High Funding Risk, Low Return

Job Market Paper

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Abstract

I develop a simple model in which hedge fund managers with access to less profitable investment strategies choose a higher exposure to funding risk in an attempt to generate competitive returns. Empirically, I find that hedge funds with a higher loading on a simple funding risk measure generate lower returns than hedge funds with a lower loading on that risk measure. In line with the model predictions, I find that (i) this underperformance is driven by a high loading on adverse funding shocks, (ii) a higher loading on funding risk predicts lower fund flows, and (iii) the results are significantly weaker for funds with less favorable redemption terms or funds with multiple prime brokers.

Keywords: Fund redemptions, funding risk, hedge funds, limits of arbitrage, lock-ups **JEL:** G01, G23, G31

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Introduction

Hedge funds are managed portfolios in which the returns depend on the fund's investment strategies and risk management. A good hedge fund follows alpha-generating strategies and simultaneously manages the funding risk that arises from the liability side of its balance sheet, that is, the risk of investor withdrawals and unexpected margin calls or increasing haircuts. If not managed properly, these funding risks can transform into severe losses because they can force a manager to unwind otherwise profitable positions at an unfavorable early point in time. Thus, while it is conceivable that a higher exposure to funding risk carries a risk premium that can increase expected returns, hedge funds with more exposure to funding risk could generate lower expected returns.

To formalize this intuition, I develop a simple model which shows that more funding risk taking is optimal for managers who have access to less profitable strategies. Utilizing a large cross-section of hedge fund returns, I find that hedge funds with a high past loading on a simple funding risk measure (funds that are more exposed to common funding shocks) severely underperform hedge funds with a low past loading on that measure (funds that are less exposed to common funding shocks). The empirical proxy for market-wide funding conditions is based on deviations from the covered interest rate parity (CIP), and I show that the proxy spikes when major institutional investors face tightening funding constraints. In line with the model's predictions, I document that hedge funds with a high loading on the funding risk measure experience lower equity flows than funds with a low loading on that measure. Furthermore, the link between a high loading on the funding risk measure and lower expected returns is less significant for funds with less exposure to common funding shocks, that is funds that impose stricter redemption terms on their investors or funds that have multiple prime brokers.

In my model, two hedge funds differ with respect to the return that they can generate from investing in an alpha-generating strategy. Funding risk arises because both funds face an exogenous risk of outflows which can force them to unwind their strategies early at a cost. Investors are initially unaware of the difference in the funds' alpha-generating strategies and withdraw from the bad fund, which is the fund with the lower alpha-generating strategy, once they can identify it. The bad fund, therefore, invests more aggressively in its funding-risky strategy to avoid being revealed as bad. Hence, if the funding shock is small, investors are unable to identify the bad fund. It is only if the funding shock is large enough that the bad fund generates losses. These losses due to the funding shock predict lower returns in the next period and enable the investors to identify the fund as the bad fund.

This mechanism gives the model's first two predictions. First, hedge funds that are exposed to more funding risk generate lower returns. More precisely, hedge funds that generate lower returns when funding conditions worsen also generate lower future returns. Second, a higher exposure to funding risk predicts fund outflows. Hence, hedge funds with a higher exposure to funding risk have lower fund flows than hedge funds with a lower exposure to that risk. The third model prediction is that the difference in returns between funds with a high exposure to funding risk and funds with a low exposure to funding risk is lower if the size of the expected funding shock is smaller. This lower expected funding shock comes from the funds liabilities and could occur, for instance, if the fund imposes stricter redemption terms on its equity investors.

To proxy market-wide funding conditions faced by hedge funds, I construct an index of deviations from the CIP across several different currencies and maturities. The index (henceforth CIP^{Index}) is similar to one in Pasquariello (2014), capturing "dislocations in international money markets" and is strongly related to other proxies of funding liquidity, such as the Treasury-Eurodollar (TED) spread and the dealer-broker leverage factor constructed by Adrian, Etula, and Muir (2014).[1] Furthermore, deviations from the CIP are an ideal measure of the funding conditions faced by hedge funds for two reasons. First, they point toward a deviation from the law of one price which would not occur if major dealer banks had ample funding to take advantage of the mispricing. Second, they indicate the shortage of one currency relative to another, which suggests that major international investors face tightening funding constraints. These tightening constraints are likely passed on to hedge funds either through their prime brokers or via equity withdrawals from major institutional investors and can force funds to unwind otherwise profitable positions at a loss.

I use CIPD_t, defined as $CIP^{Index}_{t-1} - CIP^{Index}_{t}$, in my analysis to keep consistent with the notion that a high loading on unexpected funding shocks corresponds to high risk. To test my hypothesis that a higher loading on funding risk predicts lower returns, I obtain hedge fund returns and other fund characteristics for the January 1994 – May 2015 sample period from the TASS hedge fund database. Using the returns of these funds I then form decile portfolios based on their loading on CIPD over the past three years and rebalance the portfolios on a monthly basis. I find that hedge funds with a low loading on CIPD outperform hedge funds with a high loading on CIPD by a large margin. The risk-adjusted return of the difference portfolio that is long the hedge fund portfolio with the lowest loading on CIPD and short the hedge fund portfolio with the highest loading on CIPD has a risk-adjusted monthly return of 0.54% (t-statistic of 2.46). This result demonstrates that a high loading on funding risk

[1] This strong link to other funding risk proxies distinguishes CIP^{Index} 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.

indeed predicts poor fund performance. Instead of being a "priced risk factor," funding risk, as measured by CIPD, has the opposite effect: a *higher* loading on CIPD predicts *lower* risk-adjusted returns.

To rule out the possibility that fund-specific characteristics drive this result, I perform two additional tests. First, I repeat the analysis forming style-neutral portfolios by fixing the percentage of hedge funds within a certain style in each of the decile portfolios; doing so leaves the main result unchanged. The difference portfolio – which is long hedge funds with a low loading on CIPD and short hedge funds with a high loading on CIPD – generates a monthly risk-adjusted return of 0.42% (t-statistic of 2.58). Second, I run Fama and MacBeth (1973) regressions of risk-adjusted hedge fund returns on β^{CIPD}, controlling for fund age, fund size, redemption notice period, lockup provision, investment style, minimum investment, management fee, and incentive fee. Even after controlling for all these fund characteristics, β^{CIPD} is a statistically significant explanatory variable (t-statistic of 2.78) for risk-adjusted hedge fund returns.

Because my model implies that lower returns due to an adverse funding shock predict lower subsequent returns I next investigate to which extent the results are driven by the negative part of CIPD. To that end, I split CIPD into a negative part, CIPD^{-}, which captures worsening funding conditions, and a positive part, CIPD^{-}, which captures improving funding conditions. I then repeat this sorting procedure twice, once only using CIPD^{-} and once only using CIPD^{+}. In line with my theory, I find that hedge funds with a high loading on CIPD^{-} severely underperform hedge funds with a low loading on CIPD^{-}. The difference portfolio – which is long funds with a low loading on CIPD^{-} and short funds with a high loading on CIPD^{-} – generates a monthly risk-adjusted return of 0.58% (t-statistic of 2.64), which is higher and more significant than the return of the CIPD-sorted difference portfolio described above. In contrast, there is no significant difference between hedge fund returns that are sorted based on their loading on CIPD^{+}.

The second testable prediction of my model is that the high loading on market-wide funding shocks enables hedge fund investors to distinguish bad funds from good funds and therefore triggers subsequent withdrawals. I investigate this prediction by checking whether hedge funds with a high loading on CIPD experience lower fund flows than hedge funds with a low loading on CIPD. Indeed, the difference between fund flows for hedge funds with a low loading on the funding risk proxy and fund flows for hedge funds with a high loading on that proxy is positive and statistically significant at a 1% level (t-statistic of 2.64). To disentangle the effect of a higher loading on CIPD from the effect of lower past returns, I repeat the sorting procedure conditional on past returns. Doing so lowers the significance of the result to a 5% level (t-statistic of 2.40), but leaves the main inference intact.

The third testable prediction of my theory is that the effect of a higher loading on funding shocks is less pronounced for funds with a lower risk of investor redemptions or forced deleveraging due to their prime brokers. To investigate this hypothesis, I perform the following three tests. First, I split hedge funds into two different subsamples, one with redemption notice period of one month or less and one with redemption notice period above one month. Second, I split hedge funds into one subsample of funds with a lockup provision and one subsample of funds without a lockup provision. Finally, I split the sample into funds that have more than one prime broker and funds that only have one prime broker. The difference portfolio earns a higher risk-adjusted return for funds with a shorter redemption notice period, funds without a lockup provision and funds with only one prime broker compared to funds with a longer redemption notice period, funds with a lockup provision, and funds with more than one prime broker respectively.

In addition to my main findings, I address the concern that the higher return of funds with a low loading on funding shocks is driven solely by a few severe crisis episodes. To that end, I split the full sample period into crisis periods and normal periods based on two criteria. First, I use anecdotal evidence to classify 19 months as crisis episodes and find that the difference portfolio that is long hedge funds with a low loading on CIPD and short hedge funds with a high loading on CIPD generates a monthly risk-adjusted return of 0.45 (t-statistic of 2.09) during normal periods and a monthly risk-adjusted return of 1.10% (t-statistic of 1.74) during crisis episodes. Second, I classify NBER recession periods as crisis periods and find that the difference portfolio generates a monthly risk-adjusted return of 0.52% (t-statistic of 2.29) during normal times and a monthly risk-adjusted return of 0.46% (t-statistic of 0.90) during crisis periods.

Finally, I address the following five common biases in reported hedge fund returns: backfilling bias, dropout bias, double counting, return smoothing, and selection bias. First, to address backfilling bias, I drop all returns reported before a fund was added to the database and repeat the analysis. For this subsample, the difference portfolio generates a monthly risk-adjusted return of 0.55% (t-statistic of 1.94). Second, to address dropout bias, I replace the last reported return for each hedge fund that drops out of the database with −25% and repeat the analysis. For this modification of the database, the difference portfolio generates a monthly risk-adjusted return of 0.53% (t-statistic of 2.40). Third, to address concerns about double-counting, I remove hedge funds that are likely to be subsidiaries of the same fund and repeat the analysis. For this subset, the difference portfolio generates a monthly risk-adjusted return of 0.54% (t-statistic of 2.41). Fourth, to address return smoothing, I use the return un-smoothing technique proposed by Getmansky, Lo, and Makarov (2004) and repeat the analysis. For this modification of the database, the difference portfolio generates a monthly risk-adjusted return of 0.59% (t-statistic of 2.80). Finally, concerns about selection bias are alleviated because the results hold for a subset consisting only of funds of hedge funds.

1 Related Literature

The main finding of this paper is that hedge funds that face more risk, as proxied by a higher factor loading, do generate lower expected returns. This is similar to the finding in Titman and Tiu (2011) that hedge funds whose returns are less-well explained by common risk factors deliver higher risk-adjusted returns. My finding that a higher loading on a funding risk measure predicts lower future returns is in line with Chen and Lu (2015) who construct a funding-liquidity measure based on stock returns and find that hedge funds with a lower loading on their funding risk measure outperform funds with a higher loading on that measure. Chen and Lu (2015) focus on establishing a new funding risk measure while my focus is on explaining why a higher loading on a funding risk measure causes lower expected returns. Jurek and Stafford (2015) show that the average alpha of the hedge fund industry can be explained by taking downside risk, as approximated by a put writing strategy. While Jurek and Stafford (2015) find that hedge funds are profiting from taking downside market risk, I find that exposure to deteriorating funding conditions lowers expected returns.

A large amount of theoretical literature shows how the institutional environment surrounding hedge funds restricts their optimal risk taking. My model is closest to that of Liu and Mello (2011), who show that "the fragile nature of hedge fund equity" limits a manager's ability to profit from funding-risky positions. In a similar spirit, Shleifer and Vishny (1997) find that withdrawals can occur precisely when the manager needs cash the most and Chen, Goldstein, and Jiang (2010) show that funds with illiquid asset holdings face a higher withdrawal risk. In addition to outflows, a second source of funding risk is borrowing constraints, which can arise if funds have to collateralize their positions and can force a manager to unwind otherwise profitable strategies early. These constraints have been studied by, among others, Gromb and Vayanos (2002), Liu and Longstaff (2004), Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011), and Gromb and Vayanos (2015). Finally, my model is also close to the literature that incorporates funding frictions into a hedge fund manager's investment decisions (see Dai and Sundaresan, 2011, Buraschi, Kosowski, and Sritrakul, 2014, Pangeas and Westerfield, 2009, Lan, Wang, and Yang, 2013, and Drechsler, 2014, among many others).

The empirical part of my paper is building on three streams of literature on the cross section of hedge fund returns. The first stream of literature establishes different risk measures as priced risk factors in the cross section of hedge fund returns. Sadka (2006) and Teo (2011) document that stock market liquidity, as approximated by 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. Hu et al. (2013), Bali, Brown, and Caglayan (2014), and Golez, Jackwerth, and Slavutskaya (2015) construct other risk measures and show that they are priced risk factors in the cross section of hedge fund returns. In contrast to these studies, I find that a higher exposure to a simple funding risk proxy predicts lower future returns, rather than higher future returns.

The second stream of literature focuses on the risk of equity withdrawals for hedge funds, which has been empirically studied by, among others, Aragon (2007), Klebanov (2008), and Hombert and Thesmar (2014). These authors find that hedge funds that offer less-favorable redemption terms to their equity investors outperform funds offering more favorable redemption terms. In line with these papers, I find that hedge funds with a lockup provision and with a high loading on CIPD^{-} are delivering significantly higher risk-adjusted returns than funds without a lockup provision and a high loading on CIPD^{-}. More recently, Aiken, Clifford, and Ellis (2015) point out that additionally to the redemption terms reported in commercial hedge fund databases, hedge funds are often using discretionary liquidity restrictions, such as gates and side pockets, which effectively alter redemption terms.

The third stream of literature addresses the risk of adverse funding conditions being passed on from the prime broker. It has been studied by Aragon and Strahan (2012), Mitchell and Pulvino (2012), and Ang, Gorovyy, and Van Inwegen (2011). Aragon and Strahan (2012) find that hedge funds for which Lehman Brothers was the 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) show that hedge fund leverage is counter-cyclical to the leverage of major dealer-brokers and that it decreased significantly during the financial crisis. Hence, funding risk due to margin calls or increasing haircuts is an additional source of liquidity risk for hedge funds.

The remainder of this paper is organized as follows. In Section 2, I develop a simple model to derive the main hypotheses, and in Section 3, I describe the hedge fund data and the CIP deviation measure. Section 4 presents my main results, which are complemented with additional robustness checks in Section 5. Section 6 concludes.

2 The Model

Hedge funds are exposed to severe funding risks through the liability side of their balance sheets. Their equity can be withdrawn by investors after a certain redemption period and their debt is mainly short-term, supplied by their prime brokers. A funding shock could force a manager to unwind an otherwise profitable position early at a loss.[2] In this section, I incorporate funding risk in a stylized model similar to that of Liu and Mello (2011) and show that a hedge fund with access to an alpha-generating strategy with a lower return takes on more funding risk in order to generate competitive returns.

2.1 Model Setup

There are two types of hedge funds, a “good” hedge fund g and a “bad” hedge fund b, which differ with respect to the returns they can generate from their investments. The good fund has access to two investment opportunities, a risk-free asset (cash) and an alpha-generating strategy. One dollar invested in the alpha-generating strategy is worth $1 + \alpha_g$ dollars if the strategy is held until maturity and $1 - c$ if the strategy is unwound early. Both the return α_g and the unwinding cost c are constants known to the fund. The bad fund has access to a different alpha-generating strategy that generates a return $\alpha_b < \alpha_g$ if held until maturity and is subject to the same unwinding cost c. The risk-free rate for borrowing or cash holdings is set equal to zero. Both funds are risk neutral and have a total of one unit of capital that they can invest in their alpha-generating strategies or in the risk-free asset. For simplicity, I assume that the funds cannot borrow and that the one unit of capital is equity.

There are three points in time. At time $t = 0$, fund $i \in \{g, b\}$ chooses its investment $\theta_i \in [0, 1]$ in the alpha-generating strategy and invests the remainder $1 - \theta_i$ in cash. At time $t = 1$, both funds face the risk of a funding shock λ which is uniformly distributed on the interval $[0, \bar{\lambda}]$, where $0 < \bar{\lambda} \leq 1 - c$ to avoid situations in which the funding shock can lead to bankruptcy of the fund. The funding shock can be interpreted as a fraction of investors withdrawing their money because of a sudden liquidity need. This early withdrawal is announced before time $t = 1$ and the withdrawing investors receive their investments back because the fund has not generated any returns at this point. Both funds face the same realization of this funding shock λ, which would force the fund to unwind part of its positions early at the cost c if $\lambda > 1 - \theta_i$. Time $t = 2$ corresponds to the maturity of the strategy and fund i realizes a return of $1 + \alpha_i$ on its remaining investment in the strategy.

[2] One example of such a strategy could be an arbitrage trade, which generates a safe profit if held until maturity, but can lead to losses if unwound early.

The expected fund wealth at time $t = 2$ is given as follows:

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

The first integral is up to the cash holding $1-\theta_i$. If the realization of the funding shock does not exceed the fund's cash holding, the funding shock does not lead to any unwinding costs. The second integral starts at $1-\theta_i$ and goes up to $\bar{\lambda}$. In this region, the funding shock forces the manager to unwind part of his strategy early, leading to losses at time $t = 1$.

