A STUDY OF SIZE EFFECT AND MACROECONOMICS FACTORS IN NEW YORK STOCK EXCHANGE STOCK RETURNS

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Abstract
The purpose of this paper is to look at the ‘size-effect’ question using a large sample drawn from New York Stock Exchange prices. The impact of the stock returns' size is also examined and the validity of models explaining the observed negative relations between asset returns and inflation are addressed. The generalized impulse response functions are adopted. Further, The vector error correction model (VECM) (Johansen (1991)) is utilized to determine the impact of selected macroeconomic variables on NYSE. Results reveal that size had an impact on stock returns. Further, it appears that there is reliable negative relationship between stock prices and inflation. The level of real economic activity affects stock prices positively. Finally, interest rates have a negative relationship with stock prices

Keywords: Inflation, Growth Rate, Stock Returns, Positive Accounting, Market Capitalization and Portfolio Size.

JEL Classification codes: C32, E31, F32 and G14.

1. Introduction

Efficient Market Hypothesis (EMH) states security prices adjust rapidly to the arrival of new information and, therefore, the current prices of securities reflect all information about the security. What this means, in simple terms, is that no investor should be able to employ readily available information in order to predict stock price movements quickly enough so as to make abnormal returns through trading shares. Championed by Fama (1970), the efficient market hypothesis (EMH), in particular semi-strong form efficiency, which states that stock prices must contain all relevant information including publicly available information, has important implications for policy-makers and the stock-brokering industry alike; semi-strong form of market efficiency regard stock returns as the benchmark measure of value relevance for study variables since prices encompass the historical and public information about any company in the efficient market.

Policy makers, for example, should feel free to conduct national macroeconomic policies without the fear of influencing capital formation and the stock trade process. Moreover, economic theory suggests that stock prices should reflect expectations about future corporate performance, and corporate profits generally reflect the level of economic activities. If stock prices accurately reflect the underlying fundamentals, then the stock prices should be employed as leading indicators of future economic activities, and not the other way around. Therefore, the causal relations and dynamic interactions among

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macroeconomic variables and stock prices are important in the formulation of the nation’s macroeconomic policy. Granger (1986) and Johansen and Juselius (1990) proposed to determine the existence of long-term equilibrium among selected variables through cointegration analysis, paving the way for a (by now) preferred approach to examining the economic variables-stock markets relationship. A set of time-series variables are cointegrated if they are integrated of the same order and a linear combination of them is stationary. Such linear combinations would then point to the existence of a long-term relationship between the variables. An advantage of cointegration analysis is that through building an error-correction model (ECM), the dynamic co-movement among variables and the adjustment process toward long-term equilibrium can be examined.

Size effect first reported by Banz (1981) seminal paper; main findings indicate 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. The question need to be addressed based on such results is: given the fact that the company size had an impact on stock returns then there is a need to investigate and explore the relationship between size of stock returns and the macroeconomic variables. Therefore, the purpose of this paper is use the cointegration method of Johansen (1991) to analyze the long-term equilibrium relationship among different sizes of stock returns and relevant macroeconomic variables for the New York Stock Exchange (NYSE), this study extend Shubita and Sharkas (2010) study by analyzing different variables based on different tools. Series of studies have been done to find the long-term equilibrium relationship between stock returns and macroeconomic variables for the USA, Japan, and other industrially developed countries. However, this is the first attempt to address the size effect question. Moreover, this paper is different from Lee’s (1992) paper in several points. First, the sample period window extended till June 2010. This window of the study sample covers data for many major economic events including the world financial crisis. Second, the (nominal) common stock returns (SR) are the returns on the New York Stock Exchange (NYSE) value weighted stock index obtained from the Center for Research in Security Prices (CRSP). However, unlike Lee’s paper, data on SR 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. Third, applying a relatively new and powerful methodology. The generalized impulse response functions (GIRF) are computed from estimated unrestricted vector autoregressive (UVAR) models. Unlike the traditional 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 is employed to avoid using arbitrary choice of the restrictions needed to settle the identification. Further, cointegration method of Johansen (1991) is utilized to analyze the long-term equilibrium relationship among different sizes of stock returns and relevant macroeconomic variables for the NYSE.

