Intertemporal price discovery between stock index futures and spot markets: New evidence from high-frequency data

Imtiaz Mohammad Sifat | Azhar Mohamad | Kevin Reinaldo Amin

Department of Economics and Finance, Sunway University, Malaysia
Department of Finance, International Islamic University Malaysia
Kulliyyah of Economics and Management Sciences, Malaysia
Email: dr.azharmohamad.asia

Abstract
This article utilizes high-frequency 15-s intraday data from September 2017 through to August 2018 to investigate price leadership dynamics between stock index futures (FKLI) and spot (KLCI) markets in Malaysia. Harnessing the explanatory powers of Wavelet analysis, we employ Maximal Overlap Discrete Wavelet Transform to evaluate interdependence between contemporaneous futures and spot returns. We observe that price discovery between futures and spot markets at granular level is a scale-dependent phenomenon. Moreover, we record a counter-intuitive but not unprecedented evidence of futures market lagging the spot market in price formation. This discrepancy approaches convergence in 1–8 min. Our findings constitute evidence against the efficient market hypothesis and hint at opportunities for statistical arbitrage by high-frequency trading. The results from time-frequency domain receive strong support from vector error correction robustness checks, though corroborations is less conclusive from DCC-GARCH and Baba, Engle, Kraft, and Kroner-GARCH results.

Keywords
high-frequency data, KLCI, price discovery, stock index futures, wavelet

JEL Classification
C58; G13

1 Introduction
Inter-temporal price discovery between futures and spot markets has been a topic of interest to researchers, practitioners, and regulators since the 1980s, leading to an impressive number of empirical investigations well into 1990s. Since then academic interest waned; arguably for two reasons: (a) results of futures-spot empirical amounted to a foregone conclusion with little theoretical incentive for further development and (b) the topic was overshadowed (if not subsumed) by the broader market efficiency debate. As a result, empiric attention became confined largely to traders intent on exploiting pricing inefficiency for profit. Since the new millennium, however, greater financial inclusion, technological progress, and easier access to information led to record levels of market participation in various asset classes and venues. All this resulted in exchanges producing voluminous data-sets, which researchers are now able to access and process thanks to greater CPU power and sophisticated statistical tools. Thus, the topic of price discovery between different assets, asset classes, and markets is presently undergoing a resurgence.

Prevalent empiric literature imputes several rationales for futures leading the spot and vice versa. Firstly, asymmetric sentiment has been offered as an explanation...
by Lin, Chou, and Wang (2018), who show that in high volatility periods investors exhibit preference for futures due to potential for gain. In this environment, information flows from futures to spot. Secondly, liquidity differentials could explain investors’ proclivity to engage more in one particular market (Chan & Pinder, 2000). Thirdly, in event-laden situations, some stocks may provoke higher response from traders. Since an index’s value is derived from individual assets, overreaction in particular stocks initially impacts that stock’s price, which then spurs a change in the index value. Thus, a value adjustment delay occurs from the stocks to the index. By extension, the adjustment in pricing occurs even later in futures. Hence, in these cases information flows from stocks to futures. Fourthly, in line with Abhyankar’s (1995) premise regarding futures being more liquid than spot if shorting is allowed, futures market should absorb information earlier. Accordingly, coupling short-selling provisions with non-trivial advantages like transaction cost, liquidity, and leverage, futures market emerges as a naturally superior predictor of prices.

Crux of the issue at hand is that under ideal conditions futures and spot markets should not lead (lag) each other. Put another way, new information arrival should result in instantaneous price adjustments. Real life results, however, suggest that some markets do lead others. From a market efficiency standpoint, this means some markets absorb information better (earlier) than others. Also, such a delay in price discovery invites opportunity for profit should a trader be able to consistently predict the direction and speed of information flow. Understanding the joint-behavior dynamics of futures and spot markets has serious implications for investors and institutions due to the importance of futures as the foremost risk management tool. This rings especially true for Bursa Malaysia, an emerging market that is growing in capitalization and global importance for the past two decades. Despite the advances in recent decades, futures activities in Bursa Malaysia is very thin compared to exchanges in advanced economies. Moreover, previous empirical works on this exchange reveal predictive ability of futures over spot. Therefore, further development of the exchange through attracting investors and introducing additional derivatives instruments is vital for improving the pricing efficiency between the two markets. Furthermore, tumbling yields in the established financial centers in the world have triggered strong capital flow to emerging market economies like Malaysia, as a result of which stock exchanges like Malaysia and Thailand are receiving renewed foreign portfolio investment attention. While this does give us a strong motivation for reinvestigating the Malaysian context, the high-frequency nature of our data during a sampling window between 2017 and 2018 makes this research stand out. This is because the 2017–2018 period captures a pivotal time in Malaysian history which saw expulsion of an incumbent party in the general election for the first time in over five decades. Not counting financial crisis periods, this was a watershed moment for Bursa Malaysia, which saw local and foreign investors reacting adversely to the unanticipated change in political regime and the uncertainty that comes with it. As a result, the market suffered heavily in early May of 2018, with many stocks triggering lower circuit breaker thresholds. These combined factors make our article’s contribution important to financial market literature.

Remainder of the article is organized as follows. Firstly, we review the current state of knowledge in the topic, followed by description of our empirical setting and overview of data properties. Next, we detail our estimation techniques and analyze our results. We check consistency of our results via multiple robustness checks. Lastly, we recap major findings of our research, highlight our contributions, and suggest avenues for further research.

