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# The information spillover between stock index and derivative products trading behavior in Taiwan


## Abstract

This paper has examined the dynamics of price discovery between different Taiwan stock index and derivative products (the ETF50, the ETF51, and ETF52) by applying the vector autoregressive (VAR) model. It is easy to show that four series variables are in positive correlation relationships. The finding suggests that ETF51 has the largest return and volatility. Further, it explores at least three number of co-integrating vector among the variables. The stock index and derivative products share co-integration relationship so that they will not wander arbitrarily far from each other. On the other hand, it has demonstrated the methodology of Granger causality to examine the causality linkage among the variables. The leading relation exists in stock index with stronger evidence that stock index leads derivative products. Moreover, according to the decomposition of forecast error variance, stock index is the least influenced by outside force among the four series variables. In other words, stock index is mostly influenced by its own shock, but is less by other variables shock. The stock index variance decomposition can explain more except its own influence. Secondly, they cannot trace consistently out the time path of impulse response. Consequently, investors manage trading strategies in information spillover.


**Keywords:** information spillover, derivative products, ETF, VAR.
**JEL Classification:** G13.

## Introduction

Giving the continuous status of uncertainty in financial system, the financial market, which relies on foreign equity capital in the past, will continue to become more serious in the future. In order to attract and maintain foreign capital, it is important for the efficiency of financial market to increase synchronously. Obviously, equity markets that are characterized by market province have not yet been known for their efficient pricing mechanism, especially in the crucial era of information spillover. Until recently, financial markets have made efforts to develop new index products. Exchange Traded Fund (ETF) is a derivative example. Over the past few years, the Taiwan Stock Exchange Corporation (TSEC) published its first ETF on June 30, 2003. ETF is a derivative product of stock index that measures the tendency of the securities market. Investors indirectly invest in the portfolio by keeping beneficiary certificates, which are described as the index funds. Thereafter, investors are able to follow the tendency of the index by investing in the ETF while index funds traded in the stock exchange. The ETF is divided into smaller trading units to trade in the stock exchange. According to Taiwan Stock Exchange regulation, there are three index funds in the Taiwan stock market. They are Taiwan Top50 Tracker Fund (ETF50), Polaris Taiwan Mid-Cap 100 Tracker Fund (ETF51) and Fubon Taiwan Technology Tracker Fund (ETF52).

This article explores the issue of lead-lag relations among the four different stock indices of Taiwan Stock Exchange Corporation. The objective is to learn more about the role of trading strategy and to investigate the spillover of information. The relationship among these four time-series can show the following three scenarios: (1) examining the overall information transfer effect between index fund and the trading behavior of the investors in Taiwan; (2) investigating which index product possesses the leading/lagging position; and (3) exploring whether correlated/positive feedback trading exists among ETF investors. Since the amount of related researches on the leading/lagging relationship between index fund and the stock index trading behavior in Taiwan is quite few due to data availability, the finding of this study can set a benchmark for further examinations.

The rest of this paper is organized as follows. The literature review is discussed in section 1; section 2 explains the data source; section 3 explores the methodology; the empirical findings are illustrated in section 4. Finally, the conclusion is provided in the last section.

## 1. Literature review

According to history records, stock index futures are efficiently introduced at Kansas City Board of Trade in February 1982. Some researchers have reported different market efficiency opinions between spot and futures markets (Pizziet et al., 1998; Tse, 1999; Chris et al., 1999). In particular, Gokce and George (2003) explore the dynamic relationship between Dow Jones Industrial Average (DJIA) futures and spot markets by forming a vector autoregressive (VAR) model. The results exhibit evidence of bi-directional causality, but the impact of a one-unit increase in spot returns on futures returns volatility is inferior to the impact of one-unit increase in futures returns on the spot returns volatility. Accordingly, Hyun-jung and Graham (2004) investigate the effect of stock index futures on the Korean stock market by adopting Error Correction Model. The findings are co-integrated relationship and bi-directional causality between the two markets. The lead/lag relationship is stronger indication that the stock index futures lead the spot index and weaker indication that the spot index leads futures markets.

Owain and Mike (2001) explored the lead/lag relationship between the FTSE 100 stock market index and its related futures and option contract, and also studied the interrelation between the derivatives markets. They argued that the cash index is found to lag the index futures and index option contracts. Furthermore, internationally speaking, most of the countries are affected by the developed markets. For example, Wing-Keung et al. (2004) observe the issue of co-movement between stock markets of major developed countries (United Sates, United Kingdom, Japan) and Asian emerging markets (Malaysia, Thailand, Korea, Taiwan, Singapore and Hong Kong). They suggest that Taiwan and Singapore are cointegrated with Japan. Further, United Kingdom and United States are cointegrated with Hong Kong. However, there are no long-run cointegration relationship between the emerging markets of Korea, Malaysia and Thailand and the developed markets of Japan, the United Kingdom and United States.

