Hedge Fund Funding Risk

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Abstract

This paper shows that hedge funds that take large funding risks underperform hedge funds that only take moderate funding risks. I first develop a simple theory to illustrate that better managers are taking on less funding risks. I construct a measure of funding risk that captures funding conditions faced by hedge funds and show that hedge funds with a strong loading on this measure severely underperform hedge funds with a weak loading on the same measure. In line with my theory, this underperformance is driven by a loading on adverse funding shocks and is weaker for funds that offer less favorable redemption terms to their investors. Furthermore, funds taking on more funding risk are experiencing more outflows.

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

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1 Introduction

Hedge funds are exposed to severe funding risks through the liability side of their balance sheets. In contrast to, say, a bank's equity capital, hedge fund investors can withdraw their equity investment from the fund. Furthermore, hedge funds usually employ short-term debt, which is provided by their prime broker(s) through collateralized borrowing. This debt is subject to the risk that the prime broker tightens the funding conditions. A proper management of these funding risks is crucial in order to generate high returns. Moreover, excessive funding risk taking suggest poor managerial skill.

In this article, I develop a simple model that illustrates that hedge funds taking on a lot of funding risk are unable to generate high returns. I then construct a measure of funding risk that is based on deviations from the covered interest rate parity and capturing funding conditions faced by hedge funds. Finally, I provide evidence in support of my hypotheses by utilizing a large cross-section of hedge fund returns to show that hedge funds with a strong loading on my funding measure (funds that are aggressively taking funding risk) severely underperform hedge funds with a weak loading on my measure (funds that are less aggressive in taking funding risk).

In my model, I assume that hedge funds differ with respect to the return that they can generate from investing in a funding-risky position. Investors observe hedge fund returns and move their capital to funds which can generate high returns. A manager who is only able to generate a low return takes on additional risk, trying to mimic the returns of a manager who can generate a high return. This mimicking can work in good states of the world (when there are no large funding shocks), but decreases the expected returns of the fund. The model has three testable predictions. First, the main prediction is that hedge funds that are taking on more funding risk are generating lower returns. Second, hedge funds with more funding risk tend to receive outflows while funds with less funding risk tend to receive inflows. Third, the difference between funds that take more and less funding risk becomes smaller as the size of the possible funding shock decreases.

The measure of aggregate funding conditions faced by hedge funds is based on mispricings in international money markets, captured by deviations from the covered interest rate parity (CIP). To construct a broad measure of mispricings that is not purely driven by any currency or security-specific effects, I proceed similarly to Pasquariello (2014) and construct an index of CIP mispricings. I use the 9 most liquid currency pairs (based on British Pound, Euro, Japanese Yen, Swiss Franc, and US Dollar) and contracts with 7 different maturities ranging from 1 week to 1 year. The constructed index of deviations from the CIP (henceforth CIP^D) is strongly related to other proxies for funding liquidity, such as the treasury-eurodollar

(TED) spread and the dealer-broker leverage factor constructed by Adrian, Etula, and Muir (2014). This strong link to other proxies of funding risk distinguishes my measure from other previously used liquidity measures such as the noise measure (Hu, Pan, and Wang, 2013) or the Pastor and Stambaugh (2003) stock market liquidity measure.

Apart from the strong correlation to other proxies for funding risk, CIP^D is an ideal measure for funding risk faced by hedge funds for the following reason. An increase in CIP^D points to a situation where the law of one price is violated for several different currency-maturity pairs at the same time. Such an increase in CIP^D can either be driven by a decrease in available arbitrage capital or by an increase in the demand for arbitrage capital. If there is a decrease in available arbitrage capital, major dealer banks face tightening funding constraints which are typically passed on to their hedge fund clients. An increase in the demand for arbitrage capital is driven by an imbalance between international funding supply and investment demand. This indicates a shortage of one currency relative to another and suggests that either international banks or major international investors face tightening funding constraints. Again, these tightening constraints are passed on to hedge funds either through their prime brokers or via equity withdrawals from major institutional investors.

I then obtain hedge fund returns and other fund characteristics for the January 1994 – May 2015 sample period from the Lipper/TASS hedge fund database. To test my theory in the data, I form decile portfolios of these funds based on their sensitivity to changes in CIP^D over the past three years, rebalancing the portfolios on a monthly basis. I find that hedge funds whose past returns are only weakly loading changes in CIP^D ($\beta \approx 0$) outperform hedge funds whose past returns are strongly loading on changes in CIP^D ($\beta < 0$) by a large margin. This finding demonstrates that taking on more funding risk is indeed a sign for poor managerial skill. The risk-adjusted return of the difference portfolio that is long the hedge fund portfolio with the weakest loading on ΔCIP^D and short hedge funds with the strongest loading on ΔCIP^D has a risk-adjusted monthly excess return of 0.54% (t-stat of 2.46).

This result strikingly demonstrates that a strong loading on funding risk implies poor performance. Instead of being a "priced risk factor", funding risk, as measured by CIP^D has the opposite effect; a *stronger* loading on ΔCIP^D predicts *lower* risk-adjusted returns. This is in line with my theory, which suggests that hedge funds that are more aggressive in taking on funding risk are doing so because they are otherwise unable to generate high returns. In a similar spirit, Titman and Tiu (2011) document that hedge funds whose returns are better explained by well-known risk factors outperform hedge funds whose returns are only weakly related to the same factors. In line with their findings, the returns of hedge funds with a weak loading on ΔCIP^D are also less well explained by the seven Fung and

Hshieh factors, compared to hedge funds with a strong loading on ΔCIP^D. In particular, the adjusted R^2 of regressing the first decile portfolio on the seven Fung Hsieh factors is 0.64, while the adjusted R^2 for the bottom portfolio is only 0.42. Hence, hedge funds that take on more funding risk are also taking more exposure to common risk factors.

My theory suggests that it is the relationship between negative funding shocks and hedge fund returns that predicts poor performance. To check whether this is the case, I split ΔCIP^D into a positive and negative part and repeat my analysis, sorting hedge funds based on their sensitivity to increases (or decreases) in CIP^D. In line with my theory, hedge funds with a strong loading on increases in CIP^D severely underperform hedge funds with a weak loading on ΔCIP^D. The difference portfolio that is long funds with a weak loading on increases in CIP^D and short funds with a strong loading on ΔCIP^D generates a monthly risk-adjusted excess return of 0.58 (t-statistic of 2.64). In contrast to that, there is no significant difference between hedge fund returns that are sorted based on their loading on decreases in CIP^D.

The second testable prediction of my theory is that hedge fund investors withdraw their money from funds that take on more funding risk and invest it into funds that take on less funding risk. This result is intuitive since hedge funds that take on more funding risk generate lower returns, even though they expose investors to an additional risk. I find support for this hypothesis in the data as well. The hedge fund portfolios with a strong loading on ΔCIP^D experience outflows, on average, while the hedge fund portfolio with a weak loading on ΔCIP^D experiences inflows.

The last testable prediction of my theory is that the effect of taking on more funding risk is less pronounced if hedge funds are less exposed to funding shocks. To provide evidence in favor of this hypothesis, I split the sample of hedge funds into funds which offer favorable redemption terms to their equity investors (liquid funds) and funds with less favorable redemption terms (illiquid funds). I find that illiquid funds with a strong loading on ΔCIP^D are still able to generate positive risk-adjusted returns. Furthermore, the returns of the difference portfolio that is long hedge funds with a weak loading on ΔCIP^D and short hedge funds with a strong loading on ΔCIP^D generates approximately two times higher returns for liquid funds than for illiquid funds.

To address concerns that my results are driven by other fund-specific characteristics, such as size or age, I run a Fama and MacBeth (1973) regression of risk-adjusted hedge fund returns on β^{CIP}, controlling for age, size, redemption notice period, lockup provision, and style dummies. Even after controlling for these characteristics, β^{CIP} is a statistically significant (t-statistic of 2.97) explanatory variable for risk-adjusted hedge fund returns.

I also show that the outperformance of funds with a weak loading on ΔCIP^D over funds with a strong loading on ΔCIP^D is stronger during crises periods. Splitting the sample period into months with severe deteriorations in funding conditions and normal months, I find that the difference portfolio that is long funds with a weak loading on ΔCIP^D and short funds with a strong loading on ΔCIP^D generates a striking risk-adjusted return of 1.54 during crises times, compared to 0.42 during normal times, if I classify crises times based on anecdotal evidence. This finding remains intact if I split the time series based on changes in the TED spread instead. The risk-adjusted return of the difference portfolio is 0.78 during times of strong increases in the TED spread and 0.41 during normal times.

My results are the exact opposite of those of Hu et al. (2013). They construct a "noise measure" based on US treasury bonds, which captures market-wide liquidity and show that it is a priced risk factor in the cross-section of hedge fund returns. Since their measure is a risk factor while loading on my measure captures poor managerial behaviour, combining both factors should improve the results even further. To show this, I apply a double-sorting procedure, where I first sort hedge funds based on their sensitivity to changes in the noise measure and then sort the hedge funds in each portfolio based on their loading on ΔCIP^D. The difference portfolio that is long hedge funds with the strongest loading on changes in the noise measure and weakest loading on ΔCIP^D and short hedge funds with weakest loading on changes in the noise measure and strongest loading on ΔCIP^D generates a monthly risk-adjusted return of 1.00% (t-statistic of 4.69).

Finally, my empirical finding is robust to a battery of robustness checks. First, to check that my findings are not driven by biases in reported hedge fund returns, I address backfilling bias, return-smoothing, and survivorship bias as follows. To address backfilling bias, I drop all returns that were reported before the fund was added to the database and repeat my analysis. Doing so decreases the number of observations by approximately 40% but leaves the main inference intact. Similarly, I use the return un-smoothing technique proposed by Getmansky, Lo, and Makarov (2004) and repeat my analysis. The results still hold. Finally, I replace the last reported return for each hedge fund that drops out of the database with a large negative number and repeat my analysis. The results still hold.

Second, I use an alternative index of deviations from the CIP ($CIP^{D,OIS}$, which is based on overnight lending (OIS) rates instead of Libor. The drawback of using this measure is that data on OIS rates in the five currencies are only available from 2002 on, which reduces my sample period by 6 years. However, hedge funds with a weak loading on $\Delta CIP^{D,OIS}$ still outperform hedge funds with a weak loading on $\Delta CIP^{D,OIS}$. Third, I show the result holds for funds of funds (which suffer less from selection bias). Finally, I show that the result is also robust to different hedge fund styles, by fixing the percentage of hedge funds within a certain style in each of the decile portfolios.

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. Equity withdrawals can happen precisely when the manager needs cash the most (Shleifer and Vishny, 1997) and "the fragile nature of hedge fund equity" (Liu and Mello, 2011) limits the manager's ability to profit from funding-risky positions due to the risk of early unwinding. Chen, Goldstein, and Jiang (2010) document that mutual funds with illiquid asset holdings face higher withdrawal risk than funds with liquid asset holdings because withdrawals of some investors impose a negative externalilty on remaining investors. Dai and Sundaresan (2011) and Buraschi, Kosowski, and Sritrakul (2014) explicitly incorporate the short option towards equity investors and prime brokers in the manager's risk-return tradeoff. Pangeas and Westerfield (2009), Lan, Wang, and Yang (2013), and Drechsler (2014) show that, under high-water mark compensation and facing the risk of fund liquidation after poor performance, even a risk-neutral hedge fund manager acts as if he was risk averse. The second stream of literature is related to the limits of arbitrage and, in particular, to theories emphasizing that arbitrageurs need to collateralize their positions. Assuming that acting as liquidity provider is profitable if the manager is not forced to unwind early, the need to post collateral if the trade goes against the manager imposes a risk (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, it is costly unwinding due to a funding shock that makes otherwise profitable investments risky.

The empirical part of my paper is related to the vast literature on the cross section of hedge fund returns. Sadka (2006) and Teo (2011) document that stock market liquidity, as approximated using the Sadka (2006) liquidity measure and the Pastor and Stambaugh (2003) liquidity measure is a priced risk factor in the cross-section of hedge fund returns. Cao, Chen, Liang, and Lo (2013) show that some hedge funds are capable of timing market liquidity, thereby earning higher risk-adjusted returns. Bali, Brown, and Caglayan (2014), Golez, Jackwerth, and Slavutskaya (2015), and Hu et al. (2013) construct other risk measrues and show that they are priced in the cross section of hedge fund returns. In contrast to that Titman and Tiu (2011) find that hedge funds whose returns are less well explained by common risk factors deliver higher risk-adjusted returns. Most closely to my paper, Chen and Lu (2015) construct a funding-liquidity measure based on stock returns and show that hedge funds with a weaker loading on this measure outperform funds with a stronger laoding on the measure.

The risk of equity withdrawals has been empirically studied by Aragon (2007), Klebanov

(2008), and Hombert and Thesmar (2014), who find that hedge funds offering less favorable redemption terms to their equity investors outperform funds which offer more favorable redemption terms. However, Aiken, Clifford, and Ellis (2015) point out that looking that additionally to the redemption terms, hedge funds are often using discretionary liquidity restrictions, such as gates and side pockets and that commercial hedge fund databases do not provide any information about these additional redemption restrictions. The risk of adverse funding conditions being passed on from the prime broker have been studied by Aragon and Strahan (2012), Mitchell and Pulvino (2012), and Ang, Gorovyy, and Van Inwegen (2011). Aragon and Strahan (2012) provide evidence that hedge funds who had Lehman Brothers as prime broker suffered a large funding shock in 2008. Mitchell and Pulvino (2012) show that short-term financing through prime brokers was a general issue for hedge funds during the financial crisis. Ang et al. (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.

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 as well as its relation to other funding risk proxies in Section 4. Section 5 present my main results and are complemented with robustness checks in Section 6.1. Section 7 concludes.

3 Theory and Hypotheses Development

In this section, I develop a stylized model of the hedge fund industry and use this model to develop my main hypotheses. The market consists of two investment opportunities, a risk-free asset and an alpha-generating strategy. To keep the model as simple as possible, I set the risk-free rate equal to zero and assume that the alpha-generating strategy yields a return of α_i if held until maturity. Unwinding the strategy early is subject to a cost c. Overall, one dollar invested in the strategy is worth $1 + \alpha_i$ if the strategy is held until maturity and $1 - c$ if the strategy is unwound early.

The timing of the model is as follows. At time $t = 0$, the manager is equipped with one unit of capital that he can lever up to a boundary that I normalize to one. He chooses his investment $\theta_i \in [0, 1]$ in the alpha-generating strategy at time $t = 0$. At time $t = 1$, the manager receives a funding shock which can cause him to costly unwind his alpha-generating strategy. The funding shock could either be triggered by outflows from equity investors or by prime brokers reducing the available leverage. The size of the funding shock is uniformly distributed on the interval $[0, \bar{\lambda}]$, where $0 < \bar{\lambda} < 1$. Time $t = 2$ corresponds to the maturity of the alpha generating strategy and the manager realizes a return of $1-\alpha_i$ on his investment in the strategy.

To avoid situations where the manager faces fund liquidation at time $t=1$, I impose the condition $\bar{\lambda} \leq 1-c$. Assuming that the manager is risk neutral and maximizing fund wealth at time $t=2$, his optimization problem is given as:

$$\max_{\theta_i} \mathbb{E}[W_2^i] = \frac{1}{\hat{\lambda}}\left[\int_0^{1-\theta_i} (1-\theta_i-\lambda+\theta_i(1+\alpha_i))d\lambda + \int_{1-\theta_i}^{\bar{\lambda}} \left(\theta_i - \frac{\lambda-(1-\theta_i)}{1-c}\right)(1+\alpha_i)d\lambda\right]. \tag{1}$$

The first integral is up to the $M-\theta$, which is the liquidity buffer kept by the hedge fund. If the realization of the funding shock is smaller than this liquidity buffer, the funding shock does not lead to any losses. The second integral starts at $M-\theta$, when the funding shock leads to losses and and goes up to $\bar{\lambda}$, the largest possible shock at time $t=1$. The following proposition characterizes the manager's optimal investment in the alpha-generating strategy without any other frictions.

