THE CAUSES OF STOCK MARKET VOLATILITY IN MALAYSIA

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ABSTRACT

This paper examines the causes of stock market volatility by looking at the determinants of the movement in the small, internationally integrated Kuala Lumpur Stock Market (KLSE). It gives new evidence that is easy to interpret by including both the financial and the business cycle variables. It employs low frequency monthly data including stock market returns, interest rates, exchange rates, inflation, the money supply and the industrial index for the period October 1992 to December 1999. To overcome the problem of inefficient estimations due to generated regressors, the model jointly estimates the conditional volatilities of all variables using the GLS estimation procedure and the Hendry general-to-specific estimation strategy. Among the most important determinants of the conditional volatilily in the KLSE index are the lagged conditional volatility in the index itself, the conditional volatilities in money supply, industrial index and inflation rate. The conditional volatilities that have an immediate effect on the stock volatility are those from inflation rate and the industrial index. It is also found that industrial index has the greatest and the most significant impact on the stock's conditional volatilities. No evidence is found in the impact of the conditional volatilities in foreign exchange rate and interest rate on the stock market.

INTRODUCTION

Stock market volatility has received much attention in the finance literature. Issues including causes of stocks market volatility, its increase or decrease over time, and roles of regulators are discussed. Officer (1973), Black (1976) and Christie (1982) examine the effects of volatility in business cycle variables and the relationship of stock market volatility to financial leverage respectively. Schwert (1989) conducts tests on macroeconomic cause of stock market volatility for the United States. Kock and Kock (1991), Malliaris and Urrutia (1992), Chan et al.(1992) and Rahman and Yung (1994) study whether the world's financial and capital markets are now transmitting volatility more quickly. The extent to which the volatility of stock prices determine their underlying value is examined by Scott (1991) and Timmermann (1993).

The purpose of this paper is to contribute to the literature on the cause of stock market volatility by examining the determinants of movement in the volatility of equity returns in a small, internationally integrated stock market. The Kuala Lumpur Stock Exchange (KLSE) market may serve as an example in this case as it is increasingly integrated with the international stock markets in Asia and the world. Several previous works on this Malaysian stock market study the explanatory power of alternative models of conditional volatility, but not the relationship of stock market volatility to the volatility of financial and business cycle variables. This is to say that the volatility of the stock market may be conditioned by the volatilities in variables, among others, the past volatilities of the market itself, exchange rate, interest rate, money supply and not just the change in those variables. Following the methodology employed by Kearney and Daly (1998), this paper develops and estimates a model which is capable of examining and explaining financial and business cycle determinants of movements in the conditional volatility of the KLSE. The data employed in this study are low frequency monthly dataset including stock returns, interest rates, inflation, the money supply, and industrial index over the period October 1992 to December 1999. We choose October 1992 as the starting period since "...in the early 1992, administrative measures, and the traditional monetary and fiscal measures were implemented. In September, sentiment began to turn around as clearer signs of resilient economy started to emerge,....." (Bank Negara Malaysia, 1999, p. 308)

Among the most important determinants of the KLSE volatility are the lagged market volatility and lagged money supply, the volatilities of the industrial index and the volatility of inflation rate. It is found that industrial index has the strongest influence on the market. There are no evidence in the exchange rate and interest rate on the market volatility.

To overcome the problem of inefficient estimations due to generated regressors (Pagan, 1984, 1986; McAleer and McKenzie, 1991; Oxley and McAleer, 1993), the model jointly estimates the conditional volatilities of all variables using the GLS estimation procedure and the Hendry general-to-specific estimation strategy.

The paper is structured as follows. The next section discuss on the framework of theory, methodology and the data used. This is followed by the section on model used in the analysis that focus on the causes of the volatility of the KLSE. It also describes the joint estimation of conditional volatilities and the Hendry general-to-specific approach used to obtain results. The final section gives the main results and the conclusions.

THEORY, METHODOLOGY AND DATA

Using the present value concept, the price of equity at any one point is equal to the present discounted value of all expected future cash flows to shareholders:

$$E_{t-1}Q_t^i = E_{t-1}\sum_{k=1}^{\infty}\frac{C_{t+k}^i(IP_{t+k}, M_{t+k}, P_{t+k}, S_{t+k})}{(1+R_{t+k})^k} \quad (1)$$

where Q_t^i is the price of asset i, C^i denotes the cash flows associated with it, R denotes the interest rate and E_{t-1} is the expected operator. The expected cash flows is further assumed to be a function of the development in macroeconomic variables including the level of aggregate industrial production (IP), the money supply (M), the level of price (P), and the spot exchange rate (S) which is defined as the domestic currency price of foreign exchange.

