Journal of Economics and International Finance Vol. 4 (3), pp. 69–78, 7 February, 2012
Available online at http://www.academicjournals.org/JEIF
DOI: 10.5897/JEIF11.132
ISSN 2006-9812 ©2012 Academic Journals

Full Length Research Paper

Hedge funds and their interaction with market parameters

Samet GÜNAY[1,2] and Gökberk CAN[1,3]

[1]Anadolu BİL Vocational School, İstanbul Aydin University, Florya Campus, İstanbul, Turkey.
[2]İstanbul University, İstanbul, Turkey.
[3]Marmara University, İstanbul, Turkey.

Accepted 27 January, 2012

The performance of hedge funds and other financial institutions has been carefully studied during the last financial crisis. In our study which spans through a time period of 31 December, 1999 to 21 June, 2011, the relationship between global hedge fund indice and Federal Reserve's effective interest rate, and the relationship between the 10 year-term Treasury bill and the M2 monetary supply variables as the United States' economy indicator was tested with vector autoregression analysis (VAR). Based on the results obtained, the indices stastistically and significantly reflect the developments guiding the U.S. economy and then became effective on our present variables.

Key words: Hedge funds, vector autoregression analysis (VAR).

INTRODUCTION

The term, hedge funds, was first used by a journalist, Carol Loomis, to describe an innovative investment structure created by Alfred Winslow Jones. He set up hedges by investing in securities that he determined as undervalued, funding these positions partly by taking short positions in overvalued securities, creating a market-neutral position (Lee et al., 2001). Although, there is no set definition for a hedge fund, it usually refers to an actively managed investment pool that does not advertise, and is privately organized to be exempt from the Securities Acts of 1933 and 1934 (Frumkin and Vandegrift, 2009). Bloomberg defines a hedge fund as "a fund that employs a variety of techniques to enhance returns, such as both buying and shorting stocks according to a valuation model" (Bouges, 2004). Today, the term hedge fund encompasses investment philosophies that are far from the original market- neutral strategy of Jones, and include the global macro styles of people like Soros and Julian Robertson (Brown and Goetzmann, 2003).

Hedge funds are really no different from any other for profit business enterprise, owners provide capital to managers who seek to deploy and manage that capital and turn a profit for the benefit of the owners (Earle, 2010). As private entities, hedge funds are not allowed to advertise, but they are exempted from disclosure requirements facing traditional investment funds (Hedges IV, 2005). Hedge funds differ from traditional investments in many respects including benchmarks, investment processes, fees, and regulatory environment (Dopfel, 2005). Under the US Securities Act 1933, funds offered for sale have to be registered with, and be regulated by, the Securities and Exchange Commission (SEC). But in 1982, the Reagan Administration introduced Regulation D, which allowed funds to escape SEC control if they were not sold through a public offering and were instead sold to 'accredited investors' – individuals with net worth over $1 million or income over $200,000 – and to banks, corporations and pension funds with assets over $5 million (Chapman, 2010). Hedge funds are in general exempted from securities regulations that dictate internal controls that managers must implement and maintain, fees that managers can charge investors, and disclosures that fund managers must make to investors (Cassar and Gerakos, 2010). Setting up as offshore funds, many hedge funds are able to avoid further scrutiny or tax requirements imposed in the USA (Hedges IV, 2005).

Mutual funds' typical long-only and-hold-type strategy

*Corresponding author. E-mail: gokberkcan@aydin.edu.tr. Tel: +90 551 907 21 08.

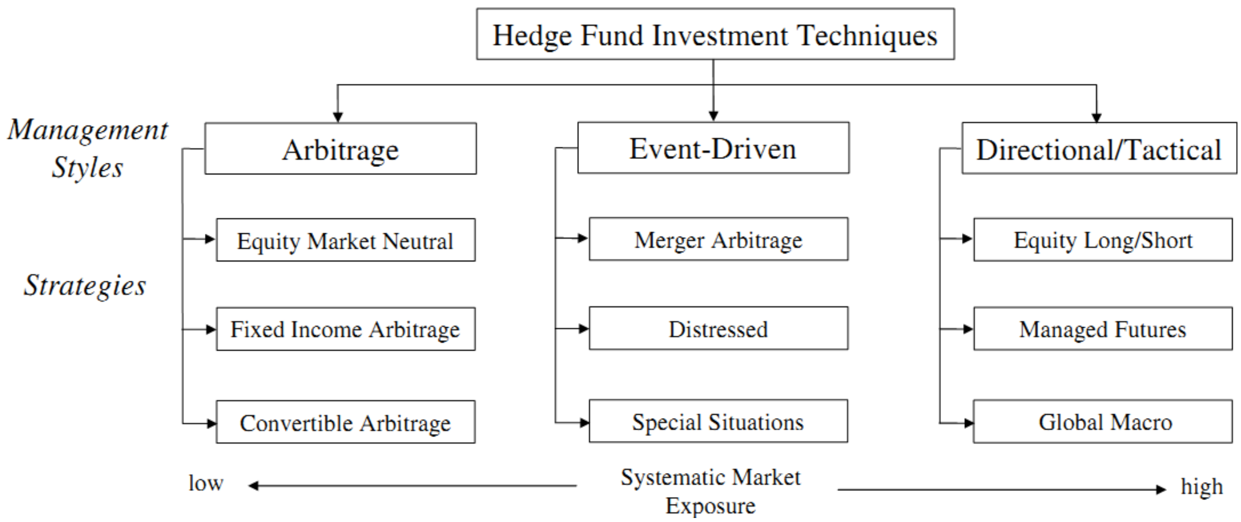

Figure 1. Hedge fund investment techniques (Fuss et al., 2007).

on standard asset classes with minimum risk is not enough in capturing risk premia associated with dynamic trading strategies or spread-based strategies. This is where the hedge funds get the starring role with their more dynamic trading strategies (Agarwal and Naik, 2003). The structure of hedge funds exposes the investor to numerous risk factors such as volatility, counter- party, or liquidity risk. Exposure to these risk factors is not only a source of a superior risk-return trade-off but also the very essence of hedge funds' extensive diversification possibilities compared to traditional investments (Christory et al., 2006). Hedge funds also suffer from opaque reporting; short track records of low-frequency returns, loosely defined investment styles, high minimum investment requirements, high fees, and low liquidity (Beckers et al., 2007). Due to their ability to short-sell and the extensive use of leverage, hedge funds have often outperformed many traditional benchmarks. This is often accredited to the ability of the hedge fund manager (Cerrato and Iannelli, 2006).