Hedge fund investors know α_g, α_b, c, and the distribution the funding shock. They can observe the realization of the funding shock at time $t = 1$ and fund returns at times $t = 1$ and $t = 2$. However, they cannot observe a fund's type $i \in \{g, b\}$ or its risk-taking θ_i and therefore invest the same amount in both funds at time $t = 0$. The investors' knowledge of α_g, c, and the distribution of the funding shock enables them to compute the good fund's wealth-maximizing investment θ_g^* and its returns $R_{1,g}$ and $R_{2,g}$. I assume that a fraction γ of the remaining investors in fund i withdraw if the fund's returns deviation from $R_{1,g}$ or $R_{2,g}$. These "performance-based withdrawals" occur at time $t = 2$ and lower a fund's terminal wealth.

Both funds maximize the fee they receive for managing the investors' money. I assume that this fee is a constant fraction of fund wealth at time $t = 2$, after performance-based withdrawals. Hence, the outflow γ can be viewed as the cost of being revealed as a bad fund. This cost gives the bad fund an incentive to increase its investment in the strategy above the wealth-maximizing investment in an attempt to mimic the returns of the good fund. Because the fee is proportional to terminal fund wealth after outflows, fund i faces the following optimization problem:

$$\max_{\theta_i}\left\{\mathbb{E}[W_{2,i}] - \gamma p^i(\theta_i)\right\}, \tag{2}$$

where $p^i(\theta_i)$ is the probability of being revealed as bad fund, which is equal to zero for the good fund and strictly positive for the bad fund.

Next, I introduce two parametric conditions that I assume to hold throughout this section.

Condition 1. *(a) The maximal funding shock $\bar{\lambda}$ satisfies the following inequality:*

$$\bar{\lambda} \geq (\alpha_g - \alpha_b)\frac{(\alpha_g + c)}{(1+\alpha_g)\alpha_g c}. \tag{3}$$

(b) The continuation value γ satisfies the following inequality:

$$\gamma > \frac{\bar{\lambda}(\alpha_g - \alpha_b)(c\bar{\lambda}[c(1+\alpha_g) + \alpha_b(\alpha_g + c)] - (\alpha_g + c)(\alpha_b + c))}{2(1-c)(\alpha_g + c)\alpha_b(c+\alpha_b)(\alpha_g(1+\alpha_g)c\bar{\lambda} + (\alpha_g + c)\alpha_b) - \alpha_g(\alpha_g + c))}. \quad (4)$$

Although these two expressions are complex, they have a simple interpretation and I show in a numerical illustration in the appendix that they are only imposing a mild restriction on the model parameters. The intuition behind Condition 1 is as follows. Because the maximal amount that the bad fund can invest in its strategy is one, Inequality (3) is necessary to ensure that it is possible for the bad fund to mimic the returns of the good fund by taking on additional risk. Inequality (4) ensures that the cost of being revealed is large enough to give the bad fund an incentive to deviate from its wealth-maximizing strategy in order to mimic the returns of the good fund.

2.2 Results

Computing the two integrals in Equation (1) and taking the first order condition (FOC) leads to the wealth-maximizing investment θ_i^* in the risky asset:

$$\theta_i^* = 1 - \frac{c(1+\alpha_i)}{\alpha_i + c}\bar{\lambda}. \quad (5)$$

This is fund i's optimal investment, assuming no performance-based withdrawals (the second derivative of Equation (1) with respect to θ is a negative constant, which ensures taking the FOC indeed leads to the optimal investment). Because $p^i(\theta^i) = 0$ for the good fund, Equation (5) gives the solution to the good fund's optimization problem. The solution to the bad fund's optimization problem is stated in the following proposition.

Proposition 1. *Assume that Condition 1 holds. Then, fund b invests $\theta_b^M = \frac{\alpha_g}{\alpha_b}\theta_g^* < 1$ in its strategy. It increases its investment in the strategy relative to the wealth-maximizing investment by:*

$$\theta_b^M - \theta_b^* = \left(\frac{\alpha_g}{\alpha_b} - 1\right) + \bar{\lambda}\frac{(1-c)(\alpha_g - \alpha_b)c}{(\alpha_g + c)(\alpha_b + c)} > 0. \quad (6)$$

The proof of this proposition can be found in Appendix A. An immediate consequence of Equation (6) is that the risk taking of Fund b in excess of its optimal investment in the strategy increases for lower α_b and for higher $\bar{\lambda}$. This additional risk taking corresponds to a higher exposure to funding risk because the fund keeps a lower cash buffer against the funding shock.

I next calculate fund returns and show that a higher sensitivity to the funding shock implies lower future performance. The observed fund returns are computed as a percentage change in fund net-asset value (NAV), which is defined as the total fund wealth divided by the amount of fund shares outstanding. Both funds have the same initial $NAV_0 = 1$ and the NAV at times $t = 1$ and $t = 2$ can be computed as $NAV_1^i = \frac{1}{1-\lambda}W_1^i$ and $NAV_2^i = \frac{1}{1-\lambda}W_2^i$. Hence, fund returns at time $t = 1$ and $t = 2$ are given as follows:

$$R_{1,i} = \begin{cases} 0, \text{ if } \lambda \leq 1 - \theta_i \\ -\frac{c(\lambda-(1-\theta_i))}{(1-c)(1-\lambda)}, \text{ if } \lambda > 1 - \theta_i \end{cases} \quad \text{and } R_{2,i} = \begin{cases} \frac{\theta_i \alpha_i}{1-\lambda}, \text{ if } \lambda \leq 1 - \theta_i \\ \alpha_i, \text{ if } \lambda > 1 - \theta_i. \end{cases} \tag{7}$$

$R_{1,i}$ is zero if the funding shock is smaller than the fund's cash holding and negative if the funding shock forces the fund to unwind part of its position early. If the funding shock does not exceed the fund's cash holdings, $R_{2,i}$ is increasing in λ. This is because in this region a higher λ lowers the cash buffer held by the fund which in turn increases the share invested in the strategy. For $\lambda \geq 1 - \theta_i$, the cash buffer is absorbed by the funding shock and the entire fund wealth is invested in the strategy. Therefore, $R_{2,i}$ for $\lambda \geq 1 - \theta_i$ is equal to α_i.

The following proposition shows that a higher sensitivity of the fund return to the funding shock at time $t = 1$ implies a lower subsequent fund return and investor withdrawals at time $t = 2$.

Proposition 2. *Assume that Condition 1 holds and that* $\frac{\partial R_{1,i}}{\partial \lambda} < \frac{\partial R_{1,j}}{\partial \lambda}$. *Then the following statements hold:*

(a) Fund i delivers a lower subsequent return than fund j.

(b) Fund i faces performance-based withdrawals at time $t = 2$.

The proposition provides the first two testable predictions of my theory: Funds that generate lower returns during times of deteriorating funding conditions (i) generate lower subsequent returns and (ii) face withdrawals. Note that more funding risk in the model is taken on indirectly by investing more aggressively in the alpha-generating strategy and leaving a lower cash buffer. It is this indirect exposure to funding risk that I later capture by computing the loadings of fund returns on changes in a market-wide funding risk measure.

Finally, the following proposition shows that past return sensitivity to the funding shock becomes less informative as the funds' exposure to the funding shock decreases.

Proposition 3 (Prediction 3)**.** *Assume that Condition 1 is satisfied and that* $\frac{\partial R_{1,i}}{\partial \lambda} < \frac{\partial R_{1,j}}{\partial \lambda} < 0$. *Then* $R_{2,j} - R_{2,i}$ *is decreasing in* $\bar{\lambda}$.

This proposition delivers the third testable prediction: A higher sensitivity to the common funding shock is less informative when the maximal size $\bar{\lambda}$ of the funding shock is smaller.

The intuition behind this prediction is that, if $\bar{\lambda}$ is small, then the difference between α_g and α_b needs to be small as well, otherwise the bad fund would not be able to mimic the returns of the good fund. Empirically, a lower $\bar{\lambda}$ could come from either the equity side of the funds' balance sheet, due to lockups and less favorable redemption terms, or from the liability side of the balance sheet, where a hedge fund with multiple prime brokers is less susceptible to an adverse funding shock than a manager with only one prime broker.

3 The Data

3.1 Hedge Fund Data

The hedge fund data for my analysis are obtained from the May 2016 version of the Lipper TASS hedge fund database. Hedge funds report voluntarily to this database, and one concern with these self-reported returns is survivorship bias because poorly performing funds might just decide to drop out of the database. To mitigate this concern, I follow the common practice and use both live hedge funds (which are still reporting to TASS as of the latest download) and graveyard funds (which stopped reporting). Because the graveyard database was not established until 1994, I focus my analysis on the January 1994 – May 2015 period. Following the literature on hedge funds (see, for instance, Cao et al., 2013 and 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 million USD.[3] For funds that do not report in USD, I use the appropriate exchange rate to convert AUM into USD equivalents. Third, I require that each fund in my sample reports at least 36 monthly returns during my sample period.

Panel A of Table 1 provides summary statistics for all hedge funds in the filtered 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 0.58% per month with a standard deviation of 3.07. On average, funds have 146 million US dollar in AUM, ranging from the minimum of 10 million up to 7,158 million. AUM is defined as the value of all claims that equity shareholders have on the fund, that is, the difference between the value of all long positions (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.

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

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 that equals one if the fund return in a given month is backfilled. "Lockup" is a dummy variable that equals one if the fund has a lockup provision. "Notice" is the number of months that investors have to notify 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

TASS also provides information on when each hedge fund began reporting to the database, which I use to compute the percentage of backfilled returns – 46.51% on average, with a high standard deviation of 32.7% across funds. In my main analysis, I include backfilled return observations and show later that the results are robust to dropping backfilled observations. The next two variables provide an overview of the funds' risk of withdrawals. The first variable is a dummy variable that equals one if the fund has a lockup provision and zero otherwise.

Nineteen percent of the funds in the database have a lockup provision. The second variable is the funds' redemption notice period which indicates 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 one month. The last two variables in Panel A show the manager's compensation. In line with the often-mentioned 2/20 rule, the median management and the median 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, average monthly returns range from 0.82% for long-short equity to 0.32% for funds of funds. There are a total of 2,987 funds of funds in my sample. I run my main analysis using all 8,541 funds and later show that my results are robust to splitting the sample into hedge funds and funds of funds. Summary statistics for hedge fund returns in different years can be found in Appendix C (Table C.1). These yearly summary statistics show that the number of funds varies from a minimum number of 711 in 1994 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 ensure a sufficient number of funds per portfolio.

3.2 Deviations from the Covered Interest Rate Parity

In this section, I construct a simple measure of market-wide funding conditions faced by hedge funds, which is based on deviations from the covered interest rate parity (CIP). The idea behind the CIP is that the theoretical forward exchange rate between currency A and currency B can be computed using the following no-arbitrage argument. One can either invest one unit of currency A at time t in a money-market account with interest rate $r^A(t,T)$ or exchange this one unit of currency A into currency B, putting it into a money-market account with interest rate $r^B(t,T)$. To avoid arbitrage opportunities from borrowing in one currency and investing into the other, the theoretical forward rate should be given as:

$$Fwd^*_{A/B}(t,T) := FX_{A/B}(t)\left(\frac{1+r^A(t,T)}{1+r^B(t,T)}\right), \tag{8}$$

where $FX_{A/B}(t)$ denotes the spot exchange rate from currency A to currency B.

The measure of deviations from the CIP, which is closely related to the measure of "dislocations in international money markets" constructed in Pasquariello (2014), is based on 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 rate. All data for constructing CIP deviations are obtained from the Bloomberg system.[4] Deviations from the CIP for currency pair A/B with maturity $T-t$ are then computed as the absolute difference between the observed forward exchange rate $Fwd_{A/B}$ and the theoretical forward exchange $Fwd^*_{A/B}$ implied by Equation (8):

$$CIP_{i,t} = \left|\ln(Fwd_{A/B}(t,T)) - \ln(Fwd^*_{A/B}(t,T))\right| \times 10^4. \tag{9}$$

The expression is multiplied by 10^4 to obtain a mispricing in basis points. In total, this leads to 63 different currency-maturity pairs, which are aggregated into one index as follows:

$$CIP_t^{Index} = \frac{1}{n_t}\sum_{i=1}^{n_t} CIP_{i,t}, \tag{10}$$

where n_t denotes the number of available mispricings at time t.

Deviations from the CIP occur if demand pressure for currency forwards is not met by a sufficient amount of arbitrage capital. The demand for currency forwards is driven by an imbalance between international funding supply and investment demand. Such an imbalance points towards a shortage of one currency relative to another (Bottazzi, Luque, Pascoa, and Sundaresan, 2012 and Ivashina, Scharfstein, and Stein, 2015, among others). The most prominent example of such a shortage is the USD shortage in 2011, in which foreign banks experienced tightening funding conditions in the U.S. money markets. The amount of available arbitrage capital decreases when major dealer banks face tightening funding constraints and can therefore no longer supply currency derivatives at the arbitrage-free rate. These tightening funding conditions can be passed on to hedge funds either through equity withdrawals by major institutional investors needing liquidity or through prime brokers passing their own tightening funding conditions to their hedge fund clients. Hence, deviations from the CIP point to a situation in which hedge funds face tightening funding conditions.

There are two main criticisms of using CIP^{Index} as measure for funding conditions. First, using LIBOR as a proxy for the risk-free rate can be problematic because LIBOR is an unfunded lending rate that can contain a credit-risk component and because LIBOR rates are potentially biased due to misreporting.[5] I address these concerns in Appendix C, where I construct CIP^{Index} using overnight lending (OIS) rates instead of LIBOR rates

[4]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.

[5]Tuckman and Porfirio (2003) argue that the credit-risk component in LIBOR is one of the primary drivers of CIP deviations. Eisl, Jankowitsch, and Subrahmanyam, 2013 investigate LIBOR misreportings.

and find that the main results remain intact when using this alternative index, even though OIS rates for most currencies are only available from 2002 on. The second concern is that deviations from the CIP are not driven by dislocations in international money markets but by trading costs in currency markets. I address the concern that CIP^{Index} might be driven by currency market liquidity in Appendix C, where I repeat my main analysis controlling for the currency liquidity measure constructed in Karnaukh, Ranaldo, and Söderlind (2015).[6] The main results remain unchanged after controlling for FX liquidity.

Figure 1 shows the time series of month-end CIP_t^{Index}, where the blue lines highlight major market events and the grey-shaded areas are US recession periods. The first larger spike in CIP^{Index} occurs in September 1998, 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, a larger spike during the bailout of Bear Stearns in March 2008, and a major spike in September 2008, when Lehman Brothers filed for bankruptcy. The next major spike of the measure occurs during the onset of the European debt crisis in autumn 2011. The blue line labelled "Euro Crisis" marks June 2011, when the rating agency Moody's put several European banks on watch for possible downgrades, which lead to tightening funding conditions for these banks. This event was followed by more negative news about European sovereigns, which subsequently lead to 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."[7] The most recent spike of the measure occurs in January 2015, when the Swiss National Bank decided to lift its currency peg.[8]

I next investigate whether changes in CIP^{Index} (ΔCIP^{Index}) are related to the following four measures of funding liquidity 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 the TED spread, ΔTED_t, (ii) changes in the implied volatility of the S&P 500 index, ΔVIX_t, (iii) stock returns of the nine largest investment banks, Ret_t^{IB}, and (iv) the dealer-broker leverage variable introduced by Adrian et al. (2014), $\Delta Leverage_t$ (more details on

[6] The correlation between CIPD and changes in the FX liquidity measure is 0.15. I am grateful to Valeri Sokolovski for his help with updating this measure.

[7] A verbatim of the speech is available on the ECB website [Link].

[8] Another observation from Figure 1 is that CIP^{Index} became more volatile after the default of Lehman Brothers and even comparably small events like the lifting of the Swiss Currency Peg triggered large spikes. One possible explanation for this observation can be the implementation of the Volcker rule which explicitly forbids banks to engage in proprietary trading, such as arbitrage. Hence, a major group of arbitrageurs who used to enforce the CIP is not allowed to do so anymore which causes smaller events to have a larger impact on the index.

