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Predictable Returns and Non-Synchronous Trading

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Abstract

The aim of this paper is to investigate non-synchronous trading effect in terms of predictability. This analysis is applied to daily and one-minute interval data on the KOREA stock market. The results indicate evidence of predictability between indices with different degrees of non-synchronous trading and when considering one-minute interval data. We then propose a simple test to infer whether such predictability is mainly attributing to non-synchronous trading or an actual delayed adjustment on part of traders. The results obtained suggest that the observed predictability is attributed to non-synchronous trading instead of delay adjustments in price to the "news".

Keywords: Return predictability, lead-lag effect, emergent market, impulse-response function, granger-causality

Introduction

Several studies have investigated the effect of non-synchronous trading on the autocorrelation of returns i.e. Lo and Mackinlay (1990), Schotman and Zalewska (2006). All the studies conclude that the non-synchronous trading increases the serial correlation of returns. Lo and Mackinlay (1990) proposed an econometric model of non-synchronous trading by analyzing its implications on returns of individual securities and portfolio. They found that ignorance of an non-synchronous trading may bias the results and generate inferences completely false: The non-synchronous trading generates a negative serial in returns of individual securities while a positive serial correlation in observed portfolio returns.

The impact of non-synchronous trading on predictability returns has been studies by Camilleri and Green (2004) on the Indian market using three approaches: Test Pesaran Timmermann, VAR model, Granger-Causality and Impulse-response function on daily and high frequency data. The results imply that non-synchronous trading appears to be the main source of the predictability of returns on the Indian stock market. More specially, the purpose of this paper is to study the impact of non-synchronous trading on the predictability of returns of Korea stock market and examine the main cause of this effect. We propose a new alternative focuses on the study of lead-lag effect on the value of indices by adopting the methodology of Camilleri and Green (2004).

To this end, this paper is organized as follows: In the first section, we go through a literature review of an non-synchronous trading. In the second section, we developed the impact of non-synchronous trading on the predictability of returns. Section three looks at the lead-lag effect on the predictability of returns using several methodologies. The forth section present the data and methodology. The empirical results are summarized in the five section.

Non-synchronous Trading: Literature Review

The effect of non-synchronous trading is generated when the securities transactions occur infrequently. In this case, the price of the last transaction may cease to reflect the fundamental value of the firm to new information available on the market. At first, this gives the impression that the stock price is delayed adjustment to this new information and therefore the apparent inefficiency as soon as the price of a transaction most recently linked to a past transaction. The problem lies in the use of time of the last transaction by the researchers for each security and it is always assumed that the prices of securities are recorded simultaneously (synchronous) at equidistant points in time (Camilleri and Green, 2004, p.3)

The non-synchronous trading generates specific characteristics in terms of prices of securities and therefore yields. For example, price indices exhibit a high degree of serial correlation than individual securities, as noted by Fisher (1966). Cohen *et al*. (1979) showed that the transaction generates an asynchronous serial correlation of returns of a market. There are several reasons to analyze why prices take longer to be adjusted to new information as follows: for example, when new information is available, such orders will be undervalued and others are over- evaluated by other market participants and the other due to delayed price adjustment comes from the fact that market participants do not devote more time to control the less liquid securities as they do with those most Liquid. Where new information relating to the less liquid security takes longer to be evaluated.

Other researchers have studied the effect of non-synchronous trading on the autocorrelation of returns i.e. Fisher (1966), Lo and Mackinlay (1990), Boudoukh, Richardson and Whitelaw (1994). These studies conclude that non-synchronous trading increases the correlation of returns. Boudoukh *et al*. (1994) suggested three explanations for the persistence of autocorrelation of returns that are related to either an non-synchronous trading, or a time variation of risk premium (expected returns) or the irrationality of investors (Sâfvenblad, 1997). In the U.S. market, Lo and Mackinlay (1990b) found that large capitalization securities leads those with low market capitalization and attributed this to an cross-correlation between the securities caused by the effect of an non-synchronous trading. This result is proved by Cohen, Maier, Schwartz and Whitcomb (1979). Mills and Jordnov (2000) reported similar evidence of a lead-lag effect for a number of UK stocks sampled at monthly intervals. These authors have constructed ten portfolios of different size and methodology is based on the Impulse Response Function. Camilleri and Green (2004) studied the relationship lead-lag between two indices of different liquidity using high frequency data (one- minute) to examine the predictability of returns in the Indian market due to the non-synchronous trading.

