Three Factors Affecting Emerging and International Hedge Fund Returns: A Behavioral Approach[1]

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ABSTRACT

This paper adds four contributions to the literature. First, it analyzes the risk characteristics for 19 hedge fund categories monthly returns which have never appeared in the previous hedge fund literature. Second, this paper introduces 3 factors that when combined with the CAPM or Fama-French CAPM models are better at measuring risk for hedge fund categories than variables currently being used. These factors are discussed in the Relative Value Hedge Fund Analysis by Swartz and Emami-Langroodi (2018). The strategy-specific CAPM and Fama-French models in this paper are more parsimonious and perform better than the Fung and Hsieh 7-factor model in 18 out of 19 (over 94%) of the categories. The three new variables include the D-Ratio, excess return over an average Drawdown percentage, the L-Ratio, a liquidity factor, and the R-Ratio, a Run-up factor related to momentum. Third, when hedge fund categories are analyzed individually, contrary to previous studies, many categories do not mimic put writing strategies. The fourth contribution is that an additional factor is not needed in this model to explain emerging market returns.

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1. Introduction

This paper identifies three new hedge fund factors that significantly aid in explaining the returns of 19 international hedge fund categories. These factors were analyzed by Swartz and Emami-Langroodi(2018), however, these factors have never been used for international and emerging hedge fund risk and return analysis. It is important for accounting, auditing and finance professionals to grasp and implement the risk factors for alternative investments, such as hedge funds, to use in many areas such as auditing, risk control, investments, cost of capital, option pricing and for many other issues. The approach taken in this paper is dramatically different than the seminal papers by Fung and Hsieh (2004, 2011), Ammann, Huber, and Schmid (2011), and Jurek and Stafford (2015). Unlike previous papers, this paper examines 19 international hedge fund categories individually and does not focus on an aggregate hedge fund index. It is not sufficient in this time period to classify all hedge funds as having the same level of risk as a hedge fund index. It is important to break down each category of hedge funds and explain what drives the returns and risks for each individual category. In this paper, a new factor is not introduced for each category of hedge funds and we do not use the option replication method as in Agarwal and Naik (2004) and Fung and Hsieh (2001) to estimate returns. This paper expands the importance of Drawdown brought forward by Jurek and Stafford (2015), which is an important contribution to the hedge fund literature. However, unlike Jurek and Stafford (2015) this paper does not use an aggregate index, rather this paper uses 19 categories of funds with an asset pricing approach. Questions related to auditing, cost of capital, investment factors, risk controls and general accounting risks require that each category of hedge funds be analyzed relative to their own category and not relative to a general hedge fund index, as in most previous studies. The construction and expansion of the three new factors to explain individual category hedge fund returns is not explored, in the previous literature. As mentioned before, this paper does not use the option pricing approach because the data for many individual hedge fund categories is not consistent with put option pricing concept during a crisis, thus, we do not implement the 9 factor model in Fung and Hsieh (2002) or Jurek and Stafford (2015). The inconsistency of hedge fund returns with option pricing for many categories will be demonstrated in **Table 1**, by considering the monthly return of the hedge fund categories during a crisis and is demonstrated in the empirical results in Section 5. These results are consistent with the Fung and Hsieh (2011), however, we demonstrate this is true across many strategies, not just Long/Short Equity (a.k.a. Equity Hedge). Instead of examining individual hedge fund returns across one category as in Fung and Hsieh (2002, 2011), this paper examines category returns across all 55 hedge fund categories listed. In contrast, common factors in addition to the controlled CAPM and Fama-French factors produce models for each of the 19 international hedge fund categories. A comparison with the Hsieh and Fung 7 factor model is conducted and the empirical results will show that the method and factors used in this paper outperform the Hsieh and Fung 7 factor model in over 94% of the categories, using the most acceptable econometric tests available (SIC, AIC, Adjusted R^2 and many others). The time period analyzed is January, 1998–December, 2014. As a result, our empirical results differ from previous studies regarding hedge fund returns. Capocci and Hubner (2004) document hedge fund outperformance versus the stock indices. Given the time period studied, the hedge fund average return performance in this paper show mixed results for hedge fund category returns outperforming stock indices. Unlike a 7-factor model in Fung and Hsieh (2004), this paper finds that 4 factors (CAPM and the 3 new factors) explain most of the 55 category returns. The dominant factors include the market benchmark return, the D-Ratio (excess return with average duration), L-Ratio (a Drawdown Duration measure), and R-Ratio (Run-up Velocity measure which is related to the momentum). The D-Ratio, L-Ratio, and R-Ratio are statistically significant in 23.6%, 21.8%, and 30.9% of the categories, respectively. The computation of these ratios can be found in Section 2.1. Other factors are occasionally significant in a few categories; however, none of the categories have more than 5 significant factors. Only 6 categories have 5 significant factors. Another contribution of this paper, in contrast to previous research, is that no additional factor is needed to explain emerging market returns.

The impact of these empirical results affects the areas of accounting, auditing, cost of capital, modern portfolio theory, investment risk and return analysis, as well as Consumption and Liquidity-based asset pricing models. Consumption-based Capital Asset Pricing Models (C-CAPM) and Liquidity-based Asset Pricing

Models have received attention as a possible process that could explain the equity premium puzzle. Some of the empirical results in this paper are consistent with the C-CAPM and Liquidity-based Asset Pricing Models.

Consumption-based asset pricing models have had little empirical support over the last 30 years and portfolio based models have been the basis of modern portfolio theory, as demonstrated in Campbell and Cochrane (1999, 2000). Consumption-based theories presented by Lucas (1978), Breeden (1979), Grossman and Shiller (1981), Stulz (1981), Hansen and Singleton (1982, 1983), and He and Modest (1995), and a liquidity based asset pricing model by Holmstrom and Tirole (2002), argue that liquidity or consumption factors should affect asset prices.

The timing of shocks to consumption is tested in Heaton (1995) and Ferson and Constantinides (1991) with some support for consumption habit and local substitution. Unlike the approach taken by Li and Patton (2007), we do not use a proxy for overall market liquidity; rather we use actual historical Drawdown and loss statistics from the past for each category. In other words, we use actual losses investors, on average, did experience in the past in each category. This is a more direct link to consumption. If the overall stock market has a decrease in liquidity this may not lead to actual losses experienced by investors and a corresponding decrease in consumption. Volume and other measures of liquidity in the stock market may decrease and the stock market could increase in value. This should cause an increase in consumption.

In this paper, liquidity-based factors are assumed to be driven by consumption concerns. Liquidity is a proxy for delayed consumption. Drawdown directly affects liquidity, and is important in at least four regards. Liquidity is affected by the level of Drawdown (magnitude), the length of the maximum Drawdown (duration), the average duration of a Drawdown, and the average Drawdown per month in each asset category. Excess returns related to Drawdown are assumed to be driven by liquidity and consumption concerns.

Empirical research in finance has explored asset pricing models using Beta (β), size, and price/book ratios (Fama-French, 1994, 1995). In addition, Fama-French (2014) explore a 5-factor model with value, size, Beta (β), profitability, and investment behavior of a firm.

Jegadeesh, Narasimham, and Sheridan Titman (1993) demonstrate that momentum is a factor in security returns. In addition, Carhart (1997) demonstrates that momentum strategies are important factors affecting stock returns. This literature has been expanded thru studies demonstrating limitations and refinements through Daniel, Grinblatt, Titman, and Wermers (1997) and Sagi (2015).

This paper uses hedge fund category data and cannot determine the underlying investment approach each specific fund (firm) is using in each category. As a result, investment, value, and profitability of previous years cannot be used to ascertain which asset class will perform better in each month or year. However, the size and momentum factors can be examined via proxies used in this study that examine the standard deviation of hedge fund category returns and momentum factors. These ideas are incorporated in this study. In addition, the liquidity and consumption related variables are included that rely on Drawdown related ratios with excess returns.

Hedge Fund returns are examined across 19 international categories (making the assumption of heterogeneous investors an arguably safe assumption). Different hedge fund categories would have payoffs in different states of the economy. These characteristics are consistent with the C-CAPM explaining large risk premiums for different asset classes.

The C-CAPM has a long history and an N-period version of the model is presented as:

$$\sum_{t=1}^{N}\left(\frac{1}{1+r_t}\right)^t C_t \leq A_0 + \sum_{t=1}^{N}\left(\frac{1}{(1+r)^t}\right) y_t \tag{1}$$

Assuming a Power utility function,

$$\frac{C_{t+1}}{C_t} = \left(\frac{1+r}{1+\rho}\right)^{1/\lambda} \tag{2}$$

yields the optimal consumption path (Semmler, 2011). The first order conditions reveal that,

$$U'(C_t) = \frac{1}{1+\rho} E_t\left[\left(1+r_{t+1}^i\right).U'(C_{t+1})\right] \tag{3}$$

which leads to the following condition that must be satisfied,

$$U'(C_t) = \frac{1}{1+\rho} E\left[1+r_{t+1}^i\right].E_t[U'(C_{t+1})] + Cov_t(1+r_{t+1}^i, U'(C_{t+1})) \tag{4}$$

Therefore, according to the C-CAPM, the higher the covariance of as asset's return with consumption, the higher the expected return must be. This covariance is a relevant factor in the C-CAPM. Unlike the empirical research on stock returns, this paper demonstrates that there is a strong covariance between consumption (with Drawdown as a proxy for liquidity and consumption) and hedge fund returns. The results in Section 3, **Table 3,** show strong correlation between hedge fund category returns and the D-Ratio (average Drawdown per month), L-Ratio (Drawdown length measure) and R-Ratio (run-up velocity).

