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High Funding Risk and Low Hedge Fund Returns

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ABSTRACT

I show that hedge funds with a high exposure to market-wide funding shocks—measured by changes in Libor-OIS spreads—subsequently *underperform* funds with a low exposure to market-wide funding shocks by 5.76% annually on a risk-adjusted basis ($t = 4.04$). To explain this puzzling result, I hypothesize that this type of funding risk exposure is connected to hedge funds' liabilities with limited upside in normal times and severe downside risk during funding crises. Supporting this hypothesis, the performance difference between low-funding-risk and high-funding-risk funds is largest when funding constraints are most binding and for funds with more fragile liabilities.

Keywords: Funding risk, hedge funds, interbank risk, Libor, Liquidity

JEL Codes: G01, G23, G31

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The main finding of this paper is that hedge funds with a high exposure to market-wide funding shocks—measured by their past return sensitivity to changes in Libor-OIS spreads (LOIS)—substantially underperform funds with a low exposure to the same shocks. This *high funding risk, low return* result seemingly challenges a key principle of financial economics: Hedge funds with a higher risk exposure should generate *higher* returns. While this principle applies to hedge funds collecting a risk premium from their investment strategies, exposure to market-wide funding shocks could also result from fragile liabilities. Hence, as hedge funds are actively managed portfolios, I argue that exposure to market-wide funding shocks indicates poor funding risk management, which is unrewarded in normal times and triggers losses when the risk manifests.

In line with these arguments, funds with a high LOIS-loading subsequently underperform funds with a low LOIS-loading by 5.76% annually on a risk-adjusted basis ($t = 4.04$). Connecting the underperformance of high-funding-risk funds to my hypothesis, I show that LOIS-exposure correlates with measures of fragile fund liabilities and that the underperformance of high-funding-risk funds is more severe for funds with more fragile liabilities. In line with being an unrewarded risk, the performance difference between low-funding-risk and high-funding risk funds is negligible in normal times, but severe during times of tight funding constraints. In addition, the performance difference persists for up to three years, suggesting that low-funding-risk funds have access to better alpha-generating strategies, and high-funding risk funds face more outflows as investors realize that these managers take excessive funding risk.

To measure market-wide funding conditions faced by hedge funds, I use changes in the spread between the Libor swap rate and the maturity-

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matched overnight index swap (OIS) rate (henceforth LOIS), which is arguably the simplest and most direct measure of major banks' funding costs. As such, LOIS is a useful proxy for market-wide funding conditions faced by hedge funds because banks, in their role as prime brokers, pass tighter funding conditions on to their clients. Moreover, as illustrated in the first panel of Figure 1, LOIS exhibits some reasonable time series properties with three major spikes around the default of Lehman Brothers, the European debt crisis (when European banks lost access to dollar funding), and the U.S. money market mutual fund (MMF) reform (which lead to elevated funding costs for banks). In addition, LOIS captures the unrewarded risk of "liquidity pullbacks" by banks (Nyborg and Östberg, 2014) which is related to the liabilities of the hedge fund and manifests when funding conditions deteriorate.

[Insert Figure 1 near here]

Using a large database of hedge fund returns (obtained by merging three commercially available databases), I investigate the impact of a higher exposure to market-wide funding shocks by forming portfolios based on a fund's past return sensitivity to changes in LOIS. More precisely, every month I form ten portfolios based on a fund's LOIS-loading (controlling for the returns of the stock market portfolio) over the past three years and rebalance the portfolios every year. The middle panel of Figure 1 shows the excess returns of hedge funds with the lowest (blue line) and highest (black line) funding risk exposures, illustrating that high-funding-risk funds underperform low-funding-risk funds and that this underperformance is most pronounced when LOIS is elevated. The average monthly excess return of the low-funding-risk portfolio is 0.64% and 0.37% higher than the returns of the high-funding-risk portfolio. The bottom panel of Figure 1 shows that the difference between high-funding risk and low-funding-risk funds becomes even more apparent when analyzing risk-adjusted returns – low-funding risk funds generate stable risk-adjusted returns while high-funding-risk funds generate negative risk-adjusted returns. Examining the statistical significance, I find that the difference portfolio that is long low-funding-risk funds and short high-funding-risk funds generates a risk-adjusted monthly return of 0.48% with a t-statistic of 4.04, clearing the high hurdle of 3.0 suggested in Harvey *et al.*, 2015. Even after controlling for a variety of up to nine additional risk factors, that are not part of the common benchmark model by Fung and Hsieh, the difference portfolio generates a virtually identical abnormal monthly return of 0.45% ($t = 2.90$).

To explain the persistent underperformance of high-funding-risk funds, I hypothesize that LOIS exposure is an unrewarded risk stemming from the liability side of hedge funds' balance sheets. The risk can manifest when financiers (such as prime brokers) need funding themselves and withdraw from the fund. Such withdrawals lead to losses if they force the fund manager to prematurely unwind otherwise profitable positions. Hence, I interpret more funding risk exposure as a sign of poor funding liquidity management; in contrast to a risk premium, as would be the case for traded assets, this funding risk exposure is penalized in crisis times but *not* rewarded in normal times. Guided by these arguments, I derive and test five hypotheses: (i) LOIS exposure is correlated with fund-specific measures of fragile liabilities; (ii) the impact of LOIS exposure is most severe for funds with fragile liabilities and (iii) during funding crises; (iv) low-funding-risk funds have access to superior alpha-generating strategies as reflected in persistent outperformance; (v) high-funding-risk funds face more outflows as investors eventually realize that these managers take excessive funding risk.

Starting with the first hypothesis, I examine the link between LOIS-loadings and fund characteristics in a cross-sectional (Fama-MacBeth) regression. My three main proxies for fragile liabilities at the individual hedge fund level are the average time it takes equity investors to withdraw from the fund (henceforth, time to withdrawal), the current drawdown, which captures that funds with worse past performance are at a higher risk of funding cuts from their financiers, and hedge fund leverage. In line with my hypothesis, I find that these variables are significant drivers of LOIS-exposure. Moreover, the link between these proxies of fragile liabilities and LOIS-exposure remains intact after controlling for other hedge fund characteristics.

Turning to my second hypothesis, I next examine different subsamples of the hedge fund database and test if LOIS-exposure is more important for funds with more fragile liabilities. As before, I use the funds' time to withdrawal, drawdown, or leverage, to quantify fragile liabilities. In line with my hypothesis, I find that the impact of LOIS-loading is strongest for funds with shorter time to withdrawal, higher drawdowns, and more leverage. In addition, I use granular data on fund investments, which are available for a subset of funds, and distinguish funds that use "synthetic leverage" through derivatives contracts from funds that do not use derivatives and are therefore relying on direct leverage from their prime brokers. In line with the intuition that funds without synthetic leverage are more dependent on prime broker financing, I find that funds with a higher LOIS exposure underperform more severely if they do not have access to synthetic leverage.

To test my third hypothesis, I examine the performance of the difference portfolio over time and first split the sample period into quintiles based on the level of LOIS. In line with my hypothesis, the difference portfolio earns a small, statistically insignificant, risk-adjusted return of 0.13% ($t = 0.47$) when LOIS is in the lowest quintile and a large, statistically significant, risk-adjusted return of 0.94% ($t = 7.28$) when LOIS is in the highest quintile. Hence, high-funding-risk funds underperform low-funding-risk funds severely when funding constraints are most binding but generate competitive returns when funding constraints are less binding. As additional tests, I examine the performance of the difference portfolio during bull and bear markets, measured either with the U.S. stock market returns or with the Credit Suisse hedge fund index and find that high-funding-risk funds, at best, generate competitive returns.

Before turning to my fourth hypothesis, I note that my approach to distinguishing high-risk funds from low-risk funds is related to a large literature establishing risk factors in the cross-section of hedge fund returns.[1] In contrast to that literature, I establish that a higher loading on funding risk predicts *lower* fund returns, which goes against the paradigm that a higher risk exposure is rewarded with higher expected returns. My result is especially surprising because Hu *et al.*, 2013 and Dahlquist *et al.*, 2019 use different proxies of funding risk – the Hu *et al.*, 2013 noise measures and the He *et al.*, 2017 primary dealer factor, respectively – and find that a higher loading on these risk measures predicts *higher* fund returns.

Guided by my hypothesis that LOIS-exposure is an unrewarded risk, I examine why different measures of funding risk generate opposite results. To that end, I compare the returns of long-short hedge fund portfolios sorted on either LOIS-exposure or one of the two alternative funding risk

[1] See, for example, Sadka, 2010, Teo, 2011, Hu *et al.*, 2013, Buraschi *et al.*, 2013, Bali *et al.*, 2014, Agarwal *et al.*, 2017a, Agarwal *et al.*, 2017b, Gao *et al.*, 2018, Dahlquist *et al.*, 2019, among others

measures, splitting the sample period into months when funding conditions, as proxied by the respective measure, worsen or improve. Corroborating the evidence in favor of Hypothesis 3, the LOIS-sorted difference portfolio generates large, positive and statistically significant, returns in months when LOIS increases (negative funding shocks) and small, positive but statistically insignificant, returns when LOIS decreases (improving funding conditions). By contrast, in line with the notion that a higher risk exposure is rewarded in normal times, the difference portfolio which is long funds with the lowest loading on the Noise measure (the primary dealer factor) and short funds with the highest loading on the Noise measure (the primary dealer factor), generates large negative and statistically significant returns in months when the Noise measure decreases (the primary dealer factor earns positive returns) and small, positive but statistically insignificant, returns when the Noise measure increases (the primary dealer factor earns negative returns). These large negative returns when funding conditions improve are in line with the intuition that both the Noise measure and the primary dealer factor capture returns of potential hedge fund trading strategies which pay off when funding conditions improve.

Turning to my fourth hypothesis, I next examine the persistence of my result by varying the holding period of LOIS-sorted portfolios between 1 and 36 months. The idea behind these tests is that, if low-funding-risk funds have access to superior alpha-generating strategies, their outperformance should persist over longer periods. While the returns, risk-adjusted returns, and the post-sorting betas of the difference portfolio remain positive for any holding period, the risk-adjusted returns and post-sorting betas of the difference portfolio remain statistically significant for holding periods up to 27 months, suggesting that low-funding-risk funds keep their access to superior alpha-generating strategies for more than two years.

Given the underperformance of high-funding-risk funds, my final hypothesis is that a higher LOIS-exposure predicts lower fund flows because high-funding-risk funds generate lower expected returns, despite their higher risk exposure. In line with this hypothesis, I document a negative link between LOIS-exposure and future fund flows in cross-sectional regressions. This link between LOIS-exposure and fund flows remains largely unchanged when controlling for other fund characteristics and past performance.

My *high funding risk, low return* finding holds in a battery of robustness checks. First, cross-sectional (Fama-MacBeth) regressions show that the impact of a higher LOIS-loading is robust to controlling for various fund characteristics. Second, the performance of the difference portfolio remains virtually unchanged with an abnormal monthly return of 0.47% ($t = 3.71$) after adjusting for common biases in hedge fund data. Third, my finding is robust to using any of the three hedge fund databases (instead of the union database), to using different subsamples of the union database, examining only hedge funds or only funds of funds, to forming portfolios with the same investment styles, and to focusing on the pre- or post-crisis period. Fourth, it is robust to forming portfolios with shorter holding periods – most noticably, using monthly rebalancing the difference portfolio generates an abnormal monthly return of 0.50% ($t = 3.48$). Finally, using different versions of Libor-OIS spreads with 2 years instead of 5 years to maturity, using 3 × 6-month forward-rate agreements (FRAs) instead of swaps, or controlling for changes in level of the benchmark rate leaves my results virtually unchanged.

Overall, my findings are consistent with LOIS-exposure being an unrewarded risk stemming from hedge fund liabilities and give a plausible explanation for why funds with more systematic funding risk exposure generate *lower* returns. While the alternative explanation for the observed patterns could simply be that funds with a high LOIS-exposure underperform because of their investments, my results are difficult to reconcile with this alternative view. High-funding-risk funds never outperform low-funding-risk funds (not even when funding conditions improve) and the performance difference between low-funding-risk and high-funding-risk funds remains significant, even after adjusting for a variety of different risk factors (including up to 5 proxies capturing the returns of trading on liquidity risk).

1 Background and Hypotheses

Before discussing LOIS as a proxy of market-wide funding conditions by hedged funds and deriving my main hypotheses, I provide a brief background on hedge funds' funding risk and reliance on prime brokers.

1.1 Hedge Funds and Funding Risk

Hedge fund liabilities are fragile because equity investors, prime brokers, and other financiers can withdraw from the fund, oftentimes at short notice. From a theoretical perspective, this fragility can lead to losses because funding withdrawals can force an expert investor to unwind otherwise profitable strategies early (Shleifer and Vishny, 1997, Gromb and Vayanos, 2002, Liu and Longstaff, 2004, Brunnermeier and Pedersen, 2009, Gârleanu and Pedersen, 2011, and Gromb and Vayanos, 2018). In theory, the funding risks arising from equity withdrawals and primer broker funding cuts incentivize managers to keep a "safety buffer" against adverse funding conditions (Panageas and Westerfield, 2009, Dai and Sundaresan, 2011, Liu and Mello, 2011, Lan *et al.*, 2013, Buraschi *et al.*, 2014, and Drechsler, 2014). While Aragon, 2007, Klebanov, 2008, and Hombert and Thesmar, 2014 examine how hedge funds that are better at managing the risk of equity withdrawals generate superior returns, my focus is on the funding risk arising from hedge funds' reliance on prime brokers.