Subsequently, these authors have proposed a test to infer whether such predictability is mainly attributed to an asynchronous transaction or a lagged adjustment of prices from investors. These results obtained from intra-day analysis assume that the asynchronous transaction appears to be the best explanation of such predictability observed in the Indian market. Lo and Mackinlay (1990) and Mills and Jordanov (2000) found relevant conclusions about this lead-lag effect.

The impact of non-synchronous trading on the predictability of returns

This section shows the different methodologies used by some empirical studies in order to test the lead-lag effect or the effect of an non-synchronous trading on the predictability of returns on stock indices. The pioneer work is of Camilleri and Green (2004) that have adopted three different techniques: The process VAR (Vector Autoregressive), Granger causality and impulse response function.

In what follows, we present these different methodologies (see Camilleri and Green, 2004, pp 13-18).

Granger-causality test

The Granger-causality methodology is based on the estimated VAR. Granger (1969) showed that a shock affects a given time series, generates a shock to other time series and then the first series is due to Granger in the second. In this case, the VAR model of a time series appears to be an AR adjusted under other delayed time series and an error term. The VAR model is a means of modeling causal and feedback effects (feedback effect) when two or more time series according to Granger cause the other. The term does not imply causality; it may be the case of inter-relationships between time series caused by an exogenous variable. A bivariate VAR model may be formulated as follows:

$$x_t = \sum_{i=1}^{n} \alpha_{1i} x_{t-i} + \sum_{i=1}^{n} \beta_{1i} y_{t-i} + \mu_{1t} \qquad (1)$$

$$y_t = \sum_{i=1}^{n} \alpha_{2i} x_{t-i} + \sum_{i=1}^{n} \beta_{2i} y_{t-i} + \mu_{2t} \qquad (2)$$

Where x_t and y_t are two variables assuming to Granger-cause each other, whilst μ_t is an error term.

The system of two equations (1) and (2) is formulated by the following vector:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} \alpha_{1i} \; \beta_{1i} \\ \beta_{2i} \; \beta_{2i} \end{bmatrix} \begin{bmatrix} x_{t-i} \\ y_{t-i} \end{bmatrix} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}$$

The Granger causality implies market inefficiency in the sense that fluctuations generate an index fluctuation leads to a fluctuation in another index. This means that if the first fluctuation was justified by new information, the latter fluctuation should have occurred at the same time, ruling out lead-lag effects. Therefore when testing for Granger-Causality using daily data, one should expect contemporaneous relationships if the markets are efficient and if there are not non-synchronous trading effects.

Impulse-response function

One of the main uses of the VAR process is the analysis of impulse response. The latter represents the effect of a shock on the current and future values of endogenous variables. VAR models can generate the Impulse-Response Functions. The response of each variable in the VAR system to a shock affecting a given variable: either a shock on a variable x_t, can directly affect the following achievements of the same variable, but it is also transmitted to all other variables through dynamic structure of the VAR. The impulse response function (IRF) of the variable y_t to a shock on the variable x_t, occurring in time t, can be viewed as the difference between the two time series:

♣ The realisations of the time series y_t after the shock in x_t has occurred; and

♣ The realisations of the series y_t during the same period but in absence of the shock in x_t.

This can be formulated in mathematical notation as follows:

$$IRF_y(n, \delta, \omega_{t-1}) = E[y_{t+n} / \varepsilon_t = \delta, \varepsilon_{t+1} = ... = \varepsilon_{t+n} = 0, \omega_{t-1}] - E[y_{t+n} / \varepsilon_t = 0, \varepsilon_{t+1} = ... = \varepsilon_{t+n} = 0, \omega_{t-1}] \qquad (3)$$

Where:

δ, is a shock at time t;

ω_{t-1} is the historical time series

ε is an innovation

IRF is generated from t to t + n.

The lead-lag effects and returns predictability

The different methodologies in the study of predictability of returns used by Camilleri and Green (2004) indicate that the most liquid index leads the less liquid index. These authors attributed this effect to a lead-lag to non-synchronous trading or delayed price adjustments to new information from investors. The analysis is based to trading break and post-trading-break returns. They assume that, during the trading-break, market participants have enough time to adjust their judgments about the fundamental values of firms. Since one may assume that any trading occurs immediately after a trading-break, will reflect the market value and exclude any delayed price adjustment on part of traders. This implies that if the lead-lag effects between the two indices persist in the post-trading-break, they are due to an non-synchronous trading effects than delayed price adjustment.

