A Conditional Volatility Feedback Moderation Modeling to the Market Timing Behavior Per Hedge Funds' Investment Styles*

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Abstract

A direct effect on the current performance of certain hedge fund investment styles by the one-month prior return of primitive trend following strategy on the short-term interest rate (PTFSIR) depends quadratically on the size of the returns of the one-month prior implied volatility index ("VIX") as a primary moderator. To investigates empirically whether the past return of implied volatility information can explain the dynamic factor exposures of hedge funds over time, this manuscript advances the quantitative behavioral science literature for making inferences about the conditional process model with a quadratic moderator. Consistent with our view that hedge funds exhibit different levels of skills in exploiting the information contents of equity implied volatilities, we document substantial heterogeneity of processing one-month prior quadratic volatility returns by altering their risky asset exposures across hedge fund investment styles. We subsequently apply the same analytical framework to three different collections of individual liquid alternative hedge funds to test if the PTFSIR factor's effect on hedge fund strategy returns is linearly moderated by one-month prior return volatilities of the VIX and the corresponding hedge funds' dynamic risky asset and factor exposure management implications.

Key words : *Hedge Funds, Market Timing, Conditional Moderation Effect, Factor Timing*

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[1] Introduction

"… since investors are not only looking for a low correlation to local equity indices, but also that they are happy to get something which can perform like what they would expect of equities, or have a higher correlation during the good times but a low to negative correlation during weaker times for equities. Clearly, people dream of the perfect investment which produces returns like equities in the good times, and then also outperforms equities enormously during the bad times, which rarely exists in practice. But most investors have been really disappointed with equities and this is why these three liquid alternative hedge fund portfolios, for instance, are not necessarily seen just as diversifiers but as a better replacement to equities. For the KOSPI 200 index from January 2011 until November 2018 for example, the total return and annualized return is exactly 0.03% and 0.00% with a realized volatility of 13.08%. We would summarize that literally a 0% return in exchange for investing in the KOSPI 200 index for nearly 8 years in a global bull equity market. It might, therefore, be possible that Korean institutional investors not even tend to KOSPI index in their minds at all, but rather to look at something like a better alternative, to begin with…"

Mr. Sebastian Schaefer, managing partner and founder of Green Shoots Group of Companies

Investors consider many portfolio characteristics, but only a limited number of systematic risk premiums empirically explain the cross-section of diversified portfolio returns. These factors are the unique source of returns that are largely independent of each other and should explain the performance variation of diversified portfolios. While many factors have been analyzed in academic as well as practitioners' literature, the market, the value, the size, the momentum, the volatility, the credit, and the term factors are relatively well-adopted in practice.

While traditional multi-factor models capture linear exposures to the various risk factors, hedge fund returns exhibit non-linear exposures to traditional asset classes. This is because the hedge fund strategies typically generate option-like returns. Some of these hedge fund strategies also appear to be earning risk premia through an economic function involving a way to transfer risk. These non-linear risk-return payoffs are manifested through significant betas (or passive market exposure) on option-based risk factors. For instance, the payoffs of event arbitrage, restructuring, event-driven, relative value arbitrage, and convertible arbitrage styles resemble that from writing a put option on the market index. This may be because these so-called "short-volatility" strategies lose money during the downturns in the equity market. It may also be the managers calibrating a payoff profile similar to that from writing a put option to improve their Sharpe ratios or to assimilate to their incentive contract.

In contrast, trend-following managed futures (MFs) funds tend to create a "long-volatility[1] (long-vol)" type of option, positively skewed return profile in global interest rate, currency, commodity, and equity markets. They are diversified in that the strategy simultaneously trades multiple markets with low correlation to each other. Their implementation is classified as systematic if the strategy is codified into a set of non-discretionary protocols to be executed by computerized trading systems. It is generally thought that trend-followers do not anticipatory in that the strategy does not attempt to time the market and just focus *ex-ante* on determining the onset of a new trend. In order to replicate the trading patterns of these "long-vol" strategies, a look-back option is introduced. A look-back option allows the holder the privilege of knowing history determining when to exercise their option. The option reduces uncertainties associated with the timing of market entry by minimizing the chances the option would expire worthlessly. A look-back straddle[2] is an option trading strategy composed of a lookback call and a lookback put options. The former (latter) grants its holder the right to buy (sell) the underlying at the lowest-ever (highest-ever) price observed during the life of the option. While, in theory, a lookback straddle can be such a holy grail institutionalizes the holder to "buy-low and sell-high," this straddle is known to be closely associated with the return profile of trend-following hedge fund strategies.

Most asset returns exhibit a serial correlation component in addition to their randomized volatility at least some discrete portion of the time. The majority of commodity trading advisors (CTAs), or MFs, can be classified as trend followers when they focus to catch up these momentary opportunities. Fung and Hsieh [2001] find that the performance of trend-following funds is not well explained using traditional linear-factor models when those traditional market-cap weighted, asset-based benchmark indices were adopted. Despite the criticism that the lookback straddles on a fixed stride[3] pattern have some empirical drawbacks to prevent accurately replicating trend-followers' actual trade patterns and do not implementable as they use data from future time periods, the trend-followers' returns are option-like in nature and by using on a recurring fixed stride pattern ("PTFS") might be adopted

1) Common usage refers to investments that perform poorly as risk aversion rises as "short volatility" because such investments behave, to some extent, as if they were short positions in an index of volatility such as the VIX. As risk aversion rises, the VIX rises and short volatility investments fall. "Long volatility" investments behave in the opposite manner. A short volatility investment tends to provide positive returns under typical market conditions, but gives up some of its returns when volatility spikes upward.

2) A strangle is similar to a straddle, except that an out-of-the money ("OTM") call is purchased at a higher strike than an OTM put. In contrast, a straddle is defined as an at-the-money ("ATM") call and an ATM put option both purchased with the same strike and time-to-maturity in the spot market.

3) In the model setting by Fung and Hsieh [2001], a lookback straddle would be used with a fixed stride as taking for each market at the payout of a lookback straddle over each three-month period as the maximum return for a trend follower, against which performance could then meaningfully be benchmarked. For instance, the payoff of a perfect market timer who may take a long position should be identical to the payoff from holding a call option, which would enable the holder to "buy low and sell high." Then the market timer's payoff will exactly correspond to the payoff of a lookback straddle. Consequently, the lookback straddle can be thought of as the PTFS used by market timers. The five trend-following risk factors defined from Fung and Hsieh [2001] are the return of bond (PTFSBD), currency (PTFSFX), commodity (PTFSCOM), short-term interest rate (PTFSIR), and stock index (PTFSSTK) lookback straddles.

as a basis for benchmarking the performance of trend-followers.

Fama [1972] mentioned that a fund manager has two types of skills; its stock selection and the market timing. The former is about the ability to select the right securities on a certain risk level and the latter is about the ability to forecast the potential market movement to adjust the risk-on positions on or before the right moment. It is generally conceived that hedge funds employing dynamic trading strategies have time-varying risky asset exposures to generate option-like return profiles. Since they are lightly regulated and more flexible to engage in leveraged transactions based on their short-selling capacities and the derivative exposures, hedge funds are better positioned for factor timing than the rest of traditional money managers. Here, the factor timing refers to the skill of a fund manager to dynamically adjust the factor exposure for a specific factor based on a customized forecast of the conditioning information. Unlike traditional portfolio diversification at the asset-class level, the factor-based investing involves identifying compensated factor exposures from their top-down analysis and constructing a portfolio by these factor allocations to harvest the compensated factor premia, rather than attempting to uncorrelated pure alpha (or the active manager skills). Measuring the true alpha of a hedge fund portfolio is one of the most frequently adopted approaches to identify active skillful manager, who may be able to repeat his/her performance going forward. An accurate measure of alpha can be obtained after isolating the manager skills by properly conditioning the risk premiums to which the portfolio is exposed.

The better understanding exists in capital market research when we can claim how some risk aversion proxy affects a specific hedge fund returns or in what context the effect exists. Several studies adopted volatility conditioning information to evaluate the performance of active portfolios: An empirical work on volatility weighting was done by Hallerbach [2014] for weighting a strategy by its trading volatility. Barroso and Santa-Clara [2015] found that weighting cross-sectional equity momentum with strategy volatility improves its risk-adjusted performance. Cho [2017b] tested a various combination of dynamic asset allocation strategies of time-series convergence and divergence trades in the KOSPI 200 futures market. The dynamic trades were based on the statistical strength of the publicly available implied volatility index ("VKOSPI")-based trading signals out of the reconstructed entropy algorithms. Recently, Cho [2017a, c] studied the information contents of the VIX and the VKOSPI in global hedge fund index returns by applying Fama and French [2012]'s global version of six equity risk factors and its potential diversification implications to Korean equity investors.

In the behavioral science study, statistical mediation and moderation analysis are one of the popular quantitative methods adopted to explore questions about how (mediation, or indirect effects) and under what circumstance (moderation, or conditional effects) operates. A mediation model is a basically causal model that any valid causal inference requires something more than a mere statistical association between and among the focal and outcome variables. Hayes [2018] elaborates corresponding indices to test how or to what extent an indirect effect is moderated in a model with moderators. In his definition, the index of partial moderated mediation quantifies the linear relationship between a moderator and an indirect effect when a second moderator is held constant. If the second moderator is conditioned at a given value, the index is called conditional moderated mediation. Meanwhile, the index of moderated moderated (thus, "dual moderated") mediation quantifies how quickly the relationship between a moderator and an indirect effect is changing as the movement of a second moderator.

While Agarwal and Naik (2004) show that some equity-biased hedge fund investment styles exhibit a relationship with option-based risk factors that consist of returns obtained by buying and selling one-month later liquid put and call options on the S&P 500 index, we further distinguish the log returns of one-month prior volatility[4] information as the conditioning moderator to one-month prior PTFSIR factor to the excess performances of hedge fund styles. This design is practical since we are only dealing with past information about market risk indicators in the analysis. For instance, while the excess returns of hedge fund-style indices (Y_t) are contemporaneous, the antecedent indicators such as primitive trend following strategy returns on the short-term interest rate ($PTFSIR_{t-1}$) and the quadratic return information of the VIX ($DVIX^2_{t-1}$) are one-month prior. At the index level as the aggregates of individual hedge funds' net-of-fee returns, the results suggest that different hedge fund investment styles show varying degrees of conditioning the information of the quadratic returns of one-month prior implied volatility: Investment styles such as emerging market (EM) and multi-strategies (MS) show relatively more significantly conditioning $PTFSIR_{t-1}$ factor as moderated through $DVIX^2_{t-1}$ versus other styles such as funds of equity long-short (LS), hedge funds (FoF), global macro (GM), and commodity trading advisors (CTA).

