Macroeconomic variables and stock returns: evidence from Singapore

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Abstract

This paper investigates the Granger-causality relationship between macroeconomic variables and stock market returns. Singapore is used as a case study. The standard time series techniques are applied. The findings tend to indicate that the stock market returns in Singapore are endogenous (follower) to macroeconomic variables such as, the interest rates, exchange rates and GDP. The money supply and inflation do not seem to have any impact. Of the three, GDP is identified to be the most exogenous (leading) variable. However, GDP least explains shocks in the Stock index at a twelve period horizon, while Interest rates and exchange rates account for more explanation. Overall, investors in Singapore stock market closely follow macroeconomic conditions and hence macroeconomic variables lead (rather than lag) the stock index returns in Singapore. The paper has strong policy implications in that the paper attracts the attention of the policy makers regarding what macroeconomic variables they may manipulate to boost confidence in the local financial markets. In general, it informs the assets and fund managers on how changes in macroeconomic variables affect stock market returns.

Keywords: Macroeconomic Variables, Stock Returns, Granger-causality, VECM, VDC, Singapore

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1. Introduction

Since the advent of the global financial crisis in September 2008, the international financial markets continue to remain volatile and there is great uncertainty amongst investors as they carefully study the world economic events. The western financial markets are feared to move towards a double dip recession as the effects of the stimulus packages wear out and the authorities have limited instruments at their disposal to revive the economies. On the other hand, there is a pessimistic environment in the Asian financial markets as well as the investors watch how the US and European countries deal with their fiscal cliff and sovereign debt issues.

In the light of such global uncertainties, what measures could various Asian governments undertake to revive performance and boost confidence in the local financial markets? In other words, can the Asian governments initiate a domestic macroeconomic policy push in order to revive their financial markets? What is the relationship between domestic macroeconomic variables and stock market returns and which variable leads or lags the other?

This paper aims to address such questions by taking Singapore as the case study of an Asian financial market. Following this introduction, Section 2 reviews the various academic studies that study the relationship between macroeconomic variables and stock returns. Section 3 lists the research objectives of this paper. Section 4 discusses the theoretical underpinnings being assumed in this paper as supported by existing studies while Section 5 details out the methodology to be adopted to achieve the research objectives. Section 6 contains the comprehensive data analysis along with empirical results. Section 7 discusses the results from the previous section. Finally Section 8 provides the conclusions and policy implications as derived from the results in this paper. References make up the end of this paper.

2. Literature Review

Emerging stock markets have been identified as being at least partially segmented from global capital markets. As a consequence, it has been argued that local risk factors rather than world risk factors are the primary source of equity return variation in these markets (Maysami et al, 2004). Accordingly, Bilson et al (1999) aimed to address the question of whether macroeconomic variables may proxy for local risk sources. They found moderate evidence to support this hypothesis.

Over the past few decades, the interaction of share returns and the macroeconomic variables has been a subject of interest among academics and practitioners (Kwon and Shin, 1999). An increasing amount of empirical evidence noticed by several researchers leads to the conclusion that a range of financial and macroeconomic variables can predict stock market returns (for e.g. see Fama and French, 1989, Cochrane, 1991, Campbell and Hamao, 1992, Ferson and Harvey, 1993, Pesaran and Timmerman, 1995, 2000).

However, most of the earlier studies adopted classical linear regression techniques that focus upon the short-run relationship between stock market and financial and macro-economic variables, which may remove important information contained in the permanent component of economic activity concerning the evolution of short-run movements. It wasn't until Nobel Prize winners Engle and Granger (1987) introduced the concept of co-integration in 1987 following which we can investigate the empirical long run relationships between stock market indices and both measures of economic activity and financial variables.

Using the new co-integration techniques, Maysami and Sims (2002) examined the relationship between macroeconomic variables and stock returns in Hong Kong and Singapore and found the relationship to be significant. Islam (2003) replicated the above study to examine the short-run dynamic adjustment and the long-run equilibrium relationships between four macroeconomic variables (interest rate, inflation rate, exchange rate, and the industrial productivity) and the Kuala Lumpur Stock Exchange (KLSE) Composite Index. His conclusions were similar: there existed statistically significant short-run (dynamic) and long-run (equilibrium) relationships among the macroeconomic variables and the KLSE stock returns.

Vuyyuri (2005) investigated the co-integrating relationship and the causality between the financial and the real sectors of the Indian economy using monthly observations from 1992 through December 2002. The financial variables used were interest rates, inflation rate, exchange rate, stock return, and real sector was proxied by industrial productivity. The results supported the long-run equilibrium relationship between the financial sector and the real sector, and the Granger test showed unidirectional Granger causality between the financial sector and real sector of the economy.

Maysami et al. (2005) assessed the existence of long-run co-integrating relationship among stocks listed dually in the US and Singapore stock markets. In addition, they used Johansen's (1988) VECM, to examine the co-movement between sectoral stock indices of the U.S. and Singapore, through examining whether the S&P 500 Electronics (Semiconductor) Price Index leads Stock Exchange of Singapore's Electronics Price Index. Their results indicated there is significant long run relationship between the stock indices of US and Singapore and that the S&P 500 Electronics (Semiconductor) Price index leads the Singapore Electronics Price Index.

However, in general, literature examining the relation of macroeconomic variables on individual stock market indices presents a mixed picture. There are no definite theories that explain this relationship while empirical results are often contradictory when applied in different markets in different settings. As a result, in this paper, we make a fresh attempt to examine the relationship between macroeconomic variables and Singapore Straits Times Index to illustrate which variables lead or lag the stock market index in Singapore.

3. Research Objectives

The objective of the current study is to unravel linkages between stock market movements and macroeconomic variables in the Asian financial markets context using modern time series techniques. Singapore is taken as a case study for this research. The period of the study has been chosen as September 1999 to September 2012. This has been the period where the effects of the Asian Financial Crisis had significantly worn off the Asian economies and most of them including Singapore had recovered to pre-crisis levels. We wish to isolate the Asian financial crisis effects on variables in our research. Our study is more focused on capturing the linkages during the era which includes the effects of the Global Financial Crisis (GFC).

The study uses monthly data for a larger number of macroeconomic variables which should have relationship with the capital market. Not only the domestic economic variables have been considered but the linkage with the external world through the exchange rate movement has also been included in the analysis. The study does not assume any a priori relationship between these variables and the stock market and is open to the possible two-way relationship between them. The study aims to reveal with more precision the major influencing variables on the Singapore stock market.

4. Theoretical Underpinnings

Our aim is to detect the relationship between macroeconomic variables and the Straits Times Index (STI), Singapore's composite index. The period we have chosen is September 1999 till September 2012 as the monthly data of all of the variables are available for this period. In this paper, we have selected five economic variables as systematically affecting stock returns as illustrated in **Table 1**. We have chosen the variables following Chen et al (1986) on what they have described as "simple and intuitive financial theory" as there does not appear to exist any particular theory that accounts for stock price movements as a function of micro- and macroeconomic variables. The following macroeconomic variables have also been used to predict stock returns in other papers such as Maysami et al (2004), Ray and Vani (2005) and most recently Hussin et al (2012).

