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Three Sections of Applications of Co-Integration: Hedge Funds, Industry and Main Global Equity Markets

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THREE SECTIONS OF APPLICATIONS OF CO-INTEGRATION: HEDGE FUNDS, INDUSTRY, AND MAIN GLOBAL EQUITY MARKETS

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Abstract

Co-integration is an econometric property of time series variables. If two or more series are themselves non-stationary (unit root process), but a linear combination of them is stationary, then the series are said to be co-integrated. If there is a co-integration among some time series, we can say there is a long-run equilibrium. That is the non-stationary time series may diverge from each other in short-run, however they would arrive at equilibrium in long-run. Therefore, we can use this methodology to test the existence of commonality of some non-stationary time series. Here we apply a semi-parametric co-integration test introduced by Cheng and Phillips (2008) to three issues: commonality of hedge funds with different strategies, the co-movement of different industries and financial markets of different countries. The test shows that there is a co-integration among nine different hedge funds strategies and this result provides a support for the factor-seeking methodology used in Agarwal and Naik (2004), Fung and Hsieh (2001), and Fung and Hsieh (2004) which find factors for hedge funds from specific strategy and use these factors to the whole industry. For industry, there is also a full rank co-integration among five industries: consumer, manufactory, high-tech, health and other and therefore different industries co-move with each other in long-run. The test of financial markets of different countries shows that there is no long-run equilibrium among financial markets of USA, UK, Germany, France, Hong Kong, Japan and Singapore.

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Section One: The commonality in hedge fund strategies: A Co-integration analysis

Abstract

Literatures suggest that it's better to construct benchmark for individual fund's performance by focus on the specific strategies the fund manager employs. Fung and Hsieh (2004) derive a seven-factor model for hedge funds from three specified hedge funds strategies, Trend-Following, Fixed Income Arbitrage and Long/Short Equity Hedge and they apply this model to main hedge funds indexes. The model shows nice performance for HFRI, CTI and MSCI, the three main hedge funds indexes from Hedge Fund Research, TASS, and Morgan Stanley Capital International. However, they haven't verified the validity of method that derives factors from specified strategies other than the main method used by Sharpe, and Fama-French which gets factor from one of characteristics of the whole market, such as market factor, size factor and book-to-market factor. This paper investigates the long-term co-movement of hedge funds indexes of nine different strategies by co-integration analysis. We show that nine hedge funds indexes perform co-integration and therefore they may diverge from each other in the short run, but they move together in long term. This result provides a support for the method used in Agarwal and Naik (2004), Fung and Hsieh (2001), Fung and Hsieh (2004). Based on the argument, we can derive benchmark from specified strategy and applied the

benchmark to whole hedge funds industry. The new factor model found in this paper outperforms the Fung and Hsieh's seven factor model.

Introduction

As well known, there are two different kinds of risk in the market, systematic risk and idiosyncratic risk. Systematic risk, also called market risk, is risk that's characteristic of an entire market, a specific asset class, or a portfolio invested in that asset class. Idiosyncratic risk is a risk that affects a very small number of assets, and can be almost eliminated with diversification. Studies on this topic show that only the systematic risk deserves a risk premium. Therefore, speculators, arbitrageurs and hedgers are seeking systematic risk in the market for every single minute. Furthermore, there are many finance models trying to find the common risk factors which reflect on systematic risk, such as CAPM (Sharpe 1964, Lintner 1965 and Mossin 1966), Fama-French three-factor model in Fama and French (1993) and momentum factor model introduced by Jegadeesh and Titman (1993). These models all look at one or more characteristics of the market and form corresponding factors. CAPM takes proxy of the whole market as factor. Fama-French form two other factors from the size and book-to-market aspect of the market. Jegadeesh and Titman found their factor from the momentum phenomenon of the whole market. To some extent, these models successfully catch the points. The Fama-French three-factor model performs well when used to 25 portfolios based on size and book-to-market ratio of firms. A combined four-factor model of market factor, size factor, book-to-market factor and momentum factor in Carhart (1997) helps explain the performance persistence of mutual funds.

Nowadays, researchers look for common factors in new industry, such as hedge funds. However, it's a different story in which researchers don't look at one or more aspect of the whole hedge funds industry. They go to specific kind of hedge funds which deploy similar investment strategy. Hedge fund industry has stayed opaque to the general investing public though they have existed for more than half a century. Hedge funds have attracted many institutional investors and wealthy individuals as alternative investments to traditional portfolios of assets. Increasingly, spectacular hedge fund activities in the last decade, such as the attack on the British Pound led by George Soros and the collapse of Long-Term Capital which prompted the intervention from federal regulators, have heightened the public's interest in the hedge funds industry. The literature on the industry has grown substantially.

Fung and Hsieh (1997) is the pioneer work on hedge funds which investigate the dynamic trading strategy employed by hedge funds other than the traditional buy-and-hold strategy. They provide an extension of Sharpe's style factor model with nine buy-and-hold asset classes and three dynamic trading strategies. This model gets a reasonably high R^2 in the regression of hedge funds returns and shows that hedge funds earn option-like returns. Brown, Goetzmann and Ibbotson (1999) examine the performance of the off-shore hedge fund industry over the period 1989 and 1995. They show that the industry is characterized by high attrition rates of funds, low covariance with U.S. stock market and positive risk-adjusted returns.

Burton and Saha (2005) discuss two biases in the hedge funds data, backfill bias and survivorship bias. They show that the backfilled returns are upwardly biased because only the hedge funds managers who have favorable initial results choose to report their funds to database and survivorship bias puts up the returns for only the successful hedge funds still reporting their performance data to database. However, Ackermann, McEnally and Ravenscraft (1999) show that the positive and negative biases offset each other and then there is no longer significant data bias.

Another import aspect is the existence of manager skill of hedge funds. Hedge funds managers are all sophisticated investors in the market. Therefore they may have some better skill in the investment. In the literatures, researchers use performance persistence to interpret manager skill. Brown, Goetzmann and Ibbotson (1999) haven't found performance persistence. Agarwal and Naik (2000) show significant performance persistence for multi-period framework. Franklin and Mustafa (2001) also show significant persistence for both winner and loser over 1-year and 2-year horizon. However, Markus and Nagel (2004) provide an interesting event study of hedge funds investment during internet bubble. They extract the long positions of hedge funds from SEC on Form 13F and find that the sophisticated managers of hedge funds were heavily invested in technology stocks, or in other words, they didn't exert correcting force on market stock prices. They capture the upturn, but, by reducing their positions in stocks that were about to decline, avoid much of the downturn. From this case we see that managers have skill.

The story of factor form in hedge funds are introduced by Fung and Hsieh (2001), Fung and Hsieh (2004) and Agarwal and Naik (2004) form factors from specific strategies hedge funds. In this paper, we provide a support to this method with a long-run equilibrium perspective.

The structure of this paper is as follows. We investigate the statistical characteristics of hedge funds indexes of different strategies in section II and identify that nine hedge funds indexes follow significant non-stationary process—unit root. Section III demonstrates the risk of hedge funds with the seven factor model. Following the method described at Appendix introduced by Cheng and Phillips (2008) we investigate the co-integration analysis of nine hedge funds indexes in section IV and conclude in section V.

Data

TASS is a good database for academic research on hedge funds because of its relative completeness and accuracy. Up to Nov 2007, TASS cover 4782 live funds and 3991 dead funds. TASS categorizes the hedge funds into eleven different strategies: Convertible Arbitrage, Dedicated Short Bias, Event Driven, Emerging Market, Equity Market Neutral, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long/Short Equity, Managed Futures and Multi-strategy. Since Fund of Funds and Multi-strategy haven't specified the detail strategy employed, here we drop these two kinds of hedge funds and get the rest nine styles. TASS provides hedge funds indexes for these nine styles and another Composite Index of all live hedge funds. In this paper we will use all these ten indexes in analysis. The database assigns the hedge fund to different styles based on the main strategy the hedge fund applies in investment.

Here we use the logarithm values of the indexes. Table I shows the statistical characteristics of the nine hedge funds indexes and Figure I plots the nine hedge funds indexes from Jan 1994 to Nov 2007. Table II shows the unit root test for nine hedge funds indexes based on nine strategies by Augmented Dickey-Fuller test and Phillips-Perron test and we can see that all nine indexes time series show non-stationarity.