Camilleri and Green (2004) showed that the yields of delayed first six minutes of the most liquid index (Nifty) are significant and to determine the value of the index less liquid (Midcap) on the Indian market. They proposed to estimate the equation between the Nifty overnight returns, the Midcap overnight returned Midcap six minute return following:

$$\underset{t\to t+1}{OR(N)} = \alpha + \underset{t\to t+1}{OR(M)} + \underset{t+1}{IR(M)} + \varepsilon \qquad (4)$$

Where:

$\underset{t\to t+1}{OR(N)}$: Log Nifty overnight return between day t and t +1;

$\underset{t\to t+1}{OR(M)}$: Log Midcap overnight return between day t and t +1;

$\underset{t+1}{IR(M)}$: Log Midcap six minutes return of the day index t +1;

α : Is a constant?

ε : Is an error term.

Both regressions indicate that the Nifty overnight return is more correlated with the Midcap six minutes return of the subsequent trading day. This lead-lag is attributed to non-synchronous trading.

Data and Methodology

In this section we study the effect lead-lag between the two indices of Korea stock market. We focuses on the lead-lag in the non-synchronous trading is the main question. Based on previous studies, we can highlight some expected results:

- The more liquid index to lead the less liquid index
- The lead-lag effect is more pronounced in the case of high frequency data.

- We anticipate that the predictability of returns is partly attributed to actual delayed in price adjustments as well as due to non-synchronous trading.

The analysis of the lead-lag effect on the predictability of returns is applied on a daily and high frequency data. The daily set constitutes of the closing observations of the Kospi and KospiMidcap indices- the main and the less liquid index respectively. The daily data period ranges from 02/01/2004 to 05/04/2008- a total of 1016 observations. The high frequency data included the value of both indices and the study period lasts between 21/01/2008 and 25/01/2008. We begin first by the unit root test (ADF). Subsequently, we will analyze the lead-lag effect on the predictability of return using three methodologies VAR, Granger Causality test and Impulse-Response function.

Empirical results

This section reports the results of the analysis of a lead-lag effect on the predictability of returns of an Asian emerging market-Korea. In both cases daily data and high frequency, the ADF test results show that the two indices are nonstationary in level (ADF values are higher than their critical values for different significance levels). However, in first differences, the logarithmic price indices are stationary I(1). To clarify this idea of stationarity of the series, we turn to study the autocorrelation of Kospi (LK) and Kospi Midcap (LKM) series at different delays. The autocorrelation coefficients are high and decline slowly indicating the existence of a unit root. What is the evidence that the logarithmic series of two indices are I (1). In what follows, we analyze the lead-lag effect on the predictability of returns using three methodologies, namely the VAR, Granger causality and impulse response function. First, we first determine the optimal order of the VAR model for both indices studied. According to both AIC and SC criteria (minimum), we obtain a VAR (1) for the logarithmic daily series of indices LK and LKM and a VAR (3) for the high frequency. Estimation of individual equations of the VAR systems is reproduced in table 1(in Appendix).

The lead-lag effect between the two indices can be derived from a significance of the coefficients of two equations. From Table1, we can see that there is no lead-lag effect, since the coefficients of LKM (-1) and LK (-1) are not significant at the 5% and therefore it no relationship between the two indices. In order to investigate further the Granger causality tests are applied to the system of two equations. The results obtained for a number of delay equal to one (for daily data) and to three (for high frequency data) are given in Table 2. The null hypothesis that LKM does not cause LK is accepted when the probability associated 0.86466 is greater than the usual statistical threshold of 5%. Similarly, the null hypothesis that LK does not cause LKM is accepted threshold of5%.

