International Research Journal of Finance and Economics
ISSN 1450-2887 Issue 96 (2012)

http://www.internationalresearchjournaloffinanceandeconomics.com

A Trading Strategy Based on the Lead – Lag Relationship between Futures and Spot Markets and Investor Sentiment

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Abstract

This paper explores the impact of trading strategy in a lead-lag relationship between futures and spot markets, and investor sentiment index. We use daily returns data from the Taiwan Stock Index, Taiwan Stock Index Futures, and MSCI Taiwan Stock Index Futures during the period 1990-2011 and consider the abnormal risk or abnormal rang as an indicator of investor sentiment. In this case conducts the unit root tests, cointegration analysis, vector error-correction, vector autoregression, the Granger causality test, impulse response analysis, and forecast error variance decomposition to reveal the effects of the lead-lag relationship among markets. We find a long-term trend exists among the markets and that MSCI Taiwan Stock Index Futures exhibits market-leading effects, and find stronger relationship between sentiment and market return by using daily data in the short run but week evidence in case of long run. Note that when abnormal sentiment appeared in the market, operating in the same direction as the leading market and covering on the third and fourth days led to positive total returns which shows that as the market information interpretation of various investors suddenly changes, suggesting the need to distinguish these types of abnormal risk in trading strategy.

Keywords: Taiwan Index Futures, Lead-Lag Relationship, Abnormal Range, Sentiment

1. Introduction

The Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), compiled by Taiwan Stock Exchange Co., Ltd. (TWSE) and otherwise known as the Taiwan Stock Index (TS), has long been considered a leading indicator of the development and decline of the Taiwanese economy. The Taiwan Stock Exchange Stock Index Futures Contract, simply referred to as Taiwan Stock Index Futures (TF) and introduced by Taiwan Futures Exchange (TAIFEX) on July 21, 1998, features the TAIEX. Another product associated with the TS is the MSCI Taiwan Stock Index Futures (MSF). Compiled by the MSCI with focus on TS, this product was introduced to Singapore International

Monetary Exchange (SIMEX) on January 9, 1997, which later became the Singapore Exchange Derivatives Trading Limited (SGX-DT) on January 15, 2000. Futures contracts serve several crucial functions for spot contracts such as price discovery, hedging, arbitrage, and speculation. A number of previous studies (Books et al., 2001; Frino and West, 2001; Nam et al., 2006; Lee et al., 2007) have indicated that the futures market leads the spot market.

However, in the event that a lead-lag relationship exists between highly relevant cross-markets, common investors are generally more interested in profit issues and whether trading strategies exist that can generate profits from this relationship. Several researchers (Simon and Wiggins, 2001; Cliff, 2004; Pai and Chang, 2008;Vermaa and Soydemir, 2009; Bohl et al., 2011) have employed investor sentiments as an indicator of market operations. Applying the abnormal range as a sentiment index involves referring to the average range of the previous few days and, when the range of a day is significantly greater than the average volatility, believing that the market will develop in a certain direction. Using this trade strategy in three markets with a lead-lag relationship, investors may yield profits by conducting trade in the lagging market in the same direction as the leading market. Because previous empirical evidence supports the existence of a lead-lag relationship between the futures and spot markets and the low-cost advantage of the futures market enables price discovery, we investigated the lead-lag relationship among three markets using price and return data by referring to the empirical models of several previous studies: (1) the unit root test, (2) the cointegration test, (3) the vector error-correction model (VECM), (4) vector autoregression (VAR), (5) the Granger causality test, (6) impulse response analysis, and (7) forecast error variance decomposition (Roope and Zurbruegg, 2002; Cliff, 2004; Hsu et al., 2005; Pradhan and Bhat, 2009; Athanasios, 2010). We employed the volatility of range as a sentiment index and integrated it into trading strategies, observing whether trading profits resulted from this. Furthermore, in the event that a lead-lag relationship exists between markets with the same subject matter, we determined whether the abnormal range of investor sentiments and the price data from the leading market can be used to predict and generate profits before equilibrium is achieved.

2. Literature Review

Index products are no longer traded only on their domestic markets; the same index among stock exchanges in different countries is also becoming increasingly competitive, and their efficiency in conveying information on different markets also varies according to the trading systems in place. There has been a considerable amount of research around the world on the relationship between futures and spot markets. Booth et al. (1999) explored German DAX index futures, spot, and options using a cointegration test and a VECM to analyze the price discovery function between markets. They discovered that markets with lower trading costs provided the advantage of price discovery, empirically proving that the price discovery function in the DAX futures market was distinctly superior to that of the options market. Kim et al. (1999) analyzed the transfer of new market information between the spot market and the futures market based on the trading cost hypothesis, indicating that the market with lower trading costs is more receptive of and responsive to information; therefore, it is apparent that trading costs are associated with price discovery. Price discovery usually occurs first in the low-cost market and often generates maximum profits in information-based transactions. New evidence related to the institutional differences between the Nikkei 225 Stock Index futures traded on Osaka Securities Exchange (OSE) and SIMEX shows that both SIMEX and OSE Nikkei futures returns lead Nikkei225 Index returns. Furthermore, SIMEX futures returns strongly lead the returns of OSE futures (Frino and West, 2001).