Table 1 summarizes the monthly returns of each category during the financial crisis of 2008. The strategies with returns highlighted in bold are clearly not related to put writing strategies. Eighteen strategies are clearly not in any way related to put writing strategies. Included in this set is Merger Arbitrage category, While the data from 1997-1998 might show that Merger Arbitrage was similar to writing put options, the data from 2008 does not indicate this behavior. Hedge Funds invest in a merger after it is announced and pre-financed. During the financial crisis almost all mergers that were announced, were funded. Almost all mergers announced prior to the financial crisis were completed successfully. In addition, many other strategies had returns of -5% to -10% during the financial crisis, highlighted in bold in **Table 1**. It is not obvious that a strategy with a -10% return, when the financial markets decline almost 50%, are equivalent to put writing strategies. An investor would expect returns to be much lower if they were equivalent to writing put options. A breakdown of the hedge funds by categories finds that the approach of using a model that has put writing is not robust and consistent for individual fund categories. In this paper, standard deviation is rarely significant. If put writing was a robust proxy variable in the individual models, the volatility would be significant frequently. Option pricing models would demand that standard deviation to be a statistically significant variable if a strategy was similar to put writing. While the put writing approach seems to be successful for an aggregate index of hedge fund returns, it is not as useful when breaking returns down by individual category.

Table 1 (*Continued*)
Hedge Fund Categories monthly rate of return percentage for the year 2008.

Hedge Fund Category	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08
Total Emerging Markets	-4.70%	3.48%	-3.32%	1.54%	2.36%	-1.85%	-2.12%	-2.86%	-7.40%	-11.00%	-1.59%	-0.12%
Emerging Markets Composite	-3.75%	2.67%	-5.52%	2.90%	2.06%	-1.50%	-1.75%	-3.76%	-6.86%	-12.90%	-0.88%	3.20%
Multi-Emerging Markets	-6.99%	4.71%	-5.32%	3.05%	2.03%	-4.23%	-2.16%	-4.02%	-10.50%	-15.72%	-5.52%	2.12%
Asia ex/Japan	-7.69%	2.31%	-5.66%	1.22%	0.47%	-7.14%	-0.27%	-4.61%	-4.99%	-8.84%	0.08%	2.56%
BRIC	-7.81%	1.28%	-6.54%	4.36%	0.25%	-4.97%	-3.01%	-4.60%	-11.72%	-13.21%	-2.52%	0.51%
Brazil	-6.27%	6.75%	-7.08%	8.58%	5.03%	-3.76%	-4.17%	-5.68%	-10.39%	-12.25%	-3.28%	0.61%
Russia	-4.15%	2.77%	-2.34%	1.62%	7.58%	-4.37%	-7.57%	-7.94%	-14.56%	-18.55%	-5.41%	-6.10%
India	-11.09%	-3.61%	-10.62%	5.72%	-5.85%	-11.94%	0.19%	-2.13%	-10.32%	-13.62%	-5.48%	3.41%
China	-6.83%	3.47%	-6.56%	2.48%	0.36%	-6.31%	-0.34%	-5.64%	-7.21%	-5.35%	0.28%	4.10%
Korea	-5.83%	4.57%	-1.61%	2.54%	0.14%	-5.20%	-3.42%	-7.00%	-6.57%	-12.26%	-0.22%	7.08%
Latin America	-2.04%	2.99%	-2.94%	3.81%	2.73%	-1.77%	-2.91%	-5.36%	-7.03%	-10.26%	-1.71%	0.21%
MENA	-3.64%	4.15%	-3.47%	3.99%	1.82%	-1.67%	-2.48%	-2.98%	-5.28%	-11.23%	-3.41%	-3.10%
Russia/Eastern Europe	-6.05%	3.50%	-2.76%	0.71%	6.55%	-4.43%	-3.66%	-3.48%	-7.61%	-16.23%	-4.73%	-3.61%
Asia Composite Hedge Fund	**-6.27%**	**1.11%**	**-4.55%**	**1.82%**	**0.66%**	**-4.15%**	**-0.75%**	**-2.20%**	**-3.29%**	**-4.50%**	**0.82%**	**1.48%**
Asia Equally Weighted	**-6.16%**	**1.16%**	**-4.53%**	**1.96%**	**0.82%**	**-3.88%**	**-0.75%**	**-1.93%**	**-3.20%**	**-4.19%**	**0.71%**	**1.46%**
Asia with Japan	**-4.15%**	**1.19%**	**-3.70%**	**1.46%**	**-0.71%**	**-2.52%**	**-1.52%**	**-0.83%**	**-1.66%**	**-1.26%**	**2.53%**	**0.58%**
Japan	**-6.65%**	**-0.03%**	**-4.23%**	**3.19%**	**2.71%**	**-1.96%**	**-0.45%**	**-0.35%**	**-2.96%**	**-2.51%**	**-0.47%**	**1.24%**
Western/ Pan Europe	-3.97%	1.00%	-1.57%	2.70%	0.96%	0.09%	-3.25%	-0.22%	-7.78%	-2.29%	-1.52%	-0.62%
Northern Europe	**0.16%**	**-0.27%**	**-2.16%**	**-0.11%**	**0.88%**	**-1.09%**	**1.00%**	**1.16%**	**-3.89%**	**-2.82%**	**0.49%**	**-0.89%**

2. Data and Summary Statistics

2.1. Data Collection and Variable Construction

For the purpose of our analysis, we have collected and utilized the monthly rate of return data, from January 1998 to December 2014 time period, for 19 international and emerging market hedge fund categories from the Hedge Fund Research (HFR) HFRX indices. The return data for main strategies such as Equity Hedge, Event Driven, Macro/CTA, and Relative Value covers the January 1998 to December 2014 period. Most of the remaining sub-strategies data cover the period of January 2005 to December 2014 and a few strategies have inception dates starting as of January 2004, 2006, or 2008.

The corresponding data for other indices used in our regression analyses such as S&P 500 total monthly return, MSCI World Index monthly return, CRB Index monthly return, as well as market indexes for various countries such as Shanghai Composite Index for China, TOPIX Index for Japan, MICEX Index for Russia, KOSPI Index for Korea, CNX NIFTY Index for India, and BOVESPA Index for Brazil are collected from "Global Financial Data" database. The 3-month and 12-month LIBOR rates based on US dollar are collected from Federal Reserve Bank of St. Louis (FRED) database.

Other variables used in our regression analyses are mainly statistical variables, calculated using the hedge funds' monthly return data. Beside the conventional statistical variables such as mean, standard deviation, skewness, excess kurtosis, Sharpe ratio, and Sortino ratio, we have also utilized our unconventional ratios and variables such as Drawdown and Run-up.

Drawdown is defined as the peak-to-trough decline during a specific record period of an investment, fund or commodity i.e. how low it goes, which is usually quoted as the percentage between the peak and the trough. The Drawdown is measured from the time a retrenchment begins to when a new high is reached. This method is used because a valley can't be measured until a new high occurs. Once the new high is reached, the percentage change from the old high to the smallest trough is recorded.

Drawdown can be mathematically described as if $X = (X(t), t \geq 0)$ is a random process with $X(0) = 0$, the Drawdown at time T, denoted by $DD(T)$, is defined as:

$$DD(T) = max\{0, max_{t\in(0,T)} X(t) - X(T)\} \tag{5}$$

Maximum Drawdown (*Max DD* or simply *DD*), up to time T is the maximum (worst) peak to valley loss since the investment's inception or over the history of the variable (typically the cumulative profit or total open equity of a financial trading strategy or Net Asset Value of an investment). More formally,

$$MaxDD(T) = max_{\tau\in(0,T)}\{max_{t\in(0,\tau)} X(t) - X(\tau)\} \tag{6}$$

The Drawdown Duration as number of Months (*DDM*) is considered as the length of any peak to peak period, or the time between new equity highs i.e. how long the Drawdown lasts. In our research we have considered the duration of maximum Drawdown at each given period of time. For example, for a 5-year period we have considered the number of month corresponding the maximum Drawdown percentage for the 5 years. In cases that we needed to use monthly data for a period of time, the duration of a specific month is calculated for the maximum Drawdown percentage till the end of that month. In other words, the maximum Drawdown percentage and its corresponding duration are re-calculated on a continuous month-to-month basis. In case that a new *Max DD* value is calculated in a given month, it means that we have reached to a new valley (low value). Then by looking back to the peak value before that new valley, we find the inception of new *Max DD* period. Then by counting the number of month from that inception peak to the current value of Drawdown, we can calculate the duration of that Drawdown until that specific point in time.

The Drawdown Velocity (*DDV*) is merely the rate by which the Drawdown happens, i.e. it is the rate by which the variable value declines from the peak to the valley. In calculating the Drawdown velocity we divide the magnitude, not the percentage, of the Drawdown by the duration that it takes for the value to reach from the peak to the valley and is represented by the following equation:

$$Drawdown\,Velocity = \frac{Valley\ value - Peak\ value}{no.\,of\ months\ between\,peak\ and\ valley} \tag{7}$$

Run-up (a.k.a. Draw-up), in this paper, is defined as the valley-to-peak increase during a specific record period of an investment, fund or commodity i.e. how low it goes, which is usually quoted as the percentage between the through and the peak. In contrast to Drawdown, The Run-up is measured from the time an upsurge begins to when a new low is reached.

Maximum Run-up (*Max RU* or simply *RU*), up to time *T* is the maximum (best) valley to peak gain since the investment's inception or over the history of the variable (typically the cumulative profit or total open equity of a financial trading strategy or Net Asset Value of an investment).

The Run-up Duration as number of Months (*RUM*) is considered as the length of any valley to peak period, which is slightly different from Drawdown duration calculation. In other words, we consider the Run-up duration as how long it takes the index value to reach to a new peak from the previous valley. In our research we have considered the duration of maximum Run-up at each given period of time. For example, for a 5-year period we have considered the number of month corresponding the maximum Run-up percentage for the 5 years. In cases that we needed to use monthly data for a period of time, the duration of a specific month is calculated for the maximum Run-up percentage till the end of that month. In other words, the maximum Run-up percentage and its corresponding duration are re-calculated on a continuous month-to-month basis. In case that a new *Max RU* value is calculated in a given month, it means that we have reached to a new peak (high value). Then by looking back to the valley value before that new peak, we find the inception of new *Max RU* period. Then by counting the number of month from that inception to the current value of Run-up, we can calculate the duration of that Run-up until that specific point in time.