2 | CURRENT STATE OF KNOWLEDGE

2.1 | Background and overview of literature

The issue of intertemporal price discovery in multiple assets is connected to investigations of co-movement patterns and spillovers. While the former helps guide portfolio composition and rebalancing strategies, the latter is useful for exploiting pricing inefficiencies for short-term profits. Researchers thus far employed several techniques to unravel delays in price discovery. Some relied on correlation coefficients to find out asset co-movements (Campbell, Koedijik, & Kofman, 2002; Longin & Solnik, 2001; Solnik, Bourcèlle, & Le Fur, 1996). Others employed VAR (Vector Auto-regression) to measure inter-market spillover effects (Mukherjee & Bose, 2008; Tse, 1995). Co-integration analysis too has been used to identify long-term and short-term co-movements (Bekiros & Diks, 2008). In addition, GARCH models have been employed to determine spillovers as a proxy for lead–lag analysis (Bohl, Salm, & Willfling, 2011). Traditional lead–lag and price linkage studies involving conventional assets normally test whether both markets move simultaneously in the same or opposite direction. Those studies furnish evidence of information flow between the two markets in the following patterns:
Due to these capabilities Wavelets have also enjoyed use in other scientific disciplines like Physics (Misti, Misti, Oppenheim, & Poggio, 2007), Medicine (Wang, Zheng, Zhang, Duan, & Chen, 2015), Biology (Griffel, Aldoubi, & Unser, 2007), Hydrology (Labat, Ronchail, & Guyot, 2003), and Economics (Aguiar-Condrella & Soares, 2011).

3 | EMPIRICAL SETTING

3.1 | Kuala Lumpur stock exchange composite index futures

Kuala Lumpur stock exchange composite index (KLSE CI) is a capitalization weighted index comprising of the 30 largest stocks listed in Bursa Malaysia. The KLSE CI index has served as a benchmark for equity market performance in Malaysia. From its inception, KLCI comprised the 100 biggest stocks in Malaysia. This changed July 6, 2009, when Bursa Malaysia and its index partner the FTSE group introduced a new benchmark: FTSE Bursa Malaysia KLCI (FBM KLCI) comprising of the 30 biggest companies. The KLCI components represent the performance of the Malaysian economy from the trading and service sector, banking and finance, oil and gas, property and consumer products. In addition to FBM KLCI, Bursa Malaysia also has other indices, for example, the FTSE BM 100, FTSE Small Cap, and FTSE BM Mid Cap. As the FBM KLCI provides insight about the performance of the Malaysian economy more broadly, market participants can predict the movement of this index by analyzing changes in macroeconomic variables. Moreover, if the stock market index performs well, the government may use it as a tool to attract capital inflow in the form of foreign portfolio investment. A stock index futures contract (FKLI) in Malaysia is offered under Malaysia Derivatives Berhad (BMD). In line with global practices, trading in FKLI requires players to have an initial margin, which acts as collateral upon entering the contract. A main tenance margin is required to maintain traders’ position, meaning when they suffer losses they will be called upon to top up additional funds. The trading hours of Bursa Malaysia Derivatives Exchange are from 8.45 a.m. to 12.30 p.m. for first session, and 2.30 p.m. to 5.00 p.m. for the second session. Table 2 below provides a summary of the contract specification for FTSE Bursa Malaysia KLCI Futures.

4 | ESTIMATION TECHNIQUES

4.1 | Wavelet approach

Wavelet analysis, much like Fourier, projects an original signal into a sequence of basic functions. These are called
<table>
<thead>
<tr>
<th>#</th>
<th>Study</th>
<th>Year</th>
<th>Data</th>
<th>Frequency</th>
<th>Focus</th>
<th>Venue</th>
<th>Method</th>
<th>Finding</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Abhyankar</td>
<td>1995</td>
<td>1986–1990</td>
<td>Hourly</td>
<td>FTSE-100</td>
<td>London</td>
<td>ECM</td>
<td>Non-conclusive</td>
<td>Non-conclusive</td>
</tr>
<tr>
<td>2</td>
<td>Abhyankar</td>
<td>1998</td>
<td>1992</td>
<td>1-min</td>
<td>FTSE-100</td>
<td>London</td>
<td>Granger</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Brooks et al.</td>
<td>2001</td>
<td>1996–1997</td>
<td>10-min</td>
<td>FTSE-100</td>
<td>London</td>
<td>ECM</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Cabrera et al.</td>
<td>2009</td>
<td>2005</td>
<td>Tick-by-tick</td>
<td>FX (CME)</td>
<td>Chicago</td>
<td>Granger</td>
<td>Spot &gt; futures</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Chen and Gau</td>
<td>2009</td>
<td>2004–2005</td>
<td>1-min</td>
<td>Taiwan</td>
<td></td>
<td>VECM</td>
<td>Spot &gt; futures</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Eross et al.</td>
<td>2018</td>
<td>2014–2016</td>
<td>5-min</td>
<td>BTC</td>
<td>BTC-e</td>
<td>Granger</td>
<td>Bi-directional</td>
<td>Return vs. volume</td>
</tr>
<tr>
<td>8</td>
<td>Frino et al.</td>
<td>2000</td>
<td>1995–1996</td>
<td>1-min</td>
<td>Australia</td>
<td></td>
<td>ARMA</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Gwilym and</td>
<td>2001</td>
<td>1993–1996</td>
<td>Hourly</td>
<td>FTSE-100</td>
<td>London</td>
<td>ARMA</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Buckle</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Judge and</td>
<td>2014</td>
<td>2006–2012</td>
<td>Daily</td>
<td>SETS90</td>
<td>Thailand</td>
<td>Granger</td>
<td>Spot &gt; futures</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reancharoen</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Kang et al.</td>
<td>2006</td>
<td>2002</td>
<td>5-min</td>
<td>KOSPI200</td>
<td>Korea</td>
<td>ARMA</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Kayussanos</td>
<td>2003</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>VECM</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td></td>
<td>and Nomikos</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Pizzii et al.</td>
<td>1998</td>
<td>1987</td>
<td>1-min</td>
<td>S&amp;P500</td>
<td>US</td>
<td>ECM</td>
<td>Bi-directional</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Roop and</td>
<td>2002</td>
<td>1999</td>
<td>5-min</td>
<td>SGX</td>
<td>Singapore</td>
<td>AR-ECM</td>
<td>Bi-directional</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Zurbuegg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Su and Tsie</td>
<td>2004</td>
<td>1999–2002</td>
<td>1-min</td>
<td>HSIF</td>
<td>Hong Kong</td>
<td>M-ECM</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Whaley</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>Streche</td>
<td>2009</td>
<td>2007–2008</td>
<td>1-min</td>
<td>RIF</td>
<td>Romania</td>
<td>GARCH</td>
<td>Futures &gt; spot</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lashgari</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>Yang et al.</td>
<td>2012</td>
<td>2010</td>
<td>5-min</td>
<td>CSI300</td>
<td>China</td>
<td>GARCH</td>
<td>Bi-directional</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows relevant literature of price leadership of futures versus spot in empirical finance.