Proposition 1. *Manager i's optimal investment in the alpha-generating strategy is given as:*

$$\theta_i^* = 1 - \frac{c(1+\alpha_i)}{\alpha_i+c}\bar{\lambda} \tag{2}$$

The proof of this proposition can be found in Appendix A. Next, assume that hedge fund managers differ with respect to the return they can generate from the alpha-generating strategy. More precisely, assume that there are good managers, who can generate a return α^G from investing one dollar in the strategy, and bad managers, who can generate a return $\alpha^B < \alpha^G$ from investing the same amount. The following lemma shows that the good manager always delivers higher returns than the bad manager, even though Equation (2) implies that $\theta_G^* < \theta_B^*$.

Lemma 1. *If both managers follow their optimal strategies, the bad manager always generates lower returns than the good manager.*

The proof of Lemma 1 can be found in Appendix A. Note that the result is intuitive: a manager with access to a low alpha-generating strategy cannot perform better than a manager with access to a high alpha-generating strategy. Next, turning to the hedge fund investor's decisions, who want their money to be managed by the good manager. Initially, the same amount of capital is invested in both funds as investors do not know which of the funds is managed by the good manager. Assume that investors know α_G and α_B and observe the change in the fund's wealth as well as the funding shock λ. If both managers follow their optimal strategies, the bad manager always underperforms the good manager and investors know for sure at time $t = 2$ whether they invested in the good or the bad fund.

This investment decision by investors has consequences for the investment behaviour of the managers. While the good manager can signal his skill by following the optimal strategy, the bad manager will receive outflows if following his optimal strategy. To formalize this consideration, assume that investor withdrawals at time $t = 2$ are associated with a cost ζ, which could be interpreted as the fund's continuation value. The following proposition summarizes the bad manager's investment decision in the light of costly fund liquidation.

Proposition 2. *1. The bad manager can evade the cost ζ by increasing his risky asset investments by*

$$\theta_M - \theta_B^* = \left(\frac{\alpha_G}{\alpha_B} - 1\right) + \bar{\lambda}\frac{(1-c)(\alpha_G - \alpha_B)c}{(\alpha_G + c)(\alpha_B + c)} > 0, \tag{3}$$

which corresponds to an investment of $\frac{\alpha_G}{\alpha_B}\theta_G^*$ in the risky asset. In this case he avoids the liquidation cost ζ with probability

$$p := \mathbb{P}(\lambda \leq M - \theta_M) = (1 - \theta_M)/\bar{\lambda}$$

2. The manager optimally does so if ζ satisfies the following sufficient condition:

$$\zeta > \frac{1}{p}\frac{c^2(1+\alpha_B)^2}{2(1-c)(c+\alpha_B))}\bar{\lambda}^2 \tag{4}$$

3.1 Testable Predictions

The main prediction from my theory is as follows:

Hypothesis 1. *Hedge funds that have lower returns when a funding shock occurs haver lower expected returns.*

This is because hedge funds with access to low alpha-generating strategies are taking on more funding risk in order to generate returns. They act more aggressive than optimal, which lowers their overall expected returns. Instead of being a risk factor, more exposure to funding risk actually predicts lower expected returns. My model abstracts from other sources of risk, but it is worth noting that hedge funds which have access to lower alpha-generating strategies are levering up on these positions. Hence, hedge funds with more funding risk exposure should also take on other risks more aggressively. The prediction can also be interpreted as good fund managers being better able to manager their funding risk. Note that it is the exposure to downside risk, or deteriorations in funding conditions, that is responsible for the lower returns of more aggressive funds.

The second hypothesis is related to hedge fund investor's behaviour.

Hypothesis 2. *Hedge funds that have lower returns when a funding shock occurs are subject to outflows.*

This prediction is based on the assumption that hedge fund investors monitor the funds' performance and are investing the money in the funds with the highest expected returns. As bad managers get uncovered through their lower returns during a funding shock, investors can start moving their money away from these funds and into funds that do not have lower returns during the same funding shock. Overall the prediction implies that there should be outflows from the aggressive funds and inflows into the less-aggressive funds.

The final prediction is a consequence of Equation (3).

Hypothesis 3. *Hedge funds that have lower returns when a funding shock occurs are performing better if the maximal size of the funding shock decreases.*

This hyposthesis is based on Equation (3), which shows that the difference between the bad manager's optimal investment in the alpha-generating strategy and the mimicking strategy decreases as $\bar{\lambda}$ (the maximum size of the funding shock) decreases. A lower funding shock could come from the equity side of the funds' balance sheet. Hedge funds that impose lockups and offer less favorable redemption terms to their investors face lower funding risk. Similarly, hedge funds with multiple prime brokers are less exposed to a funding shock transmitted from their prime broker.

4 The Data

4.1 Hedge Fund Data

The data for my analysis comes from the May 2016 version of the 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 might just decide to 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 January 1994 – May 2015 period.[1] Following the literature on hedge funds (see, for instance, Cao

[1] The return time series in the database ends in May 2015.

et al., 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 assets under management (AUM) below 10 Mio USD.[2] 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.

Panel A of 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. The first two rows of Panel A show that the average fund in the database reports a positive return of 0.56% per month with a standard deviation of 3.10. On average, funds have 140 million US dollar in AUM, ranging from the minimum of 10 million up to 7,158 million. AUM are defined as the value of all claims that equity shareholders have on the fund and is defined as the difference between the value of all long position (including cash) and the value of all short positions (including borrowing). Furthermore, 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 46.51% with a high standard deviation of 32.7% across funds. In my main analysis I include backfilled return observation and repeat my analysis later, dropping backfilled observations, which leads to a significant decreases in fund alphas but leaves my main results unchanged. The next two variables provide an overview of the funds' risk of withdrawals. The first variable is a dummy variable which equals one if the fund has a lockup provision and zero otherwise. 19% of the funds in the database have a lockup provision. The second variable is the funds' redemption notice period and gives an indication of how long it takes for equity investors to withdraw their money. The variable varies across funds from 0 to 12 months, with an average of approximately 1 month. The last two variables in Panel A show the manager's compensation. In line with the often-mentioned 2/20 rule, median management and incentive fee of funds in my sample are 1.5% and 20% respectively.

Panel B of Table 1 summarizes average hedge fund returns for the different styles. As we can see from the table, average monthly returns range from 0.80% for long-short equity to 0.29 for funds of funds. There is a total of 3,260 funds of funds in my sample. I run my main analysis using all 9,488 funds and show later that my results are robust to splitting

[2] I also experimented with different requirements for AUM, like 5 Mio USD and 20 Mio USD, which left the results unchanged.

[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.

the sample into hedge funds and funds of funds. The second-largest style in my sample are long/short equity hedge funds with a total of $2,017$ funds, followed $1,114$ multi-strategy funds.[4]

While the overall cross-section of hedge funds is fairly large, it is worth noting that the total number of funds varies significantly over time. The minimum amount of hedge funds is 711 in 1994 and ranges up 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 problem by sorting hedge funds into quintiles instead of deciles to insure a sufficient amount of funds per portfolio. Finally, it is also worth noting that, while average hedge fund returns are positive for the whole sample period, there were years with severe losses. The worst years were 2008 and 2011, where the average hedge fund in the sample generated a monthly return of -1.50% and -0.44% respectively. Detailed summary statistics by year can be found in Appendix C.

4.2 Deviations from the Covered Interest Rate Parity

In this section, I construct a simple measure of mispricings in international money markets and show that this measure is strongly related to other proxies for funding constraints and market uncertainty. The measure is based on deviations from the covered interest rate parity (CIP) across the five most liquid currency markets. The idea behind the 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 it into a money-market account with interest rate $r^B(t,T)$, and entering into a forward agreement to exchange the cashflow back into currency A (to hedge the currency risk of the transaction).

The market for currency derivatives is the largest and most liquid OTC derivatives market and aggregating a large number of mispricings across different currencies and maturities ensures that my measure captures a systematic deviation from the law of one price that could not occur in frictionless markets. There are two main reasons for a violation of the CIP and both are related to funding conditions faced by hedge funds. First, a decrease in available arbitrage capital where major dealer banks face funding constraints and are not able to supply currency derivatives at the arbitrage-free rate any more. In this situation, hedge funds are likely to face a tightening of their funding conditions as well as their prime brokers pass their constraints on to the fund. Second, an increase in the demand for currency derivatives, which is driven by an imbalance between international funding supply and investment de-

[4] Among multi-strategy funds there is a surprisingly large number of funds reporting in BRL. I experimented with using a subset of hedge funds dropping these BRL funds and obtained almost identical results.

mand and pointing towards a shortage of one currency relative to another (Bottazzi, Luque, Pascoa, and Sundaresan, 2012, Ivashina, Scharfstein, and Stein, 2015, among others). The most prominent example of this mechanism is the USD shortage, where foreign banks were unable to raise dollar funding in the US market due to distortions in the asset-backed commercial paper (ABCP) market, which again indicates tightening funding conditions. These tightening funding conditions can be passed on to hedge funds through two channels: (i) major institutional investors withdrawing from funding international banks also withdraw hedge fund equity and (ii) hedge funds might have non-US bank as prime broker, who pass their tightening funding conditions on to the fund.[5]

Additionally to these considerations, since the hedge fund data starts in 1994, I require the measure to date back until 1994, which rules out several other 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 basis (Fleckenstein, Longstaff, and Lustig, 2014). Additionally to that, the CIP^D measure is based on a large number of mispricings and therefore less prone to picking up security-specific effects of one particular asset, like the on-the-run off-the-run spread (Krishnamurthy, 2002).

Index Construction

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:

$$Fwd^*_{A/B}(t,T) := FX_{A/B}(t)\left(\frac{1+r^A(t,T)}{1+r^B(t,T)}\right), \tag{5}$$

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. For any currency-maturity pair i, with currencies A and B, deviations from the CIP can the be measured as:

$$CIP_{i,t} = \left|\ln(Fwd_{A/B}(t,T)) - \ln(Fwd^*_{A/B}(t,T))\right| \times 10^4, \tag{6}$$

where $Fwd_{A/B}$ is the observed forward rate between currencies A and B and $Fwd^*_{A/B}$ is the theoretical forward rate, implied by Equation (5). The expression is multiplied with 10^4 to obtain a mispricing in basis points. There are a vast number of different currency-maturity

[5]It is not uncommon for hedge funds to have non-US prime brokers. For instance, Aragon and Strahan (2012) report that in 2008 8.53% and 4.14% of the funds in the TASS database used UBS and Deutsche Bank as their prime brokers.

pairs and multiple ways to aggregate them into one measure of mispricings. The trade-off is between aggregating as many mispricings as possible in order to capture a market-wide effect, and avoiding mispricings with noisy data. In constructing my measure, I choose to closely follow the procedure outlined in Pasquariello (2014), using the following nine currency pairs: CHFUSD, EURUSD, GBPUSD, JPYUSD, CHFEUR, GBPEUR, JPYEUR, CHFGBP, JPYGBP, as well as spot rates and forward rates with 7, 30, 60, 90, 180, 270, and 360 days to maturity. In each of the currencies, Libor rates with the same maturity as the forward rates are used as a proxy for the risk-free. All data for constructing CIP deviations are obtained from the Bloomberg system.[6] In total, this leads to 63 different currency-maturity pairs, which are aggregated into one index as follows:

$$CIP_t^D = \frac{1}{n_t} \sum_{i=1}^{n_t} CIP_{i,t}. \tag{7}$$

Note that the number of available mispricings n_t can change over time.[7]

While it is relatively easy to measure CIP deviations, 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 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. Hence, my measure of CIP deviations is likely to overestimate the tradable dislocations in international money markets. Nevertheless, an increase in my index indicates a market-wide dislocation that should not occur in a frictionless world.

Apart from funding issues, there are two more problems with using Libor as a proxy for the risk-free rate. First, Libor is an unfunded lending rate which can contain a credit-risk component.[8] Second, Libor rates are potentially biased due to misreporting (see, for instance, Eisl, Jankowitsch, and Subrahmanyam, 2013). The concern about credit risk is mitigated by the fact that my index is constructed using the five safest and most liquid currencies. For these five currencies, Libor rates are computed with the same mechanism and the Libor panels consist of similar banks (see Du, Tepper, and Verdelhan, 2016 for an overview of Libor panels). However, to address these concerns I later modify my index, using

[6]Spot and forward exchange rates are the London closing rates (4:00 pm). Libor rates are the ICE Libor rates which are released at 11:45 am London time.

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

[8]Tuckman and Porfirio (2003) argue that this credit-risk component is one of the main drivers of CIP deviations.

overnight lending (OIS) rates instead of Libor rates to construct it and show that my main inference remains unchanged.[9] Since OIS rates for most currencies are only available from 2002 on, I use the index based on Libor rates for my main analysis.

Properties of CIP^D

Figure 1 shows the time series of month-end CIP^D_t,[10] where the blue lines indicate major market events and the grey-shaded areas are US recession periods. The graph illustrates that CIP^D spikes during times of financial distress and market uncertainty. 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. In September 2008, the month when Lehman Brothers went bankrupt, the measure reaches its peak. The next major spike of the measure occurs during the onset of the European debt crisis in Autumn 2011. In June 2011, the rating agency Moody's put several European banks on watch for possible downgrades, which lead to tightening funding conditions for these banks. Shortly after that, in August 2011, the US lost their triple-A rating and rumors about a possible downgrade of France lead to severe losses in the stock market. These events, together with further negative news about the Eurozone, lead to a deterioration in trust in the European Monetary Union and mark the onset of the European debt crisis. The measure remains elevated until July 2012 when Mario Draghi delivered his famous speech, declaring that "the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough."[11] The most recent spike of the measure occurs in January 2015, when the Swiss national bank decided to lift its currency peg. This event caught most market participants by surprise, triggering significant losses for many institutional investors.[12]

Another observation from Figure 1 is that CIP^D tends to become more volatile after the default of Lehman Brothers. Before September 2008, even relatively significant event, such

[9] The index based on Libor and based on OIS rates are highly correlated. The correlation in changes between the two indices for the 2002-2015 sample period is 0.79.

[10] One difference between my measure 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. In unreported robustness checks, I also used daily data which I then used obtain monthly averages. Both, the daily data and the monthly averages are non-stationary for my sample period. Using the monthly average measure leads to qualitatively similar, but insignificant results.

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

[12] See "Hedge fund managers and the swiss currency black swan" for more details on the consequences of lifting the currency peg for hedge funds. This industry research letter is available under: `http://www.mercer.com/content/dam/mercer/attachments/global/investments/hedge-fund-managers-and-the-swiss-black-swan-mercer-february-2015-a4.pdf`.

as the Quant crisis and the uncertainty around the bailout of Bear Stearns lead to relatively small spikes in CIP^D. In comparison, the lifting of the Swiss Currency Peg triggered a much larger spike in the measure. The reason for this higher volatility can be traced back to the new financial regulation which was implemented after the default of Lehman Brothers. The Volker rule explicitly forbids banks to engage in proprietary trading, such as arbitrage.[13] Hence, a major group of arbitrageurs who used to enforce the CIP is not allowed to do so any more. Hence, smaller events and market dislocations tend to have a larger impact on the index.

I next illustrate that changes in CIP^D coincide with shocks to funding liquidity and market uncertainty. To that end, I regress ΔCIP^D on the following four other measures of funding illiquidity and market uncertainty: (i) changes in the difference between the 3-month US Libor rate and the 3-month US treasury yield, commonly referred to as TED spread ΔTED_t, (ii) changes in the implied volatility of the S&P 500 index, ΔVIX_t, (iii) stock returns of the 9 largest investment banks,[14] Ret_t^{IB}, and (iv) the dealer-broker leverage variable introduced by Adrian et al. (2014), $Leverage_t$. I provide additional details on these variables, such as construction and datasources, in Appendx B.