The Run-up Velocity (*RUV*) is merely the rate by which the Run-up happens, i.e. it is the rate by which the variable value grows from the valley to the peak. In calculating the Run-up velocity we divide the magnitude, not the percentage, of the Run-up by the duration that it takes for the value to reach from the valley to the peak (i.e. Run-up Duration) and is represented by the following equation:

$$Run - up\ Velocity = \frac{Peak\ value - Valley\ value}{no.\ of\ months\ between\ valley\ and\ peak} \tag{8}$$

Fig. 1 illustrates the components used in calculating Drawdown and Run-up related variables.

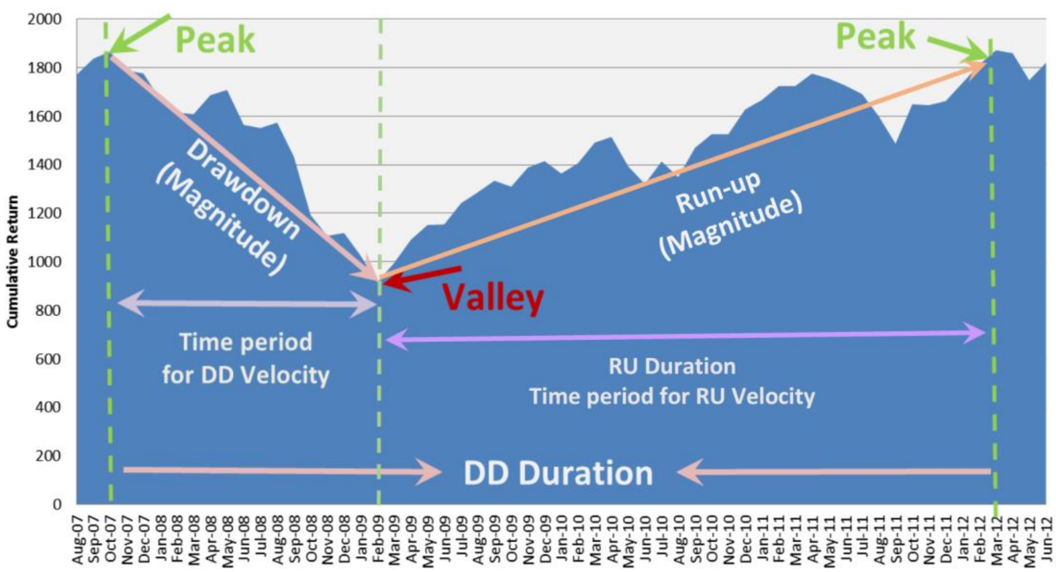


Fig. 1. Graphical illustration of the Drawdown and Run-up related variables

Consequently, the following ratios are the unconventional ratios that we have created and used in our regression modelling to compare their effect with respect to more conventional ratios such as Sharpe and Sortino ratios. The excess return of hedge fund categories, in the numerator, is calculated as the difference between hedge fund category's monthly rate of return and the 3-month LIBOR rate as the threshold.

$$S_1 = \frac{(RoR - 3M\ Libor)}{|DD|} \tag{8}$$

$$S_2 = \frac{(RoR - 3M\ Libor)}{DDM} = L - Ratio \tag{9}$$

$$S_3 = \frac{(RoR - 3M\ Libor)}{|DDV|} \tag{10}$$

$$S_4 = \frac{(RoR - 3M\ Libor)}{RU} \tag{11}$$

$$S_5 = \frac{(RoR - 3M\ Libor)}{RUM} \tag{12}$$

$$S_6 = \frac{(RoR - 3M\ Libor)}{RUV} = R - Ratio \tag{13}$$

$$S_7 = \frac{(RoR - 3M\ Libor)}{\left|\frac{DD}{DDM}\right|} = D - Ratio \tag{14}$$

where, *DD* = maximum Drawdown percentage, *DDM* = Drawdown Duration as number of Months, *DDV* = Drawdown Velocity, *RU* = maximum Run-Up percentage, *RUM* = Run-Up duration as number of Months, and *RUV* = Run-Up Velocity.

2.2. Descriptive Statistics of Hedge Fund Categories

Table A-5 has the descriptive statistics for the Emerging Market Hedge Fund categories. There are 13 categories. The highest mean return category was China with 1.01% per month. Next were India with 0.99% and BRIC 0.81% per month mean returns. The lowest mean returns were in Korea (0.02%) and Russia/Eastern Europe (0.28% per month).The magnitude of Skew was greatest for Multi-Emerging Market (-1.50) and Russia/Eastern Europe (-0.61). The most positive skew was from India category hedge funds (0.36) and China category hedge funds (0.06). The excess kurtosis is largest for Multi-Emerging Markets (5.78) and Total Emerging Markets (2.88). The lowest excess kurtosis was from Korea (0.36) and China (0.42). The data in this time period ranged from January 2005 to December 2014 or from January 2008 to December 2014 as indicated on the table.

Table A-6 lists the statistics for the Asia Region funds. Some of these categories are in Table V Emerging Markets funds. The highest mean return was from China (1.03% mean return per month) and the lowest volatility was from Korea (0.03%). Japan had a mean return of 0.46% per month and a volatility of 2.50% per month. The skew of returns in Japan was a positive 0.46 with a 1.88 kurtosis.

Table A-7 lists the descriptive statistics for Europe Region. There are three categories in Europe, they are Western/Pan Europe, Northern Europe and Russia/Eastern Europe. The highest mean return was 0.58% for Western Europe and the lowest was 0.28% for Russia/Eastern Europe. The volatility was highest in Russia/Eastern Europe (4.34%) and lowest in Northern Europe (1.32%). The category with the most excess kurtosis was Western Europe (2.16) and the least excess kurtosis was in Northern Europe (0.97). Western Europe/Pan Europe had the most negative skew (-0.71) and Northern Europe had the least negative skew (-0.40).

2.3. Drawdown, Run-up, Sharpe, and Sortino Statistics of Hedge Fund Categories

In **Table 2**, Maximum Drawdown, Drawdown Duration, and Drawdown Velocity, Run-up, Run-up Duration, and Run-up Velocity are presented, as well as the Sharpe Ratio and Sortino Ratio for each Hedge Fund category.

For Emerging Market category, the maximum Drawdown was -55.58% for Russia and -54.13% for Latin America. The Sharpe ratio varied from -0.03 for Korea to a high of 0.86 for China. The Sortino ratio varied from a low of 0.76 for Brazil to 2.66 for India and 2.62 for Emerging Markets Composite. China had a 2.46 Sortino ratio.

For Asia region indices, the maximum Drawdown varied from -14% in Asia with Japan and -36.50% for Korea which is also included in Emerging Market category. The longest Drawdown was in Japan (88) and the lowest was in India (19).

For Europe region indices, Northern Europe had a Drawdown of 8% that lasted 22 months. Russia/Eastern Europe, also included as an Emerging Market subcategory, had a Drawdown of 46.50% that lasted 80 months. The Sharpe ratio varied from 0.10 for Russia/Eastern Europe to 0.75 for Northern Europe.

Table 2
Hedge Fund Categories' Drawdown, Run-up, Sharpe, and Sortino monthly Statistics.

Period	Emerging Market Indices	Max. Drawdown (%)	Drawdown Duration (Month)	Drawdown Velocity	Max. Run-up (%)	Run-up Duration (Month)	Run-up Velocity	Sharpe Ratio	Sortino Ratio
Jan 2005 – Dec 2014	*Total Emerging Markets*	-25.56%	34	-28.23	65.64%	36	18.23	0.47	2.30
	Brazil	-33.84%	29	-75.44	73.68%	29	26.24	0.12	0.76
	BRIC	-41.86%	34	-68.55	146.48%	35	41.71	0.51	1.55
	China	-32.30%	22	-56.74	137.06%	24	55.02	0.86	2.46
	India	-25.99%	19	-53.88	78.82%	69	12.27	0.43	2.66
	Latin America	-54.13%	85	-103.03	191.05%	32	58.57	0.43	0.89
	MENA	-31.16%	24	-49.38	103.87%	67	16.91	0.58	1.61
	Multi-Emerging Markets	-39.66%	52	-38.46	107.84%	64	16.76	0.50	1.32
	Russia	-55.58%	33	-147.36	165.12%	41	40.27	0.24	0.77
	Russia/Eastern Europe	-46.57%	80	-13.63	134.13%	41	32.71	0.10	1.53
Jan 2004 – Dec 2014	*Asia ex-Japan*	-35.53%	87	-60.60	140.68%	42	30.86	0.48	0.98
Jan 2006 – Dec 2014	*Emerging Markets Composite*	-26.57%	24	-37.89	71.11%	24	29.63	0.61	2.62
Jan 2008 – Dec 2014	*Korea*	-36.57%	40	-24.38	69.70%	30	14.74	-0.03	1.22
	Asia & Europe Indices								
Jan 2004 – Dec 2014	*Asia Composite Hedge Fund*	-23.39%	39	-31.32	103.81%	131	7.92	0.62	2.18
	Asia Equally Weighted	-22.24%	39	-30.08	111.98%	124	9.00	0.67	1.77
	Asia with Japan	-14.35%	24	-19.30	143.65%	125	11.24	0.87	2.18
	Japan	-23.39%	88	-8.75	56.86%	68	9.34	0.41	1.54
Jan 2005 – Dec 2014	*Western/Pan Europe*	-19.80%	64	-21.89	66.98%	34	19.70	0.69	1.99
	Northern Europe	-8.06%	22	-7.00	71.12%	114	6.24	0.75	2.45

3. Hedge Fund Returns Correlation with Market Index and Performance Ratios

Table 3 summarizes the correlation of each hedge fund index return with the market index return and performance ratios. The market index for U.S. based hedge fund strategies is S&P 500 index, for regions in Emerging Market category, Asia, and Europe regions is MSCI World index, and for specific countries, the related market benchmark is used (e.g. Bovespa for Brazil, Nifty for India etc.).