If we denote the actual return of an asset i by q_t^i, then let the expected return of the asset conditional on the available information at time t-1 be denoted by $\hat{q}_t^i = E_t[q_t^i | I_{t-1}]$. In addition, we let σ_t^{qi} be the unconditional standard deviation of return on asset i. Thus the conditional counterpart, i.e., the conditional standard deviation is given by $\hat{\sigma}_t^{qi} = E_t[\sigma_t^{qi} | I_{t-1}]$. From equation 1, the conditional expected return on asset i is a function *f*, of the conditional expected determinants of the discounted cash flows:

$$\hat{q}_t^i = E_t[q_t^i | I_{t-1}] = f\{E_t[C_t^i(IP_t, M_t, P_t, S_t), R_t] | I_{t-1}\} \quad (2)$$

and the conditional standard deviation of returns is a function, *g*, of the conditional standard deviations of the determinants of the cash flow:

$$\hat{\sigma}_t^{qi} = E_t[\sigma_t^{qi} | I_{t-1}] = g\{E_t[\sigma_t^{IP}, \sigma_t^{M}, \sigma_t^{P}, \sigma_t^{S}, \sigma_t^{R}] | I_{t-1}\} \quad (3)$$

To empirically implement the model, we must obtained monthly estimates of the standard deviations of the relevant variables. Although in many cases, this can be obtained easily for financial variables such as interest rates and exchange rates, business cycle variables are not typically available at higher frequencies than monthly. The approach adopted here is to employ the methodology of Davidian and Carroll (1987). Now let X = X(Q, IP, M, P, S, R) denote the vector of stock market and business cycle variable, σ_t^x denote the unconditional standard deviations of these variables, and $\hat{\sigma}_t^x = E(\sigma_t^x ½I_{t-1})$, the corresponding conditional standard deviations. To begin, we obtain the unconditional standard deviations or the innovations $\sigma_t^x = \frac{1}{2}\varepsilon_{1,t}^x \frac{1}{2}$ from the regression:

$$\Delta\log(X)_t = a_i(H)\,\Delta\log(X)_t + \varepsilon_{1,t}^x \qquad (4)$$

where $\varepsilon_{1,t}^x$ is the residual and $a_i(H)$ is the 12th-order polynomial in the lag operator H. Using the innovations σ_t^x, we obtain the conditional standard deviations $\hat{\sigma}_t^x$ from $\hat{\sigma}_t^x = \sigma_t^x - \varepsilon_{2,t}^x$, where $\varepsilon_{2,t}^x$ is obtained from the regression:

$$\sigma_t^x = \beta_1(H)\sigma_t^x + \varepsilon_{2,t}^x \qquad (5)$$

where $\beta_1(H)$ is another 12th-order polynomial in the lag operator H. The conditional volatility in Equation 5 represents a generalization of the 12-month rolling standard estimator used by Officer (1973), Fama (1976) and Merton (1980) to measure stock market volatility, since it allows the conditional mean to vary over time in Equation 4 while also allowing different weights to apply to the lagged absolute unpredicted changes in stock market returns in Equation 5. Schwert (1989) uses this measure to examine the relationship between stock volatility and underlying economic volatility while Koutoulas and Kryzanowski (1996) used it to examine the role of conditional macroeconomic factors in an arbitrage pricing model. Kearney (1996) elaborates on the measure employed here and its similarity to the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982). Davidian and Carroll (1987) argue that the use of the absolute value of the prediction errors is more robust than those based on the squared residuals in Equation 4.

The dataset for the study consists of monthly observations on the KLSE and business cycle variables including the 3-month KLIBOR, the Malaysian Ringgit-US dollar exchange rate, the rate of inflation, the level of production index over the period October 1992 to December 1999.