Wavelets. Two basic wavelets are $\varphi$ (father wavelet—a scaling function) and $\psi$ (mother wavelet). The latter can be translated and scaled for Hilbert Space $L^2(K)$ of square-integrable functions (Heil & Walnut, 2005). We define the functions as follows:

$$\varphi_{jk}(t) = 2^{-j/2} \{ \varphi(2^{-j}t-k) \}$$  \hspace{1cm} (1)

$$\psi_{jk}(t) = 2^{-j/2} \{ \psi(2^{-j}t-k) \}$$  \hspace{1cm} (2)
<table>
<thead>
<tr>
<th>Underlying instrument</th>
<th>FBMKLCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contract size</td>
<td>FBMKLCI * MYR 50</td>
</tr>
<tr>
<td>Tick size</td>
<td>0.5 index point * MYR 25</td>
</tr>
<tr>
<td>Tenure</td>
<td>Spot month, the next month, and next 2 calendar quarterly months. The calendar quarterly months are March, June, September, and December</td>
</tr>
<tr>
<td>Circuit breaker</td>
<td>20% per trading session for the respective contract month except the spot month contract</td>
</tr>
<tr>
<td>Settlement</td>
<td>Cash settlement based on final statement value</td>
</tr>
<tr>
<td>Limit to speculation</td>
<td>Max. 10,000 contract for net long or net short</td>
</tr>
</tbody>
</table>

Note: This table shows the descriptive statistics for FBM KLCLI (spot) and FKLI (futures) returns used in the study.

Here, the scaling parameter is $j = 1..J$ in a J-level decomposition, while $k$ stands for the translation parameter. The father wavelet captures the long run trend of the variable, integrable to 1. Contrarily, the mother wavelet, integrable to 0, denotes fluctuations from the trend. Using the scalable $\alpha_{jk}$ and wavelet coefficients $\beta_{jk}$, we can construct a continuous wavelet transform of a square integrable time series as follows:

$$X(t) = \sum_{k} \sum_{j} \alpha_{jk} \phi_{jk}(t) + \sum_{k} \beta_{jk} \psi_{jk}(t) + \sum_{k} \beta_{j-k} \psi_{j-k}(t) + \ldots + \sum_{k} \beta_{1-k} \psi_{1-k}(t)$$

(3)

Where, $\alpha_{jk}(t) = \int \phi_{jk}(\tau)X(\tau)\,d\tau$ and $\beta_{jk}(t) = \int \psi_{jk}(\tau)X(\tau)\,d\tau$.

### 4.2 DWT or MODWT?

It is worth noting here that since we are applying Wavelet analysis to financial time series sourced at regular time intervals, we have the option of using discrete Wavelet transform or maximal overlap Wavelet transform. The latter is a linear filter, which transforms the time series into coefficients connected to variations on a scale by scale basis. In contrast with DWT, this approach sacrifices the orthogonality property but gains features, which make it more suitable for this article’s objectives.

If $X$ is an $N$-dimensional vector containing real time series values $\{X_n; t = 0, \ldots, N-1\}$, with sample size $N$ as a positive integer. For any positive integer, $J_0$, the level $J_0$, MODWT of $X$ is a transform consisting of the $J_0 + 1$, $N$-dimensional vectors: $\tilde{W}_1, \ldots, \tilde{W}_{J_0}$ and $V_{J_0}$. Here, the MODWT coefficients linked to changes at scale $\lambda_j = 2^{j-1}$ are represented by vector $W_{J_0}$. Conversely, MODWT scaling coefficients associated with averages at scale $\lambda_j = 2^{j-1}$ are contained in vector $V_{J_0}$. Therefore, we can rewrite the MODWT coefficients as follows:

$$\tilde{W}_j = W_j X$$

(4)

and

$$\tilde{V}_j = V_j X$$

(5)

MODWT approach is used to decompose sample variance of time series based on scale. This phenomenon, in accordance with energy conservation principle, can be expressed as follows:

$$\|X^2\| = \sum_{j=1}^{J_0} \|\tilde{W}_j\|^2 + \|\tilde{V}_j\|^2$$

(6)

From Equation (X), a scale-dependent analysis of variance can be derived based on wavelet and scaling coefficients. This is applicable to both stationary and non-stationary processes with backward differences. The variance equation is as follows:

$$\sigma_X^2 = \|X\|^2 - \bar{X}^2 = \frac{1}{N} \sum_{j=1}^{J_0} \|\tilde{W}_j\|^2 + \frac{1}{N} \|\tilde{V}_j\|^2 - \bar{X}^2$$

