Online Appendix
High Funding Risk and Low Hedge Fund Returns

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1 Additional Details and Results

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

Section 1.1 discusses the role of both established and additional risk measures. Section 1.2 shows the drawdowns of high-funding-risk and low-funding-risk funds over time. Section 1.3 contains additional summary statistics omitted in the body of the paper. Section 1.4 shows that using LOIS-exposure is a better predictor of future performance than measures of past performance. Section 1.5 illustrates the differences between pre-and post-sorting betas through a simple simulation exercise.

1.1 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 IA.3 shows that the difference portfolio earns positive returns which are statistically significant at a 5% l evel. Column (2) reveals that control-ling 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 fac-tors leads to a stronger increase in the risk-adjusted returns.[1] Column (5) corresponds to α^{FH} reported in Table IA.3, omitting the loadings on the three trend-following factors (which are all insignificant) for brevity.

I next add three risk factors related to market liquidity and funding liq-uidity 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. Col-umn (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 IA.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.

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

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.

1.2 Draw Downs

Figure IA.1 shows the draw downs, measured as the difference between the highest past fund value and the current fund value, for the portfolio with the highest exposure to funding risk and the portfolio with the lowest exposure to funding risk.

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.

1.3 Additional Descriptive Statistics

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

1.4 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 port-folios 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 IA.6 shows the returns and risk-adjusted returns of the four different sorts. In addition to the re-turns of the winner portfolio, Table IA.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.

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.

1.5 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 substantially 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 IA.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 simplis-tic along several dimensions, Table IA.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).

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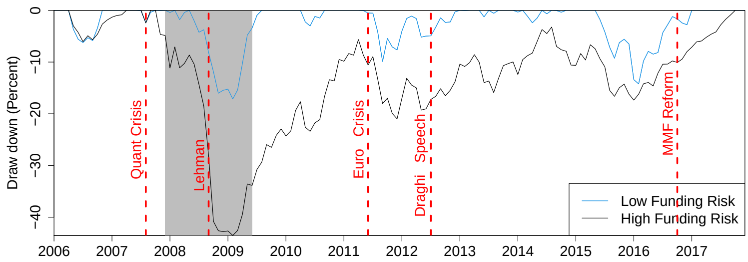

Figure IA.1: Drawdowns of LOIS-sorted hedge fund portfolios.

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 IA.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 IA.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 IA.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 IA.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 IA.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 IA.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 IA.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.