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Causal Relations among Different Sizes of Stock Returns, Interest Rates, Real Activity, and Inflation

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This paper investigates the causal relations and dynamic interactions among the different sizes of stock returns, interest rates, real activity, and inflation. The generalized impulse response functions and the generalized forecast error variance decomposition are computed in order to investigate interrelationships within the system. Results reveal that Unrestricted Vector Auto Regression outcome is a function of the size of stock returns. Specifically, the results suggest that the stock returns for the fifth and tenth deciles are leading indicators for future macroeconomic performance. However, stock return for the first decile leads the inflation rate and real interest rate but does not lead the real economic activity as represented by industrial production.
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1. Introduction

Given the recent instability permeating the American stock market since the economic crash of 2008, the study of factors that have an impact on stock returns has become more relevant than ever. While it may be impossible to develop an accurate predictor of stock fluctuations because of the human variable, many tools and methodologies have been employed in prior studies that attempt to provide us with a better understanding of the relationship between stock returns and other factors.

Studying the main factors that have an impact on stock returns is a very important topic in the Market Based Accounting Research (MBAR) and Finance. Many tools and different methodologies are employed in the literature to have a better understanding of the relationship between stock returns and other factors.

Historically, changes in the quantity of money have influenced stock prices movement, as explicitly found by Homa and Jaffee (1971), Keran (1971), Modigliani (1972), Palmer (1970), Pepper and Zwick (1971) and Sprinkel (1964, 1971). Hamburger and Kochin (1972) discovered different channels through which variables relating to money supply could affect stock prices. They demonstrated ways in which monetary growth could affect stock prices, i.e., changes in monetary growth had a number of different effects on the market.

Building on those historical connections between money and stock prices, Fama (1981) found that stock returns were determined by forecasts of more relevant real variables and that negative stock return-inflation was induced by a negative relationship between inflation and real activity. Fama (1981), Geske and Roll (1983), Kaul (1987), Shah (1989) and Barro (1990) found that more than fifty percent of the variances in stock-return could be traced to forecasted variables like real GNP, industrial production and investments, which are important determinants for the cash flows to firms.

Geske and Roll (1983) found that stock returns caused changes in inflationary expectations because of a chain of macroeconomic events that followed the returns. Ram and Spencer (1983) found evidence of unidirectional causality from inflation to stock returns. Disputing these findings, Fama (1981) hypothesized that the negative correlation between stock returns and inflation was not a causal relationship but that the relationship was indirectly affected by a positive relationship between stock returns and real activity induced by a negative relationship between real activity and inflation.

James, Koreisha and Partch (1985) investigated the causal links between stock returns, real activity, money supply and inflation, using a vector autoregressive-moving average model. Fama (1990) found that shocks to expected cash flows, time varying expected return, and shocks to expected returns were the rationality behind the variation in stock prices.

One of the most enigmatic empirical findings in finance is the size effect, first reported by Banz (1981), which seems to provide strong evidence that the shares of firms with small equity market values earn, on average, higher stock returns than firms with large equity market values. The apparent persistence of this effect is such that it has been accorded the status of an anomaly. If the size of the firm is related to its return, the relationship between size of stock returns and the macroeconomic variables should be investigated. In addition, Fama and French's (1993, 1995, 1996) proposed factors, SMB and HML, exhibit large variability over time. SMB is a zero-investment portfolio that is long on small capitalization (cap) stocks and short on big cap stocks. Similarly, HML is a zero investment portfolio that is long on high book-to-market (B/M) stocks and short on low B/M stocks. In this paper, we investigate the extent to which the monthly performance of size-sorted portfolios is related to fundamental variables in the economy. In addition, we investigate whether macroeconomic variables can help predict the returns on SMB, HML, and other size-based portfolios.

One of the common tools used to measure stock fluctuations is the multivariate Vector Auto Regression (VAR). Using this approach, Lee (1992) analyzed the causal relationship and dynamic interaction among stock returns, inflation, real activity and interest rates for the post-war USA. He found that stock returns appeared Granger-Causal and the results of his study helped explain real activity.