(7)

### 4.3 Variance

The wavelet variance for MODWT models were proposed by Whitcher, Guttorp, and Percival (2000), who also pioneered the concept of wavelet covariance and correlation between two signals. Later, estimators and confidence interval measurement techniques were added. Thereafter, wavelets saw more empirical usage in determining the degree of association between two processes. Key among this approach was the use of wavelet covariance to exploit scale by scale associations. Gallegati (2008) defined the wavelet covariance at scale $i$ as the covariance between $i$ wavelet coefficients of two signals $X$ and $Y$. Hence:
\[ \gamma_{XY,j} = \text{Cov} \left[ \omega^X_{i,j}, \omega^Y_{i,j} \right] \]  

(8)

Based on Gallegati’s covariance structure above, an estimator using MODWT can be devised by eliminating all wavelet coefficients impacted by boundary constraints:

\[ \gamma_{XY,j} = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \left[ \omega^X_{i,j} \omega^Y_{i,j} \right] \]  

(9)

4.4 Cross-correlations

In addition to variance, Wavelet approach is also able to estimate the degree to which two variables are correlated by shifting one time series (lagging or leading it) and subsequently measuring the correlation. Through this, researchers are able to extrapolate whether innovations in a certain vector precede innovations in another. If such a relationship exists, the preceding time series is considered lagging. If the cross-correlation is large in magnitude and significant, it is treated as having a predictive power vis-à-vis the lagged series. Similar to temporal domain cross-correlations, wavelet cross-correlations lead to examination of lead–lag relationships on a scale-by-scale basis. Due to our choice of Maximal Overlap Discrete Wavelet Transform, the \( \rho \) for scale \( \tau_j \) and lag \( \pi \) is as follows:

\[ \rho_{X,Y}(\tau_j, \pi) = \frac{\text{cov} \left\{ W^X_{j-1}, W^Y_{j-\pi} \right\}}{\sqrt{\text{var} \left\{ W^X_{j-1} \right\} \text{var} \left\{ W^Y_{j-\pi} \right\}} } \]  

(10)

Here, \( \rho_{X,Y}(\tau_j, \pi) \) takes a value between (inclusive) -1 and +1; for all scale \( \tau_j \) and lag \( \pi \), as evidenced by Cauchy–Schwarz inequality (Chabert, Tourneret, & Castanie, 1997).

4.5 Robustness Check-1: BEKK-GARCH

To ensure consistency of findings to be derived from Wavelet analysis, we extend the examination of price leadership via volatility spillovers between Bursa Malaysia’s futures and spot markets using the GARCH (1, 1) model with Baba, Engle, Kraft, and Kroner (BEKK) parameterization (Bauwens, Laurent, & Rombouts, 2006). In fitting the model, we assume a conditional normal bivariate distribution for the error distribution vector. The BEKK approach is convenient because it simplifies the estimation process by reducing parameter counts. It is also capable of extricating evidence on the following attributes: inter-market volatility spillover, autoregressive inclinations, volatility persistence, and clustering. We express our bivariate GARCH-BEKK model as follows:

\[ Y_t = C_0 + \epsilon_t \]  

(11)

Here, \( \epsilon_t \) is a Gaussian error term \( \Omega^{-1} \sim N(0, H_t) \), where

\[ H_t = C' + A' \epsilon_{t-1} \epsilon_{t-1}' + B' H_{t-1} B \]

and

\[ Y_t = \begin{bmatrix} \log(\text{futures price}) \\ \log(\text{spot price}) \end{bmatrix} \]

And

\[ H_t = \begin{bmatrix} c_{ff} & a_{f \pi} \\ a_{f \pi}' & c_{\pi \pi} \end{bmatrix} \begin{bmatrix} e_{2,t-1} \\ e_{2,t-1}' \end{bmatrix} + \begin{bmatrix} a_{f f} & a_{f \pi} \\ a_{f \pi}' & a_{\pi \pi} \end{bmatrix} \begin{bmatrix} e_{1,t-1} & e_{1,t-1}' \end{bmatrix} \begin{bmatrix} c_{ff} & a_{f \pi} \\ a_{f \pi}' & c_{\pi \pi} \end{bmatrix} \begin{bmatrix} e_{2,t-1} \\ e_{2,t-1}' \end{bmatrix} + \begin{bmatrix} b_{f f} & b_{f \pi} \\ b_{f \pi}' & b_{\pi \pi} \end{bmatrix} H_{t-1} \begin{bmatrix} b_{f f} & b_{f \pi} \\ b_{f \pi}' & b_{\pi \pi} \end{bmatrix} \]

The conditional variance of the model can be alternatively expressed as follows:

\[ h_{f \pi} = c_{f f} + a_{f f}^2 e_{f,t-1}^2 + 2 a_{f f} a_{f \pi} e_{f,t-1} e_{\pi,t-1} + a_{f \pi}^2 e_{\pi,t-1}^2 + b_{f f}^2 h_{f,t-1} + 2 b_{f f} b_{f \pi} h_{f,t-1} + b_{f \pi}^2 h_{\pi,t-1} \]  

(12)

\[ h_{f \pi} = c_{f f} + a_{f f}^2 e_{f,t-1}^2 + a_{f \pi}^2 e_{\pi,t-1}^2 + 2 a_{f f} a_{f \pi} e_{f,t-1} e_{\pi,t-1} + b_{f f}^2 h_{f,t-1} + 2 b_{f f} b_{f \pi} h_{f,t-1} + b_{f \pi}^2 h_{\pi,t-1} \]  

