity holders below the median with hedge funds that offer redemption terms above the median. Panels (e) and (f) compare hedge funds with lockup period above the median to hedge funds with lockup period below the median. The sample period is January 1994 to December 2014.



(a) Funds of funds (b) Long/Short equity funds (c) Other funds

Figure 7: **Risk-adjusted returns of different investment styles of CIP-beta sorted hedge fund portfolios.** Different subgroups of hedge funds are sorted into quintiles based on the sorting procedure described in the caption of Figure 4. Panel (a) illustrates the results for funds of funds only, Panel (b) for Long/short equity hedge funds only, and Panel (c) for all other hedge funds which are neither classified as funds of funds nor as long/short equity hedge funds. The sample period is January 1994 to December 2014.

Table 1: **Hedge Fund Summary Statistics.** This table provides summary statistics of average hedge fund returns in the Tass database as well as key fund characteristics over the 1994–2014 period. X is the ratio between current net-asset value (NAV) and the maximum NAV over the past months. AUM is the fund's assets under management and converted in USD for funds that report in a different currency (using the appropriate exchange rate). Reporting and Age are the number of monthly return observations and the average number of past return observations respectively. Backfilled gives the percentage of backfilled return observations. Lockup period is the number of months that a fund can lockup investor capital. Notice is the number of days that investors have to notice the manager before withdrawing capital from the fund. HWM and Personal Captial are indicator variables. HWM equals one if the fund manager's compensation is linked to a high-water-mark and Personal Capital equals one if the manager invests personal capital in the fund.

	Mean	SD	Min	Median	Max	N
Return (mean)	0.51	0.72	-7.04	0.45	7.15	8384
Return (SD)	3.27	2.64	0	2.45	33.95	8384
X	0.93	0.08	0.19	0.96	1	8384
AUM (mio USD)	147.46	322.36	10	56.25	7878.71	8384
Reporting (Months)	90.68	51.69	24	78	252	8384
Age (Months)	47.16	31.49	11.5	39.5	365	8384
Backfilled (%)	43.48	31.52	0	37.21	100	8384
Lockup Period (Months)	2.8	6.45	0	0	90	8384
Redemption Notice (Months)	36.11	33.64	0	30	365	8384
Management Fee	1.43	0.67	0	1.5	22	8330
Incentive Fee	13.94	8.35	0	20	50	8284
HWM (%)	61.49	-	-	-	-	8330
Personal Capital (%)	22.55	-	-	-	-	8384

Table 2: **Summary Statistics of Hedge Fund Returns.** This table provides summary statistics of average hedge fund returns for different investment styles (Panel A) and different periods (Panel B).

	Mean	SD	Min	Meadian	Max	N
Panel A: Summy statistics of the indicated variables for all hedge funds						
Convertible Arbitrage	0.40	0.56	-1.24	0.52	1.81	199.00
Emerging Markets	0.71	0.90	-3.14	0.67	5.58	492.00
Equity Market Neutral	0.42	0.60	-2.88	0.37	5.09	351.00
Event Driven	0.78	0.76	-3.92	0.71	6.93	536.00
Fixed Income Arbitrage	0.43	0.73	-3.01	0.50	2.19	236.00
Fund of Funds	0.23	0.50	-5.20	0.27	3.07	3029.00
Global Macro	0.58	0.82	-6.68	0.56	5.64	287.00
Long/Short Equity Hedge	0.79	0.79	-5.77	0.72	7.15	1958.00
Managed Futures	0.63	0.68	-3.99	0.55	3.99	411.00
Multi-Strategy	0.51	0.79	-7.04	0.48	4.92	524.00
Other	0.62	0.78	-2.13	0.59	5.80	361.00
Panel B: Hedge fund returns in different style categories						
1994	0.12	1.63	-10.62	0.14	10.94	711.00
1995	1.45	1.70	-6.58	1.27	16.80	918.00
1996	1.62	1.50	-4.03	1.37	11.25	1165.00
1997	1.54	1.61	-12.34	1.38	18.96	1398.00
1998	0.47	2.25	-12.85	0.57	15.66	1639.00
1999	2.28	3.10	-9.99	1.58	41.37	1966.00
2000	0.99	2.14	-23.07	0.96	23.22	2271.00
2001	0.62	1.99	-21.83	0.55	48.43	2695.00
2002	0.32	1.37	-17.05	0.27	15.91	3200.00
2003	1.33	1.69	-14.47	0.93	40.23	3791.00
2004	0.73	0.93	-5.34	0.58	10.98	4490.00
2005	0.78	1.22	-9.44	0.61	27.68	5137.00
2006	0.96	1.14	-6.14	0.81	23.72	5541.00
2007	0.87	1.46	-15.46	0.69	43.38	5720.00
2008	-1.50	2.45	-22.23	-1.39	22.37	5640.00
2009	1.14	3.65	-100.00	0.83	188.45	5036.00
2010	0.61	1.36	-34.55	0.50	26.85	4532.00
2011	-0.44	1.30	-23.93	-0.35	9.44	4153.00
2012	0.42	1.52	-48.05	0.40	35.93	3636.00
2013	0.65	1.35	-20.01	0.65	13.97	3043.00
2014	0.26	1.19	-10.38	0.20	23.17	2554.00