Prime brokers routinely lend to hedge funds to support their long positions (Aragon and Strahan, 2012) and this funding can be subject to sudden change as "primer brokers have the ability to pull this financing in many circumstances" (Ang *et al.*, 2011). These sudden changes can be problematic for the hedge fund manager as they resemble a short put option, which is deeper in the money when the fund generates larger draw downs and when the prime brokers need funding themselves (Dai and Sundaresan, 2011). As explained by Mitchell and Pulvino, 2012, "in a typical prime brokerage agreement, the terms are subject to daily adjustment depending on changes in the portfolio and overall economic conditions" and these daily adjustments allow "the lender to force a hedge fund to liquidate even when investment opportunities are attractive."

The U.S. Securities and Exchange Comission, 2020 provides an overview of hedge fund leverage; in 2018 Q1, the net asset value of "qualified hedge funds" [which are large funds disclosing their net asset value and borrowing to the SEC] was \$3,106 billion. These hedge funds borrowed a total of \$2,606 billion, of which more than half was obtained from prime brokers (\$1,418 billion)[2] and 31.6% of which were overnight borrowing. Moreover, acting as prime broker is typically a profitable business for banks and

[2] The other major form of borrowing are repo transactions, in which the hedge fund does not necessarily rely on its prime broker.

banks (especially smaller ones) usually compete for prime broker business by accepting less collateral or offering cheaper financing terms (e.g., Son, 2021). Clearly, this competition becomes less fierce when prime brokers suffer tighter funding constraints themselves.

Taken together, while a fund manager might be able to scale his abnormal returns using leverage, managing the resulting funding risk, which resembles a short put option toward the prime broker, can have a first-order effect on fund returns.

1.2 Libor-OIS Spreads and Hedge Funds

LOIS is the difference between the London interbank offered rate (Libor), which captures banks' marginal funding costs, and the Overnight Index Swap (OIS) rate, which is a proxy of the risk-free rate.[3] LOIS is a simple proxy of market-wide funding conditions and a direct measure of the banking sectors' aggregate funding costs. Because banks, in their role as primary dealers, pass adverse funding conditions on to their hedge fund clients (e.g., Rime *et al.*, 2017), LOIS is a good proxy of market-wide funding conditions faced by hedge funds.

To put my study into the broader context of hedge fund research, it is important to understand the difference between LOIS and other funding risk measures. Changes in LOIS can capture funding shocks related to hedge funds' liabilities and Nyborg and Östberg, 2014 show that increases

[3]More precisely, the OIS rate is the fixed rate in an interest rate swap against the average FED funds rate. The FED funds rate is an overnight interbank rate and the target rate of U.S. monetary policy. Because the FED funds rate is an overnight rate, bank credit risk is negligible and the OIS rate can be viewed as the risk-neutral expectation of the future monetary policy rate. Moreover, a bank funding itself by rolling over borrowing at the FED funds rate could avoid interest rate risk by paying fixed in an OIS, but would be exposed to funding risk because debt rollover might not be possible in a funding crisis. One drawback of using OIS rates is that they are only available since the end of 2001 and not since 1994, which is the start date of most other hedge fund studies. An alternative benchmark rate that is available since 1994, would be the Treasury yield. However, as argued in several influential papers (Longstaff, 2004, Feldhütter and Lando, 2008, Krishnamurthy and Vissing-Jorgensen, 2012, Greenwood *et al.*, 2015, and Nagel, 2016), Treasury yields contain a time-varying convenience premium which is driven by investors' demand for safe and liquid assets. As exemplified in Feldhütter and Lando, 2008, this convenience premium is a substantial part of the spread between Libor swap rates and Treasury yields. Hence, using OIS rates as benchmark is necessary to obtain a measure of banks' funding costs that is not affected by the Treasury convenience premium.

in LOIS cause "liquidity pullbacks" – banks unwind liquid positions to obtain funding when LOIS increases. While cutting the funding for hedge fund clients is another plausible form of liquidity pullbacks for banks, there is no obvious trading strategy that hedge funds can exploit to generate abnormal returns based on changes in LOIS. This distinguishes LOIS from other recently established funding risk measures (e.g., Adrian *et al.*, 2014, He *et al.*, 2017, Hu *et al.*, 2013, Chen and Lu, 2018), which are all linked to investment strategies that can generate abnormal returns. Hence, it is plausible that LOIS captures a downside risk stemming from funds' liabilities, while other measures capture excess returns that materialize when the underlying trading strategy generates abnormal returns.

One potential concern in using Libor to proxy banks' marginal funding costs is that Libor has been manipulated in the past (e.g., Vaughan and Finch, 2017). To alleviate this concern, I use 5-year rates in my main analysis. In contrast to the 3-month LOIS, the 5-year LOIS is the spread between two swap rates, which are the fixed rate in an interest rate swap (where the floating rate is the 3-month Libor rate) and the fixed rate in an OIS (where the floating rate is the 3-month average of the FED funds rate). Because the 5-year LOIS is based on swap rates it reflects the risk-neutral expectation of the 3-month LOIS over the next five years, which alleviates manipulation concerns because the risk-neutral expectation of the 3-month Libor rate is much harder to manipulate than the 3-month Libor rate itself.[4]

1.3 Hypotheses

The funding risk faced by hedge funds and the fact that LOIS can capture liquidity pullbacks with no obviouos reward in the form of an alpha-generating strategy lead to my main hypothesis: *LOIS exposure is not rewarded in normal times but produces significant losses when the funding risk materializes.* I next derive five testable predictions based on this hypothesis.

First, funds with more fragile liabilities should have a higher exposure to market-wide liquidity shocks because equity withdrawals on short

[4]In line with this logic, I show in Section 4 that my results remain virtually unchanged when using the 2-year LOIS (which is also based on swap rates) or the spread between 3×6 month Libor FRAs and forward-OIS rates, which captures the risk-neutral expectation of the Libor-OIS spread 3-months ahead.

notice and leverage cuts can amplify losses when funding conditions deteriorate.

Hypothesis 1. *Funds with more fragile liabilities have a higher LOIS-exposure.*

Second, while funds with more fragile liabilities are overall more exposed to market-wide funding risk, mitigating exposure to market-wide funding shocks should have a larger effect for funds with more fragile liabilities.

Hypothesis 2. *The performance difference between high-funding-risk and low-funding-risk funds is more pronounced for funds with more fragile liabilities.*

In this context, it is important to distinguish “synthetic leverage” from leverage obtained through prime brokers. Ang *et al.*, 2011 explain that leverage obtained through derivatives (which I refere to as “synthetic” leverage) generally has lower exposure to funding risk than leverage obtained from prime brokers. Hence, an additional prediction is that LOIS exposure is less severe for funds that have access to synthetic leverage.

Third, if funding risk exposure is penalized during funding crises, but not rewarded during normal times, high-funding-risk funds should generate competitive returns in normal times but produce severe draw downs in funding crises.

Hypothesis 3. *The performance difference between high-funding-risk and low-funding-risk funds is most pronounced when funding shocks materialize and diminishes during normal market conditions.*

This hypothesis illustrates the difference between LOIS and priced risk factors. While exposure to priced risk factors is rewarded in normal times, LOIS-exposure is unrewarded in normal times, but produces substantial losses in crises.

Fourth, if LOIS-exposure is indeed unrewarded, hedge funds with access to less profitable strategies load on this risk in an attempt to generate competitive returns, while funds with access to superior strategies avoid this risk. A testable implication of this logic is that the performance difference between high-funding-risk and low-funding-risk funds persists over longer periods as access to alpha-generating strategies changes slowly.

Hypothesis 4. *The performance difference between high-funding-risk and low-funding-risk funds persists over longer periods.*

Finally, while Hypothesis 4 explains why it can be optimal for a hedge fund manager to take excessive funding risk, there is no advantage investing in high-funding-funds as these funds exhibit a worse performance while exposing investors to additional risks.

Hypothesis 5. *High-fudning-risk funds face more outflows than low-funding-risk funds.*

2 The Data

To obtain a large cross-section of hedge funds, I merge three commercially available hedge fund databases – Eureka, HFR, and Lipper TASS – and henceforth refer to the merged database as “union database”. My use of the union database is motivated by Joenväärä *et al.*, 2019, who show that merging multiple databases helps obtaining a clearer picture of the hedge fund industry. However, to ensure that my results are robust and replicable, I later repeat my main analysis for the three individual databases in Section 4.

The HFR and Eureka data were obtained in January 2018, while the version of the TASS database is from July 2017. Hedge funds report voluntarily to these databases, making survivorship bias a concern because poorly performing funds might decide to drop out of the database. However, from 1994 on, all three databases contain both live hedge funds (which are still reporting to the database as of the latest download) and graveyard funds (which stopped reporting), mitigating this concern. Following the literature on hedge funds (e.g., Cao *et al.*, 2013 or Hu *et al.*, 2013), I apply three filters to the database. First, I require funds to report returns net of fees, on a monthly basis, and in U.S. dollars. Second, I require that each fund in my sample reports at least 36 monthly returns during the January 2002 – December 2017 sample period, which later enables me to compute factor loadings. Finally, I drop small hedge funds if their assets under management (AUM) are below 10 million USD. To avoid a bias toward small hedge funds due to inflation in the later part of the sample, I follow Fama and French, 2010 and adjust the AUM for changes in the consumer-price index (CPI) since January 2002.

Panel A of Table 1 contains summary statistics for all hedge funds in the filtered sample and Table A.2 in the appendix provides an overview of all variable definitions. For variables that fluctuate 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 0.37% per month with a standard deviation of 3.11. On average, funds have 216.61 million U.S. dollar in AUM with a median of 61.23 million. Furthermore, the average fund in the database is 60 months old and 26% of the funds in my sample are closed to new investors. 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. The databases also provides information on when each hedge fund began reporting to the database. I use this information to compute the percentage of backfilled returns for each fund, which is 32% on average with a standard deviation of 31%. I include backfilled return observations in my main analysis and use a bias-adjusted dataset without backfilled observations for robustness tests.

[Place Table 1 about here]

The remaining variables capture fund-specific measures of fragile liabilities. *Time to withdrawal* is the average time it takes equity investors to withdraw from the fund. To proxy this variable, I combine the redemption notice period, redemption frequency (i.e., how frequently investors are allowed to make redemptions), and lockup provision (which prevents new investors from immediately withdrawing their investment again) into one variable

$$TTW = Notice\ Period + \frac{1}{2}Redemption\ Frequency + \frac{1}{4}Lockup. \quad (1)$$

I weight the redemption frequency with 1/2, implicitly assuming that investors, on average, withdraw in the middle of the period. Lockup provisions typically keep new investors from withdrawing for approximately 1 year and the weight of 1/4 on the lockup dummy assumes that the average investor has to wait three months to withdraw. As we can see from the table, *Time to withdrawal* fluctuates between a 25% quantile of 0.08 years to a 75% quantile of 0.43 years.

Draw Down measures the percentage difference between the highest fund value at any previous time and the current fund value. Table 1 suggests a median draw down of 4%. *Leveraged* is a dummy variable that equals one if the fund self-reports the usage of leverage and zero otherwise. However, this variable is a coarse proxy for leverage as there is no unified reporting across databases – for instance, some funds self-report no use of leverage because the fund did not use leverage at the time it joined the database, even though the manager is generally allowed to use leverage. To overcome this issue, *Leveraged (details)* is an alternative proxy, which is only available for the HFR database, where the self-reporting of leverage is standardized and hedge funds also report the range of their leverage – the variable can take three values: (i) two if the fund self-reports leverage above 2; (i) one if the leverage is below or equal to 2; and (iii) zero if the fund self-reports no leverage. As we can see from the table, the average *Leveraged (Details)* is 0.66 compared to 0.51 for *Leveraged*. Finally, *Synthetic leverage* is a dummy variable, constructed for funds in the Eureka database. In Eureka, funds report if they use currencies, commodities, or derivatives in their strategies and *synthetic leverage* equals one if a fund self-reports the usage of derivatives or currency or commodity contracts.

Panel B of Table 1 summarizes average hedge fund returns for the different styles, grouping funds into categories according to the description in Agarwal *et al.*, 2009. As we can see from the table, average monthly returns range from 0.60% for other funds to 0.16% for funds of funds. There is a total of 2,618 funds of funds in my sample. I run my main analysis using all 14,682 funds and later show that my results hold separately for hedge funds and funds of funds. Summary statistics for hedge fund returns in different years, including 1994–2001, can be found in the internet appendix (Table A.4). These yearly summary statistics explain why the average returns of hedge funds in my sample are smaller compared to other studies: In the years before 2002, annual average hedge fund returns were mostly positive with four years in which the average monthly return was above 1%. By contrast, average returns in the post-crisis years never exceed 1% per month and are negative twice.

To evaluate hedge fund performance and calculate risk-adjusted (abnormal) returns, I use the seven-factor model proposed by Fung and Hsieh, 2004. The first two factors are U.S. stock market excess returns (MKT) and the returns from a small-minus big portfolio (SMB), capturing risks in the stock market. The next two factors are changes in the 10-year U.S. Treasury constant maturity yield (YLD) and in the Moody's Baa yield spread over the 10-year Treasury yield (BAA), capturing interest-rate risk and credit risk, respectively.[5] Finally, Fung and Hsieh, 2004 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). These factors are only weakly related to LOIS – the pairwise correlation between ΔLOIS and MKT, SMB, YLD, BAA, BD, FX, and COM is −0.24, − 0.05, − 0.06, 0.19, 0.13, 0.06, and 0.04 respectively. The entire correlation matrix can be found in the appendix (Panel B of Table A.5).