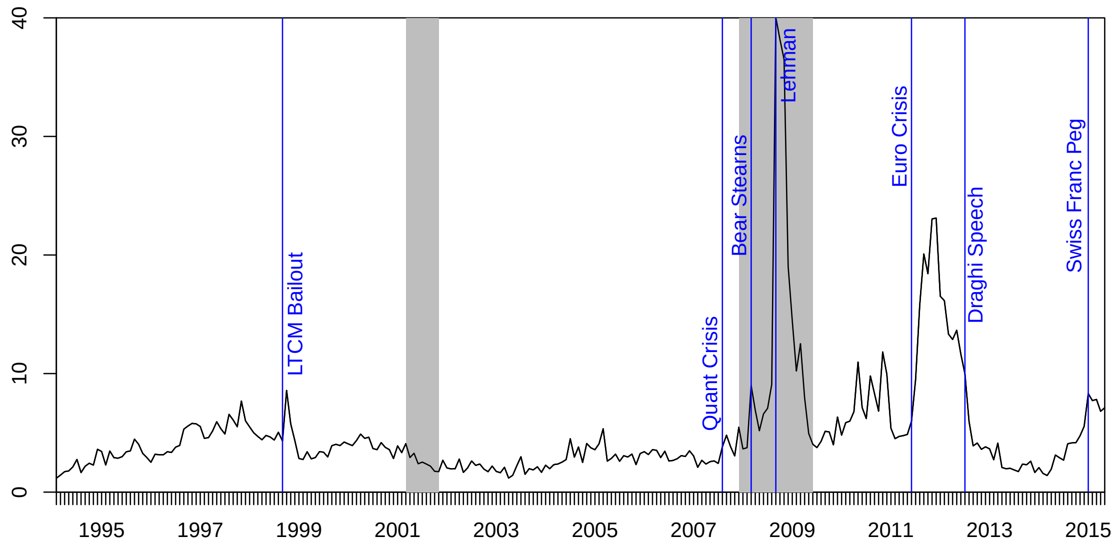


Figure 1: **Time Series of the Covered-Interest Rate Parity (CIP) Deviation Index.** This figure shows the time series of the CIP deviation index. The index is constructed as an equal-weighted average of nine of the most liquid currency pairs with seven different maturities, ranging from one week to one year, based on Equations (8)–(10). All observations are month-end. The highlighted events (blue vertical lines) are the bailout of Long-Term Capital Management (LTCM) 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 June 2011 (marked by rising concerns about European banks), Mario Draghi's speech in July 2012 declaring that the ECB will do "whatever it takes" to preserve the Euro, and the Swiss National Bank lifting the currency peg to the Euro in January 2015. The two grey-shaded areas are US recession periods.

these variables can be found in Appendix B). The results of regressing ΔCIP^{Index} on these variables are exhibited in Table 2, where I first focus on the relationship between ΔCIP^{Index} and the first three variables, which are available on a monthly basis. As we can see from columns (1)–(3) of Table 2, ΔTED_t, ΔVIX_t, and Ret^{IB_t} all have a significant effect on ΔCIP^{Index}. Increases in TED_t and VIX_t are positively related to increases in CIP_t^{Index} and CIP^{Index} tends to decrease when bank stocks deliver higher returns. The TED spread is the strongest explanatory variable and explains 36% of the variation in ΔCIP^{Index} in a univariate regression. Column (4) shows that combining the three independent variables explains 41% of the variance in ΔCIP^{Index} and confirms that ΔTED_t is the most significant explanatory variable of the three. Column (5) shows that $\Delta Leverage_t$, which is only available on a quarterly basis, explains 67% of the variation in ΔCIP^{Index}. Combining all four explanatory variables, column (6), shows that $Leverage_t$ is the most significant explanatory variable, followed by ΔTED_t. Overall, the results confirm that changes in CIP^{Index} are capturing tightening funding conditions.[9]

Table 2: **Properties of the Covered Interest Rate Parity Deviation Index**. This table shows the results for regressions of ΔCIP_t^{Index} on other proxies of funding liquidity and market uncertainty. The four different explanatory variables are (i) the change in the differences between the 3-month USD LIBOR rate and the 3-month US treasury yield (ΔTED_t), (ii) average returns of the nine major U.S. investment banks (Ret_t^{IB}), (iii) changes in the option-implied volatility of the S&P 500 Index (ΔVIX_t), and (iv) the dealer-broker leverage factor ($Leverage_t$) introduced by Adrian et al. (2014). The sample period is January 1994 to May 2015. 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

3.3 Hedge Fund Risk Factors

I now briefly describe the seven hedge fund risk factors, proposed by Fung and Hsieh (2004), that I use as benchmarks to compute risk-adjusted returns and show that these factors are only weakly related to ΔCIP^{Index}. Again, more details about the data used to construct these factors are available in Appendix B. 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). These factors are proxied by the first two Fama-French factors. The next two factors are related to fixed income markets; Fung and Hsieh (2001) suggest using the monthly change in the 10-year US treasury constant maturity yield (YLD) and the monthly

[9] An overview of the correlation between ΔCIP^{Index} and other commonly used liquidity proxies can be found in Appendix C (Table C.8). One distinct feature of ΔCIP^{Index} compared to these other liquidity proxies is its strong correlation with ΔTED_t and $Leverage_t$.

change in the Moody's Baa yield less 10-year Treasury constant maturity yield (BAA) as risk factors capturing interest-rate risk and credit risk. Finally, Fung and Hsieh (2001) 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). The pairwise correlation between ΔCIP^{Index} and MKT, SMB, YLD, BAA, BD, FX, and COM is -0.17, -0.03, 0.14, 0.07, 0.12, 0.17, and 0.13 respectively. The entire correlation matrix can be found in Appendix C (Panel B of Table C.8).

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 use excess returns of the Merril Lynch Treasury bond index with 7-10 years to maturity over the one-month risk-free rate as a tradable YLD factor. The correlation between YLD and the tradable YLD factor is -69%. Similarly, I use the difference between returns of the corporate bond index of BBB-rated bonds with 7-10 years to maturity and returns of the above Treasury bond index as a tradable BAA factor. The correlation between BAA and the tradable BAA factor is -76%. In the following, I replace YLD and BAA with the two tradable factors to compute risk-adjusted returns.

4 Results

In the following, I use the notation $\text{CIPD}_t := CIP^{Index}_{t-1} - CIP^{Index}_t$ to be consistent with the notion that lower returns during an unexpected funding shock correspond to a high factor loading. To test the model predictions, I proceed in two steps. In Section 4.1, I test the model's main prediction and document that hedge funds with a higher loading on CIPD generate lower risk-adjusted returns than hedge funds with a lower loading on CIPD. In Section 4.2, I investigate whether the mechanism behind the main prediction is consistent the data. To that end, I test the three model predictions and find evidence for the proposed mechanism.

4.1 Main Hypothesis

I now test my main hypothesis: Hedge funds with a higher exposure to funding risk generate lower returns than hedge funds with a lower exposure to funding risk. To do so, I sort hedge funds into deciles based on their loading on CIPD. Every month, for each Fund i, I run a regression of hedge fund returns over the past 36 months on CIPD, controlling for excess returns of the (stock) market portfolio:[10]

$$R_{i,t} = \alpha + \beta^{CIPD}\text{CIPD}_t + \beta^{Mkt}R_t^{Mkt} + \varepsilon_t. \tag{11}$$

Based on β^{CIPD}, 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 highest loading on CIPD while the last portfolio (P10) has the lowest loading on CIPD.

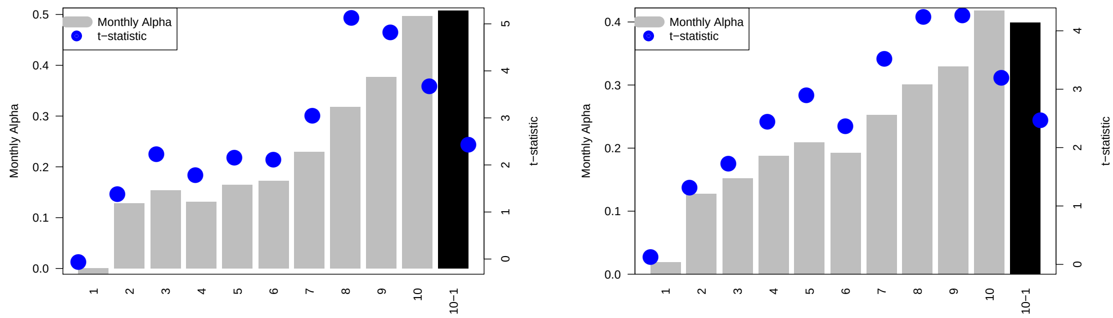
Panel (a) of Figure 4 shows the monthly risk-adjusted returns of the 10 portfolios, controlling for the seven Fung and Hsieh (2004) risk factors. As we can see from the Figure, funds with the lowest loading on CIPD (Portfolio 10) earn a monthly risk-adjusted return of 0.50%, which corresponds to an annual alpha of 6.00%. The risk-adjusted returns of hedge funds in the different deciles decrease almost monotonically. Funds in Portfolio 9 earn a monthly risk-adjusted return of 0.38% followed by funds in Portfolio 8, which earn a monthly risk-adjusted return of 0.33%. In contrast, funds with the highest loading on CIP deviations (Portfolio 1) 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 that is long hedge funds with a low loading on CIPD and short hedge funds with a high loading on CIPD. The monthly risk-adjusted return of the difference portfolio is 0.50%, illustrated by the black bar in Panel (a) of Figure 4. The blue dots in Figure 4 show Newey-West t-statistics of the respective portfolio alphas and indicate that the results are statistically significant.[11] In particular, the risk-adjusted return of the difference portfolio is significant at a 5% level (t-statistic of 2.39). Hence, the null hypothesis that funds in Portfolios 10 and 1 generate the same risk-adjusted returns can be rejected.

One obvious concern about these results is that they might simply be driven by different hedge fund styles. For example, convertible arbitrage and fixed income arbitrage are investment styles that rely heavily on leverage and Table 1 shows that these styles also generate lower average returns than other styles. To address this concern, Panel (b) of Figure 4 reports the results for style-neutral portfolios, where I repeat the sorting procedure, 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 CIPD. For

[10]Controlling only for returns of the market portfolio in the first step has been common practice in the literature (see Sadka, 2010 and Hu et al., 2013 for hedge funds, or Ang, Hodrick, Xing, and Zhang, 2006, among many others, for stocks) and ensures a sufficient amount of degrees of freedom for each independent variable.

[11]Throghout the paper the number of lags to compute Newey-West t-statistics is determined using the automatic lag selection described in Newey and West (1994).



(a) Results for unconditional sorts

(b) Style-neutral sorts

Figure 2: **Risk-adjusted returns of CIPD-beta sorted hedge fund portfolios.** Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to the CIPD measure, constructed in Section 3.2. Funds in Portfolio 1 have the highest loading on CIPD, funds in Portfolio 10 have the lowest loading on CIPD. For each fund, the CIPD beta is calculated using a regression of monthly fund returns on CIPD 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 YLD and BAA 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. Panel (a) shows the results for unconditional sorts. Panel (b) shows the results for style-neutral sorts. The sample period is January 1994 to May 2015, including all 8,541 hedge funds from the TASS database.

each decile, I then merge the 11 different style portfolios, which ensures that each portfolio has the same percentage of styles.

As we can see from Panel (b) of Figure 4, the results remain almost unchanged when portfolios are style neutral. Funds with the lowest loading on CIPD_t (Portfolio 10) earn a monthly risk-adjusted return of 0.42% and the risk-adjusted returns decreasing almost monotonically to the portfolio consisting of funds with the highest loading on CIPD (Portfolio 1), which generates a monthly alpha of 0.02%. The difference portfolio, which is long Portfolio 10 and short Portfolio 1, generates a monthly risk-adjusted return of 0.38% (t-statistic of 2.33). Because my results are almost unchanged when forming style-neutral portfolios and because forming style-neutral portfolios is an uncommon approach in the hedge fund literature, I report my main results using unconditional sorts and provide additional details for conditional sorts in Appendix C (Panel A of Table C.3).[12]

[12] In my model, a higher loading on CIPD is equivalent to lower past returns. To rule out the possibility that my finding is only driven by lower past returns, I also form past-return-neutral portfolios in which I first split the overall sample of hedge funds into deciles based on their past returns over the last 36 months and then sort each of these subsamples into decile portfolios, based on their loading on CIPD. For each decile,

More details and additional results for the unconditional sorts are reported in Table 3. The first column of the table reports the Fung and Hsieh alphas discussed previously. The second column reports the risk-adjusted returns relative to the seven Fung and Hsieh factors and five additional factors. I add more risk factors because the seven factors might not be sufficient to capture all the risks that funds with different investment styles can be exposed to. The five factors that I add to the seven-factor model are the following. First, because 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, because the CIPD is related to currency risks, I add the two currency risk factors proposed by Lustig, Roussanov, and Verdelhan (2011), which capture currency returns of a U.S. dollar investor and a carry trader, respectively. Finally, I add the excess returns of the S&P GSCI Commodity Index and the MSCI Emerging Markets Index to ensure that the risks of funds investing in commodities or emerging markets are captured as well. As we can see from the second column of Table 3, 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 moderately. Most importantly, the difference portfolio generates a monthly risk-adjusted return of 0.48% (t-statistic of 2.44) which is almost identical to the risk-adjusted returns relative to the Fung and Hsieh factors.

Columns 3 and 4 of Table 3 show the post-sorting β^{Mkt} and β^{CIPD} of the ten decile portfolios. The post-sorting β^{CIPD} is significantly different in the portfolio with the highest loading on CIPD (P1), which has a β^{CIPD} of 0.17 (t-statistic of 5.05), than in the portfolio with the lowest loading on CIPD (P10), which has an insignificantly negative beta of -0.02 (t-statistic of -0.57). Furthermore, the difference portfolio has a β^{CIPD} of -0.19 (t-statistic of 3.42) and the post-sorting betas are monotonically decreasing from Portfolio 1 to Portfolio 10. In addition to the significant difference in CIPD loadings, Portfolio 10 also has a lower loading on the market portfolio than Portfolio 1. This observation is in line with Titman and Tiu (2011) who argue that hedge funds with access to a true alpha-generating strategy choose a lower loading on well-known risk factors. Column 5 of Table 3 reports the R^2 from regressing the decile portfolio returns on the seven Fung-Hsieh risk factors.[13] In line with the results of Titman and Tiu (2011), returns of hedge funds with a lower loading on CIPD

I then merge the 10 different past return deciles. This procedure leads to qualitatively similar results as the unconditional sorts. The conditional difference portfolio which is long hedge funds with a low loading on CIPD and short hedge funds with a high loading on CIPD is generating a risk-adjusted return of 0.44 (t-statistic of 2.44). More details for this split can be found in Appendix C (Figure C.1 and Table C.3).

[13]For brevity, I do not report the loadings on all seven Fung-Hsieh factors separately. These results can be found in Appendix C (Table C.2).

Table 3: **Risk-adjusted returns and other characteristics of CIPD-sorted portfolios.** Hedge funds are sorted into deciles based on their beta to the CIPD measure described in Section 3.2. Beta is calculated using a regression of monthly hedge fund returns on CIPD, controlling for the stock market portfolio, and using the 36 months prior to portfolio formation. α^{FH} is the intercept of regressing the portfolio returns on the seven Fung Hsieh risk factors, α^{Add} is the intercept of regressing hedge fund returns on the seven Fung Hsieh factors plus five additional factors, β^{Mkt} and β^{CIPD} are the portfolio loadings on the stock market portfolio and on CIPD, respectively, R^2_{FH} is the adjusted R^2 of regressing the portfolio returns on the seven Fung Hsieh factors. Under post-sorting, all quantities are computed using the returns of the formed hedge fund portfolios. Under pre-sorting, the average factor loadings of individual hedge funds, prior to portfolio formation, are reported. The seven Fung Hsieh factors are the market excess return (MKT), a size factor (SMB), tradable factors to mimic monthly changes in the 10-year Treasury constant maturity yield (YLD) and monthly changes in the Moody's Baa yield less 10-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.

	Post-sorting					Pre-sorting	
	α^{FH}	α^{Add}	β^{Mkt}	β^{CIPD}	R^2_{FH}	β^{Mkt}	β^{CIPD}
P1	0.00	0.06	0.52***	0.17***	0.64	0.41***	1.25***
	[-0.02]	[0.49]	[8.65]	[5.05]		[9.25]	[6.45]
P2	0.14	0.15**	0.30***	0.15***	0.63	0.30***	0.51***
	[1.46]	[2.22]	[7.94]	[4.03]		[11.83]	[5.28]
P3	0.16**	0.17***	0.26***	0.12***	0.69	0.25***	0.31***
	[2.33]	[3.11]	[9.10]	[5.93]		[11.43]	[4.42]
P4	0.14*	0.13**	0.22***	0.10***	0.65	0.22***	0.18***
	[1.85]	[2.47]	[8.68]	[4.69]		[10.81]	[3.53]
P5	0.17**	0.18***	0.21***	0.10***	0.60	0.21***	0.09**
	[2.25]	[3.15]	[8.69]	[4.40]		[10.63]	[2.27]
P6	0.17**	0.19***	0.20***	0.10***	0.59	0.18***	0.02
	[2.14]	[3.01]	[7.34]	[4.37]		[10.05]	[0.43]
P7	0.23***	0.24***	0.17***	0.08***	0.51	0.18***	-0.06*
	[3.12]	[3.96]	[8.26]	[3.97]		[9.35]	[-1.76]
P8	0.33***	0.32***	0.19***	0.06***	0.56	0.21***	-0.15***
	[5.20]	[5.82]	[10.64]	[2.67]		[9.86]	[-3.47]
P9	0.38***	0.40***	0.22***	0.01	0.47	0.28***	-0.34***
	[4.86]	[5.03]	[10.32]	[0.29]		[9.54]	[-4.88]
P10	0.50***	0.53***	0.31***	-0.02	0.42	0.44***	-1.05***
	[3.71]	[4.32]	[5.67]	[-0.57]		[8.89]	[-6.20]
P10-P1	0.50**	0.48**	-0.21**	-0.19***	0.30	0.03	-2.29***
	[2.39]	[2.44]	[-2.36]	[-3.42]		[0.41]	[-7.07]

are less-well explained by common risk factors. Finally, the last two columns of Table 3 show the pre-sorting β^{Mkt} and β^{CIPD}.

Other Explanations?

I now address the question of whether the difference in returns between funds with a low loading on CIPD and funds with a high loading on CIPD is simply driven by other fund characteristics, such as age, size, redemption terms, or managerial incentives.[14] To that end, I run Fama and MacBeth (1973) regressions of risk-adjusted hedge fund returns on their CIPD beta, controlling for various fund-specific characteristics. To run the Fama-MacBeth regression, I compute the risk-adjusted excess return of each hedge fund, using the following equation:

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

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 CIPD 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^{CIPD} of Portfolio i at time t and β^{CIPD} of Portfolio j at time $t+1$. I then run regressions with the following control variables:

$$\begin{aligned} R_{i,t}^{\perp} = &\gamma_0 + \gamma^{CIPD} \beta_{i,t-1}^{CIPD} \\ &+ \gamma^{Age} Age_{i,t-1} + \gamma^{Size} \ln(AUM_{i,t-1}) + \gamma^{Notice} Notice_i + \gamma^{Lockup} DLockup_i \\ &+ \gamma^{MinInvest} MinInvest_i + \gamma^{MgFee} MgFee_i + \gamma^{IncFee} IncFee_i + \varepsilon_{i,t}, \end{aligned} \tag{13}$$

gradually adding the controls in the second and third line. $Age_{i,t-1}$ and $\ln(AUM_{i,t-1})$ are Fund i's age and log-size at time $t-1$. $Notice_i$ and $DLockup_i$ are Fund i's redemption notice period (in months) and a dummy variable that equals one if Fund i has a lockup provision and zero otherwise. $MinInvest_i$, $MgFee_i$, and $IncFee_i$ are variables capturing the minimum investment, the management fee, and the incentive fee for Fund i.