From Table I we see that nine hedge funds indexes have similar means, standard deviations and median except for Dedicated Short Bias. The Jarque-Bera tests show that all the nine indexes don't follow a normal distribution.

Table I

Statistical Characteristics of Nine Hedge Funds Indexes

Table I shows mean, standard deviation, median, skewness and kurtosis of nine log hedge funds indexes of 167 observations. All these nine indexes are initiated at 100 and we can see that all increase except for Dedicated Short Bias.

Strategy	Mean	Standard Deviation	Median	Skewness	Kurtosis	p-value of JB test
Convertible Arbitrage	5.22	0.40	5.31	-0.30	-1.30	0.0068
Dedicated Short Bias	4.50	0.15	4.53	-0.09	-1.20	0.0147
Event Driven	5.38	0.45	5.40	-0.08	-0.94	0.0389
Emerging Market	5.07	0.38	5.01	0.57	-0.61	0.0111
Equity Market Neutral	5.29	0.42	5.39	-0.31	-1.23	0.0083
Fixed Income Arbitrage	5.06	0.26	5.05	-0.28	-0.96	0.0207
Global Macro	5.51	0.55	5.52	-0.29	-0.94	0.0217
Long/Short Equity	5.42	0.50	5.59	-0.39	-1.05	0.0104
Managed Futures	5.01	0.27	4.96	0.20	-1.35	0.0074

From Table II, both ADF test and PP test provide a confirmation of unit root of the indexes. Therefore, shocks have permanent effect on the indexes and these nine hedge funds indexes are all non-stationary. Though all nine indexes show non-stationarity, they may have a long-run equilibrium and hence economic forces tend to push the indexes back toward equilibrium whenever they move away. We can do co-integration analysis on these nine hedge funds indexes thereafter.

Co-integration was first introduced by Granger (1981) and Engle and Granger (1987). Co-integration is an econometrical property of time series variables. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series are said to be co-integrated. Engle and Granger introduce a two-step method to deal with this topic. There are many papers which applied co-integration analysis to empirical economic phenomena, such as Campbell and Shiller (1987) and Kim (1990). Campbell and Shiller (1987) find new encouraging results for the rational expectation theory of the term structure and some puzzling results for the present value model of stock price with co-integration analysis. With co-integration method, Kim (1990) investigates the purchasing power parity by examining the bilateral exchange rate-price relationship between US and other five countries: Canada, France, Italy, Japan and UK. Kim concludes that deviations from PPP significantly affect exchange rate in all case except Canada dollar.

Table II

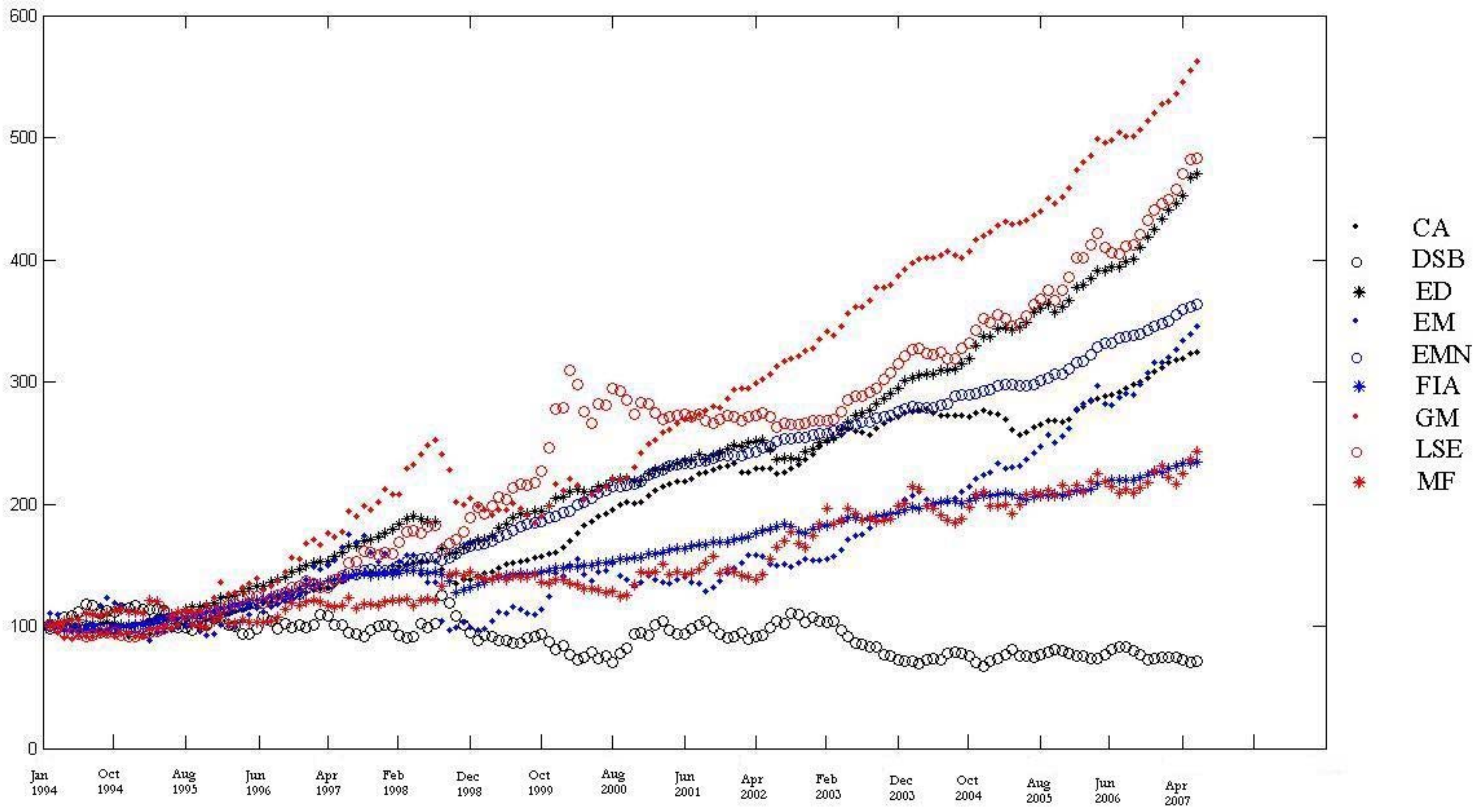
Unit Root Test of Nine Hedge Funds Indexes

Table II shows autoregressive coefficient estimate of nine hedge funds indexes and Augmented Dickey-Fuller test and Phillips-Perron test for unit root. We see from table that the estimated coefficients are around 1 and hence all nine hedge funds indexes are non-stationary. If we take <0.05 as a standard for dying away, the other nine indices should take more than 64 months ($[0.9537]^{64}$= 0.048123 and $[0.9537]^{63}$=0.050459 for High Tech industry) to clear away the shocks ε_t .

$$I_t = \alpha + \beta I_{t-1} + \varepsilon_t$$

Strategy	Estimated β	t-ratio		p-value	
		PP	ADF	PP	ADF
Convertible Arbitrage	0.9984	-0.60	-0.63	0.87	0.86
Dedicated Short Bias	0.9537	-2.04	-1.93	0.27	0.32
Event Driven	1.0006	0.05	0.23	0.96	0.97
Emerging Market	1.006	0.21	0.64	0.97	0.99
Equity Market Neutral	0.9986	-0.80	-0.95	0.82	0.79
Fixed Income Arbitrage	0.9972	-0.80	-0.86	0.82	0.80
Global Macro	0.9982	-0.44	-0.42	0.90	0.90
Long/Short Equity	0.9983	-0.42	-0.38	0.90	0.90
Managed Futures	0.9939	-0.51	-0.60	0.89	0.87

Figure I


600
500
400
300
200
100
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Jan 1994
Oct 1994
Aug 1995
Jun 1996
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Feb 1998
Dec 1998
Oct 1999
Aug 2000
Jun 2001
Apr 2002
Feb 2003
Dec 2003
Oct 2004
Aug 2005
Jun 2006
Apr 2007
CA
DSB
ED
EM
EMN
FIA
GM
LSE
MF

Risk of hedge funds

Hedge fund employs dynamic trading strategy and pursues absolute returns. They can use short selling, leverage, derivatives and highly concentrated investment positions in the market. These characteristics attract many researchers to investigate the risk of hedge funds. Ackermann, McEnally and Ravenscraft (1999) study the risk comparison between hedge funds and mutual funds. They find that hedge funds are significantly riskier than mutual funds. Elton, Gruber and Rentzler (1987) develop a methodology for assessing the contribution of an alternative investment portfolio to an existing portfolio. They shows that if the Sharpe ratio of a new asset group exceeds the product of the Sharpe ratio of the existing portfolio and the correlation of the new asset group and current portfolio, then this new asset group is a valuable addition to the existing portfolio. Ackermann, McEnally and Ravenscraft (1999) calculate the Sharpe ration of hedge funds and of eight standard indices, S&P 500, MSCI EAFE, MSCI World, Wilshire 5000, Russell 2000, Balanced, Lehman Aggregate Bond and Lehman Gov. /Corp. Bond and the correlations between hedge funds and the eight standard indices. They find that hedge funds augment the eight standard indices even applying the maximum correlation according to the method introduced by Elton, Gruber and Rentzler (1987). This means that hedge funds expose to different risk from those traditional risks in the market.

