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The Lead-Lag Effect on the Predictability of Returns: The Case of Taiwan Market

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The Lead-Lag Effect on the Predictability of Returns: The Case of Taiwan Market

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I. Introduction

The lead lag effect according to Tonin et al. (2013) is perceived when there is a relationship between the price movements of two distinct markets, when one of them leads and the other follows with some lag time when this effect is identified, there is a rupture of the Efficient Market Hypothesis (EMH) in consequent the predictability of returns.

Several studies have investigated the lead-lag effect on the predictability i.e. Lo and Mackinlay (1990), Camillerie and Green (2004). All the studies conclude that the predictability is attributed to the lead-lag effect. Thus, study aims to examine the lead-lag effect and its impact on predictability of returns of Taiwan stock market. To this end, this paper is organized as follow: in the first section, we go through a literature review of the lead-lag effect. In the second section, we presented the data and methodologies. The empirical results are summarized in the third section.

II. Literature Review

Camilleri and Green (2004) examined the lead-lag effect 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 lead-lag effect appears to be the main source of the predictability of returns.

Oliveira et al. (2009) examined the existence of lead-lag effects between U.S stock market (NYSE) and the Brazilian stock market (Bovespa). They concluded that the price movement in the NYSE is followed by similar movements in Bovespa which would enable predicting stock prices in the Brazilian market, thus providing arbitrage opportunities.

The aim study of Tonin et al. (2013) is to examine the lead lag effect between the stock market of the BRIC member countries from March 2009 until to March 2013. The result emphasizes that the Brazilian market leading others stock exchange analyzed in periods before and after the financial crises.

TSE (1995) examined the lead-lag relationship between the Nikkei spot and futures contract about Nikkei index and found that lagged changes in futures prices cause adjustments in the spot price, in the short run, but the reserve is not true.

Meric et al. (2008), study the co movement and causality to markets in the United States, United Kingdom and six asian markets. The authors used the technique of Principal Analysis to determine if the standards of co movement of the markets of USA, UK, AUSTRALIA, CHINA, RUSSIA, INDIA, JAPAN and SOUTH KOREA have changed with periods before and after September 11th, 2001.

Pena, Guelman and Rabelo (2010) analysed the relationship of Dow Jones index and the Nikkei-225 index with the Bovespa index with daily data of the variation of three indexes in the period of January 2006 to May 2008. The results identified contemporary relations between Dow Jones and Bovespa indexes. The authors also indicate the possibility of lag in the relationship between Bovespa and Nikkei 225 indexes.

Nakamura (2009) shows the existence of lead-lag effect between the equity markets and the integration of the Brazilian stock market and their deposits in the American depositary receipt (ADR s).

Mulliaris and Urratia (1992) shows that the lead-lag effect for six major stock market indexes, comaparing these indices between the periods before and after the crises of 1987 submitted significant changes between those periods.

III. Data and Methodology

The analysis of the lead-lag effect on the predictability of returns is applied on the daily and high frequency data of Taiwan stock exchange. The daily set constitutes of the closing observations of the TSEC (Taiwan stock exchange corporate) and the TSEC Midcap. The main and the less liquid index respectively. The daily data period ranges from 30/04/2002 to 05/04/2012.the high frequency data included the value of both indices and the study period lasts between 03/03/2012 to 07/03/2012. We begin first by the unit root test (ADF). Subsequently, we will analyze the lead-lag effect on the predictability of return using three

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methodologies VAR, Granger Causality test and Impulse-Response function. In what follows we present these different methodologies.

a) 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.

a) 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:

$\delta,$ 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.

IV. Empirical Results

This section reports the results of the analysis of a lead-lag effect on the predictability of returns of Taiwan stock market. In both cases daily data and high frequency, the ADF test results show that the two indices are no stationary 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 TSEC (LT) and TSEC Midcap (LTM) 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.

According to both AIC and SC criteria we obtain a VAR (1) for the logarithmic daily and high frequency series of indices LT and LTM. Estimation of ndividual equations of the VAR systems are 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. But in the the case of the high frequency data, we find that the coefficient that are significant indicating a led-lag effect and delayed returns of LTM can explain returns of the dependant variable LT.

