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Intraday Price Discovery in Emerging Equity Market: Analysis of SET50 Index, SET 50 Index Futures and THAIDEX SET50 (TDEX)

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Abstract

This study employs Vector Error Correction Model (VECM), information share and conditional information share methods to investigate price discovery in SET50 Index (cash index), SET50 Index Futures (futures index) and ThaiDex SET50 (exchange traded fund). Our findings indicate that there exists a long run relationship among three markets and a multi-market trading of derivatives markets and its underlying asset helps improve price efficiency. With respect to the degree of price formation process, SET50 Index Futures contributes most in price discovery process, followed by SET50 Index and ThaiDex SET50.

Keywords: Price discovery; cointegration; common factor; error correction model; Information share; conditional information share.

JEL Classification: G3, G5, G14

1. Introduction

Price discovery is a central function of the efficient financial markets. It serves as a crucial tool in driving price toward equilibrium by increasing the speed of price adjustment to fundamental value. Prior research suggests that multi-market trading of similar underlying asset and its derivatives improve price discovery by reducing the variability of the underlying asset. In frictionless market, prices can reach the equilibrium by simultaneously impounding new information into the asset price. In reality, however, the presence of market frictions such as illiquidity, transaction costs and market restrictions impedes the process of price formation which results in delay of price adjustment or mispricing.

In this paper, we examine the joint dynamic of price discovery process in SET50 Index (*cash index*), SET50 Index Futures (*futures index*) and ThaiDex SET50 (*exchange traded fund*) using high frequency intraday data from the Stock Exchange of Thailand. We examine whether (i) there is the long run relationship between SET50 Index Futures, ThaiDex SET50 and SET50 Index, (ii) the introduction of ThaiDex SET50 contributes to price efficiency of index markets, (iii) SET50 Index Futures and ThaiDex SET50 have the critical role in the production of efficient price. We adopt Vector Error Correction Model (VECM) to test the lead lag relationship, information share model of Hasbrouck (1995), and conditional information share of Grammig, Melvin, and Schlag (2005) to examine the extent to which derivative markets contribute to price discovery.

2. Literature Review

2.1 Futures and price discovery

Prior research on price discovery between the futures market and the cash market suggests that price transmission moves from futures market to cash market since derivatives provide greater liquidity, higher leverage, less restriction, and lower transaction cost. Using an autoregressive moving average (AR) model, Stoll, and Whaley (1990) analyse returns over five minute intervals for the S&P500 index and MMI index futures. They show that return of S&P 500 index and MMI index futures lead cash market. Using twenty shares in MMI index and underlying asset, Chan (1992) shows that futures return leads cash return by up to fifteen minutes. Tse (1999) examine the price discovery between the Dow Jones Industrial Average (DJIA) and DJIA futures from the Chicago Board of Trade (CBOT). He finds the evidence to support the notion that large portion of price discovery occurs in the futures market and information tends to flow from futures to cash market. Similar findings are reported for the international markets, Abhyankar (1998) employs AR and EGARCH model and show that FTSE 100 index futures leads underlying index by five to fifteen minutes in London market. Min, and Najand (1999) employ Granger causality approach to investigate the lead-lag relationship in returns between cash and futures markets in Korea. Consistent with the studies in U.S. and London markets, futures market leads the cash market by as long as 30 minutes. Similarly, Zhong, Darrat, and Otero (2004) examine the short-run dynamic between the futures market and stock market in Mexico and document evidence that the futures market helps improve price discovery of underlying assets in the cash market.

2.2. Exchanged trade funds (ETFs) and price discovery

Much of prior research has concluded that exchange trade funds have crucial effect on price discovery. Using information share to analyse the intraday price formation of the S&P500 index and Nasdaq100 index, Hasbrouck (2003) shows us that ETFs play an important role in the price discovery process. Specifically, the electronically traded mini futures (E-minis) contribute the most to price discovery, second in ETFs and the least in cash index. Tse, Bandyopadhyay, and Shen (2006) investigate DJIA index price formation by comparing floor based exchange to electronic exchange using information share model. They suggests that informed traders tend to use electronic trading market rather than floor trading and price discovery from ETFs should be greater than that documented in Hasbrouck (2003). Specifically, E-minis still contribute the most to the price discovery but the contribution of ETFs is much higher than previously documented. Chu, Hsieh, and Tse (1999) finds that the introduction of ETFs improves the price formation efficiency of underlying securities and those index futures still have the most significant effect on the price discovery process on a daily basis, followed by ETF (SPDR) and the spot index. Yu (2011) documents that an ETF plays an important role in price discovery of the underlying stocks. Using the decompositions of the variance of efficient price innovations, he shows that the returns innovations of SPDR, the most liquid ETF in the U.S., have a substantial contribution to the stock's return innovation.