Many researchers aim to find the new common factor of hedge funds. However, hedge funds earn option-like returns, and thus linear models using benchmark asset indices have difficulty explaining the returns. Thus literatures study option-like returns and try to find related benchmark. Glosten and Jagannathan (1994) suggest that the benchmarking of an individual fund's performance may need to incorporate specific aspects of the manager's operation. Following this suggestion, Fung and Hsieh (2001) focus on trend-following of CTA (commodity trading advisors) which has similar feature as hedge funds. They use lookback straddles to form a Primitive Trend-Following Strategies which shown to be more powerful to explain trend-following funds' returns than standard asset indices. They apply PTFS on five kinds of assets and get five portfolios, Stock PTFS, Bond PTFS, Interest rate PTFS, Currency PTFS and Commodity PTFS. When using these five benchmarks in the regression of trend-following funds' returns, Fung and Hsieh (2001) get a sympathetic R^2=0.50. These results show that PTFS returns can replicate key features of trend-following funds' returns and trend-following funds do have systematic risk which owns option-like feature.

Thereafter, Fung and Hsieh (2004) employ three of the PTFS portfolios plus S&P 500, 10-year constant-maturity yield of U.S. Federal Reserve, credit spread (measured by difference between Moody's Baa yield and 10-year constant-maturity yield) and size spread (measured by Wilshire Small Cap 1750-Wilshire Large 750 return) to form a seven-factor model to explain the returns of hedge funds. Credit spread and 10-year constant-maturity yield are benchmarks derived from Fixed

Income Arbitrage strategy and S&P 500 and size spread are derived from Long/Short Equity Hedge strategy. They show regression of the whole hedge funds index from TASS database on these seven factors from Jan 1994 through Dec 2002 and get a R^2=0.48. To say toughly, this means that these factors explain half of the reason of returns of hedge funds. Here we present a similar regression result from Jan 1994 to Jun 2007.

Statistical Table

Source	Sum of Squares	Mean Square	F value	Pr>F
Model	308.95310	44.13616	15.01	<.0001
Error	452.68480	2.93951		
Corrected Total	761.63790			
Root MSE	1.71450		R^2	0.4056
Dependent Mean	0.91153		Adjusted R^2	
Coeff Var	188.09095			

Table III Parameter Estimates

The coefficients estimate in the seven-factor model on CTI (TASS hedge funds index). The 95% significant parameter estimators are figured as bold. PTFSBD, PTFSFX, and PTFSCOM stand for Primitive Trend Follow Strategy of Bond factor, Primitive Trend Follow Strategy of Currency factor, and Primitive Trend Follow Strategy of Commodity factor respectively.

Variable	Parameter Estimate	Standard Error	t-value	p-value
Intercept	0.196	1.312	0.15	0.882
PTFSBD	**-2.43**	0.951	-2.56	0.012
PTFSFX	1.392	0.75	1.86	0.065
PTFSCOM	**2.137**	1.078	1.98	0.049
S&P 500	**0.272**	0.034	7.93	<.0001
10-year	1.635	1.907	0.86	0.393
Size spread	**0.19**	0.037	5.11	<.0001
Credit spread	-1.478	3.488	-0.42	0.672

This seven factors model supports the statement of Mitchell and Pulvino (2001) which show that the risk characteristics of specific hedge fund strategies are better explained by risk factors that are constructed to fit that purpose. However, Fung and Hsieh (2004) derive the benchmarks from three specified trading strategies while there are more strategies left and haven't perform R^2 close to 1 like Fama and French (1993). We wonder whether there is a common factor for whole hedge funds industry. In section II, we show that nine hedge funds indexes for different strategies present unit root. Therefore, they may co-move with each other at long term. In following section, we test the co-integration by the methodology in section IV and do common factor analysis with the co-integration result.

Co-integration testing of hedge funds indexes

In section III, we state that Fung and Hsieh (2004) show that hedge funds do have systematic risk which derived from trend-following, Long/Short Equity Hedge and Fixed Income Arbitrage hedge funds. Hence, with the co-integration of nine hedge funds indexes shown in Appendix II we can say hedge funds of all strategies expose to a new common systematic risk or more.

With the implication we have shown, we can now focus on one strategy deployed by hedge funds and find the risk factor for that strategy and for whole hedge funds industry. Combining the factors shown in Fung and Hsieh (2004) and Agarwal and Naik (2004), here we exclude Size Spread (highly correlated with SMB, ρ=0.922), R3000 (highly correlated with S&P 500, ρ=0.989) and MSCIUS (highly correlated with S&P 500, ρ=0.761, and R3000, ρ=0.711), we get the following factor model:

$$
\begin{aligned}
r_t = \alpha + \beta_1 \text{S\&P500}_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 Bond_t + \beta_6 PTFSBD_t \\
+ \beta_7 PTFSFX_t + \beta_8 PTFSCOM_t + \beta_9 CS_t + \beta_{10} IFCEM_t + \beta_{11} LagR3000_t + \beta_{12} GSC_t + \varepsilon_t
\end{aligned}
$$

And the estimations of the model with nine hedge funds index are shown as follows. In the table, the Adjusted R^2 of CTI is 0.51, higher than 0.38 of the seven factor model. And the model has nice explanatory power when applied to four strategies: Dedicated Short Bias, Event Driven, Emerging Market, and Long/Short Equity.

The simply combined factor-model for nine hedge funds indices and
CTI (An equally weighted average return of all hedge funds in the TASS database)

	CTI	CTICA	CTIDSB	CTIED	CTIEM	CTIEMN	CTIFIA	CTIGM	CTILSE	CTIMF
S&P 500	**0.24**	**0.08**	**-0.85**	**0.18**	0	**0.08**	0.01	**0.22**	**0.4**	-0.09
SMB	**0.12**	**0.09**	**-0.36**	**0.13**	0.03	0	0.02	0.09	**0.23**	-0.01
HML	0.03	0.07	**0.18**	**0.09**	-0.01	0.02	0.04	0.16	**-0.1**	0.16
MOM	**0.15**	0	-0.07	0.03	**0.17**	0	0.02	**0.15**	**0.24**	0.06
BOND	1.72	**3.19**	1.63	0.94	**7.67**	1.42	**2.66**	3.47	-1.16	-1.28
PTFSBD	-1.6	-1.18	0.65	**-2.09**	**-3.07**	0.4	-1.07	-1.72	-0.9	**4.51**
PTFSCOM	1.07	0.68	0.1	0.56	1.06	0.64	0.8	1.56	-0.46	2.95
PTFSFX	1.18	-0.27	-0.71	-0.08	-0.98	**0.84**	-0.66	2.07	0.73	**6.36**
Credit Spread	-0.6	**7.22**	**-15.04**	1.87	9.3	1.77	2.14	1.07	-1.1	-3.98
IFCEM	**0.09**	-0.01	-0.03	**0.07**	**0.62**	0.01	0.02	0.07	**0.06**	**0.13**
LagR3000	0.04	**0.08**	**-0.12**	**0.09**	**0.11**	0.01	0.04	-0.03	**0.09**	**-0.19**
GSC	0.01	0	-0.01	0.01	-0.04	0	0.01	-0.01	**0.05**	0.06
Adjusted R^2	0.51	0.13	0.76	0.59	0.65	0.16	0.06	0.12	0.8	0.27

Moreover, we compare different factor model in the table V. In the table, we base on the simple OLS statistics, Adjusted R^2. The Fama-French three-factor model has the lowest Adjusted R^2. The most powerful model is based on the following eight factors: SMB, S&P 500, Momentum, Credit Spread, PTFS Bond, PTFS Currency, PTFS Commodity and IFCEM (Emerging Market). In all models, the market factor (S&P 500), size factor (SMB), momentum factor (MOM), and Emerging market factor (IFCEM) are significant. In table VI, we apply this optimal eight-factor model to the nine hedge funds indexes and the results are similar to those of twelve-factor model. The abnormal returns of all indexes are positive and therefore the hedge funds could time the market.