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 and cointegration test. Section 5 reports the results. Section 6 concludes.
2. Literature Review

Chen, Roll and Ross (1986) contribute to the fact that a long-term equilibrium relationship exists between stock prices and relevant macroeconomic variables. They find that asset prices react sensitively to economic news, especially to unanticipated news. Hamao (1988) replicated the Chen, Roll and Ross (1986) study in the multi-factor APT framework. He shows that the Japanese stock returns are significantly influenced by the changes in expected inflation, and the unexpected changes in both the risk premium and the slope of the term structure of interest rates. The volatilities in real economic activity in Japan are weakly priced compared to the U.S.A. Lee (1992) investigates the causal relationship and dynamic interaction among asset return, interest rates, real activity and inflation, using a multivariate VAR model with postwar U.S. data. He shows that prior stock returns Granger-causes real stock returns. Darrat (1990) tests the joint hypothesis that the stock market of Canada is efficient and the expected returns are constant over time using the multivariate Granger-causality technique. He finds that the Canadian stock prices fully reflect all available information on monetary policy moves. Darrat and Mukherjee (1987) use a Vector Autoregression (VAR) model along with Akaike’s final prediction-error on the Indian data over 1948-84, and show that a significant causal relationship exists between stock returns and certain macroeconomic variables. Brown and Otsuki (1990) find that money supply, production index, crude oil price, exchange rate, call money rate and a residual market error are associated with risk premia and affect the Japanese stock market. Mukherjee and Naka (1995) test the dynamic relationship between six macroeconomic variables and the Japanese stock market, by employing a vector error correction to a model of seven equations. They find that a long-term equilibrium relationship exists between the Japanese stock market and the six macroeconomic variables such as exchange rate, money supply, inflation, industrial production, long-term government bond rate and call money rate. More recently, Sadorsky (1999) finds that industrial production responds positively to the shocks in stock return and that oil prices play in affecting real stock return. On the other hand, other studies left this matter as an open question as to whether there exists a significant reliable statistical relationship (Homa and Jaffee, 1971; Fama, 1981; and Gultekin, 1983).

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, Shubita and Al-Sharkas (2010) find that the stock returns for the fifth and tenth deciles are leading indicators for future macroeconomic performance. Moreover, stock return for the first deciles leads the inflation rate and real interest rate but does not lead the real economic activity as represented by industrial production. However, in this paper, we extend the work of our previous paper by adopting correlation analysis and the generalized impulse response function. Further, we use the cointegration method of Johansen (1991) to analyze the
long-term equilibrium relationship among different sizes of stock returns and relevant macroeconomic variables for the NYSE.

3. An Overview of the Data
Quarterly data on the U.S economy are used for the sample period 1964.1-2010.2. 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.

Our sample period is from March 1964 to June 2010. The (nominal) common stock returns (SR) 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 SR 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. 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. The industrial production series (IP) is taken from the same Web site.

4. The VAR Model
4.1. The UVAR Model
The VAR method is used here as the main method to examine relationships between the variables. Employing this method is of special importance for the approach used in this paper. The VAR method allows all variables to be endogenous. This is valuable because allowing all variables to affect, and to be affected, by other variables helps to examine all types of shocks in the economy. The mathematical form of a VAR is

\[ y_t = A_1 y_{t-1} + \ldots + A_N y_{t-N} + B x_t + \varepsilon_t \]  

(1)

Here \( y_t \) is a vector of endogenous variables, \( x_t \) is a vector of exogenous variables, \( B \) is a matrix of coefficients to be estimated, and \( \varepsilon_t \) is a vector of innovations that are correlated with each other, but uncorrelated with their own lagged values and uncorrelated with \( y_{t-1} \) and \( x_t \). The best estimator of each equation in a VAR is Ordinary Least Squares (OLS). The assumption here is that the disturbances are not serially correlated and is unrestrictive because any serial correlation could be absorbed by adding more lagged y's. Generalize impulse response functions (GIRF) from the VAR model are utilized to test the directions and the channels of influence between the variables.