Table 1: Selected Variables for Research

Symbol	Definition
STI	Singapore Straits Times Index
IR	3-month Singapore Interbank Offer Rate (SIBOR)
M3	Money Supply represented by M3
CPI	Consumer Price Index
ER	SGD/USD Exchange Rate
IPI	Industrial Production Index

We have taken the 3-month Singapore Interbank Offered Rate (SIBOR) as the proxy for the interest rates (IR) prevailing in the economy. To measure the money supply in the economy we have taken the most popularly used Broad Money Supply (M3). To account for inflation we have chosen Consumer Price Index (CPI). We have taken Industrial Production Index (IPI) that reflects the industrial growth in Singapore as the proxy for GDP as monthly GDP data is not available. To check the linkage with the external world, SGD/USD exchange rate (ER) has been taken as another variable. All the data is taken from Thomson-Reuters DataStream database available from the Knowledge Management Centre of INCEIF University, Malaysia. Since VAR framework does not require any specific model to begin with, we have not specified one.

5. Methodology

As mentioned earlier, most of the earlier studies studying stock market returns and macroeconomic variables relationship adopted classical linear regression techniques that focus upon the short-run relationships and which may remove important information contained in the permanent component of economic activity concerning the evolution of short-run movements. Furthermore, recent time series studies based on co-integration techniques while being an improvement on earlier studies testing Granger causality have a major limitation of basing estimates on the mechanical results of co-integrating vectors, which are atheoretical in nature. In order to overcome this limitation, the technique of Long Run Structural Modelling 'LRSM' was most recently developed that allows researchers to estimate theoretically meaningful long-run relations. A researcher may test for long-run relationship by imposing and testing for both exact identifying and over-identifying restrictions based on theories and a priori information of the economies.

In this paper, we shall be employing the most recently available co-integration techniques of time series analysis. We begin by testing the data observations of variables for presence of unit-root using Augmented Dickey-Fuller and Phillips-Perron tests followed by selecting an appropriate order of the VAR. Next, we need to identify co-integrating relationships amongst our variables in the long-run. This may be undertaken through either Engle-Granger (1987) or Johansen (1988) protocols. While Engle and Granger's (1987) two-step error correction model may be used in a multivariate context, the Johansen's (1990) VECM yields more efficient estimators of co-integrating vectors. This is because the Johansen's (1988, 1990) VECM is a full information maximum likelihood estimation model, which allows for testing co-integration in a whole system of equations in one step, without requiring a specific variable to be normalized. It also allows the avoidance of a priori of assumptions of endogenity or exogeniety of variables. Nonetheless, we shall be employing both the Engle-Granger and Johansen co-integration tests in this paper. Finally, we shall apply the LRSM technique to test for theory in our co-integrating vectors by subjecting our estimates to exact and over-identifying restrictions based on theoretical and a priori information of the economy.

The following steps highlighted above are designed to examine the long-run theoretical or equilibrium relationship amongst the variables. However, we still need to indentify the Granger causality amongst our variables, that is, which variables lead or lag the other. This is done through the vector error correction model (VECM) that indicates the direction of Granger causality amongst the variables both in the short and long run. To identify which variables are most exogenous/endogenous in our sample, we employ the variance decomposition (VDC) technique that enables us to rank our variables according to the proportion of the variance explained by its own past shocks. The variable that is explained mostly by its own shocks (and not by others) is deemed to be the most exogenous of all. The results of the VDC techniques are further confirmed through the use of the impulse response function (IRF) which is a graphical method designed to map out the dynamic response path of a variable due to a one period Standard Deviation shock to another variable. Finally, the persistence profiles technique is applied which illustrates the time period required for the variables get back to equilibrium when there is a system-wide shock (unlike the IRF which traces out the effects of a variable-specific shock on the long-run relationship).

6. Data and Empirical Results

As discussed earlier, we include a total of five macroeconomic variables and Singapore Straits Times Index in our analysis (See Table 1). All the data is taken from Thomson-Reuters DataStream database available from the Knowledge Management Centre of INCEIF University, Malaysia and the data consists of 156 observations, comprising of 13 years of monthly data from September 1999 till September 2012. The justifications for the data selection have already been presented in Section 3 and Section 4 of this paper.

6.1 Variable Transformations for Empirical Analysis

We transformed all the variables (with the exception of interest rate which is already in percentage form) into logarithms to achieve stationarity in their variance and also to make their scales comparable with each other. The definitions of each variable and time-series transformation are described in **Table 2** in the following page.

6.2 Unit Root Tests

We begin our empirical analysis by first testing for the presence of unit root in all of our variables. This is to ensure that the variables are stationary in the long run and that shocks are only temporary and will dissipate and revert to their long-run mean. The tests for stationarity or unit roots employ either the Augmented Dickey-Fuller (ADF) or the Phillips-Perron (PP) test performed on the variables in levels and first differences. Co-integration requires that all the variables be integrated of the same order.

Table 2: Variable Transformations for Empirical Analysis

Symbol	Levels Variables	Microfit Transformation
LSTI	Singapore Straits Times Index	LOG (STI)
IR	3-month Singapore Interbank Offer Rate (SIBOR)	IR
LM3	Money Supply represented by M3	LOG (M3)
LCPI	Consumer Price Index	LOG (CPI)
LIPI	Industrial Production Index	LOG (IPI)
LER	SGD/USD Exchange Rate	LOG (ER)
	First Differenced Variables	
DSTI	Singapore Straits Times Index	LSTI - LSTI(-1)
DIR	3-month Singapore Interbank Offer Rate (SIBOR)	IR - IR(-1)
DM3	Money Supply represented by M3	LM3 - LM3(-1)
DCPI	Consumer Price Index	LCPI - LCPI(-1)
DIPI	Industrial Production Index	LIPI - LIPI(-1)
DER	SGD/USD Exchange Rate	LER - LER(-1)
	Second Differenced Variables**	
D2STI	Singapore Straits Times Index	DSTI - DSTI(-1)
D2IR	3-month Singapore Interbank Offer Rate (SIBOR)	DIR - DIR(-1)
D2M3	Money Supply represented by M3	DM3 - DM3(-1)
D2CPI	Consumer Price Index	DCPI - DCPI(-1)
D2IPI	Industrial Production Index	DIPI - DIPI(-1)
D2ER	SGD/USD Exchange Rate	DER - DER(-1)

***: Required for Phillips-Perron Unit Root Tests*

6.2.1 Augmented Dickey-Fuller (ADF) Unit Root Test

When testing for unit root using the ADF test, at the levels form of the variables we looked at the regression results which included an intercept and linear trend while for the first difference form, we looked at the results that included an intercept but did not include linear trend. Furthermore, we included 5 lags for each regression and took the highest AIC and SBC number to determine which calculated statistic is to be compared with critical value. When there was a conflict between AIC and SBC, we stood with the AIC criterion given that we do have a large number of observations and hence over-parameterization is not a concern. As **Table 3** below summarizes, all our variables were founded to be I(1).