Table 2: Granger-causlity test

Daily data

Null Hypothesis		**F-Statistic**	**Probability**
LKM does not Granger Cause LK		0.02906	0.86466
LK does not Granger Cause LKM		0.04249	0.83672
VAR Pairwise Granger Causality			
Dependent variable: LK			
Exclude	**Chi-sq**	**Degrees of Freedom**	**Prob.**
LKM	0.296451	1	0.8622
All	0.296451	1	0.8622
Dependent variable: LKM			
Exclude	Chi-sq	Degrees of Freedom	Prob.
LK	0.056926	1	0.9719
All	0.056926	1	0.9719

High frequency data

Null Hypothesis	**F-Statistic**		**Probability**
LKM does not Granger Cause LK	0.52306		0.02466
LK does not Granger Cause LKM	0.65249		0.01672
VAR Pairwise Granger Causality			
Dependent variable: LK			
Exclude	**Chi-sq**	**Degrees of Freedom**	**Prob.**
LKM	0.23687	3	0.02265
All	0.20369	3	0.01287
Dependent variable: LKM			
Exclude	**Chi-sq**	**Degrees of Freedom**	**Prob.**
LK	0.0987	3	0.01956
All	0.09254	3	0.00369

These results show that, in the case of daily data, the difference in liquidity between the two indices does not generate a lead-lag effect and therefore not predictable returns. The same procedure was performed for the case of high frequency data (1 minute). Starting from two OLS estimates, we find that the coefficients are significant indicating a lead-lag effect and delayed returns of LKM can explain returns of the dependent variable LK (Table 1). Tests of non-Granger causality is applied to a VAR (3) model. The χ^2 (3) distribution and statistic of 0.52306 and 0.65249 can reject the null hypothesis of no causality between the two series.

These different VAR performed in this section confirm the existence of a strong relationship and the Kospi index generates KospiMidcap in case of high frequency data and a feedback of the effect from KospiMidcap to Kospi. One possible explanation for this is that the information is primarily reflected in the Kospi index. After a few minutes, the information is evaluated in the KospiMidcap index and therefore we obtain a lead-lag relationship at high frequency data.

The analysis of the Impulse-Response function of each indices and for both daily and high frequency data, reveals the following results:

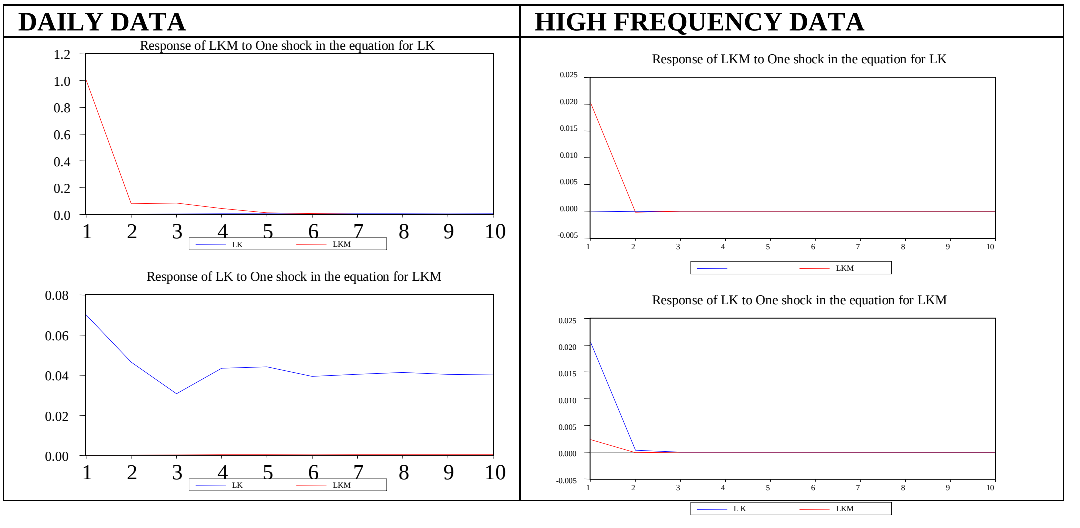

Fig. 1: Impulse-Response Function

If data is daily, a KOSPI shock had a higher impact on the Kospi Midcap index. While the latter is insensitive to a Kospi Midcap shock. For the case of one-minute frequency, a Kospi shock generate a higher impact on the Kospi Midcap index. This is attributed to a lead-lag relationship caused in part by the effect of an non-synchronous trading.