4.1 Generalized Impulse Response Function (GIRF)
The generalized impulse response function (GIRF), 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.
4.2 Granger Causality Tests

Granger (1969) proposed a time-series data based approach in order to determine causality. In the Granger-sense x is a cause of y if it is useful in forecasting y1. In this framework “useful” means that x is able to increase the accuracy of the prediction of y with respect to a forecast, considering only past values of y.

Granger causality requires that the series have to be covariance stationary, so an Augmented Dickey-Fuller test has been calculated. For all of the series the null hypothesis H0 of non stationary can be rejected at a 5% confidence level. Then, since the Granger-causality test is very sensitive to the number of lags included in the regression, both the Akaike (AIC) and Schwarz Information Criteria have been used in order to find an appropriate number of lags.

After that these requirements have been satisfied, Granger-causality tests are computed. 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 can not 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)]. Guisan (2001) concludes that the test, although interesting, has some limitations because it does not have into account the effect of current values of the explanatory variable, which very often is highly relevant, besides the method usually implies a high degree of multicollinearity and the test may lead to undue acceptances of non causal relationships or to undue rejections of true and important causal relationships.

4.3 VAR Specification Issues

The following issues are related to specifying VAR models. Alternative specifications differ with respect to ordering of variables, method of "trend" removal, lag length on the VAR equations, and level of temporal aggregation. These issues must necessarily be addressed beyond the choice of variables to be included.

4.3.1 Lag Length. 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.

4.4 Test of Cointegration

Cointegration is a method of defining the long-term relationship amongst a group of time series variables. It uses the idea of an integrated time series in describing the long run interaction and arose in the context of the spurious regression problem. To be related to one another statistically in the long run, variables must be of the same order of integration. The presence of cointegration among relevant variables implies that a linear combination of nonstationary time series variables is stationary. For example, if a two variable regression model is specified as $yt = Bxt + ut$, then ut will only be I(0),
integrated of order zero, and therefore having the property of stationary, if \( y_t \) and \( x_t \) are both of same order of integration \( I(d) \). The simplest and most common case is where \( x_t \) and \( y_t \) are both \( I(1) \). Then if \( u_t \) is \( I(0) \), the series \( x_t \) and \( y_t \) are said to be cointegrated. But for non-stationary time series data the traditional econometric analysis does not work. The most important approach to analyze the non-stationary time series data is Vector Autoregression (VAR). However, cointegration analysis is more appropriate than the VAR technique to explain the long-term equilibrium relationship between stock returns and relevant macroeconomic variables. The existence of cointegration among time series variables indicates that there exists a long-term equilibrium relation between those variables. Cointegration is closely linked to error correction models.

Testing for cointegration using the method of Engle and Granger (1987) is concerned with a single-equation while the Johansen (1991) method uses a system of equations and provides more efficient estimators of cointegrating vectors, as it does not require a specific variable to be normalized (Phillips, 1991). The cointegration testing procedure of Engle and Granger (1987) has some undesirable features as described by Enders (1995).

5. Empirical Results for the Full Sample Period

This section investigates the dynamic relationship between the variables using correlation analysis and VAR models for the full sample period 1964.1-2010.2. 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 Log Likelihood Ratio (LR) is given by the following equation:

\[
LR = (T-K) \left( \log \left| \Sigma (p_j) \right| - \log \left| \Sigma (p_i) \right| \right) \sim \chi^2 (n^2 (p_j - p_i)),
\]

where \( \Sigma \) is the covariance matrix, \( T \) is the number of observations, \( K \) is the number of parameters in each equation, \( n \) is the number of equations, and \( p \) is the number of lags, given that \( p_j > p_i \). 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. In other words, we have that Akaike (\( p \)) = \( T \log ( \left| \Sigma (p) \right| + 2pn) \), where \( \Sigma \) is the covariance matrix, \( p \) is the number of lags, \( n \) is the number of equations and \( T \) is the number of observations. Similarly, Schwarz (\( p \)) = \( T \log ( \left| \Sigma (p) \right| + (pn^2) \log T) \). The best model is the one that minimizes these two functions.