The results of regressing ΔCIP^D on these variables are exhibited in Table 2, where I first focus on the relationship between ΔCIP^D and the first three variables, which are available on a monthly basis. As we can see from panels (1)-(3), ΔTED_t, ΔVIX_t, and Ret^{IB_t} all have a significant effect on ΔCIP^D. Increases in ΔTED_t and ΔVIX_t are positively related to ΔCIP_t^D, while higher investment-bank stock returns are negatively related to ΔCIP_t^D, indicating that ΔCIP^D decreases when investment banks are doing well. The TED spread is the strongest explanatory variable, capable of explaining 36% of the variation in ΔCIP^D in a univariate regression. Panel (4) of Table 2 shows that combining the three explanatory variables explains 41% of the variance in ΔCIP^D, where ΔTED_t is the most significant explanatory variable, followed by ΔVIX_t.

Turning next to the relationship between ΔCIP^D and $Leverage_t$, which is only available on a quarterly basis, we can see from Panel (5) of Table 2 that this variable is is even more significant in explaining ΔCIP^D than the ΔTED_t and explains 67% of the variation in ΔCIP^D. Finally, in Panel (6), I regress ΔCIP^D on all four explanatory variables which explains 81% of the variation in ΔCIP^D. $Leverage_t$ is the most significant explanatory vari-

[13]See "Volker rule alert" for a summary of the implications of the Volker rule and potential loopholes. This industry research letter is available under: `https://www.wilmerhale.com/uploadedFiles/Shared_Content/Editorial/Publications/WH_Publications/Client_Alert_PDfs/Volcker%20Rule%20Alert_12%2023%2013.pdf`.

[14]These nine banks are: Bear Stearns, Citibank, Credit Suisse, Goldman Sachs, HSBC, JP Morgan, lehman Brothers, Merril Lynch, and Morgan Stanley. (See Ang et al., 2011)

able, followed by ΔTED_t. Overall, the results confirm that changes in CIP^D are capturing tightening funding conditions.

Relationship to Other Liquidity Measures

I next study the correlation between ΔCIP^D and other liquidity measures. The goal of this section is to illustrate that ΔCIP^D is strongly correlated with other measures of funding risk by faced by hedge funds (ΔTED and $Leveverage$), while other liquidity measures only show a weak correlation. Table 3 shows the correlations between seven different liquidity measures. These seven measures are the betting against beta factor proposed by Frazzini and Pedersen (2014), the Pastor and Stambaugh (2003) liquidity factor, changes in the TED spread, the dealer-broker leverage variable described above, changes in the 10-year on-the-run off-the-run spread, changes in the Hu et al. (2013) noise measure, changes in the 10-year on-the-run off-the-run spread, as well as changes in CIP^D and changes in $CIP^{D,OIS}$, which is an alternative measure of CIP deviations, constructed using OIS rates instead of Libor rates.

In line with the previous regression analysis, the table confirms that the measure is strongly correlated with ΔTED_t and $Leverage_t$, which are the two other proxies for hedge fund funding risk. On the other hand, ΔCIP^D is only weakly correlated with BAB_t and PS_t (correlation weaker than 10%). Note that ΔTED and $Leverage$ also show a weak correlation with these two stock-market factors. Furthermore, the correlation between ΔCIP^D and $\Delta Noise$ is 0.22, indicating that the two variables are only weakly related. $\Delta Noise_t$ only has a weak correlation of 0.19 with ΔTED and is most strongly correlated to $\Delta On10Yr_t$ (correlation of 0.55). These correlations suggest that $\Delta Noise$ is only weakly related to the hedge fund funding risk that I want to capture.

Finally, the table also shows that $\Delta CIP_t^{OIS,D}$ has similar properties to ΔCIP_t^D. The correlation with ΔTED_t and $Leverage_t$ is 0.74 and 0.81 respectively. As ΔCIP^D, the measure based on OIS rates also has a correlation weaker than 10% with BAB_t and PS_t and is almost uncerrelated to $\Delta Noise_t$. Note that the sample period for the measure based on OIS rates is only from January 2002 to May 2015 while the other sample periods are from January 1994 to May 2015. I show later that using $\Delta CIP_t^{OIS,D}$ as a proxy for hedge fund funding risk leads to similar results as using ΔCIP^D.

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

I now briefly describe the seven hedge fund risk factors, proposed by Fung and Hsieh (2004), that I use as benchmark to compute risk-adjusted returns and show that these factors are only weakly related to ΔCIP^D. 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, constructed from trading strategies in lookback straddles, one for bonds (BD), one for currencies (FX), and one commodities (COM), which are obtained from David Hsiesh's website.[15]

Table 2 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 generally below 20%, indicating that CIP deviations are only weakly related to the Hedge Fund risk 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 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

I now test my main hypothesis: hedge funds that are taking on more funding risk generate lower returns than hedge funds that are taking on less funding risk. To do so, I sort hedge funds into deciles based on their loading on ΔCIP_t^D. Every month, for each fund i, I run a regression of hedge fund returns over the past 36 months on ΔCIP^D, controlling for excess

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

returns of the (stock) market portfolio:[16]

$$R_t^i = \alpha + \beta^{CIP}\Delta CIP_t^D + \beta^{Mkt}R_t^{Mkt} + \varepsilon_t. \tag{8}$$

Based on β^{CIP}, I then put each hedge fund in one decile portfolio. The decile portfolios are rebalanced every month, repeating the sorting procedure.

The first portfolio (P1) has the strongest loading on ΔCIP_t^D, while the last portfolio (P10) has the weakest loading on ΔCIP_t^D. Recall that my measure captures a spread, which spikes when funding is scarce and is close to zero in normal times. Hence, hedge funds profit from decreases in CIP deviations and lose money if CIP deviations unexpectedly increase. Therefore, a strong loading on ΔCIP_t^D corresponds to a significant negative beta.

5.1 Main Results

Figure 2 shows the monthly risk-adjusted returns of the 10 portfolios, controlling for the seven Fung and Hsieh (2004) risk factors. As we can see from the Figure, funds with the weakest loading on CIP deviations (P10) earn a monthly risk-adjusted return of 0.50%, which corresponds to an annual alpha of 6.00%. The risk-adjusted returns of hedge funds in the different deciles decrease almost monotonically. Funds in P9 earn a monthly risk-adjusted return of 0.38% followed by funds in P8, which earn a monthly risk-adjusted return of 0.33%. In contrast to that, funds with the strongest loading on CIP deviations (P1) do not earn any risk-adjusted returns, having a monthly alpha of 0.00%.

Although a long-short trading strategy in different hedge funds is not possible, it is still instructive to look into the performance of 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. The risk-adjusted returns of the difference portfolio are illustrated by the black bar in Figure 2. Funds with a weak loading on CIP deviations are outperforming funds with a strong loading on CIP deviations by more than 0.50% per month, corresponding to an annual alpha of 6.00%. Turning next to the statistical significance of these results, the blue dots in Figure 2 show Newey-West t-statistics of the respective portfolios and indicate that the results are statistically significant. In particular, the risk-adjusted return of the difference portfolio is significant at a 5% level with a t-statistic of 2.41.

More detailed results with the exact parameter estimates, the post-sorting betas, and additional results are reported in Table 5. The first observation from the table is that

[16] 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).

the post-sorting ΔCIP^D betas are significantly different between P1 and P10, where the portfolio with the strongest loading on ΔCIP^D (P1) has a beta of -0.17 (t-stat of 4.22) and the portfolio with the weakest loading on ΔCIP^D has an insignificantly positive beta of 0.02 (t-stat of 0.51). Furthermore, post-sorting betas are almost monotonically increasing. Additionally to the significant difference in ΔCIP^D loadings, P10 also has a weaker loading on the market portfolio than P1. One possible explanation for this observation is that fund managers with access to a true alpha-generating strategy do exhibit a lower loading on known risk factors. To provide further evidence for this hypothesis, Table 5 also reports the R^2 from regressing the decile portfolio returns on the seven Fung-Hsieh risk factors.[17] In line with the intuition, returns of hedge funds with a weaker loading on ΔCIP^D are less explained by common risk factors.

More recently, there is a tendency among researchers to add more risk factors to the Fung-Hsieh seven-factor model. The reason behind doing so is that the seven factors might not be sufficient to capture all the risks that funds with different investment styles can be exposed to. I add the following five risk factors to the seven-factor model. First, since fund returns in a subsequent month could be a consequence of an institutional momentum effect (see, for instance, Lou, 2012 and Vayanos and Woolley, 2013), I add the UMD momentum factor from Kenneth French's website. Second, since my measure of market dislocations is related to currency risks, I add the two currency risk factors proposed by Lustig, Roussanov, and Verdelhan (2011), which capture currency returns of an US dollar investor and a the returns of a carry trader. Finally, I add the excess returns of the S&P GSCI commodity index and the MSCI emerging market index to ensure that the risks of funds investing in commodities or emerging markets are well-represented.

As the fifth column of Table 5 shows, adding these risk factors does not have a significant impact on risk-adjusted returns. If anything, risk-adjusted returns of the ten decile portfolios tend to increase slightly. Most importantly, adding more risk factors leaves the size and significance of the risk-adjusted returns of the difference portfolio virtually unchanged. Hence, I will focus my analysis on using the Fung-Hsieh benchmark model from now on.

Finally, the last three columns of Table 5 exhibit the funds' excess returns, volatility of excess returns, and Sharpe ratios. The pattern in raw average returns is less clear than for risk-adjusted returns and we can observe an almost U-shaped pattern, with funds in P4-P6 having the lowest excess returns. Overall, funds with a strong loading on ΔCIP^D still have lower returns than funds with a weak loading but the difference portfolio does not yield statistically significant returns. Even though the average excess return of funds with the

[17] Table 13 in the appendix reports the parameter estimates and t-statistics for regressing portfolio returns on the seven Fung-Hsieh factors.

strongest loading on ΔCIP^D is 0.40%, this excess return is not significantly different from zero at a 10% level, indicating that returns of funds with a strong loading on ΔCIP^D are very volatile. Indeed, the monthly Sharpe ratio confirms this intuition: funds with a strong loading on ΔCIP^D have a fairly low Sharpe ratio of 0.11. In contrast, funds with weak loading on ΔCIP^D have a Sharpe ratio of 0.27 (almost three times higher), indicating that funds with weak loading on ΔCIP^D offer a much better risk-return profile.

Negative Shocks Driving the Results

According to my model, it is the low returns during a funding shock that predict poor hedge fund performance in the future. Hence, I next study whether it is the link between deteriorating funding conditions and hedge fund returns that causes poor performance. To do so, I split ΔCIP^D into a positive and negative part and repeat the sorting procedure described above. Every month t, for each fund i, I run the following regression using the past 36 months of return observations:

$$R_t^i = \alpha + \beta^{CIP+} \max(\Delta CIP_t^D, 0) + \beta^{CIP-} \min(\Delta CIP_t^D, 0) + \beta^{Mkt} R_t^{Mkt} + \varepsilon_t \qquad (9)$$

and then sort hedge funds into decile portfolios. In a first test, I sort them based on β^{CIP+} and afterwards I sort them based on β^{CIP-} in a second test.

The results of these two tests are exhibited in Figure 3, where Panel (a) shows the results for sorting on increases in CIP^D (deteriorating funding conditions) and Panel (b) shows the results for sorting on decreases in CIP^D (improving funding conditions). Comparing Panel (a) of Figure 3 to Figure 2 shows that the results even improve when only using information about increases in CIP^D. Now, the difference portfolio that is long hedge funds with a weak loading on increases in CIP^D and short hedge funds with a strong loading on ΔCIP^D delivers a monthly risk-adjusted return of 0.58 (t-statistic of 2.64). In contrast to that, sorting on decreases in CIP^D we see an opposite pattern. Here, hedge funds with a stronger loading are generating higher risk-adjusted returns than hedge funds with a weak loading. However, the difference portfolio only generating an insignificant risk-adjusted return of -0.16 (t-statistic of -0.96).

Panels A and B of Table 6 provide additional details for the top and bottom decile as well as the difference portfolio (the results for portfolios 2-9 are omitted for brevity). Panel A confirms that using increases in CIP^D leads to moderately stronger results than using overall changes. Interestingly, only using increases as sorting variable still results in portfolios that have significantly different post-sorting loadings on CIP^D. Panel B shows that this is not the case when sorting on decreases in CIP^D, where the post-sorting loading on ΔCIP^D is not significantly different for the top and bottom portfolio. Furthermore, Panel B shows that the excess returns of the top and bottom portfolio are similarly well explained by the seven Fung and Hsieh factors.

5.2 Additional Evidence

In this section, I test Hypotheses 2 and 3 of my theory. Hypothesis 2 suggests that hedge funds with a strong loading on ΔCIP^D tend to experience outflows while funds with a weak loading on ΔCIP^D tend to experience inflows. Hypothesis 3 suggests that the difference is less severe for hedge funds which are experiencing less severe funding shocks.

Fund Flows

Hedge funds with a strong loading on ΔCIP^D are a particularly poor investment because these funds take on more funding risk and generate lower risk-adjusted returns. My theory suggests that, as investors slowly recognize that they invested in a bad fund, they tend to withdraw their money from funds with a strong loading on ΔCIP^D and invest in funds with a weak loading on ΔCIP^D instead. This conjectured investor behaviour is more sophisticated than simply assuming that investors withdraw money from funds with the worst past performance and invest into funds with the highest past performance instead.[18]

To provide evidence in favor of this hypothesis, I compute the flow in month t for each fund i as:

$$Flow_{i,t} := \frac{AUM_{i,t} - AUM_{i,t-1}}{AUM_{i,t-1}} - Ret_{i,t}, \tag{10}$$

where I adjust the change in AUM for returns over the same period (as is common in the mutual funds literature, see, for instance, Chevalier and Ellison, 1997). I then compute average portfolio flows as:

$$Flow_t^{PF} := \frac{\sum_{i=1}^{n_t} Flow_t^i AUM_{t-1,i}}{\sum_{i=1}^{n_t} AUM_{t-1,i}}, \tag{11}$$

where n_t is the number of funds in the portfolio at time t. One issue with this measure of portfolio fund flows is that outflows and inflows might occur gradually. If funds move between portfolios frequently, the flow measure is not related to the fund's sensitivity to ΔCIP^D. Since the average fund spends 52% of his time in the same decile portfolio, I split

[18] A large literature details fund flows in response to past performance. See Chevalier and Ellison (1997) and **?** who document that investor flows are convex for mutual funds. And **?**, **?**, and **?** for a discussion of hedge fund investors.

the sample into quintiles instead, where the average fund spends 65% of its time in the same portfolio.

The resulting average flows for the five portfolios as well as the difference between flows into the portfolio with the weakest loading on ΔCIP^D and funds with the strongest loading on ΔCIP^D are exhibited in Figure 6. Note that funds in the portfolio with the strongest loading on ΔCIP^D are indeed subject to outflows while funds in the portfolio with the weakest loading on ΔCIP^D are subject to inflows. Only, the difference in flows is significantly different from zero. Note that the average correlation between fund flows and fund returns is only -22% as documented by Hombert and Thesmar (2014). Hence, this result is not simply a consequence of the different risk-adjusted returns in the portfolios.