Table V performance of different factor model on CTI

In this table we present the parameters estimators and their significance of traditional Fama-French 3-factor model, 4-factor model of Mark Carkart (1997), 7-factor model of Fung and Hsieh (2004), 8-factor model of Fung and Hsieh, and combined 12-factor model. The 95% significant estimators are bold and at the bottom of table we present the adjusted R^2.

Model	3-factor	4-factor	7-factor	8-factor	12-factor	Highest Ad-R^2
abnormal returns	**0.634**	**0.455**	0.196	-0.313	-0.200	**1.116**
t-statistics	4.320	3.350	0.150	-0.240	-0.170	2.370
SMB	**0.212**	**0.191**			**0.121**	**0.117**
t-statistics	4.990	4.950			2.860	3.400
HML	0.040	0.075			0.027	
t-statistics	0.780	1.580			0.560	
S&P 500	**0.277**	**0.344**	**0.272**	**0.187**	**0.239**	**0.223**
t-statistics	7.080	9.270	7.930	4.010	5.020	5.340
MOM		**0.159**			**0.152**	**0.147**
t-statistics		6.000			5.600	5.580
Bond			1.635	2.810	1.720	
t-statistics			0.860	1.460	0.980	
Size Spread			**0.190**	**0.151**		
t-statistics			5.110	3.840		
Credit Spread			-1.478	-1.504	-0.628	-3.325
t-statistics			-0.420	-0.440	-0.200	-1.290
PTFSBD			**-2.430**	**-2.314**	-1.594	-1.652
t-statistics			-2.560	-2.480	-1.830	-1.950
PTFSFX			1.392	**1.514**	1.176	**1.373**
t-statistics			1.860	2.050	1.720	2.060
PTFSCOM			**2.137**	**2.120**	1.072	0.993
t-statistics			1.980	2.000	1.090	1.020
IFCEM				**0.088**	**0.088**	**0.090**
t-statistics				2.650	2.800	2.990
LagR3000					0.045	
t-statistics					1.350	
GSC					0.014	
t-statistics					0.630	
Adjusted R^2	0.3494	0.4674	0.3786	0.4019	0.5070	0.5083

Table V shows that size factor, market factor, momentum factor and emergence market factor are all significant for hedge funds industry index CTI in different factor models and therefore account for some premium of hedge funds. Though adjusted R^2 has many limitations for regression, it provides a suitable criterion for explanatory power of factor model. Based on the adjusted R^2, the best factor model is combined by size factor, market factor, momentum factor, credit spread factor, primitive trend following of bond factor, primitive trend following of currency factor, primitive trend following of commodity factor and emergence market factor.

What's interesting in Table V is that the four-factor model of Carhart (1997) gets a similar high adjusted R^2. The former researches on hedge funds suggest that the Fama-French and momentum factor model is not suitable for hedge funds, for hedge funds deploy the dynamic strategies. Our results show the four-factor model has high explanatory power for hedge funds index CTI. This explains that there are many hedge funds following the market trace.

Table VI The estimations of eight-factor model on the nine hedge funds indexes

In this table we apply the best factor model, based on adjusted R^2, to the nine hedge funds indexes standing for different strategies deployed by hedge funds managers. CA stands for Convertible Arbitrage strategy index, DSB stands for Dedicated Short Bias strategy index, ED stands for Event Driven strategy index, EM stands for Emerging Market strategy index, EMN stands for Equity Market Neutral strategy index, FIA stands for Fixed Income Arbitrage strategy index, GM stands for Global Macro strategy index, LSE stands for Long/Short Equity strategy index, and MF stands for Managed Futures index.

Index	CA	DSB	ED	EM	EMN	FIA	GM	LSE	MF
Abnormal returns	0.285	**3.244**	**0.955**	0.418	**0.718**	**0.735**	1.114	0.731	0.472
t-statistics	0.720	4.390	2.810	0.490	3.110	2.300	1.260	1.760	0.500
SMB	**0.068**	**-0.457**	**0.098**	0.057	-0.003	0.013	0.015	**0.288**	-0.104
t-statistics	2.340	-8.450	3.940	0.910	-0.170	0.570	0.230	9.440	-1.510
S&P 500	0.049	**-0.908**	**0.131**	0.023	**0.074**	-0.013	**0.168**	**0.426**	-0.147
t-statistics	1.380	-13.890	4.340	0.310	3.630	-0.450	2.140	11.550	-1.770
MOM	-0.014	-0.062	0.008	**0.160**	-0.001	0.011	**0.143**	**0.235**	0.087
t-statistics	-0.650	-1.490	0.420	3.360	-0.080	0.640	2.900	10.120	1.660
Credit Spread	2.328	**-14.136**	-1.092	-0.620	0.190	-1.298	-1.649	-1.916	1.235
t-statistics	1.070	-3.490	-0.590	-0.130	0.150	-0.740	-0.340	-0.840	0.240
PTFSBD	**-1.430**	0.521	**-2.519**	-2.935	0.430	-1.088	-1.935	-0.774	**4.615**
t-statistics	-2.000	0.390	-4.120	-1.910	1.030	-1.900	-1.220	-1.030	2.740
PTFSFX	0.107	-0.947	0.400	-0.680	**0.878**	-0.491	2.123	0.962	**2.740**
t-statistics	0.190	-0.900	0.830	-0.560	2.680	-1.090	1.690	1.630	4.440
PTFSCOM	0.416	-0.178	0.468	0.491	0.552	0.649	1.165	-0.143	3.086
t-statistics	0.510	-0.120	0.670	0.280	1.160	0.990	0.640	-0.170	1.600
IFCEM	-0.010	-0.041	**0.083**	**0.588**	0.009	0.019	0.062	**0.074**	**0.149**
t-statistics	-0.390	-0.870	3.840	10.830	0.640	0.910	1.110	2.810	2.510
Adjusted R^2	0.0392	0.7538	0.5168	0.6282	0.1659	0.0131	0.1148	0.7770	0.2158

In the table we can see that the factor model has a nice explanatory power for DSB, ED, EM, and LSE these four strategies. The size factor SMB is significant for CA, DSB, ED and LSE strategies. Market Factor S&P 500 is significant for DSB, ED, EMN, GM and LSE strategies. Momentum factor is significant for EM, GM and LSE strategies. IFCEM is significant for ED, EM, LSE and MF strategies. PTFSBD is significant for CA, ED and MF strategies. PTFSFX is significant for EMN and MF strategies. Credit Spread is only significant for DSB strategy. The factors derived from Primitive Trend Following Strategies are more likely to be statistically insignificant and economically significant; especially that PTFSCOM is insignificant for all strategies.

The credit spread factor is particularly important for DSB strategy. DSB is a hedge fund strategy with which the fund manager takes more short positions than long positions. The increase of credit spread means a bull market and therefore the short position would cause loss of hedge funds. Therefore there is a negative relationship between DSB hedge funds returns and credit spread. The emerging market factor IFCEM is both statistically and economically significant for EM hedge funds returns. This is straightforward.

Furthermore, the abnormal returns in the table are all positive. Based on this factor model, hedge funds can time the market in a 14 years horizon.

Conclusion

This paper investigates the mechanism of risk analysis of hedge funds industry. We provide support for the method used by Fung and Hsieh (2004) which extract risk factors from specified strategies of hedge funds and apply these factors to the whole industry. In the paper, we study nine hedge funds strategies and corresponding logarithm indexes. Nine hedge funds indexes all perform unit root and therefore are non-stationary. The co-integration analysis of these nine non-stationary time series shows that they have co-integration with rank 1. The co-integration confirms that nine different strategies own a long-run equilibrium. Thus hedge funds can be a whole unit and we can do risk analysis of specified strategy. Furthermore, we can employ the risk factor derived from specific strategy to the whole hedge funds industry. The applicability of seven factors to whole hedge funds index in Fung and Hsieh (2004) confirms this mechanism.