Hedge funds employ a wide array of dynamic, event driven, and relative value trading strategies to access statistical arbitrages in financial markets (Eberlein and Madan, 2009). Hedge funds can invest in the distressed debt of a foreign country; can buy equities "long" and/or "short"; can invest and trade using a complex computer-driven algorithm; can speculate in foreign currencies; can arbitrage commodity futures, etc. In other words, they can do anything sufficiently profitable to justify the fees they charge to investors (Donaldson, 2008) (Figure 1). Within the alternative asset universe, hedge funds are increasingly popular as possible investment opportunities for wealthy investors who possess long time horizons (Darius et al., 2002). A key determinant of hedge fund risk is the degree of similarity between the trading strategies of different funds (Adrian, 2007).

LITERATURE REVIEW

Studies on hedge funds can be diversified in many classes basically on regulation requirement for hedge funds and fraud, audit, internal control and corporate governance issues, alpha (manager skills) and beta (market exposure) components (Brunel, 2007), and return analysis.

The fact that hedge funds cease reporting because of unfavorable results implies extremely high failure rates for hedge funds. While some hedge funds have provided generous returns, investors are at high risk of buying a poorly performing fund or, even worse, a failing one (Grecu et al., 2007). Under this condition, performance of audited funds should be reviewed; audited funds have much smaller return discrepancies than non-audited funds and there is a significantly positive correlation between the auditing and fund size and funds listed on exchanges and unlevered funds have better data quality than others (Liang, 2003). Taxation and transparency is another problem about hedge funds. Hedge fund managers intentionally block transparency for strategic reasons and deny information to their own investors and to the government in order to guard their strategies from theft (Donaldson, 2008). In practice, voluntary reporting and the backfilling of only favorable past results can cause returns calculated from hedge fund databases to be biased upwards (Malkiel and Saha, 2005).

The findings on managers' skills show that practicing internal control in hedge funds reduces fraud and misstatements (Cassar and Gerakos, 2010); information asymmetry due to geographic location (distance) creates differences on return (Teo, 2009) and managers' education and work experiences' have important effect on funds' performance (Maxam et al., 2004). Another study based on hedge funds' location-manager skill relationship shows that Australian hedge fund managers do not have the skills to time market volatility (Do et al., 2009). Hedge fund managers do employ leverage; they seem to be leveraging their value added rather than simply modulating market or other factor risk exposures (Brunel, 2007). Some managers do not consistently follow a pre-specified investment style due to the hard clusters analysis and hedge funds with more than 36 months of tracking record that are more consistent do not usually generate higher future performance (Gibson and Gyger, 2007). While equity fund managers are exposed to three dominant style strategies, 'market', 'value' and 'momentum', managers vary their exposures to the 'market' in time to exploit favourable market moves. However, a similar pattern is not observed for their 'value' or 'momentum' exposures (Dupleich et al., 2010). Projected performance due to market moves and/or manager skills are the questions that investors want and need the answers of (Clark and Winkelmann, 2004).

There is a clear performance difference between live and dead funds resulted by using four models (single index market model, stale prices, Fama-French, Harvey-Siddique (2000) two-factor model) (Ding and Shawky, 2007). Results show that hedge funds' age and size have an effect on their performance; age has a negative relationship with hedge fund returns. As a fund's age increases, its managers suffer from style drift, leading to lower returns (Frumkin And Vandegrift, 2009). If an investors wish to maximise returns, they should start their hedge fund screening with younger, smaller funds, but those who wish to maximise capital preservation should begin their hedge fund screening with larger, older funds (Jones, 2007). The performance of funds is very volatile; funds with the highest return last period are generally no-alpha funds and best and worst performing funds tend to switch their places often (Manser and Schmid, 2009).

Risk components of the hedge funds are one of the key issues that need a deep review. When absolute or total risk-adjusted returns are used, Hedge funds are unable to consistently beat the market (Ackermann et al., 1999). The identification of systemic risk factors inherent in hedge fund strategies is the key input to important questions such as optimal contract design between buyers and sellers of hedge fund products (Fung and Hsieh, 2006). The volatility risk is related to returns of most hedge fund strategies in a nonlinear way. Further, the use of volatility risk as a factor in hedge fund analysis suffers from asymmetry that is similar to the impact of price risk (Peltomaki, 2005). Although, there is a beta puzzle for very specialised strategies, like the distressed securities and the short sellers one, with the help of a conditional version of the Fama and French model, there does not seem to be a beta puzzle in the hedge fund industry (Racicot and Théoret, 2007). Increases in hedge fund covariances tend to precede elevations in volatility. This result suggests that comovement measured in dollars is a more relevant indicator of risk than comovement measured in correlation, that is, covariance normalized by volatility (Adrian, 2007). Statistical properties of the 70 Asian hedge funds were tested and it showed the inappropriateness of the traditional mean-variance optimizer to form optimal hedge fund portfolios. In this study, a practical heuristic approach was used with the semi-variance as a better measure for downside risk (Fang et al., 2008).