Joel (2003) perceives an empirical result of intraday price dynamics in three U.S. equity index markets (S&P 500, S&P Midcap 400 and Nasdaq 100). He applies the Vector Error Correction Model (VECM) and indicates that the E-mini contract exists firstly of the information contribution in the S&P 500 and Nasdaq 100. Exchange Traded Fund (ETF) plays a minor role, but the regular futures and ETF lead the information contribution in the S&P Midcap 400 market. Yiuman et al. (2006) observe the dynamics of price discovery between the Dow Jones Industrial Average index and its three derivative contracts: the Diamond exchange-traded fund, the floor-traded regular futures and the electronically traded mini futures. Statistic method is used in vector error correction model to survey intraday five-minute observation from May through July 2004. The findings exhibit that the electronically traded mini futures will lead in price discovery, followed by the Diamond ETF while Dow Jones Industrial Average index and regular futures are slower in price discovery.

## 2. Data description

The stock index and derivative products are examined at Taiwan stock exchange. The stock index was set up on February 1962, other derivative products: ETF50 was set up on June 30, 2003; ETF51 was set up on August 31, 2006; and ETF52 was newly set up on September 12, 2006. For the consistence purpose, the period of intraday sample was from September 12, 2006 to July 31, 2007. Moreover, the five-minute data were retrieved from the Taiwan Economic Journal in local database management system. Overall, a total of 11718 five-minute observations have been investigated to discover the information spillover effects among them.

## 3. Methodology

In order to use the high frequency time series to explore the information spillover of stock index and derivative products, we mainly apply the VAR mode to reveal the result. First, the return for interval *t* on intraday *I* is *Ri, t = ln (Ii,t / Ii,t-1)*. Where *I* is the last value for stock index, ETF50, ETF51 and ETF52 are in an interval. According to Engel and Granger (1987) and Said (1991) researches, the proceeding confirmed that series variables are stationary before co-integration test. Otherwise, Granger and Newbold (1974) proposed spurious regression in the existence of non-stationary variables. The spurious regression has high R-Square and t-statistic. It can be significant, but the findings are without any economic intent. To the unit root process, Schwert (1987) showed that the estimation can select the appropriate lag length and the correlation of the disturbance item and shall appear to be white noise. Thus, too many lags will cause the over parameterization and the loss of degrees of freedom. On the contrary, too few lags will not be well-estimated by the bias problems. The two most commonly explored model selection criteria are the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC). Between the two criteria, the SBC is superior to large-sample properties. Thus, we use SBC to select in time series. Thereafter, the series variables are in non-stationary situation to correct them by differencing. In this paper, we exhibit Dickey and Fuller (1979) with Philip and Perron (1988) unit root test method to ascertain the series variables are integrated of different order and stationary. The Dickey-Fuller test is described by the three equations:

$$\Delta Y_t = a_0 + \beta Y_{t-1} + a_2 t + \varepsilon_t \ , \tag{1}$$

$$\Delta Y_t = a_0 + \beta Y_{t-1} + \varepsilon_t \, , \tag{2}$$

$$\Delta Y_t = \beta Y_{t-1} + \varepsilon_t \, . \tag{3}$$

The first equation includes both a drift ($a_0$) and a linear time trend ($a_2 t$), the second equation reduces a deterministic element, and the third one is a pure random walk model. Philips and Perron (1988) suggested that a nonparametric method of controlling has high-order serial correlation in time series. The PP test statistic may be accounted for the same three function forms. Researchers discuss a correction to t-statistic to explain the serial correlation in disturbance. The correction is nonparametric since we had taken an estimate of the spectrum of disturbance at frequency zero that is robust to heteroskedasticity and autocorrelation of unknown type. The parameter of interest in all of the regression equations is $\beta$, if $\beta$ = 0, the time series sequence contains a unit root and is differenced stationary.

The determination criterion usually has two important ways to test for co-integration. Engle-Granger (1987) suggested the two-step co-integration test to determine whether the disturbance of the equilibrium relationship is stationary. Besides, Johansen (1988) reported that Maximum Likelihood Estimate method to estimate time series variables in co-integration relationship and found out co-integration vector number. This paper will use Johansen's method to test in the co-integration relationship so that we can understand the trace and maximum eigenvalue statistic test. Statistic form is respective:

$$\lambda_{trace}(\gamma) = -T \sum_{i-\gamma+1}^{n} \ln(1-\hat{\lambda}_i), \quad (4)$$

$$\lambda_{\max}(\gamma, \gamma+1) = -T \ln(1-\hat{\lambda}_{r+1}), \quad (5)$$

where $\hat{\lambda}_i$ = the estimated value of the eigenvalues,

T = the number of observations.