However, the dynamic characteristic of hedge funds makes the hedge funds indexes of different strategies away from each other for short-run period. Thus the forecasting of the logarithm returns based on Reduced Rank Regression may fail for all strategies. For long-term, the co-integration explains that there is an equilibrium among the nine hedge funds indexes. Thus the mechanism to seek the common factors of hedge funds industry still works though the incorrect forecasting for some strategies. Therefore, the risk factors found by Fung and Hsieh (2004) are valid for the whole industry and we can say that there exist systematic risk factors in hedge funds industry.

Moreover, we derive an eight-factor model which has the strongest explanatory power. This model outperforms the seven-factor model of Fung and Hsieh (2004). The abnormal returns of nine hedge funds indexes adjusted by the eight-factor are positive which shows that hedge funds can time the market.

Appendix I

This section we demonstrate a semi-parametric co-integration rank selection method introduced by Cheng and Phillips (2008). It applies information criteria to the co-integration rank choice and treats co-integration rank as an order parameter in model selection. It does not require the specification of full model and is sympathetic with semi-parametric estimation approaches to co-integration analysis.

Let X_t be m-vector time series and consider a semi-parametric reduced rank regression $\Delta X_t = \alpha\beta' X_{t-1} + u_t, \quad t \in \{1,...,n\}$, where α and β are $m \times r_0$ full rank matrices, where r_0 is the true co-integration rank, and u_t is a weakly dependent stationary time series with mean zero and continuous spectral density matrix $f_u(\lambda)$. And $X_0=O_p(1)$.

The criterion takes the form

$$IC(r) = \log|\hat{\Sigma}(r)| + \frac{\log n}{n}(2mr - r^2), \text{ where r is the order parameter}$$

$$\text{and } \hat{\Sigma}(r) = \frac{1}{n}\sum_{t=1}^{n}(\Delta X_t - \hat{\alpha}\hat{\beta}' X_{t-1})(\Delta X_t - \hat{\alpha}\hat{\beta}' X_{t-1})', r = 1,...,m.$$

And the co-integrating rank selection criterion based on $IC(r)$

$$\hat{r}_{IC} = \arg\min_{0 \le r \le m} IC(r)$$

Let $S_{00} = \frac{1}{n}\sum_{t=1}^{n}\Delta X_t \Delta X_t', S_{11} = \frac{1}{n}\sum_{t=1}^{n} X_{t-1}X_{t-1}', S_{01} = \frac{1}{n}\sum_{t=1}^{n}\Delta X_t X_{t-1}'$ and $S_{10} = \frac{1}{n}\sum_{t=1}^{n} X_{t-1}\Delta X_t'$

Cheng and Phillips (2008) provides a convenient method to calculate

$\hat{\Sigma}(r)$.

$$|\hat{\Sigma}(r)| = |S_{00}| \Pi_{i=1}^{r}(1-\hat{\lambda}_i)$$

where $\hat{\lambda}_i$,$1 \le i \le r$, are the r largest solutions of $|\lambda S_{11} - S_{10}S_{00}^{-1}S_{01}| = 0$ and $1 > \hat{\lambda}_1 > \cdots > \hat{\lambda}_m$.

We also get m eigenvectors $[\hat{\upsilon}_1, \cdots \hat{\upsilon}_m]$ and then the coefficient in the Reduced rank regression

$$\hat{\beta} = [\hat{\upsilon}_1, \cdots \hat{\upsilon}_{r_{IC}}], \text{ and } \hat{\alpha} = S_{01}\hat{\beta}(\hat{\beta}' S_{01}\hat{\beta})^{-1}$$

Under assumption LP and assumption RR, Cheng and Phillips (2008) prove that $\hat{r}_{IC}$ is weakly consistent for selecting the rank of co-integration r_0.

Assumption LP Let $D(L) = \sum_{j=0}^{\infty} D_j L^j$, with $D_0 = I$ and full rank $D(1)$, and let u_t have Wold representation

$$u_t = D(L)\varepsilon_t = \sum_{j=0}^{\infty} D_j \varepsilon_{t-j}, \text{ with } \sum_{j=0}^{\infty} j^{1/2} \| D_j \| < \infty$$

for some matrix norm $\|\cdot\|$ and where ε_t is $iid(0, \Sigma_\varepsilon)$ with $\Sigma_\varepsilon > 0$. We use the notation $\Gamma_{ab}(h) = E(a_t b'_{t+h})$ and $\Lambda_{ab} = \sum_{h=1}^{\infty} \Gamma_{ab}(h)$ for autocovariance matrices and on sided long run autocovariance and set $\Omega = \sum_{h=-\infty}^{\infty} \Gamma_{uu}(h) = D(1)\Sigma_\varepsilon D(1)' > 0$ and $\Sigma_\varepsilon = E(\varepsilon_t \varepsilon_t')$.

Assumption RR (a) The determinantal equation $|I-\alpha\beta' L|=0$ has roots on or outside the unit circle, $|L|\geq 1$.

(b) Set $\Pi = I_m + \alpha\beta'$ where α and β are $m \times r_0$ matrices of full rank r_0, $0 \leq r_0 \leq m$(if $r_0 = 0$ then $\Pi = I_m$; if $r_0 = m$ then β has full rank m and $\beta' X_t$ and X_t are aymptotically stationary).

(c) The matrix $R = I_r + \beta'\alpha$ has eigenvalues within the unit circle.

This semi-parametric method of co-integration ranking selection is powerful and convenient. Furthermore, this approach is easy to implement in practice. We will apply this approach to co-integration analysis of hedge funds indexes in section V.

Appendix II

Following methodology in section III, we do co-integration analysis of hedge funds indexes. We can see from section II that X_t for hedge funds indexes is a 9×1 vector where t=1,…,167. Thus m=9, n=166.

First, we calculate S_{00}, S_{01}, S_{10} and S_{11}

$$S_{00} = 10^{-4} \times \begin{bmatrix} 2.27 & -1.81 & 1.92 & 2.54 & 0.94 & 1.14 & 1.99 & 1.84 & 0.03 \\ -1.81 & 22.93 & -4.85 & -11.91 & -1.36 & -0.59 & -2.09 & -9.85 & 0.88 \\ 1.92 & -4.85 & 3.45 & 5.69 & 1.24 & 1.13 & 2.86 & 4.00 & 0.05 \\ 2.54 & -11.91 & 5.69 & 20.91 & 1.54 & 1.71 & 6.55 & 8.55 & -0.42 \\ 0.94 & -1.36 & 1.24 & 1.54 & 1.29 & 0.53 & 1.38 & 1.59 & 0.83 \\ 1.14 & -0.59 & 1.13 & 1.71 & 0.53 & 1.39 & 2.02 & 1.17 & 0.23 \\ 1.99 & -2.09 & 2.86 & 6.55 & 1.38 & 2.02 & 10.10 & 4.68 & 3.19 \\ 1.84 & -9.85 & 4.00 & 8.55 & 1.59 & 1.17 & 4.68 & 8.82 & 1.02 \\ 0.03 & 0.88 & 0.05 & -0.42 & 0.83 & 0.23 & 3.19 & 1.02 & 12.08 \end{bmatrix}$$

$$S_{01} = 10^{-1} \times \begin{bmatrix} 0.37 & 0.32 & 0.38 & 0.36 & 0.37 & 0.36 & 0.39 & 0.38 & 0.35 \\ -0.07 & -0.08 & -0.07 & -0.06 & -0.08 & -0.07 & -0.08 & -0.07 & -0.08 \\ 0.48 & 0.41 & 0.50 & 0.47 & 0.49 & 0.47 & 0.51 & 0.50 & 0.46 \\ 0.40 & 0.33 & 0.42 & 0.38 & 0.41 & 0.38 & 0.42 & 0.42 & 0.38 \\ 0.41 & 0.36 & 0.43 & 0.40 & 0.42 & 0.40 & 0.44 & 0.43 & 0.40 \\ 0.26 & 0.23 & 0.27 & 0.25 & 0.26 & 0.25 & 0.27 & 0.27 & 0.25 \\ 0.56 & 0.49 & 0.58 & 0.55 & 0.57 & 0.55 & 0.59 & 0.58 & 0.54 \\ 0.50 & 0.43 & 0.52 & 0.48 & 0.51 & 0.49 & 0.53 & 0.52 & 0.48 \\ 0.28 & 0.24 & 0.28 & 0.27 & 0.28 & 0.27 & 0.29 & 0.29 & 0.26 \end{bmatrix}$$