The Emerging Market category correlations, indicates that the D-Ratio outperformed the Sharpe and Sortino ratios in 11 of the 13 categories. The D-Ratio varied from 55% to 21% across strategy categories. The returns of this hedge fund category has a market correlation varying between 57% and 87%. The D-Ratio correlation varies from 19% to 55%. L-Ratio is negatively related to 2 of the categories. R-Ratio has a correlation between -4% and 38%.

In the Regional (Asia and Europe) indices correlations, which may overlap with Emerging Market sub-categories, , for the Asian Region, the D-Ratio outperformed the Sharpe and Sortino ratios in 5 of 8 categories varying from 19% to 55% for the Asia Region indices returns. For the Europe Region, the D-Ratio correlation was higher than both the Sharpe and Sortino ratio in every category varying from 26% to 39%. R-Ratio matched or was higher than the Sharpe and Sortino ratios in each category, as well. For these indices (Asia and Europe), the correlation with the market varies from 57% to 87%. L-Ratio was negatively related to 3 of the 8 hedge fund categories. In the Europe Region, the correlation with the S&P 500 varies from 43% to 73%. The factor, L-Ratio, has a negative correlation with Northern Europe and a positive correlation with Western and Eastern Europe.

The **Appendix B** lists the correlations of hedge fund indices returns' standard deviations and skewness with the variables/ratios constructed in this paper. The Emerging Markets Category had 8 out of 19 D-Ratios that were significant

Table 3 (*Continued*)
Hedge Fund Categories' Rate of Return Correlations with Market Benchmark & Performance Ratios.

Emerging Market Indices	**Market RoR**	**S_1**	**S_2 (L-Ratio)**	**S_3**	**S_4**	**S_5**	**S_6 (R-Ratio)**	**S_7 (D-Ratio)**	**Sharpe Ratio**	**Sortino Ratio**
Total Emerging Markets	84%	22%	8%	19%	13%	10%	25%	27%	24%	23%
Emerging Markets Composite	69%	2%	-5%	12%	9%	2%	25%	21%	18%	16%
Multi-Emerging Markets	82%	21%	5%	22%	19%	21%	24%	25%	22%	24%
Asia ex/Japan	69%	27%	13%	30%	14%	15%	25%	19%	22%	25%
BRIC	82%	31%	4%	34%	28%	29%	32%	33%	28%	33%
Brazil	79%	-6%	16%	9%	7%	12%	33%	33%	21%	20%
China	57%	-10%	21%	-21%	-8%	-8%	10%	55%	25%	30%
India	87%	-13%	8%	-8%	-10%	-6%	3%	42%	22%	24%
Korea	79%	28%	28%	23%	29%	12%	28%	25%	26%	24%
Latin America	76%	16%	5%	17%	19%	23%	22%	23%	19%	19%
MENA	84%	15%	3%	19%	18%	13%	22%	22%	19%	20%
Russia	86%	-20%	-4%	-22%	-23%	-21%	-4%	55%	27%	28%
Russia/Eastern Europe	73%	33%	26%	34%	35%	33%	38%	38%	34%	33%
Asia & Europe Indices										
Asia Composite Hedge Fund Index	71%	1%	-2%	11%	9%	3%	29%	26%	23%	12%
Asia Equally Weighted Index	70%	3%	-2%	16%	10%	9%	28%	30%	23%	16%
Asia with Japan	58%	2%	7%	11%	16%	19%	27%	23%	20%	12%
Japan	79%	8%	-2%	9%	6%	3%	21%	10%	17%	9%
Western/Pan Europe	57%	35%	15%	32%	35%	33%	37%	39%	37%	37%
Northern Europe	43%	11%	-8%	12%	11%	7%	26%	26%	20%	20%

4. Regression Model Estimation, Selection, and Diagnostic Methodology

Each model is tested and corrected for multi-collinearity (Variance Inflation Factor stat.), autocorrelation (Durbin-Watson stat. and first order Autoregression modelling), Stationarity (Partial Autocorrelation Function, Augmented Dickey-Fuller Unit Root Test), Heteroskedasticity (White test), and Conditional Heteroskedasticity (ARCH, GARCH, and EGARCH modelling). The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are examined for the best model selection, with the SIC favored, as an indicator of the parsimony model, if there is a disagreement among these indicators. The significant variables estimations are the result of testing and correcting the models for all of these issues.

Based on the Gauss-Markov theorem we check the following assumptions to see whether Ordinary Least Squares (OLS) estimated coefficients are Best Linear Unbiased Estimators (BLUE) or not. Here "best" means giving the lowest variance of the estimate, as compared to other unbiased, linear estimators. The errors do not need to be normal, nor do they need to be independent and identically distributed (only uncorrelated with mean zero and homoscedastic with finite variance).

The requirement that the estimator be unbiased cannot be dropped, since biased estimators exist with lower variance. If these assumptions are violated, then it may be that OLS estimators are no longer “unbiased” or “efficient”. That is, they may be inaccurate or subject to fluctuations between samples.

- **Assumption (1): $E(\varepsilon_t) = 0$:** Expected value of residual error is zero. If this assumption is not satisfied, the Intercept parameter will be biased, but there will be no extreme effect on other parameters.

- **Assumption (2): $Var(\varepsilon_t) = \sigma_\varepsilon^2 < \infty$:** i.e. the variance is constant which is homoskedasticity assumption, if the errors do not have a constant variance they are said to be heteroskedastic. This assumption is specifically important for cross-section data. If the errors are heteroskedastic, the coefficient estimates would still be the "correct" (assuming that the other assumptions required to demonstrate OLS optimality are satisfied), but the problem would be that the standard errors could be wrong. Therefore, if we were trying to test the hypotheses about the true parameter values, we could end up drawing the wrong conclusions. In fact, for all of the variables except the constant, the standard errors would typically be too small, so that we would end up rejecting the null hypothesis too many times. We have tried to address the unconditional heteroskedasticity issue by using the heteroskedasticity robust standard errors which correct for the problem by enlarging the standard errors relative to what they would have been for the situation where the error variance is positively related to one of the explanatory variables. To implement this technique, HAC (Heteroskedasticity and Autocorrelation Consistent) covariance matrix estimation (i.e. Newey–West estimator) is used to provide an estimate of the covariance matrix of the parameters of a regression-type model when this model is applied in situations where the standard assumptions of regression analysis do not apply. The estimator is used to try to overcome autocorrelation, or correlation, and heteroskedasticity in the error terms in the models. This is often used to correct the effects of correlation in the error terms in regressions applied to time series data. Since we are dealing with time-series data, we give a higher priority to Conditional Heteroskedasticity issue in our residuals and in case of existence of this issue we use Autoregressive Conditional Heteroskedasticity (ARCH) estimation techniques instead of OLS. These techniques, depending on the order of heteroskedasticity and existence of sign or size bias in under-study data, can vary and in our analysis they include estimation methods such as ARCH, GARCH (Generalized ARCH), or EGARCH (Exponential GARCH).

- **Assumption (3): $E(\varepsilon_t.\varepsilon_{t-1}) = 0$:** It is assumed that the errors are uncorrelated with one another, otherwise there would be Autocorrelation (Serial Correlation). We want our residuals to be random, and if there is evidence of autocorrelation in the residuals, then it implies that we could predict the sign of the next residual and get the right answer more than half the time on average. This assumption is specifically important for time-series data. If this assumption is violated, there would be Autocorrelation (Serial Correlation) among the residuals. Then the value of estimated coefficient is Unbiased but, it is Inefficient meaning that the Standard Error is unknown, so, performing the t-test calculation and hence checking the significance of the coefficients would not be possible. If the form of the Autocorrelation is known, it would be possible to use a GLS procedure. One approach, which was once fairly popular and is used in addressing the autocorrelation issue in our models, is known as the Cochrane--Orcutt procedure. Such method works by assuming a particular form for the structure of the autocorrelation (usually a first order autoregressive, AR(1), process). Existence of Autocorrelation in our estimated models is tested by Durbin–Watson (DW) statistic and checking the existence of positive or negative serial correlation by considering the critical DW values as a test for first order autocorrelation. If the Durbin–Watson statistic is substantially less than 2, there is evidence of positive serial correlation. As a rough rule of thumb, if Durbin–Watson is less than 1.0, there may be cause for alarm. Small values of DW indicate successive error terms are, on average, close in value to one another, or positively correlated. If DW is greater than 2, successive error terms are, on average, much different in value from one another, i.e., negatively correlated.
- **Assumption (4): Nonexistence of severe Multi-Collinearity between independent variables:** This assumption is violated due to very high correlation among independent variables. Some statistical errors, caused by violation of this assumption that we can refer to include, inconsistent regression statistics and/or inconsistent signs of coefficients. This is where the individual repressors

are very closely related, so that it becomes difficult to disentangle the effect of each individual variable upon the dependent variable. This causes the estimated coefficients to be Biased, Inefficient and Inconsistent. We test the existence of severe multi-collinearity by performing coefficients diagnostics test of Variance Inflation Factor (VIF) which quantifies the severity of multi-collinearity in an ordinary least squares regression analysis. It provides an index that measures how much the variance (the square of the estimate's standard deviation) of an estimated regression coefficient is increased because of collinearity. In our analyses, the cut-off value of VIF = 10 is used as a [rule of thumb] critical value for existence of severe multi-collinearity. Solving the severe multi-collinearity issue is addressed by dropping one or some of the highly collinear variables, if possible, or by transforming the highly correlated variables into a ratio and include only the ratio and not the individual variables in the regression.