3 Empirical Evidence

I first test if hedge funds with a higher funding risk exposure generate lower returns than funds with less exposure. Every month t, for each Fund i, I run a regression of hedge fund returns on $\Delta LOIS$, using the past 36 months of observations and controlling for the excess returns of the (stock) market portfolio

$$R_{i,t} = \alpha + \beta^{LOIS}\ \Delta LOIS_t + \beta^{Mkt} R_t^{Mkt} + \varepsilon_t. \tag{2}$$

Based on β^{LOIS}, I then put each hedge fund in one decile portfolio. The decile portfolios are held for twelve months, starting in month $t+1$ and the sorting procedure therefore results in twelve overlapping portfolios.[6] The first portfolio has the strongest and most negative LOIS-loading while the tenth portfolio has the weakest loading on LOIS. Moving forward, I refer to the first and tenth portfolio as the portfolio with the highest LOIS-loading and the lowest LOIS-loading, respectively.

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[5] 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. The excess returns of the Merrill Lynch Treasury bond index with 7-10 years to maturity over the one-month risk-free rate and the difference between returns of the corporate bond index of BBB-rated bonds with 7-10 years to maturity of the Treasury bond index are tradable proxies of YLD and BAA and capture excess returns. However, as I show later, the statistical and economic significance of my results increases when I replace YLD and BAA with their tradeable counterparts. Hence, I report my main results based on the traditional Fung and Hsieh model, which gives conservative estimates.

[6] I examine alternative holding periods, ranging from one month to three years, in Section 4. Using monthly rebalancing, the difference in risk-adjusted monthly returns between low-funding-risk and high-funding-risk funds increases to 0.50% ($t = 3.48$).

Figure 2 shows the average monthly returns and risk-adjusted returns for the ten LOIS-sorted portfolios. Risk-adjusted returns are computed relative to the seven Fung-Hsieh risk factors. Funds with the lowest loading on LOIS (Portfolio 10) earn a monthly return of 0.62% and a risk-adjusted return of 0.48%, which corresponds to an annual alpha of 5.76%.[7] Moreover, the risk-adjusted returns of hedge funds in the different deciles decrease monotonically in their LOIS-loading.

[Place Figure 2 about here]

Although engaging in a long-short trading strategy of hedge funds is not possible, the performance of the difference portfolio that is long hedge funds with a low loading on LOIS and short hedge funds with a high loading on LOIS is a useful measure capturing the statistical and economic significance of the difference between the two groups of funds. The monthly return and risk-adjusted return of the difference portfolio is 0.37% and 0.48%, respectively, as illustrated by the black bar in Figure 2. The blue dots in Figure 2 show Newey-West t-statistics (using 12 lags) of the respective portfolio returns or alphas and indicate that the results are statistically significant. In particular, the t-statistic for the difference portfolio rejects the null hypothesis that funds in Portfolios 10 and 1 generate the same risk-adjusted returns at a 1% level ($t = 4.04$), even based on the more stringent criteria suggested in Harvey *et al.*, 2015.

Table 3 provides more details. The first two rows of the table report the excess returns and Fung-Hsieh alphas illustrated in Figure 2. Under α^{Add}, I report an alternative alpha, controlling for the following 8 additional factors: The Pastor and Stambaugh, 2003 liquidity factor, the He *et al.*, 2017 primary dealer factor, the Chen and Lu, 2018 funding liquidiy factor, the two currency risk factors proposed by Lustig *et al.*, 2011, the emerging market and commodity factor proposed by Fung and Hsieh, and the Fama-French momentum factor.[8] Columns 4 and 5 show the post-sorting β^{Mkt}

[7] These returns and alphas are lower than those shown in most other studies. The main reason for this difference is that my sample period starts in January 2002 (not in January 1994) and includes eight post-crisis years, when hedge fund returns were generally lower, as illustrated in the year-summary statistics in the internet appendix.

[8] Section 6.1 contains more details and shows the loadings of the difference portfolio on the additional factors. Importantly, even after controlling for up to 18 different risk factors and several proxies for trading on liquidity risk, the difference portfolio generates a substantial positive alpha. Hence, it is difficult to reconcile my findings with the investment

and β^{LOIS} of the ten decile portfolios. The post-sorting β^{LOIS} is significantly different in the portfolio with the highest LOIS-loading (P1), which has a β^{LOIS} of -0.11 ($t = -3.40$), than in the portfolio with the lowest $LOIS$-loading (P10), which has a borderline significant β^{LOIS} of -0.04 ($t = -1.75$). Furthermore, the difference portfolio has a β^{LOIS} of 0.07 ($t = 2.61$) and the post-sorting betas are decreasing from P1 to P10. The adjusted R^2 of regressing the portfolio returns on the seven Fung-Hsieh factors is reported in column 6 and columns 7-8 show the pre-sorting β^{Mkt} and β^{LOIS}.[9]

[Place Table 3 about here]

In the following five subsections, I test the five hypotheses developed in Section 1.3.

3.1 The Drivers LOIS-Exposure

I now use cross-sectional (Fama and MacBeth, 1973) regressions to examine the main drivers of β^{LOIS}. Specifically, to test Hypothesis 1, I focus on the link between β^{LOIS} and three measures that capture the fragility of hedge fund liabilities: (i) *Time to withdrawal*, which captures how long it takes the average hedge fund investor to withdraw money; (ii) *Draw Down*, which measures the hedge funds' current losses and indicates how likely equity investors and service providers are to withdraw funding; and (iii) *Leveraged*, which can measure the funds' use of leverage. All variables are defined in Table A.2 in the appendix. In interpreting these measures, a shorter time to withdrawal, a higher draw down, and more leverage correspond to higher fund-specific funding risk and should, according to my hypothesis, correlate with a higher (more negative) β^{LOIS}.

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risk of high-funding risk funds.

[9] Note that the pre-sorting betas are time series averages of monthly cross-sectional averages while the post-sorting betas are obtained by regressing the portfolio returns over the entire sample period on changes in LOIS. This different procedure results in a larger pre-sorting beta spread compared to the post-sorting beta spread, which is in line with other studies. For example, Hu *et al.*, 2013 report a spread in pre-sorting betas of 4.9 compared to a post-sorting spread of 0.79 and Dahlquist *et al.*, 2019 report a pre-sorting beta spread of 1.05 compared to a post-sorting spread of 0.19. To better understand how pre-sorting betas could differ substantially from post-sorting betas (in extreme cases with an opposite sign), I perform a simple simulation exercise in the appendix.

Panel (1) of Table 2 shows the results of cross-sectional regressions for the union database. In line with my hypothesis that β^{LOIS} correlates with more fragile hedge fund liabilities, there is a strong positive link between *Time to Withdrawal* and β^{LOIS}, suggesting that hedge funds with less fragile equity tend to have a weaker (closer to zero) exposure to market-wide funding risk. Similarly, funds with larger *Draw Downs* face higher risk of investor or stakeholder withdrawals and are more exposed to market-wide funding risk. I do not find a significant link between β^{LOIS} and *Leveraged* in this specification. However, as explained in Section 2, the leverage dummy in the union database is difficult to interpret as the TASS and Eureka databases do not have a unified way of reporting leverage. I therefore repeat my analysis with the subset of funds from the HFR database, where leverage is reported in a unified way and with additional details. As shown in Panel (4), when focusing only on the HFR database, the link between β^{LOIS} and *Time to withdrawal* or *Draw Down* remains virtually unchanged. Importantly, Panel (4) shows a significant link between hedge fund leverage and β^{LOIS}, suggesting that funds with more leverage have a higher exposure to market-wide funding shocks.

[Place Table 2 about here]

I next examine the impact of other fund characteristics on β^{LOIS} and test whether additional controls affect the link between β^{LOIS} and the measures of fragile hedge fund liabilities. Specifically, I control for fund size and age, a dummy variable that equals one if the fund is closed to new investments, past fund flows, the funds' past returns, management and incentive fees. Panel (2) shows that adding these controls leaves the statistical and economic significance of *Time to withdraw* and *Draw Down* virtually unchanged. Panel (3) shows that additionally controlling for investment style does not affect the results and Panel (5) confirms these findings focusing only on the HFR database.

While the link between β^{LOIS} and fund-specific characteristics remains virtually unchanged, Panels (3) and (5) highlight additional properties of β^{LOIS}. First, larger funds tend to be more exposed to market-wide funding shocks. To the extent that larger funds have access to less profitable strategies (e.g., Berk and Green, 2004), this result is consistent with my hypothesis. Second, higher management fees correlate with stronger LOIS-exposure while higher incentive fees correlate with less LOIS-exposure.

This result is consistent with the idea that high management fees can encourage some sort of "gambling for resurrection", where a fund manager takes excessive risks to avoid outflows; while incentive fees align the managers objectives with those of investors, attempting to generate high returns. Finally, funds that are closed to new investors have a lower exposure to market-wide funding shocks when considering the union database but a higher exposure when focusing only on the HFR database, making it inconclusive.

3.2 The Role of Fragile Fund Liabilities

Hypothesis 2 suggests that the impact of β^{LOIS} is less pronounced for funds with less fragile liabilities. To test this hypothesis, I split the hedge fund database into different subsamples based on fund-specific funding risk exposure and examine if the performance difference between high-funding-risk and low-funding-risk funds in the subsamples. Motivated by the results from Section 3.1, I focus on the following three criteria: (i) Fragility of hedge fund equity, measured by *Time to Withdrawal*; (ii) the risk of major stakeholder withdrawals, measured by *Draw Down*; (iii) The detailed leverage information, which is only available for the HFR database. Hypothesis 2 then suggests that the performance difference between high-funding-risk and low-funding-risk funds is most pronounced for funds with shorter *Time to Withdrawal*, larger *Draw Down*, and more leverage.

To test this prediction, I split the hedge fund database into three subsamples. First, funds with fragile liabilities, measured as either the 20% quantile of funds with shortest *Time to withdrawal*, the 20% funds with the largest *Draw Down*, or funds that report a leverage above 2-1 (i.e., having less than 50% equity in their trades). Second, funds with stable liabilities, measured as either the 20% quantile of funds with longest *Time to withdrawal*, the 20% funds with the lowest *Draw Down*, or funds that report that they do not rely on leverage. Finally, the middle portfolios comprise funds which do not fall in either the high or low fragility category. Table 4 shows the risk-adjusted returns of the difference portfolios, which are long funds with the lowest LOIS-exposure and short funds with the highest LOIS-exposure, for each of the subsample. In addition, the table shows the LOIS-exposure of the difference portfolio (as before, controlling for stock market returns).

[Place Table 4 about here]

As we can see from the table, for all three tests, the difference portfolio generates higher abnormal returns for the subsample of funds with the most fragile liabilities. Focusing first on Columns (1) – (3), the difference portfolio generates an abnormal monthly return of 0.17% for funds with low draw downs, which increases to 0.47% for funds with high draw downs. Similarly, Columns (4) – (6) show that, for funds with a long *Time to withdrawal*, the difference portfolio generates a small abnormal return of 0.24%, which increases to 0.39% for funds with the shortest *Time to withdrawal*. Finally, a similar pattern emerges when focusing on the *Leveraged* variable in the HFR database. For the subsample of funds with low self-reported leverage, the difference portfolio generates a monthly abnormal return of 0.26%, which increases to 0.46% for funds with high self-reported leverage. Importantly, the LOIS-exposure of the difference portfolio is positive and, with the exception of *Leveraged*, increases for funds with more fragile liabilities, suggesting more fluctuations in LOIS-exposure for funds with more fragile liabilities.

3.2.1 The Role of Synthetic Leverage

I now examine the subsample of hedge funds for which I have information about their access to synthetic leverage. As explained in Section 1.3, funds without access to synthetic leverage are more reliant on their prime brokers for financing and therefore high-funding-risk funds without access to synthetic leverage should underperform more severely. To test this assertion, I repeat my main analysis separately for funds without synthetic leverage and for funds with synthetic leverage, sorting the funds into quintiles based on their β^{LOIS}. In line with my hypothesis, Panel (a) of Figure 4 shows a striking difference in the performance of funds with high LOIS-loading and funds with a low LOIS-loading. By contrast, Panel (b) shows that the performance difference between low-funding-risk and high-funding-risk funds diminishes for funds with access to synthetic leverage.

[Place Figure 4 about here]

3.3 Performance Differences in Different Market Environments

Hypothesis 3 states that high-funding-risk funds underperform low-funding-risk funds most severely in funding crises, while exposure to funding risk is not rewarded in normal times. To test this hypothesis, I examine the performance of the difference portfolio, which is long funds with the lowest LOIS-loading and short funds with the highest LOIS-loading, in different time periods. I first split the sample period into quintiles based on the level of LOIS to examine if the performance difference depends on the level of market-wide funding conditions. In addition, to test if a higher exposure to funding risk pays off during good times, I examine the performance difference during bull and bear markets in U.S. equities. Because hedge funds are not only exposed to the stock market, I use the Credit Suisse hedge fund index, as alternative proxy for bull and bear markets.

I then report the performance of the difference portfolio in three different regimes: (i) Q1, corresponding to extremely low funding risk (lowest LOIS or bull market), (ii) Q2–Q4, corresponding to normal times, and (iii) Q5, corresponding to times with tight funding constraints (highest LOIS or bear market). Figure 3 shows the risk-adjusted returns of the difference portfolio in these three episodes. As we can see from Panel (a), the risk-adjusted returns of the difference portfolio are small and statistically insignificant when the level of funding risk is low, while the difference portfolio generates a significant positive return during normal times (Q2–Q4). During funding crises when LOIS is above its 80% quantile, the performance difference is most pronounced with a difference in monthly abnormal returns of 1%. Hence, the figure confirms that a higher exposure to funding risk is not rewarded during good times but severely punished during funding crises.

[Place Figure 3 about here]

Panels (b) and (c) confirm that high funding risk is not rewarded in bull markets. The difference portfolio earns a small and insignificant abnormal return in both bull and bear markets and a significant abnormal return in normal times. Moreover, splitting the time by the Credit Suisse hedge fund index shows a qualitatively similar performance during all market environments.