$$S_{10}=10^{-1}\times\begin{bmatrix} 0.37 & -0.07 & 0.48 & 0.40 & 0.41 & 0.26 & 0.56 & 0.50 & 0.28 \\ 0.32 & -0.08 & 0.41 & 0.33 & 0.36 & 0.23 & 0.49 & 0.43 & 0.24 \\ 0.38 & -0.07 & 0.50 & 0.42 & 0.43 & 0.27 & 0.58 & 0.52 & 0.28 \\ 0.36 & -0.06 & 0.47 & 0.38 & 0.40 & 0.25 & 0.55 & 0.48 & 0.27 \\ 0.37 & -0.08 & 0.49 & 0.41 & 0.42 & 0.26 & 0.57 & 0.51 & 0.28 \\ 0.36 & -0.07 & 0.47 & 0.38 & 0.40 & 0.25 & 0.55 & 0.49 & 0.27 \\ 0.39 & -0.08 & 0.51 & 0.42 & 0.44 & 0.27 & 0.59 & 0.53 & 0.29 \\ 0.38 & -0.07 & 0.50 & 0.42 & 0.43 & 0.27 & 0.58 & 0.52 & 0.29 \\ 0.35 & -0.08 & 0.46 & 0.38 & 0.40 & 0.25 & 0.54 & 0.48 & 0.26 \end{bmatrix}$$

$$S_{11}=\begin{bmatrix} 27.37 & 23.44 & 28.21 & 26.52 & 27.75 & 26.49 & 28.94 & 28.43 & 26.23 \\ 23.44 & 20.29 & 24.14 & 22.73 & 23.75 & 22.74 & 24.72 & 24.30 & 22.52 \\ 28.21 & 24.14 & 29.08 & 27.35 & 28.60 & 27.30 & 29.83 & 29.30 & 27.03 \\ 26.52 & 22.73 & 27.35 & 25.74 & 26.89 & 25.68 & 28.04 & 27.54 & 25.43 \\ 27.75 & 23.75 & 28.60 & 26.89 & 28.13 & 26.85 & 29.33 & 28.82 & 26.59 \\ 26.49 & 22.74 & 27.30 & 25.68 & 26.85 & 25.65 & 27.99 & 27.50 & 25.40 \\ 28.94 & 24.72 & 29.83 & 28.04 & 29.33 & 27.99 & 30.61 & 30.06 & 27.72 \\ 28.43 & 24.30 & 29.30 & 27.54 & 28.82 & 27.50 & 30.06 & 29.54 & 27.23 \\ 26.23 & 22.52 & 27.03 & 25.43 & 26.59 & 25.40 & 27.72 & 27.23 & 25.16 \end{bmatrix}$$

By $|\lambda S_{11}-S_{10}S_{00}^{-1}S_{01}|=0$, we get that $\hat{\lambda}_1$=0.68, $\hat{\lambda}_2$= 0.35, $\hat{\lambda}_3$=0.20, $\hat{\lambda}_4$= 0.14,

$\hat{\lambda}_5=0.12$, $\hat{\lambda}_6=0.08$, $\hat{\lambda}_7=0.06$, $\hat{\lambda}_8=0.02$, $\hat{\lambda}_9=0$, and

$$\hat{\mathrm{V}}=\left[\hat{v}_1,\cdots,\hat{v}_9\right]=\begin{bmatrix} 0.62 & 0.50 & 1.00 & -0.75 & -0.53 & 0.31 & 0.61 & 0.33 & 0.01 \\ 0.22 & -0.18 & 0.13 & -0.24 & 0.20 & 0.01 & 0.21 & -0.42 & -0.25 \\ -0.21 & 1.00 & -0.60 & -0.20 & 1.00 & 0.61 & 1.00 & -0.53 & -0.43 \\ 0.16 & -0.17 & 0.37 & 0.04 & -0.14 & -0.18 & -0.37 & -0.31 & -0.19 \\ -0.08 & -0.02 & -0.69 & 1.00 & 0.83 & -1.00 & -0.70 & -0.58 & -0.04 \\ -1.00 & 0.04 & -0.13 & 0.71 & -0.12 & 0.00 & -0.86 & 1.00 & 1.00 \\ 0.19 & -0.51 & -0.17 & -0.25 & -0.05 & -0.08 & -0.28 & 0.63 & 0.00 \\ -0.01 & -0.66 & 0.61 & -0.15 & -0.61 & 0.18 & 0.16 & 0.03 & -0.07 \\ 0.10 & 0.00 & -0.52 & -0.17 & -0.59 & 0.14 & 0.23 & -0.22 & -0.04 \end{bmatrix}$$

Plus $|S_{00}|=5.92\times10^{-32}$, we get that

Table VII Information Criteria

r	0	1	2	3	4	5	6	7	8	9
$\|\hat{\Sigma}(r)\|(10^{-32})$	5.92	1.92	1.24	0.99	0.85	0.75	0.69	0.65	0.63	0.63
IC(r)	-71.9	-72.51	-72.48	-72.31	-72.12	-71.97	-71.84	-71.74	-71.67	-71.64

Based on Table IV, we get $r_{IC} = \arg\min_{0 \le r \le 9} IC(r) = 1$ and we have

$$\hat{\beta} = [\hat{v}_1] = [0.62\ \ 0.22\ \ -0.21\ \ 0.16\ \ -0.08\ \ -1.00\ \ 0.19\ \ -0.01\ \ 0.10]'$$

$$\hat{\alpha} = S_{01}\hat{\beta}(\hat{\beta}' S_{11}\hat{\beta})^{-1} = [-0.07\ \ 0.00\ \ -0.08\ \ -0.08\ \ -0.09\ \ -0.05\ \ -0.10\ \ -0.10\ \ -0.04]'$$

Thus the RRR model is as following

$$\Delta\hat{X}_t = \hat{\alpha} \times \hat{\beta}' \times X_{t-1} = 10^{-2} \times \begin{bmatrix} -4.45 & -1.62 & -1.13 & 0.56 & 1.53 & 7.23 & -1.36 & 0.09 & -0.75 \\ -0.29 & -0.10 & -0.07 & 0.04 & 0.10 & 0.46 & -0.09 & 0.01 & -0.05 \\ -4.67 & -1.70 & -1.18 & 0.59 & 1.60 & 7.58 & -1.43 & 0.09 & -0.78 \\ -4.67 & -1.70 & -1.18 & 0.59 & 1.60 & 7.57 & -1.42 & 0.09 & -0.78 \\ -5.27 & -1.92 & -1.33 & 0.66 & 1.81 & 8.56 & -1.61 & 0.10 & -0.88 \\ -2.95 & -1.07 & -0.75 & 0.37 & 1.01 & 4.78 & -0.90 & 0.06 & -0.49 \\ -6.46 & -2.35 & -1.63 & 0.81 & 2.21 & 10.48 & -1.97 & 0.13 & -1.08 \\ -6.13 & -2.23 & -1.55 & 0.77 & 2.10 & 9.94 & -1.87 & 0.12 & -1.03 \\ -2.26 & -0.82 & -0.57 & 0.28 & 0.77 & 3.67 & -0.69 & 0.04 & -0.38 \end{bmatrix} \times X_{t-1}$$

The result shows that nine hedge funds indexes have co-integration and therefore hedge funds indexes of different strategies move together of long-run perspective.

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Section two: The co-movement of market: Based on industry

Abstract

There are so many industries in the market and they own different characteristics and many of them perform distinctly different from each other. So can we take the market as a whole? This study shows that there is a long-run equilibrium among five different industries: consumer, manufactory, high-tech, health and other. There is a full rank co-integration among these five industry proxy, which is there are five different linear combination of these five non-stationary time series that can be stationary.

Data

The data used here is from the website of Kenneth R. French. French releases the monthly returns from Jul 1926 to Jul 2008 for five industries: Consumer, Manufactory, High Tech, Health and Other. We here set a basis 100 to all the five industries proxy and then get five time series.