3. Data and Methodology

3.1. Data

We obtain the intraday quoted price for SET50 Index and traded prices of SET50 Index Futures and ThaiDex SET50 (TDEX hereafter, TDEX) during July 4th, 2011 to March 30th, 2012 from Bloomberg. *SET50 Index* represents the overall market performance and is computed from the top 50 largest and most liquid stocks in Stock Exchange of Thailand. *SET50 Index Futures* were introduced in 2006 as the first derivative instrument in the Thailand. Currently the SET50 Index Futures is the most popular product traded on Thailand Futures Exchange (TFEX) with the total trading volume of approximately 50% of total derivative market. There are four series of SET50 Index Futures with the maturity in March, June, September and December. In order to avoid illiquidity problem, we use futures contracts with nearest maturity to investigate the price discovery since it refers to the most active contract with highest liquidity and trading volume. *ThaiDex SET50 (TDEX)* is exchange traded fund which tracks performance of SET50 Index. It maintains the tracking error of less than 1.0% per year. The special characteristics of ETF are the combination between diversification of open-mutual and liquidity of stock.

Table 1 presents the descriptive statistics of the SET50 Index, SET50 Index Futures and ThaiDex SET50 from July 4th, 2011 to March 30th, 2012. Panel A reports the nature of price by providing the maximum, minimum and average of trading price. The price of TDEX needs to be multiplied by 100 in order to make it comparable to other markets. There are four series of futures with different maturity dates and contract multiplier is 1000 THB per index point. Panel B reports daily trading value of the sample during the study period. Trading value of futures is calculated from contract size multiply by contract value. Unlike ETFs in developed markets, the volume traded of ThaiDex SET50 of SET50 Index is relatively small compared to futures index.

Table 1. Descriptive statistics of the SET50 Index, TDEX and SET50 Index Futures

Descriptive statistics			
Panel A: Prices			
Price series	Trading Price (Baht)		
	Max	Min	Average
SET50 Index	852.25	592.57	738.28
TDEX	8.63	5.95	7.43
SET50 Index Futures (September)	802.5	628.3	738.96
SET50 Index Futures (December)	737.3	587.6	681.15
SET50 Index Futures (March)	853.8	709.3	782.67
Panel B: Trade values			
Price series	Trading Value (Million Baht)		
	Max	Min	Average
SET50 Index	49915.53	4434.51	19963.52
TDEX	109	0.85	9.9
SET50 Index Futures (September)	23663.1	2830.67	12691.56
SET50 Index Futures (December)	25849.93	3311	13010
SET50 Index Futures (March)	15911.66	3096.43	9432.06

3.2. Methodology

In our empirical test of price formation process of SET50 Index, SET50 Index Futures and ThaiDex SET50, we adopt three commonly used approaches; Vector Error Correction Model (VECM), information share, and conditional information share model. VECM determines a speed of price adjustment and price discovery. Although the coefficient in error correction term may appear to show that a market has dominant role in price discovery, it does not explicitly implies the dynamic price discovery or how market behaves to the changing of its innovation or other market's innovation. Therefore, we employ information share (IS) of Hasbrouck (1995) and conditional information share of Grammig *et al.* (2005) to provide more insight on dynamic price discovery.

3.2.1 Vector error correction model (VECM)

In general, the price discovery measurement begins with the vector error correction model (VECM). Following Engle and Granger (1987), the cointegration of price series can be shown as:

$$\Delta p_t = \gamma z_{t-1} + \sum_{j=1}^{k} A_j \Delta p_{t-j} + e_t \qquad (1)$$

where $\Delta p_t = \begin{bmatrix} p_{1,t} - p_{1,t-1} \\ p_{2,t} - p_{2,t-1} \end{bmatrix}$, the error correction term, $z_{t-1} = p_{1,t-1} - \beta_t\, p_{2,t-1}$ and e_t is a vector of serially uncorrelated residuals that have covariance matrix Ω,

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \qquad (2)$$

while β = [1, -1] is the cointegration vectors and γ is error correction vector that should be non-zero to indicate the adjustment of long-run equilibrium from the error occurring in the short-run.