3.3.1 The Difference Between LOIS and Risk Factors

I next argue that this *unrewarded risk* explains why my results go in the opposite direction of a traded risk factor. To that end, I examine why Hu *et al.*, 2013 and Dahlquist *et al.*, 2019 find the opposite result when replacing LOIS with the Hu *et al.*, 2013 Noise measure and the He *et al.*, 2017 primary dealer factor, respectively. To distinguish my unrewarded risk hypothesis from priced risk factors, recall that the difference between LOIS and these two other risk measures is that LOIS is not directly related to a trading strategy with abnormal returns while the primary dealer factor captures the abnormal returns of a trading strategy and the noise measure is related to mispricings in the U.S. Treasury market, which hedge funds could exploit. In theory, funds with a higher exposure to an unrewarded risk underperform when the risk materializes but do not outperform during normal times. By contrast, funds with a high exposure to a rewarded risk collect a risk premium in normal times.

To test this intuition, I repeat the sorting procedure described at the beginning of Section 3 and focus on the difference portfolio which is long hedge funds with the lowest LOIS-loading and short hedge funds with the highest LOIS-loading, splitting the sample period into months with improving funding conditions (ΔLOIS ≤ 0) and months with worsening funding conditions (ΔLOIS > 0). In line with the results presented in Section 3.3, Panels (1) and (2) of Table 5 confirm that funds with a high LOIS-loading generate similar returns to funds with a low LOIS-loading in months when funding conditions improve (ΔLOIS ≤ 0) and underperform significantly in months when funding conditions worsen (ΔLOIS > 0).

[Place Table 5 about here]

Next, I examine the primary dealer factor and the Noise measure and repeat the analysis, replacing ΔLOIS with the returns of the primary dealer factor (PD). Panels (3) and (4) of Table 5 show that the difference portfolio which is long hedge funds with a low PD-loading and short hedge funds with a high PD-loading generates significant negative returns in months when PD earns positive returns and insignificant positive returns in months when the factor earns negative returns. Panels (5) and (6) of Table 5 show the results of repeating the analysis using changes in the Noise measure as funding risk proxy. As for the primary dealer factor, funds with a high Noise-loading significantly outperform funds with a low Noise-loading when funding conditions improve (ΔNoise ≤ 0) and generate insignificantly different returns when funding conditions worsen (ΔNoise > 0).

Taken together, Table 5 illustrates the key difference between LOIS and a "risk factor": A high LOIS-loading indicates an unrewarded risk exposure, while exposure to a other factors can capture the risks of new trading strategies which is rewarded in normal times.

3.4 Access to Alpha-Generating Strategies

To test Hypothesis 4, which suggests that funds with a lower LOIS-loading have access to superior alpha-generating strategies, I examine the persistence of my findings over different investment horizons. Repeating the sorting procedure described at the beginning of Section 3, I form a portfolio which invests in hedge funds in the lowest LOIS decile and shorts hedge funds in the highest LOIS decile and gradually increase the holding period from one month up to 36 months.

Figure 5 shows the returns, risk-adjusted returns, and post-sorting β^{LOIS} (controlling for the returns of the stock market portfolio), as well as 95% confidence bands for different holding periods. As we can see from the graph, both the difference in returns and the difference in risk-adjusted returns remains positive for holding periods up to three years. However, the difference in returns becomes insignificant (at a 5% level) for holding periods longer than 14 months while the difference in risk-adjusted returns remains significant for holding periods of up to 27 months.

[Place Figure 5 about here]

Hence, this test suggests that funds with a low LOIS-loading keep their access to alpha-generating strategies for over two years, suggesting that these funds have access to superior alpha-generating strategies. In the appendix, I examine hedge fund investors can profit from using LOIS exposure as decision criterion for hedge fund investments and show that past LOIS exposure is a better predictor of future fund returns than past performance.

3.5 LOIS Exposure and Fund Flows

Hypothesis 5 suggests that a higher LOIS-exposure also predicts investor withdrawals because high-funding-risk funds generate lower expected returns while exposing investors to additional risks. I test this hypothesis using fund flows. Specifically, I compute fund i's flow in month t as

$$Flow_{i,t} := \frac{AUM_{i,t} - AUM_{i,t-1}}{AUM_{i,t-1}} - R_{i,t}, \tag{3}$$

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 cumulative fund flows over 12 months, replacing missing observations due to missing AUM with zero and then examine the role of β^{LOIS} in cross-sectional (Fama and MacBeth, 1973) regressions

$$Flow_{i,t} = \gamma_0 + \gamma^{LOIS} \beta^{LOIS}_{i,t-1} + \gamma Controls_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where $Controls_{i,t-1}$ include the following variables: The fund size and fund age in the previous month; a dummy variable that equals one if the fund is closed to new investments; the fund's management and incentive fee (both in percent); the time to withdrawal; the leveraged dummy; past returns; and past flows (over the previous 12 months).

[Place Table 6 about here]

Panels (1) – (3) of Table 6 show the regression results. In Column (1), I first run the Fama-MacBeth regression without controlling for any fund-specific characteristics. As we can see from Column (1), a higher LOIS-beta (corresponding to less funding risk) predicts higher fund flows. That is, funds with more funding risk are more likely to face outflows. Next, adding all controls except for past performance and past flows (which are the main drivers of fund flows) Column (2) shows that the statistical and economic impact of β^{LOIS} remains virtually unchanged. Finally, Column (3) shows that even after controlling for past flows and past performance, β^{LOIS} is a significant driver of future fund flows.

4 Robustness

I now document the robustness of my main finding to several modifications of my analysis. First, I use cross-sectional regressions to control for other variables that can affect fund performance. Second, I examine different versions of the underlying hedge fund database and subsamples of the union database. Third, I experiment with different holding periods. Finally, I show the robustness of my findings to using different versions of LOIS.

4.1 Additional Controls

I first examine if controlling for the differences in fund characteristics affects my main result by running Fama-MacBeth regressions of risk-adjusted hedge fund returns on their LOIS beta, controlling for the same fund-specific characteristics as when examining fund flows. To run the Fama-MacBeth regression, I compute the risk-adjusted excess return ($R^{\perp}_{i,t}$) of each hedge fund by subtracting the factor realizations times loadings (estimated over the entire sample period) from the funds' excess returns. I then run regression (4), replacing $Flow_{i,t}$ with $R^{\perp}_{i,t}$.

In line with the results from Section 3, Column (4) of Table 6 shows a significant link between hedge fund alphas and β^{LOIS}, with a higher β^{LOIS} (which corresponds to less funding risk) predicting higher abnormal returns. As before, I first control for all fund characteristics except past returns and past flows, and then run the full regression. Columns (5) and (6) confirm that past LOIS-loading predicts future fund alphas, even after controlling for ten fund-specific characteristics.

4.2 Biases in Hedge Fund Data

As a second robustness check, I address three of the most common hedge fund data biases and investigate if these biases in self-reported hedge fund returns affect my results.

First, backfill bias arises because once a hedge fund starts reporting to a database, it is allowed to enter past returns to the database as well. Clearly, only funds with high past returns would use that option, thereby biasing the reported returns upward. In my union database, I observe the date when a fund started reporting to a database and now drop observations before the reporting date. Second, dropout bias arises because hedge funds can choose to stop reporting to the database if they perform poorly. To address this concern, it is important to distinguish survivorship bias and dropout bias (Aiken *et al.*, 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. I mitigate this concern by adding a dropout return of −1% after a fund stops reporting to the database.[10] Finally, return smoothing arises because hedge funds investing in illiquid securities might report returns from investments in month t only in month $t+1$ due to infrequent price movements (see Asness *et al.*, 2001 and Getmansky *et al.*, 2004). To address this potential bias, I use the un-smoothing technique proposed by Getmansky *et al.*, 2004.[11]

The first row in Panel A of Table 7 repeats my main analysis with the bias-cleaned database. Comparing the performance of the difference portfolio for the bias-cleaned database with the raw database shows that these returns are virtually unchanged. Despite the decrease in risk-adjusted returns for all ten portfolios, this test confirms that the difference between high-funding-risk and low-funding-risk funds is not driven by common biases in reported hedge fund data.

[Place Table 7 about here]

4.3 *Different Databases and Subsamples*

While the union database has the advantage of giving a more complete picture of the hedge fund database, it entails the disadvantage of making

[10]Using a proprietary dataset of hedge funds, not reporting to any database, Aiken *et al.*, 2013 find that hedge funds that stop reporting to a database continue to exist but deliver returns that are, on average 0.5% lower than the returns of funds that continue reporting to the database. Hence, a dropout return of −1% is a conservative estimate.

[11]The unsmoothing technique works as follows. Let $R^o_{i,t}$ denote the observed return of Fund i at time t and $R_{i,t}$ the true return of Fund i at time t. Then, assuming that return-smoothing does not exceed more than two periods, observed returns and true returns are linked by the following equation:

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

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 a maximum-likelihood approach and the entire time series of observed returns.

the replication of my result difficult. To address this issue, I now repeat the main analysis described in Section 3 for the TASS, Eureka, or HFR database, using each database separately before merging. Rows 2–4 in Panel A of Table 7 show that funds with a low LOIS-loading outperform funds with a high LOIS-loading in all three databases. Despite the smaller samples, the risk-adjusted returns of the difference portfolio are significant at a 1% level with a t-statistic above three for the Eureka and HFR database and significant at a 5% level for the TASS database.

A second potential concern about my main analysis is that funds of hedge funds differ substantially from hedge funds. To examine if my results are affected by the inclusion of funds of funds, I next consider the subsample of funds in the union database which are not funds of hedge funds. In addition, I examine how funds of hedge funds with a different exposure to LOIS perform. As we can see from rows 5 and 6 of Panel A, dropping funds of funds from the database leads to virtually unchanged results. Moreover, funds of funds with a lower exposure to LOIS significantly outperform funds of funds with a high exposure to LOIS and in both tests the risk-adjusted returns of the difference portfolio are statistically significant at a 1% with a t-statistic above three. As an additional test, I split the sample of funds by their investment style, sort each style sample based on the LOIS-loading, and form decile portfolios that contain the same fraction of each investment styles. As can be seen from row 7 of panel A, this test leads to a marginal increase in the statistical and economic significance of my result.

Finally, I split the sample period in half and analyze the returns in the January 2005 – June 2011 period separately from the July 2011 – December 2017 period. The last two rows in Panel A show that the difference between low LOIS-loading and high LOIS-loading funds is significant in both subsamples. However, the significance in the post-crisis period comes from the under-performance of high-funding-risk funds while it is driven by the outperformance of low-funding risk funds in the pre-crisis period.

4.4 Different Holding Periods

In my main analysis, I sort hedge funds based on their LOIS-loading and rebalance the portfolios on an annual basis. In Panel B of Table 7, I repeat the main analysis with shorter holding periods of one, three, six, and nine months. As we can see from the table, the results remain similar when studying shorter holding periods and in all cases the risk-adjusted returns of the difference portfolio are statistically significant at a 1% with a t-statistic above three.

4.5 Different Versions of LOIS

I conclude this section by examining the robustness of my main finding to using Libor-OIS spreads with a 2-year tenor or the 3×6 FRA-OIS spread. Like the 5-year Libor-OIS spread, the 2-year Libor-OIS is based on swap rates, which capture the risk-neutral expectation of the 3-month Libor-OIS spread over the next two years. The 3×6 FRA-OIS spread, is the risk-neutral expectation of the 3-month Libor-OIS spread in 3 months time. Panel C of Table 7 shows that the results remain almost unchanged when using the 2-year Libor-OIS spread or the FRA-OIS spread as a proxy for funding conditions. Funds with a low loading on 2-year LOIS (FRA-OIS) outperform funds with a high loading on 2-year LOIS (FRA-OIS) by a significant margin; the difference portfolio earns a risk-adjusted return of 0.48% (0.41%) which is statistically significant at a 1% level ($t = 2.90$ and $t = 2.83$, respectively).

5 Conclusion

I show in this paper that expected hedge fund returns decrease with a higher exposure to market-wide funding shocks, as measured by a higher LOIS-loading. This finding adds a new dimension to the literature examining risks in the cross-section of hedge funds because a higher exposure to market-wide funding shocks should normally increase expected returns as compensation for the additional risk. However, my hypothesis is that, because hedge funds are managed portfolios, a fund's exposure to funding shocks can be linked to its liabilities instead of its investment strategies, and more fragile liabilities lower expected returns. While it is puzzling that hedge funds with a high LOIS-loading exist, despite having a high risk exposure and low expected returns, my findings indicate that investors gradually withdraw from these high-funding-risk funds.

In addition, my approach to measuring a fund's exposure to funding risk is useful along two other dimensions. First, it can help investors to identify fund managers with access to superior investment strategies because hedge funds with the lowest LOIS-loading generate significant positive returns for holding periods up to 25 months. Second, in contrast to hedge fund leverage or information about the funds' prime brokers (which are not readily available across databases), LOIS-loadings are based on past return observations, making it a useful alternative measure of funding risk exposure that is available across databases.