Table 3: ADF Unit Root Test Summary Statistics

Variables	Level	Variables	First Difference
	ADF		ADF
LSTI	-3.1648	DSTI	-7.5551**
IR	-1.4542	DIR	-9.0521**
LM3	-2.7835	DM3	-4.9418**
LCPI	-0.7539	DCPI	-4.9072**
LIPI	-3.2151	DIPI	-15.5543**
LER	-3.3382	DER	-6.2769**
95% CV for ADF Statistic	-3.4401	95% CV for ADF Statistic	-2.8807

**: Null hypothesis of non-stationarity rejected at 5% or lower Level of Significance

6.2.2 Phillips-Perron (ADF) Unit Root Test

When testing for unit root using the PP test, we ran 2 variable regressions where at the levels form, a first differenced variable was regressed on its own one-lag levels form variable. The t-ratio of the estimated levels form variable is then used to determine for the presence of unit root. At the first difference form, a second differenced variable was regressed on its own first differenced form variable. The t-ratio of the estimated first differenced form variable is then used to determine for the presence of unit root. To account for autocorrelation and heteroskedasticity, we corrected the standard errors of the equation using Newey-West error corrections adjusted with Bartlett weights. **Table 4** below summarizes the results. The PP test results contradict with our earlier results from the ADF tests. At least 2 variables are found to be stationary at the levels form using the 1% level of significance. The contradiction is not surprising given that PP test aims to achieve more robustness by correcting for both autocorrelation and heteroskedasticity in data points. However, given that our data is time-series and heteroskedasticity is mainly a property of cross-sectional data, we proceed with the results obtained from ADF tests that confirm all our variables are I(1) in the long run.

Table 4: PP Unit Root Test Summary Statistics

Variables	Level	Variables	First Difference
	PP		PP
LSTI	-1.2084	**DSTI**	-9.6447***
IR	-1.0975	**DIR**	-9.4491***
LM3	2.3102	**DM3**	-7.6475***
LCPI	3.6651***	**DCPI**	-20.7798***
LIPI	-3.4705***	**DIPI**	-28.4407***
LER	-0.1035	**DER**	-14.9051***
99% CV for t-test Statistic	-2.58	**99% CV for t-test Statistic**	-2.58

***: Null hypothesis of non-stationarity rejected at 1% Level of Significance

6.3 Lag Order of the VAR

Next we need to determine the optimal order of lags for our VAR model. The appropriate lag length is important as too many lags reduce the power of the test due to the estimation of additional parameters and a loss of degrees of freedom. In contrast, too few lags may not capture the dynamics of the actual error correction process, resulting in poor estimates. This paper employs the multivariate forms of the Akaike information criterion (AIC) and the Schwartz Bayesian criterion (SBC) to determine lag lengths.

We ran an unrestricted VAR including all our differenced variables and constant term to a VAR order of 6. **Table 5** below summarizes the results. We find that there is a conflict between the AIC and SBC criterion to determine the optimal number of lags. As per the AIC criteria, the optimum number of lags is 1 while the SBC criteria indicates 0. To solve for this, we test for serial correlation in our variables.

Table 5: Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Order	AIC	SBC	LR test	Adjusted LR test
6	1808	1473.8	------	------
5	1818.1	1538.1	CHSQ(36)= 51.8005[.043]	39.0231[.335]
4	1838.5	1612.7	CHSQ(72)= 82.8519[.179]	62.4151[.783]
3	1835.9	1664.3	CHSQ(108)= 160.0892[.001]	120.6005[.192]
2	1836.6	1719.2	CHSQ(144)= 230.6815[.000]	173.7801[.046]
1	**1839.8***	1776.6	CHSQ(180)= 296.2608[.000]	223.1832[.016]
0	1817.3	**1808.3***	CHSQ(216)= 413.3279[.000]	311.3737[.000]

*Highest Value

6.3.1 Autocorrelation Diagnostic Tests

We ran several regressions each time using one of the variables out of six as a dependent variable against the rest of them as explanatory variables. We changed the number of lags starting from 1 till 3 as we went along. We observed the following results as summarized in **Table 6** below.

Table 6: Tests for Serial Correlation in Single Equations

Lag Order	Dependent Variable(s) with Serial Correlation**
1	DIPI, DCPI, DM3 and DIR
2	DCPI and DIR
3	None of the variables

**: Null hypothesis of no autocorrelation rejected at 5% Level of Significance

As we can see, the choice of 1 lag has indicated serial correlation in 4 out of 6 variables. To reduce serial correlation effects, we choose VAR Order 2 for our co-integration tests. We do not choose VAR Order 3 in order to avoid losing too many degrees of freedom and reducing the power of the test due to the estimation of additional parameters.

6.4 Co-integration Tests

Having satisfied the conditions of I(1) variables and finding the optimum number of lags, we can now proceed to test for long term co-integration amongst our variables. As explained in Section 5, co-integration maybe tested either through the Engle-Granger or the Johansen test method. However, Johansen's Multivariate co-integration test yields more efficient estimators of co-integrating vectors. Therefore, while we shall be illustrating both the co-integration tests in this paper, we would be proceeding with the Johansen's estimates in the remainder of this paper.

6.4.1 Engle-Granger

According to the Engle-Granger (1987) two-step method, if two time series variables $x_t$and y_t are co-integrated, a linear combination of them must be stationary. In other words:

$y_t - \beta x_t = u_t$ Where u_t is stationary.

If we know u_t, we can test it for stationarity using unit root tests like DF or ADF. But because we don't know u_t, we must estimate this first, generally by using Ordinary Least Squares, and then run our stationarity test on the estimated $u_t$series, often denoted $\hat{u}_t$.

Therefore, in our case, we have a total of six time series variables. We ran an ordinary least squares regression with the LSTI variable as the dependent variable while others were the regressors including a constant and trend. First we ran the regression using variables in their levels form and 0 lags. However, the results achieved illustrated strong presence of autocorrelation and heteroscedasticity in the regression. Therefore, we ran a second regression using all variables in their levels form and with a lag order of 2. We had already determined lag order of 2 to be the optimal lag order in the previous sub-section. This time, the regression results and the equation were well specified as the null hypotheses of diagnostic tests were not rejected. **Table 7** below summarizes the diagnostic test results of the two regressions.

Next we ran an ADF test including 5 lags on the residuals obtained from the second equation with 2 lags and the results convincingly illustrated co-integration as the calculated test statistics for all the lags were higher than the 95% ADF critical value. Thus, we did not need to refer to the highest AIC and SBC number since at all lags, the null hypothesis of non-stationarity was convincingly rejected at the 5% significance level. **Table 7** below summarizes the unit root test results on the residuals of the second equation with 2 lags. Therefore, based on the Engle-Granger two-step method, our time series variables are co-integrated in the long run.

Table 7: Engle Granger Co-integration Test Results

Diagnostics	Dependent Variable				EG Residuals Unit Root Test	
	LSTI **(0 lags)**		LSTI **(2 lags)**		ADF (1)	-7.5248 **
Chi-Square SC (1)	98.8105	**[.000]**	11.9071	**[.453]**	ADF (2)	-6.8577 **
Chi-Square FF (1)	0.4291	[.512]	0.8714	[.351]	ADF (3)	-5.1801 **
Chi-Square N (2)	0.9812	[.612]	16.0163	[.000]	ADF (4)	-4.9253 **
Chi-Square Het (1)	3.8886	**[.049]**	0.3177	**[.573]**	ADF (5)	-5.1686 **

**: Null hypothesis of no co-integration rejected at 5% Level of Significance. P-values are in brackets [ ].
Note: The diagnostics are chi-squared statistics for: serial correlation (SC), functional form (FF), normality (N) and heteroskedasticity (Het).