Table 3: **Properties of the Covered Interest Rate Parity Deviation Index**. This table shows the results of a univariate regression of ΔCIP_t^D on other proxies for funding liquidity and market uncertainty. The six different explanatory variables are the change in the difference between the 3-month USD Libor rate and the 3-month US treasury yield (ΔTED_t), changes in the option-implied volatility of the S&P 500 index (ΔVIX_t), changes in the Noise measure ($\Delta Noise_t$) introduced Hu et al. (2013), ,the macroeconomic uncertainty index proposed by **?**, the betting-against-beta factor (BAB_t) introduced by Frazzini and Pedersen (2014), and innovations in the Pastor and Stambaugh (2003) stock market liquidity factor ($PSLiq_t$). The sample period is January 1994 to December 2014. All observations are month-end. Heteroskedasticiy-robust standard errors are reported in parenthesis. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.02	0.01	0.02	0.03	0.08	0.05
	(0.12)	(0.06)	(0.11)	(0.19)	(0.36)	(0.36)
TED	6.49**					5.84***
	(2.45)					(2.61)
VIX		0.20*				0.15**
		(1.72)				(2.56)
Noise			0.56			−0.02
			(1.20)			(−0.12)
Macro				−0.17		−0.06
				(−1.43)		(−0.67)
BAB					−6.08	−8.13*
					(−0.78)	(−1.79)
PSLiq					−3.74	3.74
					(−0.86)	(1.17)
Observations	251	251	251	251	251	251
Adjusted R^2	0.36	0.12	0.04	0.02	0.01	0.42

Table 4: **Hedge-fund risk factors and their relationship to ΔCIP_t^D.** This table shows the correlation matrix of the 7 Fung Hsieh hedge fund risk factors with ΔCIP_t. The 7 risk factors are the market excess return (MKT), a size factor (SMB), changes in the ten-year Treasury constant maturity yield (YLD), changes in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAA), as well as three trend-following factors: BD (bond), FX (currency), and COM (commodity). The sample period is January 1994 to December 2014. All observations are month-end.

Panel B: Correlation to other hedge fund risk factors

	MKT	SMB	YLD	BAA	BD	FX	COM
SMB	0.22						
YLD	0.1	0.09					
BAA	-0.28	-0.2	-0.51				
BD	-0.25	-0.1	-0.18	0.2			
FX	-0.19	-0.02	-0.17	0.28	0.27		
COM	-0.17	-0.08	-0.12	0.19	0.19	0.35	
CIP	-0.15	-0.01	-0.03	0.11	0.11	0.14	0.13