The regression results are exhibited in Table 4. In Column (1) I run a regression without controlling for any fund-specific characteristics. In Column (2), I add fund age, size, redemption notice period, lockup provision, and backfilled dummy, as well as style dummies

[14] An overview of the average fund characteristics for the 10 CIP-beta-sorted portfolios can be found in Appendix C (Table C.4).

as controls. In Column (3) I run the full regression (13), controlling for minimum investment, management fee, and incentive fee. The table shows that β_{t-1}^{CIPD} is a significant explanatory variable for the cross-section of risk-adjusted hedge fund returns, even after controlling for fund-specific characteristics. In all three specifications, β_{t-1}^{CIPD} is statistically significant at a 1% level. However, the economical and statistical significance of β_{t-1}^{CIPD} decreases with the amount of control variables added to the regression. Without additional controls an increase in β_{t-1}^{CIPD} of 0.10 corresponds to a decrease of 0.48% in monthly risk-adjusted returns and the effect is statistically significant at a 1% level (t-statistic of -3.11). Adding the first four control variables lowers the economic significance of an increase of 0.10 in β_{t-1}^{CIPD} to 0.46 with a t-statistic to -2.97. In the third specification an increase of 0.10 in β_{t-1}^{CIPD} corresponds to a decrease of 0.41 in risk-adjusted returns (t-statistic of -2.61).

In addition to the results for β^{CIPD}, it is also worth noting that all the controls have the expected signs. 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. Aragon (2007) finds that hedge funds with lockups and longer redemption notice periods outperform hedge funds without lockups and with shorter redemption notice periods, which is also the case in my sample and reflected by the positive coefficients on Notice and Lockup. Moreover, higher managerial incentives (in the form of higher fees) tend to increase returns, which is in line with Agarwal, Daniel, and Naik (2009).

4.2 Model Predictions

So far, I have established that a higher loading on CIPD predicts lower risk-adjusted returns, which is in line with the main model prediction. I now test the three model predictions in the data and obtain the following results. First, I find that it is a higher loading on past funding shocks, as proxied by the negative part of CIPD, that drives the results; this is additional evidence for the first model prediction. Second, in line with the second model prediction, I find that hedge funds with a high loading on CIPD experience significantly lower fund flows than funds with a low loading on CIPD. Finally, in line with the third model prediction, I find that the effect of a high past loading on CIPD is weaker for funds that are less exposed to funding risk.

4.2.1 Negative Shocks Driving the Results

According to my model, low returns during a funding shock predict lower future returns. However, the model does not give any predictions about the relationship between fund returns and improving funding conditions. Hence, I next investigate whether it is the link

Table 4: **Results using cross-sectional regressions.** This table reports the results of Fama and MacBeth (1973) regressions of the cross section of monthly hedge fund alphas (relative to the Fung-Hsieh seven factor model). In the first specification, the beta on CIPD, estimated over the past 36 months, is used as an independent variable. In the second specification, fund age in months, the log of the fund size, the fund's redemption notice period, a dummy variable that equals one if the fund has a lockup provision and is zero otherwise, and an investment style dummy are added as controls. In the third specification, minimum investment, fund management fee, and fund incentive fees are added as control variables. The evaluation period is January 1997 to May 2015. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

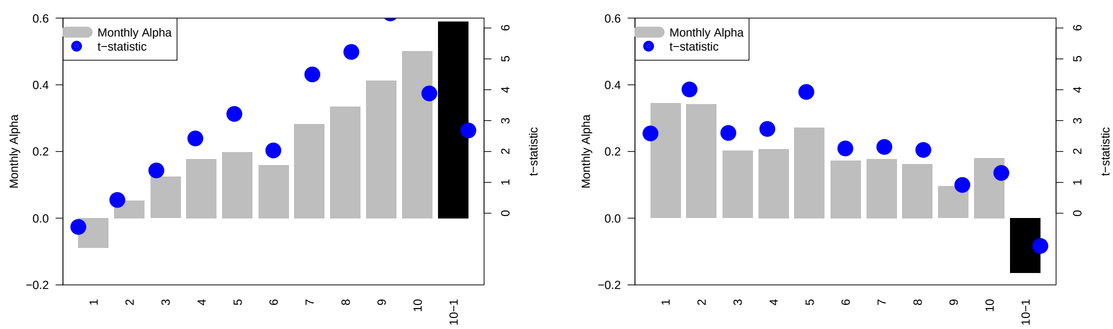
	(1)	(2)	(3)
Intercept	0.500***	0.540***	0.313***
	[5.53]	[4.55]	[2.83]
CIPD beta	-4.830***	-4.590***	-4.093***
	[-3.11]	[-2.97]	[-2.61]
Fund age (months)		-0.001	-0.001
		[-1.35]	[-1.51]
Log(fund size)		-0.014	-0.023
		[-0.72]	[-1.16]
Redemption notice (months)		0.032	0.039*
		[1.29]	[1.83]
Lockup dummy		0.124***	0.100***
		[3.45]	[2.90]
Minimum Investment (mio USD)			0.013**
			[2.19]
Management Fee (%)			0.047
			[1.53]
Incentive Fee (%)			0.010***
			[3.61]
StyleDummies	No	Yes	Yes

between deteriorating funding conditions and hedge fund returns that causes the cross-sectional difference in performance. To do so, I split CIPD into a positive and negative part and repeat the sorting procedure described above. Recall that CIPD is defined as $CIP_{t-1}^{Index} - CIP_{t}^{Index}$, and therefore a lower CIPD corresponds to deteriorating funding conditions. Every month t, for each Fund i, I run the following regression using the past 36 months of return observations:

$$R_{i,t} = \alpha + \beta^{CIPD-}\min(\text{CIPD}_t, 0) + \beta^{CIPD+}\max(\text{CIPD}_t, 0) + \beta^{Mkt}R_t^{Mkt} + \varepsilon_t \qquad (14)$$

and then perform two tests. In the first test, I sort hedge funds into decile portfolios based on β^{CIPD-} and in the second test, I sort them based on β^{CIPD+}.

The results of these two tests are exhibited in Figure 3, where Panel (a) shows the results for sorting on negative CIPD (deteriorating funding conditions; henceforth CIPD^{-}) and Panel (b) shows the results for sorting on positive CIPD (improving funding conditions; henceforth CIPD^{+}). Comparing Panel (a) of Figure 3 to Panel (a) of Figure 4 shows that the results even improve when only using the negative part of CIPD. The difference portfolio that is long hedge funds with a low loading on CIPD^{-} and short hedge funds with a high loading on CIPD^{-} delivers a monthly risk-adjusted return of 0.62 (t-statistic of 2.78). In contrast to that, we see an opposite pattern when sorting on CIPD^{+}. Here, hedge funds with a higher loading are generating higher risk-adjusted returns than hedge funds with a lower loading. However, the difference portfolio generates an insignificant risk-adjusted return of -0.27 (t-statistic of -1.63).



(a) Sorted on CIPD^{-} (b) Sorted on CIPD^{+}

Figure 3: **Results for hedge fund portfolios sorted on CIPD^{-} and CIPD^{+}**. Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to the negative part of CIPD (Panel (a)) and their historical beta to the positive part of CIPD (Panel (b)). For a detailed description of the sorting procedure as well as the computation of risk-adjusted returns see the caption of Figure 4. The grey bars represent monthly risk-adjusted portfolio returns, calculated using the Fung and Hsieh (2004) seven-factor model, where the YLD and BAA 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.

Panel A of Table 5 provides additional details for the two difference portfolios (the results for portfolios 1-10 are omitted for brevity). The first row of Panel A confirms that using CIPD^{-} instead of CIPD leads to marginally stronger results. The difference portfolio earns a higher risk-adjusted return and the post-sorting β^{CIPD} (which is computed using only CIPD$^-$ is of the same magnitude as in baseline case. The second row of Panel A shows that this is not the case when sorting on CIPD$^+$, where the difference portfolio generates an insignificant return and β^{CIPD} (which is computed using only CIPD$^+$) is insignificant. Furthermore, Panel A also confirms that adding more risk factors to the Fung and Hsieh seven factor benchmark model leaves the main inference unchanged.

4.2.2 Fund Flows

Hedge funds with a high loading on CIPD expose their investors to more funding risk and generate lower risk-adjusted returns. My theory suggests that once a hedge fund generates a lower return during a funding shock, investors realize that they invested into a fund that takes higher risks to generate its returns and withdraw their money. Hence, the second model prediction is that funds with a high loading on CIPD experience lower flows than funds with a low loading on CIPD.[15] In testing this model prediction, it is important to disentangle fund flows that occur due to a higher exposure to funding risk from fund flows that simply occur due to poor past performance.[16]

To investigate the second testable model prediction, I compute the flow in month t for each Fund i as:

$$Flow_{i,t} := \frac{AUM_{i,t} - AUM_{i,t-1}}{AUM_{i,t-1}} - R_{i,t}, \tag{15}$$

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:

$$Flow_t^{PF} := \frac{\sum_{i=1}^{n_t} Flow_{i,t} AUM_{i,t-1}}{\sum_{i=1}^{n_t} AUM_{i,t-1}}, \tag{16}$$

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 because lockups and unfavorable redemption terms can keep investors from withdrawing immediately. If funds move between portfolios frequently, the flow measure is not related to the fund's sensitivity

[15] The notion that investors are slow in changing their investments in different funds is in line with the idea of Gârleanu and Pedersen (2015) who argue that search costs for asset management and noise allocators make it difficult for investors to distinguish good funds from bad funds.

[16] A large literature details fund flows in response to past performance. See Chevalier and Ellison (1997) and Sirri and Tufano (1998) who document that investor flows are convex in past performance for mutual funds. See Baquero and Verbeek (2015), Ding, Getmansky, Liang, and Wermers (2015), and Agarwal, Green, and Ren (2015) for a discussion of hedge fund investors.

Table 5: **Additional results.** Hedge funds are sorted into portfolios based on their beta to the CIPD measure, described in Section 3.2, and based on different modifications of CIPD. For a detailed description of the sorting procedure and the different variables see the caption of Table 3. Each row reports the results for a difference portfolio. Panel A reports the results for hedge funds that are sorted into deciles based on their loading on the negative part of CIPD (1) and on the poistive part of CIPD (2). Panel B shows the results for different subsamples of the hedge fund database, where funds are sorted into quintiles based on their loading on $CIPD^{-}$. The sample is split into hedge funds with a redemption notice period longer than one month and hedge funds with a redemption notice period shorter than one month (rows (1) and (2)), hedge funds with a lockup provision and hedge funds without a lockup provision (rows (3) and (4)), and hedge funds which use more than one prime broker and hedge funds which only use one prime broker (rows (5) and (6)). Panel C shows the results for CIPD-sorted decile portfolios using six modifications of the dataset: (1) after dropping all backfilled observations, (2) replacing the last reported return with a dropout return of -25%, (3) dropping potential duplicates, (4) un-smoothing the returns using the procedure described in Getmansky et al. (2004), (5) using a subset that consists of funds of funds only, (6) using a subset without funds of hedge funds. 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.

	Post-sorting					Pre-sorting	
	α^{FH}	α^{Add}	β^{Mkt}	β^{CIP}	R^2_{FH}	β^{Mkt}	β^{CIP}
Panel A: Sorting on increases and decreases in CIP^D							
(1) Sort on CIP^{D-}	0.62***	0.63***	-0.30***	-0.18***	0.37	-0.09	-4.00***
	[2.78]	[3.04]	[-4.07]	[-5.59]		[-1.21]	[-5.86]
(2) Sort on CIP^{D+}	-0.27	-0.29**	0.17*	-0.13	0.11	0.17***	-3.84***
	[-1.63]	[-2.38]	[1.86]	[-1.33]		[2.89]	[-6.19]
Panel B: Results for funds with different liquidity risk							
(1) Longer notice	0.37**	0.35**	-0.18***	-0.13***	0.28	-0.06	-2.35***
	[2.27]	[2.41]	[-3.59]	[-4.67]		[-1.10]	[-5.92]
(2) Shorter notice	0.55***	0.57***	-0.27***	-0.14***	0.44	-0.11	-3.01***
	[3.29]	[3.64]	[-4.70]	[-5.70]		[-1.45]	[-5.86]
(3) Funds with lockup	0.20	0.25	-0.11**	-0.16***	0.19	-0.03	-2.73***
	[1.32]	[1.64]	[-2.25]	[-5.02]		[-0.61]	[-5.90]
(4) Funds without lockup	0.50***	0.51***	-0.26***	-0.15***	0.44	-0.11	-2.76***
	[3.09]	[3.50]	[-4.68]	[-6.25]		[-1.59]	[-5.88]
(5) More than one PB	0.15	0.14	-0.22***	-0.27***	0.27	-0.05	-2.30***
	[0.73]	[0.72]	[-2.88]	[-5.75]		[-0.91]	[-5.52]
(6) Only one PB	0.39**	0.42**	-0.21***	-0.16***	0.39	-0.08	-2.98***
	[2.43]	[2.57]	[-3.72]	[-4.51]		[-1.13]	[-6.08]
Panel C: Results for different robustness checks							
(1) Drop Backfilled	0.55*	0.49**	-0.24**	-0.19***	0.27	0.03	-2.29***
	[1.97]	[2.04]	[-2.50]	[-3.48]		[0.34]	[-7.00]
(2) -25% dropout return	0.52**	0.49**	-0.20**	-0.19***	0.29	0.03	-2.29***
	[2.38]	[2.41]	[-2.34]	[-3.44]		[0.41]	[-7.07]
(3) Drop duplicates	0.51**	0.49**	-0.22**	-0.20***	0.30	0.04	-2.34***
	[2.37]	[2.41]	[-2.41]	[-3.49]		[0.42]	[-7.18]
(4) Un-smoothed returns	0.58***	0.54***	-0.28***	-0.24***	0.31	0.03	-2.29***
	[2.74]	[2.83]	[-3.03]	[-4.38]		[0.41]	[-7.07]
(5) Funds of funds only	0.33***	0.32***	-0.15***	-0.04***	0.31	-0.06**	-0.87***
	[2.95]	[3.26]	[-4.50]	[-3.06]		[-2.07]	[-5.75]
(6) Without funds of funds	0.35**	0.34**	-0.15*	-0.21***	0.31	0.01	-1.78***
	[2.15]	[2.19]	[-1.93]	[-4.88]		[0.18]	[-7.47]

to CIPD. Since the average CIPD-sorted (CIPD$^-$-sorted) fund spends 52% (53%) of its time in the same decile portfolio, I split the sample into quintiles instead, where the average fund spends 65% (65%) of its time in the same portfolio.

Table 6: **Average flows for CIPD-sorted hedge fund portfolios.** Hedge funds are sorted into quintiles according to their loading on CIPD (sort on β^{CIPD}) and on their loading on the negative part of CIPD (sort on β^{CIPD-}). For a detailed description of this sorting procedure see the caption of Table 3. Average monthly flows for these portfolios are then computed according to Equations (15) and (16). *Difference* reports the mean difference for flows of P9-10 and flows of P1-2. Panel A reports the results for unconditional sorts. Panel B reports the results for sorts that are conditional on past performance. In this sort, every month, the overall sample of hedge funds is first split into deciles based on the funds' average past return over the last 36 months. Afterwards, each of the ten portfolios is sorted into quintiles based on the individual funds' loading on the funding risk measure. Finally, for each quintile, the ten different past return deciles are merged. Newey-West t-statistics are reported in square brackets. ***, **, and * indicate significance at a 1% and 10% level. The sample includes all 8,541 funds in the TASS database and the sample period is January 1994 to May 2015.

	P1-2	P3-4	P5-6	P7-8	P9-10	*Difference*
	Panel A: Unconditional results					
sort on β^{CIPD}	-0.20	0.01	0.11	0.17	0.24	0.44***
	[-1.03]	[0.04]	[0.53]	[0.84]	[1.18]	[2.64]
sort on β^{CIPD-}	-0.22	0.01	0.15	0.14	0.32*	0.55***
	[-1.09]	[0.05]	[0.69]	[0.68]	[1.80]	[2.78]
	Panel B: Conditional on past returns					
sort on β^{CIPD}	-0.25	0.08	0.23	0.11	0.17	0.41**
	[-1.27]	[0.41]	[1.13]	[0.55]	[0.84]	[2.40]
sort on β^{CIPD-}	-0.28	0.08	0.22	0.15	0.21	0.49**
	[-1.38]	[0.44]	[0.97]	[0.76]	[1.11]	[2.52]

The resulting average flows for the quintile portfolios, as well as the difference between fund flows for the portfolio with the lowest funding risk and the portfolio with the highest funding risk, are exhibited in Panel A of Table 6. The first row shows the results for funds that are sorted based on CIPD and the second row shows the results for funds that are sorted on CIPD$^-$. In both cases, funds in the portfolio with the highest loading on CIPD are on average subject to outflows while funds in the portfolio with the lowest loading on CIPD are on average subject to inflows. However, apart from one exception, the fund flows for the quintile portfolios are not significantly different from zero. In contrast to that, there is a significant difference between fund flows to hedge funds with a low loading on the funding risk measure and fund flows to hedge funds with a high loading on that measure. For portfolios sorted on CIPD the difference is 0.44% per month and statistically significant at a 1% level (t-statistic of 2.64). For portfolios sorted on $CIPD^-$ the difference is 0.55% per month and also statistically significant at a 1% level (t-statistic of 2.78).