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 and high frequency data are given in Table 2.

Table 2 : Granger-Causlity Test

Daily data

Null Hypothesis		F-Statistic	Probability
LTM does not Granger Cause LT		0.42530	0.51441
LT does not Granger Cause LTM		1.32350	0.25015
VAR Pairwise Granger Causality			
Dependent variable: LT			
Exclude	Chi-sq	Degrees of Freedom	Prob.
LTM	0.425301	1	0.5143
All	0.425301	1	0.5143
Dependent variable: LTM			
Exclude	Chi-sq	Degrees of Freedom	Prob.
LT	1.323501	1	0.2500
All	1.323501	1	0.2500

High frequency data

Null Hypothesis		F-Statistic	Probability
LTM does not Granger Cause LT		1.07610	0.29976
LT does not Granger Cause LTM		0.49364	0.48243
VAR Pairwise Granger Causality			
Dependent variable: LT			
Exclude	Chi-sq	Degrees of Freedom	Prob.
LTM	1.076101	1	0.29971
All	1.076101	1	0.29971
Dependent variable: LTM			
Exclude	Chi-sq	Degrees of Freedom	Prob.
LT	0.493649	1	0.48248
All	0.493649	1	0.48248

The null hypothesis hypothesis that LTM does not cause LT is accepted when the probability associated is greater than the usual statistical threshold of 5%. Similarly, the null hypothesis that LT does not cause LTM is accepted threshold of5%. These different VAR performed in this section confirm the evidence of a relationship and the TSEC index generate TSEC Midcap in case of 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:

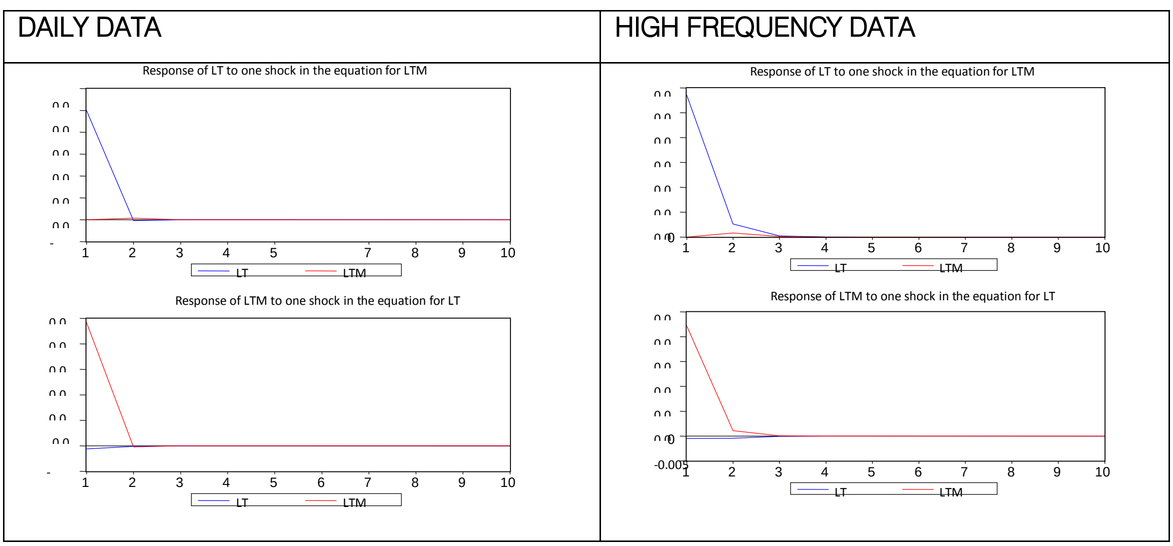

Figure 1 : Impulse-Response Function

If data is daily, a TSEC shock had a higher impact on the TSEC Midcap index. For the case of one-minute frequency, a TSEC shock generates a higher impact on the TSEC Midcap index. This is attributed to a lead-lag relationship.