The current study is in line with the multi-factor performance attribution and conditional process analysis because we apply the similar intuition and methodology from Fama and French [2012] and Hayes [2018] to the time-series of hedge fund-style indices. However, we differ from them in several important aspects. Since a major drawback of the linear factor models is linearly relating hedge fund returns to such risk factors, we propose a parsimoniously augmented method to capture the non-linear exposures of the excess returns of hedge fund investment style to the quadratic returns of one-month prior VIX as a conditioning moderator. Any non-linear *ex-post* regression models for hedge fund indices allows asset allocators mining the data for the main drivers of performance and risk factors to which a hedge fund is exposed because hedge fund returns present such non-lin-

4) While the volatility risk premium refers to the difference between option-implied volatility and the realized volatility of the same underlying asset over time, which creates a profit opportunity for the "short-vol" traders, the quadratic returns of one-month prior VIX as a conditioning moderator here represents primarily an investor risk aversion, not necessarily the volatility risk premium as one of the stylized risk factors.

ear exposures to traditional asset classes as mimicking an option payoff. Whether this time-series connection can be explained by how and in what circumstances one-month prior signals from the quadratic returns of volatility might further capture conditionalities about one-month prior primitive trend following strategy on short-term interest rate factor to hedge fund style index returns.

The general intuition is as follows: While the managers' effort to diversification at the asset allocation level is often by minimizing *ex-ante* risks for a desired level of returns, any further diversification exercise at the tactical implementation level is often his/her return enhancement tools. Out of the world of the CAPM, many alternative efficient portfolio managers are looking to increase their return by timely altering their portfolio towards various risk-on equivalent positions per their degree of risk aversion in order to collect more risk premium. This raises extra demand for risky assets and reduces demand for risk-free assets, which may explain a money manager's market-timing behavior. Certain investment styles of hedge fund managers may be more aggressive at identifying market concerns. These hedge fund managers are under the environment of less strictly regulated and are more flexible to engage in active trades such as short-selling and leverage, and should be better positioned to dynamically adjust their risky asset exposures to exercise their timing ability. When the customized forecast based on last month's returns of VIX (or squared returns in order to focus on the monthly volatility of the VIX) shows a reduced risk aversion, hedge fund managers of a certain investment style will be more willingly and actively increase the fund's exposure to the market factor or some other stylized systematic risk factors such as the size, the value, or the momentum. Such factor tilts can emanate from active views of the managers and as such should be regarded as the manger's active skill.

As Frijns, Gilbert, and Zwinkels [2016] discussed, the collective mutual fund managers included in the style indices may adjust their portfolio factor exposures conditioned to past factor returns rather than future returns, which is detrimental to their outperformance. Ang, Hodrick, Xing, and Zhang [2009] identified a negative relationship between one-month prior idiosyncratic volatility and subsequent stock returns, which is a similar challenge what this unknown but eager to be exploited information process *ex-ante* by many market participants. How these savvy hedge fund managers in the heterogeneous investment style spectrum might differ in their interpretations of the moderated information contents in $DVIX_{t-1}^2$ to the effects of $PTFSIR_{t-1}$ to their ultimate hedge fund performance? It is our focus to incorporate the insights into a practical implication that can be adopted by hedge fund investors to recap these managers' collective behavior on the past trend and the information content of implied equity market volatilities. Our conditional process model attempts to provide some understanding of the interplays among them by offering interpretations of two-way interaction terms. For robustness test, we apply the same moderation framework to the collections of liquid alternative hedge funds and obtain results that are stronger to those reported for the Barclays Hedge Fund style indices.

The remainder of this article is structured as follows: The factor modeling in moderation analysis, data analysis, and test results of isolating the volatility moderation effect are presented in section 2, the statistical inferences on the indices of conditional moderations are discussed in section 3, a robustness application to individual liquid alternative hedge funds are presented in section 4, and section 5 concludes.

[2] Developing a Moderated Factor Model

Due to idiosyncratic behavior and the parameter uncertainty, the usual factor risk models do not immediately applicable to test single hedge funds. The stability of the test also depends on the availability and the length of single managers' track records. To establish the relevance of our approach from an empirical standpoint, we evaluate the performance of the Barclays Hedge Fund Index[5] ("Barclays") and its six main strategy classification sub-indices such as emerging market (EM), equity long-short (LS), fund of hedge funds (FoF), global macro (GM), multi-strategies (MS), and commodity trading advisors (CTA) by linearly moderating a quadratic effect when considering a set of risk factors to be elaborated shortly. Since this study will focus on afore-mentioned six distinct investment styles, the trades such as fixed income or relative value arbitrages are excluded from the sample. We compare the measured alphas (i.e., constants, or intercepts) in the standard factor control regressions.

As Cho [2017c] elaborated in his study, the Barclays indices are highly diversified, which might be helpful to reduce the potential noise of fund-specific return variation commonly observed at individual hedge fund levels. Because hedge funds are typically classified into diverse categories by investment style, we naturally expect that the different investment styles might show different factor moderation mechanism. By focusing on each particular style, we examine whether the investment style differences are related to the varying effect of factor-tilting through the volatility moderation dynamics by hedge fund managers.

Any hedge fund index should represent a general proxy for some portion of the hedge fund industry. Due to the nature of private, lightly-regulated, offshore structure-favored hedge fund industry, hedge fund databases[6] are subject to biases that militate against an accurate representation of hedge fund strategies and consequently distort performance. Certain biases do inflate performance while others may skew index performance downwards.

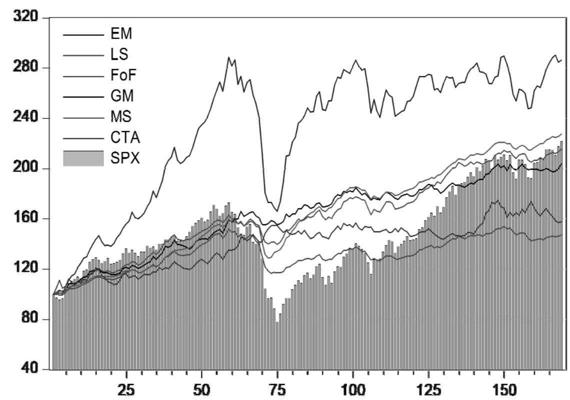
5) The Barclay Hedge Fund Index is a measure of the mean return of around 6,800 hedge funds in the database. The index is a simple arithmetic average of the net returns of all the funds that have reported that month. (http://www.barclayhedge.com/research/indices/ghs/Hedge_Fund_Index.html)

6) Joenväärä, Kosowski, and Tolonen [2012] reported that the BarclaysHedge database provides the highest-quality data among CISDM (Morningstar), Lipper (formerly TASS), Eurekahedge, and BarclaysHedge.

Because the Barclays indices may also provide some biased snapshot of the 'true' hedge fund universe, they do not include defunct funds, thus do not account for the survivorship bias. These indices didn't explicitly account for the backfill and the incubation biases that arise due to the voluntary nature of self-reporting in hedge fund databases. Furthermore, because these indices are constructed by combining hundreds of individual hedge funds into an equally weighted monthly return composite, most of the fund-specific components of risk and return characteristics in monthly returns are diversified away. Even without considering the illiquidity and stale pricing issues, such indices tend to underestimate the typical *ex-post* volatility in hedge fund investments, which would also dilute an idiosyncratic behavioral dynamics of volatility moderations by hedge fund managers.

Exhibit 1 shows the summary statistics for six Barclays sub-indices with the S&P 500 index ("SPX") returns from January 2003 to December 2016. While all six styles demonstrate positive annualized excess returns, the average Sharpe (or reward-to-risk) ratios across style indices vary from 1.14 (MS) to 0.36 (CTA), due to CTA's lower annualized returns during the sample period versus other investment styles. All return distributions are leptokurtic as mostly pronounced at MS (+9.98), and have negative skewness, except for GM (+0.25) and CTA (+0.20).

Exhibit 2. Cumulative Returns of the Barclays Sub-Investment Style Indices in Sample



Source: Internal DB of Green Shoots Capital Soultions Korea

Exhibit 1. Summary Statistics for the Barclays Sub-Investment Style Indices in Sample

	EM	LS	FoF	GM	MS	CTA	SPX
Total Return	186.3%	115.5%	47.4%	103.8%	127.6%	57.7%	121.6%
Ann. Return	7.8%	5.6%	2.8%	5.2%	6.0%	3.3%	5.8%
Ann. Volatility	11.5%	5.1%	5.0%	4.9%	4.7%	7.1%	13.8%
- Gain Stdev	6.5%	2.7%	2.2%	3.4%	2.4%	4.7%	7.6%
- Loss Stdev	9.7%	3.6%	4.7%	2.4%	5.4%	3.6%	11.6%
Sharpe Ratio	0.61	0.96	0.41	0.90	1.14	0.36	0.37
Skewness	(0.99)	(0.71)	(1.65)	0.25	(2.45)	0.20	(0.99)
Exc. Kurtosis	0.81	(2.06)	2.33	(2.98)	9.98	(2.97)	0.14
Best Month Return	11.1%	3.8%	3.0%	4.4%	3.9%	5.6%	10.20%
Worst Month Return	-15.6%	-4.9%	-6.8%	-3.3%	-7.6%	-5.8%	-18.60%
% Positive Months	66.1%	65.5%	64.9%	61.3%	73.8%	53.6%	63.10%
Avg. Draw-Down	-7.5%	-2.0%	-6.7%	-4.5%	-1.6%	-3.5%	-11.20%
Beta to S&P 500	0.62	0.29	0.25	0.17	0.22	0.00	1.00
Max Drawdown	-42.5%	-14.2%	-23.2%	-29.1%	-19.3%	-10.9%	-54.80%

Source: Internal DB of Green Shoots Capital Soultions Korea

Exhibit 3. Pearson Correlation of Risk Factors and the Barclays Style Indices

Correl/T-Stat.	$PTFSIR_{t-1}$	$DVIX^2_{t-1}$	EM_t	LS_t	FoF_t	GM_t	MS_t	CTA_t
$PTFSIR_{t-1}$	1.00							
$DVIX^2_{t-1}$	0.12	1.00						
	1.50							
EM_t	(0.39)	(0.30)	1.00					
	(5.36)	(3.98)						
LS_t	(0.35)	(0.24)	0.84	1.00				
	(4.74)	(3.17)	19.54					
FoF_t	(0.47)	(0.31)	0.85	0.90	1.00			
	(6.92)	(4.15)	20.76	27.28				
GM_t	(0.18)	(0.16)	0.64	0.72	0.07	1.00		
	(2.31)	(2.14)	10.82	13.26	13.49			
MS_t	(0.46)	(0.34)	0.81	0.83	0.92	0.60	1.00	
	(6.75)	(4.67)	17.84	18.99	29.27	9.72		
CTA_t	0.09	(0.06)	0.10	0.82	0.23	0.66	0.14	1.00
	1.14	(0.80)	1.35	2.46	3.07	11.19	1.75	

Source: Internal DB of Green Shoots Capital Soultions Korea

Its cumulative return is seen in Exhibit 2 that illustrates the hypothetical growth of $100 invested in January 2003 in the respective style indices.

