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Intraday Lead-Lag Relationship between Index Futures and Stock Index Markets: Evidence from Malaysia

Jude W. Taunson, Mohd. Fahmi Bin Ghazali, Minah Japang and Abd. Kamal Bin Char
Universiti Malaysia Sabah, Sabah, Malaysia

This paper investigates the lead-lag relationship between the stock index futures (known as FKLI) and its underlying index, the Kuala Lumpur Composite Index (KLCI) in the emerging Malaysian market. Using 15-second interval data, cross-correlation, and the partial adjustment model, we find a bi-directional asymmetric lead-lag relationship and that the KLCI's lead over FKLI is much stronger. The evidence also suggests that the KLCI returns over-react to information, more so once thin trading effects are considered. Overall, the evidences suggest that traders prefer to exploit stock specific information in the underlying market despite the advantages of trading the index futures.

Keywords: lead-lag relations, index futures, emerging market

Introduction

Futures market functions as a price discovery tool. That is, market participants use futures market to find the equilibrium price because new information may get incorporated into futures market more quickly than the underlying market. Factors such as lower trading cost, higher liquidity, and the absence of short-selling restriction may cause futures to adjust to equilibrium level ahead of the underlying (Chu, Hsieh, & Tse, 1999). If this is the case, market participants then are able to use futures prices in predicting the underlying prices and consequently assist them in their financial decision-making.

The extant literatures suggest that futures markets lead the underlying market. That is, price discovery occurs predominantly in futures markets (Brooks, Rew, & Ritson, 2001; Kawaller, P. D. Koch, & T. W. Koch, 1987; Tse, 1995). However, this may not always be the case, for example, Pizzi, Economopoulos, & ONeill (1998), find that both the stock index and index futures contribute to price discovery. While, Judge and Reancharoen, (2014), find that the SET50 index has a uni-directional lead over futures.

This study investigates the lead-lag relationship between the stock index futures (FKLI) and its underlying, the Kuala Lumpur Composite Index (KLCI). To the best of our knowledge, this is the first study that uses intraday data in investigating the price discovery role of the FKLI. More precise conclusion can be derived from using high frequency data (Liu, 2009). Further, we use most recent data, from 2nd January 2018 to 21st February 2018. This study, therefore, attempts to contribute and enrich the existing literature by investigating the case of Malaysia.

Jude W. Taunson, Ph.D., Labuan Faculty of International Finance, Universiti Malaysia Sabah, Sabah, Malaysia.
Mohd. Fahmi Bin Ghazali, Ph.D., Labuan Faculty of International Finance, Universiti Malaysia Sabah, Sabah, Malaysia.
Minah Japang, M.Sc., Labuan Faculty of International Finance, Universiti Malaysia Sabah, Sabah, Malaysia.
Abd. Kamal Char, MBA, Labuan Faculty of International Finance, Universiti Malaysia Sabah, Malaysia.

The remainder of the paper is presented as follows: The next section presents the literature review; Section three explains the data and methodology used; Section four discusses the results and finally; and Section five concludes the paper.

Theory and Literature Review

In an efficient and frictionless market, both futures and spot markets should simultaneously and instantaneously absorb new information. That is, futures and spot returns should not be cross-autocorrelated and that the concurrent returns should be perfectly positively correlated.

The extant literature, however, suggests that there exists a lead-lag relationship between futures markets and their underlying markets. Specifically, futures returns and spot returns are imperfectly, albeit strongly, concurrently correlated. Stoll and Whaley (1990), Kutner and Sweeney (1991), and Ghosh (1993) find that the S&P 500 index futures lead the spot index. Chan (1992) and Zhong, Darrat, and Otero (2004) find similar evidence for the Major Market Index (MMI) futures and *Indices de Precios y Cotizaciones* (IPC) futures, respectively. These studies suggest that index futures lead the stock index in price discovery.