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Tables and Figures

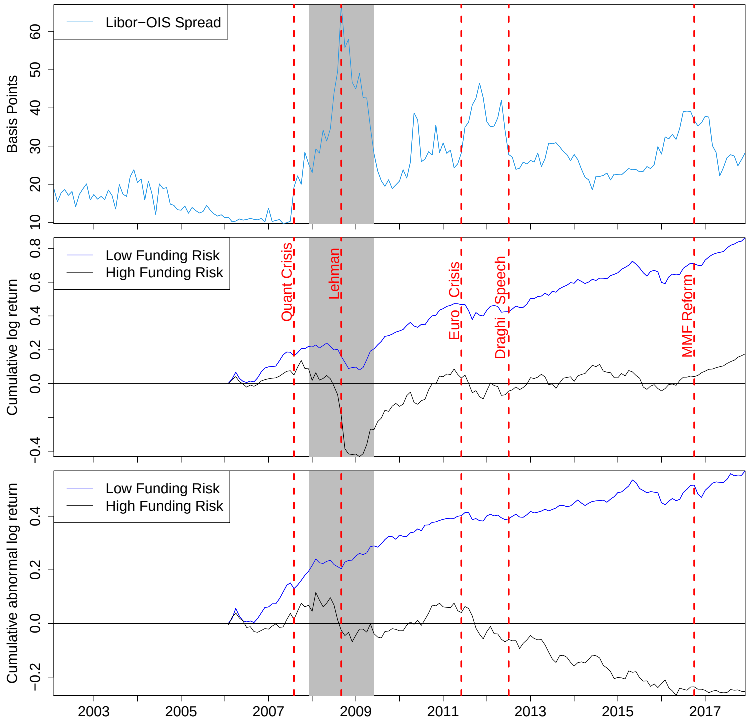
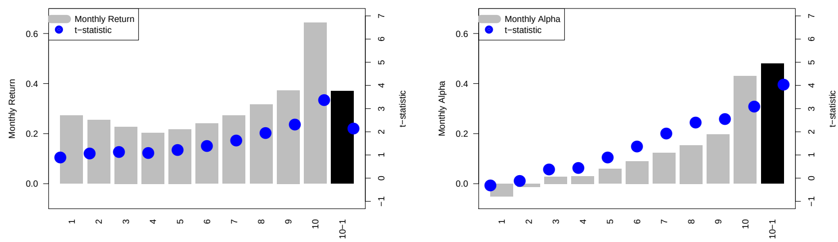


Figure 1: Time series of LIBOR-OIS spreads and hedge fund returns.

Description: The upper panel shows the spread between the fixed rate in a 5-year LIBOR swap and the fixed rate in a 5-year Overnight Indexed Swap (OIS). The middle panel shows the cumulative excess returns of hedge fund portfolios with a low loading (blue line) and a high loading (black line) on changes in the in the 5-year Libor-OIS spread. The bottom panel shows the cumulative abnormal returns (relative to the the Fungh-Hsieh benchmark) of the same hedge fund portfolios. The portfolios are formed every month based on their historical beta to changes in the 5-year Libor-OIS spread and held for the following 12 months (which results in a total of 12 overlapping portfolios). The beta is calculated using a regression of monthly fund returns on changes in the Libor-OIS spread controlling for the returns of the stock market portfolio, using the 36 months prior to portfolio formation. The sample of hedge funds is then sorted into 10 equally-weighted portfolios and the low (high) loading portfolio is the tenth (first) decile portfolio. All observations are month-end and the sample period is January 2002 to December 2017, including all funds in the union database. The highlighted events (dashed vertical lines) are the quant crisis in August 2007, 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 implementation of the U.S. money-market reform in October 2016. The grey-shaded areas are US recession periods.

Interpretation: Libor-OIS spreads increase when funding conditions deteriorate. Hedge funds with a low exposure to this risk measure (henceforth low-funding risk funds) generate higher returns than funds with a high exposure to this risk measure (henceforth high-funding-risk funds).

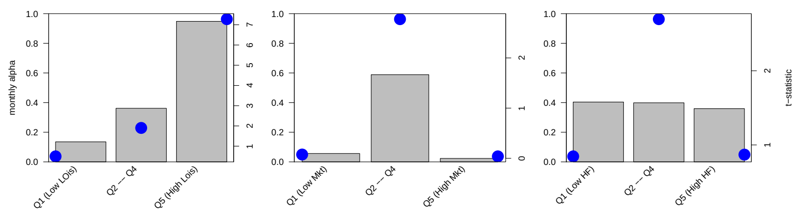


(a) Raw returns (b) Risk-adjusted returns

Figure 2: Performance of LOIS-sorted hedge fund portfolios.

Description: Each month hedge funds are sorted into 10 equally-weighted portfolios according to their historical beta to changes in the 5-year Libor-OIS spread (LOIS) and held in the respective portfolios for 12 months (resulting in 12 overlapping portfolios). Funds in Portfolio 1 (10) have the highest (lowest) LOIS-loading. For each fund, the LOIS-loading is calculated using a regression of monthly fund returns on ΔLOIS, controlling for the returns of the stock market portfolio and using the 36 months prior to portfolio formation. The bars in panels (a) and (b) represent monthly portfolio returns and risk-adjusted portfolio returns, calculated using the Fung and Hsieh (2004) seven-factor model, respectively. The blue dots are Newey-West t-statistics with 12 lags. The black bar displays the average return or 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 2002 to December 2017, including all funds in the union database.

Interpretation: Low-funding-risk funds significantly outperform high-funding-risk funds. This performance difference becomes even more pronounced when examining risk-adjusted returns.

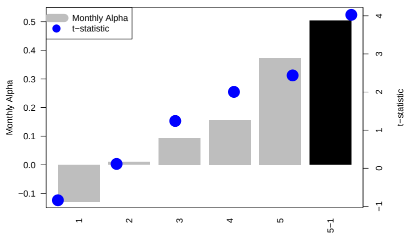


(a) Level Lois (b) Stock market (c) HF index

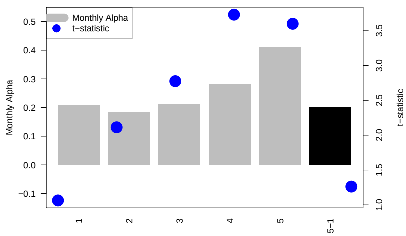
Figure 3: Performance of the LOIS-sorted difference portfolio in different times.

Description: This figure shows the risk-adjusted returns of the difference portfolio which is long hedge funds with the lowest LOIS-loading and short hedge funds with the highest LOIS-loading. For a detailed description of the sorting procedure see the caption of Figure 2. The time series is split into time periods with low, medium, and high constraints. In panel (a), the sorting criterion is the level of LOIS. In panel (b), the sorting criterion is the current return of the stock market. In panel (c), the sorting criterion is the return of the broad Credit Suisse hedge fund market index. Q1 corresponds to the time period in which LOIS is in its lowest quintile, Q2 – Q4 correspond to the time period in which LOIS is at a median level, and Q5 corresponds to the time period when LOIS is in its most elevated quintile. The blue dots are Newey-West t-statistics with 12 lags. The sample period is January 2002 to December 2017, including all funds in the union database.

Interpretation: A large part of the difference between low-funding-risk and high-funding-risk funds comes from months in which Lois is elevated, that is, when funding conditions are tight. Moreover, high-funding-risk funds do not outperform low-funding risk funds in bull or bear markets.



(a) Without sythetic leverage



(b) With synthetic leverage

Figure 4: Performance of the LOIS-sorted difference portfolios, conditional on synthetic leverage.

Description: This figure shows the risk-adjusted returns of hedge fund portfolios sorted based on their LOIS-loading. For a detailed description of the sorting procedure see the caption of Figure 2. Panel (a) shows the results for a subsample of funds with no synthetic leverage, that is, funds that do not trade derivatives, currency or commodity contracts. Panel (b) shows the results for a subsample of funds with synthetic leverage, that is, funds that trade derivatives, currency or commodity contracts. The blue dots are Newey-West t-statistics with 12 lags. The sample period is January 2002 to December 2017, including all funds in the Eureka database with the required information.

Interpretation: Funds with high LOIS exposure underperform more severely if they do not use synthetic leverage.

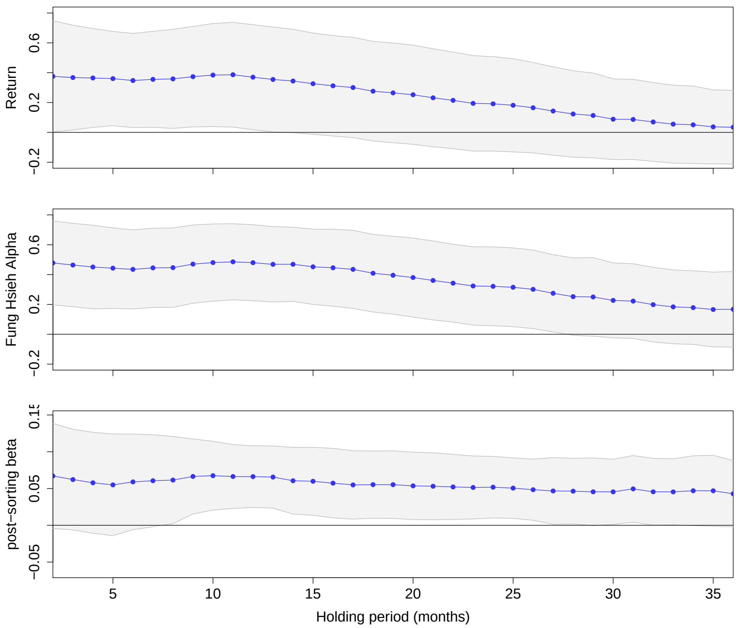


Figure 5: Performance of funds with a low LOIS-loading over longer holding periods.

Description: Each month, hedge funds are sorted into deciles based on their LOIS-loading, using the last 36 months of return observations and controlling for the excess returns of the stock market portfolio. Each point in the figure illustrates the performance of the decile portfolio with the lowest LOIS-loading for different holding periods, extending from one month to 36 months. The grey-shaded areas are 95% confidence bands using Newey-West standard errors. The sample period is January 2002 to December 2017, including all funds in the union database.

Interpretation: The performance difference between low-funding-risk funds and high-funding risk funds persists over longer holding periods up to three years.

Table 1: Hedge fund summary statistics.

	Mean	SD	25%	Median	75%	*N*
			Panel A: Summary statistics for all hedge funds			
Return (mean)	0.37	1.61	0.05	0.31	0.62	14,682
Return (SD)	3.11	2.53	1.54	2.41	3.92	14,597
AUM (mio USD)	216.61	652.03	25.00	61.23	175.16	14,682
Age (Months)	60.52	47.94	26.85	45.50	78.36	14,682
Closed	0.26	0.44	0.00	0.00	1.00	14,682
Mgt Fee	1.42	0.59	1.00	1.50	2.00	14,198
Incentive Fee	15.01	7.75	10.00	20.00	20.00	14,014
Backfilled	0.32	0.31	0.03	0.23	0.53	14,682
Time to withdrawal (years)	0.27	0.23	0.08	0.21	0.42	13,858
Draw Down (percent)	6.86	9.00	1.75	4.05	8.28	14,682
Leveraged	0.51	0.50	0.00	1.00	1.00	14,307
Leveraged (Details)	0.66	0.61	0.00	1.00	1.00	4,797
Synthetic leverage	0.45	0.50	0.00	0.00	1.00	4,925
			Panel B: Hedge fund returns for different styles			
Directional	0.42	3.45	-0.03	0.28	0.60	2,168
Multiprocess	0.36	0.81	0.06	0.31	0.61	3,007
Relative Value	0.37	1.03	0.06	0.36	0.65	1,536
Security Selection	0.42	1.02	0.08	0.41	0.76	4,490
Other	0.60	1.71	0.19	0.46	0.86	863
Fund of Funds	0.16	0.63	0.02	0.20	0.35	2,618

Note: This table provides summary statistics of average hedge fund returns and fund characteristics of funds in the union database. *AUM* is the funds' average assets under management; *Age* is the average number of past return observations; *Time to withdrawal* captures the average time it takes to withdraw equity from the fund and is defined as $RedemptionNoticePeriod + RedemptionFrequency/2 + Lockup * 0.25$; *Draw Down* measures the difference between the highest fund value at any previous time and the current fund value; *Leveraged* is a dummy variable that equals one if the fund self-reports the usage of leverage and zero otherwise; *Leveraged (details)* is only available for the HFR database and equals two if the fund self-reports a levarage above 2-1, one if the fund self-reports leverage below or equal to 2-1, and zero otherwise; *Synthetic leverage* is only available for 80% of the funds in the Eureka database and equals one if the fund self-reports the usage of derivatives or currecny/commodity contracts. *Closed* is a dummy variable that equals one if a fund is closed to new investors; *Mgt Fee* and *Incentive Fee* are the funds' management and incentive fees (measured in percent); *Flow* captures the fund flows over the past year; *Backfilled* and *Lockup* are the average fraction of backfilled return observations and the average fraction of funds with a lockup provision, respectively. Panel B provides summary statistics of hedge fund returns split into the six style categories. The sample period is January 2002 to December 2017.

Interpretation: The analysis is based on a comprehensive hedge fund database

Table 2: Cross-sectional regressions of LOIS betas.