To ensure that this difference in fund flows is not simply driven by the funds' past returns, I repeat the analysis conditional on the funds' past performance. To do so, I proceed in three steps. First, I split the overall sample of hedge funds into deciles based on their average past return over the last 36 months. Second, for each of the ten portfolios, I form quintiles based on their loading on the funding risk measure. Finally, for each quintile, I merge the ten different past return deciles. This procedure ensures that funds in each quintile have comparable past returns. Panel B of Table 6 shows the results for this conditional sort. As we can see from the table, forming quintiles conditional on past returns lowers the economical and statistical significance of the result marginally. For portfolios sorted on CIPD the difference in flows drops to 0.41% per month (t-statistic of 2.40). For portfolios sorted on $CIPD^-$ the difference drops to 0.49% per month (t-statistic of 2.52). Overall, this test confirms that the difference in fund flows for funds with a different loading on funding risk is not simply driven by a difference in past returns.

4.2.3 Fund-Specific Funding Risk

The third model prediction is that the difference between hedge funds with a different sensitivity to funding shocks is less pronounced for funds whose liabilities are less exposed to funding shocks. To investigate this model prediction, I consider three different proxies for the riskiness a fund's liabilities, repeating my main analysis for different subsamples of the hedge fund database. The first proxy is the fund's redemption notice period, the second proxy is whether a fund has a lockup provision, and the third proxy is the number of prime brokers used by different hedge funds. To ensure a sufficient number of funds in each quantile, I follow Teo (2011) and form quintile portfolios instead of decile portfolios. I run the analysis for funds sorted based on $CIPD^-$, which is closer to my theory than sorting on CIPD.[17]

First, I divide the sample based on the funds' redemption notice period. The first subsample consists of funds with favorable redemption terms, which have a redemption notice period of one month or less (recall from Table 1 that the median redemption notice period is one month). The second subsample consists of funds with less-favorable redemption terms, which have a redemption notice period of more than one month. Panels (a) and (b) of Figure 4 show the results for the two subsamples. Hedge funds with less favorable redemption terms and a high loading on $CIPD^-$ (portfolio 1) are still able to generate positive risk-adjusted returns, while hedge funds with less-favorable redemption terms and a high loading on $CIPD^-$

[17] Using CIPD instead of $CIPD^-$ leaves the results almost unchanged.

are generating negative risk-adjusted returns. The lower the loading on CIPD^- becomes, the smaller the difference between the two subsets of funds.[18] The first two rows of Panel B in Table 5 provide additional details and the exact numbers for the difference portfolio.

Second, I split the sample into funds with a lockup provisions and funds without a 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). Funds with a lockup provision are therefore less susceptible to equity withdrawals and therefore the effect of a higher loading on CIPD^- should be less pronounced. Panels (c) and (d) of Figure 4 show the results for these two subsamples.[19] Funds with a lockup provision and with a low loading on CIPD^- are still able to generate positive risk-adjusted returns while funds without a lockup provision and with a high loading on CIPD^- are generating a negative alpha. Most notably, the difference portfolio generates almost three times higher returns for funds without a lockup provision compared to funds with a lockup provision. The third and fourth row of Panel B in Table 5 provide additional details and exact parameter estimates.

Third, 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). 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 decreases the number of available funds. To overcome these issues, I combine the prime broker data from the most recent version of the database with data used in Aragon and Strahan (2012).[20] The results of these splits are exhibited in Panels (e) and (f) of Figure 4. As we can see from the figures, the results are insignificant for funds with more than one prime broker and significant for funds with only one prime broker. The fifth and sixth row of Panel B in Table 5 provide additional details, confirming that the difference portfolio earns an almost three times higher risk-adjusted return for funds with only one prime broker, compared to funds with more than one prime broker.

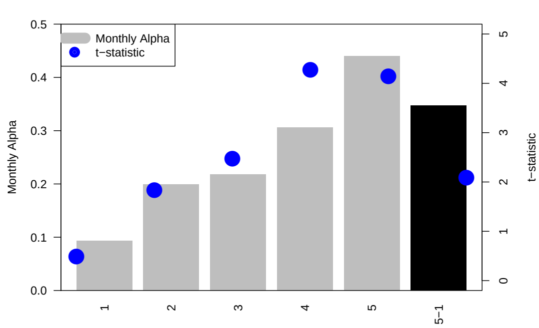
5 Robustness Checks

In this section, I test the robustness of my main result. In Section 5.1, I investigate whether few crisis episodes are responsible for the difference in returns between funds with a high

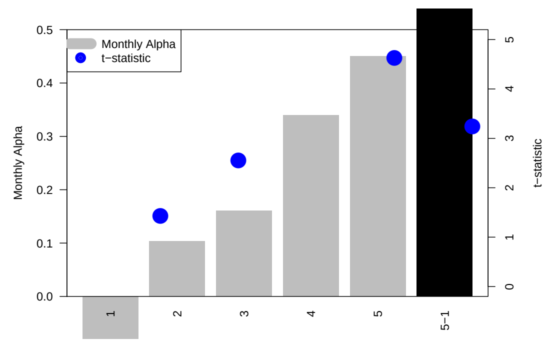
[18]Note that funds with less-favorable redemption terms overall generate higher risk-adjusted returns, which is in line with the findings of Aragon (2007).

[19]One drawback of this split is that the sample of funds with lockup provision is smaller than the sample of funds without lockup provision (recall that only 19% of the funds in the sample have a lockup provision).

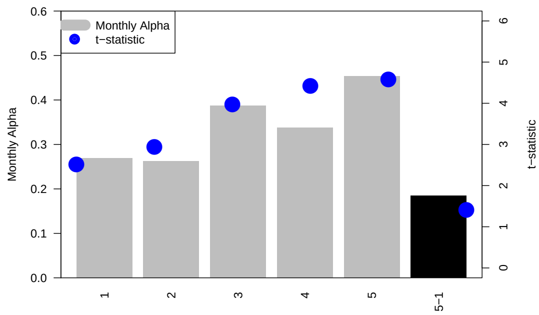
[20]I am grateful to George Aragon for providing me with these data.



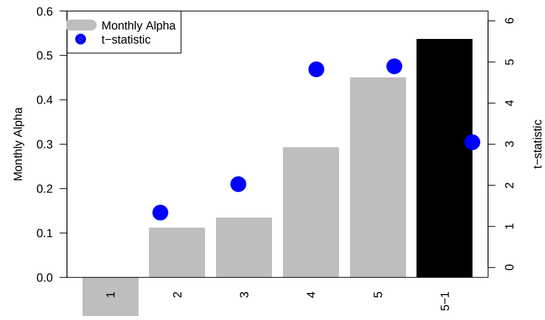
(a) Less-favorable redemption terms



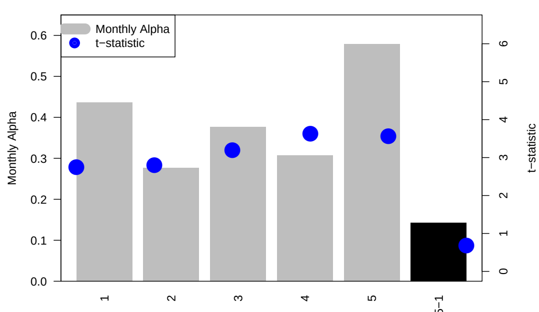
(b) Favorable redemption terms



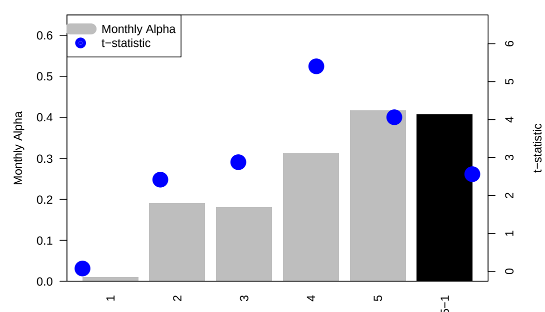
(c) Funds with lockup



(d) Funds without lockup



(e) Funds with more than one PB



(f) Funds with one PB

Figure 4: **Results for different subsamples of CIPD^{-}-sorted hedge fund portfolios** This figure presents the results of applying the sorting procedure described in the caption of Figure for different subsamples of the database using CIPD^{-} as sorting variable. Panels (a) and (b) compare the results for hedge funds with redemption notice periods of more than one month (less-favorable redemption terms) and funds with redemption notice period less than one month (favorable redemption terms). Panels (c) and (d) compare the results for hedge funds with lockup provision and funds without lockup provision. Panels (e) and (f) compare the results for hedge funds with more than one prime broker and hedge funds with only one prime broker. The sample period is January 1994 to May 2015, including all 8,541 hedge funds from the TASS database.

loading on CIPD (CIPD^-) and funds with a low loading on CIPD (CIPD^-). In Section 5.2, I address common biases in the hedge fund database and show that my main result is robust to these biases.

5.1 Robustness to Removing Major Crisis Episodes

To check whether my results are only driven by few major crisis episodes, I split the sample into periods of crisis and normal times. I use two different splits. First, I use anecdotal evidence about crisis periods to identify 19 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 - March 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). Second, I classify NBER recession periods as crisis periods and the remaining periods as non-recession periods.

As we can see from Panel (I) of Table 7, the risk-adjusted returns of the difference portfolio that is long hedge funds with a low loading on CIPD and short hedge funds with a high loading on CIPD generates a large alpha of 1.10 during the 19 crisis months and a significant, positive alpha of 0.45 during normal times. Similarly, the difference portfolio where hedge funds are sorted on CIPD^-, generates an alpha of 1.28 in crisis periods and 0.53 in normal times. Note that the alpha during normal times only shows a minor drop of 0.05 for both difference portfolios when compared to the alpha for the entire sample period. Panel (II) shows that removing NBER recession periods also leaves the main result unchanged. The alpha of the difference portfolio for hedge funds sorted on CIPD as well as for hedge funds sorted on CIPD^- is above 0.50 during normal times and significant at a 5% level (t-statistic of 2.29 and 2.44 respectively). Hence, the findings in Table 7 indicate that the results remain intact, even after removing severe crisis episodes.

5.2 Biases in Reported Hedge Fund Data

I now discuss five of the most common biases in hedge fund data and show that my results are robust to them. The five biases are the following: backfill bias, dropout bias, return smoothing, double counting, and selection bias. Backfill bias arises because once a hedge fund starts reporting to the TASS database, it is allowed to enter past returns to the database as well. Clearly, only funds with high past returns would use that option which biases returns upward. Dropout bias arises because hedge funds can choose to stop reporting to

Table 7: **Crisis versus noncrisis periods.** This table shows the risk-adjusted returns of the difference portfolio which is long portfolio 10 and short portfolio 1 for crises and non-crises periods. The decile portfolios are formed based on the individual funds' loading on CIPD and CIPD^{-}, respectively. See the caption of Table 3 for a description of the sorting procedure and for the risk-adjustment. Under (I), anecdotal evidence is used to classify crisis periods. The following 19 months form the crises periods: August-September 1998, August-October 2007, August 2008 - March 2009, August 2011 - January 2012. The remaining 200 months form the quiet period. Under (II) crisis periods are defined as NBER recession periods, which are March 2001 – November 2001 and December 2007 – June 2009. The remaining periods are quiet periods. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	(I) Anecdotal		(II) NBER Recession	
	Crises	Normal	Crises	Normal
sort on β^{CIPD}	1.10*	0.45**	0.46	0.52**
	[1.74]	[2.09]	[0.90]	[2.29]
sort on β^{CIPD-}	1.28	0.53**	0.87	0.55**
	[1.40]	[2.46]	[1.61]	[2.44]
Number of Observations	19	201	28	192

the database if they perform poorly. 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). Double counting could occur because the returns of different subsidiaries of the same fund could be reported as different entities in the database. Finally, selection bias arises because funds report voluntarily to the TASS database, which rises the question of whether the sample of funds in the database is representative for the entire hedge fund universe. I report the results of these robustness checks for CIPD-sorted portfolios and provide the results for CIPD^{-}-sorted portfolios (which are stronger and more robust) in Appendix C (Figure C.2 and Panel C of Table C.2).[21]

To address backfill bias, I utilize the information 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 all backfilled observations could significantly change the results.[22] Repeating the analysis without backfilled returns leads to significantly lower risk-adjusted returns for all

[21]In the following, I address one bias at a time and refer to Appendix C (Table C.5) for robustness checks that address multiple biases at a time.

[22]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 "truly" backfilled.

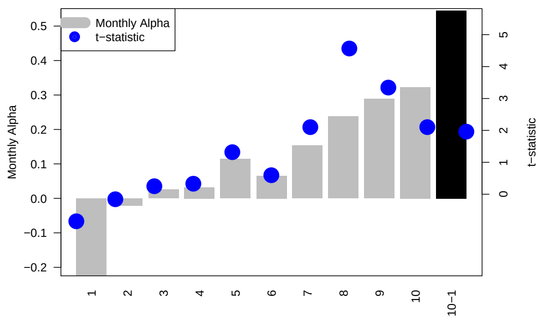
deciles, but leaves my main result unchanged. Panel (a) of Figure 5 illustrates the results for this test. As we can see from the Figure, the risk-adjusted returns of all decile portfolios decrease sharply. However, the main inference remains unchanged. The first row of Panel C in Table 5 provides additional details for the difference portfolio, which is long in hedge funds with a low loading on CIPD and short hedge funds with a high loading on CIPD and yields a monthly risk-adjusted return of 0.55% (t-statistic of 1.97).

When addressing dropout bias it is important to distinguish survivorship bias from dropout bias (Aiken, Clifford, and Ellis, 2013). 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 of 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%.[23] The results of this robustness check are reported in Panel (b) of Figure 5. As we can see from the figure, the alphas drop sharply and only four out of ten portfolios generate positive risk-adjusted returns. However, the difference portfolio still generates a monthly alpha of 0.52% (t-statistic of 2.38). Additional details for the difference portfolio can be found in the second row of Panel C in Table 5.

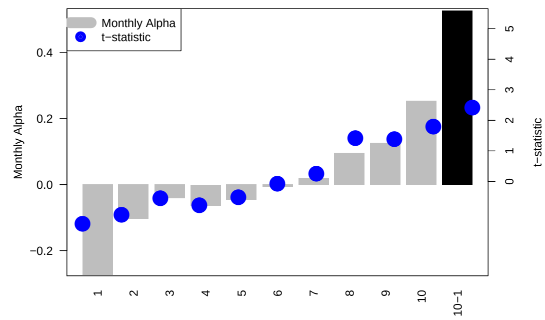
The concern that different subsidiaries of the same fund could cloud the statistical inference has been mentioned by Bali et al. (2014) who document that approximately 16% of the funds in the TASS database are duplicates. To address this concern, I compute the pairwise correlation between the returns 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 5 shows, repeating the analysis with this smaller dataset leads to virtually unchanged results. The difference portfolio that is long funds with low loading on CIPD and short funds with high loading on CIPD generates a risk-adjusted return of 0.51% (t-statistic of 2.37), which is virtually identical to the result in Table 3, where the difference portfolio earns a risk-adjusted return of 0.50%. Additional results can be found in the third row of Panel C in Table 5.

Next, 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

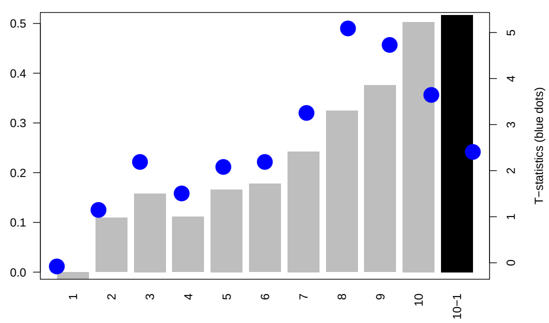
[23] I also experimented with more negative dropout returns such as −50% and −75% which decreased the alphas of all ten portfolios below zero but left the result for the difference portfolio unchanged.



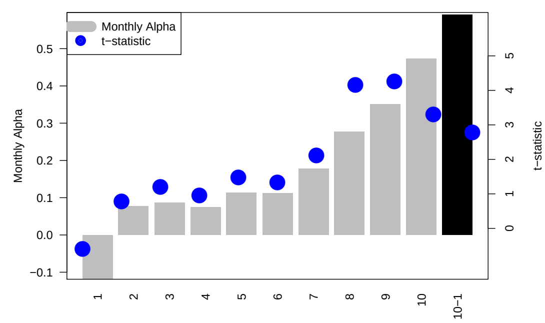
(a) Without backfilled observations



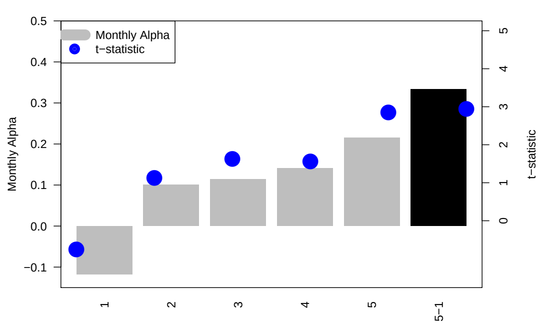
(b) Liquidation return of -25%



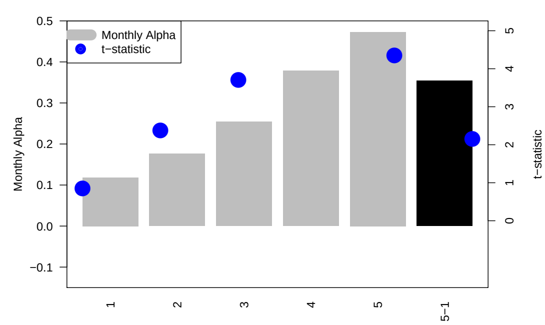
(c) Dropping potential duplicates



(d) Un-smoothed returns



(e) Funds of funds only



(f) Without funds of funds

Figure 5: **Robustness checks for CIPD-beta sorted hedge fund portfolios.** This figure presents the results of applying the procedure described in Figure 4 for different modifications of the hedge fund dataset. 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 for a modification of the database where the last reported return for each hedge fund is replaced with −25%. Panel (c) shows the results without hedge funds which are classified as duplicates by the algorithm described in Section 5. Panel (d) shows the results where observed returns are replaced by un-smoothed returns using the un-smoothing procedure described in Getmansky et al. (2004). Panel (e) shows the results for the subsample of funds of funds only. Panel (f) shows the results for the subsample without funds of funds. The sample period is January 1994 to May 2015.