(13)

Here, \( c \) is the constant (intercept) term, while \( h_t \) stands for the variance-covariance matrix in a conditional sense. Moreover, from the Matrix \( A \) we can deduce whether the impact of previous innovations (shocks) exist—a phenomenon often referred to as the ARCH effect. On the other hand, Matrix \( B \) accounts for the GARCH effect; that is, the impact of prior conditional volatility. The cross-diagonal components of these two matrices represent the effect of endogenous prior shocks and historical (realized volatility) against the present conditional variance. More pertinent to the price leadership investigation, the off-diagonal elements of matrices \( A \) (for \( s \) or \( s' \)) and \( B \) (for \( s \) or \( s' \)) measure the cross-market effects of shocks and volatility.
4.6 Robustness Check 2: DCC-GARCH

Following the BEKK-GARCH, Bollerslev's (1990) bivariate GARCH with constant conditional correlation was improved upon by Engle (2002), who proposed a time-variant correlation model capable of capturing correlation changes in different time series. This model has been empirically shown to yield results more sensitive than the CCC model. We, thus, base our DCC model upon univariate GARCH, parameters of which are estimated from GARCH (1,1).

Our mean equation for futures and spot market are:

\[ F_t = C_f + \varepsilon_t \Omega_{t-1} \tilde{N}(0, \sigma^2_f) \]  \hspace{1cm} (14)

\[ S_t = C_s + \varepsilon_t \Omega_{t-1} \tilde{N}(0, \sigma^2_s) \]  \hspace{1cm} (15)

And the conditional variation equations are:

\[ \sigma^2_f = \alpha_f + \alpha_f \varepsilon^2_{t-1} + \beta_f \sigma^2_{f-t} \] \hspace{1cm} (16)

\[ \sigma^2_s = \alpha_s + \alpha_s \varepsilon^2_{t-1} + \beta_s \sigma^2_{s-t} \] \hspace{1cm} (17)

The dynamic correlations are estimated from \( H_t = \tau \rho_t r_t \), where \( r_t \) is a diagonal matrix and \( \rho_t \) is a time-varying matrix:

\[ \text{diag} \left( \sqrt{\frac{q_{1,t1}}{q_{2,t1}}}, \ldots, \sqrt{\frac{q_{m,t1}}{q_{n,t1}}} \right)^{-1} \times \text{diag} \left( \sqrt{\frac{q_{1,t2}}{q_{2,t2}}}, \ldots, \sqrt{\frac{q_{m,t2}}{q_{n,t2}}} \right) \]

The conditional correlation can now be rewritten as \( \tilde{q}_{j,t} = \frac{\tilde{q}_{j,t}}{\tilde{q}_{j,t}} \). We estimate this model via the Quasi-Maximum Likelihood (QML) method as per Engle (2002). Hence, we rewrite the log-likelihood as the sum of volatility and correlation components as follows:

\[ L(\theta, \varphi) = L_c(\theta, \varphi) + L_v(\theta, \varphi) \] \hspace{1cm} (18)

Here, \( L_v(\theta, \varphi) = -\frac{1}{2} \sum_{t=1}^{T} (n \log(2\pi) + \log(D_1) + r_t D_t^{-2} r_t) \)

And \( L_c(\theta, \varphi) = -\frac{1}{2} \sum_{t=1}^{T} (\log|R_t| + \varepsilon_t R_t^{-1} \varepsilon_t) \)

Based on the output of estimations, the dynamic correlation coefficients between the futures and spot markets can be extracted from the GARCH optimal parameter results.

4.7 Robustness Check 3: error correction

Using vector error correction models (VECM) to identify lead-lag relationship between two time-series has a fair amount of precedents in empirical finance literature. Proceeding with this approach, we begin with the customary check for stationarity via Augmented Dickey-Fuller (ADF) and Phillips-Perron tests, followed by checking whether the spot and futures time series are co-integrated via Johansen's test. In the event that futures and spot series show co-integration, the following VECM model is specified:

\[ \delta S_t = \alpha_0 + \sum_{i=1}^{p-1} \alpha_i \delta S_{t-i} + \sum_{i=1}^{p-1} \beta_i \delta F_{t-i} + \alpha S_{t-i} + \varepsilon_t \] \hspace{1cm} (19)

\[ \delta F_t = \alpha_0 + \sum_{i=1}^{p-1} \alpha_i \delta F_{t-i} + \sum_{i=1}^{p-1} \beta_i \delta S_{t-i} + \alpha F_{t-i} + \varepsilon_{Ft} \] \hspace{1cm} (20)

In these two equations, \( F \) and \( S \) stand for futures and spot prices, while \( \alpha \) and \( \beta \) represent short-run coefficients for the corresponding time series. \( Z_{t-i} \) is the error correction term at time \( t-i \). We use akaike information criteria (AIC) to decide on the optimum number of lag in the models specified above.

5 RESULTS AND ANALYSIS

5.1 Descriptive statistics

We compute returns of futures and spot prices as differences quoted prices in 15-s intervals as follows:

\[ P_t = \ln(P_t) - \ln(P_{t-1}) \] \hspace{1cm} (21)

The first day of observation is on September 5, 2017, and last day of observation is on August 16, 2018. Total data points amount to 453,590 price quotations, leading to 453,589 points of price returns. As Table 3 below demonstrates, the Jarque–Bera tests of normality are rejected.
for both time series, which exhibit asymmetric distribution around the mean—indicating kurtosis. Moreover, skewness is observed—more pronounced in futures. Nonetheless, high leptokurtic and left skewed distributions are common in high-frequency finance literature.