VECM relies on the assumption that underlying assets and their derivatives have a common trend or their prices are cointegrated. The characteristics of the error correction terms for all three logarithms of price series can be specified by using VECM:

$$\Delta F_t = \delta_F + \gamma_F Z_{t-1} + \sum_{i=1}^{l} a_{Ft-i}\Delta F_{t-i} + \sum_{i=1}^{l} a_{Et-i}\Delta E_{t-i} + \sum_{i=1}^{l} a_{St-i}\Delta S_{t-i} + \varepsilon_{F,t} \qquad (3)$$

$$\Delta E_t = \delta_E + \gamma_E Z_{t-1} + \sum_{i=1}^{l} a_{Ft-i}\Delta F_{t-i} + \sum_{i=1}^{l} a_{Et-i}\Delta E_{t-i} + \sum_{i=1}^{l} a_{St-i}\Delta S_{t-i} + \varepsilon_{E,t} \qquad (4)$$

$$\Delta S_t = \delta_S + \gamma_S Z_{t-1} + \sum_{i=1}^{l} a_{Ft-i}\Delta F_{t-i} + \sum_{i=1}^{l} a_{Et-i}\Delta E_{t-i} + \sum_{i=1}^{l} a_{St-i}\Delta S_{t-i} + \varepsilon_{S,t} \qquad (5)$$

$$Z_{t-1} = F_{t-1} - \beta_{1t-1}\, E_{t-1} - \beta_{2t-1}\, S_{t-1} \qquad (6)$$

where ΔF_t, ΔE_t, ΔS_t are the natural logarithm of return for SET50 Index Futures, TDEX and SET50 Index at time *t*, respectively. Z_{t-1} is the error correction term which measures the differences in prices of three securities in the previous period. l is the optimum number of lags. δ is (3×1)constant vector. β = [1 -1 -1] is cointegrating vector and $\gamma = [\gamma_F\ \gamma_E\ \gamma_S]$ is a coefficient matrix for the error correction terms measuring the adjustment process of each market toward the long-run equilibrium. α is the coefficient matrix of the lag difference terms that measures dynamic price adjustment among three markets. ε_t is (3×1) column vector of white Gaussian noises with zero mean and finite variance.

VECM determines price discovery from the coefficients matrix of the error correction terms (γ) and the coefficient matrix of price adjustment (α)[5]. Regarding to the Granger representation theorem, the sum of absolute value of all error correction coefficients (γ) must be greater than zero and at least one of them must be statistically significant to confirm that prices respond to the error deviation from the long-run equilibrium of previous period**.** The magnitude of coefficient in error correction term refers to the speed of price adjustment and price discovery. The small absolute value of coefficient (γ) implies that market dominates in price discovery while the high absolute value shows that market is strongly adjusting its price to long run equilibrium. The coefficients of price adjustment (α) and error correction terms (γ) capture the relationship of those markets which can be either bidirectional or lead-lag relationship.

3.2.2. Information share (Hasbrouck 1995)

The information share is used to examine the contribution of each market to price discovery. It suggests that those price series are cointegrated since they share a common component of their price innovations. The information share is estimated as the proportion of efficient price innovations that contribute to price discovery. This approach bases on VECM equation and transform to vector moving average (VMA):

$$\Delta p_t = \Psi(L)\varepsilon_t = \varepsilon_t + \psi_1\varepsilon_{t-1} + \psi_2\varepsilon_{t-2} + \dots \quad (7)$$

Integrated form:

$$\Delta p_t = i\psi\left(\sum_{\tau=1}^{t}\varepsilon_\tau\right) + \Psi^*(L)\varepsilon_t \quad (8)$$

From the equation, $\psi\,\varepsilon_\tau$ is the permanent component of common price change impounded into the price due to new information. The first term of the right-hand side is the random walk component that is common to all prices or efficient price. Even though the efficient price is not observable without further identification restrictions, its innovations have the property of linear in the disturbances. Ψ^* is a matrix polynomial in the lag operator while $\Psi^*(L)\varepsilon_t$ is the transitory component with zero-mean and stationary covariance. i is a column vector of ones, ψ is a common row vector of $\Psi(1)$ in which its element can be computed by using impulse response functions.