The price discovery and information transfer in the Taiwanese futures market indicate that a greater volume of stronger information flows from the futures market to the spot market, increasing the significance of price discovery in the futures market (Hsieh, 2002). Roope and Zurbruegg (2002) compared market information efficiency in the Singapore Exchange and TAIFEX, revealing a number of merits to the Singapore market, including the establishment of a good reputation, lower implementation costs, and less foreign exchange risk for international traders, who are more willing to trade in USD money markets than in NTD money markets. In addition, the trading system exerts significant influence on the price discovery function of a market. Zhong et al. (2004) studied the emerging Mexican Exchange using daily data to examine the cointegration between the futures market and the spot market. Their results indicate that the trading of futures stimulates volatility in the spot market and provides a source of instability for the spot market; however, it also serves as a medium for the price discovery function in the Mexican futures market. The lead-lag relationships among the KOSPI200 stock index, index futures, and index options markets have been explored using time series and cross-sectional data analysis. As established in previous studies, the results show that the KOSPI 200 stock index futures were a leading index, and that the lead-lag relationship between futures and options was symmetric. Furthermore, the KOSPI 200 stock index futures lead the KOSPI 200 stock index (Nam et al., 2006). With regard to the same market index appearing in different exchanges, Lee et al. (2007) used the Granger causality test to investigate the interaction between SIMEX-Nikkei 225 and CME-Nikkei 225 as well as the lead-lag relationship between returns and jump behavior,. The results reveal that the returns of the SIMEX-Nikkei 225 and CME-Nikkei 225 markets present unidirectional causality on spot returns; in addition, the returns of CME-Nikkei 225 and SIMEX-Nikkei 225 have a lag-lead relationship about the direction of causation (Lee et al., 2007). Pradhan and Bhat (2009) explored price discovery, information, and forecasting in the NIFTY futures market and analyzed the causality between spot and futures priceing using the VECM. Their results indicate that the spot market leads the futures market and that spot prices are usually better suited than futures prices for the discovery of new information. They observed that the VECM considered the long-term relationship between futures and spot prices and was essential to predicting future spot prices. Athanasios (2010) investigated the dynamic relationship among the FTSE/ASE-20 spot price index, the FTSE/ASE-20 futures price index, and their volatility. Considering that in the event that information comprising the daily variations in the futures price indices induces the stock market to follow the same trend, then the changes in the Athens Derivatives Exchange (ADEX) futures market could provide a means of predicting price trends in the Athens Stock Exchange (ASE) spot market. The empirical results of this study indicate that futures returns exerted significant influence on the spot returns and futures volatility. Using the Granger causality test, it was found that bidirectional causality existed between spot and futures returns, and furthermore, the volatility of spot prices had an indirect impact on spot returns. Bohl et al. (2011) analyzed the blue-chip index, WIG20, and the flow of information between futures contracts traded on the Warsaw Stock Exchange. They found that price discovery primarily occurred in the spot market prior to regulatory changes and made less contribution towards the subsequent market. Once regulatory changes were implemented, the share of trading volume among foreign and domestic institutional investors increased substantially, which further demonstrates that large quantities of information flow from the futures to spot price. This demonstrates that an increase in common factor weights in the futures market is an indication of unidirectional volatility transmission. Although price discovery still occurs chiefly in the spot market, variations in the investor structure increases the availability of futures price information and a continuing increase in the proportion of institutional traders enhances the effects of price discovery in the futures market.

Variations in trade motives may arise, due to differences among investors and investment organizations. For example, Chang et al. (2000) investigated the relationship between stock market volatility and hedging demand in stock index futures, employing unique data to identify separately the daily open interest of large hedgers, large speculators, and smaller traders. They determined whether different types of traders could effectively allocate resources and risk. The authors indicated that in times of high volatility, the daily open interest of large hedgers increases; in such periods, the increasing demand for speculation exceeds that of hedging. Market prices fluctuate daily; regardless of whether the closing price today goes up or down in comparison with yesterday’s closing price. Market prices represent the views of investors responding to market information that day. A number of studies have therefore focused on the interpretation of market information; each type of trader has their own opinions regarding the interpretation of market information. However, the appearance of large volatility shocks in the market is an indication of a trend, such that information is being expressed in price fluctuations. This is often referred to as sentiment volatility. Based on Standard & Poor's (S&P) 500 futures, Simon and Wiggins (2001) explored the predictive power of popular sentiment indices, including the volatility index, the put-call ratio, and the trading index. They pointed out that the variables frequently have statistically and economically significant forecasting power over a variety of specifications and that they are contrarian indices; periods of extreme fear in the stock market often provide optimal buying opportunities, and when the degree of fear and doubt rise, strong stock performance follows. Cliff (2004) examined the relationship between recent stock market returns and investor sentiment, employing VAR to investigate the mutual influence between investor sentiment and short-term stock returns. The results show that past market returns and sentiments are both crucial factors related to investor sentiment. Moreover, sentiment is predictive of short-term to future stock returns; these results support the important behavioral theory in which the irrational emotions of investors can influence the evaluation of assets. Cliff further stated that asset pricing models should take the influence of investor sentiment into account. Another study utilized historical records of speculative events to investigate the influence of investor sentiment on realizing returns or predicting the cross-section of returns stock prices. Note that it has been definite that all investor sentiments have significant cross-sectional influence and, in asset pricing, accurate price and returns prediction models can be used to incorporate the unique role of investor sentiment (Baker and Wurgler, 2006). However, Pai and Chang (2008) set the difference (range) between the highest and lowest index prices of each day as an indicator of investor sentiment and the struggle between investors in the long and short positions. It is interesting to note that An expansion in the price difference implies investor sentiment and information content. A doubling in the range within one day is defined as abnormal sentiment, which can be used to observe the impact on future market returns (Pai and Chang (2008). Next, Zhang (2012) further investigated the influence of internet message boards on stock returns, using established message boards related to stock markets and constructed an effective proxy sentiment indicator with reduced predictive power in the past, and applied to data related to message boards. That study incorporated an innovative method using categorization results to prove that the new sentiment index is significant. Zhang's study provides inspiration for article classification and the construction of highly representative total sentiment indices to assist investors in developing sound investment strategies and provide procedural guidelines. Therefore, a lead-lag function exists among markets with the same subject matter. In this paper, we attempted to identify the lag length between the leading market and lagging market among three markets. We use the unit root tests, cointegration analysis, vector error-correction, vector autoregression, the Granger causality test, impulse response analysis, and forecast error variance decomposition to reveal the effects of the lead-lag relationship among markets, and employed abnormal range as the proxy variable for investor sentiment. Using the sentiment index, traders in the markets can interpret the general trends in information and formulate operational strategies accordingly.