Exhibit 3 shows the average correlations of these style indices together with risk factors applied in the moderation modeling. The pair-wise correlation among the Barclays style indices are highly discrete as ranging between 0.10 and 0.85, meaning that the style index such as CTA_t behaves rather independently, while most of the indices are closely connected across strategies, so one may not expect a high degree of diversification benefits. While the correlations between $PTFSIR_{t-1}$ and $DVIX^2_{t-1}$ factors are small positive, the correlations between $PTFSIR_{t-1}$ and excess returns of style indices Y_t are all negative, except for CTA_t (+0.09).

Recently, Cho and Kim [2017] test for the market timing ability of Korean equity long-short hedge funds by newly introducing the concept of style-tilting volatility (STV) as a measure to quantify the amount of variation or dispersion of a set of individual fund's style exposures. Their approach implies that market timing ability results in a convex relation between individual fund returns and the various style factors. The analysis makes use of daily returns instead of typical hedge fund monthly returns to increase their statistical power (and noise as well). The study evaluates the relationship between the three market-timing indicators such as STV, Volatility Timer, and Treynor-Mazuy-type Market Timer, to the excess returns and Sharpe ratios of reclassified quintile hedge fund groups to identify the active style and volatility timers. Some hedge funds demonstrated enhanced risk-adjusted returns through a wide range of volatility timing behavior, while their active style bets did not necessarily result in performance persistence compared to the peer managers.

Among Fung and Hsieh [2001]'s five trend-following risk factors[7], this study only adopts one-month prior short-term interest rate (PTFSIR) factor together with the quadratic returns of VIX[8]. The analysis here intentionally excludes the usual lookback straddles factors such as bond (PTFSBD), currency (PTFSFX), commodity (PTFSCOM), and stock indices (PTFSSTK) in order to concentrate to the interplay between a one-month prior trend-following factor of the short-term interest rate and the one-month prior volatility of implied volatility return dynamics. For the application of an implied volatility measure to tactical hedge fund allocation decisions, Goldwhite [2009] suggested using the VIX to switch hedge fund styles to enhance portfolio performance per unexpected changes in risk aversions. He divided negative, positive and non-correlated regimes following to the evolution of the VIX and suggested a hedge fund style selection framework based on the level (not the return or not even quadratic return) information of the implied volatility. The VIX performed well in capturing *a priori* market concerns about negative fat-tail events by measuring the probability of market-assigned extreme negative outcomes. Since this forward-looking implied volatility indicator works for capturing common market concerns about tail-events by instantaneously reflecting the changes in risk appetites, our study adopts the quadratic returns of one-month prior VIX as the proxy of equity market risk aversions.

Measuring the performance through alpha after controlling for systematic risk exposures delivers a stable basis for comparing hedge fund style indices. Though not all the risk factors offer persistent return premiums and some of the factors didn't even come up with explicitly definable returns, this rather parsimonious two-factor approach possibly translates alpha as an incomplete economic measure of risk-adjusted excess portfolio returns. However, identifying the existence of factor-conditioned alpha based on various risk factor models per hedge fund style is not one of the main themes of this experiment.

Based on these empirical backgrounds, Exhibit 4 presents the summary results of our baseline dual-factor model estimated on six Barclays sub-indices per investment style from January 2003 to December 2016, encompassing the periods of market stress triggered by

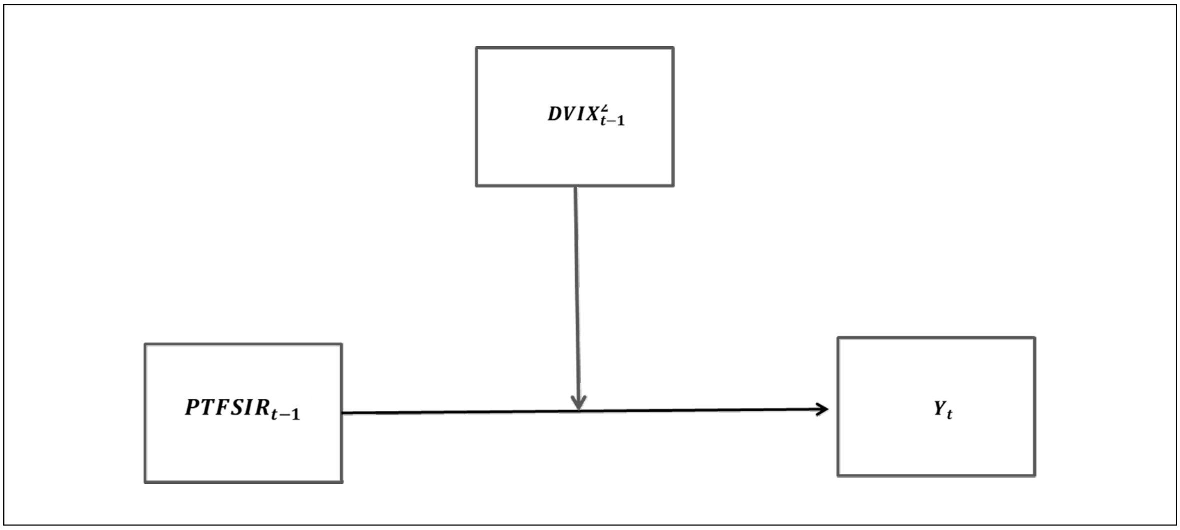
Exhibit 4. Coefficients from OLS Results

Coefficients	EM	LS	FoF	GM	MS	CTA	SPX
Intercept	1.165 ***	0.6429 ***	0.440 ***	0.518 ***	0.660 ***	0.166	0.006
$PTFSIR_{t-1}$	-0.015	-0.004	-0.007	0.007 *	-0.008	0.013 ***	-0.00025 **
$DVIX^2_{t-1}$	-0.0013**	-0.0005 **	-0.0005 **	-0.0002 *	-0.0005 **	0.0003 **	0.000
R^2	0.110	0.066	0.110	0.026	0.113	0.057	0.043

***, **, * Significance at 99.9%, 95%, 90%, respectively with Huber-White Heteroskedasticity consistent standard errors

7) I thank David A. Hsieh for providing their PTFS factors on the website: https://faculty.fuqua.duke.edu/~dah7/HFData.htm
8) VIX White Paper, www.cboe.com/micro/vix/vixwhite.pdf

Exhibit 5. Conceptual Diagram Combining Equation 2 and 4



the U.S. sub-prime mortgage crisis and the fiscal crisis in the periphery Eurozone, as offering sufficiently long data samples per Equation (1). The alpha is measured to be positive and significant at EM_t, LS_t, FoF_t, GM_t, and MS_t. The alpha (or active manager skill) measures the excess return, controlling for the risk premia associated by simply being exposed to these systematic risk premiums.

[Eq. 1] $Y_t = \alpha_t + \beta_{1,t}PTFSIR_{t-1} + \beta_{2,t}DVIX^2_{t-1} + e_t$

Exhibit 5 describes a moderation model as the effect of ($PTFSIR_{t-1}$) on (EM_t, LS_t, FoF_t, GM_t, MS_t, and CTA_t) can be said to be moderated if its size or direction is dependent on ($DVIX^2_{t-1}$). ($DVIX^2_{t-1}$) is depicted here to moderate the size of the effect of ($PTFSIR_{t-1}$) on (EM_t, LS_t, FoF_t, GM_t, MS_t, and CTA_t), therefore, the model postulates that both ($PTFSIR_{t-1}$) and ($DVIX^2_{t-1}$) interact in their influence on (EM_t, LS_t, FoF_t, GM_t, MS_t, and CTA_t). While the exposure to $PTFSIR_{t-1}$ is insignificant for almost all style indices, except for some significant positive at CTA_t, the exposure to $DVIX^2_{t-1}$ is negative and significant, except for at CTA_t ($p < 0.05$) index. The model explanatory power measured in R^2 ranges from 0.03 (GM_t) and 0.06 (CTA_t) to 0.11 in EM_t, FoF_t, and MS_t indices. The analysis seems suffering a typical model mis-specifications from the evidence of unconventionally large intercept and poor explanatory power represented by a low R^2.

Back to our main theme of the implied volatility moderation modeling, as Krieger and Sarge [2013] advance in their analysis of potential mediators of the link between vaccine framing and people's behaviors with their second stage dual moderated mediation model, our quadratic volatility effect is assumed to be linearly moderated. This can occur in models with a two-way interaction involving the independent variable ($PTFSIR_{t-1}$) and the moderator ($DVIX^2_{t-1}$). Hedge fund managers' return generating process might include the volatility mediation process as can be seen from the conceptual diagram at Exhibit 4.

The model in Exhibit 5 can be represented with Equation 2, where the moderated effect of $PTFSIR_{t-1}$ depends on $DVIX^2_{t-1}$.

$$[Eq. 2]\ Y_t = \alpha_{Y_t} + \beta_{1t} PTFSIR_{t-1} + \beta_{2t} DVIX^2_{t-1} + \beta_{3t} PTFSIR_{t-1} DVIX^2_{t-1} + e_{Y_t}$$
$$= \alpha_{Y_t} + \left(\beta_{1t} + \beta_{3t} DVIX^2_{t-1}\right) PTFSIR_{t-1} + \beta_{2t} DVIX^2_{t-1} + e_{Y_t}$$

Y_t is the contemporaneous monthly return for the Barclays hedge fund sub-indices in excess of the risk-free rate $(EM_t, LS_t, FoF_t, GM_t, MS_t, CTA_t)$. Risk-free rate is the return of one-month Treasury bills, $PTFSIR_{t-1}$ is the one-month prior primitive trend following strategy on the short-term interest rate factor, and $DVIX^2_{t-1}$ is the quadratic return of one-month prior CBOE implied volatility index (i.e., the squared return between VIX_{t-1} and VIX_{t-2}) as a conditional moderator in this setting. The errors in Equation 2 for the estimation of Y_t assumed to be identically and independently distributed with zero mean.

Then, Equation 3 shows the combined effect ($\theta_{PTFSIR_{t-1} \to Y_t}$) of $PTFSIR_{t-1}$ on Y_t.

$$[Eq. 3]\ \boldsymbol{\theta_{PTFSIR_{t-1} \to Y_t} = \beta_{1t} + \beta_{3t} DVIX^2_{t-1}}$$

The effect of $PTFSIR_{t-1}$ is a function of $DVIX^2_{t-1}$, and their product. Plugging in values $DVIX^2_{t-1}$ into Equation 3 results in the effect of $PTFSIR_{t-1}$ on Y_t conditioned on those values of $DVIX^2_{t-1}$. The relationship between the effect of $PTFSIR_{t-1}$ and the moderator $DVIX^2_{t-1}$ can be visualized by substituting estimates of $\boldsymbol{\beta_{1t}}$ & $\boldsymbol{\beta_{3t}}$ into Equation 3, which makes mathematically explicit.