$$\Psi(1)\varepsilon_t = \begin{bmatrix}\psi_{11} & \psi_{12} & \psi_{13}\\ \psi_{21} & \psi_{22} & \psi_{23}\\ \psi_{31} & \psi_{32} & \psi_{33}\end{bmatrix}\begin{bmatrix}\varepsilon_t^F\\ \varepsilon_t^E\\ \varepsilon_t^S\end{bmatrix} \quad (9)$$

where ψ_{ij} are the element in $\Psi(1)$. Each of these terms represents the permanent impact of innovation from a particular market which have been impound into the price. In other words, ψ_{ij} is the long run impact of one unit innovation in market *j* on price series *i*. Since the underlying assumption of information share states that the rows of coefficient matrix $\Psi(1)$ and innovations may be identical, it implies that those markets show the same efficient price. Thus, it is sufficient to consider only one price or one row of coefficient matrix.

[5] Kitov, Kitov, and Dolinskaya (2009) adopt VECM to examine evolution of real GDP per capita in the United States. They report that the deviations of real economic growth in the US from the growth trend, as defined by constant annual increment of real per capita GDP, are driven by the fluctuations around the growth trend.

$$\Omega = \begin{bmatrix} \sigma^2{}_F & 0 & 0 \\ 0 & \sigma^2{}_E & 0 \\ 0 & 0 & \sigma^2{}_S \end{bmatrix} \tag{10}$$

If the innovation covariance matrix is diagonal, the decomposition of long run variance used to compute the innovation is shown in the following.

$$var(\psi\varepsilon_t) = \psi\Omega\psi' = \psi_{11}^2\sigma^2{}_F + \psi_{22}^2\sigma^2{}_E + \psi_{33}^2\sigma^2{}_S \tag{11}$$

Information share of each market is the proportion of variance of its common factor's innovations to the total common factor's variance.

$$IS_j = \frac{\psi^2{}_j\Omega_{jj}}{\psi\Omega\psi'} \tag{12}$$

However, the price innovations are generally correlated across multi-market trading so the matrix of innovation covariance is not diagonal. Thus, this method is too restrictive to measure the price discovery. Baillie *et al*. (2002) argue that by performing a Cholesky decomposition of $\Omega = MM'$ to lower bound and upper bound, the correlation between the innovations can be eliminated. That is, if the price innovations are correlated (i.e. $\sigma_{ij} \neq 0$ for $i \neq j$), triangularization of the covariance matrix may be used to establish upper and lower bounds.

$$\Omega = MM' = \begin{bmatrix} m_{11} & 0 & 0 \\ m_{21} & m_{22} & 0 \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ 0 & m_{22} & m_{23} \\ 0 & 0 & m_{33} \end{bmatrix} \tag{13}$$

The information share of the market can be present as:

$$IS_j = \frac{([\psi M]_j)^2}{\psi\Omega\psi'} \tag{14}$$

The variance attributed to a particular market is $([\psi M]_j)^2$ and $[\psi M]_j$ is the j^{th} element of the row matrix ψM. The information share of each market is normalized between 0 and 1, and their sum is equal to 1. Besides, the variance decomposition depends on the variable ordering because it provides the upper (lower) bound of information share with series being the first (last) series. Therefore, we need to permute all possible orderings and the average value should be used to determine information share of each market.

3.2.3. Conditional information share (Grammig *et al.* 2005)

Grammig *et al.* (2005) argue that the rows of $\Psi(1)$ for three price series with one cointegration may not be identical and only one row of $\Psi(1)$ may not be sufficient to compute the information share of each market as in Hasbrouck (1995) model. They suggest alternative approach to obtain conditional information share for each market by decomposing each of the variances to the contributions of each market. The conditional information share of market *k* with respect to the shock in market *j* can be computed as;

$$CIS_{jk} = \frac{([\Psi(1)M]_{jk})^2}{(\Psi(1)\Omega\Psi(1)')_{jj}} \tag{15}$$

Since the result of this approach relies on the Cholesky factorization of innovation variances, it should permute across possible orderings of variables and use the average value to determine conditional information share of each market.

4. Empirical result

4.1. Univariate unit root test

In Panel A and B of Table 2, we examine the stationary of the log prices using ADF method and the cointegration of price series using Johansen's cointegration test (1988). The result indicates that we cannot reject the presence of a unit root for all of the log price series at 1% significance level, therefore, the first difference or the return of SET50 Index Futures, SET50 Index and TDEX is used instead. Besides, there are at least two cointegration ranks among these price series and the cointegrating equation shows that β values of TDEX and SET50 Index are statistically significant which implies that there are long run relationships in these three markets.