Table 5: **Portfolios sorted on covered interest rate parity (CIP) deviations.** Hedge funds are sorted into deciles based on their beta to changes in the CIP deviation index, described in Section 4.2. Beta is calculated using a regression of monthly hedge fund returns on the market portfolio and the CIP deviation, using the 36 months prior to portfolio formation. The table then shows the results of a univariate regression of these portfolio returns on changes in the CIP deviation index, controlling for the 7 Fung Hsieh risk factors. These 7 factors are the market excess return (MKT), a size factor (SMB), tradable factors to mimic monthly changes in the ten-year Treasury constant maturity yield (YLD) and monthly changes in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAA), as well as three trend-following factors: BD (bond), FX (currency), and COM (commodity). The sample period is January 1994 to December 2014. Newey-West standard errors are reported in parenthesis. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	R^{Exc}	α^{FH}	β^{CIP}	β^{Mkt}	β^{SMB}	β^{YLD}	β^{BAA}	β^{BD}	β^{FX}	β^{COM}	R^2
Top	0.39	0	-0.09**	0.36***	0.23***	0.24***	0.64***	-1.39	2.1***	0.54	0.65
	[1.21]	[-0.01]	[-2.05]	[8.59]	[3.24]	[2.86]	[6.02]	[-1.26]	[2.74]	[0.52]	
2	0.31	0.08	-0.1***	0.21***	0.13***	0.15***	0.42***	-0.07	1.16***	0.6	0.67
	[1.61]	[0.89]	[-2.83]	[7.48]	[4.22]	[3.3]	[8.74]	[-0.11]	[2.62]	[0.99]	
3	0.35**	0.16*	-0.08***	0.2***	0.11***	0.1**	0.31***	-0.37	0.83**	0.4	0.66
	[2.14]	[1.76]	[-3.05]	[7.64]	[3.5]	[2.38]	[6.44]	[-0.57]	[2.36]	[0.79]	
4	0.3**	0.14*	-0.07**	0.16***	0.11***	0.08**	0.29***	-0.06	0.82**	0.51	0.65
	[2]	[1.67]	[-2.37]	[6.74]	[3.94]	[2.17]	[5.48]	[-0.1]	[2.54]	[1.25]	
5	0.28**	0.13*	-0.08**	0.15***	0.1***	0.06*	0.23***	-0.37	0.76***	0.38	0.62
	[2.04]	[1.73]	[-2.31]	[7.77]	[4.01]	[1.66]	[5]	[-0.64]	[2.69]	[1.01]	
6	0.31**	0.17**	-0.08**	0.14***	0.08***	0.07**	0.23***	-0.47	0.91***	0.37	0.61
	[2.37]	[2.17]	[-2.2]	[8.68]	[4.1]	[2.13]	[4.98]	[-0.73]	[3.31]	[1.03]	
7	0.29**	0.16**	-0.07**	0.12***	0.08***	0.04	0.2***	-0.67	0.77***	0.61	0.58
	[2.6]	[2.37]	[-2.24]	[8.56]	[4.29]	[1.32]	[5.17]	[-1.18]	[2.63]	[1.61]	
8	0.38***	0.25***	-0.06**	0.15***	0.08***	0.04	0.14***	-0.27	0.92***	0.27	0.56
	[3.58]	[4.02]	[-2.26]	[8.21]	[3.7]	[0.95]	[3.9]	[-0.55]	[2.71]	[0.6]	
9	0.46***	0.31***	-0.03	0.21***	0.1***	0.01	0.07	-0.14	1.37***	0.47	0.53
	[3.66]	[3.98]	[-1.21]	[7.19]	[4.15]	[0.24]	[1.42]	[-0.22]	[3.78]	[0.77]	
Bottom	0.62***	0.46***	-0.03	0.3***	0.11*	-0.1	0	0.17	2.14***	1.32	0.43
	[3.56]	[3.5]	[-0.7]	[6.95]	[1.93]	[-0.84]	[0]	[0.15]	[4.07]	[1.4]	
10 - 1	0.23	0.46**	0.06*	-0.06	-0.12	-0.34**	-0.64***	1.56	0.04	0.78	0.29
	[0.88]	[2.18]	[1.95]	[-1.04]	[-1.19]	[-2.28]	[-2.78]	[1.24]	[0.04]	[0.68]	

Table 6: **Crisis versus noncrisis periods.** Hedge funds are sorted into deciles based on their β^{CIP}, which is computed using a regression of monthly hedge fund returns on the market portfolio and ΔCIP_t^D, using the 36 month prior to portfolio formation. The table reports the average returns and risk-adjusted returns of a hedge fund portfolio that is long hedge funds with the weakest loading on ΔCIP_t^D (bottom decile) factor and short hedge funds with the strongest loading (top decile) on ΔCIP_t^D. The sample period is split into crisis and noncrisis periods. Under (I), anecdotal evidence is used to classify crisis periods. The crisis periods are are August-September 1998, August-October 2007, August 2008 - January 2009, August - December 2011, and April - May 2012, and 198 non-crisis months. Under (II) crisis periods are defined as periods where the TED spread is above its 80% quantile and quiet periods are classified as periods where the TED spread is below its 20% quantile. Under (III) crisis periods are defined as periods where the average stock returns of major dealer banks (G16 banks) are below their 20% quantile and quiet periods are classified as periods where these stock returns are above its 80% quantile. Quantiles are computed using the January 1997 – December 2014 sample period. The sample period is January 1994 to December 2014, including all funds in the TASS database.

	(I) Anecdotal			(II) TED			(III) PB Stock		
	#Obs	R^{Exc}	α^{FH}	#Obs	R^{Exc}	α^{FH}	#Obs	R^{Exc}	α^{FH}
Crisis	18	3.23	1.89	44	1.27	0.9	44	1.41	0.33
		[3.05]	[5.7]		[2.41]	[2.4]		[1.57]	[0.59]
Noncrisis	198	-0.04	0.33	44	-0.05	0.28	44	-0.88	0.28
		[-0.2]	[1.56]		[-0.07]	[0.89]		[-1.28]	[0.51]

Table 7: **Characteristics of the CIP-deviation-sorted hedge fund portfolios.** This table reports the average characteristics and average allocations within hedge fund style for the 10 CIP-beta-sorted portfolios from Table 5. See Table 1 for a description of the different variables.