Liquid versus Illiquid Funds

To provide evidence in favor of Hypothesis 3, I focus on the equity side of the hedge funds' balance sheet, repeating my main analysis for different subsamples of the hedge fund database.[19] To ensure a sufficient number of funds in each quantile, I follow Teo (2011) and form quintile portfolios instead of decile portfolios. I first divide the sample based on the funds' redemption notice period into one sample of liquid funds (redemption notice one month or less – recall from Table 1 that the median redemption notice period is one month) and one sample of illiquid funds (redemption notice longer than one month). Afterwards, I also split the sample into funds with lockup provisions and funds without lockup provision. A lockup provision requires that all new capital invested in the fund cannot be withdrawn before a pre-specified period (typically one year). Illiquid hedge funds and funds with lockup provision are less susceptible to equity withdrawals in times of financial distress. Hence, the funding risk effect should be less pronounced for illiquid funds and stronger for liquid funds.

Panels (a) and (b) of Figure 4 show the results for illiquid versus liquid hedge funds. Illiquid hedge funds with a strong loading on ΔCIP^D (portfolio 1) are still able to generate positive risk-adjusted returns, while liquid hedge funds with a strong loading on ΔCIP^D are generating zero risk-adjusted returns. The weaker the loading on ΔCIP^D becomes, the smaller the difference between liquid and illiquid funds. Most notably, the difference portfolio, which is long hedge funds with a weak loading on ΔCIP^D and short hedge funds with a strong loading on ΔCIP^D generates twice as high returns for liquid funds than for

[19]Information on the liability side of the balance sheet is generally scarce. I also repeated my analysis splitting the sample into hedge funds that use only one prime broker (funds facing more funding risk) and hedge funds with more than one prime broker (funds facing less funding risk), which gave similar results as the tests below. The drawback of this split is that the TASS database only provides information on prime brokers for live hedge funds (which are still reporting to the database as of the latest version). Hence, applying this method induces survivorship bias and I therefore don't present these results.

illiquid funds.[20] Panels A and B of Table 7 provide additional details. Most notably, in both subsamples, the difference in loading on ΔCIP^D is statistically significant at a one percent level, indicating both liquid and illiquid funds differ in their loading on ΔCIP^D.[21]

Panels (c) and (d) of Figure 4 show the results for funds with lockup provision and funds without lockup provision. This split has the disadvantage that the sample of funds with lockup provision is much smaller than the sample of funds without lockup provision (recall that only 19% of the funds in the sample have a lockup provision). However, the results are qualitatively similar to the results for liquid and illiquid funds. Funds with lockup provision and with a strong loading on ΔCIP^D are still able to generate positive risk-adjusted returns while funds without lockup provision and with a strong loading on ΔCIP^D are not able to generate any alpha. Panels C and D of Table 7 provide additional details. As before, the portfolios in both subsamples show a significant difference in their loading on ΔCIP^D.

5.3 Other Explanations?

The next question is whether the difference in returns can be explained by other fund characteristics, such as size, style, or redemption terms. To address this question, Table 8 presents an overview of the characteristics of the funds in the different decile portfolios. As we can see from the table, funds in the top and bottom decile have very similar characteristics, in terms of their size, age, and redemption terms, as well as in their style allocation. However, the table also shows that funds in the middle portfolios tend to have slightly different characteristics. Most notably, portfolios 3-7 consist of more than 30% funds of funds while top and bottom portfolio only consist of approximately 10% funds of funds.

To formally test whether different characteristics can be responsible for the outperformance of funds with a weak loading on ΔCIP^D, I next run a Fama and MacBeth (1973) regression of risk-adjusted hedge fund returns on their ΔCIP^D beta, controlling for the following five fund-specific characteristics: Age, size, redemption notice period, lockup provision, and hedge fund style. To run the Fama-MacBeth regression, I compute the risk-adjusted excess return of each hedge fund, using the following equation:

$$\begin{aligned}\alpha_{i,t} = R_{i,t}^{Exc} - (&\beta_i^{Mkt} R_t^{Mkt} + \beta_i^{SMB} R_t^{SMB} + \beta_i^{YLD} R_t^{YLD} + \beta_i^{BAA} R_t^{BAA} \\ &+ \beta_i^{BD} R_t^{BD} + \beta_i^{FX} R_t^{FX} + \beta_i^{COM} R_t^{COM}),\end{aligned} \tag{12}$$

[20] Note that illiquid funds overall generate higher risk-adjusted returns, which is in line with the findings of Aragon (2007).

[21] In unreported robustness tests I also split samples by first sorting the hedge funds into five portfolios based on their loading on ΔCIP^D and the splitting them into liquid and illiquid funds. This robustness check lead to virtually identical results.

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 the ΔCIP^D betas of the respective portfolios to each fund instead of using the rolling estimates of each individual fund. 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:

$$\alpha_{i,t} = \gamma_0 + \gamma^{CIP}\beta^{CIP}_{i,t-1} + \gamma^{Age}Age_{i,t-1} + \gamma^{Size}\ln(AUM_{i,t-1}) + \gamma^{Notice}Notice_i + \gamma^{Lockup}DLockup_i + \gamma^{Style}DStyle_i + \varepsilon_{i,t}, \quad (13)$$

where I use the funds' age, AUM, redemption notice period, lockup provision, and style as additional control variables.

Panel A of Table 9 shows the results of this regression, which are in line with the results from the portfolio sorts, described above. The effect of β^{CIP} on risk-adjusted returns is statistically significant at a 1% level (t-statistic of 2.97) with a positive sign, implying that hedge funds with a weaker loading on ΔCIP^D generate significantly higher risk-adjusted returns. The signs of the control variables are in line with previous research. Aggarwal and Jorion (2010) document that younger hedge funds tend to outperform older hedge funds, which is in line with the negative coefficient on age. Furthermore, Aragon (2007) documents that hedge funds with lockups and longer redemption notice periods outperform hedge funds with shorter redemption notice periods and without lockups, which is in line with the positive coefficients on Notice and Lockup.

5.4 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. The returns from the top decile (strong loading on ΔCIP^D_t) 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 additional evidence for this results, I split the 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 deteriorations in funding conditions 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 10, 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.

As a second test, I split the sample period based on changes in the TED spread and define crisis periods as episodes where the TED spread is above its 75% quantile and non-crisis periods as episodes where the TED spread is below its 25% 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. During crisis periods the difference portfolio generates a monthly risk-adjusted return of 0.78 (t-statistic of 2.35) while the risk-adjusted return is only 0.42 in non-crisis periods (t-statistic of 1.92). Comparing excess returns during crises and non-crisis months is even more striking: the difference portfolio earns an excess return of 1.15 during crises months and -0.01 in quiet periods.

5.5 Relationship to the Noise Measure

I now show that my measure of funding conditions faced by hedge funds is indeed capturing a different aspect than the noise measure constructed by Hu et al. (2013). Hu et al. (2013) show that their measure is a priced risk factor in the cross section of hedge fund returns and a stronger loading on that measure implies higher returns. I apply a double-sorting procedure to incorporate the information content of the two measures. In a first step, I repeat the procedure described in Section 5 and compute β^{Noise} for each fund in the database using a rolling regression window of 36 months. I then sort hedge funds into 5 portfolios, based on their sensitivity to changes in the noise measure. I put funds with the weakest loading on $\Delta Noise_t$ (funds that I expect to perform poorly) in the first portfolio and funds with the strongest loading on $\Delta Noise_t$ in the fifth portfolio. Afterwards, I split each of the five noise-sorted portfolios into five CIP^D-sorted portfolios, based on β^{CIP}, computed in Section 5.

Here, I put funds with the strongest loading on ΔCIP^D (funds that I expect to perform poorly) in the first portfolio and funds with the weakest loading on ΔCIP^D in the fifth portfolio.

This conditional double sort results in 25 hedge fund portfolios. The risk-adjusted returns of these 25 portfolios (relative to the Fung Hsieh seven-factor model), as well as the returns of the difference portfolios, are exhibited in Table 11. As we can see from the table, my double sort confirms that the noise measure is a risk factor in the cross-section of hedge fund returns. Two out of the five difference portfolios generate a significant risk-adjusted return. The table also confirms that ΔCIP^D is capturing a different aspect of market conditions than $\Delta Noise$. Four out of the five difference portfolios generate a positive and statistically significant risk-adjusted return.

The number in the bottom-right corner of Table 11 is the risk-adjusted return of the difference portfolio that is long hedge funds with the strongest loading on $\Delta Noise_t$ and the weakest loading on ΔCIP^D and short the portfolio with the weakest loading on $\Delta Noise_t$ and the strongest loading on ΔCIP^D. This portfolio generates a striking risk-adjusted return of 1.00 per month (t-statistic of 4.69). Hence, combining the information content of the noise measure with the information content in CIP^D leads to even stronger results than just using any of the two measures seperately.

6 Robustness Checks

6.1 Common Biases in Reported Hedge Fund Data

I now show that my results are robust to the three most common biases in reported hedge fund returns: backfill bias, return smoothing, and dropout bias. Backfill bias arises because once a hedge fund starts reporting to the TASS database, he is allowed to enter past returns to the database as well. Clearly, only funds with high past returns would use that option which could bias returns upward. Return smoothing arises because hedge funds investing in illiquid securities might report returns from investments in month t only in month $t+1$ since prices move infrequently (see Asness, Krail, and Liew, 2001 and Getmansky et al., 2004). Finally, dropout bias arises because hedge funds can choose to stop reporting to the database if they perform poorly.

To address backfill bias, I utilize the infromation available in the TASS database and drop returns that have been reported prior the fund's inception date to the database. As summarized in Table 1, on average 43% of hedge fund returns are backfilled. Therefore, dropping backfilled observations could significantly change the results. Note that dropping all backfilled information is a conservative approach since hedge funds that start reporting to the TASS database might already have reported to other databases. Hence, not all backfilled observations classified as backfilled by my method are "truely" backfilled.

Repeating the analysis without backfilled returns leads to significantly lower risk-adjusted returns for all deciles, but leaves my main result unchanged. In Panel B of Table 9, I repeat the Fama and MacBeth (1973) regression from Section 5 without backfilled observations. As we can see from the table, the β^{CIP} coefficient is still significant in explaining risk-adjusted returns. To illustrate the drop in risk-adjusted returns for the decile portfolios, Panel (a) of Figure 7 illustrates the results for this test. As we can see from the Figure, the risk-adjusted returns of all decile portfolios decrease sharply. However, the main inference remains unchanged: the difference portfolio, which is long in hedge funds with a weak loading on ΔCIP^D and short hedge funds with a strong loading on ΔCIP^D yields a monthly risk-adjusted return of 0.52% (t-statistic of 1.99).

To address concerns about return smoothing, I use the un-smoothing technique proposed by Getmansky et al. (2004). Let $R^o_{i,t}$ denote the observed return of fund i at time t and $R_{i,t}$ the true return of fund i at time t. Then, assuming that return-smoothing does not exceed more than two periods, observed returns and true returns are linked by the following equation:

$$R^o_{i,t} = \theta_{i,0} R_{i,t} + \theta_{i,1} R_{i,t-1} + \theta_{i,2} R_{i,t-2}, \tag{14}$$

where $\sum_{k=0}^{2} \theta_{i,k} = 1$. For each fund i, the parameters $\theta_{i,k}$ $(k = 0, 1, 2)$ are estiamted using the entire time series of observed returns. I then replace the observed returns with the estimated un-smoothed returns, compute the risk-adjusted un-smoothed returns as in Section 5, and repeat my analysis. The results of the corresponding Fama and MacBeth (1973) regression are reported in Panel B of Table 9. As we can see from the table, β^{CIP} is still statistically significant at a 1% level for this specification. Additionally to that, Panel (b) of Figure 7 shows the results for un-smoothed returns. As we can see from the figure, the results improve slightly compared to the basic test in Figure 2.

As explained by Aiken, Clifford, and Ellis (2013) it is important to distinguish survivorship bias from dropout bias. While concerns about 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), dropout bias arises because poorly-performing hedge funds can choose to stop reporting to the database. Using a proprietary dataset hedge funds, not reporting to any database, Aiken et al. (2013) document that there is a dropout bias in reported hedge fund returns. To address this concern, I replace the last reported return of funds that dropped out of the database with a large negative return of −25%. The results of this robustness check are reported in the final row of Table 9. As we can see from this row, β^{CIP} is still significant at a 1% level (t-statistic of 2.71) and the size of the coefficient is almost unchanged when compared to the base case.

Additional Data Concerns

Another concern with the TASS database is that different subsidiaries of the same fund are reporting returns as different entities. For instance, a large fund might report its returns in both, Euro and USD. In this case, it is possible that the fund shows up twice in the database. Bali et al. (2014) document that approximately 16% of the funds in the TASS database are duplicates. To address this concern, I compute the pairwise correlation between the returns of all funds in the database that have at least 10 observations in common. I truncate the returns of all funds at 20% and −20% to avoid dropping funds that are strongly correlated due to a common jump in their returns. I then drop all funds with a return correlation above 99%.

Doing so leads to a drop of 14% of the observations in the database (from 8,541 funds to 7,348). As Panel (c) of Figure 7 shows, repeating the analysis with this smaller dataset leads to virtually unchanged results. The difference portfolio that is long funds with weak loading on ΔCIP^D and short funds with a strong loading on ΔCIP^D generates a risk-adjusted return of 0.51 (t-statistic of 2.39), which is virtually identical to the result in Table 5, where the difference portfolio earns a risk-adjusted return of 0.50.

Another concern that I cannot control for directly is selection bias. Hedge funds can choose whether they want to report to the database or not. Hence, a possible concern is that only funds with high returns choose to report to the database, in order to attract new investors. Fung and Hsieh (2000) argue that this concern can be mitigated by looking into the returns funds of funds. The advantage of doing so is that these funds are portfolios of different hedge funds which are not necessarily reporting to the database themselves. Hence, returns of funds of hedge funds are average returns of several hedge funds which are not necessarily reporting to any database, which mitigates selection bias.[22]

Since there are only 2,987 funds of hedge funds in my sample, I apply the sorting procedure described in Section 5.1, splitting the sample into quintiles instead of deciles. Panel (f) of Figure 7 shows the results of this split. As we can see from the figure, funds of funds with a strong loading on ΔCIP^D are performing exceptionally poorly, generating a negative

[22]There are, of course several other drawbacks of simply considering funds of hedge funds. First, the returns of funds of funds are lowered by the fees charged by the fund manager. Second, the fund manager makes an active decision on which hedge fund to invest in.

risk-adjusted return. Most importantly, however, the difference portfolio that is long hedge funds with a strong loading on ΔCIP^D and short funds with a weak loading on ΔCIP^D generates a risk-adjusted return of 0.36 (t-statistic of 2.74).

6.2 Different Funding Measures

I now repeat my analysis for a different variation of the CIP^D measure. Instead of using Libor rates, which can contain a large credit risk component and can be subject to manipulation, in now construct deviations from the CIP in Equation 5, using overnight swap (OIS) rates for the different currencies instead. The drawback with this approach is that OIS rates for most currencies are only available from January 2002 on. Hence, using this new index leads to a six year shorter sample period. The correlation between the index based on OIS rates and the original CIP^D index is 79.66%. An overview of the correlation between $\Delta CIPOIS, D$ and other liquidity proxies is shown in Table 3.

I then use the index based on OIS rates and repeat the analysis described in Section 5.1, sorting hedge funds into decile portfolios based on their sensitivity on changes in this modified measure. The results of this procedure are illustrated Panel (d) of Figure 7. As we can see from the Figure the main inference remains intact: hedge funds with a weak loading on ΔCIP^D outperform funds with a strong loading on ΔCIP^D.

6.3 Different Hedge Fund Styles

I next address the question of whether my results hold for funds with different investment styles. To that end, I repeat the sorting procedure described in Section 5.1, conditional on each of the ten portfolios consisting of the same percentage of hedge fund styles. More precisely, I first split the overall sample of hedge funds into the 11 different styles and sort each of these subsamples into decile portfolios, based on their loading on ΔCIP^D. For each decile, I then merge the 11 different style portfolios, which ensures that each portfolio has the same percentage of styles.