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:

$$R^o_{i,t} = \theta_{i,0} R_{i,t} + \theta_{i,1} R_{i,t-1} + \theta_{i,2} R_{i,t-2}, \tag{17}$$

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.[24] I then replace the observed returns with the estimated un-smoothed returns and compute the risk-adjusted un-smoothed returns of the 10 decile portfolios. Panel (d) of Figure 5 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 4. The fourth row of Panel C in Table 5 shows that the risk-adjusted return of the difference portfolio is 0.58% (t-statistic of 2.74).

Finally, selection bias raises the concern that only a specific type of hedge funds reports to the database. Since it is not possible to observe returns of funds that do not report to the TASS database, I cannot control for this bias directly. However, Fung and Hsieh (2000) argue that this concern can be mitigated by looking into the returns of funds of funds, which 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.[25]

Since there are only 2,987 funds of hedge funds in my sample, I split the sample into quintiles instead of deciles to ensure a sufficient number of funds in each portfolio. Panel (e) of Figure 5 shows the results of this split. As we can see from the figure, funds of funds with a high loading on CIPD are performing exceptionally poorly, generating a negative risk-adjusted return. Most importantly, however, the difference portfolio that is long hedge funds with a low loading on CIPD and short funds with a high loading on CIPD generates a risk-adjusted return of 0.33% (t-statistic of 2.95). To make these results comparable to other funds, panel (f) of Figure 5 shows the results for the sample of hedge funds, excluding funds of funds. While all quintile alphas are higher than for funds of hedge funds, it is important to note that the difference portfolio generates an almost identical risk-adjusted return of 0.35% (t-statistic of 2.15). The fifth and sixth row of Panel C in Table 5 provide additional details for the two difference portfolios.

[24] The estimation procedure is based on maximum likelihood, similar to estimating a moving-average model, assuming that demeaned returns are normally distributed.

[25] 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, which is a different sort of selection bias.

6 Conclusion

The main finding of this paper is that hedge funds with a higher exposure to funding risk, as proxied by a higher loading on a simple funding risk measure, underperform hedge funds with a lower exposure to that risk. This finding is surprising upon initial examination because it contrasts with a basic principle: higher risk should correspond to higher (expected) returns. Although this rule may hold for traded assets, it can be violated for hedge funds, which are actively managed portfolios whose returns depend on a manager's skill and proper risk management. The results in this paper point toward a situation in which more risk taking indicates less managerial skill, which lowers expected returns rather than increasing them.

To formalize this explanation, I develop a simple model that illustrates how a higher exposure to a common funding shock can lead to lower subsequent returns. The model delivers three testable predictions that are supported by the data. First, managers with a high loading on CIPD underperform. This underperformance is even more severe when sorting only on deteriorating funding conditions, as proxied by CIPD^{-}, and insignificant when sorting on CIPD^{+}. Second, in the model, the higher exposure to funding shocks enables investors to infer the quality of the manager and cause them to withdraw their investments. In line with this prediction, I find that hedge funds with a higher loading on CIPD experience significantly lower flows than fund with a lower loading on CIPD. Finally, the difference in returns between low-loading and high-loading funds is smaller for funds that have less favorable redemption terms and relationships with more than one prime broker.

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A Proofs and Additional Results

Proof of Proposition 1

First, note that if fund b invests θ_b^M in his strategy and the realization of the funding shock is $\lambda < 1 - \theta_b^M$ then none of the two funds makes a loss at time 1 and $W_2^b = W_2^g$. Next, Inequality (6) can be derived by plugging θ_b^* and θ_g^* into the following equation:

$$\begin{aligned}\theta_i^M - \theta_i^* &= \frac{\alpha_g}{\alpha_b}\theta_g^* - \theta_b^* \\ &= \left(\frac{\alpha_g}{\alpha_b} - 1\right) + \frac{(1-c)(\alpha_g - \alpha_b)}{(\alpha_g + c)(\alpha_b + c)}\bar{\lambda} > 0,\end{aligned}$$

where the inequality holds because $c < 1$ and $\alpha_g > \alpha_b$. Finally, fund b has an incentive to mimic the returns of fund g if:

$$\mathbb{E}[W_2|\theta = \theta_b^M] - \gamma p^b(\theta^M) > \mathbb{E}[W_2|\theta = \theta_b^*] - \gamma. \tag{18}$$

Because λ is uniformly distributed on $[0, \bar{\lambda}]$, the probability $p^b(\theta^M)$ can be computed as:

$$p^b(\theta^M) = \mathbb{P}(\lambda \leq 1 - \theta_b^M) = \frac{1 - \theta_b^M}{\bar{\lambda}}.$$

Solving for the γ that ensures equality in Inequality (18) leads to Equation (4), stated in condition 1, which completes the proof. ■

Proof of Proposition 2

(a) Because $1 - \theta_b^M < 1 - \theta_g^*$ three regions emerge. First, for $\lambda < 1 - \theta_b^M$ we have $\frac{\partial R_{1,g}}{\partial \lambda} = \frac{\partial R_{1,b}}{\partial \lambda} = 0$. Second, for $\lambda \in (1 - \theta_b^M, 1 - \theta_g^*]$ we have $\frac{\partial R_{1,g}}{\partial \lambda} = -\frac{c\theta_b}{(1-c)(1-\lambda)^2} < \frac{\partial R_{1,b}}{\partial \lambda} = 0$ and $R_{2,b} = \alpha_b$ as well as $R_{2,g} \in (\alpha_b, \alpha_g]$. Third, for $\lambda > 1 - \theta_g^*$ we have $\frac{\partial R_{1,g}}{\partial \lambda} = -\frac{c\theta_b}{(1-c)(1-\lambda)^2} < \frac{\partial R_{1,b}}{\partial \lambda} = -\frac{c\theta_g}{(1-c)(1-\lambda)^2}$ and $R_{2,b} = \alpha_b < \alpha_g = R_{2,g}$. Hence, fund b has a higher sensitivity to the funding shock. Since fund b chooses its investment in its strategy such that it generates the same returns as fund g, the returns of the fund with a higher sensitivity to the funding shock are lower.

(b) If $\frac{\partial R_{1,i}}{\partial \lambda} < \frac{\partial R_{1,j}}{\partial \lambda}$ then investors can infer that fund i is the bad fund and, by assumption, they withdraw money from the bad fund. Hence, a higher sensitivity to funding shocks does not only predict lower future returns but also future outflows. ■

Proof of Proposition 3

Because $\frac{\partial R_{1,i}}{\partial \lambda} < 0$ the return at time two is given as $R_{2,i} = \alpha_i$. Hence, it remains to show that $\alpha_g - \alpha_b$ decreases with decreasing $\bar{\lambda}$ in order to satisfy Inequality (3). Inequality (3) can be rewritten as:

$$\alpha_g - \alpha_b \leq \frac{c(1 + \alpha_g)}{\alpha_g + c}\bar{\lambda}. \tag{19}$$

Hence, for fixed α_g a decrease in $\bar{\lambda}$ implies that $\alpha_g - \alpha_b$ has to decrease as well. ■

Numerical Illustration

To illustrate the mechanics of the model in a numerical example, I choose the four model parameters as follows: $\alpha_g = 0.1,\ \alpha_b = 0.07,\ c = 0.1$, and $\bar{\lambda} = 0.75$. With these parameters $\bar{\lambda}$ fulfills Inequality (3) and Condition 1 is satisfied if $\gamma \geq 0.0063$. Hence, if the bad fund associates a benefit of 0.63% of its initial assets under management with the possibility of avoiding performance-based withdrawals, it will decide to mimic. Proposition 1 then implies that the two funds' investments in their strategies are $\theta_g^* = 0.5875$ for the good fund and $\theta_b^M = 0.8393$ for the bad fund. Figure 6 illustrates the returns of the good fund (g) and the bad fund (b) as a function of the funding shock λ. The top panel shows the returns of each fund at time $t = 2$ ($R_{2,g}$ and $R_{2,b}$) and the bottom panel shows the returns of each fund at time $t = 1$ ($R_{1,g}$ and $R_{1,b}$). As we can see from the figure, there are three regions in each panel. First, for $\lambda < 1 - \theta_b^M$ (leftmost region) both funds generate the same returns at time $t = 2$ and none of the funds generates any losses due to the funding shock at time $t = 1$. In this region the mimicking by the bad fund works. Second, for $\lambda \in (1 - \theta_b^M, 1 - \theta_g^*]$ (middle region) we observe $R_{2,b} < R_{2,g}$ and fund returns for the good fund are increasing in the funding shock while fund returns for the bad fund remain constant at their maximum of α_b. At time $t = 1$ the bad fund generates losses due to the funding shock which increase with the size of the funding shock while the good fund does not make any losses. Third, for $\lambda > 1 - \theta_g^*$ (rightmost region) the returns of both funds at time $t = 2$ are constant and equal to the returns from their strategies and both funds generate losses at time $t = 1$. The numerical example also shows that if α_g and α_b are fixed, mimicking is only possible if the maximal funding shock $\bar{\lambda} > 0.5455$ or for a fixed funding shock of $\bar{\lambda} = 0.75$ if the difference between alphas does not exceed 4.13%.

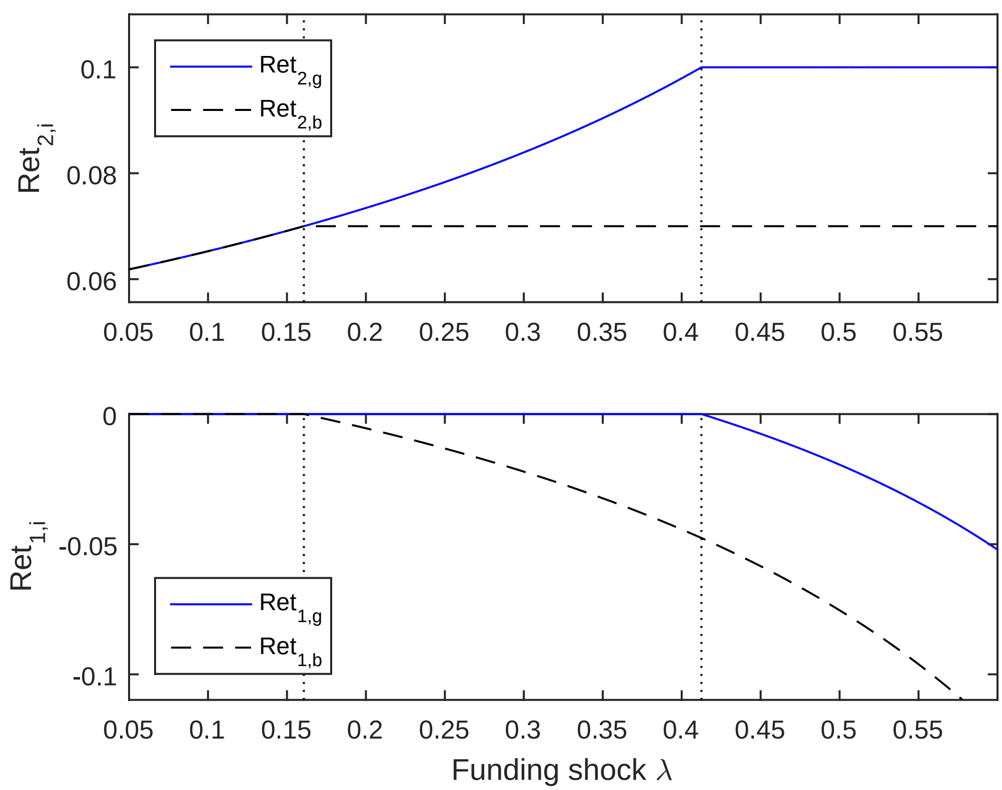


Figure 6: **Numerical Illustration.** This figure illustrates the returns of the two different funds at time $t = 2$ and $t = 1$ as a function of the funding shock. The first vertical line intersects the x-axis at $\lambda = 1 - \theta_b^M$. The second vertical line intersects the x-axis at $\lambda = 1 - \theta_g^*$. The parameters for this illustration are $\alpha_g = 0.1,\ \alpha_b = 0.07,\ c = 0.1$, and $\bar{\lambda} = 0.75$.

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 the returns of a carry trader. The data are obtained from Adrien 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, I use the financial accounts of the U.S. 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 construct the first tradable factor (YLD), I take the difference between the Merrill Lynch treasury bond index with 7-10 years to maturity over the 1-month risk-free rate. For the second factor (BAA), I use 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. **FX liquidity measure:** The measure is the one developed in Karnaukh et al. (2015) and represents an equally-weighted index, measuring the liquidity of U.S. dollar exchange rate for developed countries. The measure combines information from relative bid-ask spreads and high-low currency prices. The data are available at `http://rfs.oxfordjournals.org/content/early/2015/05/12/rfs.hhv029/suppl/DC1`. I use the procedure described by the authors to update the time series to May 2015.
8. **Investment bank stock returns:** I follow Ang et al. (2011) and 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.

9. **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/`.
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 obtained from David Hsieh's website: `https://faculty.fuqua.duke.edu/~dah7/HFData.htm`.
13. **U.S. stock market returns:** The first stock market risk factor (MKT) is the monthly return of the CRSP market portfolio in excess of the one-month treasury yield. The second stock market risk factor (SMB) is the difference of returns between small and big stocks (SMB). A third, additional stock market risk factor (UMD) is the momentum factor that is long stocks with high past returns and short stocks with low past returns (UMD). Data on all three factors are obtained from Kenneth French's website.
14. **VIX index:** Is the implied volatility of the S&P 500 index and data on VIX are obtained from the Bloomberg System.

C Additional Results

This appendix presents additional details and new results that have been omitted in the main part of the paper. Section C.1 provides additional details that complement the analysis in the main part of the paper. Section C.2 provides an additional test that sheds more light on the relationship between CIPD and the noise measure developed by Hu et al. (2013). The section shows that combining both measures leads to even stronger results than using any of them separately. Finally, Section C.3 shows that the main result, that a higher loading on a funding risk measure leads to lower returns, is robust to using different funding risk measures.

C.1 Additional Details

Table C.1 shows yearly summary statistics for the returns of all hedge funds in the sample. As we can see from the table, the years 2008 and 2011 have been especially bad years for fund managers, with negative average returns. Table C.2 shows the loadings on all seven Fung-Hsieh factors for the CIPD-sorted decile portfolios and the difference portfolio. Row (1) in Panel A of Table C.3 provides more details and the exact parameter estimates for style-neutral sorts that supplement the results exhibited in Panel (b) of Figure 4. As we can see from the table, the results are almost unchanged by fixing the allocation to styles among the decile portfolios. Figure C.1 shows the results for two additional tests. Panel (a) shows the results for the past-return-neutral sorts described in the main part of the paper. Row (2) in Panel A of Table C.3 provides additional details and the exact parameter estimates for this test. Panel (b) of Figure C.1 shows the results for a different subsample of hedge funds, removing funds that reportedly invest in FX markets. The third row (3) in Panel A of Table C.3 shows additional details and the exact parameter estimates. Overall, the main result is robust to these modifications.

Figure C.2 provides the results for robustness checks using β^{CIPD-}−sorted portfolios. As we can see from the figure, these results are even stronger than those for β^{CIP}−sorted portfolios which are presented in the main part of the paper. Panel C of Table C.3 gives additional details for these robustness checks.

Table C.4 presents an overview of the characteristics of the funds in the different CIP-beta-sorted 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, redemption terms, management fees, 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 tend to consist of larger funds and consist of more than 30% funds of funds while top and bottom portfolio only consist of approximately 10% funds of funds.

Table C.5 provides additional robustness checks, combining the robustness checks for backfilling bias, dropout bias, double counting, and return smoothing, described in Section 5. As we can see from the table, combining several robustness checks has a mixed effect. The least significant results are obtained when combining the test for backfill bias, dropout bias, and double counting. Furthermore, adding the robustness check for return smoothing tends to increase the significance of the results.

Table C.6 provides additional details and factor loadings for the difference portfolio that is long hedge funds with a low loading on CIPD^- and short hedge funds with a high loading on CIPD^-. As we can see from the table, the raw excess returns of the difference portfolio are positive but insignificant. Controlling for the two stock market risk factors or the two bond market risk factors leads to statistically significant risk-adjusted returns. Furthermore, the significance of the risk-adjusted returns increases, the more factors are added.

I next investigate whether the results remain intact for longer holding periods. To that end, hedge funds are sorted into deciles based on their loading on the negative part of CIPD, following the approach described in Section 4. Instead of rebalancing the portfolios after one month, I now allow for longer holding periods. In particular, every month, I form ten portfolios based on the funds' loading on CIPD$^-$, which are held for 1 month, 3 months, 6 months, and 12 months respectively. The results for these longer holding periods are exhibited in Table C.7. As we can see from the table, the results are robust to longer holding periods. For each holding period, the difference portfolio – which is long hedge funds with a high loading on CIPD$^-$ and short hedge funds with a low loading on CIPD$^-$ – generates positive returns which are statistically significant at a 1% level.