MODELLING THE CONDITIONAL VOLATILITY OF THE KLSE

Before using Equations (4) and (5), econometric issue of non-zero cross-equation covariances which arises from the generated regressors need to be appropriately accounted for. Using the methodology adopted by Pagan (1984,1986), McAleer and McKenzie (1991) and Oxley and McAleer (1993), Equations (4) and (5) are jointly estimated with the equations determining the conditional volatility of all variables included in the model using generalized least squares (GLS) estimation procedure. Denoting variables in bold as vector or matrix, the GLS method stacked the system of M equations and T observations each in the following form:

$$\begin{bmatrix} y_1 \\ \cdot \\ \cdot \\ y_m \end{bmatrix} = \begin{bmatrix} X_1 & \cdot & \cdot & 0 \\ \cdot & \cdot & & \cdot \\ \cdot & & \cdot & \cdot \\ 0 & \cdot & \cdot & X_m \end{bmatrix} \begin{bmatrix} \beta_1 \\ \cdot \\ \cdot \\ \beta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \cdot \\ \cdot \\ \varepsilon_m \end{bmatrix} \tag{6}$$

where each y_i is an T x 1 vector of each dependent variable, X_i, a T x K_i matrix of each independent variable, β_i, a K_i x 1 vector of each equation's coefficient, and the error term ε_1, a T x 1 vector of error for each equation's error terms. Thus Equation (6), in its compact form is **Y** = **XB** + **e**, where **Y** is an MT x 1 vector, **X** is an MT x $\left(\sum_{i=1}^{m} K_i\right)$ matrix, **B** is a $\left(\sum_{i=1}^{m} K_i\right)$ x 1 vector of coefficients and **e** is an MT x 1 vector of errors. In the model analyzed here, Equation (6) contains 13 equations (i.e., M = 13) with 80 observations (i.e., T = 80) on each variable. The first 6 equations are given by Equation (4) for each variable in the **X** vector, the next 6 equations are given by Equation (5) for each variable in **X**, and the last equation is given by

$$\hat{\sigma}_t^Q = \lambda_0 + \lambda_1(K)\hat{\sigma}_t^x + \varepsilon_{3,t} \tag{7}$$

where the **X** is the vector previously defined and $\lambda_1(K)$ are polynomials of 4[th] degree in the lag operator, K. Equation (7) relates the conditional volatility of the KLSE market, Q, to the conditional volatility of the Malaysian financial and business cycle variables including industrial production IP, the money supply M, inflation P, the exchange rate S, and interest rate R.

The cross-equation correlation among the error terms can be incorporated by considering the variance-covariance matrix of errors. Thus for the system in Equation (6) the variance-covariance matrix is:

$$E(\varepsilon\varepsilon') = \Omega \begin{bmatrix} \sigma_{11}I & \sigma_{12}I & \cdot & \sigma_{1,13}I \\ \sigma_{21}I & \sigma_{22}I & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \sigma_{13,1}I & \cdot & \cdot & \sigma_{13,13}I \end{bmatrix}$$

Where the subscripts in the matrix represent the equation number in the system. Thus the GLS estimator for the system of equations is:

$$Y = X\beta + \varepsilon \tag{8}$$

$$\beta = (X'\Omega^{-1}X)^{-1}(X'\Omega^{-1}Y) \tag{9}$$

This method of estimator's gain in efficiency over OLS depends on few conditions including the number of variables or factors, the extend of cross-equation relationship in the system and the similarity between the dependent variables across equations. In this sense, the gain in efficiency of the GLS methodology in this study is considerable.

Table 1 presents the summary statistics from the OLS estimation of the first 12 autoregressions which are the regressions of Equations (4) and (5) for each of the financial and business cycle variables. The result will later be used as input in the GLS estimation (9).

Table 1: Estimation results of the ARCH Models of Stock Return and Business Cycle Variables

October 1992 - December 1999

$$X_t = \sum_{j=1}^{12} \delta_j^x X_{t-j} + \xi_t^x$$

Variables	R^2	SEE	DW	Sum	F
Q(stock return)	0.236	0.061	1.872	0.434(0.2275)	3.1743(0.0016)*
S(exch. rate)	0.286	0.031	1.977	0.309(0.0614)	2.4940(0.0128)*
IP(ind. Index)	0.678	0.058	1.832	0.322(0.2035)	2.8623(0.0043)*
R(int. rate)	0.190	0.047	1.859	0.086(0.1333)	3.1431(0.0017)*
M(M^s)	0.612	0.008	2.060	-0.297(0.004)*	3.6618(0.0003)*
P(inflation)	0.114	0.196	1.854	-0.047(7.145)	3.8690(0.0001)*

$$\sigma_t^x = \sum_{j=1}^{12} \alpha_t^x \sigma_{t-j}^x + \varepsilon_t^x$$

Variables	R^2	SEE	DW	Sum	F
Q	0.157	0.103	1.883	0.068(0.7772)	0.3725(0.7096)
S	0.311	0.042	2.004	1.003(0.1286)	2.2911(0.0175)*
IP	0.233	0.190	1.936	0.127(0.6192)	1.5438(0.1334)
R	0.209	0.046	2.026	0.405(0.3133)	1.3478(0.2162)
M	0.211	0.013	1.913	0.551(0.012)*	1.6996(0.0896)**
P	0.199	0.31	1.855	0.230(7.1447)	2.6487(0.0082)*