This study, based on impulse response functions, can be supplemented by an analysis of variance decomposition of forecast error. The objective is to calculate the contribution of each of the innovations in the variance of the error. The results for the study of the variance decomposition are reported in a Table 3. The variance of the forecast error is due to LK for about 99.99% to its own innovations and to 0.01% with those of LKM. The variance of the forecast error is due to LKM 1.3% to the innovations of LK and 98.7% to its own innovations. We can deduce that the impact of a LK shock on LKM is important but there is almost lower than the impact of a LKM shock on LK. For the case of high frequency data: The variance of the forecast error of LK is due to 6% of LKM innovations while that of LKM 26.4% is due to innovations LK. So the impact of a LK shock on LKM is more important than the impact of a LKM shock on LK:

TABLE 3: Decomposition of the variance of the LK and LKM series

Daily data

Variance Decomposition of LK:			
Period	**S.E.**	**LK**	**LKM**
1	2.03E-09	100.0000	0.000000
2	2.03E-09	99.99713	0.002869
3	2.03E-09	99.99713	0.002869
4	2.03E-09	99.99713	0.002869
5	2.03E-09	99.99713	0.002869

6	2.03E-09	99.99713	0.002869
7	2.03E-09	99.99713	0.002869
8	2.03E-09	99.99713	0.002869
9	2.03E-09	99.99713	0.002869
10	2.03E-09	99.99713	0.002869
Variance Decomposition of LKM:			
Period	**S.E.**	**LK**	**LKM**
1	2.07E-09	1.306507	98.69349
2	2.07E-09	1.308118	98.69188
3	2.07E-09	1.308118	98.69188
4	2.07E-09	1.308118	98.69188
5	2.07E-09	1.308118	98.69188
6	2.07E-09	1.308118	98.69188
7	2.07E-09	1.308118	98.69188
8	2.07E-09	1.308118	98.69188
9	2.07E-09	1.308118	98.69188
10	2.07E-09	1.308118	98.69188
Ordering: LK LKM			

High Frequency data

Variance Decomposition of LK:			
Period	**S.E.**	**LK**	**LKM**
1	1.005212	100.0000	0.000000
2	1.008380	94.99944	4.756564
3	1.011948	93.99858	8.891424
4	1.012925	93.99646	5.893540
5	1.013013	93.99468	5.995322
6	1.013046	93.99304	5.996959
7	1.013060	93.99116	5.998837
8	1.013070	93.98931	5.998837
9	1.013079	99.98753	5.998837
10	1.013088	93.98574	5.998837
Variance Decomposition of LKM:			
Period	**S.E.**	**LK**	**LKM**
1	0.070037	26.9321	73.09968
2	0.084057	26.8470	73.09915
3	0.089502	26.1678	73.59832
4	0.099497	26.2693	73.59731
5	0.108853	26.3203	73.59680
6	0.115761	26.3644	73.59636
7	0.122618	26.4045	73.59596
8	0.129404	26.4334	73.59567
9	0.135563	26.4569	73.59543
10	0.141370	26.4774	73.5523
Ordering: LK LKM			

These results are consistent with those shown by the causality test and impulse response function. In these studies, we can attribute this predictability LKM index on LK to an effect of causality and we assume that the lead-lag effect in case of clear high-frequency data can be attributed to the effect of an asynchronous transaction or delay in the adjustment to new information.

Throughout there results, we propose a simple method of analysis of trading-break and post-trading break in order to infer whether such predictability is attributed to a non-synchronous trading or delayed price adjustment. From the estimation of VAR (3), we found that the first three minutes of Kospi lags are significant in determining the value of the KospiMidcap. In what follows, we estimate by OLS the equation linking the Kospi[1] overnight return, KospiMidcap[2] overnight return and the first three minutes returns of KospiMidcap of the trading day following:

$$\underset{t\to t+1}{OR(LK)} = \alpha + \underset{t\to t+1}{OR(LKM)} + \underset{t+1}{IR(LKM)} + \varepsilon$$

Where :

$\underset{t\to t+1}{OR(LK)}$: The Kospi overnight between day t and t+1;

$\underset{t\to t+1}{OR(LKM)}$: The KospiMidcap overnight between day t and t+1;

$\underset{t+1}{IR(LKM)}$: KospiMidcap first three minutes of a day t;

α : is a constant;

ε : is an error.