Panel (f) of Figure 7 shows the results of this modification. As we can see from the figure, the results are robust to controlling for hedge fund styles. The results are almost identical to those reported in Section 5.1. In this robustness test, the difference portfolio that is long hedge funds with a weak loading on ΔCIP^D and short hedge funds with a strong loading on ΔCIP^D is generating a monthly risk-adjusted return of 0.38% (t-statistic of 2.47).

7 Conclusion

The main finding of this paper is that hedge funds that are taking on excessive funding risk underperform hedge funds which are only taking moderate funding risks. I develop a theory where hedge fund managers with limited access to an alpha-generating strategy are taking on more funding risk in order to generate higher returns. I then construct a measure of funding risk that is strongly correlated to funding conditions faced by hedge funds and show that hedge funds with a stronger loading on this measure indeed deliver significantly lower risk-adjusted returns than funds with a strong loading on the same measure.

Additionally to that, my theory predicts that hedge fund investors learn about the type of fund they invested in and withdraw investments from funds that take on severe funding risks, investing in funds that are not taking on severe funding risks instead. In line with this hypothesis, I document that funds with a strong loading on ΔCIP^D are, on average, subject to outflows, while funds with a weak loading on ΔCIP^D are, on average, subject to inflows. Overall, my analysis provides a different view on funding risk; instead of being compensated for this additional risk, it is a predictor of poor performance.

References

Adrian, T., E. Etula, and T. Muir (2014). Financial intermediaries and the cross-section of asset returns. *The Journal of Finance 69*(6), 2557–2596.

Aggarwal, R. K. and P. Jorion (2010). The performance of emerging hedge funds and managers. *Journal of Financial Economics 96*(2), 238–256.

Aiken, A. L., C. P. Clifford, and J. Ellis (2013). Out of the dark: Hedge fund reporting biases and commercial databases. *Review of Financial Studies 26*(1), 208–243.

Aiken, A. L., C. P. Clifford, and J. A. Ellis (2015). Hedge funds and discretionary liquidity restrictions. *Journal of Financial Economics 116*(1), 197–218.

Ang, A., S. Gorovyy, and G. B. Van Inwegen (2011). Hedge fund leverage. *Journal of Financial Economics 102*(1), 102–126.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance 61*(1), 259–299.

Aragon, G. O. (2007). Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics 83*(1), 33–58.

Aragon, G. O. and P. E. Strahan (2012). Hedge funds as liquidity providers: Evidence from the lehman bankruptcy. *Journal of Financial Economics 103*(3), 570–587.

Asness, C. S., R. Krail, and J. M. Liew (2001). Do hedge funds hedge? *Available at SSRN 252810*.

Bai, J. and P. Collin-Dufresne (2013). The cds-bond basis. In *AFA 2013 San Diego Meetings Paper*.

Bali, T. G., S. J. Brown, and M. O. Caglayan (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics 114*(1), 1–19.

Bottazzi, J.-M., J. Luque, M. Pascoa, and S. M. Sundaresan (2012). Dollar shortage, central bank actions, and the cross currency basis. *Central Bank Actions, and the Cross Currency Basis (October 27, 2012).*

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial studies 22*(6), 2201–2238.

Buraschi, A., R. Kosowski, and W. Sritrakul (2014). Incentives and endogenous risk taking: A structural view on hedge fund alphas. *The Journal of Finance 69*(6), 2819–2870.

Cao, C., Y. Chen, B. Liang, and A. W. Lo (2013). Can hedge funds time market liquidity? *Journal of Financial Economics 109*(2), 493–516.

Chen, Q., I. Goldstein, and W. Jiang (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics 97*(2), 239–262.

Chen, Z. and A. Lu (2015). A market-based funding liquidity measure. In *Paris December 2015 Finance Meeting EUROFIDAI-AFFI*, pp. 14–01.

Chevalier, J. and G. Ellison (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy 105*(6), 1167–1200.

Dai, Q. and S. M. Sundaresan (2011). Risk management framework for hedge funds: role of funding and redemption options on leverage. *Available at SSRN 1439706*.

Drechsler, I. (2014). Risk choice under high-water marks. *Review of Financial Studies*, hht081.

Du, W., A. Tepper, and A. Verdelhan (2016). Covered interest rate parity deviations in the post-crisis world. *Available at SSRN 2768207*.

Eisl, A., R. Jankowitsch, and M. G. Subrahmanyam (2013). Are interest rate fixings fixed? an analysis of libor and euribor. *An Analysis of Libor and Euribor (January 15, 2013).*

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607–636.

Fleckenstein, M., F. A. Longstaff, and H. Lustig (2014). The tips-treasury bond puzzle. *The Journal of Finance 69*(5), 2151–2197.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Fung, W. and D. A. Hsieh (2000). Performance characteristics of hedge funds and commodity funds: Natural vs. spurious biases. *Journal of Financial and Quantitative Analysis 35*(03), 291–307.

Fung, W. and D. A. Hsieh (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial studies 14*(2), 313–341.

Fung, W. and D. A. Hsieh (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal 60*(5), 65–80.

Gârleanu, N. and L. H. Pedersen (2011). Margin-based Asset Pricing and Deviations from the Law of One Price. *Review of Financial Studies 24*(6), 1980–2022.

Getmansky, M., A. W. Lo, and I. Makarov (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics 74*(3), 529–609.

Golez, B., J. C. Jackwerth, and A. Slavutskaya (2015). Funding liquidity implied by s&p 500 derivatives. *Available at SSRN 2640697*.

Gromb, D. and D. Vayanos (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics 66*(2-3), 361–407.

Gromb, D. and D. Vayanos (2015). The dynamics of financially constrained arbitrage. Technical report, National Bureau of Economic Research.

Hombert, J. and D. Thesmar (2014). Overcoming limits of arbitrage: Theory and evidence. *Journal of Financial Economics 111*(1), 26–44.

Hu, G. X., J. Pan, and J. Wang (2013). Noise as information for illiquidity. *The Journal of Finance 68*(6), 2341–2382.

Ivashina, V., D. S. Scharfstein, and J. C. Stein (2015). Dollar funding and the lending behavior of global banks. *The Quarterly Journal of Economics 130*(3), 1241–1281.

Junge, B. and A. B. Trolle (2014). Liquidity risk in credit default swap markets. *Swiss Finance Institute Research Paper* (13-65).

Klebanov, M. M. (2008). Betas, characteristics and the cross-section of hedge fund returns. *Characteristics and the Cross-Section of Hedge Fund Returns (January 7, 2008).*

Krishnamurthy, A. (2002). The bond/old-bond spread. *Journal of Financial Economics 66*(2), 463–506.

Lan, Y., N. Wang, and J. Yang (2013). The economics of hedge funds. *Journal of Financial Economics 110*(2), 300–323.

Liu, J. and F. A. Longstaff (2004). Losing money on arbitrage: Optimal dynamic portfolio choice in markets with arbitrage opportunities. *Review of Financial Studies 17*(3), 611–641.

Liu, X. and A. S. Mello (2011). The fragile capital structure of hedge funds and the limits to arbitrage. *Journal of Financial Economics 102*(3), 491–506.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of financial studies 25*(12), 3457–3489.

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common risk factors in currency markets. *Review of Financial Studies 24*(11), 3731–3777.

Mitchell, M. and T. Pulvino (2012). Arbitrage crashes and the speed of capital. *Journal of Financial Economics 104*(3), 469–490.

Pangeas, S. and M. M. Westerfield (2009). High watermarks: High risk appetites? hedge fund compensation and portfolio choice. *Journal of Finance*.

Pasquariello, P. (2014). Financial market dislocations. *Review of Financial Studies 27*(6), 1868–1914.

Pastor, L. and R. F. Stambaugh (2003). Liquidity risk and price discovery. *Journal of Political Economy 111*(3), 642–685.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics 80*(2), 309–349.

Sadka, R. (2010). Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics 98*(1), 54–71.

Shleifer, A. and R. W. Vishny (1997). The limits of arbitrage. *The Journal of Finance 52*(1), 35–55.

Teo, M. (2011). The liquidity risk of liquid hedge funds. *Journal of Financial Economics 100*(1), 24–44.

Titman, S. and C. Tiu (2011). Do the best hedge funds hedge? *Review of Financial Studies 24*(1), 123–168.

Tuckman, B. and P. Porfirio (2003). Interest rate parity, money market basis swaps, and cross-currency basis swaps. *Fixed income liquid markets research, Lehman Brothers 1.*

Vayanos, D. and P. Woolley (2013). An institutional theory of momentum and reversal. *Review of Financial Studies 26*(5), 1087–1145.

Figures and Tables

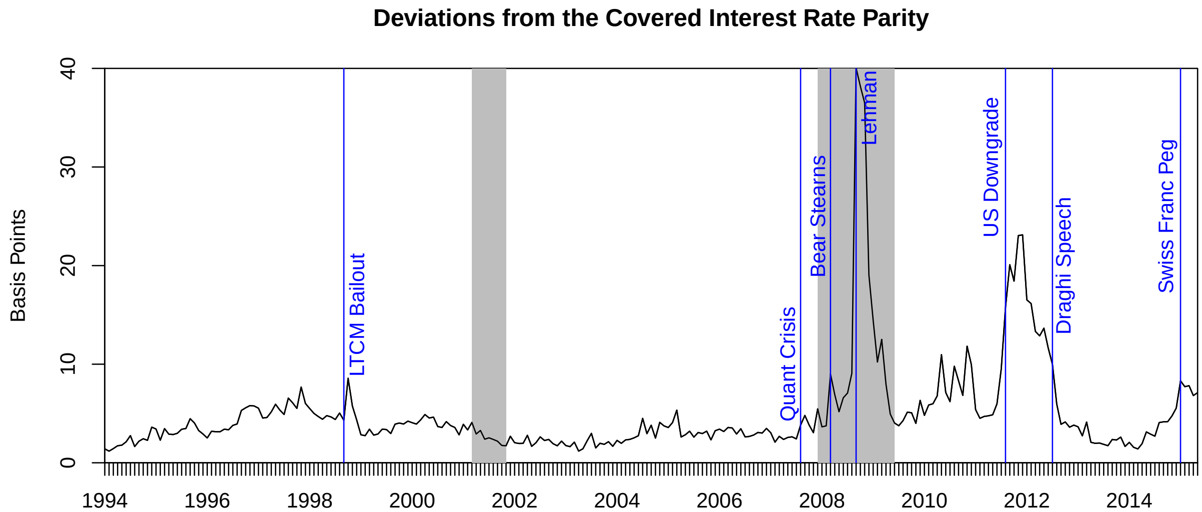


Figure 1: **Time Series of the Covered-Interest Rate Parity (CIP) Deviation Index.** This figure shows the time series of the CIP deviation index. The index is constructed as equal-weighted average of 9 different currency pairs of developed economies with 7 different maturities, ranging from one week to one year. The index construction is based on Equations (5)–(7), all observations are month-end. The highlighted events (blue 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 onset of the European debt crisis in August 2011, the date of Mario Draghi's speech in July 2012, declaring that the ECB will do "whatever it can" to preserve the Euro, and the data when the Swiss national bank lifted the currency peg to the Euro in January 2015. The two shaded areas are US recession periods.

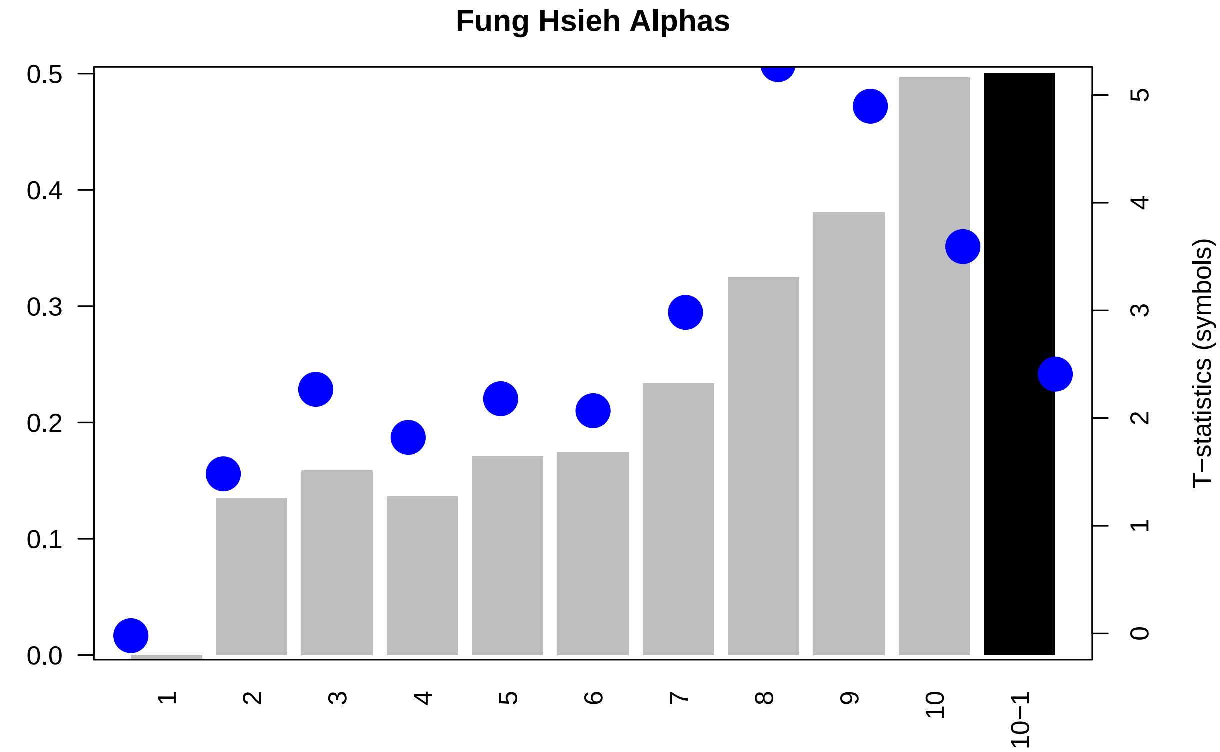
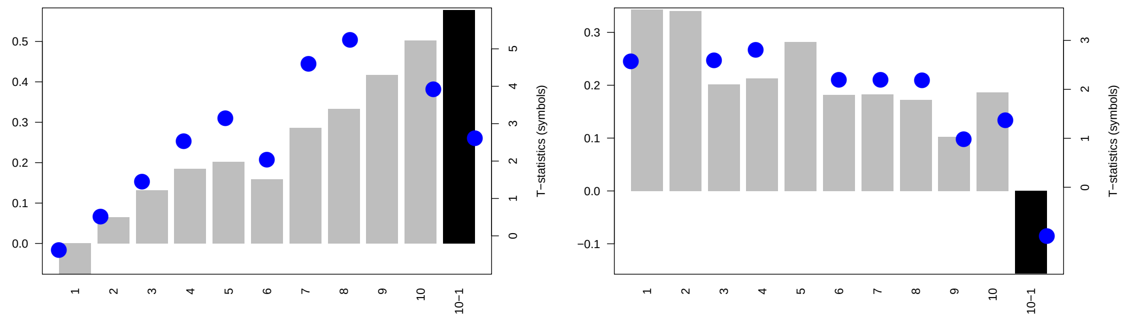
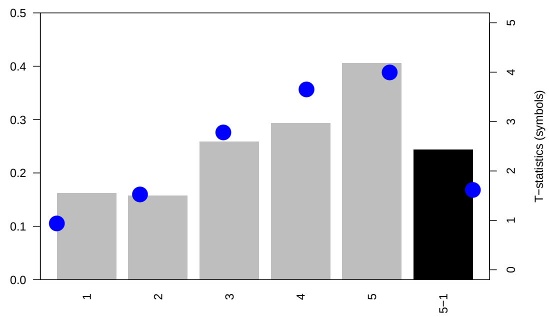


Figure 2: **Risk-adjusted returns of CIP-beta sorted hedge fund portfolios.** Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to changes in the covered interest rate parity deviation index (ΔCIP_t^D), constructed in Section 4.2. Funds in portfolio 1 have the strongest loading on ΔCIP_t^D (the most negative beta), funds in portfolio 10 have the weakest loading (beta close to zero). For each fund, the CIP beta is calculated using a regression of monthly fund returns on ΔCIP_t^D, controlling for the returns of the stock market portfolio, using the 36 months prior to portfolio formation. The bars represent monthly risk-adjusted portfolio returns, calculated using the Fung and Hsieh (2004) seven-factor model, where the credit and term factors are replaced by factor-mimicking tradable portfolios. The blue dots are Newey-West t-statistics of the respective risk-adjusted returns. The black bar displays the risk-adjusted return of the difference portfolio, which is long hedge funds in portfolio 10 and short hedge funds in portfolio 1. The sample period is January 1994 to May 2015, including all 8,541 hedge funds from the TASS database.