This paper, like Lee's (1992) paper, uses VAR to measure stock fluctuations, but differs from his study in critical ways. First, by using a sample period that extends from January 1964 to March 2009, our sample includes data from the world financial crisis, making it more relevant to today's stock fluctuations. Second, like Lee's (1992) paper, the (nominal) common stock returns are returns on the New York Stock Exchange (NYSE) that have been value weighted to the stock index obtained from the Center for Research in Security Prices (CRSP), but unlike Lee's paper, data on stock returns represent size portfolios. The size portfolios are sorted into deciles based on market capitalization at the end of each quarter and represent a value-weighted average.

Analyzing the size variable is a critical component in measuring stock fluctuations, and we investigate the causal relations and dynamic interactions among different sizes of stock returns, interest rates, real activity, and inflation. In other words, we are exploring how the relationships among these variables are affected by the size of the stock returns

Third, rather than use the VAR, we are applying a relatively new and powerful methodology. The generalized forecast error variance decomposition components and the generalized impulse response functions are computed from estimated unrestricted vector autoregressive (UVAR) models. Unlike the traditional forecast error variance decomposition and impulse response functions, these approaches do not require orthogonalization of shocks and is invariant to the ordering of the variables in the UVAR model, while the widely used Choleski factorization is known to be sensitive to the ordering of the variables.

In addition, the UVAR as employed in this study, can avoid using arbitrary choice of restrictions needed to settle identification. The findings suggest that future stock returns for the first decile can be estimated by using the time paths of growth in GDP and real interest rate. Future stock returns for the fifth decile can only be estimated by using the time paths of the real interest rate. Finally, future stock returns for the tenth decile cannot be estimated by using the time paths of any macroeconomic variable questioned in this study. These results indicate that the VAR results are sensitive to changing the sizes of stock return.

The organization of the paper is as follows. Section 2 presents the literature review. Section 3 describes the data. Section 4 introduces the VAR model. Section 5 reports evidence from the VAR model. Section 6 concludes.

2. Literature Review

As indicated earlier, this topic is analyzed in the MBAR and Finance literature. Bali et al (2008), in a recent study in this field, tried to identify variables that forecasted the stock returns based on different factors, based on a quarterly data from 1972 to 2002. Results contradicted with Lamont's (1998) study due to the different time periods. Their conclusion was that not all factors had the same impact over different periods. They found the earnings yield was one of the stable factors to predict the future stock returns.

Grigoris et al 2007 based on Greek data span 1970 to 2003 concluded that some factors like beta, size and E/P could be considered as redundant factors for explaining average returns. Based on UK data Morelli (2007) approached different conclusion by saying that beta and book to market equity was an important factor for security returns. A recent study based on Malaysian data Roselee and Fung (2009) concluded that other macro factors should be combined with the size in order to provide better understanding about the stock returns. In a much related study to ours, Lee (1992) investigated the causal relationship and dynamic interaction among asset returns, interest rates, real activity and inflation using a multivariate VAR model with postwar U.S. data. He showed that prior stock returns Granger causes real stock returns. He found strong positive response of industrial production growth to real stock returns. But he did not find any consistent negative response of inflation (stock returns) to innovations in stock returns (inflation). Innovation in real interest rates can explain the error variance of real inflation substantially and real inflation can explain only a low percentage of the variation in the industrial production growth. So stock returns can signal the changes in real activity and the relation between them is positive. But no causal relationship is found between stock returns and inflation. Rather, the negative relationship between stock returns and inflation is treated as a possible proxy for the relations between real activity and stock return.

Darrat (1990) tested the joint hypothesis that the stock market of Canada is efficient and the expected returns were constant over time using the multivariate Granger-causality technique. He found that the Canadian stock prices fully reflect all available information on monetary policy moves. Darrat and Mukherjee (1987) used a VAR model along with Akaike's final prediction-error on the Indian data over 1948-84 and showed that a significant causal relationship existed between stock returns and a certain macroeconomic variable. Brown and Otsuki (1990) found that money supply; production index, crude oil price, exchange rate, call money rate and a residual market error were associated with risk premia and affected the Japanese stock market.

Investigating the pricing of macroeconomic variables of the Japanese stock market Hamao (1988) replicated the Chen, Roll and Ross (1986) study in the multi-factor APT framework. He showed that Japanese stock returns were significantly influenced by the changes in expected inflation and unexpected changes in both the risk premium and in the slope of the term structure of interest rates. The volatilities in real economic activity in Japan were weakly priced compared to the U.S.A. Changes in monthly production and trade terms were weakly priced and the unanticipated changes in the exchange rate and changes in oil prices were not priced in the Japanese stock market.