Conditional correlations between hedge funds and other investments are generally symmetric, and therefore find no evidence supporting contagion between hedge funds and other investments in extreme down versus extreme up markets (Li and Kazemi, 2007). On a risk-adjusted basis, the average hedge fund outperformed the average mutual fund in the period January 1992 through December 1996; this performance difference cannot be explained by survivorship bias (Liang, 1998). By applying stacked cross-sectional regression and quartile portfolio approach methods for detecting the performance persistence of five different hedge fund styles; the results showed that both the degree and existence of performance persistence vary among hedge fund styles (Pätäri and Tolvanen, 2009). Using active currency management was beneficial to an international equity portfolio for Japanese investors from 2001 to 2006, especially when used with hedge funds; while the trading model adopted from Reinert works well for the JPY portfolio, was not effective on the various European currency-based portfolios (Tee, 2009).

ECONOMETRIC ANALYSIS

The volume of discussions on the United States' financial system started increasing with the mortgage crisis which started in 2007. Corporations working in audit-free markets and many financial institutions went bankrupt and some has been publicized. Along with corporations gone bankrupt like banks and insurance companies another concern was about the hedge funds. Their secrecy, active structure and levered transactions with investments in high-risk sectors and instruments created a concerned and careful audience about the future of these funds back in the '90s until now. With their position in most risky tranche in complex instruments like Collateral Debt Obligation, hedge funds' interaction with the markets, the attentions were drown to these institutions again.

The objective of this study is; to determine hedge funds' relation with the parameters of United States' financial markets containing the leading indicators in the global finance markets during the period lodging the previously mentioned developments. Ultimately this interaction and results are becoming determinant on global markets in terms of liquidity and risk perception. The variables used in our study are presented in Table 1 with their codes in the model as the vector auto-

Table 1. Data codes table.

Data	Code
Eurekahedge fund of funds index	lnfohf
Monthly effective fed interest rate	lnfedrate
Market yield on U.S. treasury securities at 10-year	lntbond_10
Components of non-M2 M3 / RPS Total (Billions of dollar)	lnm2

regressive model is preferred as the econometric analysis.

The time interval of variables' used in our study is December, 31 1999 to June, 21 2011. Our variables have a monthly frequency and in total, 140 months of time period is in subject. While Lnfohf variable was obtained from Eureka Hedge, other variables are downloaded from Federal Reserve's (Fed) web site.

VAR model

We often want to model the dynamic relationships among several timeseries variables. A simple way to do so without making many assumptions is to use what is called a vector autoregression, or VAR, model, which is the multivariate analog of an autoregressive model for a single time series (Davidson and Mackinnon, 1999). As a matter of fact, in our study a relation between more than one variable is desired to be determined. The direction of interaction in economic and financial variables is not fully known. In VAR model, in question there is no constraint to discriminate between fixed and independent variable. Therefore the most suitable model for our study is VAR analysis.

Given a set of K time series variables $y_t = (y_{1t}, \ldots, y_{Kt})'$, the basic VAR model is of the form

$$y_t = A_1 y_{t-1} + \ldots + A_p Y_{t-p} + u_t \quad (1)$$

where $u_t = (u_{1t}, \ldots, u_{Kt})$ is an unobservable zero-mean independent white noise process with time invariant positive definite covariance matrix $E(u_t u_t) = \Sigma u$ and A_i are $(K \times K)$ coefficient matrices. This model is often briefly referred to as a VAR(p) process because the number of lags is p (Lütkepohl, 2003).

Prior to going over to the VAR analysis Dickey Fuller and Philips-Perron unit root tests will be realized aimed at our variables' stationarity. Ahead of unit root tests, every variable's logarithm was derived and examined unit root test by doing so to level up the variables. Studying on non- stationary time series might backfire in producing misleading results as showing substantial relations as existing.

Unit root test

In some studies, interest rates, foreign exchange rates, or the price series of an asset are of interest. These series tend to be nonstationary. For a price series, the nonstationarity is mainly due to the fact that there is no fixed level for the price. In the time series literature, such a nonstationary series is called unit-root nonstationary time series (Tsay, 2005).

$$Y_t = {}_{\rho}Y_{t-1} + u_t \qquad -1 \leq \rho \leq 1 \quad (2)$$

This model resembles the Markov first-order autoregress-ive model. If ρ = 1, becomes a Random Walk Model (RWM) (without drift). If ρ is in fact 1, we face what is known as the unit root problem, that is, a situation of nonstationarity. If, however, $|\rho| \leq 1$, that is if the absolute value of ρ is less than one, then it can be shown that the time series Y_t is stationary in the sense we have defined it. In practice, then, it is important to find out if a time series possesses a unit root (Gujarati, 2004). Results obtained from unit root tests are presented in Table 2 and 3.

The lag value in ADF models are picked in accordance with AIC criteria. Both in two tables values are reflected as if, between paranthesis the test statistics values, values marked with (*) test statistics' probability value and finally numbers between the square brackets optimum laglevel for every test. Accordingly, given MacKinnon critical values under the tables for variables are not stationary both fixed and trend, and fixed and both not fixed and not trend. All variables as seen in the fourth row have become stationary series with their first differ-ences. As one can see from the results in the table all of our variables have become stationary in their first difference. There in after, all tests have been examined with stationary variables. I(0) and I(1) form graphics of variables are shown in Figure 2.

A critical element in the specification of VAR models is the determination of the lag length of the VAR. The importance of lag length determination is demonstrated by Braun and Mittnik (1993) who show that estimates of a VAR whose lag length differs from the true lag length are inconsistent as are the impulse response functions and variance decompositions derived from the estimated VAR (Ozcicek and Douglas, 1999). For selection of the lag length of the VAR, we consider the VAR Lag Order Selection Criteria. Obtained results are as shown in Table 4.