Then, $\boldsymbol{\beta_{1t}}$ is the conditional effect of $PTFSIR_{t-1}$ on Y_t when $DVIX^2_{t-1}$ is zero. $\boldsymbol{\beta_{3t} DVIX^2_{t-1}}$ quantifies the rate of change in the effect of $PTFSIR_{t-1}$ as $DVIX^2_{t-1}$ changes. According to Hayes [2018], the term $\boldsymbol{\beta_{3t} DVIX^2_{t-1}}$ can be the index of conditional moderation of the effect of $PTFSIR_{t-1}$ by $DVIX^2_{t-1}$, which quantify the relationship between the moderator and the size of $PTFSIR_{t-1}$ to the effect on Y_t.

$$[Eq. 4]\ \boldsymbol{\theta_{DVIX^2_{t-1} \to Y_t} = \beta_{2t} + \beta_{3t} PTFSIR_{t-1}}$$

With a little algebra, Equation 3 can be written in an equivalent form in Equation 4, as the relationship between the effect of $DVIX^2_{t-1}$ is a linear function of $PTFSIR_{t-1}$: $(\boldsymbol{\beta_{2t} + \beta_{3t} PTFSIR_{t-1}})$. If one were to plot the relationship between an effect of $DVIX^2_{t-1}$ in two-dimensional space, with $PTFSIR_{t-1}$ on the horizontal axis, $(\boldsymbol{\beta_{2t} + \beta_{3t} PTFSIR_{t-1}})$ in Equation 4 quantifies the rate of changes in the effect of $DVIX^2_{t-1}$ on Y_t as $PTFSIR_{t-1}$ is changing. $\boldsymbol{\beta_{2t}}$ estimates how the effect of $DVIX^2_{t-1}$ varies when $PTFSIR_{t-1}$ equals to zero and $\boldsymbol{\beta_{3t}}$ quantifies how that moderation effect of $DVIX^2_{t-1}$ as $PTFSIR_{t-1}$ changes.

[3] Statistical Inference

It makes sense to probe the effect of moderation by testing whether the effect of $PTFSIR_{t-1}$ is moderated by $DVIX_{t-1}^{2}$ at chosen values and corresponding inference procedures. In Exhibit 5, there is a two-way interaction term ($PTFSIR_{t-1}$* $DVIX_{t-1}^{2}$). Probing this interaction reveals how one-month prior quadratic VIX returns moderates the effect of one-month prior PTFSIR, which is the inference methodology adopted in this article.

The constants reported in Exhibit 5 indicate the excess returns (or alphas) after additionally controlling for the two-way interaction term or the moderation effect. While the alpha of CTA_t index in our baseline estimation in Exhibit 3 was insignificant, the alphas of almost all indices became significantly positive at 5% (10% for CTA_t index) or above level after controlling for conditional moderation effects. However, the magnitude of alphas in almost all indices, except for CTA_t index, was significantly declined after controlling the moderation effect. This is another expression that the moderation effect can explain the Barclays EM_t, LS_t, FoF_t, GM_t, and MS_t indices and may be an illustration of the importance of both fees (retainer and performance) and transaction costs in their respective style space.

Market timing and security selection skills are believed to represent some significant forecasting abilities of fund managers in top-down and bottom-up scales. While the estimated value of alpha is typically assumed to be driven by the manager's security selection ability within the context of hedge funds, the estimated values of alphas are affected by factors other than the security selection skills as well. According to Mamaysky, Spiegel, and Zhang (2008), if a mutual fund's alpha may be decomposed into a portion due from successful market timing and transaction costs, the estimated alpha becomes significantly reduced or even negative with the presence of market timing skills by fund managers. This is because the estimated alpha tends to be significantly reduced whenever the market timing abilities of hedge funds are not sufficient to cover dual fee structures such as asset management and incentive fees. In our case, as the moderation factor is added to our base case model in Equation 1 and the more variability in the Barclays style index returns is explainable by the conditional moderation effect, the negative moderation effect nevertheless drives down the Barclays EM_t, LS_t, FoF_t, GM_t, and MS_t index alphas. This reflects the fact that after the portion of return explained by timing ability is accounted for, whatever leftover in idiosyncratic performance is drastically reduced but still economically significant at 1% level or above, which may be further reduced by the addition of conditioning systematic risk factors.

According to Goetzmann, Ingersoll, and Ivkovich [2000], hedge funds may change their systematic risk exposures more frequently than their usual schedule of monthly reporting to public databases. This mismatches between portfolio factor rebalancing and reporting frequencies could lead to an over-estimation of

Exhibit 6. Estimations of Moderation Model

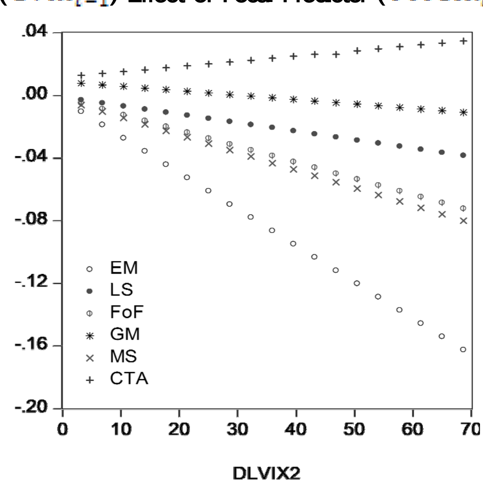
Coefficients	EM	LS	FoF	GM	MS	CTA	SPX
Constant	0.7497 ***	0.4850 ***	0.2654 ***	0.4350 ***	0.5223 ***	0.2543 *	0.0043
$PTFS_{t-1}$	-0.0030	-0.0120	-0.0017	0.0086 **	0.0026	0.0116 **	-0.0003 **
$DVIX^2_{t-1}$	-0.0011 ***	-0.0004***	-0.0004 ***	-0.0001 *	-0.0004 ***	0.0003 **	0.0000
$PTFS_{t-1}*DVIX^2_{t-1}$	-0.000023***	-0.000054***	-0.0000103***	-0.0000029**	-0.0000113***	0.0000034*	0.00000
R^2	0.1869	0.0876	0.1902	0.0324	0.2252	0.0610	0.0468
R^2 Increment	0.0771 ***	0.0219 ***	0.0799 ***	0.0063 **	0.1118 ***	0.0044 *	0.0034
F(1, 163, HCO) Stat.	54.0482	23.5958	75.6583	4.1988	91.8591	3.4658	0.6392

***, **, * Significance at 99.9%, 95%, 90%, respectively with Huber-White Heteroskedasticity consistent standard errors

spurious security selection or market timing skills when none exists. The use of our dual-factor-based moderation model does not completely solve the inefficiency of the proxies and maybe another version of the poor description of portfolio risk exposure problems as these models are not necessarily covering of all significant risk factors to be exposed by the portfolios.

Using a less-specified model as in Exhibit 4 might lead to the conclusion that certain styles of hedge fund managers might deliver consistent alphas, though this specific skill-set is, in fact, nothing more than just the return premium rewarding some omitted risk factors such as the moderation effects as can be seen in Exhibit 6. In terms of improvement in the model fit, the Barclays EM_t, LS_t, FoF_t, GM_t, and MS_t indices are statistically significant after the two-way interaction term is included. The incremental increase in R^2 due to allowing the moderation effect of $DVIX^2_{t-1}$ by ($PTFSIR_{t-1} * DVIX^2_{t-1}$) is ΔR^2 = 0.077, F(1, 163) = 54.05, p 〈 0.01 for the Barclays EM_t index, ΔR^2= 0.022, F(1, 163) = 23.60, p 〈 0.01 for LS_t index, ΔR^2= 0.080, F(1, 163) = 75.66, p 〈 0.01 for FoF_{t-1} index, ΔR^2= 0.006, F(1, 163) = 4.20, p 〈 0.05 for GM_t index, ΔR^2= 0.112, F(1, 163) = 91.86, p 〈 0.01 for MS_t index, and ΔR^2= 0.004, F(1, 163) = 3.47, p 〈 0.10 for CTA_t index. The market-cap weighted passive S&P 500 index fails to reveal any evidence of significant moderation effect as expected. This is the same as the inference when framed instead as a test of (i) the improvement in model fit due to the two-way interaction term when the sign of the effect of $PTFSIR_{t-1}$ appears to vary with $DVIX^2_{t-1}$ or (ii) the test of statistical significance as the regression coefficient of $\beta_{3,t}$. Therefore, a hypothesis test for $\beta_{3,t}$ in the regression analysis is mathematically equivalent to this hypothesis test for ΔR^2.

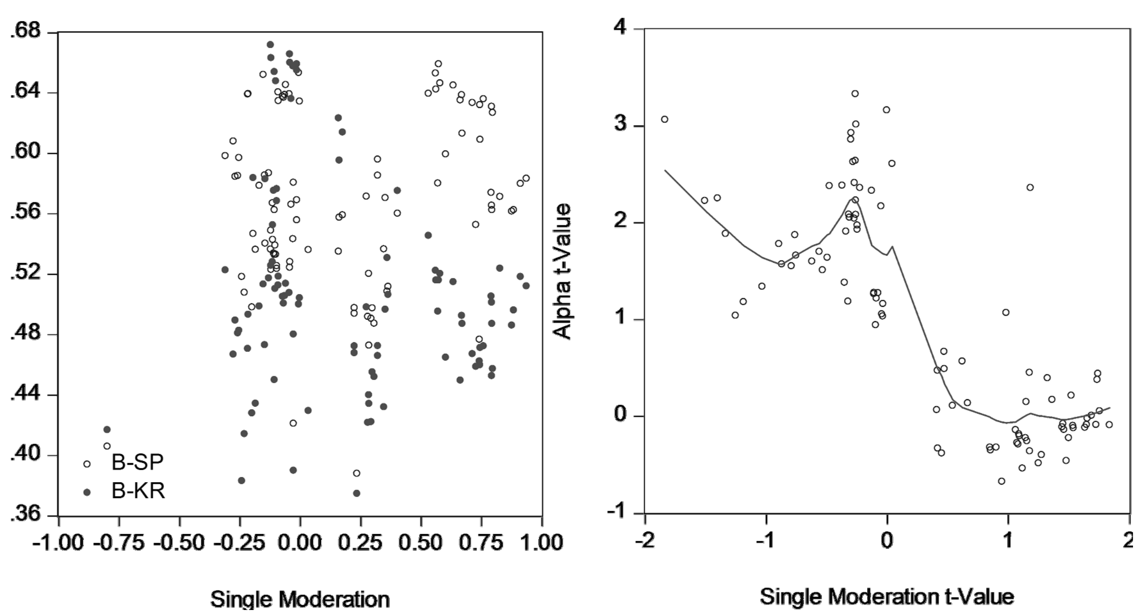
Exhibit 7. Conditional Moderation ($DVIX^2_{t-1}$) Effect of Focal Predictor ($PTFSIR_{t-1}$)



Using Equation 3, $DVIX_{t-1}^2$ is on the horizontal axis as depicted in Exhibit 7 and the conditional moderation effect is recorded on the vertical axis. The estimated equation of these lines is $\beta_{1,t} + \beta_{3,t} DVIX_{t-1}^2$, which is the index of conditional moderation by $DVIX_{t-1}^2$. If $\beta_{3,t}$ is zero, then $DVIX_{t-1}^2$ does not moderate $PTFSIR_{t-1}$. Such a phenomenon would take the form of a set of parallel lines relating to $PTFSIR_{t-1}$ at the various value of $DVIX_{t-1}^2$. If $\beta_{3,t}$ is statistically different from zero, the changes in the conditional effect of $PTFSIR_{t-1}$ depends on $DVIX_{t-1}^2$ as the cases in the Barclays EM_t, LS_t, FoF_t, GM_t, and MS_t indices. A negative conditional moderation effect is strongest among EM_t and MS_t style hedge fund managers, while the CTA_t index reveals a positive conditional moderation effect. Since the covariance between $PTFSIR_{t-1}$ and $DVIX_{t-1}^2$ as a reliable proxy of general market risk aversions might be helpful to understand hedge fund return profiles, it might be also intuitive whether the differences in the magnitude of conditional moderation effects will be able to tell which style groups are relatively more tactically responsive in altering their risky asset or factor exposures.