3. An Overview of the Data

Quarterly data on the U.S economy are used for the sample period January 1964 to March 2009. Following the recent trend in empirical research, this paper applies the VAR method. A four-variable VAR model is estimated to capture the time series relationships among the real stock returns (SRE), real interest rates (IRE), growth rate in industrial production (IPG), and rate of inflation (INF). Real returns (SRE, IRE) are computed as nominal returns less the inflation rate. The data for IPG and INF are seasonally adjusted.

The (nominal) common stock returns are the returns on the New York Stock Exchange (NYSE) value weighted stock index obtained from the Center for Research in Security Prices (CRSP). Data on stock returns represent size portfolios. The size portfolios are sorted into deciles based on market capitalization at the end of each quarter and represent value-weighted average. For example, SRE1 is real stock returns on the portfolio with the smallest market capitalization and SRE10 is the real stock returns on the portfolio with the biggest market capitalization. As in Lee (1992), the nominal interest rates (IR) are the returns on one-month Treasury bills. The rate inflation (INF) is computed by using the monthly Consumer Price Index (CPI) series obtained from the Federal Reserve Bank of St. Louis Web Site. Then we compute using the following formula: INFt = (CPIt-CPIt-1)/CPIt-1. The industrial production series (IP) is taken from same Web site, and the IPG is computed by IPGt = (IPt-IPt-1/IPt-1). Table 1 shows the descriptive statistics of the variables.

Table 1
Descriptive Statistics

Statistics	INF	IPG	IRE	SRE1	SRE5	SRE10
Mean	0.046	0.034	0.062	0.247	0.154	0.129
Median	0.039	0.039	0.055	0.138	0.146	0.140
Maximum	0.156	0.181	0.151	2.852	1.891	0.88
Minimum	-0.010	-0.312	0.028	-1.424	-1.317	-1.01
Std. Dev.	0.032	0.063	0.025	0.703	0.508	0.312
Skewness	4.879	-5.908	0.013	3.073	0.484	-1.89
Kurtosis	16.941	35.327	0.049	15.808	15.339	16.97
Jarque-Bera	189.41	1,082.598	0.695	82.758	19.261	62.31

INF: inflation rate, IPG: industrial production, IRE: real interest rate, SER1: the stock return for the first decile, SER5: the stock return for the fifth decile, and SRE10: the stock returns for the tenth decile.

4. The VAR Model

This study adopts an unrestricted vector autoregression (UVAR) framework to analyze the dynamic relationship between the variables. The UVAR does not impose arbitrary restrictions of the effects of the endogenous variables. It was common in earlier VAR-type analyses to rely on a Choleski factorization. Unfortunately, the Choleski factorization is known to be sensitive to the ordering of variables when the residual covariance matrix is non-diagonal. This paper employs generalized forecast error variance decomposition developed in Koop, Pesaran and Lee (1996) and Pesaran and Shin (1998) to deal with this problem. Unlike the orthogonalized forecast error variance decomposition, the generalized approach is invariant to the ordering of the variables in the UVAR model. The generalized forecast error variance decomposition from the UVAR model is computed in order to investigate interrelationships within the system. The empirical work undertaken in this study is based on estimating the UVAR on eight definitions of money.

The UVAR approach, introduced by Sims (1980), suggests a standard tool to analyze time series relationships among macroeconomic variables. A VAR is a system in which every equation has the same right hand variables, and those variables include lagged values of all of the endogenous variables. VARs are well suited to forecasting variables where each variable helps forecast other variables.

The mathematical form of a UVAR is

$$y_t = m + A_1 y_{t-1} + \cdots + A_N y_{t-N} + \varepsilon_t \quad (1)$$

Here y_t is a vector of endogenous variables; m is a vector of constant, N is the vector autoregressive order, A_i are matrices of lag coefficients of y_t up to some lag length N, and ε_t is a vector of innovations. The components of ε_t vector are each white noise process with zero mean, constant variance, and are individually serially uncorrelated. However, the components of ε_t vector could be contemporaneously correlated.

UVARs have proven successful for forecasting systems of interrelated time series variables. Vector autoregression is also frequently used, although with considerable controversy, for analyzing the dynamic impact of different types of random disturbances on systems of variables. However, the estimated coefficients of UVARs themselves are difficult to interpret. We will look at the generalized forecast error variance decomposition and the generalized impulse response functions of the system to draw conclusions about a UVAR.