In the contrast to this lead-lag relationship, Granger (1969) addressed to the question of whether independent variables causing dependent variables are to see how much of the current dependent variables could be interpreted by past values of dependent variables and to see whether adding lagged value of independent variables could improve interpretation. Consequently, the null hypothesis is that *Y* does not Granger cause *X* in the sixth regression and that *X* does not Granger cause *Y* in the seventh regression. Granger causality model:

$$x_t = a_0 + a_1 x_{t-1} + .... + a_n x_{t-1} + \beta_1 y_{t-1} + \beta_2 y_{t-2} + .. + \beta_1, \quad (6)$$

$$y_t = a_0 + a_1 y_{t-1} + .... + a_n y_{t-1} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + .. + \beta_1. \quad (7)$$

In the past study, Sims (1980) implies that it allows you to depict the time path of the variables shocks on the variables contained in the vector autoregressive (VAR) system. Furthermore, it illustrates the insight into the four variables relationships which are provided by simulating the response of one standard deviation innovation from the estimated VAR system. In other words, consider the following multivariate system:

$$\begin{bmatrix} x_t \\ y_t \\ z_t \\ \delta_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \\ a_{40} \end{bmatrix} + \begin{bmatrix} a_{11}a_{12}a_{13}a_{14} \\ a_{21}a_{22}a_{23}a_{24} \\ a_{31}a_{32}a_{33}a_{34} \\ a_{41}a_{42}a_{43}a_{44} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ z_{t-1} \\ \delta_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}. \quad (8)$$

Thereafter, we modify the equation to the multivariate form:

$$I_t = A_0 + A_1 I_{t-1} + A_2 I_{t-2} + ... + A_p I_{t-p} + e_t, \quad (9)$$

$I_t$ : an (n,1) vector containing each of the four variables included in the VAR respectively, stock index, ETF50, ETF51, ETF52;

$A_0$ : an (n,1) vector of intercept terms, and exogenous variables;

$A_i$ : (n,n) matrices of variables coefficients;

$e_t$ : an (n,1) vector of disturbance terms and are uncorrelated white-noise disturbance.

Of course, such a system could be used to capture the feedback effect in time series studies, where the system is being estimated as a VAR (8).

## 4. Empirical result

From the measures of the four time series variables, Table 1 presents the descriptive statistic and correlation matrix for the corresponding. We observed that time series variables are all leptokurtic distribution and positive skewness. The standard deviation is much larger for stock index in four time series. In the contrast, ETF51 is much smaller in standard deviation. All the four time series are not normally distributed as evidenced by the Jarque-Bera normality test. The correlation relationship of stock index and ETF50 in four time series variables is better. In addition, they are positively correlated in four time series. Investor will assume the positive discrimination.

Table 1. Stock index and derivative products

Panel A. Descriptive statistic for four time series variables

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| Mean | 7863. 809 | 58.41013 | 32.28680 | 38.83778 |
| Maximum | 9803.860 | 69.85000 | 42.40000 | 47.80000 |
| Minimun | 6554.220 | 52.95000 | 26.00000 | 34.00000 |
| Std. dev. | 691.1974 | 3.922181 | 3.057162 | 3.167356 |
| Skewness | 0.763260 | 1.416386 | 0.848659 | 1.185670 |
| Kurtosis | 3.364122 | 4.210036 | 4.181603 | 3.564604 |
| Jarque-Bera (p-value) | 0.000** | 0.00000** | 0.00000** | 0.00000** |
| Observation | 11718 | 11718 | 11718 | 11718 |

Note: ** significant at the 1% level.

Panel B. Correlation matrix for four time series variables

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| Stock index | 1.000000 | 0.913712 | 0.983925 | 0.972696 |
| ETF50 | | 1. | 0.876565 | 0.958818 |
| ETF51 | | | 1.000000 | 0.936718 |
| ETF52 | | | | 1.00000 |

Note: ** significant at the 1% level.

To depend on the variation of the changes/returns, Table 2 reports the descriptive statistic and correlation matrix for the corresponding measure of the four series variable in change/returns. The average return and the volatility are much larger for ETF51. The stock index and ETF50 are negative skewness and other variables are positive. The four time series variables are whole leptokurtic distribution and the Jarque-Bera normality tests are not normal distributions. Moreover, the four time series variables are positive correlation and much better between stock index and ETF50. The market investors could simultaneously respond to a universal shock that causes them to move in a positive direction and rejects normality at 1% level for all distributions.