The estimated over a period of 11/06/2007 to 16/11/2007 (106 observations) gives the following results:

1 $\frac{\text{index returns in day } t+1\,(\text{open}) - \text{index returns in day } t\,(\text{close})}{\text{index returns in day } t\,(\text{close})}$

2 $\frac{\text{index returns in day } t+1\,(\text{at } 9:03) - \text{index returns in day } t+1\,(\text{at } 9:00)}{\text{index returns in day } t+1\,(\text{at } 9:00)}$

TABLE 4: Kospi overnight return regressions

	Coefficients	St. Error	t-statistic
α	0.0000835	0.0000823	10.14638
$OR(LKM)_{t\to t+1}$	-0.098786	0.097459	-1.013619
$IR(LKM)_{t+1}$	1.359517	0.472374	2.878052
R-squared Adjusted R-squared	0.311731 0.307647		

The regression indicates that Kospi overnight return is more correlated with KospiMidcap of three first minutes. The lead-lag effect is attributed to an non-synchronous trading or a delay in price adjustments to the "news". The same conclusion is presented by Lo and Mackinlay (1990). These authors found that portfolios of smaller stocks are characterized by a high level of autocorrelation cannot be explained by a non-synchronous trading alone, and therefore one cannot rule out the presence of actual lead-lag effects running from larger to smaller stocks in addition to non-synchronous trading effects (Camilleri and Green, 2004)

Conclusion

The purpose of this chapter is to study the effect of an non-synchronous trading on the predictability of returns Korea stock exchange via the examination of the lead-lag effect. Three methodologies were adopted on daily and high frequency data of two indices. These are different levels of liquidity based on bid-ask spread. Specifically, in the high-frequency data, the results show that the more liquid index leads the less liquid. Several authors have associated this lead-lag either an asynchronous transaction or delay price adjustments to new information. To show how these two causes of predictability is more relevant in explaining the lead-lag effect, we analyzed the returns during a trading –break period and we got the persistence of lead-lag effect. In this case, such predictability cannot be attributed to delays in price adjustments on the part of investors that during the overnight market participants had sufficient time to adjust their expectations. Therefore, we conclude that the lead-lag effect is mainly caused by an asynchronous transaction and that this predictability will not likely be abnormal profits. In addition, based on previous studies, the asynchronous transaction is not the main cause of predictable returns. Moreover, the fact that stock prices contain predictable components does not necessarily imply that predictability is economically significant and this need not be a symptom of market inefficiency.

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APPENDIX

TABLE 1: OLS estimation of VAR equations (daily data and high frequency data)

OLS estimation of a single equation in the unrestricted VAR

Dependent Variable: LOG Kospi(LK)
Method: Least Squares
Sample(adjusted): 02/01/2004 05/02/2008
Included observations: 1016 after adjusting endpoints

Regressor	Coefficient	Std. Error	t-Statistic	Prob.
Constante	0.0064	0.00247	3.5549	0.0000
LK(-1)	0.0095	0.0316	-0.3009	0.7635
LKM(-1)	-0.0007	0.0309	-0.1704	0.8647

R-squared	0.000131	Mean dependent var	6.37E+09
Adjusted R-squared	-0.001843	S.D. dependent var	2.03E+09
S.E. of regression	2.03E+09	Akaike info criterion	45.70184
Sum squared resid	4.17E+21	Schwarz criterion	45.71638
Log likelihood	2323.53	Durbin-Watson stat	2.001528
Fstas	4.1025[0.035]	System LogLiklihood	4644.090

Diagnostic tests

Test Statistics	LM version	F version
A : Serial Corrélation	5.338193 [0.228]	F(1, 1015)=5.345261 [0.220]
B : Normality	170.062 [0.0000]	Not applicable
C : Heteroscedasticity	33.096964	F(1, 1015)=120.772786 [0.5429]

A : Lagrange Multiplicateur Test of residual serial correlation
B : Based on a test of skewness and kurtosis of fitted values
C: Based on the regression of squared residuals on squared fitted values.