Variables must be stationary as they should be indivually and also as whole. Therefore, inverse roots of the AR characteristic polynomial's should be examined.

Table 2. Augmented Dickey- Fuller (ADF) test.

Variable	ADF (Intercept)	ADF (Trend and intercept)	ADF (None)	ADF stationary series	ADF stationary level
Infedrate	(0.316155) 0.9183* [3]	(-1.210863) 0.9038* [3]	(0.714449) 0.4056* [3]	(4.485041) 0.0003* [2]	I(1)
Infohf	(1.694508) 0.4318* [1]	(-1.483692) 0.8307* [1]	(2.032527) 0.9899* [1]	(8.162819) 0.0000* [0]	I(1)
lnm2	(1.504963) 0.5283* [2]	(-2.375994) 0.3904* [2]	(4.399679) 1.0000* [2]	(5.153254) 0.0000* [1]	I(1)
Lntbond_10	(2.532002) 0.1102* [1]	(-3.756723) 0.0219* [1]	(1.247038) 0.1946* [1]	(9.756374) 0.0000* [0]	I(1)

MacKinnon critical values (for 1%): 1st row: -3.478911, 2nd row: -4.026942, 3rd row: -2.582076, 4th row: -3.478911

Table 3. Determination of effective lag level.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1150.223	NA	2.95e-13	-17.49959	-17.41180	-17.46392
1	1210.528	116.0050	1.50e-13	-18.17599	17.73703*	-17.99763
2	1240.039	54.96759	1.22e-13	-18.38227	-17.59214	18.06121*
3	1257.472	31.40639*	1.20e-13*	18.40415*	-17.26286	-17.94039
4	1267.058	16.68424	1.33e-13	-18.30623	-16.81376	-17.69978
5	1278.993	20.04228	1.42e-13	-18.24416	-16.40052	-17.49501
6	1285.153	9.969977	1.66e-13	-18.09394	-15.89914	-17.20209
7	1299.430	22.23269	1.72e-13	-18.06764	-15.52166	-17.03309
8	1311.892	18.64550	1.85e-13	-18.01362	-15.11648	-16.83638

As can be seen from Figure 3, the AR characteristic polynomial's inverse roots' dispersion in the circle shows the model does not have a problem in terms of stationary. As a consequence of that, it validates VAR model in a consistent structure.

Granger causality test

Let's approach to a VAR model as the following

$$y_t = \delta_0 + \alpha_1 y_{t-1} + \gamma_1 z_{t-1} + \alpha_2 y_{t-2} + \gamma_2 z_{t-2} + \dots \quad (3)$$

This equation allows us to test whether, after controlling for past y, past z help to forecast y_t. Generally, we say that z Granger causes y if

$$E(y_t | I_{t-1}) \neq E(y_t | J_{t-1}) \quad (4)$$

where I_{t-1} contains past information on y and z, and J_{t-1} contains only information on past y. When (4) holds, past z is useful, in addition to past y, for predicting y_t. The term “causes” in “Granger causes” should be interpreted with caution. The only sense in which z “causes” y is given in (4). In particular, it has nothing to say about contemporaneous causality between y and z, so it does not allow us to determine whether z_t is an exogenous or endogenous variable in an equation relating y_t to z_t (Wooldridge, 2002).

Interaction trend

Granger causality test informs about the interactions' direction of variables on the VAR model. Based on the results, graphics on the interactions' direction are presented as shown in Figure 4. On the graphics, it can be seen that changes in hedge funds' performance has an effect on Fed interest rate, 10 year-term treasury bond and M2 monetary supply. Theoretically, although it is not easy to say hedge funds' performance affects these three variables, on the grounds of results we can tell hedge funds have effects on Fed's and other policy-makers' decisions by accepting hedge funds' managers, as of the