3. Data and Methodology

3.1. Data Description

This study investigated the lead-lag relationship among three markets: Taiwan Stock Index (TS), Taiwan Stock Index Futures (TF), and MSCI Taiwan Stock Index Futures (MSF). We first performed a unit root test on the price series to check for non-stationary series. If the test results did not reject the unit root null hypothesis, a first difference was required before administering an additional unit root test. If the test results rejected null hypothesis on the unit root test, then two series were I(1) series that satisfied the conditions of a cointegration model. This enabled us to use cointegration to determine whether a stable long-term relationship existed between the two series and examine the price movements between the series using an error-correction model. We then observed the lead-lag relationships between markets according to short-term returns using the Granger causality test, VAR, impulse response analysis, and variance decomposition. Finally, we developed a prediction model based on these results to simulate trading strategies. For TS, we used daily closing price data provided by the Taiwan Stock Exchange, covering the period from January, 1990, to December, 2011. For TF and MSF, we obtained daily closing prices of the nearby contract from the Taiwan Economic Journal (TEJ). According to Tse (1998) and Booth et al. (1999), taking the natural logarithm of daily price data for rationalized analysis. Note that the spot and futures prices mentioned are lnS, lnF, and lnSGX. The first difference of these variables can be converted into the return rates of TS, TF, and MSF using the following formula:

$$R_{i,t} = \ln \frac{P_{i,t}}{P_{i,t-1}} \tag{1}$$

where:

$R_{i,t}$:the return rate of variable *i* during period *t*;

$P_{i,t}$:the closing price of variable *i* during period *t*;

$P_{i,t-1}$:the closing price of variable *i* during period *t - 1*;

i indicates the TS, TF, and MSF.

3.2. Unit Root Test

In this paper, we referred to the augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981) and the Phillips-Perron (PP) test proposed by Phillips and Perron (1988) and assumed that relevance and heterogeneity are allowed to exist in the interference term (error), to determine whether the series possess stationary time series. Dickey and Fuller (1981) included lag length as a dependent variable depending on whether a unit root was present in the time series and further considered whether drifts and linear time trends existed, using three basic test models:

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=2}^{P} \beta \Delta Y_{t-i+1} + \varepsilon_t \tag{2}$$

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \sum_{i=2}^{P} \beta \Delta Y_{t-i+1} + \varepsilon_t \tag{3}$$

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \alpha_2 t + \sum_{i=2}^{P} \beta \Delta Y_{t-i+1} + \varepsilon_t \tag{4}$$

The null hypothesis (H_0) and alternative hypothesis (H_1) of ADF are:

$H_0 : \gamma = 0$

$H_1 : \gamma \neq 0$

3.3. Cointegration Test

The presence of cointegration between two markets indicates a stable long-term relationship. We referred to the approach used by Engle and Granger (1987) when cointegration exists between two variables and employed the trace statistic ($\lambda_{trace}(r)$) as well as the maximum eigenvalue test ($\lambda_{\max}(r, r+1)$) proposed by Johansen and Juselius (1990) to conduct a cointegration test to examine whether long-term equilibrium exists among TS, TF, and MSF. The test statistic of this is:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \tag{5}$$

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{6}$$

where r represents the cointegrated vector; T is the number of observed values, and $\hat{\lambda}_i$ is the estimate of the eigenvalue.

3.4. Vector Error-Correction Model (VECM)

The VECM is used to make revisions and adjustments during the current period, when the interference term of the previous period has deviated from the long-term equilibrium price. Using a VECM enables a clear view of the lead-lag relationship between two markets, such that trading strategies can be formulated to predict price movement and detect profit opportunities. Granger proposed that when cointegration exists between two series, error correction is required:

$$\Delta S_t = \gamma_1 \varepsilon_{1t-1} + \sum_{i=1}^{m} \delta_{1i} \Delta S_{t-i} + \sum_{j=1}^{n} \theta_{1j} \Delta F_{t-j} + u_{1t} \tag{7}$$

$$\Delta F_t = \gamma_2 \varepsilon_{2t-1} + \sum_{i=1}^{m} \delta_{2i} \Delta S_{t-i} + \sum_{j=1}^{n} \theta_{2j} \Delta F_{t-j} + u_{2t} \tag{8}$$

In the formulas above, ε_{1t} and ε_{2t} are respectively estimated using $\varepsilon_{1t} = S_t - \alpha - \beta F_t$ and $\varepsilon_{2t} = F_t - \alpha - \beta S_t$; γ_1, γ_2, δ_{1i}, δ_{2i}, θ_{1j}, and θ_{2j} denote coefficients; u_{1t} and u_{2t} are white noise, and γ_1 and γ_2 represent the degree of long-term influence exerted by the independent variable on the dependent variable.

3.5. Vector AutoRegression (VAR)

Sims (1980) applied VAR in econometrics. Because we cannot know whether the variable is an endogenous variable or an exogenous variable, a VAR model is useful in predicting the inter-related time series between variables and analyzing the impact of random interference on the system. This phenomenon explains the influence of various shocks on economy. The equation of a general VAR model is as follows:

$$Y_t = \alpha + \sum_{i=1}^{P} \beta_i Y_{t-i} + \varepsilon_t \tag{9}$$

where α is an $(n \times 1)$ normal vector; β_i is an $(n \times n)$ coefficient matrix; Y_{t-i} is the $(n \times 1)$ vector comprising the *i* th lag length of vector Y, and ε_t is the forecast error comprising the $(n \times 1)$ vector.