6.4.2 Johansen

The Johansen test is a test for co-integration that allows for more than one co-integrating relationship, unlike the Engle-Granger method. This is because the Johansen's (1988, 1990) co-integration test is a full information maximum likelihood estimation model, which allows for testing co-integration in a whole system of equations in one step, without requiring a specific variable to be normalized. It also allows the avoidance of a priori of assumptions of endogeneity or exogeneity of variables. We have already discussed this in Section 5 (Methodology) in this paper. The results of the Johansen's Maximum Eigenvalue and Trace tests are summarized in **Table 8** below.

At the 5% significance level the Maximum Eigenvalue test statistics suggests that the variables are co-integrated with r = 2 while the Trace test suggested that the variables are co-integrated with r = 3. That is, there are 2 or 3 long-run relationships identified between the variables. It is common for the estimated test statistics to show different results (Harris, 1995). Moreover, the inclusion of more than two macroeconomic variables usually results in the co-integration tests identifying more than one long-run relationship (Abdullah and Hayworth, 1993). In such circumstances, the theoretical framework should dictate the appropriate choice of the number of co-integrating vectors.

Table 8: Johansen's Co-integration Test Results

Null	Alternate	Max Eigenvalue statistic	95% Critical Value	Trace Statistic	95% Critical Value
r ≤ 0	r ≥ 1	62.88**	43.61	177.07**	115.85
r ≤ 1	r ≥ 2	49.14**	37.86	114.19**	87.17
r ≤ 2	r ≥ 3	24.81	31.79	65.05**	63
r ≤ 3	r ≥ 4	19.30	25.42	40.24	42.34

**: Null hypothesis of r number of co-integration vectors rejected at 5% Level of Significance. The underlying VAR model is of order 2 and is computed using 155 monthly observations. *Note: The statistics are based on co-integration with unrestricted intercepts and restricted trends in the VAR.*

However, as we discussed in Section 4, there are no specific theories that account for stock price movements as a function of micro- and macroeconomic variables. Therefore, we arbitrarily select r = 2 as the number of co-integrating vectors and proceed to apply the LRSM technique to test for theory in our co-integrating vectors by subjecting our estimates to exact and over-identifying restrictions. The limitation at this point in our research is that due to lack of definite theory, these exact and over-identifying restrictions too are arbitrary. This limitation becomes more evident when results for the LRSM technique are collected.

6.5 Long Run Structural Modelling (LRSM)

6.5.1 Two Co-integrating Vectors – Exact and Over Identification

We experimented with a number of restrictions in our variables when applying the LRSM technique. Since we had proceed with two co-integrating relationships (r = 2), we had to specify four restrictions in the exact-identifying stage. Most of the results at the exact identification stage however were not that comforting. At times, many of the variables were found to be insignificant at the 5% level of significance while at other times, some significant variables were indicating the wrong sign compared to reality. When a combination of restrictions achieved meaningful results at the exact-identification stage, we faced another challenge at the over-identification stage as no convergence was found in the variables even after 1000 iterations and hence the analysis could not proceed. We experimented with a number of combinations of restrictions at the over-identification stage and almost all of them gave the same error that no convergence was found in the variables or very large values were encountered. An example of one such combination of restrictions that gave results in exact-identification but could not proceed in over-identification is presented in **Table 9** below. In table 9 below, when we normalized the relationship in Vector 1 on Stock index returns while restricting inflation effects to 0, and in Vector 2 on Stock index returns while restricting GDP effects to 0, we achieved the results as illustrated in Table 8 below. However, no combination of restrictions in the over-identification stage would yield results. The error generated was either no convergence found even after 1000 iterations or too large values encountered. Therefore, due to lack of theory to govern our restrictions, <u>we could not proceed with a choice of two co-integrating relationships</u> in our analysis.

Table 9: Exact and Over-indentifying restrictions with 2 co-integrating vectors

	Vector 1		Vector 2	
LSTI	1.0000	(*NONE*)	1.0000	(*NONE*)
IR	-0.0857**	(-0.0409)	-0.1237**	(-0.0434)
LM3	-1.8376**	(-0.7013)	-2.1745**	(-1.0007)
LCPI	0.0000	(*NONE*)	-2.1440	(3.1006)
LIPI	-0.7390	(-0.7627)	0.0000	(*NONE*)
LER	-2.0877	(-1.3018)	-3.3391	(2.8290)
Trend	0.0088**	(-0.0038)	0.0086	(-0.0053)
Log Likelihood	1996.8			
Chi-Square	None			

**: Denotes Significance at 5% level; Standard Errors are in brackets ( )

2 One Co-integrating Vector – Exact and Over Identification

From a research objective point of view, we are primarily interested in what is the long run relationship between macroeconomic variables and stock index returns in Singapore. Thus, while there may exist a number of co-integrating relationships amongst our six variables, we may proceed with selection of r =1 as we are mainly interested in the causality amongst our 5 macroeconomic variables and the stock market index. What is more important is that the co-integration test results from both Engle-Granger and Johansen illustrate that is there is a theoretical relationship among the variables and that they are in equilibrium in the long run. Therefore, we proceed with one long run co-integrating relationship amongst our variables for the remainder of this paper.

We now proceed to apply the LRSM technique to test for theory in our co-integrating vector by subjecting our estimates to exact and over-identifying restrictions based on research objectives of this paper. As our focus is on causality between Stock Index returns and macroeconomic variables, we normalized the macroeconomic variables on stock index returns at the exact identification stage. The results are summarized in **Panel A** of **Table 10** below. Only the money supply variable is found to be significant at 5% level of significance criteria. This result is disappointing and we conjure that the industrial production index variable is best dropped from the estimation since it is found to be the most insignificant variable (t-statistic calculated is lowest at 0.26). Therefore, we imposed an over-identification restriction of industrial production index = 0. The results are illustrated in **Panel B** of **Table 10** below.

Table 10: Exact and Over-indentifying restrictions on the co-integrating vector

	Panel A		Panel B	
LSTI	1.0000	(*NONE*)	1.0000	(*NONE*)
IR	-0.1111	(-0.0630)	-0.1241**	(-0.0430)
LM3	-2.0625**	(-0.9307)	-2.1534**	(-0.9803)
LCPI	-1.4311	(-3.5417)	-2.0726	(3.0314)
LIPI	-0.2457	(-0.9371)	0.0000	(*NONE*)
LER	-2.9230	(-2.7473)	-3.2828	(2.7681)
Trend	0.0087	(-0.0047)	0.0084**	(-0.0051)
Log Likelihood	1971.4		1971.3	
Chi-Square	None		0.057	[0.812]

**: Denotes Significance at 5% level; Standard Errors are in brackets ( ); For Chi-Square p-value in parenthesis [ ]. *Note: The output above shows the maximum likelihood estimates subject to exactly identifying (Panel A) and over identifying (Panel B) restrictions. The over-identifying restriction on GDP = 0 is not rejected (with a p-value of 0.812) and as a result we proceed with 'Panel B' in this paper.*

When we imposed an over-identifying restriction of zero on the coefficient of industrial production index, the Chi-squared statistic is not rejected at any of the usual levels of significance. <u>Hence, our restrictions are correct. As a result, we proceeded with Panel B (rather than Panel A) in this paper.</u>

6.6 Vector Error Correction Model (VECM)

So far, we have completed identifying long-run relationship amongst our variables and testing for theory in our analysis. However, we still haven't identified the direction of relationship or the Granger causality amongst the variables. In order to do this, we need to apply the vector error correction model (VECM) technique. The VECM technique allows us to identify which variables in our sample are exogenous, that is leading others in the long run, or are endogenous, that is following/lagging others in the long run. **Table 11** below summarizes the results of the VECM.