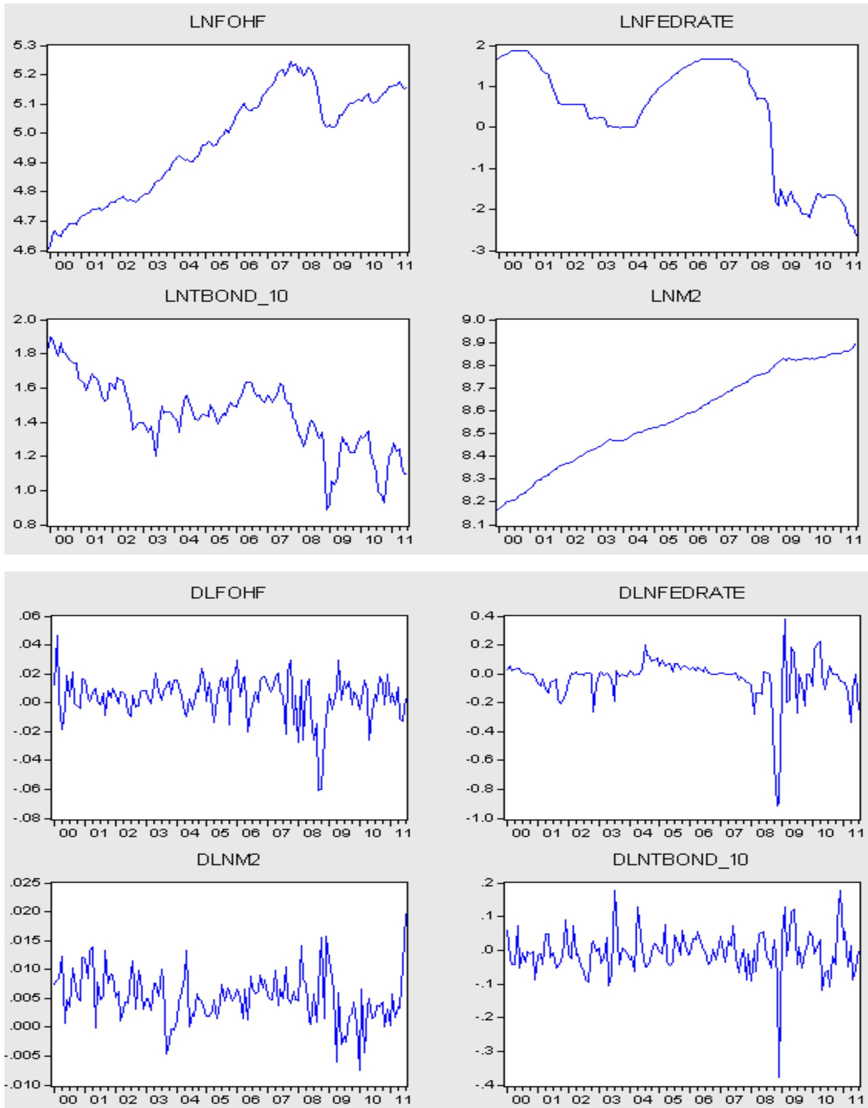

Figure 2. I(0) and I(1) series graphs.

Table 4. Granger causality table.

Null hypothesis	FStatistic	Probability
DLNFEDRATE does not Granger cause DLNFOHF	0.24001	0.86830
DLNFOHF does not Granger cause DLNFEDRATE	11.1330	1.5E-06
DLNM2 does not Granger cause DLNFOHF	0.68483	0.56288
DLNFOHF does not Granger cause DLNM2	3.64523	0.01451
DLNTBOND_10 does not Granger cause DLNFOHF	0.13842	0.93688
DLNFOHF does not Granger cause DLNTBOND_10	6.65055	0.00033
DLNM2 does not Granger cause DLNFEDRATE	0.91971	0.43338
DLNFEDRATE does not Granger cause DLNM2	2.22602	0.08825
DLNTBOND_10 does not Granger cause DLNFEDRATE	2.9 1228	0.03696
DLNFEDRATE does not Granger cause DLNTBOND_10	2.08266	0.10569
DLNTBOND_10 does not Granger cause DLNM2	8.64022	2.9E-05
DLNM2 does not Granger cause DLNTBOND_10	1.23751	0.29886

Model's Cholesky ranking based on the data gathered from Granger causality test is: fohffedrate tbond_10 m2.

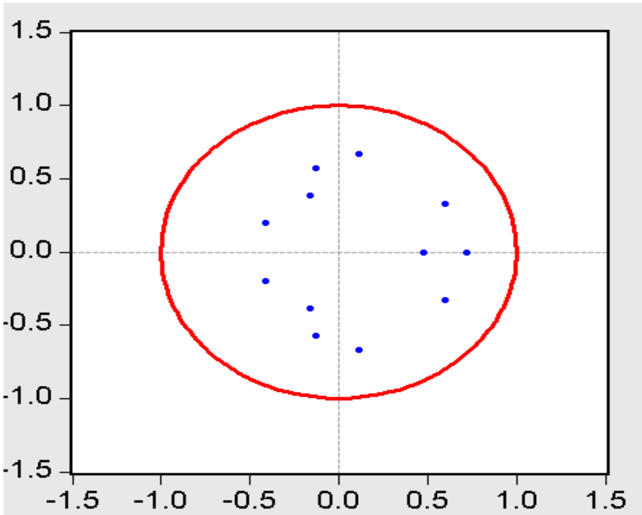

Figure 3. Inverse roots of AR characteristic polynomial. One common use of vector autoregressions is to test the hypothesis that one or more of the variables in a VAR do not "Granger cause" the others.

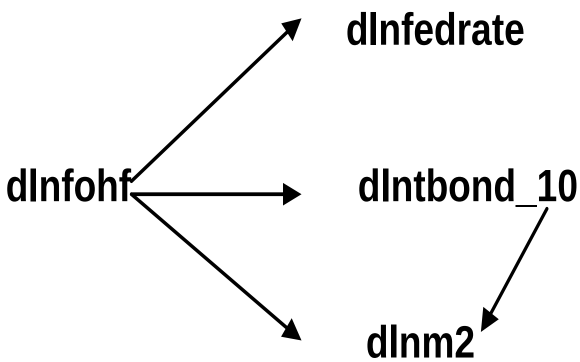

Figure 4. Interaction trend graph.

markets' most professional players,risk-return performance is an important indicator on the market's general trend.

Block F-tests and an examination of causality in a VAR will suggest which of the variables in the model have statistically significant impacts on the future values of each of the variables in the system. But F-test results will not, by construction, be able to explain the sign of the relationship or how long these effects require to take place. Therefore, throughout performing financial evaluations on the model, model's residulas considering impulse responses analysis and variance decomposition analysis is benefited instead of interpreting parameters of model. Variance decompositions determine how much of the s-step-ahead forecast error variance of a given variable is explained by innovations to each explanatory variable for s = 1, 2, . . . Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks each of the variables (Brooks, 2008).

As is shown in Table 5, all changes in DLNFOHF variable is explained by its own shocks; more details of variance decomposition analysis are given in appendix. 34% of variance of estimation error in DLNFEDRATE variable is explained by DLNFOHF variable; variance fluctation in DLNTBOND_10 and DLNM2 variables explained by other variables in both long and short term which remains in low level.