Table 2. Test results of stationary and cointegration of sample price series

Test results of stationary and cointegration			
Panel A. Unit root test			
Log price series	Test statistic	Critical value (1%)	
SET50 Index Futures	-0.921	-3.43	
TDEX	-0.56	-3.43	
SET50 Index	-0.737	-3.43	
Panel B. Cointegration rank			
Cointegration rank			
Maximum rank	Trace statistic	Critical Value (5%)	
0	75.8875	29.68	
1	35.0116	15.41	
2	0.8770*	3.76	
Cointegrating Equation			
Estimate β Value	SET50 Index Futures	TDEX	SET50 Index
β Value	1	-.3422**	-.6962**
		-0.1226	-0.1283

Note: "*" by trace statistic of cointegration rank indicates there are two or fewer cointegrating equitions with a 5% significance level. "**" indicates significantly different from zero at 5% significance level.

4.2. Price discovery: VECM estimation

We employ VECM estimation to investigate price discovery of pair markets; SET50 Index Futures versus SET50 Index, SET50 Index Futures versus TDEX and TDEX versus SET50 Index.

Panel A of Table 3 presents the VECM estimation of SET50 Index Futures and SET50 Index returns. The results indicate that the coefficients in error correction terms of SET50 Index Futures and SET50 Index returns are statistically significant, and thus two markets respond and adjust to long run equilibrium. The sign of error correction term can be interpreted as follows. If the equilibrium error between SET50 Index Futures and SET50 Index prices is positive (negative), SET50 Index Futures price will decrease (increase) and SET50 Index price will increase (decrease) to meet the equilibrium price. The speed of price adjustment can be calculated by taking 1 over the absolute value of coefficient in error correction term. Based on five minutes time interval, the speed of price adjustment of SET50 Index Futures to long run equilibrium is 100 periods (500 minutes), and SET50 Index is 125 periods (625 minutes). Furthermore, SET50 Index Futures return dominates in price discovery process since all lags of SET50 Index Futures return are able to explain SET50 Index return but only several lags of SET50 Index return can predict the return of SET50 Index Futures.

Panel B shows the relationship of SET50 Index Futures and TDEX returns. SET50 Index Futures return does not react to the equilibrium error, whereas TDEX return does by increasing (decreasing) its price when the error of long run equilibrium between SET50 Index Futures and TDEX prices is positive (negative). The speed of price adjustment to equilibrium of TDEX is 100 periods (500 minutes). Considering the dynamic of price adjustment, SET50 Index Futures return dominates in price discovery since all lags significantly explain the return of TDEX but only the first lag of TDEX return can explain the return of SET50 Index Futures.

Panel C shows us that only TDEX return reacts to the equilibrium error. With the negative sign of error correction term, TDEX decreases (increases) its price when long run equilibrium error between TDEX and SET50 Index prices is positive (negative). The speed adjustment to equilibrium of TDEX is

77 periods (385 minutes). SET50 Index return dominates in price discovery since its all lags have power to explain the return of TDEX but only some lags of TDEX return can predict return of SET50 Index. Overall, our findings indicate that SET50 Index Futures has a dominant role in price discovery, followed by SET50 Index and TDEX contributes the least to price discovery.

4.3. Price discovery: information share

Table 4 presents the coefficients of moving average, $\Psi(1)$, residual correlation matrix and information shares per market. Panel A reports the results between SET50 Index Futures and SET50 Index. SET50 Index Futures shock has a larger long-run impact on itself and SET50 Index than the shock from SET50 Index. There exists the significant correlation of innovation variances. On average, SET50 Index Futures has a major contribution on price discovery accounting for 59.89% of information share, while SET50 Index takes a minor role in price discovery of approximately 40.11%. Panel B replaces SET50 Index with TDEX to investigate the relationship between futures market and ETF market. SET50 Index Futures dominates in permanent effect for both markets with residual correlation of 0.4628. Moreover, SET50 Index Futures accounts for 80% of information share while TDEX accounts for approximately 20%. Panel C reports the relationship between TDEX and SET50 Index, the permanent effect of TDEX and SET50 Index is very similar with the residual correlation significantly exists at the value of 0.5292. The average information shares of TDEX and SET50 Index are 41.26% and 58.74%, respectively. SET50 Index dominates in price discovery process with higher degree in information share. Overall, our findings are consistent with the general consensus in that futures market contributes more to price discovery process than cash market and ETF market.