	Union database			HFR	
	(1)	(2)	(3)	(4)	(5)
$Time\ to\ withdrawal_i$	0.052***	0.046***	0.039***	0.055***	0.038***
	[3.17]	[2.97]	[3.39]	[3.16]	[3.54]
$Draw\ Down_{i,t-1}$	–0.137**	–0.133***	–0.129***	–0.164**	–0.163**
	[–2.57]	[–2.75]	[–2.87]	[–2.22]	[–2.47]
$Leveraged_i$	0.003	0.000	0.001	–0.005**	–0.005*
	[0.70]	[0.12]	[0.28]	[–2.12]	[–1.86]
$\log(AUM)_{i,t-1}$		–0.004***	–0.003***		–0.003*
		[–3.45]	[–3.28]		[–1.83]
$Closed_i$		0.005***	0.004**		–0.009***
		[2.85]	[2.06]		[–3.41]
$Age_{i,t-1}$		0.000	0.000		0.000
		[0.70]	[1.20]		[0.95]
$Flow_{i,t-1}$		0.000	0.000		0.000*
		[1.17]	[0.78]		[1.86]
$RET_{i,t-1}$		0.001	0.001		0.001
		[1.09]	[0.94]		[1.11]
$Mgt\ Fee_i$		–0.011***	–0.010***		–0.006*
		[–4.19]	[–4.08]		[–1.73]
$Incentive\ Fee_i$		0.001***	0.001**		0.001**
		[2.74]	[2.09]		[2.56]
StyleDummies	No	No	Yes	No	Yes

Note: This table reports the results of Fama-MacBeth regressions of the cross section of monthly hedge fund beta on LOIS, estimated over the past 36 months on the indicated variables. $Time\ to\ withdrawal_i$ captures the average time it takes to withdraw equity from the fund and is defined as $RedemptionNoticePeriod + RedemptionFrequency/2 + Lockup * 0.25$; $Draw\ Down_{i,t-1}$ measures the difference between the highest fund value at any previous time and the fund value at time $t-1$; $Leveraged_i$ for the union database is a dummy variable that equals one if the fund self-reports the usage of leverage and zero otherwise. For the HFR database, the variable is equal to two if the fund self-reports a levarage above 2-1, one if the fund self-reports leverage below or equal to 2-1, and zero otherwise; $Flow_{i,t-1}$ captures the previous fund flows; $\log(AUM)_{i,t-1}$ captures the fund size in month $t-1$; $Closed_i$ is a dummy variable that equals one if a fund is closed to new investors; $Age_{i,t-1}$ is the fund age measured in years; $RET_{i,t-1}$ is the fund's past return over the last 36 months; $Mgt\ Fee_i$ and $Incentive\ Fee_i$ are the funds' management and incentive fees (measured in percent); *Style Dummies* include dummy variables for each of the investment styles. Panels (1)-(3) show the results for the union database, Panels (4)-(5) repeat the analysis for the HFR database, using the more granular leverage data. Newey-West t-statistics with 12 lags are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2002 to December 2017.

Interpretation: LOIS-exposure is correlated with proxies of fund-specific funding risk.

Table 3: Risk-adjusted returns and other characteristics of LOIS-sorted portfolios.

	Post-Formation						Pre-Formation	
	RET	α^{FH}	α^{Add}	β^{Mkt}	β^{LOIS}	R^2_{FH}	β^{Mkt}	β^{LOIS}
P1	0.27	–0.05	0.01	0.49***	–0.11***	0.64	0.46***	–0.39***
	[0.90]	[–0.32]	[0.14]	[20.01]	[–3.40]		[17.18]	[–18.41]
P2	0.25	–0.01	0.02	0.41***	–0.08***	0.74	0.37***	–0.17***
	[1.07]	[–0.13]	[0.33]	[18.58]	[–4.45]		[25.31]	[–19.43]
P3	0.23	0.03	0.03	0.32***	–0.07***	0.75	0.30***	–0.11***
	[1.13]	[0.38]	[0.42]	[14.93]	[–3.82]		[30.07]	[–18.94]
P4	0.20	0.03	0.02	0.29***	–0.06***	0.73	0.27***	–0.08***
	[1.09]	[0.45]	[0.27]	[12.68]	[–3.43]		[33.94]	[–15.70]
P5	0.22	0.06	0.04	0.27***	–0.05***	0.74	0.25***	–0.05***
	[1.23]	[0.90]	[0.68]	[12.38]	[–3.47]		[29.03]	[–9.09]
P6	0.24	0.09	0.07	0.26***	–0.05***	0.73	0.25***	–0.03***
	[1.39]	[1.36]	[1.18]	[11.95]	[–3.19]		[37.40]	[–6.65]
P7	0.27	0.12*	0.10**	0.26***	–0.05***	0.74	0.27***	-0.01
	[1.63]	[1.92]	[2.02]	[13.34]	[–2.92]		[42.80]	[–0.93]
P8	0.32*	0.15**	0.14***	0.28***	–0.04**	0.76	0.31***	0.03***
	[1.94]	[2.40]	[2.97]	[14.38]	[-2.16]		[37.67]	[4.47]
P9	0.37**	0.20**	0.20***	0.29***	–0.03*	0.72	0.37***	0.08***
	[2.32]	[2.55]	[3.53]	[13.03]	[–1.78]		[33.30]	[7.30]
P10	0.64***	0.43***	0.47***	0.33***	–0.04*	0.57	0.55***	0.27***
	[3.36]	[3.08]	[4.60]	[10.35]	[–1.75]		[18.98]	[8.98]
P10 – P1	0.37**	0.48***	0.45***	–0.16***	0.07***	0.27	0.09**	0.66***
	[2.14]	[4.04]	[2.90]	[–4.93]	[2.61]		[2.07]	[12.26]

Note: This table provides additional details that supplement the results in Figure 2 (for a detailed description of the sorting procedure, see the caption of Figure 2). *RET* is the average return of the portfolio; α^{FH} (α^{Add}) is the intercept of regressing the portfolio returns on the seven Fung-Hsieh factors (and eight additional factors); β^{Mkt} and β^{LOIS} are the portfolio loadings on the stock market portfolio and $\Delta LOIS$, respectively; R^2_{FH} is the adjusted R^2 of regressing the portfolio returns on the seven Fungh-Hsieh factors. Under Post-Formation, all quantities are computed using the returns of the formed hedge fund portfolios. Under Pre-Formation, the average pre-ranking betas as calculated in Equation (2) are reported. Newey-West $t-$statistics with 12 lags are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2002 to December 2017, including all funds in the union database.

Interpretation: In addition to significantly different returns and Fung-Hsieh alphas, high-funding risk and low-funding risk funds also have significantly different pre- and post-sorting Lois betas. Moreover, computing alphas with additional risk factors leaves the results virtually unchanged.

Table 4: Results for different subsamples of the hedge fund database.

	Draw downs			Time to withdrawal			Leverage		
	Low (1)	*Med* (2)	*High* (3)	*Long* (4)	*Med* (5)	*Short* (6)	*Low* (7)	*Med* (8)	*High* (9)
α^{FH}	0.17**	0.21***	0.47***	0.24**	0.24***	0.39***	0.26***	0.30***	0.46***
	[2.22]	[2.81]	[2.88]	[2.60]	[3.06]	[2.67]	[4.18]	[3.18]	[3.51]
β^{LOIS}	0.04**	0.05**	0.08***	0.05**	0.05*	0.10***	0.04**	0.04*	0.04*
	[2.26]	[2.52]	[2.76]	[2.48]	[1.79]	[3.13]	[2.45]	[1.77]	[1.95]

Note: This table shows the results of applying the sorting procedure described in the caption of Figure 2 to different subsamples of the database. Each column shows the risk-adjusted return of the difference portfolio that is long hedge funds with the lowest β^{LOIS} and short hedge funds with the highest β^{LOIS} and the post-sorting β^{LOIS}, using a different subsample of the database. Columns (1)–(3) show the results for funds, where the sample is split into quintiles based on their draw downs in the previous month. *Low* and *High* correspond to the 20% funds with the lowest and highest past draw downs, respectively. Columns (4)–(6) show the results for funds split into quintiles based on their time to withdrawal, where *Long* and *Short* correspond to the 20% of funds with the longest and shortest time to withdrawal. Columns (7)–(9) examine only the HFR database and split the sample into three subsamples, depending on whether the detailed leverage variable equals zero (*Low*), one (*Med*), or two (*High*). The sample period is January 2002 to December 2017, including either all funds in the union database or all HFR funds.

Interpretation: The performance difference between low-funding-risk and high-funding-risk funds is more pronounced for funds with more fragile liabilities.

Table 5: Performance of different funding-risk-sorted difference portfolios.

	LOIS		PD factor		Noise	
	Improve (1)	Worsen (2)	Improve (3)	Worsen (4)	Improve (5)	Worsen (6)
R^{Exc}	–0.12	0.86***	–0.47**	0.20	–1.04***	0.15
	[–0.40]	[4.49]	[–2.15]	[0.53]	[–4.31]	[0.49]
α^{FH}	0.23	0.72***	–0.64***	0.42*	–0.65***	–0.09
	[1.66]	[4.25]	[–2.81]	[1.81]	[–3.17]	[–0.24]

Note: This table compares the returns of three different long-short portfolios. To obtain the difference portfolios, all funds in the union database are sorted into deciles, depending on their past loading on the respective funding risk measure. Each difference portfolio is long hedge funds with the lowest exposure to the respective funding risk measure and short hedge funds with the highest exposure to the respective funding risk measure. The time series of the returns of the difference portfolio is then split into months when the respective funding risk measure indicates improving funding conditions and when it indicates worsening funding conditions. In Panels (1) and (2) the funding risk measure is LOIS. In Panels (3) and (4) the funding risk measure is the primary dealer factor constructed in He *et al.*, 2017. In Panels (5) and (6) the funding risk measure is the Noise measure constructed in Hu *et al.*, 2013. Uneven Panels report the performance of the difference portfolios in months of improving funding condition, according to the respective funding risk measure. Even Panels report the performance of the difference portfolios in months of worsening funding condition, according to the respective funding risk measure. Under R^{Exc} and α^{FH}, the excess returns and risk-adjusted returns (using the seven-factor Fung and Hsieh benchmark) of the difference portfolio are reported. The numbers in parantheses are Newey-West t-statistics with 12 lags. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2002 – December (2017) for Panels (1) – (2), January 1994 – December 2017 for Panels (3) – (4), and January 1994 – December 2016 for Panels (5) – (6).

Interpretation: LOIS is the opposite of a risk factor. Funds with a low LOIS-loading significantly outperform funds with a high Lois-loading, but only when funding conditions deteriorate. By contrast, funds with a low loading on the primary dealer factor (Noise measure) significantly underperform funds with a high loading on the primary dealer factor (Noise measure), but only when funding conditions improve.

Table 6: Results using cross-sectional regressions.

	Flow			Fung-Hsieh alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta^{LOIS}_{i,t-1}$	0.045***	0.044***	0.036**	0.042***	0.032***	0.027**
	[2.66]	[2.67]	[2.50]	[3.11]	[2.67]	[2.03]
$\log(AUM)_{i,t-1}$		–0.005	–0.008**		–0.001	–0.001
		[–1.55]	[–2.44]		[–0.98]	[–1.12]
$Age_{i,t-1}$		–0.007***	–0.006***		–0.001***	–0.001***
		[–10.51]	[–10.13]		[–6.13]	[–5.66]
$Closed_i$		–0.008**	–0.009***		0.003*	0.003*
		[–2.45]	[–2.99]		[1.79]	[1.75]
Mgt Fee$_i$		–0.011***	–0.012***		0.002	0.001
		[–3.49]	[–3.89]		[0.62]	[0.53]
Incentive Fee$_i$		0.000	0.000		0.001***	0.001***
		[–1.26]	[–1.22]		[8.31]	[8.79]
Time to withdrawal$_i$		0.024**	0.015		0.017**	0.016**
		[2.21]	[1.36]		[2.37]	[2.43]
Leveraged$_i$		0.047***	–0.006*		0.007***	0.007***
		[2.71]	[–1.90]		[3.00]	[2.97]
$RET_{i,t-1}$			0.009***			0.003***
			[10.45]			[4.88]
$Flow_{i,t-1}$			0.010***			0.000***
			[21.19]			[3.74]
StyleDummies		Yes	Yes		Yes	Yes

Note: This table reports the results of Fama-MacBeth regressions of the cross section of hedge fund flows (Panels 1–3) or hedge fund alphas (relative to the Fung-Hsieh seven factor model; Panels 4–6) over the next twelve months. The main independent variable is $\beta^{LOIS}_{i,t-1}$ (calculated over the past 36 months), which captures the funds' past exposure to funding risk. $\log(AUM)_{i,t-1}$ captures the fund size in month $t-1$; $Age_{i,t-1}$ is the fund age measured in years; *Closed*$_i$ is a dummy variable that equals one if a fund is closed to new investors; *Mgt Fee*$_i$ and *Incentive Fee*$_i$ are the funds' management and incentive fees (measured in percent); *Time to withdrawal*$_i$ captures the average time it takes to withdraw equity from the fund and is defined as $RedemptionNoticePeriod + RedemptionFrequency/2 + Lockup * 0.25$; *Leveraged*$_i$ is a dummy variable that equals one if the fund self-reports the usage of leverage and zero otherwise; $RET_{i,t-1}$ is the fund's past return over the last 36 months; $Flow_{i,t-1}$ captures the previous fund flows; *Style Dummies* include dummy variables for each of the investment styles. Panels (1)-(3) show the results for the union database, Panels (4)-(5) repeat the analysis for the HFR database, using the more granular leverage data. Newey-West t-statistics with 12 lags are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2002 to December 2017, including all funds in the union database.

Interpretation: A higher LOIS (which corresponds to a weaker exposure to funding risk) predicts higher fund flows and higher risk-adjusted fund returns. This result is robust to controlling for several fund characteristics and past performance.

Table 7: Additional robustness tests.