Results obtained in impulse-responses analysis confirm the ones gathered in variance decomposition. As shown in Figure 5, in the first row, the most important reaction happens to DLNFEDRATE variable in the face of a standart deviation shock to DLNFOFH variable. A decrease is observed after increases in DLNFEDRATE variable in every two-month period. It can be said that the effect of the shock is totally removed on the tenth month. Another attention-grabbing interaction is the volatility occuring in DLNFEDRATE variable when a standart deviation shock is given to DLNTBOND_10 variable. We observed that DLNM2 variable has no effect on other parameters. In respect of existing variables, DLNM2 is an exogenous variable.

Conclusion

As previously mentioned in our study's literature review, different results were obtained from analysis by several researchers on the performance and interaction of hedge funds and other financal instruments. Due to the difficulty encountered during the research period and the high volatility in the global financial system, a chaotic stage was created. Generally, Fed's changes in policy interest cause incidences in other countries' money and capital markets. Stock exchanges react to these changes on the instant. The interactions' in the parities volatility definitely creates return opportunities for investors like hedge funds. In our study, instead of Fed policy interest rate, we exercised effective Fed interest rates used by banks lending to each other and in pricing daily developments much faster.

Our study's results reveal Fed interest rate, the United States' M2 monetary supply and 10 year-term Treasury Bonds' returns are affected by the global hedge funds' performances. Of course, the point to notice is the variable we used as the global hedge fund performance is an index formed by the result of the most professional investors' positions' returns and losses. Over here, opened and closed positions guide the markets in the light of returns or losses. A change in the short-term affects the Fed's effective interest rates and the rates in turn change dependently in long-term treasury bonds as a result of the market players' positions. Fed serves the

Table 5. Variance decomposition.

Period	DLNFOHF	DLNFEDRATE	DLNTBOND_10	DLNM2
1	100.0000	0.000000	0.000000	0.000000
10	97.24690	0.522814	1.021505	1.208785
1	2.116337	97.88366	0.000000	0.000000
10	33.95163	59.64281	5.206976	1.198583
1	3.319119	2.547136	94.13374	0.000000
10	16.24260	4.631515	77.20123	1.924654
1	2.223214	4.241441	1.812861	91.72248
10	15.17407	6.341919	14.14115	64.34286

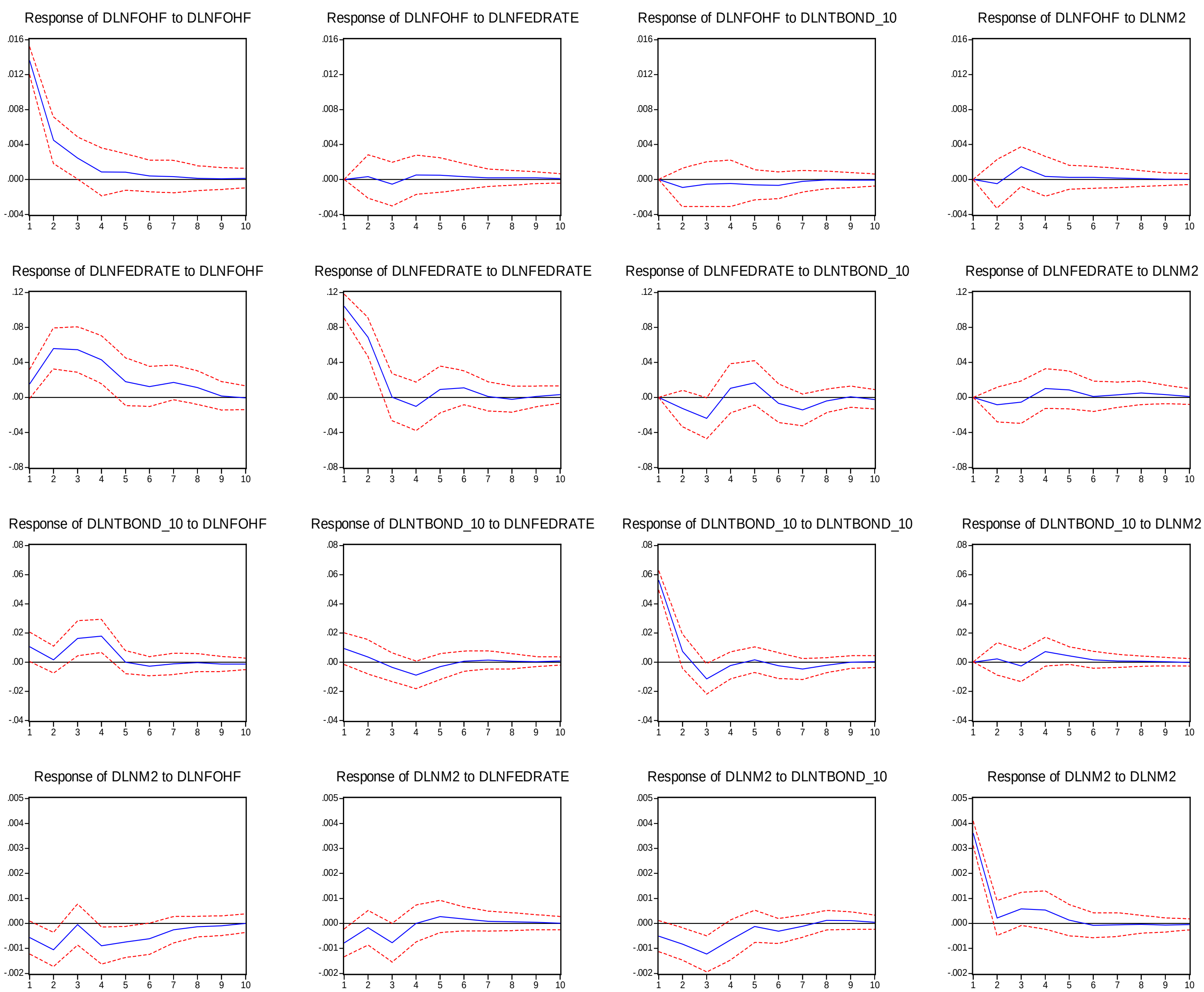

Figure 5. Impulse responses analysis (Response to Cholesky One S.D. Innovations ± 2 S.E.).

purpose of liquidity within the frame of its goals in inflation, unemployement and economic growth. As a consequence within both the U.S.A and the global market frame, hedge fund indices are vulnerability reflecting index.