The table presents the regression results for Equations 2 and 3 in the text.
SEE = standard error of the regression
Sum = sum of coefficients of the lagged dependent variables in each equation
Marginal significance levels for test statistics are presented in the brackets
*Significant at 5%
**Significant at 10%

The top part of Table 1, which summarizes the equations for the conditional means, shows that the variations in the dependent variables are explained less by the equations for the financial variables. These variables are the stock market returns, exchange rate and the interest rates. On the other hand, the variables IP (industrial index) and M (money supply), which are the business cycle variables have higher explanatory powers. From the Durbin-Watson statistics, all the equations are also free from first-order autocorrelation. The sum of the lagged dependent variables are given in the fourth column and the fifth column represents the test statistics for exclusion of respective lagged variables. Clearly, the F tests are all significant for all variables.

The second part of Table 1 shows the conditional standard deviation. All variables are also free from first-order autcorrelation as shown by the Durbin-Watson statistics. In this result, the variable S (exchange rate) has highest explanatory power of 0.311 compared to the lowest for Q (stock return) at 0.157. The F-tests are significant for exchange rate, money supply and inflation.

Table 2 shows the summary of descriptive statistics for the variables used. The mean ranges from 0.0091 (money supply) to 0.2062 (inflation). The Jarque-Bera statistics which measure the null hypothesis of normality for the variables show evidence of non-normality for all the variables. Before the final model specification is made, the order of integration of variables used is tested to avoid spurious regression. Given the non-normality of variables, Table 3 presents the unit root test for each variables using the Augmented Dickey-Fuller (1979) and the Phillip-Perron (1988). As expected, each test strongly suggests stationarity of every variable employed in the model.

Table 2: Descriptive statistics for the conditional volatilities of variables used in the analysis

Variable	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
Q	0.068	0.053	$0.276(91_1)$	$0.001(98_3)$	0.062	1.441	4.522	38.058	0.000
S	0.020	0.009	$0.224(97_4)$	$0.001(98_1)$	0.032	3.954	22.162	1539.865	0.000
IP	0.062	0.045	$0.229(93_4)$	$0.001(98_3)$	0.055	1.328	4.150	30.024	0.000
R	0.039	0.023	$0.277(99_1)$	$0.001(98_1)$	0.045	2.585	11.838	375.704	0.000
M	0.009	0.007	$0.038(96_1)$	$0.000(94_2)$	0.007	1.359	5.340	46.081	0.000
P	0.206	0.149	$0.999(98_4)$	$0.003(92_3)$	0.197	1.669	5.757	67.135	0.000

The descriptive are all calculated for the period October 1992 – December 1999. The figures in the parenthesis following the minimum and maximum indicate the year and the subscripts are the months. The probabilities are the significant levels for the Jarque-Bera normality tests.

Table 3: Unit root tests financial and business cycle variables

Variable	Dickey-Fuller test	Philips-Perron test
Q	-5.799697	-8.869877
S	-5.170641	-9.047053
IP	-5.905850	-9.418482
R	-3.614427	-5.994466
M	-4.186913	-8.600647
P	-5.835909	-14.03600

All the test statistics are statistically significant at 0.05 level.

The model in study was estimated using the general-to-specific strategy GLS (Mizon, 1995), since financial theory does not contain predictions about the form of the lag structure that is appropriate for this analysis. Thus the estimation involves the use of Equation (6) with the general specified lag structure for the conditional volatility described in Equation (7). After Equation (6) has been estimated, the latter equation is sequentially restricted by excluding its statistically insignificant components. The final form of the conditional volatility equation for the stock market is presented in Equation (10) and the estimation results are presented in Table 4.

$$\hat{\sigma}_t^Q = \lambda_0 + \lambda_1\hat{\sigma}_{t-1}^Q + \lambda_2\hat{\sigma}_{t-1}^S + \lambda_3\hat{\sigma}_{t-3}^S + \lambda_4\hat{\sigma}_t^{IP} + \lambda_5\hat{\sigma}_{t-3}^{IP} \qquad (10)$$
$$+ \lambda_6\hat{\sigma}_{t-1}^R + \lambda_7\hat{\sigma}_t^M + \lambda_8\hat{\sigma}_{t-4}^M + \lambda_9\hat{\sigma}_t^P + \varepsilon_t$$

The overall performance of the estimation for Equation (10), presented by the R^2 statistic shows that it explains about 76% of the variation in the conditional standard deviation. This is much better than the related works, for example, Steward (1993) and Kearney and Daly (1998). The Durbin-Watson statistic indicates that the estimation is free from first-order autocorrelation. The ARCH statistic also shows that the model is free from heteroskedasticity, which is expected as we are working with the conditional volatilities of all variables.