Indeed, price discovery may occur in both markets. Pizzi et al. (1998), for example, find both the stock index and index futures contribute to price discovery. Specifically, they find that the S&P500 index futures lead by eleven (11) minutes, while the stock index leads the futures by two (2) minutes. In other words, although futures' contributions are dominant, both futures and spot markets contribute to price discovery. Similar findings are observed in the Share Price Index (SPI) futures market (Frino & West, 1999) and the Hang Seng Index (HSI) (Chiang & Fong, 2001). That is, a bi-directional asymmetrical lead-lag relationship exists between futures and spot.

Other studies find stronger lead of stock index overs index futures (Wahab & Lashgari, 1993). Judge and Reancharoen (2014) find the SET50 stock index has a uni-directional lead over futures because of the higher trading volume[1]. Thus, in this case, the futures market does not function as a price discovery tool as it supposed to given its distinctive market design.

Regardless of the above, there are several reasons as to why price discovery should occur dominantly in futures market as outlined by Chu et al. (1999). First, futures are high leverage instrument. With minimum initial outlay, traders have the same exposure as in trading the underlying instrument. In other words, futures market may provide higher return on investment. Second, it is more feasible to execute information in futures market due to no short selling restriction, especially for bearish information[2]. Further, even if the constituent stock is not subjected to the restriction, selling short is constrained by the uptick rule, which stipulates that short sale be implemented only in rising market, i.e., when the last recorded stock price change is positive. Third, the cost of trading index futures is much lower in comparison to trading all the constituent stocks. Finally, informed traders may prefer to exploit market-wide information in futures market because it is a tradeable instrument. In short, the above inherent advantages of trading futures explain why futures are expected to lead spot in price discovery.

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[1] The average number of contracts traded in the Thailand is 45,000, while trading volume in the underlying ranges from one billion to six billion shares.

[2] In September 1996, Regulated Short Selling (RSS) was introduced in Bursa Malaysia. Following the Asian currency RSS was suspended but reinstated in January 2007 for select few stocks.

In Malaysian context, Tan (2002) and Pok (2007) investigate the impact of the imposition of selective capital control on the lead-lag relationship between the FKLI and the KLCI. Tan (2002) find the FKLI leads the KLCI in the long run and a bi-directional short-run causality for periods before and after the implementation of selective capital controls. Pok (2007) find that the lead of FKLI over KLCI intensifies due to withdrawal of foreign institutional investors. This implies higher magnitude of deviation from the cost of carry relationships. Although higher "lead-lag gap" between these two markets is favorable to arbitrageurs, the role of the FKLI as a price discovery (and hedging) instrument may be adversely affected.

This paper attempts to investigate the lead-lag relationship between the FKLI index futures and KLCI. In doing so, we contribute and enrich the existing literatures by investigating the case of Malaysia. It is worth noting that the lead-lag relationship between stock index and index futures is a dynamic process. We believe that the relationship between the FKLI and KLCI has changed over time due to maturation effects (Stoll & Whaley, 1990). This may be true because numerous initiatives[3] have been taken by the Malaysian authority, since the 1997/1998 financial crisis, to enable price discovery (and promote liquidity) in the capital markets.

Using most recent high frequency data, cross-correlation function and several speed of adjustment factors, we find that, both markets contribute to price discovery, however, KLCI's lead over FKLI is much stronger. In other words, KLCI reverts to equilibrium price at a greater speed in comparison to FKLI. Further, the KLCI seems to over-react to information, more so once thin trading effects are considered. Overall, the evidences suggest that traders are actively or prefer to exploit stock specific information in the underlying market despite the advantages of trading the index futures (Frino, Walter and West, 2000).

Data and Methodology

Data

The KLCI was first launched in Malaysia on 4 April 1986. The index is calculated in real-time for every 15 seconds and serves as an indicator for the stock market as it tracks the performance of thirty constituent stocks with the largest market capitalization. Its futures contract, known as FKLI, was first traded on the 15 December 1995 and derived its value from the KLCI. Since its inception, the FKLI grows steadily both in terms of trading volume and open interest due to its importance as a price discovery (and hedging) tool.