Figure 1 below plots the log returns of the two time series.

Though this period does not coincide with any major crisis (local or global), a brief period of turbulence is noticed right after the surprise election results in May 2018. This period is shaded in the graphs. The event triggered a brief period of capital pull-out from Bursa Malaysia predicated on the apprehension surrounding the newly elected government’s policy of decoupling infrastructural investment ties from China and the general surprise stemming from incumbent's failure. In this period, a number of stocks were seen to trip the circuit breakers, which were already liberally set at ±30%.

5.2 MODWT

We transform the returns’ series using Daubechies least asymmetric filter (L8). Its use is fairly routine in empirical research on financial markets. We calibrate the maximum level of MODWT at 6 (J0 = 6) as is common in time series analysis to attain a balance between sample size and filter length. Thereafter, we conduct wavelet variance decomposition to show that much of the time series volatility is accounted for by smaller levels of MODWT coefficients (Figure 2). Additionally, Figures 2 and 3 demonstrate scale-based energy decomposition of Futures and Spot returns in terms of $J$-th wavelet scale energy in proportion to overall energy of the corresponding signal.

In these figures, low scale (high frequency) MODWT coefficients account for higher energy. For instance, Level 1 coefficients stand for short term (15-s and its multiplications) fluctuations against a shock, accounting for 51.02% of spot market returns versus 49.95% for the futures. This finding is in line with prior empirical literature (Fernandez, 2005). Intuitively, too, it stands to reason since high-frequency data is supposed to capture short term traders’ brisk response to short-term movements vis-a-vis long-term investors who react less frequently to external shocks.

Next, we examine the cross-correlations between futures and spot returns. We achieve this by lagging the second (spot) time series by 30 units ($-30 \leq \pi \leq 30$), where each unit constitutes 15 s. Thereafter, cross-correlation for other time shifts (30 lags counting down to 3, 2, 1) are conducted. Cross-correlations for the two return time series which are time concordant result in wavelet correlation coefficients. When no correlation coefficients for a time series is statistically significantly different than zero, no series is leading or lagging another. However, when there are significant cross correlations, one series is leading/lagging other. Meanwhile, cross-correlations at zero lag account for co-movement or concurrent relationship between the futures and spot market. Conversely, non-zero cross correlation displays
spillover relationship. Since Wavelet also operates in space scales, cross-correlations are computed from raw returns (no transformations), scale \( r_1 \), to scale \( r_6 \) MODWT transformed series.

The computations (presented from Figure 4 and Figure 5) reveal co-movement dynamics between the spot and futures prices at various time scales. Despite the high levels of cointegration, the two series exhibit varying degrees of correlation changes per time scale. This suggests that the co-movement between futures and spot is indeed a multi-scale phenomenon. More interestingly, however, the level of correlation increases with time-scale, with the highest achieved at scale 32. This indicates the highest level of convergence between spot and futures to occur in around 8 min. Considering the intraday nature of our investigation, this suggests opportunities for arbitrage exploitation for up-to 4 scales, that is, 1 min before correlations begin to jump, reaching the pinnacle in 8 min. This indicates relatively efficient synchronization of spot-futures prices. However, it is worth remembering that high-frequency or algorithmic trading is scarce in Bursa Malaysia. Thus, exploiting the inefficiencies at such a small time scale should prove difficult for the average retail investor.

The finding that co-movement between futures and spot markets is usually expected to increase with the progression of investment windows since at smaller windows the leading market is influenced—inter alia—by sporadic events, market sentiments, and behavioral factors. Such temporary shocks lead to a lot of noise trading, which naturally registers in price action but typically does not detract the greater trend. As the time scale increases, however, markets become more synched as news becomes more available, liquidity providers gain more opportunities to participate—leading to amelioration of potential order imbalance, and overall effect of macro-market variables. For the raw returns, however, the cross-correlation at zero lag is the greatest and statistically significant for all time scales.

Lastly, from Figure 6 above, wavelet coherence spectrograms are presented whereby the horizontal and vertical axes denote time and frequency, respectively. Wavelet coherence’s utility becomes apparent in regions of time-frequency space whereby futures and spot time series co-vary. Lower the frequency, higher the time scale. We derive significance values from Monte Carlo simulation at 5% significance. Moreover, in terms of color codes, the power ranges from low coherence (blue) to high (red).
FIGURE 3  Energy decomposition of futures returns. Note: This figure represents scale-based energy decomposition of futures returns for $j$-th wavelet scale energy in proportion to overall energy [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 4  Wavelet correlation results. Note: This figure presents the classical plot of wavelet correlation between futures and spot market returns in Bursa Malaysia. The surrounding blue lines correspond to upper and lower bounds at 95% confidence interval [Colour figure can be viewed at wileyonlinelibrary.com]
Figure 5. Wavelet cross-correlation results. Note: This figure displays wavelet multiple cross-correlation between futures and spot returns in Bursa Malaysia. The red lines represent upper and lower bounds of 95% confidence interval. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 6. Wavelet cross-coherence results. Note: This figure shows the time scale in X-axis and Wavelet cross-coherence in Y-axis. Coherence magnitude and relative phase at a given time scale and point in time is denoted by color and the orientation of the arrow. The legends are as follows: In phase, eastward arrows; anti-phase, westward arrows; confederate leading, northeast arrows; and confederate lagging, southwest arrows. [Colour figure can be viewed at wileyonlinelibrary.com]

The price leadership (lead/lag) dynamics can be examined via directions of the phase through the arrows (Vacha & Barunik, 2012). A zero-phase difference denotes joint movement in futures and spot. The right-pointing arrows suggest phase and the left-pointing arrows anti-phase. For the former, futures and spot move
in the same direction. The paucity of anti phase arrows bears testament to near-ubiquitous co-movements between the two assets. Interestings findings, however, arise from the North-East and South-West arrows, suggesting spot leads futures. Conversely, far fewer number of North-West and South-East arrows suggest futures can predict spot. While overall the results contain elements of bi-directional causality, evidence from Wavelet cross-coherence points towards significantly more dominance of spot leading futures.