Table 2. Stock index and derivative products in changes/returns

Panel A. Descriptive statistic for four time series variables in changes/returns

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| Mean | 0.001216 | 0.000723 | 0.001487 | 0.000915 |
| Maximun | 0.760139 | 0.634563 | 2.569084 | 0.924562 |
| Minimun | -1.412814 | -3.055811 | -2.079141 | -0.934003 |
| Std. dev. | 0.050261 | 0.064485 | 0.075202 | 0.066765 |
| Skewness | -0.652635 | -10.40598 | 1.115212 | 0.412255 |
| Kurtosis | 100.1459 | 475.4033 | 210.4046 | 36.34846 |
| Jarque-Bera (p-value) | 0.000000** | 0.000000** | 0.000000** | 0.000000** |

Note: ** significant at the 1% level.

Panel B. Correlation matrix for four time series variables in change/returns

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| Stock index | 1.000000 | 0.60442 | 0.376789 | 0.394330 |
| ETF50 | | 1.0000 | 0.281975 | 0.323329 |
| ETF51 | | | 1.000000 | 0.217452 |
| ETF52 | | | | 1.00000 |

Following the introduction of unit root test, the result is exhibited in Table 3.

We do not reject null hypothesis in this paper. Hence, the data-generating process is non-stationary and adopts action by appropriate differencing. Clearly, it is easy to show that four time series reject null hypothesis and are stationary variables. Such a process is integrated of order one and is expressed by I (1).

Table 3. Unit root test. Panel A. The unit root test results of the four time series variables

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| ADF statistic | 2.3643 | 1.3401 | 2.8383 | 1.6910 |
| PP statistic | 2.4577 | 1.2990 | 2.7750 | 1.6825 |
| Lag length | 1 | 1 | 1 | 1 |

Note: ** significant at the 1% level. ADF critical value: -2.5652. * significant at the 5% level. ADF critical value: -1.9408.

Panel B. The unit root test results of the four time series variables by appropriate differencing

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| ADF statistic | -100.0647** | -116.1922** | -73.4899** | -67.9544** |
| PP statistic | -99.7840** | -116.1447** | -133.9769** | -120.0894** |
| Lag length | 0 | 0 | 2 | 2 |

Note: ** significant at the 1% level. ADF critical value: -2.5652. * significant at the 5% level. ADF critical value: -1.9408.

In addition, we use Johansen cointegration test to examine the effect depending on whether co-integration has relationship or not. Table 4 illustrates the results of the co-integration test for the change/returns time series. From trace statistic and eigenvalue specification, we obtain at least three co-integrating vectors. It could be clear that long-run relationships exist among a set of integrated variables so that investors cannot wander arbitrarily far from each other. Accordingly, the more co-integration, the "more steady" the formation will be (Dickey et al., 1994).

Table 4. Co-integration rank test

| Hypothesized | Eigenvalue | Trace statistic | 5 percent | 1 percent |
|---|---|---|---|---|
| No of CE (S) | | | Critical value | Critical value |
| None** | 0.162713 | 6656.314 | 39.89 | 45.58 |
| At most 1** | 0.150253 | 4577.112 | 24.31 | 29.75 |
| At most 2** | 0.121632 | 2670.855 | 12.53 | 16.31 |
| At most 3** | 0.093743 | 1152.445 | 3.84 | 6.51 |

Note: *(**) denotes rejection of the hypothesis at the 5% (1%) level.

In particular, Table 5 performs Granger's causality method to explore the result.

We can see that some evidence of a significant bi-directional information flows among stock index and ETF52, ETF50 and ETF51, ETF51 and ETF52.

Furthermore, it appears that Granger causality runs one-way from stock index to ETF52, stock index to ETF51, ETF50 to ETF52. According to F-statistic strength, the stock index is the first to lead operator among the time series. The secondary sequence is ETF50 because a causal relation exists from ETF50 to both ETF51 and ETF52; but ETF50 leads ETF51 much stronger than ETF51 leads ETF50. Thereafter, it might be stronger causal relation from ETF51 to ETF52. The results overall indicate that the contract is induced to buy/sell by causal relation. Hence, if the market is existed in the information effect, the market trading strategy is employed in causal relation sequence.