REFERENCES

Ackermann C, McEnally R, Ravenscraft D (1999). The Performance of Hedge Funds: Risk, Return, and Incentives. J. Financ., 54(3): 833-874. doi:10.1111/0022-1082.00129.

Adrian T (2007). Measuring Risk in the Hedge Fund Sector. Current Issues In Economics and Finance, 13(3): 2-7.

Agarwal V, Naik N Y(2003): Risks and Portfolio Decisions Involving Hedge Funds. Rev. Financial Stud., 17(1): 63-98. doi:10.1093/rfs/hhg044.

Beckers SE, Curds R, Weinberger S (2007). Funds of Hedge Funds Take the Wrong Risks. J. Portf. Manag., 33(3): 108-121. doi:10.3905/jpm.2007.684758.

Bouges JC (2004). Alternative Hedge Fund Product Performance: The Impact of Regulation on Performance. J. Altern. Investments, 7(3): 70-80. doi:10.3905/jai.2004.461459.

Brooks C (2008). Introductory Econometrics for Finance, Second Edition, Cambridge University Press.

Brown SJ, Goetzmann WN (2003). Hedge Funds with Style. J. Portfolio Manag., 29(3): 101-112. doi:10.3905/jpm.2003.319877.

Brunel JLP (2007). Are Hedge Fund Strategies Just About Leverage? J. Wealth Manag., 10(3): 40-51. doi:10.3905/jwm.2007.698895.

Cassar G, Gerakos J (2010). Determinants of Hedge Fund Internal Controls and Fees. Account. Rev., 85(6): 1887-1919. doi:10.2308/accr.2010.85.6.1887.

Cerrato M, Iannelli A (2006). Testing For Random Walk and Structural Breaks in Hedge Funds Returns. Int. J. Theor. Appl. Financ., 9(3): 341-358.

Chapman J (2010). Phasing out hedge funds. Public Policy Res., 17(1): 36-41. doi:10.1111/j.1744-540X.2010.00599.x

Christory C, Daul S, Giraud JR (2006). Quantification of Hedge Fund Default Risk. J. Alternative Investments, 9(2): 71-86. doi:10.3905/jai.2006.655938.

Clark KA, Winkelmann K (2004). Active Risk Budgeting In Action: Understanding Hedge Fund Performance. J. Alternative Investments, 7(3): 35-46.doi:10.3905/jai.2004.461456.

Darius D, Ilhan A, Mulvey J, Simsek K, Sircar R (2002). Trend-following hedge funds and multi-period asset allocation. Quant. Financ., 2(5): 354-361. doi:10.1088/1469-7688/2/5/304.

Davidson R, Mackinnon JG (1999). Econometric Theory and Methods. Oxford University Press, UK.

Ding B, Shawky H (2007). The Performance of Hedge Fund Strategies and the Asymmetry of Return Distributions. Eur. Financial Manag., 13(2): 309-331. doi:10.1111/j.1468-036X.2006.00356.x.

Do V, Faff R, Veeraraghavan M (2009). Do Australian hedge fund managers possess timing abilities? Appl. Financial Econ., 19(1): 27-38. doi:10.1080/09603100701735987.

Donaldson T (2008). Hedge Funds Ethics. Bus. Ethics Q., 18(3): 405-416.

Dopfel FE (2005). How Hedge Funds Fit. J. Portfolio Manag., 31(4): 9-20. doi:10.3905/jpm.2005.570144.

Dupleich R, Giamouridis D, Mesomeris S, Noorizadeh N (2010). Unbundling Common Style Exposures, Time Variance and Style Timing of Hedge Fund Beta. J. Asset Manag., 11(1): 19-30. doi:10.1057/jam.2010.2.

Earle JE (2010). Compensating Hedge Fund Managers with Stock Options: A New Path to Alignment of Interests with Investors. Benefits Law J., 23(3): 80-94.

Eberlein E, Madan D B (2009): Hedge Fund Performance: Sources and Measures. Int. J. Theoretical Applied Financ., 12(03): 267-282. doi:10.1142/S0219024909005282.

Fang V, Phoon KF, Xiang VYD (2008). A Heuristic Approach to Asian Hedge Fund Allocation. J. Wealth Manag., 10(4): 42-52. doi:10.3905/jwm.2008.701850.

Frumkin D, Vandegrift D (2009). The Effect of Size, Age, Beta and Disclosure Requirements On Hedge Fund Performance. J. Derivatives Hedge Funds, 15(3): 241-251. doi:10.1057/jdhf.2009.12

Fung WKH, Hsieh DA (2006). Hedge Funds: An Industry in Its Adolescence. Econ. Rev., (4): 1-35.

Fuss R, Kaiser DG, Adams Z (2007). Value at risk, GARCH modelling and the forecasting of hedge fund return volatility. J. Derivatives, 13(1): 2-25. doi:10.1057/palgrave.dutr.1850048.

Gibson R, Gyger S (2007). The Style Consistency of Hedge Funds. Eur. Financial Manag., 13(2): 287-308. doi:10.1111/j.1468-036X.2006.00355.x.

Grecu A, Malkiel BG, Saha A (2007). Why Do Hedge Funds Stop Reporting Performance? J. Portf. Manag., 34(1): 119-126. doi:10.3905/jpm.2007.698041.