Portfolio Rank	Top	2	3	4	5	6	7	8	9	Bottom
Panel A: Characteristics										
Backfilled	0.28	0.33	0.35	0.36	0.36	0.36	0.34	0.33	0.31	0.32
USD	0.83	0.81	0.78	0.74	0.73	0.72	0.73	0.77	0.79	0.83
X	0.83	0.90	0.93	0.94	0.94	0.95	0.95	0.94	0.92	0.86
AUM	199.61	223.93	254.67	251.29	236.76	219.31	217.91	205.33	175.23	164.07
LockUpPeriod	3.06	2.97	2.63	2.46	2.37	2.22	2.46	2.71	2.98	3.14
RedemptionNoticePeriod	31.94	34.78	36.88	38.64	39.88	38.54	38.56	37.52	33.80	30.25
MinimumInvestment	1.02	1.35	1.35	7.59	12.05	5.81	4.36	2.21	2.60	2.32
ManagementFee	1.51	1.47	1.43	1.39	1.37	1.36	1.35	1.36	1.41	1.50
IncentiveFee	16.09	14.94	12.98	13.36	13.52	13.33	14.57	15.87	16.85	17.55
HighWaterMark	0.59	0.55	0.54	0.52	0.47	0.50	0.50	0.50	0.56	0.60
Leveraged	0.66	0.58	0.52	0.51	0.48	0.48	0.49	0.52	0.57	0.64
PersonalCapital	0.39	0.34	0.30	0.28	0.27	0.27	0.28	0.31	0.35	0.37
Age	85.92	89.25	90.34	87.63	87.22	87.58	87.70	87.27	87.54	87.83
Panel B: Allocation within hedge fund style (%)										
Convertible Arbitrage	2.15	2.89	3.47	2.81	2.70	3.16	3.32	2.72	1.44	1.23
Fund of Funds	11.52	26.68	42.34	49.76	53.60	52.78	46.05	35.24	21.42	11.51
Long Short Equity	36.04	29.85	21.95	17.32	15.51	14.59	16.22	23.05	31.29	40.10
Emerging Markets	14.32	8.29	5.06	3.49	2.81	2.46	2.79	3.92	5.89	9.14
Equity Market Neutral	2.42	2.91	2.89	3.11	2.45	2.72	3.59	4.52	5.05	4.27
Event Driven	4.24	5.83	7.01	7.61	8.59	9.01	10.39	11.34	10.25	5.29
Global Macro	5.57	3.38	2.48	1.79	1.45	1.48	1.58	2.44	3.42	4.78
Fixed Income Arbitrage	3.94	3.29	2.57	2.87	2.49	2.72	3.10	2.61	2.96	1.60
Multi Strategy	5.67	6.39	5.11	5.47	4.81	4.97	5.82	6.41	5.27	3.67
Managed Futures	10.65	6.87	4.12	3.37	3.47	3.57	4.06	5.22	8.89	15.48
Other	3.48	3.63	2.99	2.41	2.12	2.54	3.09	2.54	4.12	2.93

Table 8: **Robustness checks using cross-sectional regressions.** Fama and MacBeth (1973) regressions of the cross section of monthly hedge fund alphas (relative to the Fung-Hsieh 7 factor model). In the first and second regression, alphas are computed using all returns reported in the database. Under Backfill, I repeat the analysis dropping backfilled return observations. Under unsmoothed, I use the procedure by Getmansky et al. (2004) to un-smooth hedge fund returns before repeating the analysis. Under Survivorship, I replace the last alpha with -20% before repeating the analysis. Newey-West standard errors are reported in parenthesis. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	Intercept	CIP beta	Age	Size	Redemption Frequency	Redemption Notice	Lockup Period	Style Dummies
No Controls	0.49***	4.103**						
	[3.89]	[2.34]						
Controls	0.238	4.202**	-0.071**	0.06***	-0.001	0.043**	0.008***	Yes
	[1.64]	[2.46]	[-2.01]	[5.28]	[-0.2]	[2.52]	[3.44]	
Backfill	-0.03	3.821**	-0.075*	0.088***	-0.002	0.064***	0.009***	Yes
	[-0.2]	[2.06]	[-1.86]	[6.38]	[-0.37]	[3]	[3.02]	
Unsmoothed	0.26*	2.516**	-0.106***	0.054***	0	0.023	0.008***	Yes
	[1.86]	[2.38]	[-2.72]	[3.84]	[-0.09]	[1.41]	[3.41]	
Survivorship	-0.263	4.714**	-0.046	0.114***	-0.007	0.044**	0.009***	Yes
	[-1.24]	[1.99]	[-1.14]	[6.94]	[-1.51]	[2.18]	[3.11]	