Table 11: Vector Error Correction Model (VECM)

Regressors	Dependent Variables											
	DSTI		DIR		DM3		DCPI		DIPI		DER	
DSTI (-1)	0.1972	[.035]	0.2432	[.413]	0.0012	[.931]	0.0178	[.013]	0.1907	[.208]	-0.0402	[.120]
DIR (-1)	0.0280	[.282]	0.0320	[.700]	-0.0070	[.079]	-0.0016	[.426]	-0.0373	[.379]	-0.0043	[.550]
DM3 (-1)	1.2375	[.018]	-5.5220	[.001]	0.1425	[.072]	0.0224	[.572]	-0.3710	[.660]	-0.0942	[.512]
DCPI (-1)	-1.0407	[.294]	0.8607	[.785]	-0.4667	[.002]	-0.3122	[.000]	-1.3667	[.396]	-0.2910	[.290]
DIPI (-1)	-0.0487	[.282]	0.1523	[.293]	-0.0116	[.092]	0.0078	[.026]	-0.4761	[.000]	0.0281	[.027]
DER (-1)	0.4831	[.169]	0.8558	[.444]	0.0232	[.663]	0.0903	[.001]	-0.4658	[.414]	-0.1958	[.045]
ECM (-1)	**-0.0346***	**[.095]**	**0.0733**	**[.274]**	**0.011*****	**[.001]**	**0.0095*****	**[.000]**	**0.1654**	**[.628]**	**0.0024**	**[.678]**
Chi-Square SC (1)	11.1376	[.517]	20.2988	[.062]	18.1709	[.111]	39.0482	[.000]	38.4612	[.000]	11.8343	[.459]
Chi-Square FF (1)	0.15195	[.697]	0.0389	[.844]	0.0924	[.761]	8.5765	[.003]	0.5849	[.444]	0.0028	[.957]
Chi-Square N (2)	32.7524	[.000]	89.6415	[.000]	5.6764	[.059]	32.5994	[.000]	7.3774	[.025]	77.1333	[.000]
Chi-Square Het (1)	1.8585	[.173]	3.5791	[.059]	0.8529	[.356]	0.4698	[.493]	0.4576	[.499]	0.4682	[.494]

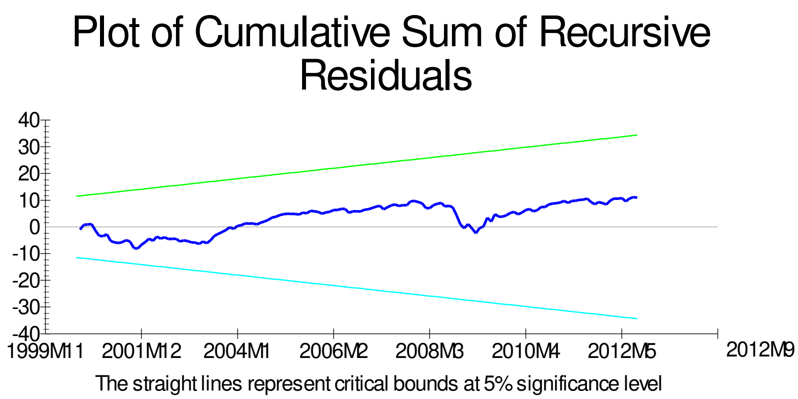
***: Denotes Significance at 1% level; *: Denotes Significance at 10% level; P-values are in brackets [ ]. *Note: The diagnostics are chi-squared statistics for: serial correlation (SC), functional form (FF), normality (N) and heteroskedasticity (Het).*

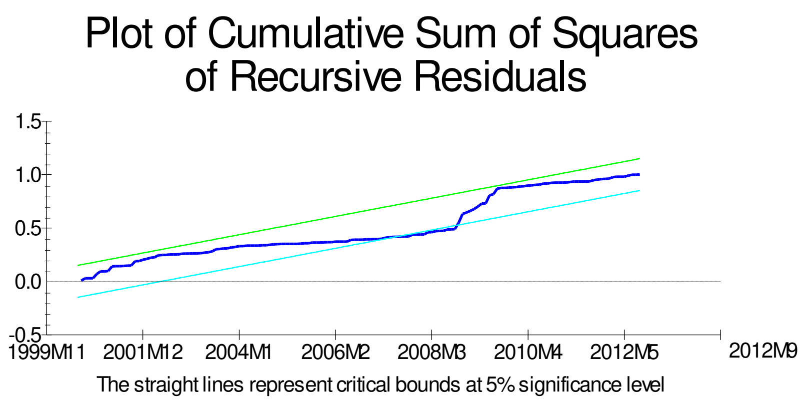
The error correction term consists of the long term trend amongst the variables and hence a significant 'ecm' coefficient indicates that the dependent variable is a follower or endogenous variable to others in the long run. This means that the dependent variable significantly responds to changes in other variables to bring about long-term equilibrium. From **Table 11** above, we identify three 'follower' (endogenous) variables: the stock index, money supply and inflation rates. Variables of interest rates, exchange rates and industrial production index are found to be leaders or exogenous in the long run.

From a common hindsight, the results are very comforting. We suspected stock index to be dependent upon macroeconomic variables in the long run and our VECM results confirm that. Furthermore, it is logical for money supply to be a follower as we have interest rates as a leader in the sample. Moreover, inflation too is theoretically expected to be a follower towards interest rates, exchange rates and GDP. Overall, the VECM indicates both long run and short run relationships amongst the variables. While the 'ecm' term contains the long term relationship, the short run relationships are indicated by the coefficients on the lags of the differenced variables. **Table 11** above illustrates all such results including the respective p-values for each in the brackets.

The diagnostics of the equations of the error correction model (testing for autocorrelation, functional form, normality and heteroskedasticity) tend to indicate that the equations are more or less well-specified as the null hypotheses of 'no problems' for most diagnostic tests were not rejected. We further checked for the stability of the coefficients by the CUSUM and CUSUM SQUARE tests. All the outputs of CUSUM tests indicated no structural breaks although the CUSUM SQUARE test indicated structural breaks for three equations in the year 2008 indicating the influence of the financial crisis. For the purpose of our research here, we focus on the DSTI equation and **Figure 1** below illustrates the CUSUM and CUSUM SQUARE test output for the DSTI equation. The CUSUM test indicates structural stability in the coefficients while the CUSUM SQUARE test indicates possible borderline instability at the 5% level of critical bounds. However, at the 10% critical level, the null hypothesis of structural stability is not rejected and hence we proceed.

Figures 1: CUSUM and CUSUM SQUARE Test - DSTI





6.7 Variance Decomposition (VDC)

While VECM results have identified interest rates, exchange rates and industrial production index variables to be leaders or exogenous in the long run, we still haven't identified which of these is the most exogenous variable, that is, having the greatest influence over others in the long run. Such knowledge is particularly important from a policy maker's perspective as they would like to shock the variable which is likely to have the most impact on the follower(s). To identify the relative endogeneity/exogeneity of a variable, we apply the variance decomposition technique.