4.4. Price discovery: conditional information share

Table 5 presents the conditional information shares of three markets. Panel A shows the permanent effect of innovations from SET50 Index Futures, TDEX and SET50 Index. There are the strong correlations between markets, especially in SET50 Index Futures and SET50 Index with the value of 0.8289. Panel B presents the average conditional information shares. SET50 Index Futures has the most contribution to price discovery since it accounts for 50% of information share while SET50 Index and TDEX contribute approximately 35% and 10%, respectively. Panel C shows the upper and lower bounds of information shares. After permuting all orderings of variables in the Cholesky decomposition, the results demonstrate that the bounds of information shares for both upper and lower bounds of each market are not sensitive to the alternative orderings of variables. The results from the conditional information share reemphasis the important roles of futures, exchange traded funds and cash market index in price discovery process.

Table 3. Test results of VECM for SET50 Index, SET50 Index Futures and TDEX

Panel A : VECM estimation of SET50 Index Futures and SET50 Index				
	Coef.	Std. Err.	Coef.	Std. Err.
Z_{t-1}	-0.010**	0.005	0.008**	0.004
L1.	0.001	0.018	0.317**	0.015
L2.	0.014	0.019	0.180**	0.016
L3.	0.073**	0.019	0.147**	0.016
L4.	0.049**	0.019	0.117**	0.016
L5.	0.042**	0.019	0.087**	0.016
L6.	0.102**	0.019	0.091**	0.016
L7.	0.030	0.019	0.058**	0.016
L8.	0.048**	0.018	0.062**	0.015
ΔS_t				
L1.	0.002	0.021	-0.230**	0.018
L2.	-0.084**	0.022	-0.224**	0.018
L3.	-0.095**	0.022	-0.191**	0.018
L4.	-0.031	0.022	-0.111**	0.018
L5.	-0.013	0.022	-0.092**	0.018
L6.	-0.074**	0.022	-0.089**	0.018
L7.	-0.014	0.021	-0.038**	0.018
L8.	-0.047**	0.020	-0.053**	0.016

Panel B: VECM estimation of SET50 Index Futures and TDEX				
	Coef.	Std. Err.	Coef.	Std. Err.
Z_{t-1}	-0.006	0.004	0.010**	0.003
L1.	0.017	0.011	0.422**	0.009
L2.	-0.030**	0.013	0.246**	0.010
L3.	-0.003**	0.014	0.180**	0.010
L4.	0.013	0.014	0.178**	0.010
L5.	0.030**	0.014	0.147**	0.011
L6.	0.060**	0.014	0.112**	0.011
L7.	0.012	0.014	0.102**	0.011
L8.	0.012	0.014	0.091**	0.011
ΔE_t				
L1.	-0.032**	0.015	-0.311**	0.011
L2.	-0.004	0.016	-0.210**	0.012
L3.	0.001	0.016	-0.180**	0.012
L4.	0.004	0.016	-0.164**	0.012
L5.	-0.007	0.016	-0.129**	0.012
L6.	-0.025	0.016	-0.113**	0.012
L7.	0.016	0.016	-0.099**	0.012
L8.	-0.003	0.016	-0.079**	0.012

Panel C: VECM estimation of TDEX and SET50 Index				
	Coef	Std.Err.	Coef.	Std.Err.
Z_{t-1}	-0.013**	0.003	0.001	0.003
L1.	-0.321**	0.012	0.003	0.013
L2.	-0.191**	0.012	0.039**	0.014
L3.	-0.153**	0.013	0.039**	0.014
L4.	-0.134**	0.013	0.034**	0.014
L5.	-0.099**	0.013	0.036**	0.014
L6.	-0.096**	0.013	0.023	0.014
L7.	-0.083**	0.013	0.042**	0.014
L8.	-0.065**	0.013	0.021	0.014
ΔS_t				
L1.	0.513**	0.011	0.099**	0.012
L2.	0.220**	0.012	-0.080**	0.013
L3.	0.159**	0.012	-0.082**	0.014
L4.	0.181**	0.013	-0.021	0.014
L5.	0.118**	0.013	-0.031**	0.014
L6.	0.121**	0.013	-0.012	0.014
L7.	0.108**	0.013	-0.002	0.014
L8.	0.073**	0.013	-0.023	0.014

Note: "**" indicates significantly different from zero at 5% significance level.