Table 5. Granger causality tests

| Null hypotheses | F-statistic | Probability |
|---|---|---|
| ETF50 does not Granger cause stock index | 0.01718 | 0.98297 |
| Stock index does not Granger cause ETF50 | 271.457 | 0.00000** |
| ETF51 does not Granger cause stock index | 1.01960 | 0.36077 |
| Stock index does not Granger cause ETF51 | 436.592 | 0.00000** |
| ETF52 does not Granger cause stock index | 20.0304 | 2.1E-09** |
| Stock index does not Granger cause ETF52 | 307.468 | 0.00000** |
| ETF51 does not Granger cause ETF50 | 16.8537 | 4.9E-08** |
| ETF50 does not Granger cause ETF51 | 158.557 | 0.00000** |
| ETF52 does not Granger cause ETF50 | 2.88122 | 0.05611 |
| ETF50 does not Granger cause ETF52 | 138.626 | 0.00000** |
| ETF52 does not Granger cause ETF51 | 38.5462 | 0.00000** |
| ETF51 does not Granger cause ETF52 | 85.7372 | 0.00000** |

Note: ** significant at the 1% level.

In addition to the determination of the set of series variables to include in VAR, it is a critical time to determine the appropriate lag length. If the residual series is still autoregressive, it will add lag length. In terms of Table 6 results, we can observe the relationship of residual correlation matrix. In the same time, the stock index and ETF50 is high residual correlation (0.612692), but other variables will be small. Therefore, it could be inferred that information transmission activity is low and the lag status exists among the four variables.

Table 6. Residual correlation matrix

| | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| Stock index | 1.0 | 0.612692 | 0.399131 | 0.392186 |
| ETF50 | | 1.0 | 0.282989 | 0.317410 |
| ETF51 | | | 1.0 | 0.213746 |
| ETF52 | | | | 1.0 |

The illustrative purpose decomposition of residual variance is reported in Table 7. For the entire period, the forecast residual variance of only 1, 4, 7, 10, 13 and 16 days in the VAR system is explored. To be precise, the first period decomposition for the stock index in the VAR ordering is completely due to its own innovation. Further, the first period decomposition for the ETF50 is affected by its own and stock index innovation, other first period decomposition for the ETF51 is affected by its own and both stock index and ETF50 innovation. Besides, the first period decomposition of the ETF52 is affected by its own and the other variables innovation. It can readily be presumed from figures in Table 7 that the trading behavior of stock index is least influenced by outside forces among the four time series variables. By contrast, the trading behavior of ETF50 is the most heavily influenced by the other three outside forces. For example, the 99% volatility for stock index intraday changes could be explained by itself in the sixteen days while the figure for ETF50 is only 62%. The stock index returns are explained more by the intraday change of ETF52 than by those of ETF50 and ETF51. Furthermore, the trading of ETF51 is influenced not only by stock index but also by its own. An elaborate analysis exhibits that the stock index returns would affect all three variables investors, and will disclose the fact that investors' trading behavior in Taiwan has a significant impact on the market because the stock index has significantly relative relationship with the three exchange traded funds. Consistently with Table 5, the F-statistic of stock index is the largest to affect derivative products.

Table 7. Decomposition of forecast residual variance of the four time series variables

| | | By residual item in | | | |
|---|---|---|---|---|---|
| Dependent variable | Lagging day | Stock index | ETF50 | ETF51 | ETF52 |
| Stock index | 1 | 100.0000 | 0.000000 | 0.000000 | 0.000000 |
| | 4 | 99.48727 | 0.036886 | 0.056837 | 0.419010 |
| | 7 | 99.34792 | 0.042774 | 0.178160 | 0.431147 |
| | 10 | 99.27101 | 0.048224 | 0.193473 | 0.487293 |
| | 13 | 99.26719 | 0.048363 | 0.193629 | 0.490820 |
| | 16 | 99.26696 | 0.048384 | 0.193703 | 0.490948 |
| ETF50 | 1 | 37.53910 | 62.46090 | 0.000000 | 0.000000 |
| | 4 | 36.93548 | 62.78314 | 0.017737 | 0.263636 |
| | 7 | 36.90145 | 62.72155 | 0.017737 | 0.263636 |
| | 10 | 36.90920 | 62.68716 | 0.091675 | 0.311960 |
| | 13 | 36.90969 | 62.68613 | 0.091675 | 0.312416 |
| | 16 | 36.90967 | 62.68593 | 0.091793 | 0.312603 |
| ETF51 | 1 | 15.93055 | 0.236634 | 83.83281 | 0.000000 |
| | 4 | 16.18790 | 0.239537 | 83.46182 | 0.110746 |
| | 7 | 16.18918 | 0.253896 | 83.41577 | 0.141160 |
| | 10 | 16.20872 | 0.259501 | 83.30465 | 0.227125 |
| | 13 | 16.21092 | 0.259604 | 83.30147 | 0.228002 |
| | 16 | 16.21103 | 0.259651 | 83.30121 | 0.22811 |
| ETF52 | 1 | 15.38096 | 0.952228 | 0.328348 | 83.33847 |
| | 4 | 16.59646 | 0.901269 | 0.337958 | 82.16431 |
| | 7 | 16.56952 | 0.905803 | 0.400801 | 82.12387 |
| | 10 | 16.68506 | 0.918420 | 0.456013 | 81.94051 |
| | 13 | 16.69876 | 0.918443 | 0.456337 | 81.92646 |
| | 16 | 16.69877 | 0.918442 | 0.456516 | 81.92627 |