Gujarati DN (2004). Basic Econometrics, Fourth Edition, The McGraw−Hill Companies.

Hedges IV JR (2005). Hedge Fund Transparency. Eur. J. Financ., 11(5): 411-417. doi:10.1080/1351847042000286685.

Jones M (2007). Examination of fund age and size and its impact on hedge fund performance. Derivatives Use, Trading Regulation, 12(4): 342-350. doi:10.1057/palgrave.dutr.1850052.

Lee DKC, Lwi S, Phoon KF (2001). An Equitable Structure for Hedge Fund Incentive Fees. J. Altern. Investments, 4(2): 43-48. doi:10.3905/jai.2001.319009.

Li Y, Kazemi H (2007). Conditional Properties of Hedge Funds: Evidence from Daily Returns. Eur. Financial Manag., 13(2): 211-238. doi:10.1111/j.1468-036X.2006.00352.x.

Liang B (1998). On the Performance of Hedge Funds. J. Financ., 54(3): 833-874. doi:10.2139/ssrn.89490.

Liang B (2003). The Accuracy of Hedge Fund Returns. J. Portfolio Manag., 29(3): 111-122. doi:10.3905/jpm.2003.319889.

Lütkepohl H (2003). Vector Autoregressions: A Companion to Theoretical Econometrics, Blackwell Publishing, USA.

Malkiel BG, Saha A (2005). Hedge Funds: Risk and Return. Financial Anal. J., 61(6): 80-88. doi:10.2469/faj.v61.n6.2775.

Manser S, Schmid MM (2009). The performance persistence of equity long/short hedge funds. J. Deriv. Hedge Funds, 15(1): 51-69. doi:10.1057/jdhf.2008.28.

Maxam CL, Nikbakht E, Petrova M, Spieler AC (2004). Manager Characteristics and Hedge Fund Performance. J. Appl. Financ., 16(2): 57-70.

Ozcicek O, McMillin WD (1999). Lag Length Selection in Vector Autoregressive Models: Symmetric and Asymmetric Lags, Applied Economics, Taylor Francis J., 31(4): 517-24.

Peltomaki J (2009). The Asymmetric Impact of Volatility Risk on Hedge Fund Returns. J. Appl. Financ., 17(1): 88-95.

Pätäri EJ, Tolvanen J (2009). Chasing performance persistence of hedge funds – Comparative analysis of evaluation techniques. J. Deriv. Hedge Funds, 15(3): 223-240. doi:10.1057/jdhf.2009.11

Racicot F-É, Théoret R (2007). The beta puzzle revisited: A panel study of hedge fund returns. J. Derivatives Hedge Funds, 13(2): 125-146. doi:10.1057/palgrave.jdhf.1850062.

Tee K-H (2009). Is active currency management effective for international equity portfolios involving managed futures and hedge funds?J. Derivatives Hedge Funds, 15(2): 137-148. doi:10.1057/jdhf.2009.7.

Teo M (2009). The Geography of Hedge Funds. Rev. Financial Stud., 22(9): 3531-3561. doi:10.1093/rfs/hhp007.

Tsay RS (2005). Analysis of Financial Time Series, Second Edition, John Wıley & Sons, New Jersey.

Wooldridge J (2002). Introductory Econometrics: A Modern Approach, Second Edition, South-Western College Publishing.

Appendix. Variance decomposition (All periods).

Period	DLNFOHF	DLNFEDRATE	DLNTBOND_10	DLNM2
1	100.0000	0.000000	0.000000	0.000000
2	99.42357	0.052746	0.404381	0.119308
3	98.17373	0.190202	0.528048	1.108017
4	97.91381	0.314313	0.617729	1.154152
5	97.61369	0.423583	0.787755	1.174968
6	97.33868	0.472241	0.993605	1.195468
7	97.29141	0.488378	1.015231	1.204977
8	97.27216	0.502438	1.016897	1.208509
9	97.25516	0.516945	1.019147	1.208752
10	97.24690	0.522814	1.021505	1.208785
1	2.116337	97.88366	0.000000	0.000000
2	1.748964	81.30543	0.849708	0.355229
3	2.781920	68.53818	3.211359	0.431257
4	3.280326	63.02231	3.368499	0.805932
5	3.309041	61.50531	4.343448	1.060830
6	3.326994	61.20719	4.469808	1.053069
7	3.373445	60.03981	5.162265	1.063472
8	3.398187	59.67213	5.190553	1.155441
9	3.397271	59.64220	5.189279	1.195816
10	3.395163	59.64281	5.206976	1.198583
1	3.319119	2.547136	94.13374	0.000000
2	3.322913	2.841190	93.69294	0.142960
3	9.858333	2.864814	86.95776	0.319093
4	1.625555	4.417034	77.86835	1.459068
5	1.613968	4.616946	77.36859	1.874783
6	1.626204	4.606143	77.21138	1.920431
7	1.619515	4.625224	77.26029	1.919337
8	1.617836	4.625326	77.27171	1.924606
9	1.621232	4.624312	77.23837	1.924995
10	1.624260	4.631515	77.21230	1.924654
1	2.223214	4.241441	1.812861	91.12248
2	8.821149	3.933925	5.852948	81.39198
3	7.678583	6.657326	13.11716	72.54693
4	11.08961	6.151441	14.31436	68.44459
5	13.40731	6.320579	13.92918	66.34292
6	14.85402	6.321914	14.05108	64.77298
7	15.09895	6.331547	14.04922	64.52028
8	15.15316	6.340633	14.09605	64.41015
9	15.17673	6.342596	14.13515	64.34552
10	15.17407	6.341919	14.14115	64.34286