4.1. The Generalized Forecast Error Variance Decomposition, Innovation Accounting Analysis

Innovation accounting analysis refers to two tools used to trace the impact of shocks (innovations) in the VAR system. These tools were introduced by Sims (1980) to measure the dynamic interaction among the variables. The first, the forecast error variance decomposition (FEVD), analyzes the errors the model would tend to make if it is used to forecast its variables. The FEVD shows how much of the average squared forecast error, which the model tends to make, is caused by innovations associated with each of the variables in the model. The FEVD of a variable, thus, can suggest that forces associated with one variable are major influences on the evolution of another variable.

The generalized FEVD shows how much of the average squared forecast error, which the model tends to make, is caused by innovations associated with each of the variables in the model. The generalized FEVD of a variable thus can suggest that forces associated with one variable are major influences on the evolution of another variable. In other words, the generalized FEDV of a VAR provides information about the relative importance of the random innovations. It was common in earlier VAR-type analyses to rely on a Choleski factorization. Unfortunately, the innovation accounting results based the Choleski factorization is sensitive to the ordering of variables in the VAR model. In this paper, we apply generalized forecast error variance decomposition developed by Koop, Pesaran and Lee (1996) and Pesaran and Shin (1998) to deal with this problem. Unlike the orthogonalized method, the generalized approach is invariant to the ordering of the variables and does not impose the constraint that the underlying shocks to the VAR are orthogonalized before decompositions are computed. The generalized approach explicitly takes into account the contemporaneous correlation of the variables in the VAR model. The approach provides meaningful results at all the horizons including initial impact.

We calculate separate variance decomposition for each endogenous variable. The first column is the forecast error of the variable for different forecast horizons. The source of this forecast error is variation in the current and future values of the innovations. The remaining columns give the percentage of the variance due to specific innovations. One period ahead, all of the variation in a variable comes from its own innovation, so the first number is always 100 percent.

4.2. Generalized Impulse Response Function

The other tool, the impulse response function, shows how one variable responds over time to a single innovation in itself or in another variable. Specifically, it traces the effect on current and future values of the endogenous variable of a one standard deviation shock to one of the innovations. Innovations or surprise movements are jointly summarized by the error terms of the UVAR model.

4.3. Granger Causality Tests

If we have two time series m_t and y_t interacting according to the following model:

$$m_t = \pi_{11} m_{t-1} + \pi_{12} y_{t-1} + u_{mt} \tag{2.1}$$

$$y_t = \pi_{21} m_{t-1} + \pi_{22} y_{t-1} + u_{yt} \tag{2.2}$$

The series y_t fails to Granger-cause m_t according to the Granger test if, in a regression of mt on lagged m and lagged y_t, the latter takes on a - not significantly different from - zero coefficient. That is, the coefficient π_{12} in the first equation must equal zero. Similarly, y_t fails to Granger-cause m_t according to Sims (1972) if, in a regression of y_t on lagged y_t and future m_t (if we add m_{t+1} to the right hand sides of 2.2), the latter takes on a - not significantly different from - zero coefficient.

In these cases, it is said that $m_t$is exogenous with respect toy_t. If on the other hand, the coefficient π_{21} is nonzero, then m_t does Granger-cause y_t.

This test is criticized on the ground that it does not imply a cause-and-effect relationship. It implies the existence of empirical correlation between the variables. To show that, consider again the above two-variable VAR model. It is a reduced form of the following structural model:

$$m_t = \emptyset y_t + \beta_{11} m_{t-1} + \beta_{12} y_{t-1} + \varepsilon_{1t} \tag{2.3}$$

$$y_t = \gamma m_t + \beta_{21} m_{t-1} + \beta_{22} y_{t-1} + \varepsilon_{2t} \tag{2.4}$$

where the error terms, $\varepsilon_{1t}$and $\varepsilon_{2t}$are contemporaneously and serially uncorrelated. From these equations, m is predetermined for y if $\emptyset$=0, while m is strictly exogenous for y if $\emptyset=\beta_1$ =0. From the reduced form model, y fails to Granger-cause m if π_{12} =0. Now, π_{12} is given by $\pi_{12} = (\emptyset\beta_{22} + \beta_{12})/(1 - \emptyset\gamma)$.