3.6. Causality Tests

Granger (1969) referred to the testing of two time series variables as a causality test. This approach involves observing the mutual explanatory power of two variables to predict the relevancy between a variable's current value and the past values of other variables. The two variables ΔS_t and ΔF_t are stationary time series that can be expressed as:

$$\Delta S_t = \sum_{i=1}^{m} \alpha_{1i} \Delta S_{t-i} + \sum_{j=1}^{n} \beta_{1j} \Delta F_{t-i} + \varepsilon_{1t} \tag{10}$$

$$\Delta F_t = \sum_{i=1}^{m} \alpha_{2i} S_{t-i} + \sum_{j=1}^{n} \beta_{2j} \Delta F_{t-j} + \varepsilon_{2t} \tag{11}$$

3.7. Impulse Response Analysis

Analyzing the shock of a single variable on all of the other variables in a VAR system indicates the impulse response generated by each variable when a dependent variable is exposed to shock. Impulse response equation reveals the influence of impulse on TF and MSF during the current period when a unit of impulse is presented to the error term of TS.

3.8. Decomposition of Variance in Forecast Error

Decomposition of variance in forecast error is used to measure changes in the relationship between variables. In terms of the forecast error variance associated with a single variable, the proportion resulting from the variable itself and the proportion attributable to other variables can be used to represent the degree of interaction among the variables within a given period of time. Therefore, forecast error variance decomposition is used primarily to identify the forecast variance most likely to affect other variables in a VAR system when unexpected variance occurs.

We determined the optimal lag length in time series analysis, by referring to the generally applied Akaike information criterion (AIC) and Schwartz Bayesian criterion (SBC), which are calculated as follows (Zhong et al., 2004; Hsu et al., 2005; Lee et al., 2007; Pradhan and Bhat, 2009):

$$AIC = T\ln\left|\Sigma\right| + 2K \tag{12}$$

$$SBC = T\ln\left|\Sigma\right| + K\ln\left(T\right) \tag{13}$$

where T is the number of observed values; Σ represents the covariance matrix, and k is the number of parameters to be estimated in the time series. In the study of time series, issues related to residual correction and autocorrelation may arise, and deterred periods that are too many or too few in number may lead to overly excessive or simplified parameters. In large samples, SBC provides progressive consistency, which makes it a better criterion. Thus, this study applied SBC to determine the optimal lag length.

3.9. Sentiment Index

The ability to diversify sentiment risk remains an open and important issue (Berger and Turtle, 2012). Initial research by Lee et al. (1991) found that small stock returns are positively (and significantly) related to sentiment, relative to portfolios of large stocks, although the relation has weakened over time. In contrast, Elton et al. (1998) provide evidence that sentiment sensitivity is subsumed by other systematic risks. We use the difference (range) between the daily highest and lowest prices to determine the sentiment index of the investing public at the time (Pai and Chang, 2008). Assuming that the mean range of the previous three days (Zivot, 2008; Dong and Song, 2009; Haruman et al., 2009; Hendrawan, 2010; Mantri et al., 2010) is a normal value, a daily range that is twice that of the normal range is considered an abnormal range, expresses as:

$$\frac{P_t^H - P_t^L}{\sum_{s=1}^{3} \frac{P_{t-s}^H - P_{t-s}^L}{3}} \geq 2 \tag{14}$$

where P_t^H and P_t^L are the highest and lowest prices on day t, respectively.

3.10. Trading Strategy Simulation

This study examined 12 years of data from TS, TF, and MSF to investigate the lead-lag relationship among the three markets. Using the leading market, we applied abnormal sentiment indices to simulate trading strategies and identify profit opportunities. In the event that abnormal ranges appeared, we purchased lagging indices at the closing price when today’s closing price was higher than yesterday’s (the price rose) and shorted lagging indices at the closing price when today’s closing price was lower than yesterday’s (the price fell). This study did not consider trading costs or implement a stop-loss mechanism. The primary objective of this study was to identify profit opportunities in lead-lag markets; therefore, we hypothesized that the spot index enabled trading.

4. Empirical Results

4.1. Descriptive Statistics

This study selected three variables from the daily returns in TS, TF, and MSF for analysis. Our data source was the TEJ database. We selected the period from January 5, 1999, to December 30, 2011, as our observation period. A total of 3,265 pieces of data were used for model construction and goodness-of-fit testing. In addition, 3,273 pieces of data from December 29, 1998, to January 6, 2012, were used to evaluate the forecasting performance of the model. We took the natural logarithms of all variables, which were then converted into return rates to facilitate empirical analysis. Table 1 shows definitions of the variables employed In this paper, and Table 2 presents the descriptive statistics, in which TS price *S*, TF price *F*, and MSF price *SGX* are natural log values. The first difference in daily closing prices (ΔS, ΔF, and ΔSGX), are the return rates of each index. In Table 2, we can see that the average prices in the TS and TF series are very close. The mean return rates of the three market indices are all positive and approach 0. The return rates of MSF are lower than those of TS and TF. In terms of standard deviation, the volatility in TF prices is the highest, whereas the volatility of MSF prices is the lowest. The circumstances associated with return volatility are the opposite; the volatility of MSF returns is the highest. The data indicate that the price and return distributions in all three markets are skewed to the left. The prices and returns of MSF and the returns of TS and TF display leptokurtic distribution. Finally, using the Jarque-Bera normal distribution test, we discovered that the prices and returns of all three markets significantly rejected the normal distribution hypothesis.