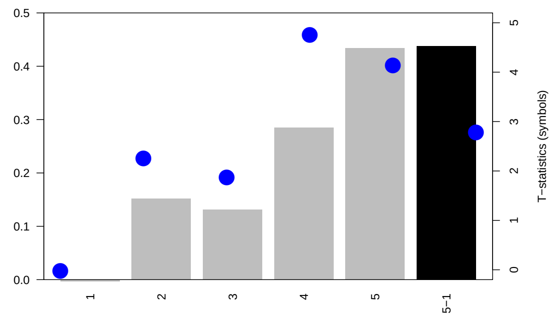


(a) Sorted on increases in CIP^D (b) Sorted on decreases in CIP^D

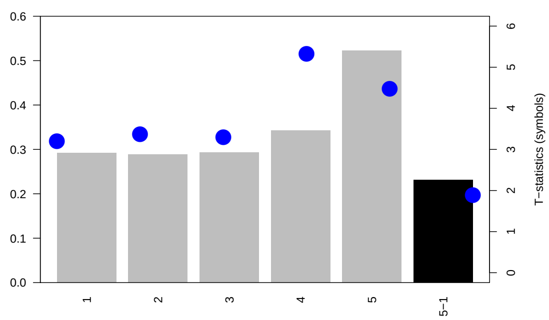
Figure 3: **Risk-adjusted hedge fund returns sorted on increases and decreases in CIP^D.** Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to increases in CIP^D (Panel (a)) and their historical beta to decreases in CIP^D (Panel (b)). For a detailed description of the sorting procedure as well as the computation of risk-adjusted returns see the caption of Figure 2



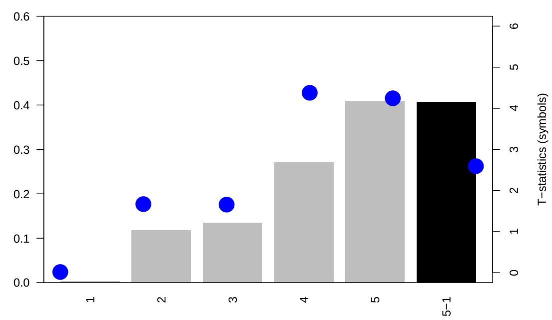
(a) Illiquid funds



(b) Liquid funds



(c) Funds without lockup



(d) Funds with lockup

Figure 4: **Risk-adjusted returns of different subgroups of CIP-beta sorted hedge fund portfolios.** Different subgroups of hedge funds are sorted into quintiles based on their loading on changes in the covered interest rate parity deviation index (ΔCIP_t^D), constructed in Section 4.2 (see the caption of Figure 2 for a description of the sorting procedure). Panels (a) and (b) compare the results for hedge funds with redemption notice periods of more than one month (illiquid hedge funds) and funds with redemption notice period less than one month (liquid hedge funds). Panels (c) and (d) compare the results for hedge funds with lockup provision and funds without lockup provision. The sample period is January 1994 to May 2015.

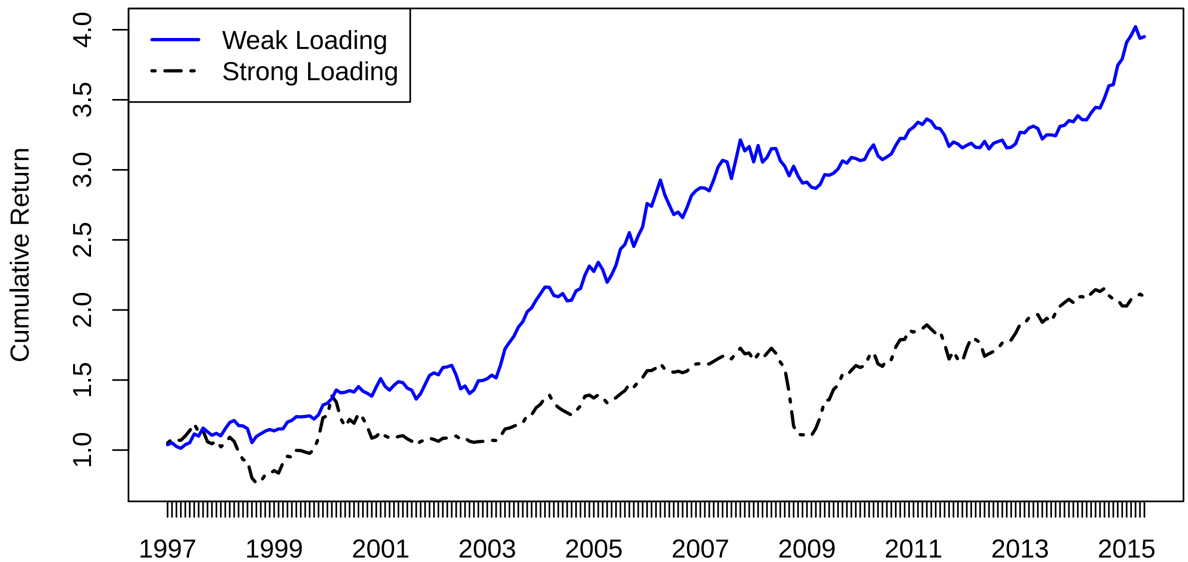


Figure 5: **Cumulative excess returns from investing in high and low loading funds.** This figure shows the cumulative excess returns of hedge funds with a strong loading (solid line) and weak loading (dashed line) on changes in the covered interest rate parity deviation index (ΔCIP_t^D), constructed in Section 4.2. See the caption of Figure 2 for a description of the sorting procedure. The high (low) loading portfolio is the first (tenth) decile portfolio.

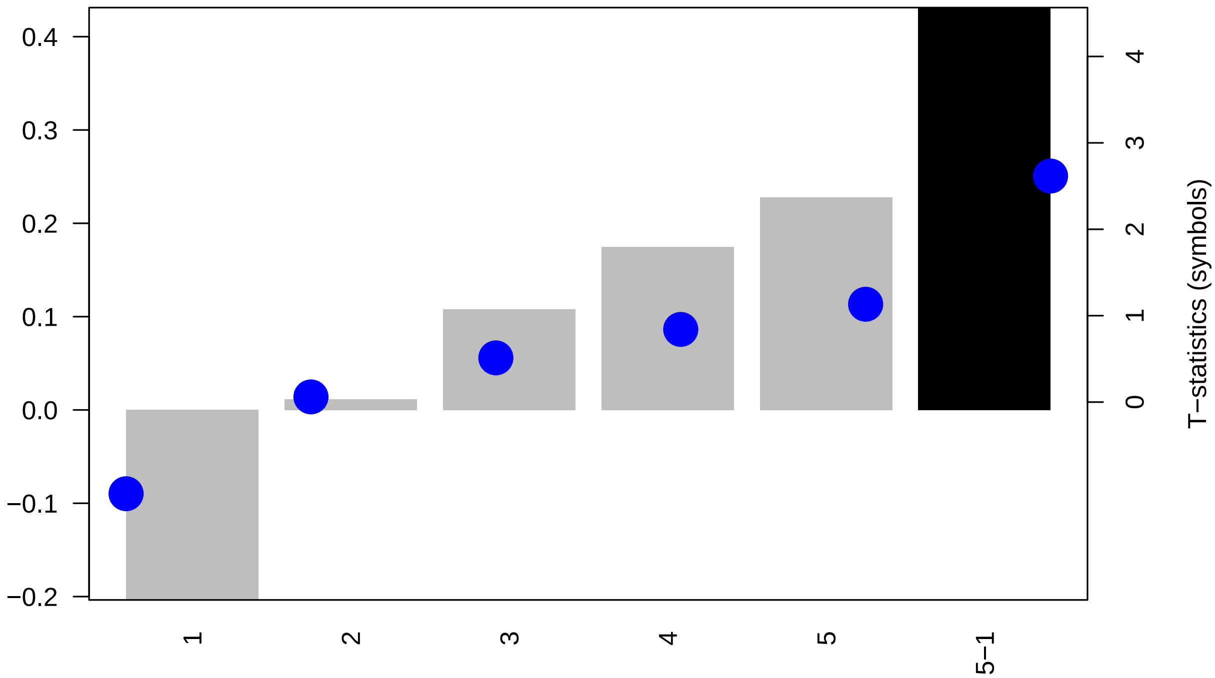
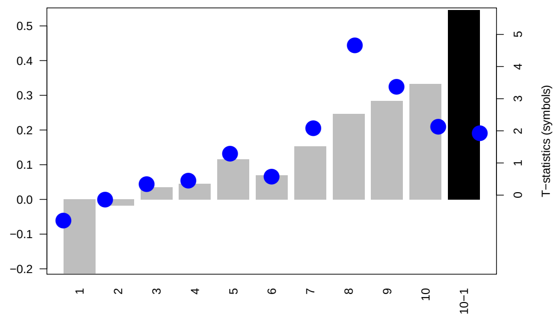


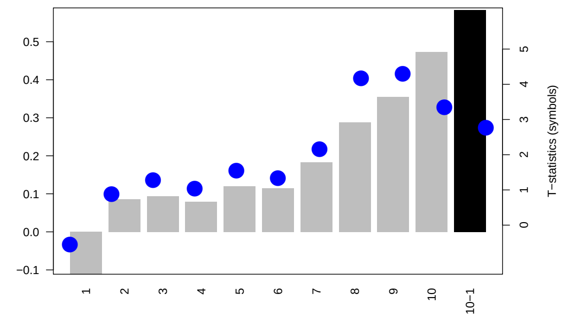
Figure 6: **Average flows for the different CIP-beta sorted hedge fund portfolios.** Hedge funds are sorted into quintiles according to their loading on ΔCIP^D. For a detailed description of this sorting procedure see the caption of Figure 2. Average monthly flows for these portfolios are then computed as:

$$Flow_t^{PF} := \frac{\sum_{i-1}^{n_t} Flow_t^i AUM_{t-1,i}}{\sum_{i-1}^{n_t} AUM_{t-1,i}},$$

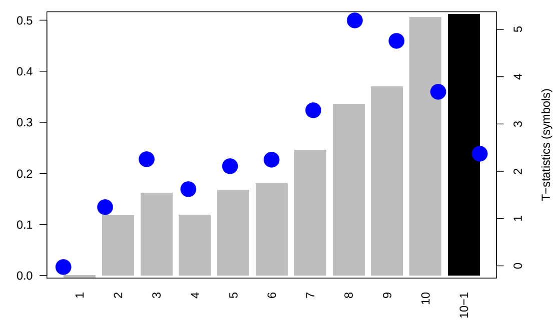
where n_t is the number of funds in the portfolio at time t. The grey bars correspond to the average monthly fund flows for the five portfolios. The black bar is the average difference of fund flows in portfolio 5 minus fund flows in portfolio 1. The blue dots indicate Newey-West t-statistics. The sample period is January 1994 to May 2015.



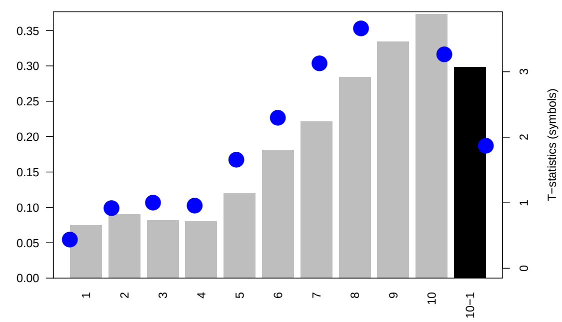
(a) Without backfilled observations



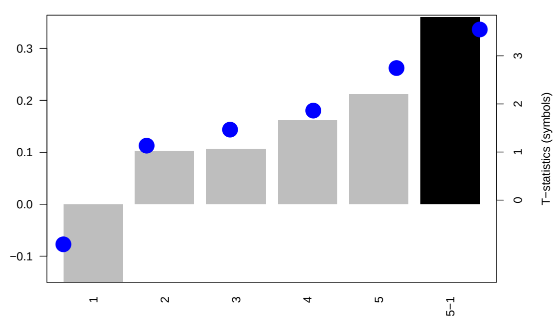
(b) Anti-smoothed returns



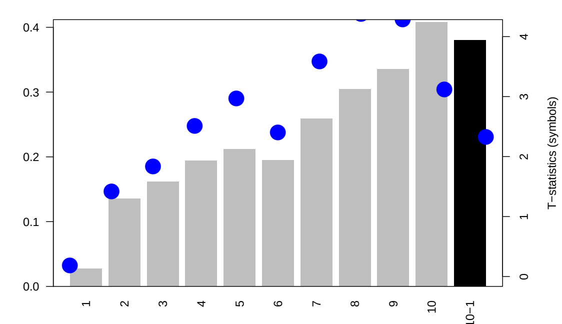
(c) Dropping potential duplicates



(d) Sorting based on $\Delta CIP^{OIS,D}$



(e) Funds of funds only



(f) Conditional Style Sorts

Figure 7: **Risk-adjusted returns of different modifications 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 2. Panel (a) illustrates the results where all backfilled returns (returns before the fund was added to the TASS database) are removed. Panel (b) shows the results where observed returns are replaced by un-smoothed returns using the un-smoothing procedure described in Getmansky et al. (2004). Panel (c) shows the results without hedge funds which are classified as duplicates by the algorithm described in Section 6.1. Panel (d) shows the results of sorting hedge funds into decile portfolios based on a different version of the CIP^D index, where deviations from the CIP are measured using overnight swap (OIS) rates in the respective currencies instead of Libor. Panel (e) shows the results for the subsample of funds of funds only. Panel (f) shows the results for conditional sorts, ensuring the same percentage of styles per decile. The sample period is January 1994 to May 2015.

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. 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 is a dummy variable which is equal to one if the fund return in a given month is backfilled. Lockup is a dummy variable which is equal to one if the fund has a lockup provision. Notice is the number of months that investors have to notice the manager before withdrawing capital from the fund. Panel B reports summary statistics of hedge fund returns per style. The sample period is January 1994 to May 2015.