- **Assumption (5): Stationary Variables:** A time-series variable is Stationary if its mean, variance and Covariance are stationary. We check the Stationary assumption using following methods:

  1) Checking the existence of any kind of trend (upward or downward) or any kind of evidence to show non-constant mean or variance in the variable graph.

  2) Corrologram: As a sign of Non-Stationary data, the Partial Autocorrelation Function's (PACF) first lag should be significant with a value close to 1 while the rest of the lags are insignificant or much smaller than 1, and Autocorrelation Function (ACF) should show many significant lags that are gradually decreasing in value.

3) Augmented Dickey-Fuller Unit Root Test: the Null Hypothesis for this test states that the under-study variable has a unit root, i.e. it is Non-Stationary. By checking the P-value of this test, we can decide whether reject the null or fail to reject the null hypothesis for confidence level α = 5%.

Since we are utilizing the Rate of Return (%) as our dependent variable, and after performing the above-mentioned methods, no non-stationarity is observed in our under-analysis dependent variables. In specific situations that we used some of the risk factors such as Skewness or Standard Deviation as our dependent variables, the non-stationary behavior is observed in which case the estimation is performed on the first difference transformation of the under-study variables.

For the purpose of model selection, among possible candidate reliable models, we have utilized the information criteria, AIC and SIC, as the basis of our judgement.

Let:

- n = number of observations (e.g. data values, frequencies)
- k = number of parameters to be estimated (e.g. the Normal distribution has 2: μ and σ)
- L_{max} = the maximized value of the log-Likelihood for the estimated model (i.e. fit the parameters by Maximum Likelihood Estimation (MLE) and record the natural log of the Likelihood.)

▪ SIC (Schwarz Information Criterion):

$$SIC = ln[n]\, k - 2ln[L_{max}] \tag{15}$$

- AIC (Akaike Information Criterion):

$$AIC = \left(\frac{2n}{n-k-1}\right) k - 2\, ln[L_{max}] \tag{16}$$

The aim is to find the model with the lowest value of the selected information criterion. The ($-\,2ln[L_{max}]$) term appearing in each formula is an estimate of the deviance of the model fit. The coefficients for k in the first part of each formula show the degree to which the number of model parameters is being penalized. For $n > \sim 20$ or so the SIC (Schwarz, 1997) is the strictest in penalizing loss of degree of freedom by having more parameters in the fitted model. For $n > \sim 40$ the AIC (Akaike, 1974, 1976) is the least strict of the two.

In most cases, we prefer the model that has the fewest parameters to estimate, provided that each one of the candidate models is correctly specified. This is called the most parsimonious model of the set. The AIC does not always suggests the most parsimonious model, because the AIC function is largely based on the log likelihood function. Davidson and McKinnon (2004) indicates that whenever two or more models are nested, the AIC may fail to choose the most parsimonious one, if that these models are correctly specified. In another case, if all the models are non-nested, and only one is well specified, the AIC chooses the well-specified model asymptotically, because this model has the largest value of the log likelihood function.

The SIC avoids the problem discussed above by replacing $2n/(n - k - 1)$ in the AIC function with the $ln(n)$ term. As $n \to \infty$, the addition of another lag would increase the SIC value by a larger margin. Hence, asymptotically, SIC would pick the more parsimonious model than AIC might suggest.

5. Empirical Results

5.1. *Emerging Market Category Empirical Results Analysis*

The 3D Plot of Multi-Emerging Market category return with the MSCI index return and the D-Ratio indicates a positive relationship with both factors, with a couple of outlier points at the high end of Multi-Emerging Market returns.

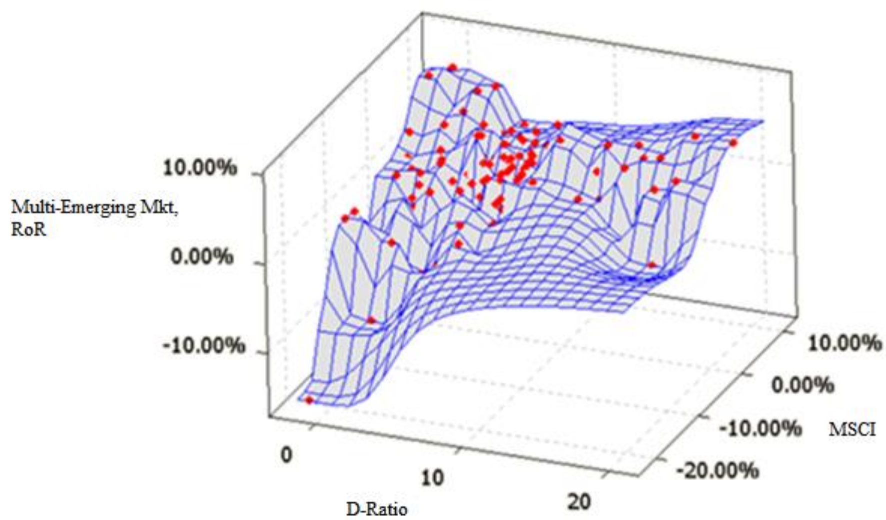


Table 8 lists the results for the Emerging Markets hedge fund strategies. It lists models using GARCH, OLS, and EGARCH depending on the characteristics of each set of returns. Total Emerging Markets had the MSCI index return, Sharpe Ratio, and Kurtosis as significant variables in an EGARCH model with an adjusted R-squared of 75%. Multi-Emerging Markets had a model with the MSCI index return and D-Ratio in a GARCH model with an adjusted R-squared of 66.70%. The Emerging Market Composite model used a GARCH process with the MSCI index return, R-Ratio, and Drawdown (negatively related) to generate a model with an adjusted R-squared of 49%.

Asia ex-Japan was an EGARCH process with the MSCI index return and S_3 (Drawdown Velocity Ratio) as significant variables. Brazil hedge fund returns had a model with local market benchmark return (BOVESPA) significant with adjusted R-squared of 61%. The correlation of many emerging market hedge funds to the local domestic stock market is unusually high indicating the strategies may be relatively simple long related strategies with little diversification benefits.

BRIC category funds generated a model that has an EGARCH process with the MSCI index return, S_1, SD, L-Ratio (negatively related), and S_4. This model has an SIC of -4.74 and an adjusted R-squared of 79.50%. The China hedge fund category had a model with the Shanghai Composite index return, D-Ratio, Sharpe Ratio, and R-Ratio as significant factors. The SIC was -4.54 and the adjusted R-squared was 57.60%.

India hedge fund category had only the Nifty market index return as a significant factor with an adjusted R-square of 75.60%. Korea had only the KOSPI market index return as a significant factor with an adjusted R-squared of 62%. The correlations of returns across this category with only the local stock market index as a factor raising questions on the benefits of these funds for local investors in terms of diversification and risk management.

In the Latin America hedge fund category, only the MSCI index return and the D-Ratio were significant with an approximate adjusted R-squared of 62%. The Middle East North Africa (MENA) category had only the MSCI index return and the D-Ratio, also. The adjusted R-squared for the MENA category was 71%.

The Russia hedge fund category listed the MICEX market index return, Sharpe Ratio, and R-Ratio in a GARCH process with an adjusted R-squared of 78.90%. The Russia/Eastern Europe category had the MSCI index return, R-Ratio (Run-up Velocity Ratio), and L-Ratio (Drawdown Month Ratio was negatively related).

The Emerging Market category indicated that the CAPM controlled models outperformed the Fung and Hsieh 7-factor model in 11 out of 13 categories. Only the Korea and Middle East North Africa (MENA) hedge fund categories showed outperformance for the Fung and Hsieh 7-factor model. The

Fama-French model, if available, outperformed in 7 of 7 categories. Some Fama-French models did not have SML (Size premium) or HML (Value premium) as a significant factor, in which case the model does not generate results which are different from the CAPM model and hence the model is excluded.

Nine of the thirteen categories have at least one of the three new factors, with the R-Ratio and D-Ratio being equally dominant. Only one category (BRIC) has standard deviation as a significant variable. The standard deviation is one of the six variables in every option pricing model. Unlike the index returns, the lack of significance of standard deviation (volatility) in most models provides evidence against the concept that individual hedge fund category returns are simulating put writing strategies.

Recall that all models have been tested and corrected for multi-collinearity, serial correlation, heteroscedasticity, and conditional heteroscedasticity in order to guarantee the robustness and stability of the final generated models. Therefore, none of these issues exist in the presented models.

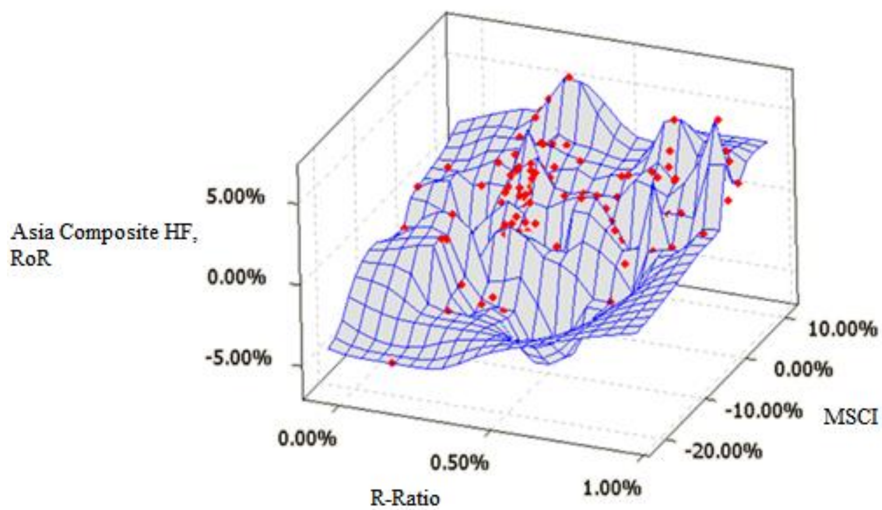
Table 8
Emerging Market Category Regression Models.