For the consistence purpose, the spillovers of returns (changes) within sixteen trading days are examined.

As discussed in Table 8, it is clear to demonstrate the speed of information spillovers to one standard deviation unit shock in stock index. Only stock index variable induces instantaneous movement and the other three variables are zero state in the first period. However, in the second period, only ETF52 is a negative impulse response and the other three variables are positive. As such, it will be possible to trace out the time paths of the effect of pure positive or negative shocks. Table 9 presents the results for the trivial effect of information spillovers in ETF50. The effect of one unit shock causes the value of ETF50 and stock index increases positively and the other two variables are zero state in the first period. In the subsequent period, the ETF50, ETF51 and ETF52 are negative shocks, but stock index is positive shock. Table 10 delineates the slight effect of information spillovers in ETF51. It appears that stock index and ETF50 will be the same when ETF51 is positively responded in the first period. Thereafter, the noise effect is not significant. In the contrast, Table 11 exhibits that the speed of information spillovers is frivolous in ETF52. It may be reasonably posited that one unit shock will make positive response of the four time series in the first period. In sum, there is no consistent effect in impulse responses. Notwithstanding it might asymptotically decay to zero state. The succeeding consequence of impulse response indicates that the information spillover effect for four time series variables does not exist and investors will adopt different trading strategies. In the meantime, Figure 1 shows the average impulse response to one standard deviation innovation for the four time series in a period of sixteen days. Apparently, it could be presumed graphically that all impulse responses do not exist or disintegrate quickly. These results are consistent with convergence.

Table 8. Impulse response to a unit shock for stock index

| Period | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| 1 | 0.049880 | 0.000000 | 0.000000 | 0.000000 |
| 2 | 0.003997 | 0.000166 | 0.000695 | -0.002815 |
| 3 | -0.000981 | 0.000296 | 6.37E-05 | 0.000483 |
| 4 | -0.001346 | 0.000902 | 0.000972 | -0.001550 |
| 5 | -0.001555 | 0.000304 | 0.001691 | 0.000501 |
| 6 | -0.000619 | -7.65E-05 | 0.000418 | -2.16E-05 |
| 7 | 0.000555 | 0.000231 | -0.000183 | 0.000289 |
| 8 | 0.000550 | -0.000370 | -0.000547 | -0.000961 |
| 9 | -0.000279 | 1.07E-05 | 8.11E-05 | -0.000646 |
| 10 | -0.000250 | -3.84E-05 | -0.000293 | 0.000298 |
| 11 | -0.000128 | -5.78E-05 | 3.35E-05 | 0.000196 |
| 12 | -7.27E-05 | 5.85E-06 | -3.74E-05 | 0.000200 |
| 13 | 6.15E-05 | 1.41E-05 | 4.05E-05 | 0.000107 |
| 14 | 2.47E-05 | 1.27E-05 | 3.14E-05 | 1.26E-05 |
| 15 | -2.27E-05 | -1.93E-05 | 2.94E-05 | -5.60E-05 |
| 16 | -6.98E-05 | -9.05E-07 | 7.67E-06 | 1.80E-06 |