5.3 | BEKK-GARCH

Having examined the cross-correlations between futures and spot prices both temporally and on scale by scale basis, to ensure robustness of our findings first we exploit the conditional variance-covariance equation in the BEKK-GARCH model to understand the volatility spillover between spot and futures markets in Bursa Malaysia. The BEKK-GARCH model is useful in unraveling price leadership through the diagonal parameters of Matrix A, which captures past shock effects of a market versus the present volatility; that is, the dependence of one market’s volatility against its own lagged innovations. We notice these coefficients are statistically significant, which is indicative of ARCH effect in both markets. Meanwhile, Matrix B’s diagonal parameters capture past volatility effects on current volatility of the markets individually, which too are found statistically significant. This counts as evidence of GARCH effect for both markets. Thus, we arrive at a primary conclusion that the present conditional variances of both markets rely heavily on their own past shocks and past conditional variances. This finding confirms prior observations by (Kang, Cheong, & Yoon, 2013) in futures and spot markets. It is worth remembering that Matrix A captures recent effect, while Matrix B is relevant for a longer term. The statistically significant values of $\alpha_f$ and $\beta_f$ indicate that the delayed shocks and historical conditional volatility in the futures market affect the present conditional volatility of spot market. Lastly, a spillover effect is recorded in both directions, but the magnitude is far greater from spot to futures, rather than futures to spot. These findings form evidence in favor of price formation in cash market leading the futures market, which is in line with findings from Wavelet analysis. Table 4 below presents the results of Multivariate BEKK-GARCH, and Figure 7 shows the evolution of dynamic conditional correlations for futures and spot returns for the entire sample period from BEKK approach.

5.4 | DCC-GARCH

As a final robustness check, we exploit the utility of DCC-GARCH model in capturing time-varying capabilities of capturing correlation changes within the GARCH framework (Tse, 2000). Table 5 and Figure 8 present the results of the DCC-GARCH (MVT) fit models and the time varying conditional correlations and covariance. The statistically significant values of coefficients in Table 5 support the dynamic fit of the model. Moreover, the significant 1, 2, 3, 4 values indicate both markets exhibit

| TABLE 4 | Multivariate BEKK-GARCH results |
| BEKK-GARCH | Estimate | SE | z Statistic | Prob. |
| C_{ff} | 0.000*** | 0.000 | -2.353 | 0.019 |
| C_{sf} | 0.104*** | 0.004 | -23.332 | 0.000 |
| C_{ss} | 0.000 | 0.000 | -1.442 | 0.149 |
| A_{ff} | (-0.072)*** | 0.004 | -18.037 | 0.000 |
| A_{sf} | 0.000** | 0.000 | 140.605 | 0.000 |
| A_{ss} | 0.000** | 0.000 | 228.552 | 0.000 |
| B_{ff} | 0.000*** | 0.000 | 127.308 | 0.000 |
| B_{sf} | 0.204*** | 0.001 | 277.114 | 0.000 |
| B_{ss} | 0.191*** | 0.000 | 408.313 | 0.000 |
| B_{sf} | 0.968*** | 0.000 | 4,998.342 | 0.000 |
| B_{ss} | 0.976*** | 0.000 | 7,130.886 | 0.000 |

Note: This table shows multivariate BEKK-GARCH results. $A_{ff}$ and $B_{ff}$ represent the ARCH and GARCH parameters for futures and spot returns. Statistical significance at 10%, 5%, and 1% are represented by *, **, and *** respectively.
ARCH and GARCH effects. Meanwhile, Joint.dcc(A1) reflects the past shocks on current conditional correlation, while Joint.dcc(B1) stands for impact of past correlation. Both these values are significant. The results suggest that the conditional correlations are not constant and support the anticipated existence of dynamic correlations. Moreover, it demonstrates that the DCC model is superior to the CCC model. Additionally, since Joint.dcc(A1) + Joint.dcc(B1) < 1, the dynamic conditional correlations show mean reversion tendencies (Engle, 2002). This means that following a shock the conditional correlation reverts to unconditional level—that is, the long run equilibrium. DCC conditional correlation in Figure 8 produces no noticeable pattern or regimes in correlations changing over time. In fact, the correlation consistently stays positive, hovering between 0.4 and 0.6 threshold, with minor episodes in negative territory. Thus, DCC-GARCH tests indicate no discernible pattern of correlations changing in a systematic way between futures and spot markets.

### 5.5 Error correction approach

Before getting to the results of VECM models specified in Equations 19 and 20, we present the results of the unit
roots via ADF test in Table 6, which show both futures and spot returns series are stationary at level. Thereafter, we present the following long-run equations:

$$\delta S = -1.03e^{-t} + 0.201\delta F$$  \hfill (22)
$$\delta F = 0.000 + 0.1256S$$  \hfill (23)

The long-run equation reveals whether these variables will move together in the long run. The results show that the effect of spot on futures is only marginally insignificant due to a probability of 0.9499 with a coefficient in the long run of 0.1247. In addition, the long-run equation shows that the effect of the futures market is more decisively significant because it has a probability 0.9693. Next, we check if a long-run cointegration exists between the series via Johansen’s co-integration test, presented in Table 7 below.