Table 4. Test results of information shares for SET50 Index, SET50 Index Futures and TDEX

Panel B: Price discovery in SET50 Index Futures and TDEX		
Vector moving average coefficients, Ψ(1)		
	SET50 Index Futures Shock	TDEX Shock
SET50 Index Futures	0.0021	0.0006
TDEX	0.0021	0.0007
Residual correlation matrix		
	SET50 Index Futures	TDEX
SET50 Index Futures	1	
TDEX	0.4628	1
Information Shares		
	SET50 Index Futures	TDEX
Upper bound	0.9704	0.3702
Lower bound	0.6298	0.2960
Average	0.8001	0.1999

Panel A: Price discovery in SET50 Index Futures and SET50 Index		
Vector moving average coefficients, Ψ(1)		
	SET50 Index Futures Shock	SET50 Index Shock
SET50 Index Futures	0.0020	0.0006
SET50 Index	0.0019	0.0006
Residual correlation matrix		
	SET50 Index Futures	SET50 Index
SET50 Index Futures	1	
SET50 Index	0.8280	1
Information Shares		
	SET50 Index Futures	SET50 Index
Upper bound	0.9863	0.7885
Lower bound	0.2115	0.1370
Average	0.5989	0.4011

Panel C: Price discovery in TDEX and SET50 Index		
Vector moving average coefficients, Ψ(1)		
	TDEX Shock	SET50 Index Shock
TDEX	0.0012	0.0018
SET50 Index	0.0013	0.0018
Residual correlation matrix		
	TDEX	SET50 Index
TDEX	1	
SET50 Index	0.5292	1
Information Shares		
	TDEX	SET50 Index
Upper bound	0.6715	0.8464
Lower bound	0.1536	0.3285
Average	0.4126	0.5874

Table 5. Test results of conditional information shares for SET50 Index, SET50 Index Futures and TDEX

Test results of conditional information shares			
Panel A: Price discovery in SET50 Index Futures, TDEX and SET50 Index			
Vector moving average coefficients, Ψ(1)			
	SET50 Index Futures Shock	TDEX Shock	SET50 Index Shock
SET50 Index Futures	0.0020	0.0005	0.0006
TDEX	0.0019	0.0008	0.0004
SET50 Index	0.0020	0.0003	0.0007
Residual correlation matrix			
		TDEX	SET50 Index
SET50 Index Futures	1		
TDEX	0.4673	1	
SET50 Index	0.8289	0.5042	1
Panel B: Average Conditional Information Shares per market			
		Average	Standard error
SET50 Index Futures Conditional Information Shares			
SET50 Index Futures		0.5265	0.1465
TDEX		0.5049	0.1423
SET50 Index		0.5330	0.1482
TDEX Conditional Information Shares			
SET50 Index Futures		0.1235	0.5940
TDEX		0.1671	0.6880
SET50 Index		0.1070	0.5460
SET50 Index Conditional Information Shares			
SET50 Index Futures		0.3500	0.1442
TDEX		0.3281	0.1395
SET50 Index		0.3600	0.1462
Panel C: Bounds of Price discovery			
Conditional Information Shares in SET50 Index Futures			
CIS	SET50 Index Futures	TDEX	SET50 Index
Upper bound	0.9711	0.3376	0.7921
Lower bound	0.1844	0.1180	0.1340
Conditional Information Shares in TDEX			
CIS	SET50 Index Futures	TDEX	SET50 Index
Upper bound	0.9488	0.4148	0.7674
Lower bound	0.1777	0.3610	0.0550
Conditional Information Shares in SET50 Index			
CIS	SET50 Index Futures	TDEX	SET50 Index
Upper bound	0.9763	0.3040	0.8018
Lower bound	0.1848	0.0510	0.1340

Conclusion

This study investigates the price discovery during the overlapping trading hours of SET50 Index (*cash index*), SET50 Index Futures (*futures index*) and ThaiDex SET50 (*exchange traded fund).* We employ three methods to document dynamic price discovery; Vector Error Correction Model (VECM), information share and conditional information share. Our results indicate that there exists the long run relationship among three markets.

While price may deviate from equilibrium in short run, it will eventually move toward the long run equilibrium. More importantly, the empirical evidence supports the notion that SET50 Index Futures contributes the most in price discovery, followed by SET50 Index and least in TDEX. In sum, the results suggest that multi-market trading of derivatives markets and its underlying help to improve price efficiency.

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