The stronger the negative conditional moderation effect, the larger the portion of decay from the initial alpha estimated from Exhibit 4 and the model fits improvement is mostly pronounced in the Barclays EM_t index. On the other hand, a positive conditional moderation effect in CTA_t index leads to some revival of the estimated portion of *ex-post* alpha, so does model fits in a less significant margin. The positive conditional moderation effect in CTA_t index is interesting because most of these managers are of trend-following "long-vol"

Exhibit 8. Conditional Moderation Effects ($\beta_{3,t-1}$) vs. Betas and Alphas: Barclays EM Index Case



traders. At the robustness test in Section 4, we will further elaborate this "long-vol" effect found in tail-risk hedgers in liquid alternative space.

According to Mamaysky, Spiegel, and Zhang (2008), this reflects the fact that once the portion of alpha explained by timing ability is accounted for, the leftover in performance is significantly reduced and sometimes to the negatives. Therefore, if any in-house *ex-ante* factor generating process signals a certain degree of unfavorable PTFSIR environment (especially when $DVIX_{t-1}^{2}$ moves in a jump), EM_t style managers would be the most active in tilting the fund's exposure to or from the trend following factor, under the influence of the prior month's quadratic returns of implied volatilities. These managers would respond by reducing overall passive market exposures of their strategy returns when we measure an appropriate market benchmark such as the S&P 500 as the beta for equity-biased hedge fund styles.

To examine the robustness of our results, we use a 36-month window rolling regression to examine the time variation of alpha and the conditional moderation effects. This type of analysis of passive market benchmark exposure versus conditional moderation effect can be interesting because at the left-hand panel of Exhibit 8 plots the full dispersion of the Barclays EM strategy's beta exposures of the S&P 500 ("B-SP") and Morgan Stanley Korea Index ("MXKR", "B-KR") against the moderation effects. While investors tend to focus on net-of-fee returns of hedge fund-style indices, the panel displays a random relationship (the slope of +0.033, P 〈 0.05, R^2=0.05) between the moderation effect and the excess returns of the S&P 500 index. As Roll [1977] showed, the result of factor-tilting behavior with respect to the moderation effect may change depending on the index chosen as a market benchmark. For Korean investors, the more appropriate market benchmark would be MXKR rather than the S&P 500. A subsequent interpretation with respect to the effect of the moderation might slightly be different but the distributions are, again, basically random (the slope of -0.033, P 〈 0.1, R^2=0.034). The right-hand side panel plots t-values of alpha against the t-values of conditional moderation effects, where both t-statistics are based on Huber-White heteroskedasticity-consistent standard errors. The significance of positive alpha is more pronounced when conditional moderation effect is in negative territory. This negative relationship is linearly summarized as the slope -0.9299 (p 〈 0.0000) with R^2=0.596.

Suppose the return of a hedge fund is estimable by a multi-factor model and the hedge fund manager specifically adjusts her exposures to the market factor (MKT_t) based on the signal from the conditional moderation. Then the following equations are the basis for our empirical tests:

[Eq. 5] $\beta_{1,t}^{*} = \beta_{1,t-1}(1-\gamma_{t-1})MKT_{t-1} + \nu_t$

[Eq. 6] $Y_{v,t} = \alpha'_{1,t} + \beta_{1,t}^{*}MKT_t + \sum \beta_{i,t}F_{i,t} + \omega'_{1,t}$

[Eq. 7] $Y_{v,t} = \alpha_{i,t} + \beta_{1,t}MKT_t + \sum \beta_{i,t}F_{i,t} + \omega_{i,t}$

Equation 5 describes how a hedge fund manager determines her market exposure, $\beta_{1,t}^{*}$, adaptively to the observed one-month prior

Exhibit 9. Estimation of Equation 6 and 7 on the Barclays EM index

Factor	Alpha	MKT_t	$(1-\gamma_{t-1}MKT_t)$	SMB_t	HML_t	CMA_t	RMW_t	$PTFSCOM_t$	R^2
Equation 6	-0.0029 *		0.5558 ***	0.2608 **				-0.016 **	0.70
Equation 7	-0.0026	0.5516***		0.3497***	0.2546 **	-0.5424***	0.3329 **	-0.0180 *	0.83

***, **, * Significance at 99.9%, 95%, 90%, respectively with Newey-West HAC consistent standard errors

conditional moderation signal, γ_{t-1}, whereas Equation 6 describes the return process of this hedge fund. The noise term, $e_{\gamma,t}$, of Equation 2 of the timing signal is assumed to be uncorrelated with v_t and $\omega'_{1,t}$, the error terms in Equation 5 and 6. Equation 5 postulates a successful market-timing manager of convergence trade in her mind might increase market exposures after watching a negative one-month prior conditional moderation effect with a positive expected return and decrease the exposure if the opposite is true. This would create a convex relationship between the hedge fund's return and the market factor.

Correlation between $(1-\gamma_{t-1})MKT_t$ is 0.99 (MKT_t), -0.02 (SMB_t), +0.02 (HML_t), -0.25 (CMA_t), -0.42 (RMW_t), -0.21 (WML_t), -0.44 ($PTFSBD_t$), -0.30 ($PTFSCOM_t$), -0.23 ($PTFSFX_t$), -0.27 ($PTFSIR_t$), and -0.34 ($PTFSSTK_t$). Exhibit 9 shows a step-wise OLS estimation result of Equation 6 and 7, where Equation 6 managers exhibit more responsive *ex-ante* risk-factor allocation versus Equation 7 managers. Between Equation 7 and 6 managers, the weights on SMB_t factor is declined quite a bit, so does the statistical significance. While no significant average exposure is estimated in HML_t, CMA_t, and RMW_t factors at Equation 6 managers, the estimated negative alpha becomes marginally significant at 10% level after the market-timing ability measured by conditional moderation effect has been accounted for. We speculate that, within the context of emerging market-focused hedge funds, the time-varying nature of one-month prior volatility moderation effect leads the managers to alter the subsequent month's risk-on positions pro-actively and results in not enough overall consistency in their exposures as revealed in factors such as HML_t, CMA_t, and RMW_t.

[4] Robustness: Application to Single Hedge Funds

For robustness test, we run the same moderation test for the collection of individual hedge funds. We come up with three different collections of diversified liquid alternative hedge funds: Diversified 1 (or "HKM")[9] is a portfolio of hard-closed capacity hedge funds in the industry.

As can be found in Exhibit 10, the underlying

9) HKM portfolio consists of ten highly successful hedge fund management firms, including firms like Millennium, Point72, Bridgewater, Renaissance, and BlackRock. The minimum investment for the HKM portfolio is designed as USD 1,000,000 per investor. Liquidity is quarterly with 60-day notice and the product has a 2-year soft lock with 5% exit penalty.

Exhibit 10. The composition of HKM Portfolio

	Manager Name	Strategy	Fund	Inception	U$ AUM Firm
1	BlackRock	Equity Long-Short	European Hedge Fund	Feb-12	$6,300bln
2	Bridgewater	Global Macro	Pure Alpha Major Markets	Jan-75	165bln
3	Point72	Multi Strategy	ShoreBridge Point72 Select	Jan-03	13bln
4	Och Ziff	Equity Hedge	OZ Overseas Fund II	Jan-98	32bln
5	PFM	Equity Long-Short	PFM Healthcare Offshore Fund	Jan-04	6bln
6	Renaissance	Statistical Arbitrage	RIEF	Aug-05	62bln
7	Stone Milliner	Global Macro	Stone Milliner Macro Fund	Jan-12	5bln
8	Third Point	Event Driven	Third Point Offshore Fund	Jan-95	18bln
9	World Quant / Millennium	Statistical Arbitrage	WMQS Global Equity Active Extension Offshore Fund	Jan-09	10bln
10	Millennium	Multi Strategy	Millennium International	Jan-89	36bln

Source: Internal DB of Green Shoots Capital Soultions Korea

portfolio allocates to 10 highly complementary and industry-leading managers. Since January 2008 until October 2018, the HKM has demonstrated following performance characteristics: (i) an annualized return of 7.50%, (ii) a total return of 119.1%, (iii) robustness during the equity market drawdowns as a proven maximum loss of less than half of equity indices. The appendix lists the summary of single manager details of HKM portfolio.

The second diversified portfolio (Owl Diversified, or "OWL") is a multi-manager portfolio focused on broad strategy diversification and downside protection. The underlying portfolio allocates to 10-plus highly complementary and institutional quality single managers. High liquidity strategies allow for the fastest and transparent risk management. Since January 2008 until October 2018, the OWL portfolio has demonstrated following performance characteristics: (i) an annualized return of 11.2%, (ii) a total return of 215.60%, (iii) no year of negative performance, and (iv) a maximum loss of less than -5%. The portfolio has 20% target allocation to global macro, 40% to equity long-short, 10% each to U.S. arbitrage and private debt, and the remaining 20% dedicated to U.S. tail-hedge strategies.

The third diversified portfolio (Multi-Protect, or "MP") is a multi-manager portfolio focused on systematic and downside protection trading strategies, often with a tail-hedge dedication. The portfolio allocates to 4-plus highly complementary and institutional quality managers trading 5 different investment strategies. High liquidity strategies and the use of managed accounts allow for fast and transparent risk management. Since January 2008 until October 2018, the MP portfolio has demonstrated following performance characteristics: (i) an annualized return of 11.6%, (ii) a total return of 228.10%, (iii) positive performance during equity drawdowns, and (iv) a maximum loss of less than -4%. The portfolio has a 10% target allocation to systematic global macro, 30% to volatility arbitrage, 20% each to U.S. tail-hedge and VIX-hedge, and the remaining 20% dedicated to Asia tail-hedge strategies. The U.S. tail-hedge manager is the largest provider of the tail-hedge protection portfolios with high convexities proven during 2008. Asia tail-hedge manager combines its Asian option arbitrage and Asia-focused tail-hedge strategies. VIX-hedge manager together with volatility arbitrage manager is specifically focused on the S&P 500 implied volatility index market to address the volatility spike, gamma, and gap risks with downside protection. The systematic global macro manager runs a globally diversified systematic strategy allocation in over 200 instruments and 80 markets.

