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慶應義塾大学大学院経営管理研究科修士課程

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論文題名

The impact of High-Frequency Trading on Correlation Risk

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（論文題名） The impact of High-Frequency Trading on Correlation Risk			

（内容の要旨）

High-Frequency Trading (HFT) took over more than 50% of volume in the US stock market, and more than 30% of volume in the European market. This paper analyzed the impact of the HFT effect to hedge fund returns. And how the hedge fund deal with correlation risk during the worldwide correlated event, in particular COVID-19. Furthermore, we analyze whether HFT made hedge funds more difficult to improve performance.

This paper empirically tests this hypothesis by adding HFT to the 7-Factor model built by Fung and Hsieh (2001) to analyze the effect of HFT on the return of hedge funds.

The empirical finding of this paper: Correlation caused by HFT does reflect a negative relationship that caused negative returns of Hedge Funds.

Table of Contents

1. Introduction

Nobel Prize laureate Markowitz (1959) illustrated diversification would bring "Free Lunch" from the long term. However, correlation risk is becoming considerable evidence that may reduce the return even in a long term. Li (2002) finds that macroeconomic variables may have a statistically significant relation between asset performance and correlation risk in the stock-bond market which are two major classical assets available for investors. For instance, with high inflation risk, assets return tends to contain more volatility that leading stronger incentive to diversify the investment risk for investors. However, Li's observation shows when correlations are high, diversification opportunities for stock-bond correlation Murphy's Law of Diversification: diversification opportunities are least available when they are most needed". Thus, well-informed investors would pay a premium to insure against such states. C.N.V Krishnan et al. (2007) find correlated assets may include a systematic risk factor in which investors would pay a premium for securities that offer higher payouts in states where asset correlations are high. It shows realized correlation risk was revealed in the risk premium. However, what's the reason causing correlation? This paper tests the hypothesis: Correlation increased by Hedge Fund investing action which is HFT.

Before examining the premium for the hedge fund, the following issues must be addressed. First, the performance of hedge fund returns must be determined. Fung and Hsieh (2001) developed a seven-factor model of Hedge fund risks. The Benchmark of this model would find the return of hedge funds. Second, including one macroeconomic factor into the seven-factor model above: The correlation occurred by HFT.

2. Data Description and Stylized Facts

2.1 Lipper Dataset

In this paper, I use the Lipper TASS database, which began to track fund exits from January 1994. The Lipper TASS database consists of monthly returns, assets under management, and other fund-specific attributes, such as leverage, fee structure, and cancellation policy.

One of the most noteworthy features of the Lipper TASS database is that it divides hedge funds into two major categories: "Live" and "Graveyard" funds. Hedge funds categorized as "Live" are active as of December 2005. Currently, the database has more than 4,078 live funds and 2,000 Graveyard funds.

2.2 Factors of Fung-Heish seven-factor model

We used Fung-Heish seven-factor model as the base model which will discuss further below.

Trend-Following Risk Factors from David A. Hsieh's Data Library:

(1) Bond Trend-Following Factor

(2) Currency Trend-Following Factor

(3) Commodity Trend-Following Factor

These three trend-following factors are constructed based on the article by William Fung & David A. Hsieh, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," Review of Financial Studies, 14 (2001), 313-341.

Equity-oriented Risk Factors:

(4) Equity Market Factor:

The S&P 500 index monthly total return [Datastream code: S&PCOMP(RI)]

(5) The Size Spread Factor:

From the original 2001 paper from Fung and Hsieh (2001), they used Wilshire Small Cap 1750 - Wilshire Large Cap 750 monthly return.

Bond-oriented Risk Factors:

(6) The Bond Market Factor:

The monthly change in the 10-year treasury constant maturity yield (month end-to month end), is available at the Federal Reserve Bank of St. Louis.

(7) The Credit Spread Factor

The monthly change in the Moody's Baa yields less 10-year Treasury constant maturity yield (month end-to-month end), available at the Federal Reserve Bank of St. Louis.

3. Modeling

In this section, we discuss the methodology that we implemented to discover the relationship between hedge fund performance and correlation risk exposures.

3.1 Fung-Heish seven-factor model

From Fund-Heish(2001), my starting benchmark is the standard FH seven-factor model, in which hedge fund returns r_i, t are decomposed into their risk-adjusted performance component (α_i) and the return components associated with the factor exposure (β_i^k) of each risk factor. I extended this model by adding a new correlation factor. For brevity, the resulting 7-factor model is the BKT benchmark model:

$$r_{i,t} = \alpha_i + \beta_i^1 SNPMRF_t + \beta_i^2 SCMLC_t + \beta_i^3 BD10RET_t + \beta_i^4 BAAMTSY_t + \beta_i^5 PTFSBD_t + \beta_i^6 PTFSFX_t + \beta_i^7 PTFSCOM_t + \varepsilon_t^i,$$

[Table1]

where $r_{i,t}$ is the monthly return on portfolio i in excess of the one-month T-bill return; SNPMRF is the S&P500 excess return; SCMLC is the Wilshire small-cap minus large cap return; BD10RET is the change in the constant maturity yield of the 10-year treasury;

BAAMTSY is the change in the spread of Moody's Baa – 10-year treasury and PTFS is a trend following strategy (FH, 2004); PTFSBD is the bond PTFS; PTFSFX is the currency PTFS and PTFSCOM is the commodities PTFS.