The data used in this study were obtained from the BursaStation Professional[4]. We have intraday transactions prices for the FKLI index futures[5], and intraday data on the KLCI stock index prices from 2nd January to 21st February 2018. We choose this time-frame so as to provide recent assessment of the lead-lag relationship between the FKLI index futures and KLCI index. The first 15 minutes and last 30 minutes observations for the FKLI index futures were removed. This is done to account for trading hour differential between these two markets[6]. Similarly, observations from 1230hrs to 1245hrs for the FKLI index futures were also removed given that the KLCI stock index ceases trading at 1230hrs for the morning session. Both markets reopen for business at 1430hrs for the afternoon session.

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[3] Interested readers may refer to the Capital Market Masterplan 1 and 2 for list of the initiatives.
[4] BursaStation Professional is a state-of-the-art Stock Market Tracker/Charting Software. It is a user-friendly yet full of powerful features that enable instant access to fundamental, technical, and trading data, via the internet, anywhere, anytime.
[5] We use the nearby futures contract as it is usually the most actively traded.
[6] The underlying market opens for business from 0900hrs to 1700hrs. While the futures market opens 15 minutes early and closes at 1730hrs.

The KLCI index is calculated every 15 seconds, however, the FKLI index futures prices are not equally spaced through time. We address this problem by first identifying transactions that occur at the same time (matched transactions). Next, the nearest 15 second transactions are used. In the event that there are two trades that are nearest to the 15 second observations, transactions that occur before the nearest 15 second is used. For example, suppose there are two transaction prices for the FKLI at the 09:01:14hrs and 09:01:16hrs, in this case, the former observation is used. The KLCI and FKLI prices are as plotted in Figure 1. There are 49,028 15-second observations altogether. Time series of continuously compounded returns were calculated from the prices of the FKLI and the KLCI as given by $f_t = 100*[\ln((f_t)/(f_{t-1}))]$ and $s_t = 100*[\ln((s_t)/(s_{t-1}))]$, respectively. Descriptive statistics for f_t and s_t are shown in Table 1.