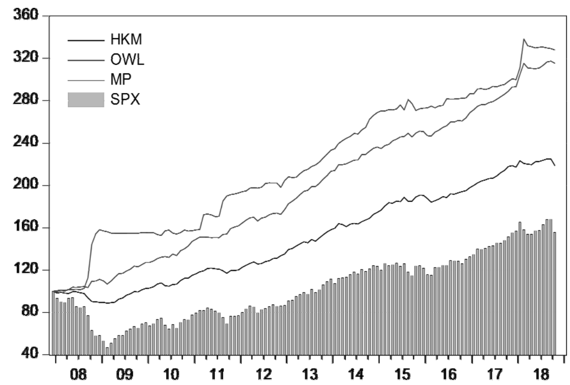
Exhibit 11. HKM, OWL, MP-Diversified vs. U.S. Equities (S&P 500) since 2008

	HKM	OWL	MP	SPX
Total Return	119.1%	215.6%	228.1%	55.7%
Ann. Return	7.5%	11.2%	11.6%	4.2%
Ann. Volatility	4.7%	4.3%	10.5%	15.2%
- Gain Stdev	2.7%	3.5%	11.8%	7.9%
- Loss Stdev	3.4%	2.4%	2.1%	13.0%
Sharpe Ratio*	1.00	1.94	0.83	0.09
Skewness	(0.79)	0.46	6.18	(1.00)
Exc. Kurtosis	(1.85)	(1.16)	47.20	(0.51)
Best Month	3.3%	5.9%	28.1%	10.2%
Worst Month	-4.3%	-2.7%	-2.4%	-18.6%
% (+) Months	70.8%	80.8%	70.0%	63.1%
AVG Draw-Down	-1.2%	-0.2%	-0.7%	-10.3%
Beta to S&P 500	0.24	0.14	(0.31)	1.00
Max Drawdown	-10.9%	-4.0%	-3.7%	-50.1%

Source: Internal DB of Green Shoots Capital Soultions Korea

Exhibit 11 illustrates the hypothetical growth of $100 invested at the end of December 2007 in three diversified liquid alternative portfolios versus the S&P 500 index.

Exhibit 12. Cumulative Returns of HKM, OWL, MP-Diversified vs. U.S. Equities (S&P 500) since 2008



Its cumulative return is seen in Exhibit 12 that illustrates the hypothetical growth of $100 invested in January 2008 in the respective three liquid alternative hedge fund portfolios versus U.S. large-cap equity index.

While the OWL Diversified focusing on managers above U$200mn in assets under management at a minimum and with the focus on downside protection by using appropriate strategies, the Multi-Protect is even more dedicated to downside protection. Exhibit 13 illustrates the downside protection capacities of MP portfolio during the latest severe equity market draw-down periods.

Exhibit 13. Liquid Alternative Portfolios during the Severe Equity Market Draw-Down Periods

No.	Period	MSCI World	S&P 500	MSCI Korea	HKM	OWL	MP
1	May - August 2013	-0.23%	2.19%	0.00%	1.67%	3.96%	3.79%
2	September - December 2014	-2.26%	2.73%	-9.55%	5.12%	3.08%	5.42%
3	February - October 2018	-10.81%	-7.23%	-24.13%	-1.83%	3.58%	5.51%
4	April - May 2012	-8.65%	-11.70%	-7.92%	-0.36%	-1.78%	0.01%
5	January - March 2008	-10.52%	-10.96%	-10.07%	-1.82%	0.17%	1.08%
6	August - September 2015	-10.99%	-9.14%	-2.91%	-1.92%	-0.19%	2.21%
7	April - June 2010	-14.26%	-12.66%	-0.28%	-1.96%	0.80%	2.75%
8	May - September 2011	-22.94%	-18.68%	-22.65%	-3.95%	2.01%	9.81%
9	June 2008 - February 2009	-71.62%	-65.17%	-57.43%	-11.33%	3.11%	53.66%

Source: Green Shoots Investment Solutions Korea Research

Exhibit 14. Coefficients from the Base Case Model

Coefficients	Diversified 1 (HKM)	Diversified 2 (OWL)	Diversified 3 (MP)
Intercept	0.0063 ***	0.0093 ***	0.0088 **
$PTFSIR_{t-1}$	-0.0118 **	0.003	0.05113 *
$DVIX^2_{t-1}$	-0.018	-0.004	0.082
R^2	0.072	0.004	0.272

***, **, * Significance at 99.9%, 95%, 90%, respectively with Huber-White Heteroskedasticity consistent standard errors

Exhibit 15. Conditional Moderation Model

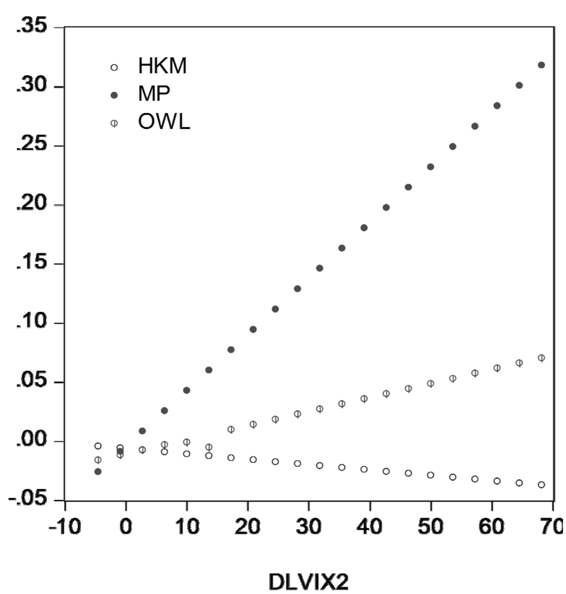
Coefficients	Diversified 1 (HKM)	Diversified 2 (OWL)	Diversified 3 (MP)
Constant	0.6361 ***	0.8377 ***	0.7291 ***
$PTFS_{t-1}$	-0.0064	-0.0109 **	-0.0047
$DVIX^2_{t-1}$	-0.0152 *	-0.0114	0.0543 ***
$PTFS_{t-1}*DVIX^2_{t-1}$	-0.0005 **	0.0012 ***	0.0047 ***
R^2	0.0874	0.1303	0.6022
R^2 Increment	0.0155 **	0.1263 ***	0.3304 ***
F(1, 126, HCO) Stat.	4.3514	23.1290	68.7586

***, **, * Significance at 99.9%, 95%, 90%, respectively with Huber-White Heteroskedasticity consistent standard errors

HKM as the collection of “short-vol” managers, OWL as the composition of both “short-vol” and 20% allocation to “long-vol” managers, and MP as more commercially viable “long-vol” bias, Exhibit 14 presents the estimation results of our two-factor base-case model estimated on three alternative diversified portfolios, HKM, OWL, and MP from January 2008 to the latest October 2018, encompassing two periods of market stress triggered by the U.S. sub-prime mortgage crisis and the fiscal crisis in the periphery Eurozone. Alpha is measured to be positive and significant at HKM_t, OWL_t, and MP_t. While the exposure to $PTFSIR_{t-1}$ is only significantly negative at HKM_t, the exposure to ($DVIX^2_{t-1}$) is negative but insignificant, except for MP_t portfolio. The model explanatory power measured in R^2 ranges from extremely poor at 0.004 (OWL_t), 0.07 (HKM_t) to 0.27 in (MP_t). The analysis seems to be suffering model mis-specifications in (OWL_t) portfolio from the evidence of unconventionally large intercept and poor explanatory power represented by a low R^2. As this collection of individual hedge funds may change their systematic risk exposures more frequently, the use of the base-case model does not even close to solving the inefficiency of the proxy problems.

Using a mis-specified model as in Exhibit 14 still lead us to an indecent conclusion that these diversified pools of liquid alternatives might deliver consistent alphas, though this specific skill-set can be another form of premium rewarding some omitted risk factors such as the moderation effects as can be seen in Exhibit 15. All HKM_t, OWL_t, and MP_t portfolios become more statistically significant after the two-way interaction term is included. The incremental increase in R^2 due to allowing the moderation effect of $DVIX^2_{t-1}$ by ($PTFSIR_{t-1} * DVIX^2_{t-1}$) is ΔR^2 = 0.087, $F(1, 126) = 4.35$, $p < 0.05$ for HKM_t, ΔR^2 = 0.13, $F(1, 126) = 23.13$, $p < 0.01$ for OWL_t, and ΔR^2 = 0.33, $F(1, 126) = 68.76$, $p < 0.01$ for MP_t. Therefore, a test of the improvement in model fit due to the conditional moderation in the effect of $PTFSIR_{t-1}$ appears to vary with $DVIX^2_{t-1}$.

Exhibit 16. Conditional Moderation Effect of Focal Predictor ($PTFSIR_{t-1}$) at Values of the Moderator ($DVIX^2_{t-1}$)



Using Equation 4, $DVIX^2_{t-1}$ is on the horizontal axis as depicted in Exhibit 16 and the conditional moderation effect is recorded on the vertical axis. The slope of these lines is $\beta_{1,t} + \beta_{3,t} DVIX^2_{t-1}$, which is the index of conditional moderation by $DVIX^2_{t-1}$. Since $\beta_{3,t}$ is statistically different from zero, the changes in the conditional effect of $PTFSIR_{t-1}$ depends on $DVIX^2_{t-1}$ as the cases in the MP_t and OWL_t portfolios. Positive conditional moderation effect is strongest among MP_t portfolio managers, while the HKM_t managers reveal slightly negative moderation effect. Then, the original question is whether the differences in the magnitude of conditional moderation effects (i.e., the slope of $\beta_{3,t}$) might be able to explain more responsive managers within certain investment styles by tilting their risky asset or factor exposures more dynamically in order to timely adjust their overall passive market exposures.

A positive conditional moderation effect in both MP_t and OWL_t portfolios lead to the improvement of *ex-post* alpha estimation, so does model fits in a significant margin. The stronger the positive conditional moderation effect, the larger the portion of restoration from the initial alpha estimated from Exhibit 14. Therefore, if any in-house *ex-ante* factor generating process shows a certain degree of favorable PTFSIR environment (or when $DVIX^2_{t-1}$ moves in a jump), MP_t and OWL_t portfolio managers become more active in altering the fund's exposure to or from the trend following factor, under the influence of the simultaneous considerations of $DVIX^2_{t-1}$, and they would change overall passive market exposures of their strategy returns.