Table 4: GLS estimation of the ARCH model of conditional volatility of KLSE (1994:03 1999:12)

Explanatory variable	Model coefficient	Coefficient	t-Statistic	Probability
Constant	λ_0	-0.037296	-2.553822	0.0132
$\hat{\sigma}_{t-1}^Q$	λ_1	0.287563	3.781419	0.0004
$\hat{\sigma}_{t-1}^S$	λ_2	0.058550	1.983238	0.0519
$\hat{\sigma}_{t-3}^S$	λ_3	0.049778	1.621215	0.1102
$\hat{\sigma}_t^{IP}$	λ_4	0.760544	8.744567	0.0000
$\hat{\sigma}_{t-3}^{IP}$	λ_5	0.142417	1.605538	0.1136
$\hat{\sigma}_{t-1}^R$	λ_6	-0.024164	-1.368933	0.1761
$\hat{\sigma}_t^M$	λ_7	-0.354167	-0.411754	0.6820
$\hat{\sigma}_{t-4}^M$	λ_8	2.169376	2.536570	0.0138
$\hat{\sigma}_t^P$	λ_9	0.055809	1.609586	0.1127
R-squared	0.765528	Mean dependent var		0.071928
Adjusted R-squared	0.730357	S.D. dependent var		0.035631
S.E. of regression	0.018502	Akaike info criterion		-5.010315
Sum squared residual	0.020539	Schwarz criterion		-4.689101
Log likelihood	185.3610	F-statistic		21.76600
Durbin-Watson stat	2.012149	Prob(F-statistic)		0.000000
ARCH-test (nR^2)		0.0425 (0.83667)		
Chow Breakpoint Test: 1998:09 (LR)		16.88966 (0.026841)		

Looking at the individual coefficient estimates for the period of the studies, we observe that only three variables are significant at 5% significant level. They are the one-month lagged stock volatility, current production index and the four-month money supply. This shows that the volatility in the Malaysian stock market is influenced by the volatilities in the financial and business cycle variables. The significant coefficient of the constant term is an indication that the stock market proceeds independently from the variables included in the model. The positive significant coefficients also tell us that an increase in the volatilities of lagged stock index, money supply and the current production index will increase the volatility of the stock market. It should also be noted the coefficient of the four-month lagged money supply has the largest coefficient with the current index being the most significant. Another result from Table 4 is that there is no evidence of volatility spillover from exchange rate, interest rate, current money supply and current inflation.

The Malaysian government moved to fixed exchange rate on September 2, 1998. To test for any structural break in the model, the Chow breakpoint test is applied. The result shows that at 5% significant level, we reject the null hypothesis of no structural break. Tables 5 and 6 give the results for the conditional volatilities for the two regimes. For the period before the fixed exchange rate, the result in Table 5 is almost similar to that obtained in Table 4. Table 6 shows the result for the conditional volatility for the fixed exchange rate. We have excluded the exchange rate variable to avoid the singularity of data. Surprisingly, the one-month lagged stock volatility is not significant anymore. Only two variables are found to be significant; the current production index and the current inflation rate. Thus when comparing between the two regimes, the importance of

Table 5: GLS estimation of the ARCH model of conditional volatility of KLSE (1994:03 1998:08)