OLS estimation of a single equation in the unrestricted VAR				
Dependent Variable: LOG kospI(LK) Method: Least Squares Sample(adjusted): 21/01/2008 25/01/2008 Included observations: 1859 after adjusting endpoints				
Regressor	Coefficient	Std. Error	t-Statistic	Prob.
Constante	0.3571	0.7862	6.8130	5.3571
LK(-1)	0.0794	0.0386	2.0572	0.0794
LK(-2)	0.0780	0.0386	2.0218	0.0780
LK(-3)	0.0310	0.0386	0.8043	0.0310
LKM(-1)	0.0341	0.5229	0.0653	0.0341
LKM(-2)	0.0170	0.6393	0.0267	0.0170
LKM(-3)	0.0341	0.5229	0.0653	0.9479
R-squared	0.0173	Mean dependent var		740.92
Adjusted R-squared	0.0085	S.D. dependent var		1.0147
S.E. of regression	1.0104	Akaike info criterion		286.89
Sum squared resid	685.08	Schwarz criterion		291.55
Log likelihood	965.56	Durbin-Watson stat		2.0009
Fstas	19.715 [0.000]	System LogLiklihood		4644.090
Diagnostic tests				
Test Statistics	LM version		F version	
A : Serial Corrélation	3.2145 [0.311]		F(1, 1850)=3.5371[0.060]	
B : Normality	566.01[0.0000]		Not applicable	
C : Heteroscedasticity	520.08[0.000]		F(1, 1850)=853.1230 [0.000]	
A : Lagrange Multiplicateur Test of residual serial correlation B : Based on a test of skewness and kurtosis of fitted values C: Based on the regression of squared residuals on squared fitted values.				

OLS estimation of a single equation in the unrestricted VAR				
Dependent Variable: LOG kospi Midcap(LKM) Method: Least Squares Sample(adjusted): 02/01/2004 05/02/2008 Included observations: 1016 after adjusting endpoints				
Regressor	Coefficient	Std. Error	t-Statistic	Prob.
Constante	0.00637	0.00280	2.275409	0.0000
LK(-1)	-0.00660	0.03227	-0.206138	0.8367
LKM(-1)	0.0175	0.03162	0.555299	0.5788
R-squared	0.0003	Mean dependent var		6.44E+09
Adjusted R-squared	0.0016	S.D. dependent var		2.07E+09
S.E. of regression	2.07E+09	Akaike info criterion		45.742
Sum squared resid	4.34E+21	Schwarz criterion		45.756
Log likelihood	2323.405	Durbin-Watson stat		1.9918
Fstas	15.258[0.000]	System LogLiklihood		4644.090
Diagnostic tests				
Test Statistics	LM version		F version	
A : Serial Corrélation	6.5132 [0.2612]		F(1, 1015)=6.5132 [0.2594]	
B : Normality	351.1496 [0.0000]		Not applicable	
C : Heteroscedasticity	75.83201 [0.0000]		F(1, 1015)=58.4308 [0.0000]	
A : Lagrange Multiplicateur Test of residual serial correlation B : Based on a test of skewness and kurtosis of fitted values C: Based on the regression of squared residuals on squared fitted values.				

OLS estimation of a single equation in the unrestricted VAR				
Dependent Variable: LOG Kospi Midcap(LKM) Method: Least Squares Sample(adjusted): 21/01/2008 25/01/2008 Included observations: 1859 after adjusting endpoints				
Regressor	Coefficient	Std. Error	t-Statistic	Prob.
Constante	5.5393	5.4784	1.0111	0.3123
LK(-1)	0.0001	0.0026	0.0469	0.0266
LK(-2)	0.0001	0.0026	0.0457	0.0369
LK(-3)	0.0001	0.0026	0.0446	0.0444
LKM(-1)	0.6636	0.0364	18.212	0.0000
LKM(-2)	-0.0015	0.0445	-0.0340	0.9728
LKM(-3)	0.3302	0.0364	9.0646	0.0000
R-squared	0.9751	Mean dependent var		766.274
Adjusted R-squared	0.9749	S.D. dependent var		0.4450
S.E. of regression	0.0704	Akaike info criterion		245.89
Sum squared resid	3.3257	Schwarz criterion		241.226
Log likelihood	840.57	Durbin-Watson stat		1.93228
Fstas	43.96304 [0.000]	System LogLiklihood		4644.090
Diagnostic tests				

Test Statistics	LM version	F version
A : Serial Corrélation	5.400 [0.4626]	F(1, 1850)=2.8519 [0.019]
B : Normality	572.057[0.0000]	Not applicable
C : Heteroscedasticity	99.2016[0.0000]	F(1, 1850)=99.368[0.0000]

A : Lagrange Multiplicateur Test of residual serial correlation
B : Based on a test of skewness and kurtosis of fitted values
C: Based on the regression of squared residuals on squared fitted values.