Table 1: Definition of variables

Variable	Symbol	Definition
Taiwan Stock Index spot price	S	natural log of closing price in Taiwan Stock Index
Taiwan Stock Index Futures price	F	natural log of closing price in Taiwan Stock Index Futures
MSCI Taiwan Stock Index Futures price	SGX	natural log of closing price in MSCI Taiwan Stock Index Futures
Taiwan Stock Index spot return rate	ΔS	first difference of natural log of closing price in Taiwan Stock Index
Taiwan Stock Index Futures return rate	ΔF	first difference of natural log of closing price in Taiwan Stock Index Futures
MSCI Taiwan Stock Index Futures return rate	ΔSGX	first difference of natural log of closing price in MSCI Taiwan Stock Index Futures

Table 2: Descriptive Statistics

Variable	S	F	SGX	ΔS	ΔF	ΔSGX
Observations	3265	3265	3265	3264	3264	3264
Mean	8.7936	8.7923	5.5978	4.27E-05	4.29E-05	8.21E-06
Median	8.8046	8.8018	5.5973	2.57E-04	4.06E-04	0.00E+00
Maximum	9.2304	9.2449	6.1205	0.0652	0.0849	0.1122
Minimum	8.1450	8.1394	5.0093	-0.0691	-0.0878	-0.1355
Std. Dev.	0.2229	0.2248	0.2004	0.0156	0.0180	0.0198
Skewness	-0.3562	-0.3678	-0.2407	-0.1425	-0.1698	-0.2033
Kurtosis	2.3386	2.3790	3.1161	4.9644	5.8865	7.6362
Jarque-Bera	128.55	126.07	33.37	535.88	1148.86	2945.77
Probability	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00

4.2. Unit Root Test Results

This study employed the ADF and PP unit root tests and selected an optimal lag length based on SBC, the results of which are presented in Table 3. As can be seen, the ADF and PP unit root test results did not reach significance in the price series of TS, TF, and MSF, indicating that unit roots existed in the prices of the three markets. Following first difference, we performed the ADF and PP unit root tests again, the results of which rejected the unit root null hypothesis at a 1 % significance level. This shows that the return rates of the three markets form stationary series. We further administered unit root tests on circumstances with and without drift terms and trends, and derived similar results.

Table 3: Unit Root Tests

Variable		ADF Test		PP Test	Critical Values at the 1% Level
		k	ADF value	PP value	
Index price					
S	with drift, with trend	1	-2.2623	-2.2634	-3.9609
	with drift, no trend	1	-2.1412	-2.1466	-3.4322
	no drift, no trend	1	0.0829	0.0933	-2.5657
F	with drift, with trend	0	-2.4009	-2.3752	-3.9609
	with drift, no trend	0	-2.2918	-2.2512	-3.4322
	no drift, no trend	0	0.0775	0.0837	-2.5657
SGX	with drift, with trend	0	-2.8550	-2.6396	-3.9609
	with drift, no trend	0	-2.8369	-2.6207	-3.4322
	no drift, no trend	0	-0.0777	-0.0648	-2.5657
First difference					
ΔS	with drift, with trend	0	-53.3409***	-53.3153***	-3.9609
	with drift, no trend	0	-53.3491***	-53.3235***	-3.4322
	no drift, no trend	0	-53.3569***	-53.3315***	-2.5657
ΔF	with drift, with trend	0	-58.6593***	-58.6648***	-3.9609
	with drift, no trend	0	-58.6683***	-58.6738***	-3.4322
	no drift, no trend	0	-58.6770***	-58.6825***	-2.5657
ΔSGX	with drift, with trend	0	-59.7970***	-60.0938***	-3.9609
	with drift, no trend	0	-59.8055***	-60.1022***	-3.4322
	no drift, no trend	0	-59.8147***	-60.1119***	-2.5657

Note: ADF denotes the statistics for the augmented Dickey-Fuller unit root test, and the figures in the parentheses are the optimal lag lengths selected according to SBC; PP represents the statistics for the Phillips-Perron unit root test.

4.3. Johansen Cointegration Test Results

After confirming that the series were stationary, we tested whether cointegration existed among the series. In the event that two series are non-stationary and a stationary linear combination is present, then cointegration exists between the two series. Table 4 shows the results of the Johansen cointegration test; according to the SBC, the optimal lag length was 1. Furthermore, we found that the P values in both the trace test and the maximum eigenvalue test were 0.0001, thereby indicating that cointegration existed among TS, TF, and MSF during the data period and that the three markets had already established a stable long-term relationship.

Table 4: Johansen Cointegration Test Results

H_0	λ_{max}	λ_{trace}	**Eigenvalue**
$r \leq 0$	375.7765(<0.0001) ***	384.7196(<0.0001) ***	0.1088
$r \leq 1$	8.8263(>0.0500)	8.9431(>0.0500)	0.0027
$r \leq 2$	0.1168(>0.0500)	0.1168(>0.0500)	3.58E-05

Note: P-values are in parentheses; ***Significant at the 1% level.

4.4. VECM Estimation Results

With the existence of cointegration among TS, TF, and MSF, we can use VECM to explain the random movements among the series. According to SBC, the VECM identified an optimal lag length of 3. In Table 5, we can see that the adjustment of the deviated equilibrium error in the TS prices was weaker than those of the TF and MSF prices; the coefficient of 0.1206 was relatively small. In response to price movements in TF and MSF, TS prices adjusted the most swiftly at 0.3984, reaching the 1 % level of significance. The adjustment speed of MSF was 0.2525, also reaching the 1 % level of significance. This shows that when new information in the market cause prices to deviate, all three markets will adjust towards long-term trends. Adjustment of the three markets to establish an equilibrium pricing relationship must be accomplished from the aspect of futures and not from spot price movement. In other words, futures have a low-cost advantage as well as a stronger dominant position.