The VDC technique can indicate which variable is explained most by its own shocks in the past. Hence, the variable which depends most on shocks of its own self and not of others in the past is considered to be the most exogenous or greatest leader amongst a given set of variables. The variable which is least explained by its own self and mostly by others is considered to be the most endogenous or greatest follower amongst a given set of variables. The VDC technique employs two different methods: Orthogonalized and Generalized. In the orthogonal method, the VDC technique assumes that when a particular variable is shocked, all other variables in the system are switched off. Moreover, it is biased to the ordering of variables in the VAR with the first variable reporting the highest percentage and thus likely to be specified as the most exogenous variable. In the generalized, such biasness and assumptions are not made and hence the estimates are more realistic. We present results using both methods in **Tables 12 and 13.**

6.7.1 Orthogonalized Variance Decomposition

The VDC methods provide forecast error variance for each variable over several horizons. In our research, we are using monthly data and hence **Table 12** provides forecast error variance for 3 horizons: one month, six months and 12 months. We choose to focus on the 12 period horizon in our research as the impact of change in macroeconomic variables on financial markets is quickly incorporated by the investors. Moreover, we are concerned with relatively quicker-fix macroeconomic policy options that can boost confidence in financial markets.

At the end of 12 periods, the contributions of own shocks towards explaining the forecast error variance of each variable are as follows: stock index returns (85.4%), interest rates (83.9%), money supply (79.8%), inflation (33.8%), exchange rates (56.5%) and industrial production (94.7%). As it's evident, the VDC orthogonal results suggest that the GDP proxy variable of industrial production index is the most exogenous variable. The inflation variable is found to be the most endogenous variable in our sample.

Table 12: Variance Decomposition (VDC) - Orthogonalized

Months	LSTI	IR	LM3	LCPI	LER	LIPI
LSTI						
1	0.96149	0.008325	0.016313	0.0030887	0.008156	0.002631
6	0.9012	2.18E-02	0.041341	0.0095377	0.023171	0.003
12	**0.85408**	0.036687	0.051824	0.011201	0.043645	0.002569
IR						
1	0.052763	0.91235	0.031361	2.67E-05	8.82E-04	0.002622
6	0.078541	0.85494	0.059905	9.71E-04	0.001167	0.004477
12	0.08999	**0.83918**	0.064163	0.0010289	0.001014	0.004623
LM3						
1	0.001804	0.014816	0.95491	0.022078	1.65E-04	0.006229
6	0.029451	3.81E-02	0.88553	0.023407	0.010373	0.013114
12	0.091363	0.049772	**0.79799**	0.023338	0.021514	0.016022
LCPI						
1	0.065018	0.03612	0.017821	0.84419	0.020137	0.016808
6	0.36556	6.81E-02	0.005718	0.54844	0.007142	0.005086
12	0.56704	0.075664	0.002265	**0.33824**	0.014746	0.002041
LER						
1	0.3049	0.049867	0.001575	0.02001	0.61023	0.014225
6	0.35614	3.87E-02	0.005858	0.017739	0.56998	0.011604
12	0.36302	0.036418	0.006709	0.017732	**0.56474**	0.011383
LIPI						
1	0.01423	0.011745	0.017554	0.0062983	0.004198	0.94597
6	0.013951	7.14E-03	0.023359	0.0071491	0.003274	0.94513
12	0.0126	0.00584	0.02433	0.0075499	0.002921	**0.94676**

6.7.2 Generalized Variance Decomposition

To reconfirm the results, we applied the VDC generalized method and the weighted average results for the 12-period horizon are presented in **Table 13** below. At the end of 12 periods, the contributions of own shocks towards explaining the forecast error variance of each variable are as follows: stock index returns (75.5%), interest rates (82.2%), money supply (74.9%), inflation (34.1%), exchange rates (68.4%) and industrial production (93.9%). Once again, the VDC generalized results also indicate that the GDP proxy variable of industrial production index is the most exogenous of all while inflation is the most endogenous variable. The results seem to suggest that the investors in Singapore stock markets closely follow macroeconomic growth information which significantly influences their investment decisions.

Table 13: Variance Decomposition (VDC) - Generalized

Months	LSTI	IR	LM3	LCPI	LER	LIPI
LSTI						
12	**0.754794**	0.119147	0.052181	0.005796	0.067505	0.000577
IR						
12	0.080678	**0.822019**	0.067521	0.004035	0.010206	0.015541
LM3						
12	0.083339	0.023549	**0.748887**	0.039972	0.102319	0.001934
LCPI						
12	0.406219	0.010371	0.001154	**0.340777**	0.236049	0.005429
LER						
12	0.258023	0.003298	0.007462	0.033683	**0.68437**	0.013164
LIPI						
12	0.01216	0.007671	0.023457	0.01079	0.007338	**0.938583**

Note: Weighted averages where each row = 100%.

These variances forecast results given by the orthogonalized and generalized variance decompositions are consistent with our earlier within-sample results given by the error-correction model: the macroeconomic variables lead (rather than lag) the Stock index variable. However, on closer inspection, we observe that while the GDP proxy variable is the most exogenous, it least explains the shocks in the stock index. In fact, interest rates and exchange rates seem to explain more of the shocks in the stock index after its own self. To further test this observation, we applied the impulse response function technique that explains the response of other variables to a one standard deviation shock to a specified variable.

6.8 Impulse Response Function (IRF)

The impulse response function technique also consists of two methods: orthogonal and general. Moreover, it also requires a time horizon to be specified. The impulse response function essentially produces the same information as the VDCs, except that it can be presented in graphical form. So consistent with our time horizon in VDC, we select 12 periods and this time focus on the variables of GDP, interest rates, exchange rates and stock index returns as we are interested on the relative exogeneity/endogenity of these variables. The graphical results of the IRF techniques are provided in the following pages (**Figures 2-9**).

6.8.1 Orthogonalized Impulse Response

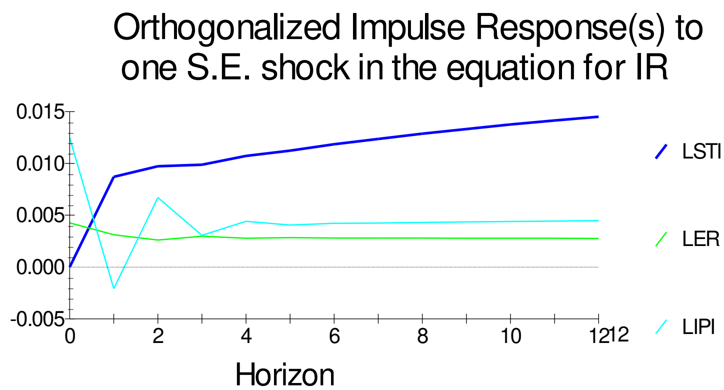
Consistent with our results from VDC, the results from the graphs illustrate that the GDP proxy variable of industrial production index (LIPI) is the least sensitive to a one standard deviation shock to other variables. Hence, the GDP proxy variable is the most exogenous. Furthermore, our earlier observation of the GDP proxy variable least explaining shocks to the stock index are confirmed from **Figures 2 and 5** of the IRF: when GDP is shocked in figure 5, the stock index is least impacted while in figure 2, when stock index is shocked, GDP is least impacted. On the other hand, **Figures 3 and 4** illustrate that when the interest rates and exchange rates are shocked, the greatest impact is on the stock index variable.