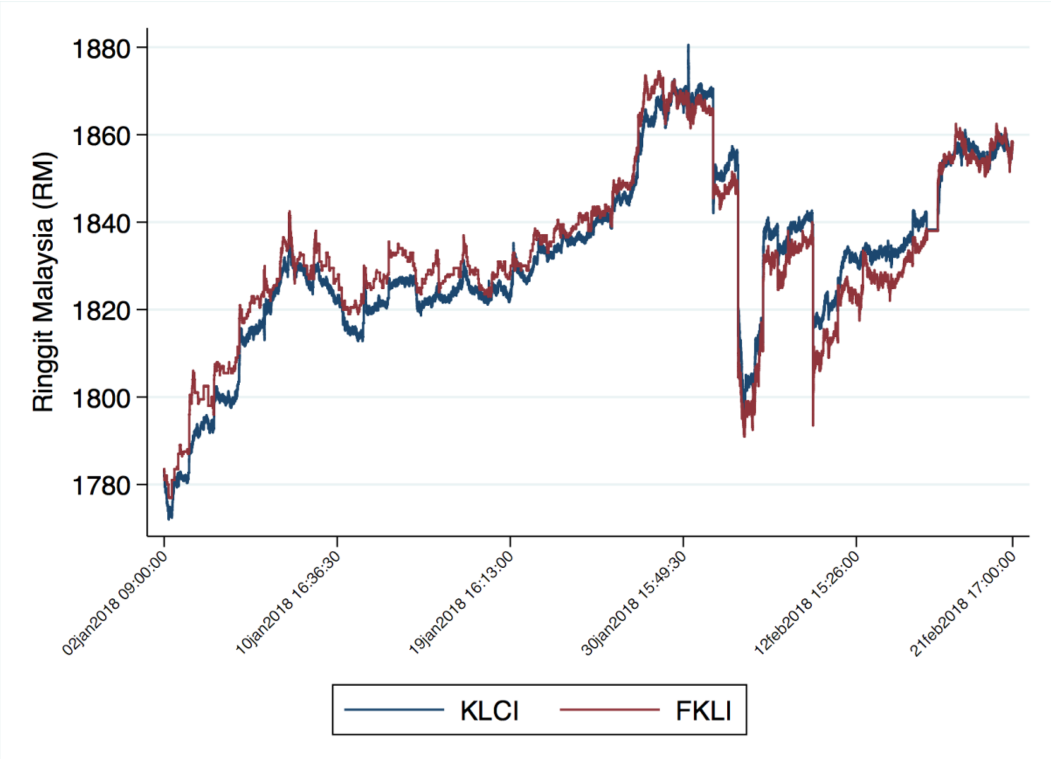

Figure 1. Movements of the KLCI stock index and the FKLI index futures at 15-second interval during 2nd January 2018 to 21st February 2018

Methodology

Cross-correlations. We examine the lead-lag relationship between FKLI and KLCI returns using the cross-correlation function as follows:

$$\rho_{f_t s_t}(k) = \frac{E\{(f_t - \mu_{f_t})(s_{t+k} - \mu_{s_t})\}}{\sigma_{f_t}\sigma_{s_t}} \tag{1}$$

where f_t and s_t represent the KLCI and FKLI returns, respectively; k represents the number of leading or lagging periods. Positive values for the coefficients at leads $k > 0$ (at lags $k < 0$) indicates that the FKLI (KLCI) returns tend to lead KLCI (FKLI); $k = 0$ measures the strength of the concurrent relationship.

Partial adjustment delays. In addition to the cross-correlation function, we also employ the partial adjustment model of Amihud and Mendelson (1987). One advantage of the model is that it provides a readily interpretable measure of the magnitude of the differential price movement and is given by:

$$P(i,t)-P(i,t-1)=g(i)\left\{V(i,t)-P(i,t-1)\right\}+u(i,t) \tag{2}$$

Where $P(i, t)$ is the price for the instrument i at time t[7], which adjusts partially to the intrinsic value, $V(i, t)$ assumed to follow a logarithmic random walk with drift process (Amihud & Mendelson, 1987), that is:

$$V(i,t)=\mu+V(i,t-1)+\upsilon(i,t) \tag{3}$$

$v(i, t)$ is the noise process and $v(i, t)$ is *i.i.d.* with zero mean and represents innovations in the true pricing process; $g(i)$ is the speed of the adjustment factor, which measures the speed at which observed price reverts to its intrinsic price. The observed price is assumed to partially absorb information, while the intrinsic value is assumed to fully absorb information. Thus, $g(i) = 1$ represents full adjustment towards intrinsic price, whereas $g(i) < 1$ and $g(i) > 1$ correspond to under-adjustment and over-adjustment towards intrinsic price, respectively.

Cross-covariance ratio. Theobald and Yallup(1998) proposed the following cross-covariance ratio which is based on the partial adjustment model. The speed of adjustment factors for futures, $g(f)$ and spot, $g(s)$ are respectively given by:

$$1-g(f)=\mathrm{cov}[R(f,t),R(s,t-1)]\{\mathrm{cov}[R(f,t),R(s,t)]\}^{-1} \tag{4}$$

and

$$1-g(s)=\mathrm{cov}[R(f,t-1),R(s,t)]\{\mathrm{cov}[R(f,t),R(s,t)]\}^{-1} \tag{5}$$

Thin trading effect in the underlying index is model as:

$$R(m,s,t)=\sum_{i=0}\theta(i)R(s,t-i)+\upsilon(m,s,t) \tag{6}$$

where m indicates returns that is subject to thin trading, $\theta(i)$ variables such that when $\theta(o)$ equal one there is no thin trading and $\upsilon(m,s,t)$ is a noise term, then:

$$\begin{aligned}\mathrm{cov}\{R(f,t-1),R(m,s,t)\}&=\{(\theta(0)(1-g(s))+\theta(1)\}\,\mathrm{cov}\{R(f,t),R(s,t)\}\\&=\{1-\theta(0)g(s)\}\,\mathrm{cov}\{R(f,t),R(s,t)\}\end{aligned} \tag{7}$$