Table 9. Impulse response to a unit shock for ETF50

| Period | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| 1 | 0.038424 | 0.049564 | 0.000000 | 0.000000 |
| 2 | 0.007622 | -0.012208 | -0.000639 | -0.002864 |
| 3 | 0.000374 | -0.001791 | 0.000519 | 0.000374 |
| 4 | -0.000379 | 0.000170 | 0.000244 | -0.001616 |
| 5 | 2.14E-05 | -0.000950 | 0.001062 | 0.000974 |
| 6 | 0.000406 | 1.83E-05 | 0.001015 | -0.000741 |
| 7 | 0.000677 | 3.30E-05 | 0.000164 | 0.000559 |
| 8 | 0.000997 | -0.000431 | -0.000935 | -0.000262 |
| 9 | 0.000179 | -0.000195 | 0.000140 | -0.000375 |
| 10 | -0.000554 | 0.000250 | -5.37E-05 | -0.000126 |
| 11 | -0.000166 | -3.65E-07 | 5.17E-05 | 0.000112 |
| 12 | -0.000132 | 2.19E-05 | -2.81E-05 | 6.12E-05 |
| 13 | 2.91E-05 | -1.14E-05 | 1.91E-05 | 5.33E-05 |
| 14 | 2.92E-05 | 1.45E-05 | -1.95E-05 | 4.64E-05 |
| 15 | 1.66E-05 | -6.10E-06 | 2.69E-05 | -7.18E-05 |
| 16 | -5.59E-05 | -1.38E-05 | 8.67E-06 | -2.21E-05 |

Table 10. Impulse response to a unit shock for ETF51

| Period | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| 1 | 0.028041 | 0.003418 | 0.064327 | 0.000000 |
| 2 | 0.010829 | -0.000964 | -0.022895 | -0.001723 |
| 3 | 0.003218 | -0.000926 | -0.004477 | -0.000364 |
| 4 | 9.25E-05 | -0.000237 | -0.005485 | -0.001775 |
| 5 | 0.000440 | -0.000143 | 0.000653 | 0.001050 |
| 6 | -0.000915 | 0.000786 | 0.000993 | -0.000510 |
| 7 | -0.000244 | -0.000435 | -0.001111 | -0.000603 |
| 8 | 0.000834 | -0.000117 | -2.35E-05 | 0.002026 |
| 9 | 0.001122 | 0.000567 | 7.90E-05 | -0.000319 |
| 10 | -0.000863 | -8.63E-05 | 0.001382 | -0.000820 |
| 11 | -0.000347 | 2.70E-05 | -9.40E-05 | -0.000210 |
| 12 | -0.000215 | -5.80E-05 | -9.22E-05 | 6.58E-06 |
| 13 | 5.87E-05 | -4.79E-05 | -0.000186 | 7.88E-05 |
| 14 | 6.93E-05 | -1.70E-05 | -4.75E-05 | 4.25E-05 |
| 15 | 2.48E-05 | 3.35E-05 | -3.59E-05 | -1.10E-05 |
| 16 | 6.46E-05 | -3.63E-05 | -3.21E-05 | -6.56E-05 |

Table 11. Impulse response to a unit shock for ETF52

| Period | Stock index | ETF50 | ETF51 | ETF52 |
|---|---|---|---|---|
| 1 | 0.025110 | 0.006248 | 0.003669 | 0.058450 |
| 2 | 0.008223 | -0.000375 | 0.000809 | -0.013531 |
| 3 | 0.005987 | 0.000175 | -0.000668 | -0.005220 |
| 4 | 0.001565 | 0.000887 | -0.000661 | -0.004382 |
| 5 | 0.000861 | 0.000160 | 0.001379 | -0.001259 |
| 6 | 0.000304 | 0.000318 | -7.46E-05 | -0.003087 |
| 7 | 0.000771 | 0.000467 | 0.000972 | -0.000303 |
| 8 | 0.001536 | 0.000663 | -0.001171 | -0.000803 |
| 9 | 0.001893 | -0.000433 | 0.001006 | -0.000881 |
| 10 | -0.001180 | -0.000237 | -0.000368 | 0.001076 |
| 11 | -0.000799 | -8.94E-05 | 0.000125 | 0.000502 |
| 12 | -0.000393 | -2.75E-05 | -5.06E-05 | 0.000218 |
| 13 | -0.000109 | -5.36E-05 | 4.02E-05 | 0.000139 |
| 14 | -4.44E-05 | 4.73E-06 | -3.79E-05 | 9.98E-05 |
| 15 | 8.75E-05 | -5.70E-06 | -8.14E-05 | -0.000140 |
| 16 | -1.47E-05 | -2.06E-05 | 1.40E-05 | -9.04E-05 |