Following the similar process of co-integration test in section one of hedge funds, we first do the unit root test with two methods: Augmented Dickey-Fuller test Phillips-Perron test. Table I shows that all five industry proxies perform as unit root process and four of them are slightly explosive (with $\beta > 1$). If we take <0.05 as a standard for dying away, the other nine indices should take more than 1247 months

($[0.9976]^{1247}$= 0.049967 and $[0.9976]^{1246}$=0.050087 for High Tech industry) to clear away the shocks ε_t. These five proxies are all non-stationary and therefore we do the co-integration analysis.

Table I Unit root test of five industries

In this table we show the PP and ADF test of unit root of five industry proxies. Both methodologies show that all proxies perform as unit root.

$$I_t = \alpha + \beta I_{t-1} + \varepsilon_t$$

Industry	estimated β	t-ratio		p-value	
		PP	ADF	PP	ADF
Consumer	1.0038	3.129	2.909	1	1
Manufactory	1.0086	7.568	6.041	1	1
High tech	0.9976	-1.11	-0.7873	0.7139	0.8218
Health	1.0032	2.309	2.242	1	1
Other	1.0018	0.98	1.123	0.9965	0.9977

Co-integration analysis of the five industry proxies

We use the same semi-parametric co-integration test method introduced by Cheng and Phillips (2008). Here are five time series and all with 985 observations. The procedure here is the same as in the Appendix II of section one.

$$S_{00} = 10^7 \times \begin{Bmatrix} 2.08 & 1.02 & 1.37 & 2.51 & 0.71 \\ 1.02 & 1.51 & 0.96 & 1.43 & 0.40 \\ 1.37 & 0.96 & 4.47 & 1.94 & 0.58 \\ 2.51 & 1.43 & 1.94 & 12.75 & 1.10 \\ 0.71 & 0.40 & 0.58 & 1.10 & 0.35 \end{Bmatrix}$$

$$S_{01} = 10^7 \times \begin{Bmatrix} 7.05 & 4.52 & 4.05 & 17.14 & 2.51 \\ 11.30 & 8.01 & 6.09 & 24.27 & 3.97 \\ 2.11 & 0.78 & -0.48 & 1.52 & 0.52 \\ 15.06 & 10.44 & 12.70 & 30.89 & 5.12 \\ 1.38 & 0.42 & 1.05 & 3.66 & 0.48 \end{Bmatrix}$$

$$S_{10} = 10^7 \times \begin{Bmatrix} 7.05 & 11.30 & 2.11 & 15.06 & 1.38 \\ 4.52 & 8.01 & 0.78 & 10.44 & 0.42 \\ 4.05 & 6.09 & -0.48 & 12.70 & 1.05 \\ 17.14 & 24.27 & 1.52 & 30.89 & 3.66 \\ 2.51 & 3.97 & 0.52 & 5.12 & 0.48 \end{Bmatrix}$$

$$S_{11} = 10^9 \times \begin{Bmatrix} 15.74 & 11.67 & 9.20 & 34.52 & 5.32 \\ 11.67 & 9.02 & 6.61 & 25.32 & 3.96 \\ 9.20 & 6.61 & 6.28 & 20.87 & 3.12 \\ 34.52 & 25.32 & 20.87 & 77.26 & 11.72 \\ 5.32 & 3.96 & 3.12 & 11.72 & 1.81 \end{Bmatrix}$$

By $|\lambda S_{11} - S_{10}S_{00}^{-1}S_{01}| = 0,$ we get that $\hat{\lambda}_1$=0.1105, $\hat{\lambda}_2$= 0.0972, $\hat{\lambda}_3$=0.0013, $\hat{\lambda}_4$= 0.0446,

$\hat{\lambda}_5 = 0.0332$, and

$$\hat{V} = \left[\hat{v}_1, \cdots, \hat{v}_5\right] = \begin{bmatrix} -0.11 & -0.85 & 0.22 & -0.96 & -0.58 \\ -0.03 & -0.02 & 0.05 & 1 & -0.17 \\ 0.04 & -0.37 & -0.003 & 0.20 & 0.47 \\ -0.09 & 0.35 & 0.05 & 0.15 & 0.04 \\ 1 & 1 & -1 & -0.70 & 1 \end{bmatrix}$$

Plus $|S_{00}| = 6.788 \times 10^{35}$, we get that

r	0	1	2	3	4	5
$\|\hat{\Sigma}(r)\| (10^{35})$	6.788	6.0379	5.451	5.444	5.2012	5.0285
IC(r)	82.5056	82.4515	82.3983	82.432	82.4073	82.3806

Thus $r_{IC} = \arg\min_{0 \le r \le 5} IC(r) = 5$

Conclusion

There is a full rank co-integration among the five industries. That is there are five independent linear combinations of these five non-stationary time series which are stationary. Therefore these industries may diverge from each other in short run, but get a long-run equilibrium. Though different industries have distinct characteristics, they would follow a similar trend in the long run.

Many researches use contagion to explain the co-movement of market. However, the co-integration analysis provides a measure of long run co-movement of market.

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Section Three: Co-integration analysis of the financial markets of different countries

Abstract

There are many financial markets in the world and therefore many indices measuring the performance of the corresponding markets. Do the boundaries separate the financial market? Here we investigate the long run characteristics of ten indices of USA, UK, Germany, France, Japan, China, Hong Kong and Singapore: Dow Jones, S&P 500, Nasdaq, Financial Times Stock Exchange, DAX, CAC 40, Nikkei 225, Shanghai Composite, Hang Seng and Strait Times. The methodology used here is the same as the one used in the above two sections. The unit root test explains that all indices except Shanghai Composite perform as unit root process. For China financial market is a very different market from other developed countries and region's financial market, we can take it out of the co-movement analysis of world financial markets. For the rest nine indices, the co-integration analysis shows there is no long run equilibrium among them, even for the three indices of USA financial market. The financial markets diverge from each other in the long run.

Data

We get the indices data from the yahoo finance website. There are three indices from America, Dow Jones, S&P 500, and Nasdaq, three from Europe, FTSE of UK, DAX of Germany, and CAC 40 of France, and four from Asia, Shanghai Composite of China, Nikkei 225 of Japan, Hang Seng of Hong Kong, and Strait Times of Singapore. For different indices launched at different date, we will do some tail cut when doing co-integration analysis.

The unit root test, based on Augmented Dickey-Fuller and Phillips-Perron criteria, shows that all indices except Shanghai Composite perform as unit root process. Chinese financial market is newly market and the system which controls the market is different from the other countries and region. And the rest three indices of Asia can be good proxies for Asia financial market, therefore we can drop Shanghai Composite index to proceed to co-integration analysis. If we take <0.05 as a standard for dying away, the other nine indices should take more than 104 months ($[0.9714]^{104}= 0.0489$ and $[0.9714]^{103}=0.05035$ for Singapore Market) to clear away the shocks ε_t. For DAX is the latest launched index in Nov 1990, we adjust other eight indices to begin with this month. Therefore there are nine indices and each with 218 observations.