	N	Mean	SD	Min	Median	Max
	Panel A: Summary statistics for all hedge funds					
Return (mean)	8,541	0.58	0.64	-6.68	0.54	5.80
Return (SD)	8,541	3.07	2.62	0.00	2.30	45.74
AUM (mio USD)	8,541	146.26	320.79	10.00	53.92	7158.02
Reporting (Months)	8,541	97.63	49.72	36.00	85.00	257.00
Age (Months)	8,541	50.53	30.45	17.50	42.50	365.00
Backfilled	8,541	0.46	0.33	0.00	0.40	1.00
Lockup?	8,541	0.19	-	-	-	-
Notice (Months)	8,541	1.07	1.12	0.00	1.00	12.17
Management Fee	8,480	1.41	0.74	0.00	1.50	22.00
Incentive Fee	8,046	13.43	8.67	0.00	20.00	50.00
	Panel B: Hedge fund returns for different styles					
Convertible Arbitrage	170	0.49	0.49	-1.24	0.53	1.81
Emerging Markets	445	0.78	0.84	-3.14	0.72	5.58
Equity Market Neutral	315	0.47	0.47	-1.08	0.40	2.64
Event Driven	474	0.76	0.67	-3.92	0.72	5.35
Fixed Income Arbitrage	251	0.56	0.60	-2.88	0.61	2.11
Fund of Funds	2,987	0.32	0.47	-5.20	0.31	3.03
Global Macro	337	0.72	0.77	-6.68	0.74	5.64
Long Short Equity	1,812	0.82	0.67	-2.11	0.76	4.89
Managed Futures	402	0.68	0.65	-3.99	0.60	3.80
Multi-Strategy	1,019	0.73	0.58	-2.61	0.78	5.73
Other	329	0.65	0.79	-1.75	0.58	5.80

Table 2: **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 the funding liquidity of major financial institutions. The four 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), returns of the nine major US investment banks Ret_t^{IB}, changes in the option-implied volatility of the S&P 500 index (ΔVIX_t), and the dealer-broker leverage factor introduced by Adrian et al. (2014). The sample period is January 1994 to December 2014. In columns (1)-(4), observations are month-end, in columns (5)-(6) observations are quarter-end. Newey-West t-statistics are reported in parenthesis. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.02	0.03	0.02	0.02	0.42	0.01
	(0.21)	(0.20)	(0.18)	(0.25)	(1.17)	(0.03)
ΔTED_t	0.07**			0.06**		0.05***
	(2.16)			(2.10)		(2.81)
Ret_t^{IB}		−0.10**		−0.02		−0.06**
		(−2.06)		(−0.76)		(−2.21)
ΔVIX_t			0.22*	0.12*		0.07
			(1.89)	(1.67)		(1.30)
$Leverage_t$					0.23***	0.13***
					(6.38)	(6.09)
Observations	257	257	257	257	85	85
Adjusted R^2	0.36	0.12	0.12	0.41	0.67	0.82

Table 3: **Correlation between ΔCIP^D and other liquidity proxies.** This table shows the correlation between ΔCIP_t^D as well as $\Delta CIP^{D,OIS}$ and other common liquidity measures. The other measures are the betting against beta factor (BAB_t) constructed in Frazzini and Pedersen (2014), the Pastor and Stambaugh (2003) stock market liquidity factor (PS_t), changes in the treasury-eurodollar spread (ΔTED_t), the dealer-broker leverage factor suggested by Adrian et al. (2014) ($Leverage_t$), changes in the 10-year on-the-run off-the-run spread ($\Delta On10Yr_t$), and changes in the Hu et al. (2013) noise measure ($\Delta Noise_t$). The sample period is January 1994 to May 2015, all observations are month-end.

	BAB_t	PS_t	ΔTED_t	$Leverage_t$	$\Delta On10Yr_t$	$\Delta Noise_t$	ΔCIP_t^D
PS_t	0.06						
ΔTED_t	-0.06	-0.15					
$Leverage_t$	0.00	-0.06	0.68				
$\Delta On10Yr_t$	-0.03	-0.13	0.12	0.21			
$\Delta Noise_t$	-0.08	-0.12	0.19	0.43	0.55		
ΔCIP_t^D	-0.10	-0.07	0.60	0.82	0.07	0.22	
$\Delta CIP_t^{D,OIS}$	-0.08	0.05	0.74	0.81	-0.05	-0.02	0.78

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 May 2015. All observations are month-end.

	MKT	SMB	YLD	BAA	BD	FX	COM
SMB	0.24						
YLD	0.07	0.14					
BAA	-0.32	-0.25	-0.42				
BD	-0.25	-0.07	-0.12	0.24			
FX	-0.2	-0.02	-0.06	0.22	0.29		
COM	-0.17	-0.07	0.01	0.14	0.18	0.34	
CIP	-0.17	-0.03	0.14	0.07	0.12	0.17	0.13

Table 5: **Risk-adjusted returns and other characteristics of CIP^D-sorted portfolios.** 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. α^{FH} is the intercept of regressing the portfolio returns on the 7 Fung Hsieh risk factors, β^{Mkt} and β^{CIP} are the portfolio loadings on the market portfolio and on CIP^D respectively, R^2_{FH} is the adjusted R^2 of regressing the portfolio returns on the seven Fung Hsieh factors. α^{Add} is the intercept of regressing hedge fund returns on the 7 Fung Hsieh factors plus five additional factors, Ret^{Exc} are the excess returns of the different hedge fund portfolios, SD^{Ret} is the standard deviation of the hedge fund portfolio returns, and SR is the Sharpe ratio of the hedge fund portfolios. The 7 Fung Hsieh 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 five additional factors are a stock market momentum factor, the two currency risk factors proposed by Lustig et al. (2011), excess returns of the S&P GSCI commodity index, and excess returns of the MSCI emerging market index. The sample period is January 1994 to May 2015. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	α^{FH}	β^{Mkt}	β^{CIP}	R^2_{FH}	α^{Add}	Ret^{Exc}	SD^{Ret}	SR
P1	0.00	0.51***	-0.15***	0.64	0.06	0.40	3.48	0.11
	[-0.02]	[9.77]	[-3.82]		[0.48]	[1.20]		
P2	0.14	0.30***	-0.14***	0.63	0.15**	0.36*	2.07	0.17
	[1.48]	[8.71]	[-4.22]		[2.56]	[1.94]		
P3	0.16**	0.26***	-0.11***	0.69	0.17***	0.35**	1.70	0.21
	[2.27]	[9.48]	[-5.93]		[3.21]	[2.35]		
P4	0.14*	0.22***	-0.09***	0.65	0.13**	0.29**	1.49	0.20
	[1.82]	[8.96]	[-4.84]		[2.43]	[2.07]		
P5	0.17**	0.21***	-0.09***	0.60	0.18***	0.32**	1.45	0.22
	[2.18]	[8.49]	[-4.56]		[3.00]	[2.38]		
P6	0.17**	0.20***	-0.09***	0.59	0.19***	0.33**	1.42	0.23
	[2.07]	[7.14]	[-4.21]		[2.82]	[2.49]		
P7	0.23***	0.17***	-0.07***	0.51	0.24***	0.36***	1.26	0.28
	[2.98]	[8.85]	[-3.71]		[3.81]	[3.21]		
P8	0.33***	0.19***	-0.05**	0.56	0.32***	0.47***	1.32	0.35
	[5.28]	[9.01]	[-2.35]		[5.55]	[4.53]		
P9	0.38***	0.22***	0.00	0.47	0.40***	0.52***	1.57	0.33
	[4.90]	[8.07]	[-0.22]		[4.93]	[4.15]		
P10	0.50***	0.31***	0.03	0.42	0.53***	0.65***	2.40	0.27
	[3.59]	[6.63]	[0.79]		[3.84]	[3.72]		
P10-P1	0.50**	-0.20**	0.18***	0.30	0.48**	0.26	2.98	0.09
	[2.41]	[-2.22]	[4.57]		[2.40]	[0.93]		

Table 6: **Risk-adjusted returns and other characteristics of for funds sorted on increases and decreases in CIP^D.** Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to increases in CIP^D (Panel (a)) and their historical beta to decreases in CIP^D (Panel (b)). For a detailed description of the sorting procedure and the different variables see the caption of Table 5. The sample period is January 1994 to May 2015. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	α^{FH}	β^{Mkt}	β^{CIP}	R^2_{FH}	α^{Add}	Ret^{Exc}	SD^{Ret}	SR
	Panel A: Sorting on $\max(\Delta CIP^D, 0)$							
P1	-0.08	0.56***	-0.15***	0.62	-0.03	0.32	3.67	0.09
	[-0.38]	[10.26]	[-4.40]		[-0.26]	[0.96]		
P10	0.50***	0.24***	0.01	0.34	0.54***	0.65***	2.04	0.32
	[3.90]	[6.31]	[0.29]		[4.01]	[4.32]		
P10-P1	0.58***	-0.32***	0.16***	0.37	0.57***	0.33	3.10	0.11
	[2.64]	[-4.50]	[4.82]		[3.05]	[1.10]		
	Panel B: Sorting on $\min(\Delta CIP^D, 0)$							
P1	0.34**	0.35***	-0.11***	0.56	0.41***	0.62***	2.56	0.24
	[2.39]	[7.75]	[-3.61]		[3.70]	[2.84]		
P10	0.19	0.48***	-0.06	0.57	0.23**	0.46*	3.20	0.14
	[1.42]	[10.42]	[-1.39]		[2.57]	[1.79]		
P10-P1	-0.16	0.12*	0.05	0.06	-0.18	-0.16	2.38	-0.07
	[-0.96]	[1.90]	[0.88]		[-1.32]	[-0.94]		

Table 7: **Risk-adjusted returns and other characteristics for different subgroups of CIP^D-sorteg portfolios.** Different subgroups of hedge funds are sorted into quintiles based on their loading on changes in the covered interest rate parity deviation index (ΔCIP_t^D), constructed in Section 4.2. Panels A and B compare the results for hedge funds with redemption notice periods of more than one month (illiquid hedge funds) and funds with redemption notice period less than one month (liquid hedge funds). Panels C and D compare the results for hedge funds with lockup provision and funds without lockup provision.. For a detailed description of the sorting procedure and the different variables see the caption of Table 5. The sample period is January 1994 to May 2015. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	α^{FH}	β^{Mkt}	β^{CIP}	R^2_{FH}	α^{Add}	Ret^{Exc}	SD^{Ret}	SR
	Panel A: Illiquid hedge funds							
P1	0.16	0.43***	-0.15***	0.63	0.22**	0.47*	2.95	0.16
	[0.92]	[8.77]	[-4.71]		[2.11]	[1.68]		
P5	0.41***	0.32***	0.00	0.56	0.44***	0.59***	2.07	0.29
	[3.96]	[8.56]	[0.16]		[4.37]	[3.52]		
P5-P1	0.24	-0.11*	0.16***	0.25	0.22*	0.12	2.02	0.06
	[1.57]	[-1.97]	[5.67]		[1.75]	[0.66]		
	Panel B: Liquid hedge funds							
P1	0.00	0.40***	-0.15***	0.63	0.03	0.32	2.76	0.12
	[-0.03]	[8.62]	[-5.00]		[0.32]	[1.27]		
P5	0.43***	0.24***	0.01	0.38	0.46***	0.57***	1.98	0.29
	[4.12]	[6.70]	[0.44]		[3.98]	[4.06]		
P5-P1	0.44***	-0.16**	0.16***	0.30	0.43***	0.25	2.26	0.11
	[2.72]	[-2.15]	[6.37]		[2.74]	[1.25]		
	Panel C: Funds with lockup provision							
P1	0.29***	0.42***	-0.20***	0.70	0.35***	0.58**	2.68	0.22
	[3.08]	[11.82]	[-5.29]		[4.27]	[2.39]		
P5	0.52***	0.36***	0.01	0.54	0.57***	0.71***	2.33	0.30
	[4.57]	[10.68]	[0.43]		[4.95]	[3.99]		
P5-P1	0.23*	-0.06	0.21***	0.18	0.22*	0.12	2.03	0.06
	[1.81]	[-1.10]	[6.39]		[1.84]	[0.73]		
	Panel D: Funds without lockup provsion							
P1	0.00	0.40***	-0.13***	0.62	0.04	0.32	2.76	0.12
	[0.02]	[9.08]	[-3.75]		[0.42]	[1.23]		
P5	0.41***	0.24***	0.01	0.42	0.43***	0.55***	1.86	0.30
	[4.06]	[6.99]	[0.28]		[4.20]	[4.04]		
P5-P1	0.41***	-0.16**	0.13***	0.32	0.39***	0.23	2.12	0.11
	[2.60]	[-2.34]	[5.69]		[2.77]	[1.18]		

Table 8: **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.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
	Panel A: Characteristics									
AUM (mio USD)	260.31	395.76	467.86	566.03	396.32	328.82	357.69	391.96	396.62	343.16
Reporting (months)	138.55	140.24	140.58	141.19	139.23	138.08	138.88	136.73	135.17	139.59
Age (months)	87.04	89.15	89.46	87.86	87.68	86.37	85.28	85.01	85.51	87.90
Backfilled	0.26	0.28	0.30	0.30	0.29	0.29	0.30	0.31	0.29	0.29
Lockup?	0.24	0.24	0.23	0.20	0.19	0.19	0.20	0.21	0.23	0.25
Notice (Months)	1.02	1.15	1.20	1.26	1.28	1.19	1.16	1.10	1.05	1.00
Management Fee	1.52	1.44	1.39	1.37	1.38	1.37	1.34	1.36	1.39	1.47
Incentive Fee	17.30	16.54	15.35	15.03	14.47	14.66	15.55	16.60	17.60	18.34
	Panel B: Allocation within hedge fund style (%)									
Convertible Arbitrage	2.12	2.85	3.90	3.13	2.98	3.25	3.63	2.80	1.60	1.41
Emeging Markets	14.10	8.88	5.17	3.59	3.02	2.41	2.71	3.79	5.83	9.45
Equity Market Neutral	2.01	2.68	3.00	3.55	2.86	3.28	3.99	4.36	5.43	4.53
Event Driven	4.34	5.91	7.47	7.98	8.75	9.98	10.66	11.12	9.09	3.98
Fixed Income Arbitrage	4.10	3.95	3.28	3.49	3.06	3.13	3.72	3.17	3.38	1.71
Fund of Funds	10.77	23.34	36.58	43.53	46.51	43.87	37.12	29.52	19.18	10.00
Global Macro	5.47	4.00	2.95	2.47	2.39	2.35	2.57	3.25	3.81	5.40
Long Short Equity	35.29	30.21	23.37	18.06	16.72	15.13	16.49	22.62	31.38	40.24
Managed Futures	11.88	7.17	4.34	3.90	3.86	3.96	4.41	5.58	8.67	15.76
Multi-Strategy	5.99	7.62	6.75	7.65	7.63	10.00	12.12	11.62	8.44	4.69
Other	3.93	3.38	3.19	2.64	2.23	2.65	2.59	2.17	3.19	2.82

Table 9: **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 $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	Intercept	beta CIP	Age	Size	Notice	Lockup?	Style Dummies
	Panel A: Base case						
All Data	0.540***	4.579***	-0.001	-0.014	0.031	0.124***	Yes
	[4.56]	[2.97]	[-1.30]	[-0.73]	[1.28]	[3.44]	
	Panel B: Robustness checks addressing hedge fund data quality						
Backfill	0.357***	4.365**	-0.001	-0.001	0.061**	0.152***	Yes
	[2.71]	[2.45]	[-1.63]	[-0.06]	[2.25]	[3.04]	
Survivorship	-0.152	4.302***	0.000	0.065**	0.045	0.124***	Yes
	[-0.97]	[2.71]	[-0.43]	[2.57]	[1.30]	[2.70]	
Unsmoothed	0.486***	2.893***	0.000	-0.014	0.026	0.130***	Yes
	[4.14]	[3.08]	[-0.83]	[-0.72]	[1.01]	[3.59]	

Table 10: **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 ΔCIP_t^D, controlling for returns of the stock market portfolio, using the 36 months 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) 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 2011 - January 2012, and 204 non-crisis months. Under (II) crisis periods are defined as periods where increases in the TED spread are above their 75% quantile. The remaining periods are quiet periods. Quantiles are computed using the January 1997 – May 2015 sample period. The sample period is January 1994 to May 2015, including all funds in the TASS database. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	(I) Anecdotal			(II) TED		
	#Obs	α^{FH}	R^{Exc}	#Obs	α^{FH}	R^{Exc}
Crisis	17	1.54***	2.86*	66	0.78**	1.15***
		[3.24]	[1.89]		[2.35]	[2.79]
Quiet	204	0.41*	0.04	155	0.42*	-0.01
		[1.90]	[0.17]		[1.92]	[-0.04]