The lags are examined up to 16 quarters. There is no significant increase in the explanatory power by adding more lags than six quarters. 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 Correlations

Contrary to Lee’s (1992) findings, the stock return for the first decile (the smallest (SRE1) ) and inflation are weakly positively correlated. This positive relation with inflation holds also with the stock for the fifth decile (SRE5). However, consistent with Lee (1992), this is not the case for the tenth decile (largest (SRE10)). The stock return of the tenth decile that represents the largest size portfolios and inflation are weakly negatively correlated. Further, nominal interest rates and inflation are positively correlated. This agrees with the findings of Lee (1992). Finally, contrary to Lee (1992), stock returns are negatively correlated with growth in industrial production.

5.2 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. We have the following results from this test (see Table 1 and 2):

5.2.1 In Presence of Stock Returns for the first deciles. Table 1 indicates that IPG Granger-causes INF and INF Granger-causes IPG. Also, it indicates that means that IRE Granger-causes INF. However, INF does not Granger-cause IRE. IRE Granger-causes IPG, and IPG does not Granger-cause IRE. As for the SRE1 results, the results show that SRE 1 does not Granger-cause INF and IPG, but, INF and IPG do not Granger-cause SRE1. Finally, we reject the null hypothesis for null hypothesis that SRE1 does not Granger-cause IRE and IRE does not Granger-cause SRE1. This means that SRE1 Granger-causes IRE and IRE Granger-causes SRE1.

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>F-Statistic</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPG does not Granger Cause INF</td>
<td>7.08640</td>
<td>0.00116</td>
</tr>
<tr>
<td>INF does not Granger Cause IPG</td>
<td>10.9741</td>
<td>3.6E-05</td>
</tr>
<tr>
<td>IRE does not Granger Cause INF</td>
<td>5.34132</td>
<td>0.00578</td>
</tr>
<tr>
<td>INF does not Granger Cause IRE</td>
<td>4.41122</td>
<td>0.01381</td>
</tr>
<tr>
<td>SRE1 does not Granger Cause INF</td>
<td>4.97539</td>
<td>0.00813</td>
</tr>
<tr>
<td>INF does not Granger Cause SRE1</td>
<td>0.48292</td>
<td>0.61797</td>
</tr>
<tr>
<td>IRE does not Granger Cause IPG</td>
<td>7.40925</td>
<td>0.00086</td>
</tr>
<tr>
<td>IPG does not Granger Cause SRE1</td>
<td>1.61985</td>
<td>0.20149</td>
</tr>
<tr>
<td>SRE1 does not Granger Cause IPG</td>
<td>2.33162</td>
<td>0.10077</td>
</tr>
<tr>
<td>IPG does not Granger Cause SRE1</td>
<td>4.82283</td>
<td>0.00938</td>
</tr>
<tr>
<td>SRE1 does not Granger Cause IRE</td>
<td>3.47636</td>
<td>0.03350</td>
</tr>
<tr>
<td>IRE does not Granger Cause SRE1</td>
<td>5.91728</td>
<td>0.00338</td>
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</tbody>
</table>
5.2.2 In Presence of Stock Returns for the fifth deciles. Table 2 indicates that IPG Granger-causes INF and INF Granger-causes IPG. Also, IRE Granger-causes IPG, and IPG does not Granger-cause IRE. In addition, SRE 5 Granger-causes INF, IPG, and IRE. However, INF, IPG, and IRE do not Granger-cause SRE 5.