It is clear that non-causality is neither necessary nor sufficient for predeterminedness: $\emptyset$=0 neither implies nor is implied by π_{12}=0. Cooley and LeRoy (1985) argued that Granger and Sims tests were irrelevant to whether a causal interpretation of a conditional correlation was justified. Further, predeterminedness was also the exogeneity concept relevant for econometric estimation. Therefore, Granger causality test results cannot be used to prove the direction of causation from one variable to another. It can be used to show that one variable can help forecast another variable [Hamilton (1994)].

The empirical evidence from a VAR model is very sensitive to the choice of lag length in the equations of the model. Alternative choices will give different innovations series and, thus, will likely make a difference in the variance decomposition results. The appropriate lag length could be tested using the likelihood ratio test, the Akaike Information Criterion, or the Schwarz Criterion. In this study, the lag length will be specified based on these criteria and the results obtained in each case will be compared. Changing the lag length will also test the robustness of the empirical results.

5. Empirical Results

This section investigates the dynamic relationship between the variables using correlation analysis and VAR models for the full sample period 1964.3-2000.4. Before estimating final models, a few issues need to be addressed regarding the application of the VAR method. Given the sensitivity of the VAR results to the lag length, for each model the lag length will be determined before final estimation according to three criteria. These are the Likelihood Ratio (LR), the Akaike Information Criterion (AIC), and the Schwarz Criterion (SC). Finally, the results should be robust to the ordering of the variables to be considered conclusive.

To determine the best lag length, the three criteria mentioned earlier are applied to the results from running the EC model using different lags. The other two criteria, the AIC and the SC, try to minimize a function that depends on two elements: the determinant of the covariance matrix of residuals and a penalty for including a large number of parameters in the model. The lags are examined up to 16 quarters. There is no significant increase in the explanatory power by adding more lags than six quarts. This is confirmed by the SC statistics: the minimum value is reached at the 16th lag. So the final estimation of this model will be carried out using five lags for each variable.

5.1. Granger-Causality

The Granger approach to the question whether X causes Y is to see how much of the current Y can be explained by past values of Y and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y, or equivalently if the coefficients on the lagged Xs are statistically significant.

The tests are whether all the coefficients of the lagged Xs in the second equation may be considered to be zero, and similarly whether the coefficients of the lagged Ys in the fourth equation are zero. Thus, the null hypotheses being tested are that X does not Granger-cause Y and that Y does not Granger-cause X. Output from the test gives the relevant F-statistics for these two hypotheses.

5.1.1. In Presence of SRE1

The results show that SRE 1 Granger-causes INF and IRE but does not Granger-causes IPG. In addition, IPG and IRE Granger-cause SRE1. However, INF does not Granger-cause SRE 1. Our results suggest that stock return for the first decile is the leading indicator for the inflation rate and real interest rate but not for the growth in GDP. Furthermore, Future stock return for the first decile can be estimated by using the time paths of growth in GDP and real interest rate.

Table 2
Granger Causality Tests

	INF		IPG		IRE	
	Direction of Causality					
	→	←	→	←	→	←
SRE1	Yes (4.97539) ((0.00813))	No (0.48292) ((0.61797))	No (2.33162) ((0.10077))	Yes (4.82283) ((0.00938))	Yes (3.47636) ((0.03350))	Yes (5.91728) ((0.00338))
SRE5	Yes (3.21261) ((0.00560))	No (1.15429) ((0.33475))	Yes (6.52245) ((0.00476))	No (1.18665) ((0.31724))	Yes (2.46915) ((0.02688))	Yes (2.14474) ((0.02688))
SRE10	Yes (4.96539) ((0.00413))	No (0.3592) ((0.71297))	Yes (6.52245) ((0.00325))	No (2.45162) ((0.11077))	No (0.28292) ((0.52797))	No (1.23429) ((0.4472))

INF: inflation rate, IPG: industrial production, IRE: real interest rate, SER1: the stock return for the first decile, SER5: the stock return for the fifth decile, and SRE10: the stock returns for the tenth decile. (): F-statistic, (()): P-value.

5.1.2. In Presence of SRE5

Table 2 indicates that SRE5 Granger-causes INF, IPG, and IRE. In addition, only IRE Granger-cause SRE5. These results indicate that that stock return for the fifth decile is the leading indicator for any macroeconomic variable questioned in this study. However, future stock return for the fifth decile can be only estimated by using the time paths of real interest rate.