	1	2	3	4	5	6	7	8	9	10	10 - 1
Panel A: Different databases and subsamples											
Bias	–0.08	–0.06	–0.01	0.01	0.03	0.06	0.09	**0.14**	**0.17**	**0.39**	**0.47**
	[–0.50]	[–0.50]	[–0.18]	[0.11]	[0.51]	[0.91]	[1.52]	**[2.25]**	**[2.09]**	**[2.72]**	**[3.71]**
TASS	0.06	0.02	0.06	0.05	0.07	0.09	0.11	**0.15**	**0.18**	**0.33**	**0.28**
	[0.41]	[0.24]	[0.71]	[0.71]	[0.94]	[1.27]	[1.54]	**[2.03]**	**[2.15]**	**[2.53]**	**[2.39]**
Eureka	–0.04	–0.04	0.02	0.02	0.06	0.08	0.12	**0.16**	**0.23**	**0.42**	**0.46**
	[–0.22]	[–0.35]	[0.20]	[0.35]	[0.87]	[1.17]	[1.81]	**[2.40]**	**[2.76]**	**[2.83]**	**[3.31]**
HFR	0.00	0.00	0.04	0.06	0.08	0.11	**0.13**	**0.17**	**0.21**	**0.40**	**0.40**
	[0.00]	[0.02]	[0.53]	[0.93]	[1.24]	[1.72]	**[1.96]**	**[2.67]**	**[2.80]**	**[3.13]**	**[3.59]**
no FoF	–0.04	–0.01	0.05	0.07	0.11	**0.15**	**0.17**	**0.21**	**0.25**	**0.48**	**0.52**
	[–0.24]	[–0.04]	[0.58]	[0.98]	[1.75]	**[2.37]**	**[3.11]**	**[3.42]**	**[2.78]**	**[3.15]**	**[4.14]**
only FoF	–0.16	–0.06	–0.02	–0.02	0.00	0.01	0.03	0.04	0.04	0.11	**0.28**
	[–1.44]	[–0.71]	[–0.31]	[–0.24]	[0.03]	[0.18]	[0.33]	[0.49]	[0.42]	[1.01]	**[3.42]**
Style	–0.19	0.00	0.06	0.06	0.13	**0.17**	**0.16**	**0.18**	**0.21**	**0.32**	**0.50**
	[–1.25]	[0.01]	[0.79]	[0.88]	[1.92]	**[2.86]**	**[2.63]**	**[2.86]**	**[2.76]**	**[2.58]**	**[4.15]**
< 2012	0.22	0.14	0.10	0.05	0.07	0.11	0.16	0.19	**0.25**	**0.66**	**0.44**
	[0.88]	[0.80]	[0.74]	[0.37]	[0.56]	[0.94]	[1.48]	[1.92]	**[2.23]**	**[3.50]**	**[2.30]**
≥ 2012	**–0.35**	**–0.15**	–0.04	0.03	0.07	0.10	0.10	0.10	0.09	0.14	**0.49**
	[–3.42]	**[–2.47]**	[–0.67]	[0.48]	[1.28]	[1.54]	[1.45]	[1.17]	[0.88]	[0.99]	**[2.53]**
Panel B: Shorter holding periods											
Hold 1m	–0.08	0.04	0.05	0.06	0.09	**0.13**	**0.15**	**0.19**	**0.26**	**0.42**	**0.50**
	[–0.48]	[0.42]	[0.62]	[0.94]	[1.36]	**[2.07]**	**[2.64]**	**[3.26]**	**[3.06]**	**[3.13]**	**[3.48]**
Hold 3m	–0.02	0.04	0.07	0.06	0.10	**0.13**	**0.16**	**0.18**	**0.24**	**0.44**	**0.46**
	[–0.15]	[0.38]	[0.88]	[0.88]	[1.48]	**[1.97]**	**[2.56]**	**[2.98]**	**[2.90]**	**[3.15]**	**[3.32]**
Hold 6m	–0.01	0.04	0.06	0.05	0.08	0.12	**0.15**	**0.18**	**0.21**	**0.43**	**0.43**
	[–0.04]	[0.34]	[0.83]	[0.80]	[1.26]	[1.79]	**[2.45]**	**[2.85]**	**[2.63]**	**[3.12]**	**[3.27]**
Hold 9m	–0.03	0.01	0.05	0.05	0.08	0.11	**0.15**	**0.18**	**0.21**	**0.44**	**0.47**
	[–0.17]	[0.13]	[0.64]	[0.72]	[1.16]	[1.65]	**[2.30]**	**[2.74]**	**[2.59]**	**[3.12]**	**[3.73]**
Panel C: Different measures											
2y LOIS	–0.06	0.00	0.05	0.07	0.07	0.08	0.09	0.12	**0.19**	**0.43**	**0.48**
	[–0.27]	[0.04]	[0.63]	[1.01]	[1.03]	[1.20]	[1.44]	[1.94]	**[2.64]**	**[3.42]**	**[2.90]**
FRA-OIS	0.02	0.05	0.06	0.07	0.09	0.11	**0.13**	**0.18**	**0.24**	**0.43**	**0.41**
	[0.10]	[0.56]	[0.85]	[1.18]	[1.50]	[1.88]	**[2.26]**	**[3.16]**	**[3.62]**	**[3.75]**	**[2.83]**
Contr. Level	–0.04	0.01	0.03	0.04	0.06	0.09	0.12	**0.15**	**0.21**	**0.44**	**0.48**
	[–0.26]	[0.15]	[0.45]	[0.63]	[0.82]	[1.32]	[1.73]	[2.41]	[2.55]	[3.13]	[4.14]

Note: This table shows the Fung-Hsieh alphas of LOIS-sorted hedge fund portfolios for different robustness tests. See the caption of Figure 2 for a detailed description of the sorting procedure. Panel A shows the results for using different variations of the union database. *Bias* reports the results using a bias-cleaned modification of the database; dropping all backfilled observations, adding a delisting return of −1% after the last reported return, and un-smoothing the returns using the procedure described in Getmansky *et al.*, 2004). Under *TASS*, *Eureka*, or *HFR* the individual databases are used instead of merging the three databases into the union database. Under *no FoF* and *FoF* the union databse is split into hedge funds and funds of hedge funds. Under *Style* hedge fund portfolios are formed conditional on the hedge fund investment style, ensuring the same proportion of styles in each decile. Under $<$ 2012 and $\geq$ 2012 the alphas for the January 2006 – December 2011 and the January 2012 – December 2017 subperiods are reported. Panel B shows the results for shortening the holding period of the portfolios from 12 months to 1, 3, 6, and 9 months. Panel C shows the results of repeating the sorting procedure described in the caption of Figure 2, replacing the 5-year LIBOR-OIS spread with the 2-year and 3-month LIBOR-OIS spread, or using the 5-year LIBOR-OIS spread, controlling for the level of the 5-year OIS rate. Newey-West t−statistics with 12 lages are reported in square brackets. Boldface numbers indicate significance at a 5% level.

Interpretation: The performance difference between low-funding-risk and high-funding-risk funds remains significant in a battery of robustness tests.

6 Additional Details and Results

This appendix presents additional details and results. Tables A.1 and A.2 contain detailed data descriptions.

[Place Table A.1 about here]

[Place Table A.2 about here]

Section 6.1 discusses the role of both established and additional risk measures. Section 6.2 shows the drawdowns of high-funding-risk and low-funding-risk funds over time. Section 6.3 contains additional summary statistics omitted in the body of the paper. Section 6.4 shows that using LOIS-exposure is a better predictor of future performance than measures of past performance. Section 6.5 illustrates the differences between pre- and post-sorting betas through a simple simulation exercise.

6.1 The Role of Established Risk Measures

Because the risk-adjusted returns of the difference portfolio, which is long funds with the lowest LOIS-loading and short funds with the highest LOIS-loading, is stronger after controlling for the seven Fung-Hsieh factors, I now examine how the returns of the difference portfolio change when adjusting for common risk factors and how adding more risk factors affects the results.

Starting with the raw returns of the difference portfolio, Column (1) of Table A.3 shows that the difference portfolio earns positive returns which are statistically significant at a 5% level. Column (2) reveals that controlling for the two stock-related factors – the excess returns of the U.S. stock market and the small-minus-big factor – sharply increases the risk-adjusted returns of the difference portfolio. Column (3) shows that controlling for TERM and CREDIT also increases the risk-adjusted returns of the difference portfolio, but by a smaller margin. That smaller margin is likely related to the fact that these two factors are not excess returns and Column (4) shows that repeating the analysis with tradable versions of these two factors leads to a stronger increase in the risk-adjusted returns.[12] Column

[12]Comparing Columns (3) and (4) shows that using the original seven Fung and Hsieh

(5) corresponds to α^{FH} reported in Table 3, omitting the loadings on the three trend-following factors (which are all insignificant) for brevity.

[Place Table A.3 about here]

I next add three risk factors related to market liquidity and funding liquidity conditions – the Pastor and Stambaugh, 2003 market liquidity factor (PS), the He *et al.*, 2017 primary dealer factor (HKM), and the Chen and Lu, 2018 funding risk measure (CL). All three capture excess returns and, as we can see from the alpha reported in Column (6), if anything, adding these factors strengthens the performance of the difference portfolio. Column (7) shows that controlling for the returns of a long-short hedge fund portfolio sorted on the Hu *et al.*, 2013 noise measure does not affect the statistical and economic significance of my result.

Finally, in Column (8), which corresponds to α^{Add} in Table 3, I add five more factors which can capture returns of common hedge fund trading strategies that are not captured by the Fung and Hsieh benchmark model. 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, to control for currency risk, I add the two currency risk factors proposed by Lustig *et al.*, 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 column (8), the alpha of the difference portfolio decreases moderately compared to column (7) but remains statistically significant at a 1% level. Hence, established risk measures cannot explain the different performance of low-funding risk and high-funding risk funds.

6.2 Draw Downs

Figure A.1 shows the draw downs, measured as the difference between the highest past fund value and the current fund value, for the portfolio

factors instead of the tradeable adjustment gives a conservative estimate of the difference portfolio's significance. Hence, I report all following results using the original seven Fung and Hsieh factors.

with the highest exposure to funding risk and the portfolio with the lowest exposure to funding risk.

[Place Figure A.1 about here]

As we can see from the figure, both high-funding-risk and low-funding-risk funds generate losses around the default of Lehman Brothers and other major funding events. However, the drawdawns of the low-funding-risk portfolio are less severe and less frequent.

6.3 Additional Descriptive Statistics

Table A.4 contains summary statistics of hedge fund returns by year and Table A.5 provides pairwise correlations between LOIS and other hedge fund risk measures.

[Place Table A.4 about here]

[Place Table A.5 about here]

6.4 Making Money on LOIS Loadings?

Comparing the performance of LOIS-sorted hedge fund portfolios to funds sorted based on their past performance, I sort hedge funds into decile portfolios based on their returns over the past 36 months, using either (i) raw returns, (ii) Fung-Hsieh seven factor alphas, (iii) the alpha relative to the returns of the overall hedge fund market (proxied by the Credit Suisse Hedge Fund index), or (iv) the LOIS-loading. As in the main analysis, I report the returns using annual rebalancing. Table A.6 shows the returns and risk-adjusted returns of the four different sorts. In addition to the returns of the winner portfolio, Table A.6 also shows the returns of the loser portfolio (with the lowest past performance or highest LOIS-loading) and the difference portfolio which is long the past winner portfolio and short the past loser portfolio.

[Place Table A.6 about here]

As we can see from the table, the portfolio with the lowest LOIS-loading generates monthly average returns of 0.64% ($t = 3.36$) and risk-adjusted returns of 0.43% ($t = 3.08$), which are higher than the returns of the three alternative portfolios. Moreover, the difference between past winners and past losers is most pronounced for LOIS-sorted portfolios and mostly insignificant for portfolios sorted based on their past performance; only the portfolio sorted based on past alphas generates a significant alpha.

6.5 Simulation of Pre- and Post-Sorting Betas

In this section, I use a simple simulation exercise to illustrate that spreads in pre-sorting betas are expected to be substitantially larger than spreads in post-sorting betas. To do so, I assume that, for each fund and each point in time we observe a noisy estimate of beta, which can be interpreted as the beta estimate based on data from the past years. I set the number of months to 200 and assume a total of $10,000$ hedge funds. For simplicity, I further assume that there are only two types of funds – high-funding-risk funds with $\beta^{High} \sim \mathcal{N}(0.5, \sigma)$ and low-funding-risk funds with $\beta \sim \mathcal{N}(0, \sigma^2)$ – and that the realizations are iid across funds. I set $\sigma = \frac{0.5}{1.64}$ such that we are 90% confident that the high beta will be positive and I assume that half of the funds are high-funding-risk.

Based on the simulation results I the sort hedge funds into deciles based on the realized beta from the previous period. In particular, at time t, I form 10 portflios based on the realization of β at time $t-1$. Table A.7 shows the average pre-sorting beta (measured as average of all time $t-1$ betas) and the average post-sorting beta (simply measured as average of all time t betas). While this simulation exercise is arguably overly simplistic along several dimensions, Table A.7 shows that there are substantial differences between pre-sorting and post-sorting betas. Even though the true β^{Low} has a mean of zero, three of the ten portfolios have a negative average pre-sorting beta. Moreover, the pre-sorting β of portfolio 10 is almost twice as large as the post-sorting β (which is close to the true mean of 0.5).

[Place Table A.7 about here]

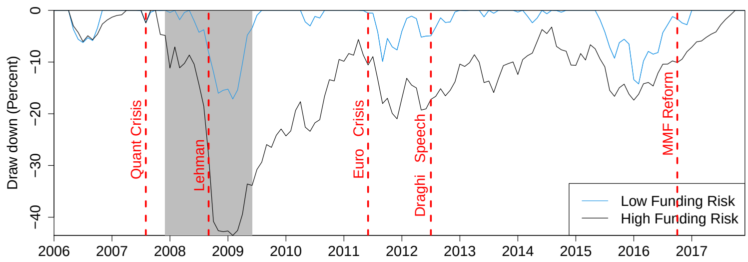


Figure A.1: Drawdowns of LOIS-sorted hedge fund portfolios.

Description: This figure shows the draw downs of hedge fund portfolios with a low loading (blue line) and a high loading (black line) on changes in the in the 5-year Libor-OIS spread. The portfolios are formed every month based on their historical beta to changes in the 5-year Libor-OIS spread and held for the following 12 months (which results in a total of 12 overlapping portfolios). The beta is calculated using a regression of monthly fund returns on changes in the Libor-OIS spread controlling for the returns of the stock market portfolio, using the 36 months prior to portfolio formation. The sample of hedge funds is then sorted into 10 equally-weighted portfolios and the low (high) loading portfolio is the tenth (first) decile portfolio. All observations are month-end and the sample period is January 2002 to December 2017, including all funds in the union database. The highlighted events (dashed vertical lines) are the quant crisis in August 2007, 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 implementation of the U.S. money-market reform in October 2016. The grey-shaded areas are US recession periods.