EMERGING MARKET	Model	Regression Model									Est. Method	Adj. R^2	AIC	SIC
Total Emerging Markets	FH 7-factor	$R_{Total\ EM}$ =	0.002 +	0.36R_{MSCI} -	0.08SML +	6.45T10Y +	0.88CRSPRD -	0.98BdOpt -	0.03FXOpt+	0.13ComOpt	OLS	75.8%	-5.77	-5.58
			(0.92)	(9.24)	(-1.47)	(0.68)	(0.72)	(-1.01)	(-0.43)	(3.73)				
	CAPM	$R_{Total\ EM}$ =	-0.02 +	0.45R_{MSCI} +	0.01SHARPE +	0.004KURT					EGARCH	75.20%	-5.92	-5.78
			(-3.43)	(22.6)	(4.74)	(3.02)								
	FF	$R_{Total\ EM}$ =	-0.03 +	0.44R_{MSCI} +	0.02SHARPE +	0.006KURT -	0.25HML				OLS	78.30%	-5.90	-5.78
			(-3.91)	(18.24)	(4.74)	(3.51)	(-3.90)							
Multi-Emerging Markets	FH 7-factor	$R_{Multi\text{-}EM}$ =	0.002 +	0.51R_{MSCI} -	0.19SML -	19.57T10Y +	1.00CRSPRD -	1.20BdOpt +	0.19FXOpt+	0.18ComOpt	OLS	71.9%	-5.23	-5.04
			(0.70)	(9.93)	(-2.48)	(-1.58)	(0.62)	(-0.95)	(1.90)	(4.19)				
	CAPM	$R_{Multi\text{-}EM}$ =	-0.001 +	0.43R_{MSCI} +	0.001D-Ratio						GARCH	66.70%	-5.32	-5.18
			(-0.41)	(16.71)	(2.26)									
	FF	$R_{Multi\text{-}EM}$ =	-0.02 +	0.51R_{MSCI} -	0.38HML +	0.02SORTINO -	0.09DD -	0.03RU			OLS	76%	-5.40	-5.26
			(-2.55)	(16.41)	(-4.67)	(4.80)	(-4.09)	(-3.41)						
Emerging Markets Composite	FH 7-factor	$R_{EM\ Comp}$ =	-0.003 +	0.33R_{MSCI} -	0.13SML -	0.88T10Y +	3.60CRSPRD +	0.58BdOpt +	0.18FXOpt+	0.17ComOpt	OLS	52.6%	-5.11	-4.91
			(-0.81)	(5.84)	(-1.51)	(-0.06)	(2.10)	(0.42)	(1.59)	(3.54)				
	CAPM	$R_{EM\ Comp}$ =	-0.04 +	0.23R_{MSCI} +	6.06R-Ratio -	0.10DD					GARCH	49.46%	-5.31	-5.13
			(-3.52)	(7.05)	(4.29)	(-2.86)								
	FF	$R_{EM\ Comp}$ =	-0.05 +	0.33R_{MSCI} -	0.35HML +	6.02R-Ratio -	0.11DD				OLS	58.76%	-5.28	-5.15
			(-2.96)	(9.77)	(-3.80)	(3.58)	(-2.57)							
Asia ex-Japan	FH 7-factor	$R_{Asia\ ex\text{-}Japan}$ =	0.001 +	0.32R_{MSCI} +	0.04SML -	2.90T10Y +	2.85CRSPRD -	1.24BdOpt -	0.03FXOpt+	0.19ComOpt	OLS	42.7%	-4.48	-4.28
			(0.09)	(4.27)	(0.35)	(-0.18)	(0.86)	(-0.81)	(-0.27)	(3.40)				
	CAPM	$R_{Asia\ ex\text{-}Japan}$ =	-0.001 +	0.45R_{MSCI} +	6.06S_3 +	[AR(1) = 0.29]					EGARCH	55.16%	-4.90	-4.72
			(-0.32)	(11.54)	(2.66)	(3.33)								
	FF	$R_{Asia\ ex\text{-}Japan}$ =	-0.005 +	0.46R_{MSCI} +	4.18S_3 -	0.26HML +	[AR(1) = 0.29]				GARCH	56.20%	-4.89	-4.71
			(-1.60)	(10.61)	(4.26)	(-2.67)	(3.05)							
BRIC	FH 7-factor	R_{BRIC} =	-0.001 +	0.71R_{MSCI} -	0.11SML +	0.82T10Y +	3.20CRSPRD -	0.57BdOpt +	0.22FXOpt+	0.17ComOpt	OLS	68.8%	-4.78	-4.27
			(-0.11)	(9.32)	(-1.02)	(0.05)	(1.06)	(-0.34)	(1.56)	(2.73)				
	CAPM	R_{BRIC} =	-0.15 +	0.68R_{MSCI} +	0.016S_1 +	3.03SD -	0.45L-Ratio +	0.03S_4			EGARCH	79.58%	-4.98	-4.74
			(-6.26)	(25.57)	(6.64)	(6.09)	(-5.51)	(3.68)						
	FF	R_{BRIC} =	-0.15 +	0.69R_{MSCI} +	0.017S_1 -	0.33HML +	2.96SD -	0.49L-Ratio +	0.03S_4		OLS	81.53%	-5.02	-4.86
			(-5.30)	(18.83)	(7.42)	(-3.33)	(5.12)	(-6.77)	(2.85)					

	Model	Regression Model									Est. Method	Adj. R^2	AIC	SIC
Brazil	FH 7-factor	R_{Brazil} =	0.004 +	0.39R_{IBOV}+	0.07SML +	15.25T10Y -	1.80CRSPRD +	0.46BdOpt -	0.11FXOpt+	0.11ComOpt	OLS	63.6%	-4.57	-4.38
			(0.97)	(8.62)	(0.68)	(0.87)	(-0.81)	(0.26)	(-0.85)	(1.67)				
	CAPM	R_{Brazil} =	-0.0004 +	0.48$R_{IBOVESPA}$							OLS	61.51%	-4.56	-4.52
			(0.17)	(13.65)										
China	FH 7-factor	R_{China} =	0.002 +	0.18R_{SHCOMP} +	0.17SML +	1.98T10Y +	4.97CRSPRD -	1.83BdOpt -	0.15FXOpt+	0.16ComOpt	OLS	44.7%	-4.37	-4.18
			(0.36)	(6.78)	(1.54)	(0.10)	(2.03)	(-0.95)	(-1.11)	(2.43)				
	CAPM	R_{China} =	0.002 +	0.14$R_{SHANGHAI}$ +	0.01D-Ratio +	0.04SHARPE +	8.93R-Ratio				OLS	57.62%	-4.66	-4.54
			(0.39)	(4.91)	(5.84)	(4.27)	(3.76)							
	FF	R_{China} =	0.001 +	0.13$R_{SHANGHAI}$ +	0.01D-Ratio +	0.03SHARPE +	8.19R-Ratio -	0.29HML +	0.19SML		OLS	60.36%	-4.71	-4.54
			(0.19)	(4.43)	(6.02)	(4.21)	(3.62)	(-2.89)	(1.98)					
India	FH 7-factor	R_{India} =	0.01 +	0.79R_{NIFTY} -	0.27SML +	37.97T10Y -	2.71CRSPRD -	1.03BdOpt -	0.56FXOpt-	0.12ComOpt	OLS	78.4%	-4.03	-3.84
			(0.97)	(16.86)	(-2.05)	(1.66)	(-0.94)	(-0.45)	(-3.43)	(-1.56)				
	CAPM	R_{India} =	-0.0003 +	0.80R_{NIFTY} +	0.009D-Ratio						OLS	77.16%	-4.01	-3.94
			(-0.10)	(10.14)	(2.66)									
Korea	FH 7-factor	R_{Korea} =	0.006 +	0.54R_{KOSPI} +	0.20SML +	22.2T10Y -	3.56CRSPRD +	5.63BdOpt -	0.58FXOpt+	0.002ComOpt	OLS	73.7%	-4.46	-4.23
			(1.24)	(8.30)	(1.58)	(1.08)	(-1.44)	(2.78)	(-3.81)	(0.03)				
	CAPM	R_{Korea} =	-0.0004 +	0.67R_{KOSPI}							OLS	62.00%	-4.16	-4.10
			(-0.12)	(11.47)										
Latin America	FH 7-factor	R_{LATAM} =	-0.0001 +	0.40R_{MSCI} -	0.08SML -	0.31T10Y +	2.40CRSPRD -	1.43BdOpt +	0.05FXOpt+	0.15ComOpt	OLS	63.5%	-5.07	-4.85
			(-0.03)	(7.06)	(-1.00)	(-0.02)	(1.03)	(-1.17)	(0.50)	(3.31)				
	CAPM	R_{LATAM} =	-0.004 +	0.47R_{MSCI} +	0.002D-Ratio +	[AR(1) = 0.26]					OLS	61.67%	-5.06	-4.96
			(-1.15)	(12.65)	(2.52)	(2.84)								
MENA	FH 7-factor	R_{MENA} =	0.003 +	0.49R_{MSCI} +	0.03SML +	28.01T10Y +	1.79CRSPRD -	1.21BdOpt +	0.13FXOpt+	0.11ComOpt	OLS	76%	-5.36	-5.17
			(0.87)	(10.3)	(0.37)	(2.42)	(1.20)	(-1.02)	(1.44)	(2.74)				
	CAPM	R_{MENA} =	-0.001 +	0.55R_{MSCI} +	0.001D-Ratio						OLS	71.35%	-5.22	-5.15
			(-0.53)	(16.46)	(2.77)									
Russia	FH 7-factor	R_{Russia} =	0.005 +	0.51R_{MICEX} -	0.02SML +	23.35T10Y -	1.96CRSPRD -	0.05BdOpt -	0.30FXOpt+	0.09ComOpt	OLS	79.9%	-4.37	-4.16
			(0.74)	(13.35)	(-0.16)	(1.35)	(-0.54)	(-0.03)	(-2.40)	(1.33)				
	CAPM	R_{Russia} =	-0.007 +	0.57R_{MICEX} +	0.03SHARPE +	4.56R-Ratio +	[AR(1) = 0.38]				GARCH	78.91%	-4.50	-4.31
			(-1.90)	(20.0)	(3.10)	(2.56)	(4.70)							
	FF	R_{Russia} =	0.002 +	0.57R_{MICEX} +	0.29HML +	0.01D-Ratio +	[AR(1) = 0.14]				GARCH	79.1%	-4.49	-4.30
			(0.65)	(20.66)	(2.33)	(3.00)	(1.33)							
Russia/East EU	FH 7-factor	$R_{Russia/East EU}$ =	0.007 +	0.52R_{MSCI} -	0.08SML +	20.07T10Y -	4.12CRSPRD -	1.09BdOpt -	0.01FXOpt+	0.14ComOpt	OLS	58.4%	-4.23	-4.02
			(1.09)	(5.95)	(-0.69)	(1.04)	(-1.26)	(-0.57)	(-0.09)	(1.92)				
	CAPM	$R_{Russia/East EU}$ =	-0.03 +	0.61R_{MSCI} +	9.69R-Ratio -	0.58L-Ratio					OLS	67.10%	-4.51	-4.42
			(-6.13)	(12.86)	(5.06)	(-2.80)								