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 LT for about 99.97% to its own innovations and to 0.02% with those of LTM. The variance of the forecast error is due to LTM 0.067% to the innovations of LT and 99.93% to its own innovations. We can deduce that the impact of a LT shock on LTM is important but there is almost lower than the impact of a LTM shock on LT. For the case of high frequency data: The variance of the forecast error of LT is due to 8% of LTM innovations while that of LKM 75.09% is due to innovations LT. So the impact of a LT shock on LTM is more important than the impact of a LTM shock on LT:

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

Données journalières

Variance Decomposition of LT:			
Period	S.E.	LT	LTM
1	2.50E-09	100.0000	0.000000
2	2.50E-09	99.97866	0.021340
3	2.50E-09	99.97865	0.021345
4	2.50E-09	99.97865	0.021345
5	2.50E-09	99.97865	0.021345
6	2.50E-09	99.97865	0.021345
7	2.50E-09	99.97865	0.021345
8	2.50E-09	99.97865	0.021345
9	2.50E-09	99.97865	0.021345
10	2.50E-09	99.97865	0.021345
Variance Decomposition of LTM:			
Period	S.E.	LT	LTM
1	2.42E-09	0.065231	99.93477
2	2.42E-09	0.067311	99.93269
3	2.42E-09	0.067312	99.93269
4	2.42E-09	0.067312	99.93269
5	2.42E-09	0.067312	99.93269
6	2.42E-09	0.067312	99.93269
7	2.42E-09	0.067312	99.93269
8	2.42E-09	0.067312	99.93269
9	2.42E-09	0.067312	99.93269
10	2.42E-09	0.067312	99.93269
Ordering: LT LTM			

Intervalle d'une minute

Variance Decomposition of LT:			
Period	S.E.	LT	LTM
1	0.054759	100.0000	0.000000
2	0.067947	99.92130	0.078704
3	0.068060	99.91973	0.080267
4	0.068061	99.91972	0.080284
5	0.068061	99.91972	0.080284
6	0.068061	99.91972	0.080284
7	0.068061	99.91972	0.080284
8	0.068061	99.91972	0.080284
9	0.068061	99.91972	0.080284
10	0.068061	99.91972	0.080284
Variance Decomposition of LTM:			
Period	S.E.	LT	LTM
1	0.016367	24.50274	75.04973
2	0.019423	24.90636	75.05936
3	0.019435	24.91379	75.07862
4	0.019435	24.91387	75.08861
5	0.019435	24.91387	75.08861
6	0.019435	24.91387	75.08861
7	0.019435	24.91387	75.08861
8	0.019435	24.91387	75.08861
9	0.019435	24.91387	75.08861
10	0.019435	24.91387	75.08861
Ordering: LT LTM			

These results concluded that the predictability of LTM index by LT returns. These results are consistent with those shown by the impulse response function. In these studies, we can conclude that the lead-lag effect can generate a predictability of returns of the two indices of Taiwan stock exchange in the case of frequency data.

V. Conclusion

The purpose of this chapter is to study the impact of the lead-lag on the predictability of returns Taiwan stock exchange via the examination of 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. In the conclusion the lead-lag effect cause the predictability returns on the Taiwan stock exchange.

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 TSEC(LT) Method: Least Squares Sample(adjusted): 30/04/2002 12/03/2008 Included observations: 1452 after adjusting endpoints				
Regressor	Coefficient	Std. Error	t-Statistic	Prob.
Constante	0.00746	0.00304	24.5594	0.0000
LT (-1)	0.0151	0.0271	0.5561	0.5782
LTM(-1)	-0.00692	0.0263	-0.2630	0.7926
R-squared	0.000266	Mean dependent var		7.9200
Adjusted R-squared	-0.001114	S.D. dependent var		2.50E+09
S.E. of regression	2.50E+09	Akaike info criterion		46.12207
Sum squared resid	9.08E+21	Schwarz criterion		46.13298
Log likelihood	3348.162	Durbin-Watson stat		1.997158
Fstas	0.192[0.0245]	System LogLiklihood		6691.312
Diagnostic tests				
Test Statistics	LM version		F version	
A : Serial Corrélation	6..1997 [0.0450]		F(1, 1451)=3.1024 [0.0452]	
B : Normality	6.40340[0.0000]		Not applicable	
C : Heteroscedasticity	77.30856[0.12045]		F(1, 1451)=51.8300 [0.1205]	
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.				

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