<table>
<thead>
<tr>
<th>Null Hypothesis:</th>
<th>F-Statistic</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPG does not Granger Cause INF</td>
<td>4.40555</td>
<td>0.00043</td>
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<tr>
<td>INF does not Granger Cause IPG</td>
<td>3.84254</td>
<td>0.00145</td>
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<tr>
<td>IRE does not Granger Cause INF</td>
<td>6.01959</td>
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<tr>
<td>INF does not Granger Cause IRE</td>
<td>0.72653</td>
<td>0.62899</td>
</tr>
<tr>
<td>SRE5 does not Granger Cause INF</td>
<td>3.21261</td>
<td>0.00560</td>
</tr>
<tr>
<td>INF does not Granger Cause SRE5</td>
<td>1.15429</td>
<td>0.33475</td>
</tr>
<tr>
<td>IRE does not Granger Cause IPG</td>
<td>10.5505</td>
<td>1.5E-09</td>
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<tr>
<td>IPG does not Granger Cause IRE</td>
<td>0.70329</td>
<td>0.64745</td>
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<tr>
<td>SRE5 does not Granger Cause IPG</td>
<td>6.52245</td>
<td>4.7E-06</td>
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<tr>
<td>IPG does not Granger Cause SRE5</td>
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<td>0.31724</td>
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<tr>
<td>SRE5 does not Granger Cause IRE</td>
<td>2.46915</td>
<td>0.02688</td>
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<tr>
<td>IRE does not Granger Cause SRE5</td>
<td>2.14474</td>
<td>0.05230</td>
</tr>
</tbody>
</table>

5.2.3 In Presence of Stock Returns for the tenth deciles. The results in this case are similar to the presence of SRE5, except that we accept that IRE does not Granger-cause SRE10.

5.3 Evidence from the VAR Model

5.3.1 Stock Returns and Industrial Real Activity. Figure 1, in the Annex, depicts the GIRF for INF, IGP, IRE, and SRE1. This figure shows how one variable responds over time to a single innovation in itself or in other variables.

c) Figures 1 and 2, in the Annex, show that a positive shock to SRE1 or SRE5 has no impact on IGP for the first 3 quarters, after that the impact becomes positive up to the sixth quarter. This impact starts to die out after 7 quarters. This is not the case for SRE10. A positive shock to SRE10 has immediate negative impact on IGP for the first three quarters. After that the impact becomes positive up to the first seven quarters ahead. After quarter nine the effect becomes negative (see Figure 3 in the Annex).

5.3.2 Stock Returns and Inflation. Figure 1 shows that a positive shock to SER1 or SRE10 has a negative impact on INF for the first three quarters and after that the impact becomes positive. A positive shock to SER5 has a higher negative impact for the first quarters while after that the impact starts to die out. SRE 1 and SRE 5 respond positively to a shock in INF. In contrast, SR10 responds negatively to a shock in INF.

5.3.3 Interest Rate and Inflation. Figure 1 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.
5.3.4 Inflation and Industrial Real Activity. Figure 1 shows that IPG responds negatively to shocks in INF. This finding is broadly inconsistent with Lee's (1992) findings.

5.4 Results from the Test for Long-run Equilibrium Relationship

Table 3 represents the $\lambda_{\text{Trace}}$ and $\lambda_{\text{Max}}$ tests. Both the tests show that there exists only one cointegrating relation. The $\lambda_{\text{Trace}}$ test rejects the null hypothesis of $r=0$ in favor of $r>0$ and the $\lambda_{\text{Max}}$ test rejects the null hypothesis of $r=0$ in favor of $r=1$ at a 1% level of significance.

Following Johansen and Juselius (1990), we base my analysis on the cointegrating vector represented by the largest eigenvalue. The long-run equilibrium relationship among the tested variables is based on the following cointegrating vector:

$$\beta_1' = [1.00, -0.569, 0.425, -0.826, 9.07].$$

These values represent the coefficient for SRE1 (normalized to one), SRE1, IRE, INF and GIP. So the long-run equilibrium relationship can be expressed as:

$$\text{SRE1} = 0.569\text{IR} - 0.425\text{CPI} + 0.826\text{IP} - 9.07$$

<table>
<thead>
<tr>
<th>Null Hypothesis ($H_0$)</th>
<th>Alternative Hypothesis ($H_A$)</th>
<th>$\lambda_{\text{Trace}}$ Value</th>
<th>99% Critical Value</th>
<th>Null Hypothesis ($H_0$)</th>
<th>Alternative Hypothesis ($H_A$)</th>
<th>$\lambda_{\text{Max}}$ Value</th>
<th>99% Critical Value</th>
</tr>
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<tbody>
<tr>
<td>$r = 0$</td>
<td>$r &gt; 0$</td>
<td>146.82*</td>
<td>173.09</td>
<td>$r = 0$</td>
<td>$r = 1$</td>
<td>83.56*</td>
<td>51.91</td>
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<td>$r \leq 1$</td>
<td>$r &gt; 1$</td>
<td>111.47*</td>
<td>141.01</td>
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<td>$r = 2$</td>
<td>72.42*</td>
<td>46.82</td>
</tr>
<tr>
<td>$r \leq 2$</td>
<td>$r &gt; 2$</td>
<td>65.05*</td>
<td>94.45</td>
<td>$r = 2$</td>
<td>$r = 3$</td>
<td>43.99</td>
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<td>$r \leq 3$</td>
<td>$r &gt; 3$</td>
<td>36.06</td>
<td>54.16</td>
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<td>$r = 4$</td>
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<td>$r = 5$</td>
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<tr>
<td>$r \leq 5$</td>
<td>$r &gt; 5$</td>
<td>1.02</td>
<td>22.60</td>
<td>$r = 5$</td>
<td>$r = 6$</td>
<td>1.92</td>
<td>20.20</td>
</tr>
</tbody>
</table>

Notes: The $\lambda_{\text{Trace}}$ and $\lambda_{\text{Max}}$ test statistics are based without a linear trend. The critical values at 1% level are taken from Osterwald-Lenum. The null hypothesis, $H_0$, refers at most $r$ cointegrating vectors when $r$ is the order of cointegration.

The likelihood ratio test shows that SRE1 contributes to the above cointegrating relation. The test statistic is 19.11 and is significant at the 1 percent level, with 2 degrees of freedom. It appears that there is reliable negative relationship between stock prices and inflation. This is consistent with Chen, Roll and Ross (1986) for US data, and Mukherjee and Naka (1995) for Japanese data. The level of real economic activity (output), represented by IP, affects stock prices positively. A similar relation is found in the United States (Fama (1990), Cheske and Roll (1983)). Interest rates (IRE) have a negative relationship with stock prices. Mukherjee and Naka (1995) also find a positive
relationship between share prices and short-term interest rates. Industrial production is one of the positive determinant factors of NYSE stock prices and this is consistent with the findings of Chen, Roll and Ross (1986), Mukherjee and Naka (1995) and Naka, Mukherjee and Tufte (1998). The results are similar for SRE 5 and SRE 10.

6. Conclusion

This paper attempts to investigate how the relations among macro variables are affected by the size of stock returns. The generalized impulse response functions computed in order to investigate interrelationships within the system. In addition, the cointegration method of Johansen (1991) adopted to analyze the long-term equilibrium relationship among different sizes of stock returns and relevant macroeconomic variables for the NYSE. The evidence presented in the paper underscores the importance of the changing sizes of the stock returns in examining the impact of stock returns on economic activity. Further, it appears that there is reliable negative relationship between stock prices and inflation. The level of real economic activity affects stock prices positively. Finally, interest rates have a negative relationship with stock prices.

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Annex

Figure 1. Generalized Impulse Response Function (INF, IPG, IRE, SRE1)
Figure 2. Generalized Impulse Response Function (INF, IPG, IRE, SRE5)

Response to One S.D. Innovations

- Response of INF to INF
- Response of INF to IPG
- Response of INF to IRE
- Response of INF to SRE5
- Response of IPG to INF
- Response of IPG to IPG
- Response of IPG to IRE
- Response of IPG to SRE5
- Response of IRE to INF
- Response of IRE to IPG
- Response of IRE to IRE
- Response of IRE to SRE5
- Response of SRE5 to INF
- Response of SRE5 to IPG
- Response of SRE5 to IRE
- Response of SRE5 to SRE5
Figure 3. Generalized Impulse Response Function (INF, IPG, IRE, SRE10)