5.2. Asia & Europe Region Categories Empirical Results Analysis

The 3D Plot of the Asia Region returns vs. the MSCI index return and R-Ratio indicate that both factors are positively related to the hedge fund category return. For the Europe Region, the 3D Plot of the Western/Pan Europe return vs. the MSCI index return and R-Ratio shows a positive relationship with both factors.



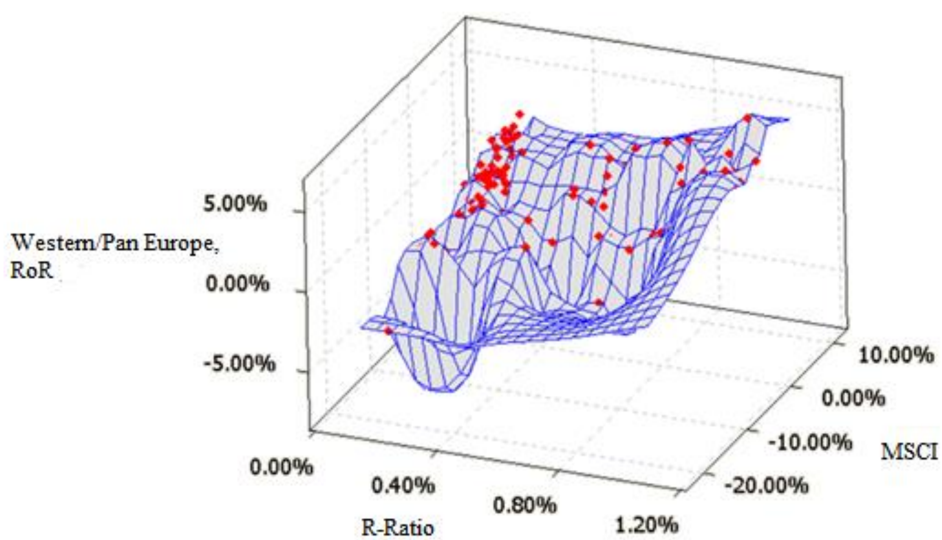


Table 9 lists the regression models for the Asian and European Region Categories. The models for Asia ex-Japan, China, India, and Korea categories were listed earlier in the Emerging Market category table and can also be considered for Asia region category. They are not included in this section to avoid redundancy.

The Asia Composite Hedge Fund category has the MSCI index return and R-Ratio (Run-up Velocity Ratio) as significant factors in an EGARCH model with an adjusted R-squared of 52%. Asia Equally Weighted category uses an EGARCH process with the MSCI index return and the D-Ratio with an adjusted R-squared of 50%. Asia with Japan has the MSCI index return, R-Ratio, and Kurtosis as significant variables.

The model for Japan has only the TOPIX market index return as a significant factor, similar to India and Korea, where only local domestic stock market returns are significant. The adjusted R-squared for the Japan hedge fund model was 62.70% and is between the adjusted R-squared resulted by the models for India and Korea.

The Western Europe Region model includes the MSCI index return, Drawdown (negatively related), L-Ratio, and Run-up (negatively related) as significant factors, with an SIC of -5.48 and an adjusted R-squared of 57%. The Northern European model had only the MSCI index return as a significant factor with an SIC of -5.89 and an adjusted R-squared of 17%. The Russia/Eastern Europe category had the MSCI index return, R-Ratio (Run-up Velocity Ratio), and L-Ratio (negatively related). The adjusted R-squared was 67% for this model.

The Asia and Europe hedge fund categories indicate that the CAPM controlled model outperformed the Fung and Hsieh 7-factor model in all six categories. Only one category has a separate Fama-French model and it outperforms the 7-factor model, also. Again, simpler models controlling for CAPM or Fama-French variables outperform the Fung and Hsieh 7-factor model.

In this table, four categories out of six have at least one of the three new factors, with the R-Ratio being dominant factor. The standard deviation is not significant in any model, indicating that none of these categories can be described as simulating put writing strategies. Standard deviation is one of the six major variables in any option pricing model.

Finally, that all models have been tested and corrected for multi-collinearity, serial correlation, heteroscedasticity, and conditional heteroscedasticity in order to guarantee the robustness and stability of the final generated models.

Table 9
Regional (Asia & Europe) Categories Regression Models.

ASIA & EUROPE REGION	Model	Regression Model									Est. Method	Adj. R^2	AIC	SIC
Asia Composite Hedge Fund	FH 7-factor	$R_{Asia\ Comp\ Hedge\ Fund}$ =	0.0003 +	0.37R_{MSCI} -	0.03SML +	14.04T10Y +	2.06CRSPRD +	0.12BdOpt +	0.16FXOpt +	0.06ComOpt	OLS	52.6%	-5.39	-5.19
			(0.08)	(7.83)	(-0.46)	(1.37)	(1.06)	(0.11)	(1.94)	(1.62)				
	CAPM	$R_{Asia\ Comp\ Hedge\ Fund}$ =	-0.003 +	0.36R_{MSCI} +	1.44R-Ratio						EGARCH	52.04%	-5.57	-5.41
			(-1.06)	(13.69)	(2.41)									
	FF	$R_{Asia\ Comp\ Hedge\ Fund}$ =	-0.005 +	0.34R_{MSCI} +	1.91R-Ratio -	0.15HML					GARCH	54.50%	-5.55	-5.40
			(-1.96)	(13.64)	(4.30)	(-2.20)								
Asia Equally Weighted	FH 7-factor	$R_{Asia\ Equally\ Weighted}$ =	0.001 +	0.37R_{MSCI} -	0.03SML +	14.90T10Y +	1.63CRSPRD +	0.07BdOpt +	0.16FXOpt +	0.05ComOpt	OLS	50.7%	-5.37	-5.17
			(0.37)	(7.65)	(-0.52)	(1.43)	(0.85)	(0.07)	(1.86)	(1.36)				
	CAPM	$R_{Asia\ Equally\ Weighted}$ =	-0.004 +	0.35R_{MSCI} +	0.001D-Ratio						EGARCH	50.93%	-5.58	-5.43
			(-1.87)	(14.93)	(3.99)									
Asia with Japan	FH 7-factor	$R_{Asia\ w/Japan}$ =	0.002 +	0.26R_{MSCI} -	0.04SML +	8.28T10Y +	2.13CRSPRD -	0.05BdOpt +	0.11FXOpt +	0.08ComOpt	OLS	34.6%	-5.20	-5.00
			(0.60)	(5.08)	(-0.57)	(0.72)	(1.09)	(-0.05)	(1.24)	(1.97)				
	CAPM	$R_{Asia\ w/Japan}$ =	-0.007 +	0.30R_{MSCI} +	2.80R-Ratio +	0.006KURT					EGARCH	36.41%	-5.54	-5.36
			(-2.44)	(11.1)	(3.78)	(3.35)								
Japan	FH 7-factor	R_{Japan} =	0.002 +	0.37R_{TOPIX} -	0.02SML +	26.87T10Y +	0.40CRSPRD +	1.44BdOpt +	0.04FXOpt -	0.03ComOpt	OLS	64.1%	-5.56	-5.38
			(0.89)	(13.45)	(-0.31)	(2.69)	(0.31)	(1.40)	(0.59)	(-0.99)				
	CAPM	R_{Japan} =	0.003 +	0.36R_{TOPIX}							OLS	62.73%	-5.57	-5.52
			(1.97)	(6.94)										
Western/ Pan Europe	FH 7-factor	$R_{West./Pan\ Europe}$ =	0.006 +	0.32R_{MSCI} -	0.13SML +	8.85T10Y -	1.21CRSPRD -	0.27BdOpt +	0.31FXOpt +	0.06ComOpt	OLS	39.7%	-5.25	-5.04
			(1.55)	(6.14)	(-1.81)	(0.77)	(-0.58)	(-0.24)	(3.36)	(1.45)				
	CAPM	$R_{West./Pan\ Europe}$ =	-0.026 +	0.20R_{MSCI} +	8.73R-Ratio -	0.26DD -	0.42L-Ratio -	0.06RU			OLS	57.24%	-5.62	-5.48
			(-2.65)	(5.65)	(5.95)	(-3.98)	(-4.19)	(-4.15)						
Northern Europe	FH 7-factor	$R_{Northern\ Europe}$ =	0.0003 +	0.18R_{MSCI} +	0.002SML +	7.68T10Y +	1.62CRSPRD +	0.79BdOpt +	0.30FXOpt +	0.05ComOpt	OLS	28.5%	-6.03	-5.84
			(0.16)	(5.30)	(0.05)	(0.91)	(1.50)	(0.91)	(4.32)	(1.81)				
	CAPM	$R_{Northern\ Europe}$ =	0.003 +	0.16R_{MSCI}							OLS	17.73%	-5.94	-5.89
			(2.85)	(4.97)										