The results indicate the existence of cointegration between futures and spot returns. Thereafter, lag selection criteria based on AIC values suggest that we should choose a lag value of 6.

Table 8 above shows the VECM model results for spot and futures returns. We can observe that the coefficient for the spot market is lower than for the futures market. According to Kharbanda and Singh (2017), when testing lead and lag using the VECM model, when one coefficient is smaller than the other this means it performs at a slower rate of adjustment to reach equilibrium; hence, the smaller coefficient will lead the other. In this case, the spot market leads the futures market since the latter performs at a faster rate of adjustment to reach equilibrium. Thus, the results of the VECM test reinforce the findings from the Wavelet analysis.

FIGURE 8  DCC-GARCH results. Note: This figure shows the evolution of dynamic conditional correlations for futures and spot returns for the entire sample period from DCC-GARCH approach

<table>
<thead>
<tr>
<th></th>
<th>Spot returns</th>
<th>Prob.</th>
<th>Futures returns</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADF test stat.</td>
<td>-426.5329</td>
<td>0.000</td>
<td>-265.242</td>
<td>0.000</td>
</tr>
<tr>
<td>1% level</td>
<td>-3.43</td>
<td></td>
<td>-3.43</td>
<td></td>
</tr>
<tr>
<td>5% level</td>
<td>-2.86</td>
<td></td>
<td>-2.86</td>
<td></td>
</tr>
<tr>
<td>10% level</td>
<td>-2.57</td>
<td></td>
<td>-2.57</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows the results of Augmented Dickey-Fuller (ADF) test for both spot and futures returns.

TABLE 6  Unit root results
### TABLE 7 Co-integration results (trace)

<table>
<thead>
<tr>
<th># of hypothesized co-integrating equations</th>
<th>Eigen value</th>
<th>Trace stat.</th>
<th>Critical value at 5%</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0.001413</td>
<td>643.4192</td>
<td>15.49471</td>
<td>0.000</td>
</tr>
<tr>
<td>Max. 1</td>
<td>0.000</td>
<td>1.8551</td>
<td>2.4815</td>
<td>0.1732</td>
</tr>
</tbody>
</table>

Note: This table shows the results of Johansen co-integration test between spot and futures returns.

### TABLE 8 Vector error correction model results

<table>
<thead>
<tr>
<th>Error correction</th>
<th>Spot returns</th>
<th>Futures returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>CointEQ(1)</td>
<td>0.000941</td>
<td>0.001333</td>
</tr>
<tr>
<td></td>
<td>(0.00010)</td>
<td>(0.00008)</td>
</tr>
<tr>
<td>[-9.05709]</td>
<td>[16.2119]</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows the VECM results for both spot and futures returns.

### 5.6 | Connection to previous works

Compared to prior empirical precedents for Malaysia, our findings are in stark contrast to Abdullah (2001), who was among the first to report that for a particular period (1995–1997) futures market led the spot market in the then Kuala Lumpur Stock Exchange. The author’s test for 1998–2000, however, yielded inconclusive results. Later, Jusoh et al. (2014) observe bi-directional spillover between futures and spot market in the intraday segment of their investigation, while the daily data portion showed no evidence of any market leading/lagging the other. Our finding, does, however accord with Taumson, Ghazali, Iapang, and Char’s (2018) intraday findings which affirm dominance of spot market over the futures, albeit bi-directional causality was present to some extent.

In a global context, our findings of price adjustment within a minute mirrors Inci and Seyhun’s (2018) investigation in the Brent Crude Oil market. Our work can be further extended by investigating multiscale properties of concurrent futures-spot time series and utilizing change-point detection techniques along with pairs trading strategies to see if the price leadership phenomenon can be consistently exploited by arbitrageurs.

### 6 | CONCLUSION

In this article, we engage in high-frequency data-based analysis of intraday price discovery between futures and spot markets in Bursa Malaysia. Our investigation was grounded in leveraging the time-frequency characteristics of 15-s frequency data based on Maximum Overlap Discrete Wavelet Transform. The results from cross-correlation and cross-coherence unambiguously point towards spot market being a price leader, with futures market lagging by up to 1-min before high convergence between the two markets in around 8-minute mark. There was, however, no discernible regime-specific or clustered patterns of cross-correlations changing over time. The results survive three rounds of robustness checks from traditional econometric tools: DCC-GARCH, BEKK-GARCH, and VECM.

Our findings contribute to empirical finance literature in several ways. Firstly, we present evidence against efficient market hypothesis. Secondly, our use of time-frequency based signal processing techniques allow us to generate insights into speed of adjustment between futures and spot markets. Moreover, our results from Wavelet coherence tests did not detect any specific change in the evolution of the spot-future dynamics during the turbulent post-election trading sessions. Lastly, we demonstrate that potential opportunities for arbitrage exist in an emerging market like Malaysia, though its exploitation requires high-frequency trading tools since the inefficiency does not linger for long.

### DATA AVAILABILITY STATEMENT

Data availability statement The data that support the findings of this study could be subscribed from Bursamalaysia. Authors are restricted from sharing the data used in this study.

### ORCID

Azhar Mohamad Ⓞ https://orcid.org/0000-0002-1075-598X

### REFERENCES


Alzahrani, M., Masih, M., & Al-Titi, O. (2014). Linear and nonlinear Granger causality between oil spot and futures prices: A


How to cite this article: Mohammad Sifat I, Mohamad A, Amin KR. Intertemporal price discovery between stock index futures and spot markets: New evidence from high-frequency data. *Int J Fin Econ*. 2020;1–16. https://doi.org/10.1002/ijfe.1827