Table C.7 reveals that selecting hedge funds based on their past loading on CIPD$^-$ can be profitable in praxis. While it is not feasible to form long-short hedge funds portfolio or to rebalance hedge fund portfolios on a monthly basis, it is usually possible to invest in several funds and to hold this investment for 12 months.[26] As we can see from the table, the risk-adjusted returns of Portfolio 10 (the portfolio with the lowest loading on CIPD$^-$) remain virtually unchanged when increasing the holding period from 1 month to 6 months and even increase for a holding period of 12 months. In particular, implementing a trading strategy that invests in hedge funds with a low loading on unexpected funding shocks generates a monthly risk-adjusted return of 0.57% (t-statistic of 4.69). The advantage of implementing such a strategy is that these returns are not generated by an additional loading on a new risk factor, but by a lower exposure to a simple funding risk factors.

Relationship Between ΔCIP^{Index} and Other Liquidity Measures

In this section, I study the correlation between ΔCIP^{Index} and other common liquidity measures. The goal of this section is to illustrate that ΔCIP^{Index} is strongly correlated with other measures of funding risk faced by hedge funds (ΔTED and $Leverage$), while other liquidity measures only show a weak correlation. Panel A of Table C.8 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 factor by Adrian et al. (2014), changes in the 10-year on-the-run off-the-run spread, changes in the Hu et al.

[26]Difficulties with such an investment strategy can arise because some funds might be closed to new investments, have a significant minimum investment, or have a combination of lockup provision and long redemption notice period that forces new investors to keep their money in the fund for more than one year.

(2013) noise measure, changes in the 10-year on-the-run off-the-run spread, as well as changes in CIP^{Index} and changes in $CIP^{Index,OIS}$, which is an alternative measure of CIP deviations, constructed using OIS rates instead of Libor rates.

In line with the regression results from Section 3.2, the table confirms that ΔCIP^{Index} is strongly correlated with ΔTED_t and $Leverage_t$, which are the two other proxies for market-wide funding conditions faced by hedge funds. On the other hand, ΔCIP^{Index} 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^{Index} 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).

The table also shows that $\Delta CIP_t^{Index,OIS}$ has similar properties compared to ΔCIP_t^{Index}. The correlation with ΔTED_t and $Leverage_t$ is 0.74 and 0.81 respectively. As ΔCIP^{Index}, 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^{Index}.

Panel (b) of Table C.8 shows the correlation between the seven Fung and Hsieh factors as well as their correlation with ΔCIP^{Index}. As we can see from the table, the correlation among factors is generally low. Most importantly, the correlation between ΔCIP^{Index} and the seven Fung and Hsieh factors is low, ranging from -0.17 between stock market returns and ΔCIP^{Index} to 0.17 between the FX trend-following factor and ΔCIP^{Index}.

Cumulative Excess Returns of ΔCIP^D-sorted Decile Portfolios

To get a better understanding of the decile excess returns, Figure C.3 plots the time series of cumulative excess returns of the top and bottom decile portfolios for CIPD-sorted portfolios. Note that the portfolio with a high loading on CIPD generates major losses during crises episodes and that these losses are partly recovered afterwards. Furthermore, the returns of the portfolio with a high loading on CIPD are more volatile and generally lower than those of the portfolio with a low loading on CIPD. 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. However, as is clear from the figure, the difference in returns between these two portfolios is not purely driven by these few crises episodes.

C.2 Relationship to the Noise Measure

I now show that CIPD is capturing a different risk than the noise measure constructed by Hu et al. (2013), who show that their measure is a priced risk factor in the cross section of hedge fund returns and that a higher 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 4 and compute β^{Noise} for each fund in the database using a rolling regression window of 36 months. I then sort hedge funds into quintile portfolios based on their sensitivity to changes in the noise measure. I put funds with the lowest loading on $\Delta Noise_t$ (funds that I expect to perform poorly) in the first portfolio and funds with the highest loading on $\Delta Noise_t$ in the fifth portfolio. Afterwards, I split each of the five noise-sorted portfolios into five CIPD-sorted portfolios, based on β^{CIPD} computed in Section 4. Here, I put funds with the highest loading on CIPD (funds that I expect to perform poorly) in the first portfolio and funds with the lowest loading on CIPD in the fifth portfolio.

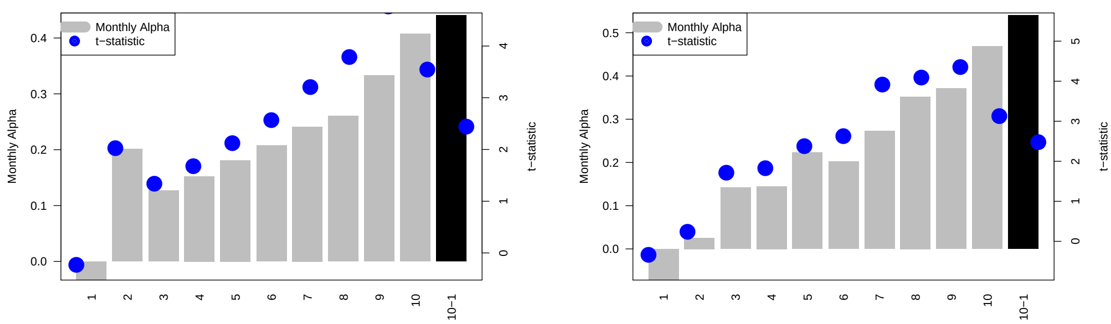
This conditional double sort results in 25 hedge fund portfolios. The risk-adjusted returns of these 25 portfolios (relative to the Fung Hsieh seven-factor model), as well as the returns of the difference portfolios, are exhibited in Table C.9. As we can see from the table, the double sort confirms that the noise measure is a risk factor in the cross-section of hedge fund returns, even conditional on CIPD and when returns are risk-adjusted for the seven Fung and Hsieh factors. Two out of the five difference portfolios generate a significant risk-adjusted return. The table also confirms that CIPD is capturing a different aspect of market conditions than $\Delta Noise$. All five difference portfolios generate a positive and statistically significant risk-adjusted return.

The number in the bottom-right corner of Table C.9 is the risk-adjusted return of the difference portfolio that is long hedge funds with the highest loading on $\Delta Noise_t$ and the lowest loading on CIPD and short the portfolio with the lowest loading on $\Delta Noise_t$ and the highest loading on CIPD. This portfolio generates a striking risk-adjusted return of 0.99 per month (t-statistic of 5.03). Hence, combining the information content of the noise measure with the information content in CIPD leads to even stronger results than just using any of the two measures separately.

C.3 Different Funding Measures

I now repeat my analysis for several alternative funding risk measures. First, I use a different variation of CIPD, where CIP^{Index} is constructed using OIS rates instead of LIBOR. The advantage of using this measure is that OIS rates is that they do not contain a credit-risk component and are not susceptible to manipulations like the LIBOR rates. The drawback is that OIS rates for most currencies are only available from January 2002 on. Hence, using this alternative index leads to a six year shorter sample period. Second, I use the original CIPD but add the FX liquidity proxy, constructed by Karnaukh et al. (2015), as an additional control variable to ensure that my results are not driven by currency market illiquidity. Third, I use changes in the difference between the 3-months U.S. LIBOR and 3-month OIS rate (henceforth LIBOR-OIS spread) instead of CIPD as sorting variable. The advantage of this measure is that it is easy to construct and clearly capturing funding conditions faced by major banks. The drawback is that the time series starts only in 2002 and shows virtually no variation before 2007. Finally, I compute average flows, defined as the average flow of all hedge funds in my sample, and use changes in this measure instead of CIPD to form decile portfolios.

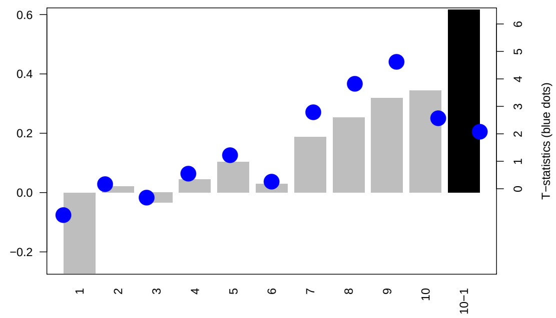
Figure C.4 shows the results for these four additional tests. As we can see from Panel (a) and (b), using different modifications of CIPD leaves the main result intact: hedge funds with a high loading on CIPD generate lower returns than hedge funds with a low loading on CIPD. Panels (c) and (d) show that qualitatively similar results can be obtained for different funding risk measures. In particular, hedge funds with a strong loading on changes in the LIBOR-OIS spread underperform hedge funds with a weak loading on changes in the LIBOR-OIS spread. For sorts based on changes in average flows the results are insignificant but qualitatively similar: hedge funds that generate low returns when the average hedge fund experiences outflows generate lower returns than hedge funds that perform well during times of average outflows. In future work, I plan to further investigate the impact of average fund flows on hedge fund performance and, more broadly, on asset prices.



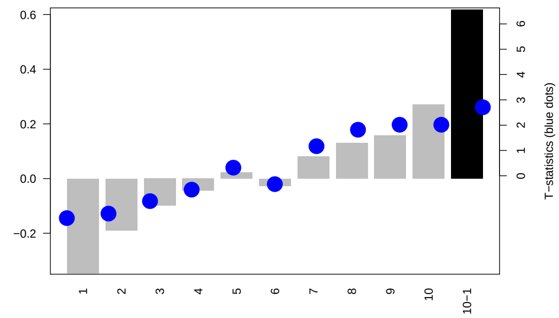
(a) Conditional on past returns

(b) Without FX funds

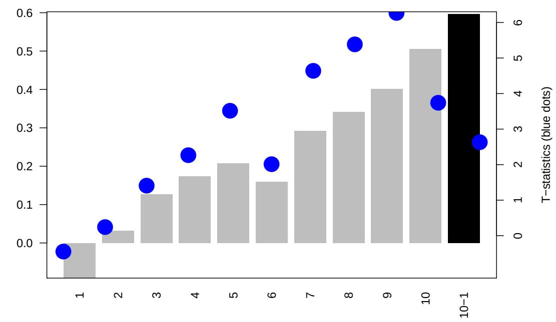
Figure C.1: **Results for different modifications of the CIPD-sort.** Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to CIPD. In panel (a) the sort is performed conditional on past performance. In this sort, every month, the overall sample of hedge funds is first split into deciles based on the funds' average past return over the last 36 months. Afterwards, each of the ten portfolios is sorted into deciles based on the individual funds' loading on the funding risk measure. Finally, for each quintile, the ten different past return deciles are merged. Panel (b) reports the results of an unconditional sort where hedge funds that report that they are investing in FX markets are dropped. For a detailed description of the sorting procedure as well as the computation of risk-adjusted returns see the caption of Figure 4. The grey bars represent monthly risk-adjusted portfolio returns, calculated using the Fung and Hsieh (2004) seven-factor model, where the YLD and BAA 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.



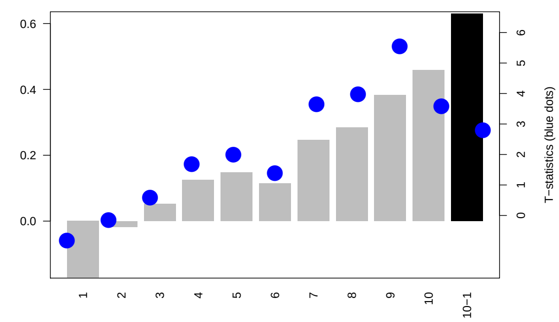
(a) Without backfilled observations



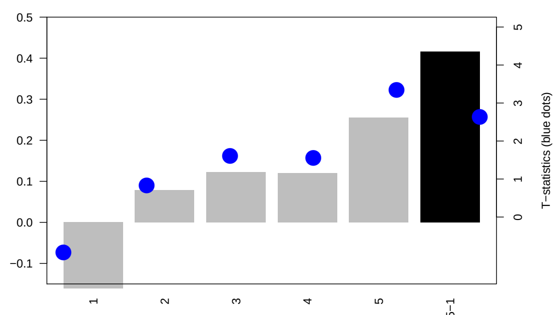
(b) Liquidation return of -25%



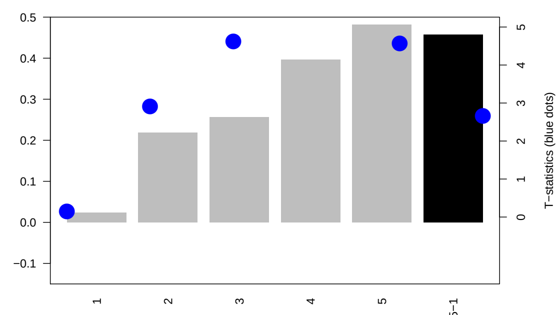
(c) Dropping potential duplicates



(d) Anti-smoothed returns



(e) Funds of funds only



(f) Without funds of funds

Figure C.2: **Robustness checks for CIPD$^-$-beta sorted hedge fund portfolios.** This figure presents the results of applying the procedure described in Figure 4 for different modifications of the hedge fund dataset using CIPD$^-$ as signal. 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 for a modification of the database where the last reported return for each hedge fund is replaced with -25%. Panel (c) shows the results without hedge funds which are classified as duplicates by the algorithm described in Section 5. Panel (d) shows the results where observed returns are replaced by un-smoothed returns using the un-smoothing procedure described in Getmansky et al. (2004). Panel (e) shows the results for the subsample of funds of funds only. Panel (f) shows the results for the subsample without funds of funds. The sample period is January 1994 to May 2015.

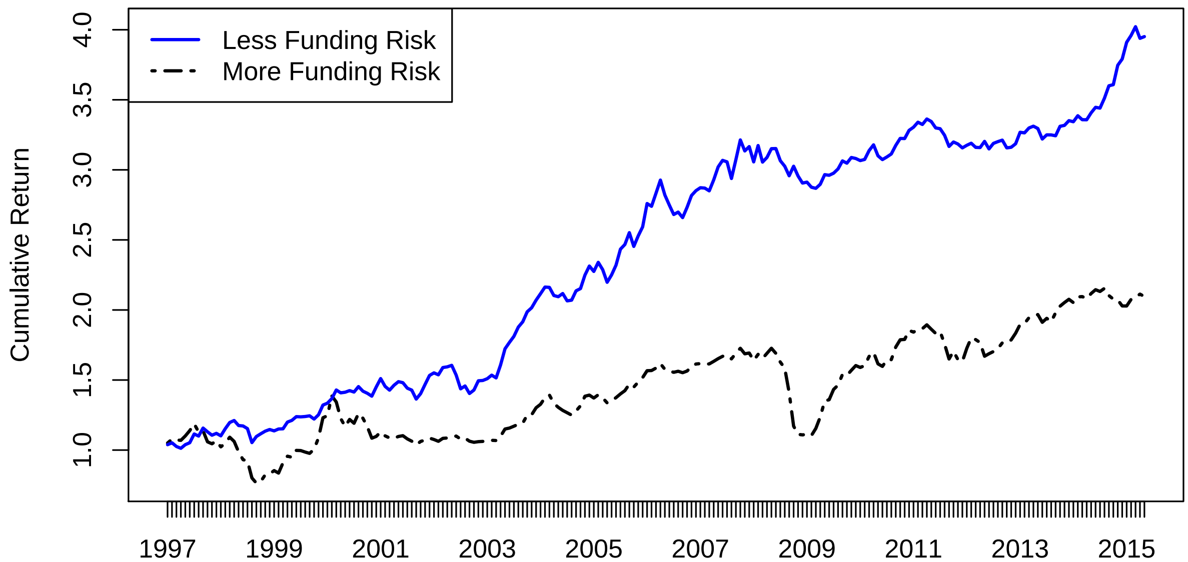
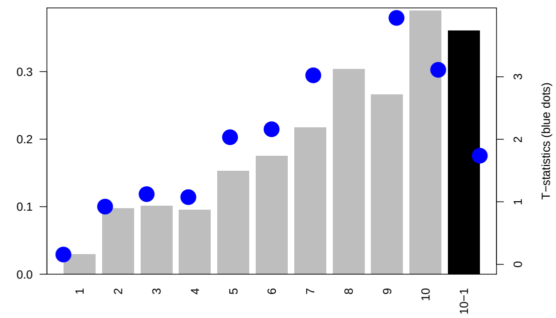
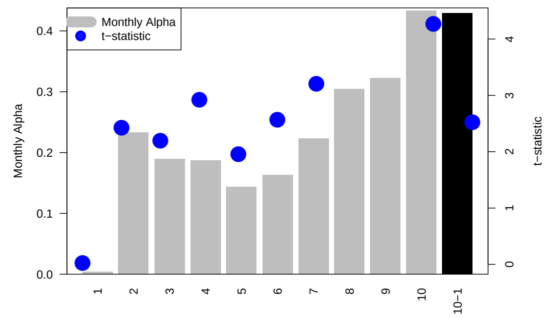


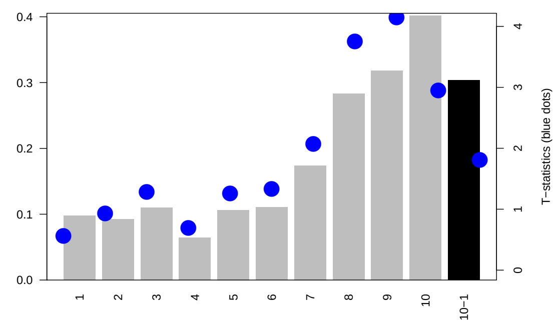
Figure C.3: **Cumulative excess returns from investing in high and low loading funds.** This figure shows the cumulative excess returns of hedge funds with a strong loading (solid line) and weak loading (dashed line) on changes in the covered interest rate parity deviation index (ΔCIP_t^D), constructed in Section 3.2. See the caption of Figure 4 for a description of the sorting procedure. The high (low) loading portfolio is the first (tenth) decile portfolio.