The thin trading parameter $\theta(i)$ is given by:

$$\theta(o)=\frac{\{\mathrm{cov}(f(t),s(t))\}-\{\mathrm{cov}(f(t-1),s(t)}{g(s)\{\mathrm{cov}(f(t),s(t)\}} \tag{8}$$

The ARMA estimators. Theobald and Yallup (2004) proposed time series estimators by first differencing and rearranging Eq.(2) as follows:

$$R(i,t)=(1-g(i))R(i,t-1)+g(i)\Delta V(i,t)+\Delta u(i,t) \tag{9}$$

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[7] i represents either futures or spot prices.

and by substituting for $\Delta V(i,t)$ from Eq.(3), Eq.(9) becomes:

$$R(i,t) = g(i)\mu + (1-g(i))R(i,t-1) + g(i)e(i,t) + u(i,t) - u(t-1) \tag{10}$$

The speed of adjustment estimates are given by the AR(1) coefficient. When $g(i) = 1$, the process will be an MA(1) process. That is, return process is driven by bid-ask bounce effects. When bid-ask bounces effect is assumed to be non-existent, the speed of adjustment factor is given by ARMA(1, 1). Further, when non-synchronicities are present Eq.(10) modifies to:

$$\begin{aligned} R(i,m,t) = g(i)\mu + (1-g(i))R(i,m,t-1) + \sum_{j=0}^{q} w(j)L^{j}\{g(i)e(t-j) \\ +u(t-j) - u(t-1-j)\} + (1-(1-g(i)L)R(t) \end{aligned} \tag{11}$$

Thin trading effect is captured by the moving average component which is determined by the Aikaiki Information Criterion (AIC). Similarly, the autoregressive coefficient provides an estimator for the speed of adjustment, i.e., $1 - g(i)$.

Empirical Results

Descriptive Statistics

Table 1 presents the descriptive statistics of both futures returns (f_t) and spot returns (s_t) for the entire sample period, from 2nd January 2018 to 21st February 2018. The spot and futures returns are identical. However, the spot returns are more volatile. This indicates that, during the sample period considered, the spot is more responsive to information. Both returns series exhibit significant first order autocorrelation. Bid-ask bounce effect (non-synchronous effect) induces negative (positive) autocorrelation in the futures (spot) return series. In addition, both returns series are negatively skewed. The Augmented-Dickey-Fuller test indicates that both series are stationary.

Table 1

Descriptive Statistics of Spot and Futures Indices Returns[a]

	s_t	f_t
T	49027	49027
Mean	0.0000841	0.000084
Minimum	-2.107229	-2.23242
Maximum	0.8055981	0.8524732
σ	0.0218685	0.0206733
Skewness	-31.42022	-41.37742
Kurtosis	2923.375	4689.984
Jarque-Bera	1.743e+10 (0.0000)	4.489e+10 (0.0000)
ρ_1	-0.1180 (0.0000)	-0.0246 (0.0000)
Q(48)	825.7499 (0.0000)	130.50651 (0.0000)
$Q^2(48)$	6.8622 (1.0000)	0.6371 (1.0000)
ADF	-249.283 (0.0000)	-226.932 (0.0000)

Notes. [a] The sample period is from 2nd January to 21st February 2018. T is the sample size; σ is the sample standard deviation; ρ_1 is the first-order autocorrelation coefficient; Q(48) is the Ljung-Box (1978) portmanteau test for the first 48 lags of the autocorrelation function; $Q^2(48)$ is the corresponding statistic for the squared data; ADF is the Augmented-Dickey Fuller test for stationarity; and JB is Jarque-Bera test of normality. p-values are in the parentheses.