5.1.3. In Presence of SRE10

The results in this case are similar to the presence of SRE5, except that SRE10 does not Granger-cause IRE and IRE does not Granger-cause SRE10. The results suggest that future stock returns for the tenth decile cannot be estimated by using the time paths of any macroeconomic variable questioned in this study. Contrarily, stock returns for the tenth decile is the leading indicator for the macroeconomic performance.

5.2. Evidence from the VAR Model

5.2.1. Stock Returns and Real Activity

Tables 3, 4, and 5 are based on our VAR estimated using the quarterly. These tables reports variance decompositions for various time horizons based on the estimation period. Each row shows the fraction of the 2-step ahead forecast error variance for a specific variable that is attributed to shocks to the column variable.

a) When we study the variation of each variable explained by its own shocks, SRE1 and SRE10 account for 85% of its own variation while SRE5 accounts for 88% of its own variation.

b) Between stock return and growth in industrial production (IPG), SRE1 and SRE5 seem to explain a substantial fraction (9%) of variance in IPG. However, SRE10 explains larger fraction by 17% of IPG variance. This indicates that SRE 10 has a strong impact on IPG variation than SRE 1 and SRE 5.

Table 3
Generalized Forecast Error Variance Decomposition Using SRE1

Variance Decomposition of INF:				
Period	INF	IPG	IRE	SRE1
1	100.0	0.0	0.0	0.0
12	82.3	10.1	5.9	1.5
16	81.5	10.9	6.0	1.4
Variance Decomposition of IPG:				
Period	INF	IPG	IRE	SRE1
1	0.0	99.9	0.0	0.0
12	16.5	54.6	19.4	9.3
16	22.3	50.9	18.0	8.6
Variance Decomposition of IRE:				
Period	INF	IPG	IRE	SRE1
1	4.3	1.3	94.2	0.0
12	7.4	17.1	63.9	11.4
16	7.4	17.7	62.8	12.0
Variance Decomposition of SRE1:				
Period	INF	IPG	IRE	SRE1
1	0.2	0.3	1.1	98.2
12	1.7	5.4	7.1	85.6
16	2.3	5.4	7.1	85.0

INF: inflation rate, IPG: industrial production, IRE: real interest rate,SER1: the stock return for the first decile.

Table 4
Generalized Forecast Error Variance Decomposition Using SRE5

Variance Decomposition of INF:				
Period	INF	IPG	IRE	SRE5
1	100.0	0.0	0.0	0.0
12	81.9	10.2	6.4	1.3
16	81.2	11.1	6.5	1.0
Variance Decomposition of IPG:				
Period	INF	IPG	IRE	SRE5
1	0.0	99.9	0.0	0.0
12	16.7	54.5	18.6	10.0
16	22.6	50.8	17.3	9.2
Variance Decomposition of IRE:				
Period	INF	IPG	IRE	SRE5
1	5.4	1.2	93.3	0.0
12	9.7	18.6	58.2	13.4
16	9.6	19.2	56.9	14.1
Variance Decomposition of SRE5:				
Period	INF	IPG	IRE	SRE5
1	0.1	0.0	2.6	97.2
12	2.0	4.0	5.7	88.1
16	2.3	4.0	5.7	87.8

INF: inflation rate, IPG: industrial production, IRE: real interest rate,SER5: the stock return for the fifth decile.

c) Between stock return and real interest rate (IRE), SRE1 and SRE5 seem to explain a substantial fraction ranges from 12% to 14% of variance in IRE. However, SRE10 explains larger fraction by 22% of IRE variance. This indicates that SRE 10 is more important in explain fluctuation in IRE than SRE1 and SRE5.

5.2.3. Interest Rate and Inflation

In presence of SRE 1 and SRE 5, neither IRE nor INF appears to explain a substantial fraction of the forecast error variance of each other. However, in the presence of SRE10, IRE shocks explain 17% of INF variation. Also, INF shocks explain 13% of IRE variation. The generalized impulse response function shows that, in response to shock in IRE, INF declines for two quarters then recovers quickly. This effect becomes positive after that. This result is inconsistent with the findings of Lee (1992). He finds that INF declines in response to shocks in IRE.