Table 5: VECM Estimation Results

Parameters/Test	**Dependent Variables**		
	ΔS	ΔF	ΔSGX
Error Correction Terms	0.1206** (2.5619)	0.3984*** (7.4003)	0.2525*** (4.1978)
ΔS **Lags**			
ΔS_{t-1}	-0.3314*** (-4.7952)	-0.1657** (-2.0965)	-0.0929 (-1.0523)
ΔS_{t-2}	-0.1787*** (-2.6619)	-0.1050 (-1.3670)	-0.0596 (-0.6950)
ΔS_{t-3}	-0.1481** (-2.5444)	-0.1289** (-1.9354)	-0.1294* (-1.7386)
ΔF **Lags**			
ΔF_{t-1}	0.0564 (0.8771)	-0.2169*** (-2.9494)	0.0379 (0.4619)
ΔF_{t-2}	-0.0353 (-0.5518)	-0.1076 (-1.4712)	-0.0612 (-0.7488)
ΔF_{t-3}	0.0471 (0.8222)	0.0618 (0.9433)	0.0615 (0.8392)
ΔSGX **Lags**			
ΔSGX_{t-1}	0.2827*** (6.3481)	0.3513*** (6.8953)	0.0084 (0.1479)
ΔSGX_{t-2}	0.2266*** (4.8776)	0.2335*** (4.3947)	0.1034* (1.7423)
ΔSGX_{t-3}	0.1325*** (3.0549)	0.1110** (2.2362)	0.0833 (1.5017)

Note: ***Significant at the 1% level; **Significant at the 5% level;*Significant at the 10% level.

4.5. VAR Estimation Results

In Table 6, with TS as the dependent variable, the estimated coefficients ΔSGX_{t-1} through ΔSGX_{t-4} all demonstrate significant and positive correlation with TS. This indicates that in the first few periods, MSF presented positive returns. We can thus predict that the returns in TS will be positive as well. Using MSF as the dependent variable, the returns in first few periods of TS had no significant influence on MSF. The results of the Granger causality tests in Table 7 show that MSF significantly rejects the null hypothesis of connection with TS. However, TS does not reject the null hypothesis of causality with MSF. This is in agreement with the VAR results, and MSF unidirectionally leads TS by four periods. With TF as the dependent variable, the estimated coefficients ΔSGX_{t-1} through ΔSGX_{t-4} are also positively and significantly correlated to TF. With MSF as the dependent variable, ΔF_{t-1} and ΔF_{t-2} present a negative correlation with MSF.

Table 6: VAR Estimation Results

Parameters/Test	Dependent Variables		
	ΔS	ΔF	ΔSGX
Constant	5.99E-05 (0.2212)	5.74E-05 (0.1843)	-2.52E-06 (-0.0073)
ΔS Lags			
ΔS_{t-1}	-0.2552*** (-4.1320)	0.1182* (1.6625)	0.0945 (1.1967)
ΔS_{t-2}	-0.1261* (-1.9542)	0.1230* (1.6570)	0.0990 (1.1997)
ΔS_{t-3}	-0.1202* (-1.8808)	0.0490 (0.6662)	0.0189 (0.2315)
ΔS_{t-4}	-0.0366 (-0.6421)	0.0873 (1.3301)	0.0204 (0.2794)
ΔF Lags			
ΔF_{t-1}	-0.0260 (-0.4663)	-0.5007 (-7.7946)	-0.1377* (-1.9285)
ΔF_{t-2}	-0.0988 (-1.6324)	-0.3342*** (-4.7950)	-0.1964*** (-2.5355)
ΔF_{t-3}	-0.0090 (-0.1489)	-0.1396*** (-2.0052)	-0.0671 (-0.8680)
ΔF_{t-4}	-0.0484 (-0.8695)	-0.1848*** (-2.8847)	-0.1060 (-1.4884)
ΔSGX Lags			
ΔSGX_{t-1}	0.2868*** (6.3980)	0.3527*** (6.8354)	0.0008 (0.0133)
ΔSGX_{t-2}	0.2355*** (4.9407)	0.2336*** (4.2565)	0.0847 (1.3892)
ΔSGX_{t-3}	0.1557*** (3.2959)	0.1312** (2.4136)	0.0673 (1.1136)
ΔSGX_{t-4}	0.0741** (1.6990)	0.0833** (1.6605)	0.0387 (0.6933)

Note: ***Significant at the 1% level; **Significant at the 5% level;*Significant at the 10% level.

Once the variables have been confirmed as stationary, using unit root tests, we can perform the Granger causality test to analyze the relationship among MSF (ΔSGX), TF (ΔF), and TS (ΔS). First, the results in Table 6 show that ΔSGX leads ΔF by 4 periods, and ΔF leads ΔSGX by 2 periods. The Granger causality test results in Table 7 indicate that at the 10 % level of significance, the test probabilities all reject the null hypothesis, thereby indicating that ΔSGX is influenced by ΔF, and vice versa. In addition, ΔS and ΔSGX display a feedback relationship with ΔF in the short run; in other words, ΔS and ΔSGX interact with ΔF on a short-term basis. However, ΔSGX demonstrates unidirectional causality on ΔS in the short term, with the implication that ΔSGX is influenced by ΔS in the short run, but not vice versa.

Table 7: Granger Causality Tests

Null Hypothesis（H_0）	F-Statistic	Probability
ΔS does not Granger Cause ΔF	7.1423***	0.00<
ΔF does not Granger Cause ΔS	2.7709***	0.03<
ΔSGX does not Granger Cause ΔF	19.0147***	0.00<
ΔF does not Granger Cause ΔSGX	1.9591*	0.10<
ΔSGX does not Granger Cause ΔS	14.9190***	0.00<
ΔS does not Granger Cause ΔSGX	0.2548	0.91>

Note: ***Significant at the 1% level; **Significant at the 5% level;*Significant at the 10% level.