Cross-Correlations

Table 2 shows the concurrent, five-period lagging, and leading return cross-correlations between FKLI and KLCI returns. The concurrent cross-correlations (0.4876) are relatively high which suggest that both react to the same underlying information. The result suggests that the KLCI leads the FKLI more strongly than lagging it, although both markets contribute to price discovery. This finding is in contrast to previous studies in Malaysia. For example, Pok (2007) found that the FKLI's lead over KLCI increases after the imposition of selective capital controls in 1998, due to foreign investors withdrawal from the markets. The frequency of our data and the sample period considered may explain our finding. Further, as we noted earlier, the lead-lag relationship between FKLI and KLCI is a dynamic process.

Table 2

Cross-Correlation Structures Between Futures and Spot Returns[a]

Lag	Cross-correlations
-5	0.0074
-4	0.0294
-3	0.0201*
-2	0.0254
-1	0.0326
0	0.4876*
1	0.0066*
2	0.0080
3	0.0025*
4	-0.0108*
5	0.0140

Notes. [a] The sample period from 2nd January to 21st February 2018; * Significantly different from zero at 5% level.

Speed of Adjustment Estimates

We examine the speed of adjustment of the FKLI and the KLCI returns towards their intrinsic prices. The objective is to assess how responsive these markets towards new information. There are four speeds of adjustment estimators: (i) the co-variance ratio; (ii) AR(1); (iii) ARMA(1,1); and (iv) ARMA (1, *X*), as discussed in the literature section of this paper. These are shown in Table 3.

Table 3

Estimates of Adjustment Speeds and Underlying Process[a]

	Cross-covariance ratio	AR(1)	ARMA(1, 1)	ARMA(1, X)[b]
$g(f)$	0.9332	1.0246*	0.8215*	1.0246*
$g(s)$	0.9864	1.1180*	0.7839	1.2643*

Notes. [a] The sample period is from 2nd January 2018 to 21st February 2018. [b] The optimal MA components are determined by the Akaike Information Criterion (AIC). * Statistically significantly different from one at the 5% significance level. Equivalently $1 - g(i)$ is significantly different from zero at 5% level.

The partial adjustment factor for the KLCI, $g(s)$ is significantly higher than for the FKLI, $g(f)$ (except for the ARMA(1, 1) specification). This implies that, in general, the KLCI reverts to equilibrium level at a greater speed. This finding is not altered even after controlling for bid-ask bounce and thin trading effects. In fact, it is interesting to note that the KLCI reverts to equilibrium level at a greater speed once thin trading effects are taken into account (refer to fifth column in Table 3). Given that thin trading is not applicable for the futures market, the ARMA(1, *X*) estimates of speed of adjustment factors for the FKLI is similar to those of the ARMA (1, 1) specification. The evidence also suggests that the KLCI over-adjusts towards intrinsic price. Overall, our results suggest that the underlying stock index is more responsive to information, as opposed to its index futures contract.

Conclusion

We have examined the lead-lag relationship between Kuala Lumpur Composite Index (KLCI) and its associated index futures contract, FKLI. Specifically, we investigate the lead-lag relationship between FKLI and KLCI and the speed at which both KLCI and FKLI revert to equilibrium level. Using 15-second interval data, from 2nd January 2018 to 21st February 2018, cross-correlation and several speeds of adjustment measures, we find that, although both markets contribute to price discovery, the KLCI's lead over FKLI is much stronger. In other words, there's a bi-directional asymmetrical lead-lag relationship between FKLI and KLCI. The evidences also suggest that the KLCI reverts to equilibrium level at a greater speed compared to the FKLI. Further, the KLCI seems to over-react to information, more so once thin trading effects are taken into account. Our finding is in contrast to previous studies in emerging Malaysian market, perhaps this may be due to data frequency, sample period considered, and the dynamic nature of price movements. More importantly, it is likely that stock specific information may be incorporated first in the underlying index, while market wide information in the index futures (Frino et al., 2000). Thus, traders in using the FKLI as a price discovery tool must consider information from the underlying market to arrive at the equilibrium price.

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