Explanatory variable	Model coefficient	Coefficient	t-Statistic	Probability
Constant	λ_0	-0.031470	-1.924491	0.0608
$\hat{\sigma}^{Q}_{t-1}$	λ_1	0.270640	2.794348	0.0077
$\hat{\sigma}^{S}_{t-1}$	λ_2	0.053976	1.799451	0.0788
$\hat{\sigma}^{S}_{t-3}$	λ_3	0.078191	2.379738	0.0217
$\hat{\sigma}^{IP}_{t}$	λ_4	0.734590	7.560222	0.0000
$\hat{\sigma}^{IP}_{t-3}$	λ_5	0.125684	1.208804	0.2332
$\hat{\sigma}^{R}_{t-1}$	λ_6	-0.008131	-0.370155	0.7130
$\hat{\sigma}^{M}_{t}$	λ_7	-0.216096	-0.242728	0.8093
$\hat{\sigma}^{M}_{t-4}$	λ_8	1.817996	2.176297	0.0349
$\hat{\sigma}^{P}_{t}$	λ_9	0.022430	0.615266	0.5415
R-squared	0.778577	Mean dependent var		0.068239
Adjusted R-squared	0.733286	S.D. dependent var		0.032614
S.E. of regression	0.016844	Akaike info criterion		-5.164125
Sum squared resid	0.012483	Schwarz criterion		-4.795795
Log likelihood	149.4314	F-statistic		17.19051
ARCH-test (nR^2)	2.12E-05 (0.99632)			
Durbin-Watson stat	1.783650	Prob(F-statistic)		0.000000

Table 6: GLS estimation of the ARCH model of conditional volatility of KLSE (1998:09 1999:12)

Explanatory variable	Model coefficient	Coefficient	t-Statistic	Probability
Constant	λ_0	-0.029301	-0.614109	0.5562
$\hat{\sigma}^{Q}_{t-1}$	λ_1	0.237807	1.301173	0.2294
$\hat{\sigma}^{IP}_{t}$	λ_4	0.717131	3.209334	0.0124
$\hat{\sigma}^{IP}_{t-3}$	λ_5	0.028639	0.156512	0.8795
$\hat{\sigma}^{R}_{t-1}$	λ_6	-0.068605	-1.752576	0.1178
$\hat{\sigma}^{M}_{t}$	λ_7	-0.196742	-0.066378	0.9487
$\hat{\sigma}^{M}_{t-4}$	λ_8	2.871535	0.760508	0.4688
$\hat{\sigma}^{P}_{t}$	λ_9	0.179900	1.883864	0.0963
R-squared	0.862138	Mean dependent var		0.084376
Adjusted R-squared	0.741509	S.D. dependent var		0.043211
S.E. of regression	0.021969	Akaike info criterion		-4.491471
Sum squared resid	0.003861	Schwarz criterion		-4.105177
Log likelihood	43.93177	F-statistic		7.147025
ARCH-test (nR^2)	0.787018 (0.375003)			
Durbin-Watson stat	2.035233	Prob(F-statistic)		0.006335

variables in explaining the volatility of stock market volatility changes. The results also show that the R^2 statistics for Tables 5 and 6 increase slightly compared to Table 4. Since this study focuses on the monthly conditional volatility rather than on the levels of the market returns, the replication of the results for higher frequency data would be a possible area for further research.

SUMMARY AND CONCLUSIONS

The purpose of his paper has been to contribute to the literature on the causes of stock market volatility by looking at the determinants of the movement in the small, internationally integrated stock market of the KLSE. The method used is capable of explaining the movements in the conditional volatility of the KLSE Composite index by employing low frequency monthly data including stock market returns, interest rates, inflation, the money supply and the industrial index for the period October 1992 to December 1999.

This paper also gives new evidence that is easy to interpret by including both the financial and the business cycle variables. To overcome the problem of inefficient estimations due to generated regressors, the model jointly estimates the conditional volatilities of all variables using the GLS estimation procedure and the Hendry general-to-specific estimation strategy

Among the most important determinants of the conditional volatilily in the KLSE index are the lagged conditional volatility in the index itself, the conditional volatilities in the money supply, industrial index and inflation rate. The conditional volatilities that have an immediate effect on the stock volatility are those from inflation rate and the industrial index. It is also found that industrial index has the greatest and the most significant impact on the stock's conditional volatilities. No evidence is found in the impact of the conditional volatilities in foreign exchange rate and interest rate on the stock market.

Money supply may work through the transmission mechanism. For example, to implement planned changes in monetary policy, the central bank engages in open market operation to adjust bank reserves. The effect on the government bond market create excess liquidity. Rising or falling in government bond prices will then affect corporate bonds, followed by common stock and then the real goods market. The significant of the volatility of current inflation rate in the study may indicate that investors, on month to month basis, are relatively able to adjust prices for inflation, thus affecting the market in aggregate. The contribution of the volatility in production index may not be surprise as it may indicate the activity in the economy. However, the significant of the current volatility of production index may be due to the frequency of the data used. This can be explained by the study that the industrial production index normally lead by one-half month (Reilly & Brown, 2000). The implication of this study to the market participant shows the important of financial and business cycle determinants, especially the past volatility of stock market, industrial production index, money supply and inflation rate, in determining the volatility of the market.

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