Exhibit 17 shows a step-wise OLS estimation result of Equation 6 and 7 by encompassing six Fama-French global equity factors and five Fung-Hsieh PTFS factors, where Equation 6 managers exhibit more responsive risk-factor allocation versus Equation 7 managers, *ex-post*. For OWL portfolio, there are no sig-

Exhibit 17. Estimation of Equation 6 and 7 on Three Liquid Alternative Portfolios

	Factor	Alpha	MKT_t	$(1-\gamma_{t-1}MKT_t)$	SMB_t	HML_t	CMA_t	RMW_t	WML_t	$PTFSCOM_t$	$PTFSIR_t$	$PTFSSTK_t$	R^2
HKM	Equation 6	0.0049***		0.2378***	-0.1352*		-0.1773**	-0.2383***	0.1798***				0.73
	Equation 7	0.0053***	0.2332***				-0.1598***	-0.1492**	0.1433***				0.75
OWL	Equation 6	0.0081***		0.2170***								0.0291***	0.50
	Equation 7	0.0102***	0.2008***								0.0146**	0.0295***	0.49
MP	Equation 6	0.0143***								0.0450**	0.094**		0.34
	Equation 7	0.0157***								0.0256**	0.0588**	0.0543***	0.51

***, **, * Significance at 99.9%, 95%, 90%, respectively with Newey-West HAC consistent standard errors

nificant changes in the weights on ($PTFSSTK_t$) factor in both equations and no significant exposure is estimated in ($PTFSIR_t$) factor in Equation 6. We speculate that in the context of OWL portfolio, the time-varying nature of one-month prior conditional moderation effect leads the managers to alter the subsequent month's risk-on positions in an adaptive manner and therefore, not enough overall consistency in their exposures is revealed in ($PTFSIR_t$) factor. The same phenomenon is observed in MP portfolio as there is no consistency in their exposures in ($PTFSSTK_t$) factor between the two equations. On the other hand, the weights on (CMA_t), (RMW_t), and (WML_t) factors are less intensified in Equation 7 at HKM portfolio. The size of estimated alpha all declined in Equation 6 versus Equation 7 and there are not many meaningful differences in estimated R^2 value, except for MP's significant differences between the two equations.

Both OWL and MP portfolios have outstanding underlying components of tail-risk protection, where the extreme left-hand side of the distribution curve represents the experience of lowest returns. Tail-risk hedgers asymmetrically protect against extreme negative returns while maintaining the upside participation at a certain degree in order to preserve the marketability of their products.

[5] Conclusion

For a money manager who believes a pervasive bullish market, it makes sense to tactically allocate to risky assets, and particularly build up high-beta trading positions, as they are likely to benefit most out of the rising market. It should be the other way around when it comes to a bearish view. According to this reasoning, an overconfident market timer might actively exploit the general risk appetite as proxied by, for instance, the implied equity market volatilities. In this respect, the volatility moderation effect may be important for the performance of active hedge funds under analysis and allow one to discard spurious factors that only have a marginal influence in explaining the behavior of hedge fund managers. Our major empirical finding is that the multi-factor conditioned alpha valuations depend on the signs and the magnitude of the conditional moderation effect measure in general as comparing the active performances exhibited with or without elaboration of the linearly moderating volatility of implied equity market volatility effect. Furthermore, the time-varying nature of conditional moderation effect leads the managers to adaptively alter the subsequent month's risk-on positions proactively and therefore, not enough overall consistency in their exposures is revealed even in the list of well-documented systematic risk factors.

While in the exposures to different systematic factors of the standard factor control regressions are assumed to be static, Mamaysky, Spiegel and Zhang [2008] find strong evidence that active management adds value by creating dynamic exposures to systematic factors. Our paper applied the concept of conditional moderation to the time-series of hedge fund investment styles and the Barclays sub-indices such as EM_t, MS_t, and FoF_t is mostly pronounced as $DVIX^2_{t-1}$ conditionally moderating $PTFSIR_{t-1}$ on Y_t. From Exhibit 5, in case of the Barclays EM_t, LS_t, FoF_t, GM_t, and MS_t indices, the regression coefficients of $\beta_{3,t}$ are small negatives but all statistically different from zero. In fact, EM_t, MS_t, and FoF_t style managers demonstrated a more consistent pattern of the interplay between $PTFSIR_{t-1}$ and $DVIX^2_{t-1}$.

While we have provided a framework for understanding hedge fund manager's conditional volatility moderation feedback process per managers' investment style categories, further study is needed to determine their impact on risky asset exposure adjustment decisions. We have made some simplifications by intentionally dropping other systematic risk factors such as market, size, value, momentum, and primitive trend-following systems in order to concentrate our main point of one-month prior PTFSIR and the past volatilities of VIX dynamics. The less parsimonious multi-factor models can be more viable alternatives without losing a lot of explanatory power by considering the conditional moderation effect as reflecting both the risk-on/risk-off behavior of hedge fund managers.

We would focus on the factor timing skills of hedge fund managers to measure the ability to adjust the factor exposure for a specific factor based on a forecast of certain macro-relevant commonalities. For instance, it is also sensible by incorporating dual moderation effect between the level and the changes of VIX to the market and factor-timing dynamics of hedge fund managers. On the other hand, the analysis may take the form such as in Equation 7 where the more sophisticated cases by containing conditional volatility moderation feedback process factors.

$$\text{[Eq. 7]}\ Y_{v,t} = \alpha'_{1,t} + \sum \beta^{*}_{i,t-1} F_{it} + \omega'_{1,t}$$

The factors, F_{it}, might represent the ten Fung-Hsieh factor model such as an equity market, size, monthly change in the ten-year U.S. Treasury yields, monthly changes in the spread between BBB bonds and the ten-year U.S. Treasury yields, emerging market, and five trend-following factors for bonds, commodity, foreign exchange, short-term interest rates, and stock markets. It, therefore, provides a broader image of the timing skills of hedge fund managers than the studies of particular styles.

Lastly, Agarwal and Nail [2004] pioneered to include volatility exposure through the put options written on the S&P 500 index to explain the differences in returns across the alternative investment styles of hedge fund managers. Whether these dynamic long option-like payoffs of underlying tail-risk protection managers of OWL and MP portfolios of liquid alternatives might still generate alpha and, as Jagannathan and Korajczyk (1986) show, whether the creation of the synthetic long option-like payoffs might cause some significant spurious timing results of these tail-risk protection managers is not clear. Clearly, the original cause of the differences in conditional volatility moderation feedback interplays among the investment styles of hedge fund managers is not properly covered in this paper[10]. Therefore, these are the interesting topics of our next empirical research.

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Appendix. Single Managers of HKM Portfolio[11]

BlackRock European Hedge Fund was launched in 2011 and invests long-short with an emphasis on Pan-European equities. It is managed by Alister Hibbert who joined the BlackRock European Equity team in March 2008 from Scottish Widows. Alister Hibbert is supported by Michael Constantis (co-portfolio manager) and 2 dedicated analysts but also leverage expertise from the rest of the broader European equity team as Alister Hibbert is able to synthesize a lot of micro inputs in part leveraging the broader Black Rock organization to form a wider thematic view. The strategy is funda-

10) I thank the referee for raising this distinction.
11) Being the partner managers of Green Shoots Capital, the following qualitative single manager information is available from the internal source of Green Shoots Capital Solutions Korea LLP.

mental, bottom-up driven, long-short focusing on alpha generation within the Pan-European Space. Its predominantly bottom-up approach aims to unearth companies with medium to long-term earnings power significantly higher than the market and not factored into the share price. Exposure is in three areas: classic growth, long duration sustainable franchise growth stocks where the market is discounting fading growth, and classic value. The portfolio is diversified with about 100 longs and 80 shorts. Typical turnover of the portfolio is the 2-4x year. The fund objective is to make a 10 to 15% annualized return, with a 6 to 12% *ex-ante* volatility target.

Bridgewater is on the Lyxor Managed Account Program and is managed in the pure alpha major market strategy from January 2011. Bridgewater as a firm has successfully navigated a long history of fund management stretching back to 1975 and its three chief investment officers, who oversee the entire investment management process, have spent an average of more than two decades with the firm. The fund seeks to trade a diversified set of liquid markets across fixed income, currency, commodities, and equities. It seeks also to make both long and short trades in these areas without bias to any given market or economic environment. This high level of diversification is important to the ethos of the fund to ensure as no single view or set of views has a disproportionate impact on the total portfolio's return and risk.

Point72 Capital is the successor firm to S.A.C. Capital. Launched in August 1992 by Steve Cohen, S.A.C has been one of the longest standing and most successful hedge funds. Rebranded as Point 72, it continues to employ a multi-portfolio manager investment model, predicated on trading teams that are largely independent, and each has a well-defined investment universe and specializations. The teams then seek to generate absolute returns, typically with a market neutral approach, from trading their respective strategies. The fund is anchored in fundamental long-short equity trading, representing approximately 75% of the capital allocation, with around 20% of the remaining capital allocated to systematic tradings and the remaining 5% to global macro and other strategies.

OZ Management LP (a.k.a. Och Ziff) invests in OZ Master Fund, Ltd., which was launched in January 1998. The investment objective is to achieve consistent positive absolute return with low volatility primarily by seeking to exploit pricing inefficiencies in equity and debt securities. This will be through investments in merger arbitrage, long-short equity in special situations, corporate credit, structured credit, convertible arbitrage, derivative arbitrage, and private investment deals. Preservation of capital is a top priority with the capital dynamically allocated across strategies and geographies based on perceived opportunities. There are no predetermined commitments to any given investment discipline or geography other than a strong focus on portfolio diversification and risk management.

Partner Fund Management (PFM) was established in 2004 by formerly portfolio manager of Andor Diversified Growth Fund manager Christopher James, and the fund was launched in January 2006 by another co-founder Brian Grossman of Andor. The fund invests across global healthcare sub-sectors with a strong bias to the U.S. The strategy is focused on identifying new product innovation, regulatory complexity, and powerful demographic trends that the manager believes to create a dynamic long-short environment within the healthcare sector. Liquidity is an essential element to the strategy and as such, the manager invests mostly in mid to large-cap stocks and has been disciplined about keeping capacity limited in the main fund. The manager seeks to generate long-term risk-adjusted returns by integrating macro framework, bottom-up stock selection, and risk management. This contributed to PFM's exemplary handling of the environment created by the 2008 melt-down as their internal macro and credit work enabled them to see the looming crisis and reduce gross and net exposures drastically to limit the downside.

Renaissance Technologies invests solely in the U.S.-listed equities in a quantitative long-biased methodology to produce a higher Sharpe ratio than the S&P 500 at a beta of 0.4 or less. The fund employs an automated proprietary set of statistical models for price forecasting, risk estimation, and cost calculation through their internal trade generation algorithm to produce a portfolio designed to be net long 100% with modest leverage. Renaissance approaches investing as a scientific problem, relying on human acumen, advanced mathematical and statistical methods, as well as state-of-the-art technology. To this extent the firm considers itself a scientific entity which manages money, not a money manager that applies a scientific approach; this ethos comes through at every level of the firm from hiring of talent to the process through which new signals are constructed. Correspondingly the fund employs a rigorous peer review process, on par with scientific journals, meaning improvements to the system go through an extensive, robust and lengthy vetting process.