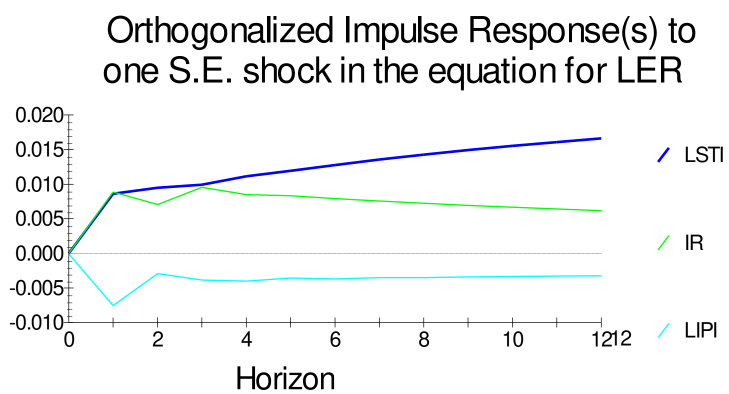
6.8.2 Generalized Impulse Response

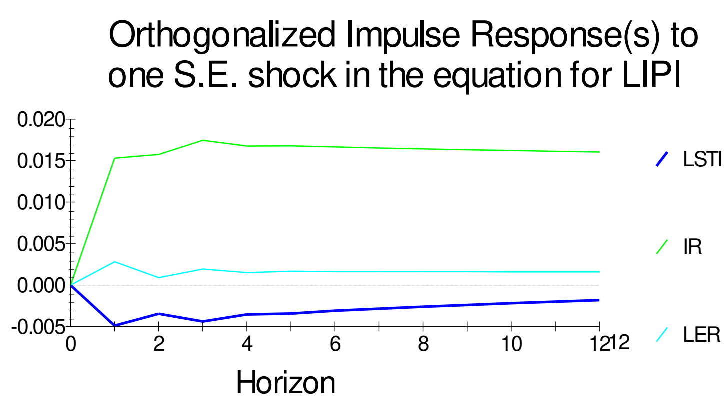
Similarly, consistent with our results from VDC, the results from the generalized graphs also illustrate that the GDP proxy variable of industrial production index (LIPI) is the least sensitive to a one standard deviation shock to other variables. Hence, the GDP proxy variable is the most exogenous. Furthermore, our earlier observation of the GDP proxy variable least explaining shocks to the stock index are confirmed from **Figures 6 and 9** of the generalized IRF: when GDP is shocked in figure 9, the stock index is least impacted while in figure 6, when stock index is shocked, GDP is least impacted. On the other hand, **Figures 7 and 8** illustrate that when the interest rates and exchange rates are shocked, the greatest impact is on the stock index variable. These results are critical from a policy implications perspective. They indicate that policy makers' need to be mindful of their monetary policy decisions as these policies have a significant impact on the financial markets returns.

6.9 Persistence Profile (PP) Finally, we conduct a persistence profile analysis to indicate the time it would take for the long-run relationship to get back to equilibrium if the whole co-integrating relationship is shocked. The difference between the IRF and PP technique is that in the IRF, only one variable is shocked and the effect on others is analyzed, where as in the PP technique, the effect of a system-wide shock on the long-run relations is the focus. **Figure 10** in the following pages shows the persistence profile for the co-integrating vector of this study. The figure indicates that if the whole co-integrating relationship is shocked, it will take about 32 months for the equilibrium to be restored

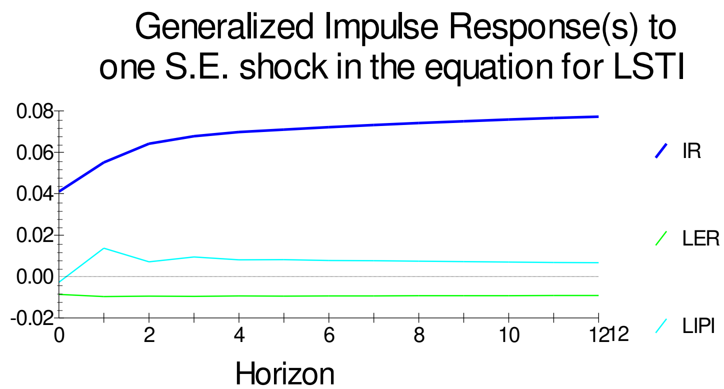
Figures 2, 3, 4 & 5: Impulse Response Functions (IRF) - Orthogonalized

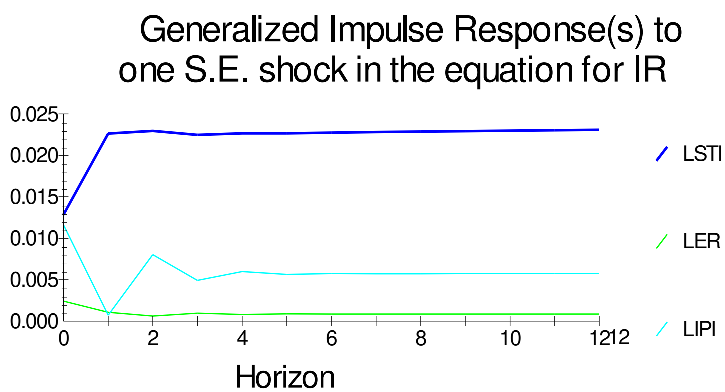


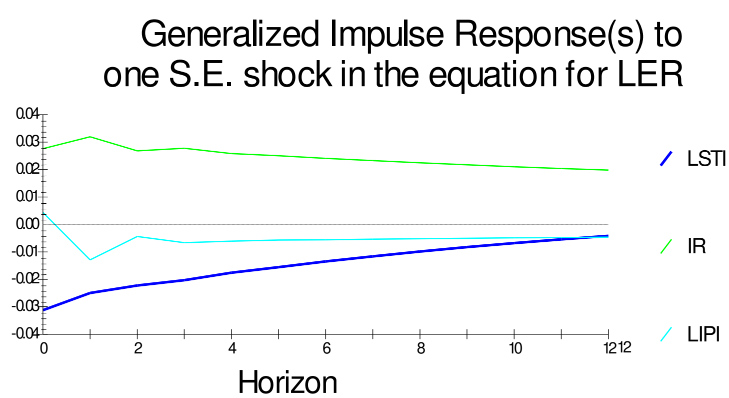




Figures 6, 7, 8 & 9: Impulse Response Functions (IRF) – Generalized







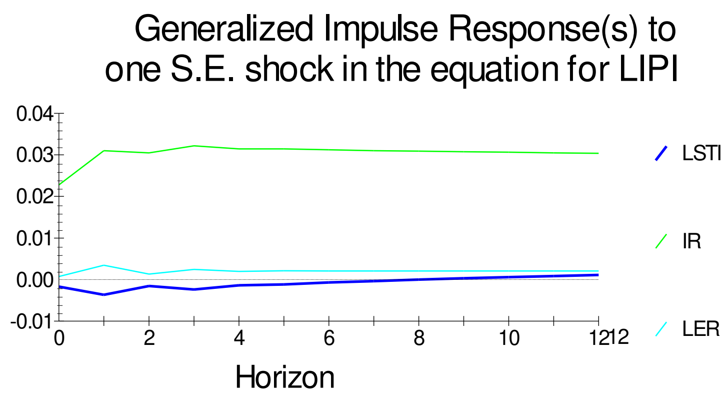
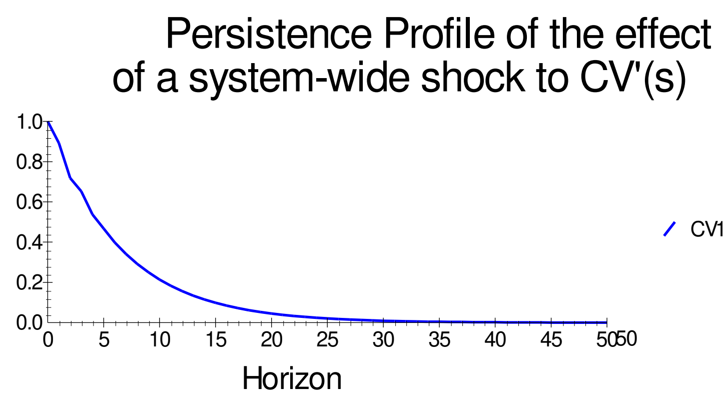