4.6. Impulse Response Analysis

Impulse response analysis indicates the influence of a variable on all other variables during a given period when the variable shifts by a standard deviation. Figure 1 shows the observed impulse results of TS, TF, and MSF returns using the estimated coefficients of 10 periods. We discovered that TS returns provoked the strongest impulse response in itself, the intensity of which did not gradually converge until the fifth period. However, TF and MSF returns showed no response to the impulse of TS returns in the first period; positive responses appeared in the second period and began converging in the fourth period. In the first period, TF returns triggered positive responses in itself and in TS returns. In the second period, however, negative responses appeared in both markets and did not approach 0 until the sixth period. MSF returns exhibited no response to TF returns in the first period but converged to normal levels in the third period. Finally, we observed the influence of MSF returns, which elicited positive responses from TS returns, TF returns, and itself in the first period. The former two, however, presented negative responses starting in the second period, when the response of MSF itself approached 0. In conclusion, MSF returns responded the most quickly to the returns of the three markets, followed by TF returns.

4.7. Forecast Error Variance Decomposition

According to Tse (1998), when a market with higher efficiency receives an unexpected shock, the shock is less likely to be affected by other markets. On the contrary, the shock will influence other markets. Applying forecast error variance decomposition and impulse response analysis enables further analysis of the degree of short-term change among the variables. Using forecast error variance decomposition, we can observe the transmission speed of information shock to other variables and thereby measure the short-term relationship among them. Because different sequences can affect the results of forecast error variance decomposition, we rotated the three market indices in the first place to explain the mutual influence among them. By observing the estimated coefficients of 10 periods (in Tables 8, 9, and 10), we can see that the highest explained 99.69 % of the variance in MSF returns. In Table 8, 1.65 % of TS returns can be explained by MSF returns, exceedign the 0.32 % that can be explained by TF returns. This shows that variance in MSF returns is better able to explain the forecast error variance of TS returns. Table 9 shows that MSF also explains 2.29 % of TF, which is more than 15 times greater than the 0.15 % by TS. This indicates that variance in MSF returns is also better able to explain the forecast error variance of TF returns. Finally, in Table 10 we can see that TF explains 0.27 % of MSF, whereas TS only explains 0.03 %; therefore, variance in TF returns is better able to explain the forecast error variance of MSF returns compared to TS returns.

Table 8: Forecast error variance decomposition of Taiwan Stock Index returns

Period	ΔS	ΔF	ΔSGX
1	100.0000	0.0000	0.0000
2	98.5248	0.2515	1.2237
3	98.1721	0.2603	1.5676
4	98.0953	0.2837	1.6210
5	98.0621	0.3153	1.6226
6	98.0370	0.3171	1.6459
7	98.0343	0.3189	1.6468
8	98.0343	0.3189	1.6468
9	98.0337	0.3194	1.6469
10	98.0336	0.3195	1.6469

Table 9: Forecast error variance decomposition of Taiwan Stock Index Futures returns

Period	ΔS	ΔF	ΔSGX
1	0.0000	100.0000	0.0000
2	0.0818	97.9190	1.9992

Table 9: Forecast error variance decomposition of Taiwan Stock Index Futures returns - continued

3	0.1079	97.7342	2.1579
4	0.1095	97.7153	2.1752
5	0.1225	97.6573	2.2202
6	0.1508	97.5637	2.2856
7	0.1508	97.5637	2.2855
8	0.1510	97.5635	2.2855
9	0.1511	97.5627	2.2863
10	0.1516	97.5615	2.2868

Table 10: Forecast error variance decomposition of MSCI Taiwan Stock Index Futures returns

Period	ΔS	ΔF	ΔSGX
1	0.0000	0.0000	100.0000
2	0.0003	0.1125	99.8872
3	0.0047	0.2126	99.7827
4	0.0072	0.2159	99.7769
5	0.0255	0.2510	99.7235
6	0.0268	0.2719	99.7013
7	0.0268	0.2722	99.7010
8	0.0269	0.2727	99.7004
9	0.0269	0.2733	99.6997
10	0.0269	0.2737	99.6993

4.8. Analysis of Simulated Trading Strategies

In this paper, assuming that the markets have same subject matter and a lead-lag relationship and in which the market price information follows the leading market, we analyzed simulated trading strategies to determine whether using the abnormal volatility of investor sentiment as an indicator can facilitate trading strategies to obtain profits before the markets achieve equilibrium. The analysis of simulated trading strategies refers to using the discovery of futures prices leading spot prices in active trading markets to conduct profitable transactions when shock information enters lead-lag markets (Books et al., 2001). Furthermore, we employed MSF as an indicator to conduct transactions when abnormal ranges appear in the market; the leading market that was the fastest in transmitting information regarding prices and returns. For example, in the event that today's closing price was higher than yesterday's closing price, we purchased TS and TF at the closing price; when today's closing price was lower than yesterday's closing price, we shorted TS and TF at the closing price. The covering returns at the opening/closing price are listed in Tables 11 and 12. The results shown in these two tables indicate that when abnormal ranges appear, TS and TF are purchased at the closing of stock exchange regardless of covering total returns at the opening or closing. The first day shows the lowest returns among the first four days; on the fifth day, negative returns appear in short position trading; in Table 11, the total returns are already negative. From the total returns, we can see that the third and fourth days present the best performance. This supports the results of 4 as the period in the VAR test. However, we find stronger relationship between sentiment and market return in the short run but week evidence in case of long run.