6. Conclusion

The models presented in this paper outperform the Fung and Hsieh 7-factor models in 12 out of 13 categories or over 92% of the time for emerging market hedge fund categories and 18 of 19 for the entire international set of hedge fund categories (94%). The models presented analyze individual hedge fund categories that have never been presented in the previous hedge fund literature. The models presented do not add an extra factor for the Emerging Market returns. The models presented are controlled for CAPM and Fama-French variables and usually finish with four or fewer variables. A few models have five significant variables. This paper analyzed 55 categories of hedge fund returns and introduced 3 new factors (D-Ratio, L-Ratio and R-Ratio) that are better at measuring risk for hedge fund categories than variables currently being used. The three new factors appear as significant in the Emerging Market and International regional categories (at least one of these variables is significant in 74% of these models). In addition, this paper has shown that many hedge fund strategies are not simulations of put option writing, although some categories do seem to exhibit characteristics that could be mimicked using option replication techniques. The D-Ratio outperforms the Sharpe and Sortino ratios across most hedge fund categories. The three new factors are intuitive for investors and provide evidence supporting a consumption based or liquidity based theory of asset prices. The D-Ratio, which includes excess return divided by the prior average Drawdown per month is significant in 8 of 19 categories (42%). Another Drawdown related factor, L-Ratio, which is Drawdown duration (a liquidity factor) is significant in 3 of 19 categories (15.7%). In addition, R-Ratio, a Run-up factor, is related to momentum and is significant in 6 of 19 categories (31.5%). Assuming that Drawdown is correlated to consumption and liquidity, this paper provides evidence that liquidity and delayed consumption both play a role in asset prices. These alternative investments do seem to price liquidity and consumption factors.

Appendix A: Hedge Fund Categories Descriptive Statistics

Table A-5
Emerging Market Strategies' Descriptive Statistics.

Emerging Market Indices	Mean	Median	Std. Dev.	Excess Kurtosis	Skew	Min	Max	Count	Period
Total Emerging Markets	0.52%	0.70%	2.65%	2.88	-0.95	-11.00%	6.99%	120	Jan 2005 - Dec 2014
Multi-Emerging Markets	0.62%	1.03%	3.20%	5.78	-1.50	-15.72%	6.83%	120	
Emerging Markets Composite	0.63%	0.38%	2.78%	5.06	-0.93	-12.90%	8.20%	108	Jan 2006 - Dec 2014
Asia ex-Japan	0.61%	0.93%	3.27%	0.62	-0.17	-8.84%	9.79%	132	Jan 2004 - Dec 2014
BRIC	0.81%	0.79%	4.42%	0.83	-0.33	-13.21%	14.05%	120	Jan 2005 - Dec 2014
Brazil	0.29%	0.77%	3.90%	1.25	-0.55	-12.25%	10.64%	120	
Russia	0.55%	0.85%	5.79%	0.71	-0.28	-18.55%	15.07%	120	
India	0.99%	1.94%	6.65%	2.46	0.36	-14.99%	30.39%	120	
China	1.03%	1.16%	3.52%	0.42	0.06	-7.21%	10.60%	120	
Latin America	0.53%	0.69%	3.02%	2.11	-0.44	-10.26%	9.82%	120	
MENA	0.70%	0.71%	3.25%	1.52	-0.18	-11.23%	9.30%	120	
Russia/Eastern Europe	0.28%	0.59%	4.34%	1.25	-0.61	-16.23%	11.50%	120	
Korea	0.02%	0.03%	4.82%	0.36	-0.33	-14.91%	11.16%	84	Jan 2008 - Dec 2014

Table A-6
Regional (Asia & Europe) Hedge Fund Strategies' Descriptive Statistics.

Asia & Europe Region Indices	Mean	Median	Std. Dev.	Excess Kurtosis	Skew	Min	Max	Count	Period
Asia ex-Japan	0.61%	0.93%	3.27%	0.62	-0.17	-8.84%	9.79%	132	Jan 2004 - Dec 2014
Asia with Japan	0.68%	0.64%	2.12%	0.36	-0.10	-4.82%	6.66%	132	
Asia Composite Hedge Fund	0.56%	0.78%	2.28%	0.55	-0.32	-6.27%	6.68%	132	
Asia Equally Weighted	0.59%	0.77%	2.25%	0.47	-0.30	-6.16%	6.57%	132	
Japan	0.46%	0.45%	2.50%	1.88	0.46	-6.65%	9.26%	132	
China	1.03%	1.16%	3.52%	0.42	0.06	-7.21%	10.60%	120	Jan 2005 - Dec 2014
India	0.99%	1.94%	6.65%	2.46	0.36	-14.99%	30.39%	120	
Western/Pan Europe	0.58%	0.61%	2.16%	2.16	-0.71	-7.78%	6.25%	120	
Northern Europe	0.44%	0.54%	1.32%	0.97	-0.40	-3.89%	4.15%	120	
Russia/Eastern Europe	0.28%	0.59%	4.34%	1.25	-0.61	-16.23%	11.50%	120	
Korea	0.02%	0.03%	4.82%	0.36	-0.33	-14.91%	11.16%	84	Jan 2008 - Dec 2014

Appendix B: Hedge Fund Categories' Standard Deviation & Skewness Correlation with Performance Ratios

Emerging Market Indices	Correlation	S_1	S_2 (L-Ratio)	S_3	S_4	S_5	S_6 (R-Ratio)	S_7 (D-Ratio)
Total Emerging Markets	Std. Dev.	-92%	-82%	-78%	-66%	-57%	-95%	-85%
	Skew	89%	74%	82%	71%	65%	91%	88%
Emerging Markets Composite	Std. Dev.	-9%	-14%	-17%	-9%	1%	-37%	-27%
	Skew	27%	39%	55%	60%	39%	87%	69%
Multi-Emerging Markets	Std. Dev.	-73%	-59%	-65%	-79%	-78%	-77%	-53%
	Skew	80%	69%	68%	70%	75%	67%	40%
Asia ex/Japan	Std. Dev.	10%	27%	4%	43%	43%	24%	28%
	Skew	2%	-6%	2%	-19%	-19%	-14%	-29%
BRIC	Std. Dev.	-47%	-13%	-55%	-57%	-45%	-46%	-47%
	Skew	8%	4%	15%	47%	46%	-4%	-16%
Brazil	Std. Dev.	78%	66%	68%	67%	46%	53%	-38%
	Skew	-66%	-19%	-54%	-65%	-44%	-16%	41%
China	Std. Dev.	-8%	-27%	2%	-27%	-26%	-39%	-13%
	Skew	-15%	12%	-26%	-7%	-15%	23%	15%
India	Std. Dev.	76%	55%	65%	65%	68%	56%	-25%
	Skew	65%	66%	54%	61%	64%	74%	-21%
Korea	Std. Dev.	43%	27%	2%	23%	-3%	7%	-1%
	Skew	-75%	-81%	-90%	-77%	-83%	-76%	-84%
Latin America	Std. Dev.	-64%	-54%	-36%	-40%	-9%	-46%	-22%
	Skew	24%	8%	29%	27%	19%	21%	17%
MENA	Std. Dev.	-63%	-56%	-60%	-33%	-5%	-71%	-62%
	Skew	28%	24%	26%	-4%	-27%	17%	17%
Russia	Std. Dev.	57%	58%	55%	43%	37%	49%	-15%
	Skew	-76%	-72%	-74%	-56%	-65%	-59%	20%
Russia/Eastern Europe	Std. Dev.	-39%	-38%	-37%	-20%	-13%	-40%	-39%
	Skew	82%	85%	80%	57%	64%	75%	72%

Asia & Europe Indices	Correlation	S_1	S_2 (L-Ratio)	S_3	S_4	S_5	S_6 (R-Ratio)	S_7 (D-Ratio)
Asia Composite Hedge Fund Index	Std. Dev.	-39%	-35%	-47%	-61%	-44%	-49%	-39%
	Skew	47%	57%	67%	49%	45%	74%	75%
Asia Equally Weighted Index	Std. Dev.	-42%	-32%	-44%	-56%	-51%	-23%	-27%
	Skew	38%	46%	64%	40%	43%	77%	70%
Asia with Japan	Std. Dev.	-43%	1%	-22%	-3%	1%	42%	8%
	Skew	13%	41%	40%	70%	72%	79%	60%
Asia ex/Japan	Std. Dev.	10%	27%	4%	43%	43%	24%	28%
	Skew	2%	-6%	2%	-19%	-19%	-14%	-29%
China	Std. Dev.	-8%	-27%	2%	-27%	-26%	-39%	-13%
	Skew	-15%	12%	-26%	-7%	-15%	23%	15%
India	Std. Dev.	76%	55%	65%	65%	68%	56%	-25%
	Skew	65%	66%	54%	61%	64%	74%	-21%
Japan	Std. Dev.	38%	76%	39%	73%	75%	44%	38%
	Skew	16%	28%	18%	56%	50%	53%	18%
Korea	Std. Dev.	43%	27%	2%	23%	-3%	7%	-1%
	Skew	-75%	-81%	-90%	-77%	-83%	-76%	-84%
Western/Pan Europe	Std. Dev.	3%	41%	-27%	-10%	4%	28%	-40%
	Skew	-24%	-63%	12%	-6%	-26%	-56%	-15%
Northern Europe	Std. Dev.	-87%	-60%	34%	-77%	-73%	-71%	-39%
	Skew	-73%	-66%	59%	-75%	-74%	-33%	5%
Russia/Eastern Europe	Std. Dev.	-39%	-38%	-37%	-20%	-13%	-40%	-39%
	Skew	82%	85%	80%	57%	64%	75%	72%

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