Table 11: **Combining Noise and CIP^D.** This table shows the results of a conditional double sort. I a first step, all hedged funds are sorted into five different portfolios based on their sensitivity to changes in the noise measure. Funds with the strongest loading on $\Delta Noise$ are in portfolio 5 and funds with the weakest loading on $\Delta Noise$ are in portfolio 1. In a second step, each of the five portfolios is split into five more portfolios based on their loading on ΔCIP^D. Funds with the strongest loading on ΔCIP^D are in portfolio 1 and funds with the weakest loading on ΔCIP^D are in portfolio 5. The figure in the bottom-right corner shows the risk-adjusted returns of the difference portfolio that is long hedge funds with the strongest loading on $\Delta Noise_t$ and the weakest loading on ΔCIP^D and short the portfolio with the weakest loading on $\Delta Noise_t$ and the strongest loading on ΔCIP^D. All figures are risk-adjusted returns using the Fung Hsieh seven factor model. The sample period is January 1994 to May 2015. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	Weak N1	N2	N3	N4	Strong N5	N5-N1
Strong CIP1	-0.32*	-0.06	0.00	0.09	0.23	0.54**
	[-1.78]	[-0.44]	[0.01]	[0.85]	[1.16]	[2.33]
CIP2	0.22**	0.07	0.20**	0.11	0.39**	0.17
	[2.38]	[0.69]	[2.05]	[0.95]	[2.32]	[0.95]
CIP3	0.24**	0.21***	0.17*	0.19**	0.44***	0.20
	[2.29]	[2.95]	[1.93]	[2.53]	[3.50]	[1.28]
CIP4	0.35***	0.36***	0.24***	0.17**	0.28**	-0.06
	[3.50]	[5.00]	[3.34]	[2.18]	[2.50]	[-0.53]
Weak CIP5	0.37***	0.34***	0.30***	0.27**	0.68***	0.31**
	[2.89]	[4.34]	[4.13]	[2.29]	[3.68]	[2.22]
CIP5-CIP1	0.68***	0.40***	0.30**	0.18	0.45*	1.00***
	[3.80]	[2.89]	[2.25]	[1.55]	[1.82]	[4.69]

A Proofs

Proof of Proposition 1

Computing the two integrals in Equation (1) leads to the following form of the expected value:

$$\mathbb{E}[W_2] = \left(\frac{1}{2} + \alpha\theta - \frac{\theta^2}{2} - \alpha\theta^2\right) + \frac{(1+\alpha)(\bar{\lambda} - 1 + \theta)(\bar{\lambda} - 1 + (2c-1)\theta))}{2(c-1)}. \tag{15}$$

Taking the first-order condition (FOC) of Equation (15) and solving for the optimal investment gives:

$$\theta_i^* = \frac{\alpha_i + c - c\bar{\lambda}(1+\alpha_i)}{c + \alpha_i}. \tag{16}$$

The second derivative is given as: $-\frac{c+\alpha}{(1-c)\bar{\lambda}} < 0$ and hence the point is indeed a local maximum. Furthermore, the function is increasing on $[0, \theta_i^*)$ and decreasing on $(\theta_i^*, 1]$, indicating that the point is a global maximum. ■

Proof of Lemma 1

I start by showing that mimicking the good manager's returns entails more risk taking for the bad manager. Let θ_M denote the mimicking investment. Then Equation(3) can be derived as follows:

$$\begin{aligned}
\theta_M - \theta^* &= \frac{\alpha_G}{\alpha_B}\theta_G^* - \theta_B^* \\
&= \frac{a}{\alpha}\left(1 - \frac{c(1+a)}{a+c}\bar{\lambda}\right) - \left(1 - \frac{c(1+\alpha)}{\alpha+c}\bar{\lambda}\right) \\
&= \left(\frac{a}{\alpha} - 1\right) - \left(\frac{1+a}{a+c} - \frac{1+\alpha}{\alpha+c}\right)c\bar{\lambda} \\
&= \left(\frac{a}{\alpha} - 1\right) + \frac{(1-c)(a-\alpha)}{(a+c)(\alpha+c)}\bar{\lambda} > 0,
\end{aligned}$$

where the inequality holds because $c < 1$ and $a > \alpha$. Hence, mimicking the good manager's returns entails more risk taking than is optimal for the bad manager.

To formally prove this result, we need to distinguish three cases. First, if $\lambda \leq 1 - \theta_B^*$, the following inequality holds:

$$1 + \alpha_B\theta_B^* < 1 + \alpha_B\theta_M = 1 + \alpha_G\theta_G^*.$$

Second, if $\lambda \geq 1 - \theta_G^*$, the following inequality needs to hold:

$$\left(\theta_G - \frac{\lambda - (1-\theta_G)}{1-c}\right)(1+\alpha_G) > \left(\theta_B - \frac{\lambda - (1-\theta_B)}{1-c}\right)(1+\alpha_B)$$
$$\Leftrightarrow \underbrace{\alpha_G(1-\lambda-c\theta_G^*) - \alpha_B(1-\lambda-c\theta_B^*)}_{>(\alpha_G-\alpha_B)(1-\lambda-c\theta_B^*)} + \underbrace{c(\theta_B^* - \theta_G^*)}_{>0} > 0$$

and $1 - \lambda - c\theta^*$ Finally, for $\lambda \in (1-\theta_B^*, 1-\theta_G^*)$, we have:

$$1 + \alpha_B\theta_B^* - \lambda > \left(\theta_B^* - \frac{\lambda - (1-\theta_B^*)}{1-c}\right)(1+\alpha_B)$$
$$\Leftrightarrow \frac{(c+\alpha)(\lambda - (1-\theta_B^*))}{1-c} > 0,$$

which is fulfilled since $\lambda > 1 - \theta$. Hence, we have

$$1 + \alpha_G\theta_G^* - \lambda > 1 + \alpha_B\theta_B^* - \lambda > \left(\theta_B - \frac{\lambda - (1-\theta_B)}{1-c}\right)(1+\alpha_B),$$

which completes the proof. ■

Proof of Proposition 2

Equation (3) has been proven in the proof of Lemma 1 and the equation for p follows from the fact that λ is uniformly distributed on $[0, \bar{\lambda}]$. To prove the second part, note that the bad manager has an incentive to mimic the good manager if

$$\mathbb{E}[W_2|\theta = \theta_B^*] < \mathbb{E}[W_2|\theta = \theta_M] + p\zeta.$$

Therefore, if ζ exceeds the following threshold, the manager has an incentive to take on additional risk:

$$\zeta > \frac{1}{p}\left(\mathbb{E}[W_2|\theta = \theta_B^*] - \mathbb{E}[W_2|\theta = \theta_M]\right)$$
$$= -\frac{(\bar{\lambda}(a-\alpha)^2(-c(a+c) + (1+a)c^2\bar{\lambda} + (a+c)(-1+cL)\alpha)^2}{2(-1+c)(a+c)\alpha(c+\alpha)(-a(a+c) + a(1+a)cL + (a+c)\alpha))}$$

The simplified, sufficient condition can be derived using the following inequality:

$$\begin{aligned}\zeta &> \frac{1}{p}\left(\mathbb{E}[W_2|\theta=\theta_B^*] - \mathbb{E}[W_2|\theta=\theta_M]\right) \\ &\geq \frac{1}{p}\left(\mathbb{E}[W_2|\theta=\theta_B^*] - \mathbb{E}[W_2|\theta=1]\right) \\ &= \frac{1}{p}\frac{c^2(1+\alpha_B)^2}{2(1-c)(c+\alpha_B))}\bar{\lambda}^2,\end{aligned}$$

which completes the proof. ■

B Data Description

This appendix provides additional details about the data used for my analysis.

1. **BAB factor:** This is the betting against beta factor described in Frazzini and Pedersen (2014). The data are obtained from Lasse Pedersen's website: `http://www.lhpedersen.com/data`.
2. **Commodity Risk:** The commodity risk factor is constructed using the returns of the S&P GSCI index over the one-month risk-free rate. Data for this index comes from datastream.
3. **Currency Risk Factors:** These factors capture currency returns of an US dollar investor and a the returns of a carry trader. The data are obtained from Adrian Verdelhan's website: `http://web.mit.edu/adrienv/www/Data.html`
4. **Dealer Broker Leverage:** This variable captures the leverage of US broker-dealers and is described in more detail in Adrian et al. (2014). Until Q4 2009, data on this variable are obtained from Tyler Muir's website. Since the data ends in Q4 2009, we use the financial accounts of the US data, following the procedure described in Adrian et al. (2014) to supplement the time series with more recent observations for the Q1 2010 – Q4 2015 period.
5. **Emerging Markets Risk:** The emerging markets risk factor is constructed using the returns of the MSCI emerging market index over the one-month risk-free rate. Data for this index comes from datastream.
6. **Fixed Income Risk Factors:** To compute risk-adjustd returns, I use tradable fixed income risk factors. These two factors are the excess returns of the Merrill Lynch treasury bond index with 7-10 years to maturity over the 1-month risk-free rate and the difference between the Merrill Lynch corporate bond index with BBB-rated bonds and 7-10 years to maturity over the treasury bond index. The data on the two bond indices

are obtained from the Bloomberg system, the one-month risk-free rate is obtained from Kenneth French's website.

7. **Investment Bank Stock Returns:** I use the stock returns of the 9 largest investment banks, which are: Bear Stearns, Citibank, Credit Suisse, Goldman Sachs, HSBC, JP Morgan, lehman Brothers, Merril Lynch, and Morgan Stanley. These returns are obtained from the Bloomberg system.
8. **Noise measure:** This is the noise measure developed by Hu et al. (2013). The data are obtained from Jun Pan's website: `http://www.mit.edu/~junpan/`.
9. **On-the-run spread:** The spread is computed for bonds with 10-years to maturity because estimates of the 30-year spread are noisy and suffer from the 2002-2005 period where the US treasury reduced its debt issuance. The 10-year on-the-run yield is obtained from the FED H.15 website and the 10-year off-the-run yield is constructed as explained in **?** and data are obtained from `http://www.federalreserve.gov/pubs/feds/2006`.
10. **PS Liquidity factor:** This is the Pastor and Stambaugh (2003) stock market liquidity factor, obtained from Lubos Pastor's website: `http://faculty.chicagobooth.edu/lubos.pastor/research/`.
11. **TED Spread:** The treasury eurodollar spread is the difference between the 3-month US Libor rate and the 3-month US treasury rate. Both rates are obtained from the Bloomberg system.
12. **Trend Following Factors:** The three Fung and Hsieh trend-following are capturing returns from trend followers in the bonds, currency, and commodities markets. The factors are directly obtained from David Hsieh's website: `https://faculty.fuqua.duke.edu/~dah7/HFData.htm`.
13. **U.S. Stock Market Returns:** The stock market data used in my analysis are obtained from Kenneth French's website and consist of the monthly returns the CRSP market portfolio in excess of the one-month treasury yield (Mkt), the difference between small and big stocks (SMB), and the momentum factor that is long stocks with high past returns and short stocks with low past returns (UMD)
14. **VIX:** Is the implied volatility of the S&P 500 index and data on VIX are obtained from the Bloomberg System.

C Additional Results

This section presents additional results that have been omitted in the main part.

Table 12: **Hedge fund summary statistics.** This table provides summary statistics of average hedge fund returns in the TASS database separately for every year. The sample period is January 1994 to May 2015.

	N	Mean	SD	Min	Meadian	Max
1994	1,059	0.06	1.74	-10.62	0.04	12.69
1995	1,365	1.59	8.8	-6.58	1.18	317.99
1996	1,718	1.44	1.82	-17.72	1.29	12.89
1997	2,017	1.38	1.94	-12.34	1.3	18.96
1998	2,319	0.46	2.38	-13.44	0.57	16.8
1999	2,730	2.15	3.18	-22.62	1.55	41.37
2000	3,156	0.85	2.32	-23.07	0.91	23.22
2001	3,800	0.57	1.96	-25.9	0.54	48.43
2002	4,590	0.35	1.53	-20.93	0.28	23
2003	5,669	1.32	2.05	-14.54	0.94	85.74
2004	6,964	1.42	58.55	-29.17	0.59	4885.86
2005	8,212	0.82	1.22	-11.95	0.64	27.68
2006	9,228	0.97	1.93	-9.91	0.82	145.74
2007	10,069	0.95	7.87	-21.65	0.72	733.63
2008	10,406	-1.07	16.92	-44.82	-1.23	1394.6
2009	10,068	1.07	2.99	-100	0.83	188.45
2010	9,652	0.62	1.58	-38.34	0.56	75.36
2011	9,208	-0.29	1.73	-27.08	-0.22	76.9
2012	8,404	0.48	1.81	-48.05	0.5	88.37
2013	7,224	0.59	1.94	-30.03	0.57	79.37
2014	6,121	0.38	11.21	-62.16	0.27	866.68
2015	4,939	0.83	3.74	-21.14	0.72	212.08

Table 13: **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 square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

PF	Intercept	β^{CIP}	β^{Mkt}	β^{SMB}	β^{YLD}	β^{BAA}	β^{BD}	β^{FX}	β^{COM}	R^2
P1	0.01	-0.09	0.36	0.25	0.24	0.65	-1.93	2.19	0.46	0.65
	[0.03]	[-2.17]	[8.87]	[3.54]	[3.00]	[7.12]	[-1.53]	[2.96]	[0.44]	
P2	0.15	-0.11	0.21	0.12	0.16	0.41	0.19	1.21	0.48	0.64
	[1.72]	[-2.30]	[6.93]	[3.96]	[3.27]	[8.25]	[0.31]	[2.71]	[0.83]	
P3	0.17	-0.08	0.18	0.11	0.11	0.33	-0.52	1.01	0.31	0.70
	[2.49]	[-2.40]	[8.95]	[5.58]	[3.12]	[9.77]	[-0.75]	[3.37]	[0.67]	
P4	0.14	-0.07	0.15	0.10	0.08	0.29	-0.28	0.98	0.33	0.66
	[2.01]	[-1.79]	[7.58]	[4.02]	[2.51]	[6.60]	[-0.49]	[3.28]	[0.86]	
P5	0.18	-0.08	0.15	0.10	0.07	0.22	-0.14	0.79	0.28	0.62
	[2.37]	[-2.03]	[8.36]	[4.86]	[2.20]	[4.61]	[-0.22]	[2.84]	[0.70]	
P6	0.18	-0.07	0.15	0.08	0.08	0.24	-0.73	0.92	0.57	0.60
	[2.17]	[-1.56]	[8.37]	[3.87]	[2.67]	[6.38]	[-0.87]	[3.18]	[1.41]	
P7	0.24	-0.06	0.12	0.06	0.04	0.19	-0.71	0.78	0.60	0.53
	[3.18]	[-1.80]	[7.49]	[3.03]	[1.39]	[4.87]	[-0.92]	[3.01]	[1.42]	
P8	0.33	-0.05	0.17	0.08	0.06	0.13	-0.02	0.83	0.45	0.56
	[5.50]	[-1.51]	[8.44]	[4.50]	[1.72]	[3.00]	[-0.04]	[2.66]	[0.99]	
P9	0.38	-0.02	0.20	0.09	0.02	0.07	0.13	1.22	0.45	0.47
	[4.81]	[-0.47]	[6.89]	[3.54]	[0.38]	[1.34]	[0.21]	[3.60]	[0.68]	
P10	0.50	-0.02	0.32	0.10	-0.11	-0.02	0.53	2.57	1.33	0.41
	[3.59]	[-0.56]	[6.59]	[1.77]	[-0.90]	[-0.17]	[0.46]	[4.09]	[1.39]	
P10 - P1	0.49	0.06	-0.04	-0.16	-0.34	-0.66	2.47	0.37	0.88	0.30
	[2.31]	[1.88]	[-0.67]	[-1.47]	[-2.33]	[-3.20]	[1.91]	[0.43]	[0.75]	