Table 5
Generalized Forecast Error Variance Decomposition Using SRE10

Variance Decomposition of INF:				
Period	INF	IPG	IRE	SRE10
1	100.0	0.0	0.0	0.0
12	74.4	6.5	16.4	2.5
16	73.9	6.7	16.7	2.5
Variance Decomposition of IPG:				
Period	INF	IPG	IRE	SRE10
1	0.4	99.5	0.0	0.0
12	13.2	46.5	23.2	16.9
16	15.4	44.6	22.7	17.0
Variance Decomposition of IRE:				
Period	INF	GIPG	IRE	SRE10
1	6.6	1.8	91.4	0.0
12	12.5	12.3	54.8	20.2
16	12.3	12.4	53.2	21.9
Variance Decomposition of SRE10:				
Period	INF	IPG	IRE	SRE10
1	0.1	0.05	2.1	97.6
12	7.4	3.0	3.1	86.2
16	8.5	3.0	3.1	85.21

INF: inflation rate, IPG: industrial production, IRE: real interest rate,SER10: the stock return for the tenth decile.

5.2.4. Inflation and Real Activity

Table 3 shows that inflation has some explanatory power for growth in the industrial production in the presence of SRE1 and SRE5. Inflation explains 22% of the variance of IPG. With SRE10, inflation explains 15.5% of the variance of IPG. These findings are broadly inconsistent with Lee's (1992) findings.

6. Conclusion

This paper attempts to investigate both causal relations and dynamic interactions among different sizes of stock returns, interest rates, real activity, and inflation. The generalized impulse response functions and the generalized forecast error variance decomposition are computed in order to investigate interrelationships within the system. A number of important results in this regard are represented using different sizes of stock returns. The results of this paper suggest that the empirical conclusion may differ when stock returns of different sizes are measured. For example, the results suggest that the stock returns for the fifth and tenth deciles are important for predicting future macroeconomic performance. However, stock return for the first decile is a leading indicator for the inflation rate and real interest rate but not for growth in GDP. Further, future stock return for the first decile can be estimated by using the time paths of growth in GDP and real interest rate. Future stock return for the fifth decile can only be estimated by using the time paths of real interest rate. Finally, future stock returns for the tenth decile cannot be estimated by using the time paths of any macroeconomic variable questioned in this study. In conclusion, VAR results are sensitive to changing the sizes of stock return.

References

Bali, T. G., O. Demirtas, and H. Tehranian, 2008, Aggregate earnings, firm-level earnings, and expected stock returns. *Journal of Financial and Quantitative Analysis* 43, 3, 657-684.

Barro, R. J., 1990, The stock market and investment. *Review of Financial Studies* 3, 115-31.

Bulmash, S. B., and G. W. Trivoli, 1991, Time-lagged interactions between stock prices and selected economic variables. *Journal of Portfolio Management*, 61-7.

Chen, N. F, R. Roll, and S. A. Ross, 1986, Economic forces and the stock market. *Journal of Business* 59, 383-403.

Darrat, A. F., 1990, Stock returns, money and fiscal policy. *Journal of Financial and Quantitative Analysis* 25, 387-98.

Darrat, A. F., and T. K. Mukherjee, 1987, The behavior of the stock market in a developing economy. *Economics Letters* 22, 273-78.

Dickey, D. A., and W. A. Fuller, 1981, Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica* 49, 1057-72.

Enders, W., 1995. *Applied Econometric Time-Series*, John Wiley & Sons.

Engle, R. F., and C. W. J. Granger, 1987, Cointegration and error correction: Representation, estimation and testing. *Econometrica* 55, 251-76.

Fama, E. F., 1981, Stock returns, real activity, inflation, and money. *The American Economic Review* 71, 545-65.

Fama, E. F., 1990, Stock returns, expected returns, and real activity. *Journal of Finance* 45, 1089-1108.

Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Fama, E. F., and K. R. French, 1995, Size and book-to-market factors in earnings and returns. *Journal of Finance* 50, 131-156.

Fama, E. F., and K. R. French, 1996, Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51, 55-84.

Geske, R., and R. Roll, 1983, The monetary and fiscal linkage between stock returns and inflation. *Journal of Finance* 38, 1-33.

Granger, C. W. J., 1986, Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and Statistics* 48, 213-27.