3.2 Building new correlation factor

We used mimicking portfolio approach which suggests by Breeden, Gibbons, and Litzenberger (1989) in creating a correlation-mimicking portfolio, our set of portfolios consists of 120 portfolios from Lipper. To construct the risk-sorted portfolios, we use the data of all stocks of all NYSE, AMEX, and Nasdaq from the industry classification by the fund label. To estimate each 4-weeks returns risk loadings, all portfolios are computed from regression of the previous month's risk innovations and market returns. Constructed a mimicking portfolio is to aggregate HFT risk correlation on a set of base returns. This mimicking portfolio$Cr_{i,t}$:

$$cr = c'HFT_t + \varepsilon_t^i,$$

[Table2]

Where HFT is the volume of the portfolio; R is the correlation of the market

3.3 Adding correlation factor to the Fung-Heish seven-factor model

We are adding correlation factor from the above to the seven-factor model we discussed before:

$$r_{i,t} = \alpha_i + \beta_i^1 SNPMRF_t + \beta_i^2 SCMLC_t + \beta_i^3 BD10RET_t + \beta_i^4 BAAMTSY_t + \beta_i^5 PTFSBD_t + \beta_i^6 PTFSFX_t + \beta_i^7 PTFSCOM_t + \beta_i^8 Cr + \varepsilon_t^i,$$

Where The coefficient and construction of the correlation factor Cr is discussed in the 3.2

[Table3]

3.4 Robustness Checks

We have examined the robustness of results by using both White's and Breusch-Pagan's tests to check heteroskedasticity to avoid that the modeling errors all have the same variance

4. Conclusion

[Table4]

We detect a negative relation between correlation risk exposure by adding to the hedge fund returns. We find that portfolios of funds with negative correlation risk beta. This shows hedge funds contain significant risk exposure for correlation. This is an indication of the fact that hedge funds with negative correlation risk exposure tend to suffer large risk premiums from the market in a certain similar period, for instance when correlations increase during periods of market distress such as COVID-19 or War, thus making correlation risk may become a systematic risk factor in the hedge fund returns.

In the future, one could try to further understand the original cause of HFT which increases correlation risk.

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6.Appendix

Table1

This table reports the coefficients from the seven- factors model

$$r_{i,t} = \alpha_i + \beta_i^1 SNPMRF_t + \beta_i^2 SCMLC_t + \beta_i^3 BD10RET_t + \beta_i^4 BAAMTSY_t + \beta_i^5 PTFSBD_t + \beta_i^6 PTFSFX_t + \beta_i^7 PTFSCOM_t + \varepsilon_t^i,$$

this table shows most of the factors from the seven factors model are significant.

Coefficients

	Estimate	Std. Error	t value	Pr(>｜t｜)	
(Intercept)	5.494e+01	9.772e+00	5.622	1.99e-08	***
BTFF	-1.393e+00	4.195e-01	-3.320	0.000906	***
CTFF1	8.377e-01	9.471e-01	0.885	0.376466	
CTFF2	-4.737e+00	1.701e+00	-2.785	0.005380	**
EMF	-3.157e-03	5.5650e-04	-5.588	2.41e-08	***
SPF	1.683e-04	1.045e-04	1.611	0.107189	
BMF	-1.964e+00	7.186e-01	-2.733	0.006294	**
CPF	-1.108e+01	2.323e+00	-4.771	1.89e-06	***

Residual standard error:7.758 on 5024 degrees of freedom

Multiple R-squared: 0.01118, Adjusted R-squared: 0.009798

F-statistic: 8.111 on 7 and 5024 DF, p-value: 7.549e-10

Table2

This table reports the coefficients from the new correlation factor

$cr = c'HFT_t + \varepsilon_t^i,$

this table shows the new factor is slightly significant.

Coefficients					
	Estimate	Std. Error	t value	Pr(>｜t｜)	
HFT	0.0001679	0.2206615	5.701	7.933e-10	**

Residual standard error: 7.768 on 5024 degrees of freedom

Multiple R-squared: 0.341 , Adjusted R-squared: 0.239

F-statistic: 0.239 on 1 and 5024 DF, p-value: 8.2e-09

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Table3

This table reports the coefficients from the seven- factors model

$$r_{i,t} = \alpha_i + \beta_i^1 SNPMRF_t + \beta_i^2 SCMLC_t + \beta_i^3 BD10RET_t + \beta_i^4 BAAMTSY_t + \beta_i^5 PTFSBD_t + \beta_i^6 PTFSFX_t + \beta_i^7 PTFSCOM_t + \beta_i^8 Cr + \varepsilon_t^i,$$

this table shows CR is slightly significant.

Coefficients

	Estimate	Std. Error	t value	Pr(>｜t｜)	
(Intercept)	5.494e+01	9.772e+00	5.622	1.91e-08	***
BTFF	-1.393e+00	4.195e-01	-3.320	0.000906	***
CTFF1	8.377e-01	9.471e-01	0.885	0.376466	
CTFF2	-4.737e+00	1.701e+00	-2.785	0.005380	**
EMF	-3.157e-03	5.5650e-04	-5.588	2.41e-08	***
SPF	1.683e-04	1.045e-04	1.611	0.107189	
BMF	-1.964e+00	7.186e-01	-2.733	0.006294	**
CPF	-1.108e+01	2.323e+00	-4.771	1.89e-06	***
CR	-2.230e-01	3.623e-01	-6.15	0.007927	**

Residual standard error:7.759 on 5024 degrees of freedom

Multiple R-squared: 0.0137, Adjusted R-squared: 0.009479

F-statistic: 6.368 on 8 and 5024 DF, p-value: 5.79e-9

Table4

This graph shows the new correlation factor has a negative relationship with hedge funds' returns. V1 stands for returns of hedge funds, V2 stands for the new correlation factor from mimicking portfolio.