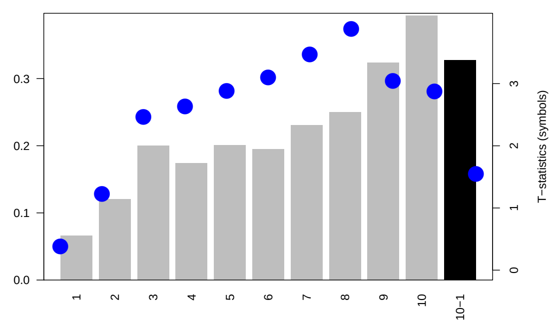
(a) Sorting based on $\Delta CIP^{OIS,D}$



(b) Controlling for FX Liquidity



(c) Sorting based on $\Delta LOIS$



(d) Sorting on Flows

Figure C.4: **Results for different modifications of the funding risk measure.** Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to different modifications of the funding risk measure. Panel (a) shows the results for sorts based on CIPD^{OIS}. Panel (b) reports the results, when sorts are performed controlling for the Karnaukh et al. (2015) FX liquidity measure. Panel (c) shows the results for sorts on changes in the difference between the 3-month U.S LIBOR rate and the 3-month U.S. OIS rate. Panel (d) shows the results for sorts on changes in average fund flows. For a detailed description of the sorting procedure as well as the computation of risk-adjusted returns see the caption of Figure 4. The grey bars represent monthly risk-adjusted portfolio returns, calculated using the Fung and Hsieh (2004) seven-factor model, where the YLD and BAA 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.

Table C.1: **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	679	0.01	1.66	-10.62	0.05	10.94
1995	877	1.51	1.70	-6.58	1.30	16.80
1996	1,132	1.68	1.47	-3.96	1.44	11.25
1997	1,397	1.52	1.40	-12.34	1.39	11.74
1998	1,647	0.51	2.25	-12.85	0.59	15.66
1999	1,973	2.25	2.88	-9.99	1.60	32.54
2000	2,288	1.01	2.09	-23.07	1.00	23.22
2001	2,715	0.66	1.92	-21.83	0.58	48.43
2002	3,237	0.37	1.39	-17.05	0.29	15.91
2003	3,848	1.38	1.68	-14.47	0.97	40.23
2004	4,553	0.77	0.92	-5.34	0.61	10.98
2005	5,205	0.83	1.19	-9.44	0.64	27.68
2006	5,568	0.99	1.11	-6.14	0.85	23.72
2007	5,860	0.88	1.42	-15.46	0.73	43.38
2008	5,941	-1.27	2.40	-22.23	-1.23	14.95
2009	5,554	1.15	2.38	-100.00	0.88	18.93
2010	5,251	0.67	1.29	-34.55	0.62	26.85
2011	4,967	-0.19	1.25	-23.93	-0.18	10.24
2012	4,453	0.53	1.35	-48.05	0.54	24.97
2013	3,834	0.65	1.41	-20.01	0.63	29.76
2014	3,297	0.31	1.69	-62.16	0.32	34.53
2015	2,718	0.78	1.51	-21.14	0.74	12.93

Table C.2: **Factor loadings for CIPD-sorted portfolios.** Hedge funds are sorted into deciles based on their beta to the CIPD measure described in Section 3.2. Beta is calculated using a regression of monthly hedge fund returns on CIPD, controlling for the stock market portfolio, and using the 36 months prior to portfolio formation. The seven Fung Hsieh factors are the market excess return (MKT), a size factor (SMB), tradable factors to mimic monthly changes in the 10-year Treasury constant maturity yield (YLD) and monthly changes in the Moody's Baa yield less 10-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. Newey-West $t-$statistics are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively.

	Intercept	β^{CIPD}	β^{Mkt}	β^{SMB}	β^{YLD}	β^{BAA}	β^{BD}	β^{FX}	β^{COM}	R^2
P1	0.00	0.07	0.36	0.25	0.24	0.65	-1.95	2.19	0.45	0.65
	[0.03]	[2.02]	[8.56]	[3.43]	[2.98]	[7.01]	[-1.55]	[2.83]	[0.42]	
P2	0.15	0.10	0.21	0.12	0.16	0.41	0.17	1.22	0.48	0.64
	[1.72]	[2.13]	[7.41]	[3.92]	[3.28]	[7.49]	[0.28]	[2.53]	[0.80]	
P3	0.17	0.07	0.18	0.11	0.11	0.33	-0.53	1.01	0.30	0.70
	[2.51]	[1.69]	[9.43]	[5.41]	[3.46]	[8.97]	[-0.77]	[2.92]	[0.65]	
P4	0.14	0.06	0.15	0.10	0.08	0.29	-0.29	0.98	0.32	0.66
	[2.05]	[1.83]	[7.46]	[3.97]	[2.45]	[6.26]	[-0.51]	[2.98]	[0.84]	
P5	0.18	0.07	0.15	0.10	0.07	0.22	-0.15	0.79	0.27	0.62
	[2.70]	[1.52]	[8.34]	[4.97]	[2.22]	[4.89]	[-0.26]	[2.39]	[0.69]	
P6	0.18	0.06	0.15	0.08	0.08	0.24	-0.74	0.92	0.56	0.60
	[2.29]	[2.02]	[7.75]	[3.70]	[2.59]	[5.78]	[-0.88]	[3.11]	[1.31]	
P7	0.24	0.06	0.12	0.06	0.04	0.19	-0.72	0.78	0.60	0.53
	[3.11]	[2.16]	[6.93]	[3.03]	[1.16]	[4.57]	[-0.91]	[2.54]	[1.35]	
P8	0.33	0.04	0.17	0.08	0.06	0.13	-0.03	0.83	0.45	0.56
	[5.33]	[1.63]	[8.13]	[4.73]	[1.53]	[3.30]	[-0.05]	[2.28]	[0.96]	
P9	0.38	0.01	0.20	0.09	0.03	0.08	0.13	1.22	0.45	0.47
	[4.88]	[0.34]	[6.74]	[3.51]	[0.38]	[1.53]	[0.20]	[3.39]	[0.64]	
P10	0.50	0.02	0.32	0.10	-0.11	-0.02	0.53	2.56	1.33	0.41
	[3.70]	[0.40]	[6.48]	[1.83]	[-0.84]	[-0.15]	[0.46]	[3.94]	[1.36]	
P10 - P1	0.49	-0.06	-0.04	-0.16	-0.34	-0.66	2.47	0.37	0.88	0.30
	[2.36]	[-1.65]	[-0.63]	[-1.42]	[-2.20]	[-3.68]	[1.81]	[0.42]	[0.74]	

Table C.3: **Supplementing additional results.** Hedge funds are sorted into portfolios based on their beta to the CIPD measure, described in Section 3.2, and based on different modifications of CIPD. For a detailed description of the sorting procedure and the different variables see the caption of Table 3. Each row reports the results for a difference portfolio. The results for the individual portfolios are omitted for brevity. Panel A reports the results for hedge funds that are sorted into deciles based on their loading on CIPD. In (1) the sorting is conditional on the funds' investment style, in (2) the sorting is conditional on the funds' performance over the past 36 months, in (3) funds that report that they invest in FX markets are dropped. Panel B shows the results for CIPD^{-}-sorted decile portfolios using six modifications of the dataset: (1) after dropping all backfilled observations, (2) replacing the last reported return with a dropout return of -25%, (3) dropping potential duplicates, (4) un-smoothing the returns using the procedure described in Getmansky et al. (2004), (5) using a subset that consists of funds of funds only, (6) using a subset without funds of hedge funds. 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.

	Post-sorting					Pre-sorting	
	α^{FH}	α^{Add}	β^{Mkt}	β^{CIPD}	R^2_{FH}	β^{Mkt}	β^{CIPD}
	Panel A: Additional results						
Style neutral	0.38**	0.39***	-0.16***	-0.15***	0.31	0.03	-2.00***
	[2.33]	[2.60]	[-2.82]	[-2.87]		[0.42]	[-6.99]
Past return neutral	0.44**	0.42**	-0.19***	-0.19***	0.33	0.00	-1.93***
	[2.44]	[2.42]	[-2.64]	[-3.58]		[-0.02]	[-6.83]
Without FX investors	0.54**	0.53**	-0.19**	-0.21***	0.25	0.06	-2.31***
	[2.48]	[2.40]	[-2.50]	[-3.79]		[0.74]	[-6.66]
	Panel B: Results for different robustness checks						
(1) Dropping Backfilled	0.60**	0.60**	-0.32***	-0.19***	0.31	-0.10	-4.07***
	[2.11]	[2.47]	[-4.15]	[-4.28]		[-1.32]	[-5.83]
(2) Dropout return	0.64***	0.67***	-0.30***	-0.17***	0.35	-0.09	-4.00***
	[2.80]	[3.16]	[-4.06]	[-4.88]		[-1.21]	[-5.86]
(3) Drop duplicates	0.63***	0.64***	-0.31***	-0.20***	0.36	-0.09	-4.07***
	[2.70]	[2.96]	[-4.01]	[-5.96]		[-1.20]	[-5.90]
(4) Un-smoothed	0.67***	0.67***	-0.38***	-0.23***	0.39	-0.09	-4.00***
	[3.00]	[3.16]	[-4.87]	[-6.28]		[-1.21]	[-5.86]
(5) FoFs only	0.39***	0.38***	-0.19***	-0.07***	0.35	-0.12***	-1.64***
	[2.83]	[3.58]	[-5.14]	[-3.23]		[-3.14]	[-5.83]
(6) Without FoFs	0.44***	0.46***	-0.27***	-0.19***	0.44	-0.11	-3.09***
	[2.63]	[2.76]	[-4.05]	[-5.81]		[-1.54]	[-6.05]

Table C.4: **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 3. 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 C.5: **Additional robustness checks.** Hedge funds are sorted into portfolios based on their beta to the CIPD measure, described in Section 3.2, and based on the negative part of CIPD. For a detailed description of the sorting procedure and the different variables see the caption of Table 3. Each row reports the results for a difference portfolio. The results for the individual portfolios are omitted for brevity. Panel A reports the results for hedge funds that are sorted into deciles based on their loading on CIPD. Panel B reports the results for hedge funds that are sorted into deciles based on their loading on $CIPD^{-}$. In both panels, Row (1) shows the results after dropping all backfilled observations and replacing the last reported return with a dropout return of -25%, Row (2) shows the results when dropping potential duplicates additionally to the first two steps, Row (3) shows the results when un-smoothing the returns using the procedure described in Getmansky et al. (2004) additionally to the first two steps, and Row (4) shows the results when combining all four robustness checks. 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.

	Post-sorting					Pre-sorting	
	α^{FH}	α^{Add}	β^{Mkt}	β^{CIPD}	R^2_{FH}	β^{Mkt}	β^{CIPD}
Panel A: Results for CIPD-sorted portfolios							
(1) Backfil & dropout	0.56*	0.50*	-0.24**	-0.19***	0.26	0.03	-2.29***
	[1.92]	[1.97]	[-2.42]	[-3.39]		[0.34]	[-7.00]
(2) All (1) & duplicates	0.56*	0.50*	-0.24**	-0.21***	0.26	0.03	-2.33***
	[1.84]	[1.91]	[-2.35]	[-3.42]		[0.37]	[-7.12]
(3) All (1) & un-smoothed	0.68**	0.59**	-0.32***	-0.24***	0.27	0.03	-2.29***
	[2.27]	[2.43]	[-2.83]	[-4.13]		[0.34]	[-7.00]
(4) All of them	0.67**	0.58**	-0.32***	-0.25***	0.26	0.03	-2.33***
	[2.20]	[2.34]	[-2.75]	[-4.23]		[0.37]	[-7.12]
Panel B: Results for $CIPD^{-}$-sorted portfolios							
(1) Backfil & dropout	0.59**	0.62**	-0.32***	-0.18***	0.29	-0.10	-4.07***
	[1.98]	[2.44]	[-4.21]	[-4.06]		[-1.32]	[-5.83]
(2) All (1) & duplicates	0.59*	0.62**	-0.33***	-0.19***	0.30	-0.10	-4.13***
	[1.92]	[2.39]	[-4.16]	[-4.21]		[-1.29]	[-5.87]
(3) All (1) & un-smoothed	0.66**	0.68***	-0.42***	-0.22***	0.32	-0.10	-4.07***
	[2.19]	[2.73]	[-4.90]	[-5.40]		[-1.32]	[-5.83]
(4) All of them	0.66**	0.68***	-0.43***	-0.23***	0.32	-0.10	-4.13***
	[2.14]	[2.68]	[-4.86]	[-5.66]		[-1.29]	[-5.87]

Table C.6: **Factor loadings and alphas for the CIPD$^-$-sorted difference portfolio.** Hedge funds are sorted into portfolios based on their beta to the negative part of the CIPD measure, described in Section 3.2. For a detailed description of the sorting procedure see the caption of Table 3. The table reports the results of regressing the returns of the difference portfolio – which is long hedge funds with a low loading on CIPD$^-$ and short hedge funds with a high loading on CIPD$^-$ – on the indicated variables. The independent variables are the excess returns of the U.S. stock market portfolio (MKT), a size factor (SMB), tradable factors to mimic monthly changes in the 10-year Treasury constant maturity yield (YLD) and monthly changes in the Moody's Baa yield less 10-year Treasury constant maturity yield (BAA), the three Fung and Hsieh trend-following factors: BD (bond), FX (currency), and COM (commodity), excess returns of the MSCI Emerging Market Index (EM), excess returns of the S&P GSCI Commodity Index (GSCI), and the two currency risk factors proposed by Lustig et al. (2011) (Cncy US and Cncy Carry). 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.36	0.56**	0.46**	0.60***	0.62***	0.63***
	[1.31]	[2.37]	[2.17]	[2.74]	[2.78]	[3.04]
Mkt		-0.28***		-0.16***	-0.16***	-0.05
		[-3.59]		[-3.18]	[-2.96]	[-0.62]
SMB		-0.18		-0.18	-0.18	-0.12
		[-1.56]		[-1.48]	[-1.52]	[-1.37]
YLD			-0.21	-0.25*	-0.27**	-0.26**
			[-1.65]	[-1.81]	[-2.01]	[-2.25]
BAA			-0.91***	-0.65***	-0.61***	-0.57***
			[-4.95]	[-3.40]	[-3.17]	[-3.64]
BD					0.93	0.13
					[0.75]	[0.13]
FX					0.94	0.97
					[1.27]	[1.25]
COM					-0.17	0.44
					[-0.13]	[0.34]
UMD						-0.12**
						[-2.44]
EM						-0.17***
						[-2.91]
GSCI						-0.02
						[-0.80]
Cncy US						0.22**
						[2.50]
Cncy Carry						-0.01
						[-0.11]
Adj. R^2	0	0.27	0.28	0.37	0.37	0.45

Table C.7: **Risk-adjusted returns for longer holding periods.** Hedge funds are sorted into portfolios based on their beta to the negative part of the CIPD measure, described in Section 3.2. For a detailed description of the sorting procedure see the caption of Table 3. The first column shows the base case where portfolios are rebalanced monthly. Columns 2-4 exhibit the results of a modification of the sorting procedure where portfolios are held for 3 months, 6 months, and 12 months, respectively. 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.

	1 month	3 months	6 months	12 months
P1	-0.10	-0.08	-0.07	0.06
	[-0.52]	[-0.42]	[-0.36]	[0.36]
P10	0.52***	0.51***	0.51***	0.57***
	[3.61]	[3.63]	[3.95]	[4.69]
P10 - P1	0.62***	0.59***	0.58***	0.51***
	[2.78]	[3.02]	[3.11]	[2.82]

Table C.8: **Correlation between ΔCIP^{Index} and other variables.** Panel A shows the correlation between ΔCIP_t^{Index} as well as $\Delta CIP^{Index,OIS}$ 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 ($\Delta Noise_t$). Panel B 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.

	Panel A: Correlation between ΔCIP_t^{Index} and other liquidity measures						
	BAB_t	PS_t	ΔTED_t	$Leverage_t$	$\Delta On10Yr_t$	$\Delta Noise_t$	ΔCIP_t^{Index}
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^{Index}	-0.10	-0.07	0.60	0.82	0.07	0.22	
$\Delta CIP_t^{Index,OIS}$	-0.08	0.05	0.74	0.81	-0.05	-0.02	0.78
	Panel B: Correlation between ΔCIP^{Index} and hedge fund risk factors						
	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 C.9: **Combining Noise and CIPD.** 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 highest loading on $\Delta Noise$ are in portfolio 5 and funds with the lowest 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 CIPD. Funds with the highest loading on CIPD are in portfolio 1 and funds with the lowest loading on CIPD 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 highest loading on $\Delta Noise_t$ and the lowest loading on CIPD and short the portfolio with the lowest loading on $\Delta Noise_t$ and the highest loading on CIPD. 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.

	Low N1	N2	N3	N4	High N5	N5-N1
High CIP1	-0.31*	-0.06	0.00	0.08	0.23	0.54**
	[-1.68]	[-0.42]	[0.00]	[0.84]	[1.18]	[2.22]
CIP2	0.22***	0.07	0.20**	0.11	0.39**	0.18
	[2.92]	[0.65]	[2.19]	[0.98]	[2.27]	[0.93]
CIP3	0.25***	0.21***	0.18**	0.19***	0.44***	0.19
	[2.81]	[2.95]	[2.08]	[2.61]	[3.31]	[1.20]
CIP4	0.35***	0.36***	0.23***	0.17**	0.29**	-0.06
	[3.65]	[5.07]	[3.16]	[2.16]	[2.51]	[-0.50]
Low CIP5	0.36***	0.35***	0.30***	0.27**	0.67***	0.31**
	[2.81]	[4.19]	[4.08]	[2.33]	[3.55]	[2.20]
CIP5-CIP1	0.68***	0.41***	0.30**	0.19*	0.45*	0.99***
	[3.71]	[3.01]	[1.98]	[1.72]	[1.80]	[5.03]