Table I Unit root tests of 10 indices

$$I_t = \alpha + \beta I_{t-1} + \varepsilon_t$$

Index	Estimated β	t-ratio PP	t-ratio ADF	p-value PP	p-value ADF
Dow Jones	1.0001	-0.015	0.09	0.956	0.9649
Nasdaq	0.992	-1.461	-1.383	0.5528	0.5915
SandP 500	0.9989	-0.6495	-0.5263	0.8567	0.8833
Shanghai Composite	0.0005	-47.06	-47.04	0.5098	0.5033
Hang Seng	0.9838	-1.621	-1.583	0.4704	0.4898
Nikkei 225	0.9841	-1.587	-1.493	0.4882	0.536
Singapore	0.9714	-2.36	-2.166	0.1543	0.2194
FTSE	0.9905	-1.583	-1.577	0.4901	0.4931
DAX	0.9846	-1.608	-1.522	0.4769	0.5208
CAC 40	0.988	-1.426	-1.294	0.569	0.6328

Co-integration analysis

In the unit root test, all indices except Shanghai Composite perform as unit root process. And we drop China market because of its particularity. After doing the observation match of the rest nine indices, we do the co-integration analysis of the rest nine indices from USA, UK, Japan, Germany, France, Singapore, and Hong Kong with the same methodology of Cheng and Phillips (2008).

$$S_{00}=10^4\times\begin{Bmatrix}13.60 & 3.38 & 1.50 & 23.97 & 13.87 & 3.06 & 5.57 & 7.89 & 5.43\\ 3.38 & 2.89 & 0.54 & 9.70 & 6.43 & 1.06 & 1.81 & 3.26 & 2.21\\ 1.50 & 0.54 & 0.19 & 2.90 & 1.82 & 0.36 & 0.68 & 0.98 & 0.69\\ 23.97 & 9.70 & 2.90 & 116.08 & 38.50 & 10.66 & 13.48 & 18.21 & 12.24\\ 13.87 & 6.43 & 1.82 & 38.50 & 100.11 & 5.50 & 7.51 & 10.75 & 7.89\\ 3.06 & 1.06 & 0.36 & 10.66 & 5.50 & 1.71 & 1.57 & 2.14 & 1.46\\ 5.57 & 1.81 & 0.68 & 13.48 & 7.51 & 1.57 & 3.77 & 4.29 & 3.23\\ 7.89 & 3.26 & 0.98 & 18.21 & 10.75 & 2.14 & 4.29 & 8.30 & 5.34\\ 5.43 & 2.21 & 0.69 & 12.24 & 7.89 & 1.46 & 3.23 & 5.34 & 4.23\end{Bmatrix}$$

$$S_{01}=10^4\times\begin{Bmatrix}8.6 & 2.1 & 1.4 & 6.9 & 54.3 & 3.4 & 9.2 & 1.2 & 3.7\\ 0.1 & -1.0 & 0.0 & -3.3 & 11.4 & 0.3 & 1.0 & -2.4 & -1.5\\ 0.1 & 0.0 & 0.1 & -0.5 & 5.5 & 0.2 & 0.6 & -0.4 & -0.1\\ 25.1 & 3.5 & 3.2 & -7.9 & 109.6 & 8.2 & 16.7 & 3.4 & 10.7\\ -60.4 & -15.5 & -7.2 & -118.7 & -148.9 & -15.5 & -33.7 & -43.1 & -32.0\\ -0.9 & -0.4 & 0.0 & -8.3 & 5.5 & -0.4 & 0.0 & -2.1 & -0.3\\ -0.4 & -0.2 & 0.1 & -3.4 & 21.0 & 0.8 & 1.3 & -2.6 & -1.1\\ 7.6 & 2.2 & 1.1 & 8.7 & 36.1 & 2.9 & 6.1 & 0.4 & 2.1\\ 1.6 & 1.2 & 0.4 & -3.0 & 20.2 & 0.6 & 2.6 & -1.6 & -0.4\end{Bmatrix}$$

$$S_{10}=10^4\times\begin{Bmatrix}8.6 & 0.1 & 0.1 & 25.1 & -60.4 & -0.9 & -0.4 & 7.6 & 1.6\\ 2.1 & -1.0 & 0.0 & 3.5 & -15.5 & -0.4 & -0.2 & 2.2 & 1.2\\ 1.4 & 0.0 & 0.1 & 3.2 & -7.2 & 0.0 & 0.1 & 1.1 & 0.4\\ 6.9 & -3.3 & -0.5 & -7.9 & -118.7 & -8.3 & -3.4 & 8.7 & -3.0\\ 54.3 & 11.4 & 5.5 & 109.6 & -148.9 & 5.5 & 21.0 & 36.1 & 20.2\\ 3.4 & 0.3 & 0.2 & 8.2 & -15.5 & -0.4 & 0.8 & 2.9 & 0.6\\ 9.2 & 1.0 & 0.6 & 16.7 & -33.7 & 0.0 & 1.3 & 6.1 & 2.6\\ 1.2 & -2.4 & -0.4 & 3.4 & -43.1 & -2.1 & -2.6 & 0.4 & -1.6\\ 3.7 & -1.5 & -0.1 & 10.7 & -32.0 & -0.3 & -1.1 & 2.1 & -0.4\end{Bmatrix}$$

$$S_{11} = 10^7 \times \begin{Bmatrix} 7.59 & 1.62 & 0.88 & 11.23 & 12.19 & 1.70 & 4.10 & 3.90 & 3.30 \\ 1.62 & 0.36 & 0.19 & 2.39 & 2.61 & 0.36 & 0.88 & 0.85 & 0.72 \\ 0.88 & 0.19 & 0.10 & 1.31 & 1.44 & 0.20 & 0.48 & 0.46 & 0.39 \\ 11.23 & 2.39 & 1.31 & 17.47 & 18.97 & 2.67 & 6.12 & 5.83 & 4.89 \\ 12.19 & 2.61 & 1.44 & 18.97 & 27.65 & 3.25 & 7.17 & 6.32 & 5.47 \\ 1.70 & 0.36 & 0.20 & 2.67 & 3.25 & 0.43 & 0.95 & 0.88 & 0.75 \\ 4.10 & 0.88 & 0.48 & 6.12 & 7.17 & 0.95 & 2.28 & 2.13 & 1.81 \\ 3.90 & 0.85 & 0.46 & 5.83 & 6.32 & 0.88 & 2.13 & 2.06 & 1.73 \\ 3.30 & 0.72 & 0.39 & 4.89 & 5.47 & 0.75 & 1.81 & 1.73 & 1.47 \end{Bmatrix}$$

By $|\lambda S_{11} - S_{10}S_{00}^{-1}S_{01}| = 0,$ we get that $\hat{\lambda}_1 = 0.2359$, $\hat{\lambda}_2 = 0.165$, $\hat{\lambda}_3 = 0.1348$, $\hat{\lambda}_4 = 0.0045$,

$\hat{\lambda}_5 = 0.0926$, $\hat{\lambda}_6 = 0.0286$, $\hat{\lambda}_7 = 0.0333$, $\hat{\lambda}_8 = 0.0642$, $\hat{\lambda}_9 = 0.052$, and

$$\hat{\mathrm{V}} = [\hat{v}_1, \cdots, \hat{v}_9] = 10^{-2} \times \begin{bmatrix} -6.86 & 15.22 & 5.63 & -44.79 & -2.93 & -5.43 & -15.35 & -12.52 & -8.46 \\ -7.05 & 58.57 & 7.46 & -4.97 & -12.94 & -8.14 & -13.54 & 34.96 & -3.73 \\ 100 & -100 & -100 & 100 & 100 & 100 & 100 & -74.45 & 100 \\ 0.93 & -7.65 & 4.24 & -5.26 & 0.3 & 1.71 & -0.85 & 11.55 & 0.51 \\ 0.19 & 1.42 & 1.13 & -0.6 & 1.67 & -0.27 & -0.89 & 0.32 & -0.57 \\ -3.2 & 21.99 & -26.51 & 72.1 & -7.22 & -13.5 & 2.02 & -42.8 & 10.7 \\ -4.08 & -12.4 & 6.76 & 5.84 & -20.41 & -8.55 & 8.86 & -8.77 & -6.5 \\ -3.53 & 24.45 & -3.34 & 20.48 & 7.77 & 2.31 & 13.73 & -63.26 & 2.02 \\ -0.55 & -40.89 & 0.79 & 13.21 & -0.87 & -2.28 & -6.24 & 100 & -4.77 \end{bmatrix}$$

Plus $|S_{00}| = 2.578 \times 10^{39}$, we get that

r	0	1	2	3	4	5	6	7	8	9
$\lvert\hat{\Sigma}(r)\rvert\,(10^{39})$	2.578	1.97	1.645	1.432	1.417	1.286	1.249	1.207	1.13	1.071
IC(r)	90.75	90.90	91.09	91.27	91.54	91.66	91.81	91.90	91.91	91.88

Thus $r_{IC} = \arg\min_{0 \le r \le 9} IC(r) = 0$

There is no co-integration among the nine indices, even for those three indices from the same US market, Dow Jones, S&P 500, and Nasdaq. In the long run, there is no co-movement of the main financial market: America, Asia and Europe.

Conclusion

Major equity markets in the world are non-stationary process of econometrical perspective. Therefore we can investigate the long run characteristics of the major world equity markets with a co-integration methodology. The co-integration analysis shows that there is no co-integration among the nine indices from America, Asia, and Europe.

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