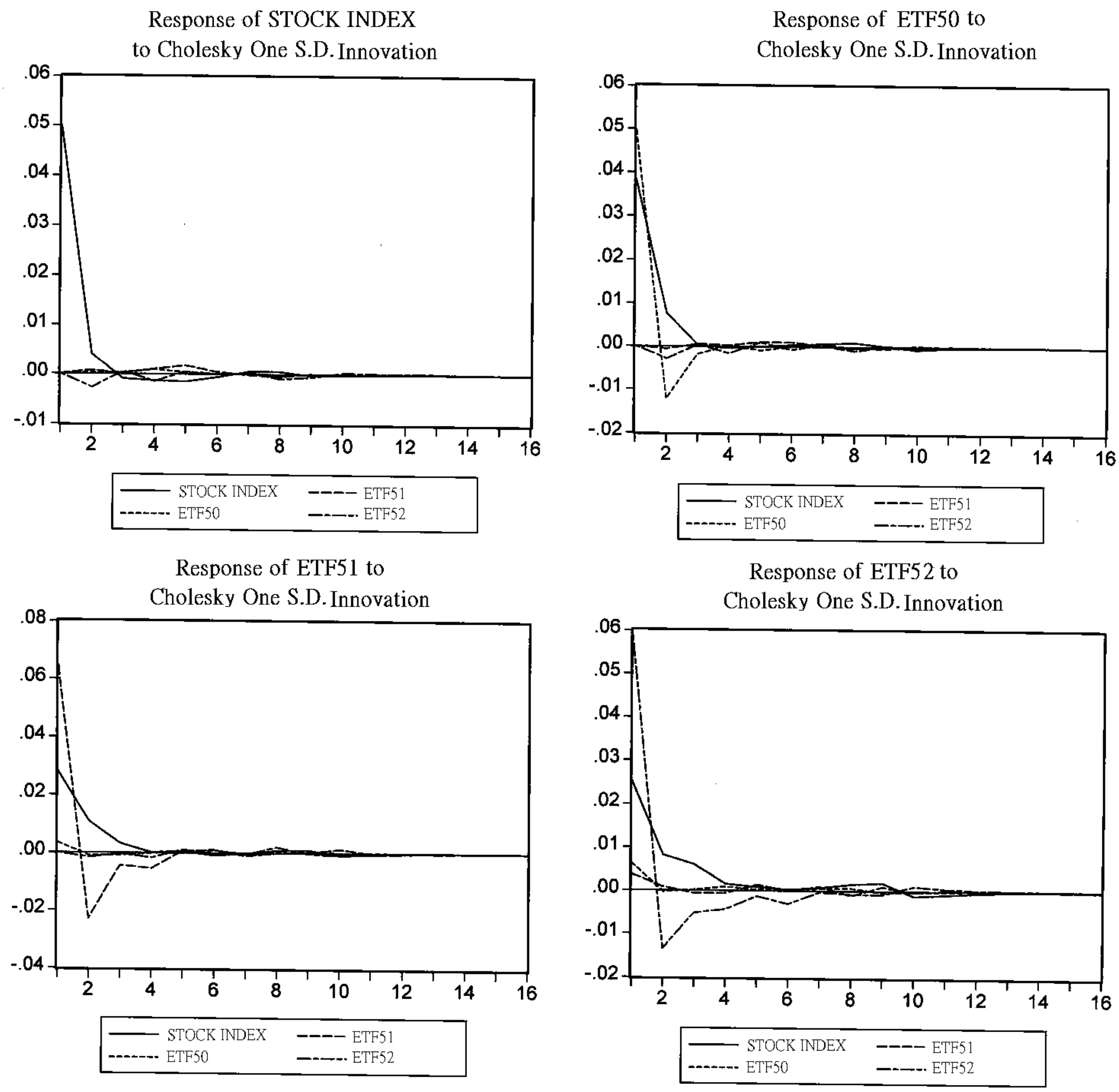


**Fig. 1. Average impulse response**

## Conclusion

This paper has examined the evidence for co-integration between stock index and derivative products: ETF50, ETF51, and ETF52. The finding determines at least three numbers of co-integrating vectors among the variables. It could be clear that long-run relationship exists among a set of integrated variables. Therefore, investors will not wander arbitrarily far from each other.

On the other hand, it has demonstrated the methodology of Granger causality to examine the causality linkage among the variables. The result indicates that stock index leads the derivative products, while the ETF50 leads both ETF51 and ETF52. However, the ETF51 leads ETF52 much stronger than ETF52 leads ETF51. Therefore, if the existing information spillover affects the market trading strategy, it is employed in causal relation sequence. Due to the stationary variables in a VAR system, it can indicate two policy implications for investors. Firstly, forecast residual variance decomposition reports the proportion of the movement in a sequence due to its "own" shocks versus shocks to the other variables. Therefore, stock index is mostly by its own shock, but is less by other variables shock. Further, stock index is closely correlated with other variables in addition to itself. Secondly, a one-unit shock may cause series variables to shift, it is merely temporality movement. In other words, there is no contemporaneous effect on the trend time.

Overall, investors can use the information spillover to decide their trading strategies. For example, stock index leads derivative products; and ETF51 has the largest return and volatility. Consequently, more investors want to request higher returns, we can take this action to promote interest.

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