Figure 10: Persistence Profile (PP) Analysis



7. Discussion of the Results

The dynamic relationship between macroeconomic variables and stock market returns have been widely discussed and debated. The basis of these studies has been the use of models which state that share prices can be written as expected discounted cash flow. Thus, the determinants of share prices are the required rate of return and expected cash flows (Elton and Gruber, 1991). Economic variables which impact future cash flows and required returns can therefore be expected to influence share prices.

In our results, we discovered GDP, interest rates and exchange rates to be leading stock returns in the long run. These observations are broadly consistent with existing literature and market practice. It has been documented that there is a positive relationship between stock prices and real GDP

(Maysami and Koh, 2000). According to Fama (1986), Mukherjee and Naka (1995) and Ibrahim and Aziz (2003), the increase in GDP will affect the price of the stock through the impact towards corporate profit. This happens because when there is an increase in the real GDP, the expected future cash flow in company will increase and the price of the stock increases. Thus, our results are logical and indicate that investors account for movements in GDP and reflect this information in their investment decisions.

Theory and market practice also explains how interest rates can be leaders of stock returns. The relationship between interest rate and stock price is usually in the negative form. The increase in interest rate will increase the free risk nominal rate and at the same time will increase the discount rate (Abdullah and Hayworth, 1993). As a result, the price of the stock will decrease (Mukherjee and Naka, 1995). On the other hand, Abdullah and Hayworth (1993) proved that interest rate can influence the level of corporate profit through expectation where the investor will get higher dividend in the future. Most of the companies support their equipment and inventory through loans. Reduction in the interest rate will cut down the cost of borrowing and at the same time it provides an incentive to the company to expand their operation. Consequentially, the future expected value of the company will increase.

An interesting observation in our results is the higher impact of interest rates on stock returns. Even though interest rates are not the most exogenous variable; during a period of 12 months, their impact on stock returns is higher compared to GDP. This observation in fact can be logically explained with market practice. Maysami et al (2004) explained that most of the stock is bought through the money the investor borrowed from financial institutions. The increase in interest rate will increase the cost of buying stocks. The investor will try to find the stock that can give a higher rate of return to balance the cost of borrowing, which they borrow from financial institution. When this happens, the demand towards the stock will decrease and at the same time decrease the price of the stock. Thus, investors more quickly react to changes in interest rates compared to changes in GDP since the impact of interest rate changes are instantly felt by the investors.

Finally, it is no surprise that exchange rates are exogenous in the long run. Stock prices can have either positive or negative relationship with the foreign exchange rate. Any changes in value of exchange rate will give a big impact towards the price of the stock. Mukherjee and Naka (1995), Maysami and Koh (2000) and Ibrahim and Aziz (2003) proposed that the relationship between these two variables are in positive form. Looking at the situation where there is a decrease in value of the currency can prove this. This causes the product that is being exported from this country to become cheaper in the international market. As a result, if the products experience elasticity, the volume of the export from that country will increase. The flow of cash will increase in line with the profit and local stock price. Ibrahim and Wan (2001) shared a different perspective. They believed that the relationships between these two variables are negative. They believed that if the country depends on the export, the decrease in currency value will increase the growth of export. Nevertheless, the decrease in currency value will increase the cost of production impact as well as increase the domestic price. As a result, the profit margin in the company will decrease.

Overall, our results are in line with existing theory and logic when they indicate that GDP, interest rates and exchange rates lead stock returns in the long run. Moreover, our observation that within the 12 period horizon, interest rates and exchange rates have comparatively greater impact on stock returns than GDP is also explained by the instant effects interest rates and exchange rates have on investors positions compared to changes in GDP.

8. Conclusions, Policy Implications and Limitations

In this article, we test the possible direction of Granger causality between macroeconomic variables and stock market returns in Asian stock markets. Singapore was selected as a case study owing to its prominence amongst the Asian financial markets. We included 5 macroeconomic variables of GDP, inflation, interest rates, money supply and exchange rates following Chen et al (1986) on what they have described as "simple and intuitive financial theory" as there does not appear to exist any particular theory that accounts for stock price movements as a function of micro- and macroeconomic variables. The variable of exchange rates was included as a control variable to account for foreign country effects.

Using standard time series techniques, firstly we confirmed macroeconomic variables and stock index returns in Singapore have a long-run theoretical relationship using both Engle-Granger and Johansen's Co-integration analysis. Secondly, using LRSM technique, we tested the estimated Johansen long-run coefficients of the variables for significance and proceeded with a co-integrating vector that best constituted a stationary error correction term. Thirdly, using VECM, our research indicates that macroeconomic variables of GDP, interest rates, and exchange rates lead (rather than lag) stock index returns in Singapore. On the other hand, variables of inflation and money supply were not found to be leading stock index returns in the long run. Fourthly, by employing the VDC technique, we identified GDP to be the most exogenous variable in our sample compared to interest rates and exchange rates. However, we observed that the impact on Stock index was more from interest rates and exchange rates rather than GDP. Fifth, we employed the impulse response function method to verify our results obtained from VDC. IRF confirmed GDP to be the most exogenous while also maintaining the impact of interest rates and exchange rates to be more on stock index compared to GDP. Sixth and finally, we applied the persistence profile method to identify that if the whole co-integrating relationship is shocked, it will take about 32 months for the equilibrium to be restored.

From a policy implications perspective, our results indicate that the macroeconomic conditions of Singapore play a vital role in the long run movements of its stock market. Critically, we identified exchange rates (which we used as a control variable for foreign economic effects) to be an exogenous (leading) variable and hence, there are significant foreign country effects on stock market returns in Singapore. This is in conformation with reality as we witness a pessimistic environment in the Asian financial markets due to economic worries in the US and European markets.

From a domestic macroeconomic perspective, GDP and interest rates were identified to be leading stock index returns in the long run, although the impact of interest rates (and exchange rates) on stock index returns seemed to be greater than that from GDP. As a result, the Singaporean government is encouraged to introduce a monetary policy push within the domestic economy to revive its financial markets. The impact from monetary policy instruments (interest rates and exchange rates) appear to be greater for stock index returns in Singapore.

As financial markets are considered to be the backbone of a country's economic health and well being, the results from this research indicate that effective monetary policy implementation can help revive financial markets of a country better than through a fiscal stimulus package. However, caution needs to be taken in generalizing these results universally as they are only based on one sample which is Singapore. Therefore, future research may include a cluster of countries in the region as sample to further identify whether similar observations are consistent across different financial markets in the region.

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