Table 11: Simulations of trading in Taiwan Stock Index from 1998/12/29 to 2012/01/06

Trading method	**Purchase at closing, selling at opening, shorting at closing, covering at opening**				
Holding days	1	2	3	4	5
Long position returns	12.3305	26.3395	61.9569	54.6370	80.7169
Short position returns	7.0818	15.0569	2.8857	4.5746	-31.8170
Total returns	**19.4123**	**41.3963**	**64.8427**	**59.2116**	**48.8998**

Table 11: Simulations of trading in Taiwan Stock Index from 1998/12/29 to 2012/01/06 - continued

Trading method	**Purchase at closing, selling at closing, shorting at closing, covering at closing**				
Long position returns	10.4779	30.8440	18.2614	61.2807	40.7892
Short position returns	29.7760	17.4532	40.7248	2.9461	-39.1639
Total returns	**40.2539**	**48.2972**	**58.9862**	**64.2268**	**1.6253**

Note: Return (%)

Table 12: Simulations of trading in Taiwan Stock Index Futures from 1998/12/29 to 2012/01/06

Trading method	**Purchase at closing, selling at opening, shorting at closing, covering at opening**				
Holding days	1	2	3	4	5
Long position returns	-1.3817	11.4867	38.7644	34.0256	51.2047
Short position returns	0.3567	36.0697	6.0383	22.6557	-25.4094
Total returns	**-1.0250**	**47.5564**	**44.8027**	**56.6814**	**25.7953**
Trading method	**Purchase at closing, selling at closing, shorting at closing, covering at closing**				
Long position returns	12.7934	30.4855	16.5581	59.5226	30.5276
Short position returns	34.8373	11.7045	56.5426	1.0879	-43.1079
Total returns	**47.6307**	**42.1900**	**73.1007**	**60.6106**	**-12.5803**

Note: Return (%)

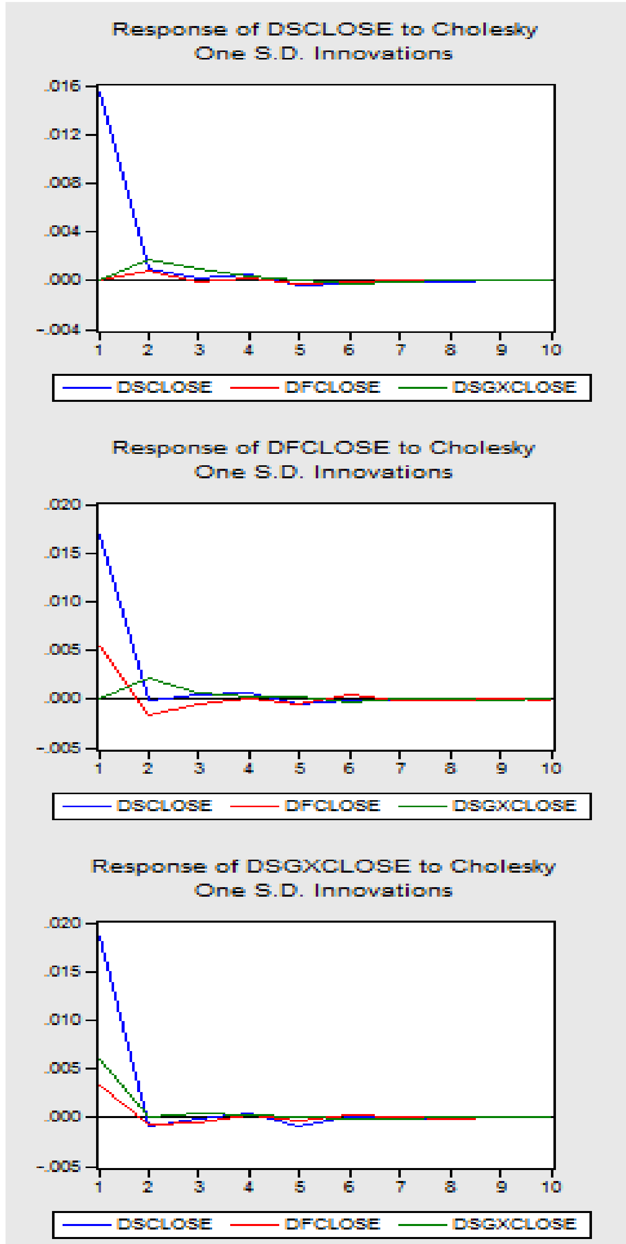
5. Summary and Conclusions

In this paper, we analyze the lead-lag relationship among from Taiwan Stock Index, Taiwan Stock Index Futures, and MSCI Taiwan Stock Index Futures. We formulated trading strategies and conducted simulations in situations in which abnormal sentiment signals appeared in the markets. Unit-root test results indicate that the price series in the three markets were non-stationary; following first difference, they became stationary, and a cointegration model indicates that when a common long-term trend existed between two price series, the two markets also had a long-term random trend and an equilibrium relationship. An error-correction model established that futures have a stronger dominant position and incline the markets to adjust to a long-term trend.

Causality among the markets was not an issue in the VAR model, because the model regarded the markets as endogenous variables. This enabled further analysis of the short-term interaction among the markets, whereby we discovered a lead-lag relationship among TS, TF, and MSF. This supports the results of the Granger causality tests, indicating feedback causality among the three markets. Furthermore, MSF was found to lead TF by 4 periods, and TF was found to lead MSF by 2 periods. This is similar to the conclusions of impulse response analysis, in which two to four periods were required for the shock of a variable shifting one standard deviation on all the variables to fade. Finally, forecast error variance decomposition indicated that variance in MSF returns was most effectively explained by its own innovations. In addition, the variance in MSF returns was better able to explain the forecast error variance of TS returns and that of TF returns, and the variance in TF returns was better able than TS returns to explain the forecast error variance of MSF returns.

Finally, in our trading strategy simulation, we found that when abnormal sentiment appeared in the market, operating in the same direction as the leading market and covering on the third and fourth days led to positive total returns. This shows that as the market information interpretation of various investors suddenly changes, referencing information left by the price aspect and employing lead-lag responses and information conveyance between markets with the same subject matter as indicators provide profit opportunities and operation reference to investors.

Figure 1:



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