The principals of Stoner Milliner have managed the current investment strategy since 2006 when they were employed at Moore Capital. The manager follows a discretionary global macro investment strategy with the objective of consistently maximizing risk-adjusted returns across asset classes in both developed and emerging markets. The manager applies a multi-portfolio manager directional discretionary trading approach to macro investing with a core focus on liquid foreign exchange and interest rate markets. They also invest in equities and commodities to a lesser extent. The manager follows a top-down approach based on macroeconomic analysis and bottom-up country and individual instrument analysis. Individual portfolio managers are responsible for implementing investment ideas, which are then aggregated into a larger portfolio under the leadership of the principals. The portfolio is diversified by asset class, geography and time horizon. The portfolio mainly consists of cash, futures and OTC instruments that have a high degree of liquidity.

Third Point is to achieve superior risk-adjusted returns in investments with a favorable risk-reward scenario across select asset classes, sectors, and geographies, both long and short. The manager identifies these opportunities using a combination of top-down asset allocation decisions and a bottom-up, value-oriented approach to single security analysis. The manager seeks dislocations in certain areas of the capital markets or in the pricing of the particular security. The manager also supplements single security analysis with an approach to portfolio construction that includes sizing each investment based on upside and downside calculations, all with a view towards appropriately positioning and managing overall exposures across specific asset classes, sectors, and geographies. The resulting portfolio expresses its overall tolerance for risk.

World Quant Millennium Quantitative Strategies (WMQS) is a joint venture, formed in 2015, bringing together Millennium and WorldQuant (WQ). WMQS runs a long bias active equity extension, 170/70, product across global developed markets, employing systematic model-based strategies developed by WQ. The fund targets an outperformance versus MSCI World of 3 to 6% per annum over a market cycle. WQ founder Igor Tulchinsky spun the firm out of Millennium in 2007 after being employed there for the previous 12 years. Since inception, it has been run as a separate management company whilst originally running capital exclusively for Millennium. WQ still runs circa 15 to 20% of Millennium allocation. In this joint venture WQ runs the investment strategies and is solely responsible for their development, selection, evaluation, and allocation; Millennium provides all other functionality across the fund infrastructure, by way of middle and back office functions including risk management, technology, legal, compliance, operations, finance, and trade processing.

Millennium and its affiliates have a 20-plus year record from investing in a portfolio of diverse and substantially uncorrelated strategies while maintaining a tight risk management framework, significant liquidity, and a high Sharpe ratio. To meet its objectives, the fund invests across a diverse set of strategies and asset classes seeking the optimal mix of return and risk. Those strategies include relative value fundamental equity, fixed income, statistical arbitrage, and quantitative strategies, among others. The firm consists of around 200 trading teams subject to centralized capital allocation and risk management discipline: A key competitive advantage of a centralized trading platform allowing for a significant reduction in trading costs.

참고문헌

Agarwal, V. and Naik, N.Y., 2004, Risk and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies*, Vol. 17, No. 1, pp. 63-98.

Ang, A., Goetzmann, W. N., and Schaeffer, S. M., 2009, Evaluation of Active Management of the Norwegian Government Pension Fund – Global, *Report to the Norwegian Ministry of Finance*. Retrieved on 13-04-2015 from https://www.regjeringen.no/globalassets/upload/fin/statenspensjonsfond/rapporter/ags-report.pdf.

Ang, Andrew, Hodrick, Robert J., Xing, Yuhang, and Zhang, Xiaoyan, 2009, High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence, *Journal of Financial Economics*, Vol. 91, Issue 1 (2009), pp. 1-23.

Barroso, P. and Santa-Clara, P., 2015, Momentum Has Its Moments, *Journal of Financial Economics*, Vol. 116, No. 1, pp. 111-120.

Blocher, J., Cooper, R., and Molyboga, M., 2015, Performance (and) Persistence in Commodity Funds, *Working Paper*, CME Group, Chicago.

Carhart, M.M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, Vol. 52, No. 1, pp. 57-82.

Cho, J.K. and Kim, G.W., 2017, Making a Bet at a Right Time: Style and Volatility Timing Abilities of Korean Equity Hedge Funds, *Asset Management Review*, Vol. 5, Issue 2.

Cho, J.K., 2017(a), Implied Equity Volatility and Liquid Alternative Hedge Fund Investing by Qualified Korean Investors, *International Information Interdisciplinary Journal*, Vol. 20, No. 10(B).

Cho, J.K., 2017(b), Information Content of the VKOSPI Entropy Indicator - A Dynamic Asset Allocation Approach, *International Information Interdisciplinary Journal*, Vol. 20, No.7(B).

Cho, J.K., 2017(c), Qualified Korean Investors' Liquid Alternative Global Hedge Fund Investing under Autocorrelation Effects, *Journal of Economic Studies (Korean)*, Vol. 35, Issue 2.

Cho, J.K., 2016, The VKOSPI Spread as a Forward-Looking Short-Term Dynamic Asset Allocation Indicator, *Journal of Economic Studies (Korean)*, Vol. 34, Issue 2.

Fama, E.F., 1972, Components of Investment Performance, *Journal of Finance*, Vol. 27, pp. 551-567.

Fama, E. and French, K., 2010, Luck versus Skill in the Cross-Section of Mutual Fund Returns, *Journal of Finance*, Vol. 65, No. 5, pp. 427-465.

Fama, E. and French. K., 2012, Size, Value and Momentum in International Stock Returns, *Journal of Financial Economics*, Vol. 105, No. 3, pp. 1915-1947.

Fama, E. and Macbeth, J.D., 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, Vol. 18, No. 3, pp. 607-636.

Frijns, B., Gilbert, A., and Zwinkels, R.C.J., 2016, On the Style-based Feedback Trading of Mutual Fund Managers, *Journal of Financial* *and Quantitative Analysis,* Vol. 51, pp. 771-800.

Fung, W. and Hsieh, D.A., 2001, The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, *Review of Financial Studies*, Vol. 14, No. 2, pp. 313-41.

Goetzmann, W. N., Ingersoll J., and Ivkovich Z., 2000, Monthly Measurement of Daily Timers, *Journal of Financial and Quantitative Analysis*, Vol 57, pp. 257-290.

Goldwhite, P., 2009, Diversification and Risk Management: What Volatility Tells Us, *Journal of Investing*, Vol. 18, No. 3, pp. 40-48

Hallerbach, W.G., 2014, On the Expected Performance of Market Timing Strategies, *Journal of Portfolio Management*, Vol. 40, No. 4, pp. 42-51.

Hayes, A.F., 2018, Partial, Conditional, and Moderated Moderated Mediation: Quantification, Inference, and Interpretation." *Communication Monographs*, Vol. 85, No. 1, pp. 4-40.

Hayes, A.F., 2012, PROCESS: A Versatile Computational Tool for Observed Variable Mediation, Moderation, and Conditional Process Modeling, *White Paper*. Retrieved from http://afhayes.com/public/process2012.pdf.

Hayes, A.F., 2015, An Index and Test of Linear Moderated Mediation, *Multivariate Behavioral Research*, Vol. 50, pp. 1-22.

Hayes, A.F., 2018, *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Perspective*, 2nd ed., The Guilford Press, New York.

Jagannathan, R. and Korajczyk, R.A., 1986, Assessing the Market Timing Performance of Managed Portfolios." *Journal of Business*, Vol. 59, pp. 217-235.

Jegadeesh, N. and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance*, Vol. 48, No. 1, pp. 65-91.

Krieger, J.L. and Sarge, M.A., 2013, A Serial Mediation Model of Message Framing on Interactions to Receive the Human Papillomavirus (HPV) Vaccine: Revising the Role of the Threat and Efficacy Perceptions, *Health Communications*, Vol. 28, pp. 5-19.

Mamaysky H., Spiegel I.M., and Zhang H., 2008, Estimating the Dynamics of Mutual Fund Alphas and Betas, *Review of Financial Studies*, Vol. 21, pp. 233-264.

Roll, R., 1997, A Critique of the Asset Pricing Theory's Tests, *Journal of Financial Economics*, Vol. 4, Issue 2, pp 129-176

Barclays 헤지펀드 스타일별 Market Timing 행태의 조건부 내재변동성 조절효과 모형 연구

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Abstract

다양한 헤지펀드 스타일 지수의 2003년1월부터 2016년 12월 (강건성 분석은 2018년 12월)까지 월간자료 분석을 통해, 특정스타일 헤지펀드 (emerging market 및 equity long-short)에서 전월 단기이자율시장 트렌트추종형요인 (PTFSIR)은 직전월 CBOE VIX지수 변화량 조절변수에 따라 그 조건부 효과가 통계적으로 유의한 효과를 확인하였다.

본 연구는 Emerging Market, Equity Long-Short, Fund of Hedge Funds, Global Macro, Multi-Strategies, 및 commodity trading advisors 등 Barclays 헤지펀드 스타일지수에 대한 Conditional Process Model과 Factor Risk Model 분석을 결합한 특징을 가진다. 특히, 당월 헤지펀드지수 성과에 영향을 주는 요인으로서 절대적인 영향을 행사하는 당월 시장초과수익률을 제외시키고 직전월의 단기이자율시장 트렌트추종형요인 및 직전월의 주식시장 내재변동성지수의 월간 변화량을 동시에 고려할 수 있는 단순한 형태의 조절효과 (Moderation) 모형을 구성하여, 기존 선형모형 대비 헤지펀드 매니저의 직전월의 시장모멘텀, 직전월 VIX지수의 월간 변화량 정보의 소화를 통한 위험자산 Exposure의 Tilting Process를 추정하였다.

본 연구는 Behavioral Science에서 널리 활용되는 1개 또는 그 이상의 조절변수가 존재하는 경우의 Conditional Process Model과 투자분석에 활용되는Factor Risk Model을 결합하여 글로벌 헤지펀드 시계열자료에 적용하는 최초의 시도를 통해 시장위험요인의 다양한 헤지펀드 스타일 지수분석에서 Liquid Alternative Hedge Fund Collection Pool로 실질적인 분석을 확장하는 Moderation 효과의 변화에 대한 검증을 Manager의 Factor-Tilting Activity에 대한 Adaptive Modeling Framework을 통해 제시한다.

조절된 과거 단기이자율시장 트렌트추종요인의 월간 VIX 변화량 조절효과 분석 결과, 헤지펀드는 그 투자스타일별로 펀드 매니저가 단기이자율 트렌드 요인에 근거한 위험자산 Exposure 조절에서 주식시장 내재변동성 변화량 정보를 Process하는 정도가 상이하였으며, 이는 스타일별 Factor-Controlled Alpha Decay와 변동성 매개효과의 관계를 규명함으로써 일부 확인이 가능하였다.

주제어: *Hedge Funds, Market Timing, Conditional Moderation Effect, Factor Timing*

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