Hafer, R. W., and D. W. Jansen, 1991, The demand for money in the United States: Evidence from cointegration tests. *Journal of Money, Credit and Banking* 23, 155-68.

Hamao, Y, 1988, An empirical investigation of the arbitrage pricing theory. *Japan And the World Economy* 1, 45-61.

Hamburger, M. J., and L. A. Koshin, 1972, Money and stock prices: The channels of influences. *Journal of Finance* 27, 231-49.

Homa, K. E., and D. W. Jaffee, 1971, The supply of money and common stock prices. *Journal of Finance* 26, 1045-66.

James, C., S. Koreisha, and M. Partch, 1985, A VARMA analysis of the causal relations among stock returns, real output and nominal interest rates. *Journal of Finance* 40, 1375-84.

Johansen, S., 1991, Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models. *Econometrica* 59, 1551-80.

Kaul, G., 1987, Stock returns and inflation: The role of the monetary sector. *Journal of Financial Economics* 18, 253-76.

Keran, M. W., 1971, Expectations, money and the stock market review. *Federal Reserve Bank of St. Louis* 16-31.

Lamont, O., 1998, Earnings and expected returns. *Journal of Finance* 53, 1563-1587.

Lee, Bong-soo, 1992, Causal relations among stock returns, interest rates, real activity and inflation. *Journal of Finance* 47, 1591-1603.

Merton, R. C., 1973, An intertemporal capital asset pricing model. *Econometrica* 41, 867-87.

Michailidis, G., S. Tsopoglou, and D. Papanastasiou, 2007, The cross-section of expected stock returns for the Athens Stock Exchange. *International Research Journal of Finance and Economics* 8, 63-69.

Morelli, D., 2007, Beta, size, book-to-market equity and returns: A case study based on UK Data. *Journal of Multinational Financial Management* 17, 3, 257-272.

Modigliani, F., 1972, Monetary policy and consumption : The linkages via interest rate and wealth effects in the FMP model, consumer spending and monetary policy : The linkages, Federal Reserve Bank of Boston.

Mukherjee, T., and A. Naka, 1995, Dynamic linkage between macroeconomic variables and the Japanese Stock Market : An application of a vector error correction model. *Journal of Financial Research* 18, 223-37.

Naka, A., T. K. Mukherjee, and D. Tufte, 1998, Macroeconomic variables and the performance of the Indian Stock Market. *University of New Orleans Working Paper*.

Osterwald-Lenum, M., 1992, A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Statistics and Economics* 54, 461-71.

Palmer, M. 1970, Money supply, portfolio adjustments and stock prices. *Financial Analysts Journal* 19-22.

Pepper, N., and B. Zwick, 1971, Liquidity and income effects of monetary changes in stock rices, mimeo. *U.C.L.A.*

Perron, P., 1989, The great crash, the oil price shock and the unit root hypothesis. *Econometrica* 57, 1361-1401.

Pesaran, M., and Y. Shin., 1998, Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58, 17 – 29.

Phillips, P. C. B., 1991, Optimal inference in cointegrated systems. *Econometrica* 59, 283-306.

Phillips, P. C. B., and P. Perron, 1988, Testing for a unit root in time series regression. *Biometrika* 75, 335-46.

Ram, R., and D. E. Spencer, 1983, Stock returns, real activities, inflation and money; Comment. *American Economic Review* 73, 463-70.

Ross, S. A., 1976, The arbitrage theory of capital assent pricing. *Journal of Economic Theory* 13, 341-60

Schwert, W. G., 1987, Effects of model specification on tests for unit roots in macroeconometric data. *Journal of Monetary Economics* 20,73-103.

Shah, H., 1989, Stock returns and anticipated aggregate real activity. University of Chicago Unpublished Ph.D. thesis.

Shaharudin, R. S., and H. S. Fung, 2009, Does size really matter? A study of size effect and macroeconomics factors in Malaysian stock returns. *International Research Journal of Finance and Economics* 24, 101-116.

Sims, C., 1980, Macroeconomics and reality. *Econometrica* 48: 1 – 48.

Sprinkel, B. W., 1964, Money and stock prices. (Homewood III : Richard D Irwin, Inc.).

Sprinkel, B. W., 1971, Money and markets; A monetarist view. (Homewood III : Richard D Irwin, Inc.).

Willem Thorbecke, 1997, On stock market returns and monetary policy. *Journal of Finance* 52,635-654.