Interpretation: Both high-funding-risk and low-funding-risk funds produce draw downs during funding crises.

Table A.1: **Description & Interpretation:** This table defines the different time series variables used in this study and shows the relevant sources.

Variable	Definition	Source
Libor-OIS spreads	The LIBOR-OIS spread is the difference between the U.S. LIBOR rate and the fixed rate in an U.S. OIS with the same maturity. For 2-year and 5-year LOIS, I use the fixed rate in an interest rate swap in which the 3-months LIBOR rate is exchanged against a fixed rate to capture LIBOR and compute the spread to the matching OIS contract. For the FRA-OIS spread, I use the 3×6 FRA rate and construct the 3-month forward OIS rate from 6-month and 3-month OIS contracts using money market discounting.	Bloomberg
Broker-Dealer Leverage	This is the traded primary dealer leverage factor constructed in He *et al.*, 2017.	Asaf Manela's website
Commodity risk	The commodity risk factor is constructed using the excess returns of the S&P GSCI index over the one-month risk-free rate.	Datastream
Currency risk factors	These factors capture currency returns of an U.S. dollar investor and the returns of a carry trader.	Adrien Verdelhan's website
Emerging markets risk	The emerging markets risk factor is constructed using the excess returns of the MSCI emerging market index over the one-month risk-free rate.	Datastream
Fixed income risk factors	The yield factor (YLD) is the 10-year constant maturity Treasury yield and the credit factor (BAA) is the spread between the Moody's seasoned Baa corporate bond yields and the 10-year constant maturity Treasury yield.	FRED
Noise measure	This is the noise measure developed by Hu *et al.*, 2013.	Jun Pan's website
P/S liquidity factor	This is the Pastor and Stambaugh, 2003 stock market liquidity factor.	Lubos Pastor's website

Tradable 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.	Bloomberg
Trend following factors	The three Fung-Hsieh trend-following are capturing returns from trend followers in the bond, currency, and commodity market. These factors were originally constructed in Fung and Hsieh, 2001.	David Hsieh's website
U.S. stock market returns	The first stock market risk factor (MKT) captures 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).	Kenneth French's website

Table A.2: **Description & Interpretation.** This table defines the different hedge-fund specific variables used in this study.

Variable	Definition
β^{LOIS}	The beta from a regression of hedge fund returns on changes in LOIS, controlling for the returns of the (stock) market. The beta is computed using the previous 36 months of return observation.
Time to Withdrawal	This variable captures the average time it takes an equity investor to withdraw from the fund. It is computed as the redemption notice period, plus the redemption frequency divided by two (assuming that, on average an investor wants to withdraw in the middle of the period), and an additional three months if the fund has a lockup provision.
Draw Down	The draw down is computed as the percentage difference between the highest past fund value and the current fund value.
Leveraged	A dummy variable that equals one if the fund self-reports the use of leverage and zero otherwise.

Leveraged (detailed)	A variable that is only available for the HFR database. The variable is equal to zero if the fund self-reports no usage of leverage, equal to one if the fund self-reports a maximum leverage of 2-1 (i.e., the fund posts margins above 50%), and equal to two if the fund self-reports a leverage above 2-1.
Synthetic leverage	A variable that is only available for approximately 80% of the funds in the Eureka database. In this database, hedge funds self-report which financial instruments they use. I classify funds as using synthetic leverage if they self-report the usage of commodity or currency contracts, or the usage of derivatives. Funds without synthetic leverage self-report not using any of these three instruments.
AUM	This variable captures reported assets under management. If the value in month t is missing, I use the value from the previous month, multiplied with the returns from the previous to the current month.
Flow	The difference between percentage changes in assets under management and percentage returns.
Closed	A dummy variable that equals one if a fund is closed to new investors and zero otherwise.
Age	The fund age, measured from the first available observation in the database.
Mgt Fee	The fund's management fee in percent.
Incentive Fee	The fund's incentive fee in percent

Table A.3: Factor loadings and alphas for the LOIS-sorted difference portfolio.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
alpha	0.37**	0.51***	0.39***	0.47***	0.48***	0.53***	0.51***	0.45***
	[2.14]	[4.05]	[3.15]	[4.52]	[4.04]	[4.19]	[3.97]	[2.90]
Mkt		−0.21***			−0.17***	−0.23***	−0.19***	−0.11
		[−6.11]			[−4.06]	[−4.06]	[−3.01]	[−1.54]
SMB		0.14**			0.14**	0.15**	0.13**	0.10*
		[2.60]			[2.24]	[2.22]	[2.11]	[1.75]
TERM			1.45**		1.27	0.98	0.47	0.57
			[2.04]		[1.44]	[1.30]	[0.59]	[0.78]
CREDIT			3.37***		2.14***	2.21***	1.58*	1.41*
			[9.19]		[4.88]	[2.73]	[1.96]	[1.78]
TERM *trade*				−0.28***				
				[−2.94]				
CREDIT *trade*				−0.45***				
				[−7.27]				
PS						0.22	2.42	4.71
						[0.06]	[0.62]	[1.25]
HKM						5.89*	6.42**	6.60**
						[1.82]	[2.08]	[2.29]
CL						−1.01	0.70	1.55
						[−0.19]	[0.13]	[0.31]
Noise L/S							−0.15*	
							[−1.70]	
3 FH Factors	No	No	No	No	Yes	Yes	Yes	Yes
Add Factors	No	No	No	No	No	No	No	Yes
N Obs	143	143	143	143	143	143	143	143
Adj R2	0	0.22	0.18	0.27	0.27	0.27	0.3	0.37

Note: This table reports the results of regressing the returns of the difference portfolio which is long hedge funds with the lowest LOIS-loading and short hedge funds with the highest LOIS-loading on the indicated varibales. A detailed description of the sorting procedure can be found in the caption of Figure 2. The independent variables are the excess returns of the U.S. stock market portfolio (Mkt), a size factor (SMB), changes in the spreads between 10-year Treasury constant maturity yield and the one-month risk-free rate and the spread between Moody's Baa yield less 10-year Treasury constant maturity yield (TERM and CREDIT), tradable factors to mimic TERM and CREDIT (TERM *trade* and CREDIT *trade*), the three Fung-Hsieh trend-following factors for bonds, currencies, and commodities (omitted for brevity), the traded Pastor and Stambaugh, 2003 liquidity factor (PS), the He *et al.*, 2017 primary dealer factor (HKM), the Chen and Lu, 2018 liquidity factor (CL), and a long-short hedge fund portfolio that is long hedge funds with a high loading on the Hu *et al.*, 2013 noise measure and short hedge funds with a low loading on the noise measure (Noise L/S). Panel (8) shows the results controlling for 5 additional factors (loadings omitted for brevity): The two currency risk factors proposed by Lustig *et al.*, 2011, the emerging market and commodity factor proposed by Fung and Hsieh, and the Fama-French momentum factor. Newey-West t-statistics with 12 lags are reported in square bracets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2002 to December 2017 in Panels (1)–(6) and January 2002 to December 2016 in Panels (7) and (8), including all funds in the union database.

Interpretation: The performance difference between low-funding-risk and high-funding risk funds remains significant for different risk-adjustments.

Table A.4: Hedge fund summary statistics.

	N	Mean	SD	Q 25	Meadian	Q 75
2002	4,001	0.2	1.6	–0.33	0.14	–0.33
2003	4,775	1.45	2.49	0.51	0.97	0.51
2004	5,799	0.78	1.45	0.25	0.56	0.25
2005	6,592	0.6	1.39	0.09	0.4	0.09
2006	7,107	0.74	1.37	0.23	0.54	0.23
2007	7,521	0.64	1.6	0.02	0.44	0.02
2008	7,638	–1.74	2.75	–2.85	–1.6	–2.85
2009	7,054	1.63	2.75	0.44	1.15	0.44
2010	7,019	0.87	1.67	0.31	0.7	0.31
2011	7,003	–0.32	1.32	–0.76	–0.24	–0.76
2012	6,872	0.64	1.46	0.16	0.58	0.16
2013	6,725	0.8	1.55	0.19	0.76	0.19
2014	6,587	0.32	1.24	–0.07	0.29	–0.07
2015	6,133	0.04	1.74	–0.38	0.05	–0.38
2016	5,473	0.3	1.37	–0.18	0.26	–0.18
2017	4,953	0.72	1.4	0.14	0.53	0.14

Note: This table provides summary statistics of average hedge fund returns in the union database separately for every year. In addition to the returns between January 2002 and December 2017, which are used in the main analysis, it reports the returns between 1994 and 2001.

Interpretation: Hedge fund returns in different years are comparable to other studies.

Table A.5: Correlation between LOIS and other variables.

Panel A: Correlation with the seven Fung and Hsieh Factors

	MKT	SMB	TERM	CREDIT	PTFSBD	PTFSFX	PTFSCOM
SMB	0.31						
TERM	0.35	0.22					
CREDIT	–0.57	–0.23	–0.49				
PTFSBD	–0.32	–0.04	–0.34	0.31			
PTFSFX	–0.24	0.07	–0.14	0.31	0.45		
PTFSCOM	–0.19	–0.05	–0.06	0.15	0.23	0.34	
ΔLOIS	–0.24	–0.05	-0.06	0.19	0.13	0.06	0.04

Panel B: Correlation between LOIS and other funding risk measures

	PD	C/L	P/S	ΔNoise	3m ΔLOIS	2y ΔLOIS
C/L	0.38					
P/S	0.08	0.29				
ΔNoise	–0.26	–0.28	–0.12			
3m ΔLOIS	–0.02	–0.26	–0.12	0.30		
2y ΔLOIS	–0.20	–0.19	0.01	0.24	0.72	
5y ΔLOIS	–0.17	–0.14	0.03	0.05	0.53	0.84

Note: Panel A shows the pairwise correlation between the seven Fung and Hsieh factors and the correlation of these factors with ΔLOIS. Panel B shows pairwise correlations of PD (the He *et al.*, 2017 primary dealer factor), C/L (the Chen and Lu, 2018 liquidity factor), P/S (the Pastor and Stambaugh, 2003 liquidity factor), ΔNoise (changes in the Hu *et al.*, 2013 Noise measure), and changes in LIBOR-OIS spreads with 3 month, 2 year, and 5 year tenor. The sample period is January 2002 to December 2017.

Interpretation: Changes in are only weakly correlated with established hedge fund risk factors.

Table A.6: Low LOIS portfolio outperforms over longer holding periods.

	Returns			Fung-Hsieh alphas		
	Loser	Winner	W - L	Loser	Winner	W - L
Past Return	0.36	0.46	0.10	0.15	0.15	0.00
	[1.43]	[1.39]	[0.34]	[0.98]	[0.80]	[0.00]
Past FH Alpha	0.26	0.54*	0.27	–0.03	0.29*	0.33
	[1.09]	[1.74]	[1.21]	[–0.21]	[1.73]	[1.51]
Past HF Alpha	0.37	0.51***	0.14	–0.02	0.38***	0.39**
	[1.01]	[3.92]	[0.48]	[–0.08]	[4.21]	[2.13]
beta LOIS	0.27	0.64***	0.37**	–0.05	0.43***	0.48***
	[0.90]	[3.36]	[2.14]	[–0.32]	[3.08]	[4.04]

Note: This table shows the raw returns and risk-adjusted returns of hedge fund portfolios sorted on four different measures. In each row, hedge funds are sorted into deciles based on their return characteristics over the past 36 months and the resulting portfolio is rebalanced every 12 months. The table reports the returns of the past loser portfolio (lowest decile), past winner portfolio (highest decile) and the difference portfolio which is long the past winners and short the past losers. Under *Past Return*, hedge funds are sorted based on their past returns. Under *Past FH Alpha*, hedge funds are sorted based on their Fung-Hsieh seven-factor alpha. Under *Past HF Alpha*, hedge funds are sorted based on their alpha relative to the Credit Suisse hedge fund market index. Under *beta* LOIS, hedge funds are sorted based on their loading on LOIS over the past 36 months. The first three columns report raw returns and the last three columns report risk-adjusted returns relative to the Fung and Hsieh benchmark. Newey-West t-statistics with 12 lags are reported in square brackets. ***, **, and * indicate significance at a 1%, 5%, and 10% level respectively. The sample period is January 2002 to December 2017, including all funds in the union database.

Interpretation: A portfolio of low-funding-risk funds outperforms hedge fund portfolios formed on past performance. Hence, hedge fund investors can benefit from picking hedge funds based on
LOIS .

Table A.7: Simulation of pre-sorting betas.

Portfolio	pre-sorting β	post-sorting β
p1	–0.43	0.02
p2	–0.17	0.05
p3	–0.03	0.09
p4	0.09	0.15
p5	0.20	0.21
p6	0.30	0.29
p7	0.41	0.35
p8	0.53	0.41
p9	0.68	0.45
p10	0.93	0.48

Note: This table shows the results of a simple simulation exercise. Assuming 200 time steps and two types of funds – a high-funding risk fund with expected beta equal to 0.5 and a low-funding-risk fund with expected beta equal to zero – I assume that, for each fund and at each point in time, it is possible to observe a noisy estimate of the true beta. Assume $\beta^{High} \sim \mathcal{N}(0.5, \sigma^2)$ and $\beta^{Low} \sim \mathcal{N}(0, \sigma^2)$ with a standard deviation of $\sigma = \frac{0.5}{1.64}$, for the high-funding-risk and low-funding-risk fund, respectively. Each time period funds are put into 10 portfolios based on the observed β from the previous period. The table shows the average pre-sorting beta and average post-sorting beta for a simulation of $10,000$ with $5,000$ high-funding-risk funds.

Interpretation: It is expected that pre-sorting betas are substantially more volatile than post-sorting betas.