國立交通大學

管理科學系

博 士 論 文

No. 054

隱含波動度，投資人情緒與市場指數之

互動關係與策略應用

The Interaction and Strategy Application between

Implied Volatility, Investor Sentiment and Market Index

研 究 生：魏裕珍

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國 立 交 通 大 學

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中文摘要

本文由行為財務學角度剖析隱含波動度、投資人情緒與市場指數之互動關係，並以臺灣證券市場資料構建波動度指數及投資人情緒指標之代理變數進行相關實證分析及策略應用。

研究內容主要分為三個部分。第一部分應用門檻模型(Chan, 1993)檢測投資人情緒過度反應之門檻水準，並剖析不同市場狀況下，投資人情緒與市場報酬間之因果關係，實證結果顯示若未考慮市場狀態，投資人情緒指標與市場報酬之間存在雙向之因果關係，然而，當投資人情緒在極端高或低之區域時，對於市場報酬將具有指引效果。第二部分則應用門檻共整合模型(Hansen and Seo, 2002)探討波動度指數之資訊內涵與標的指數間之關聯性，實證結果顯示，當買權之隱含指數領先加權股價指數時，臺灣證券市場之參與者可應用此資訊做為投資組合調整之參考。第三部分進一步考量投資人情緒指標進行波動度預測，並應用至選擇權交易策略，比較結果顯示，若納入投資人情緒指標，模型之配適與預測績效將優於其他比較模型，特別是納入市場週轉率與市場恐慌指標代理變數-選擇權隱含波動度。

綜而觀之，在探討波動度、投資人情緒與市場指數之互動關係時，應將投資人情緒可能存在的不對稱效果納入考量，未來的研究亦可進一步納入投資人情緒的不對稱效果進行波動度預測，並將研究結果實際應用至交易策略中。

關鍵詞：隱含波動度、投資人情緒、波動度預測、門檻模型、因果、選擇權交易策略

The Interaction and Strategy Application between Implied Volatility, Investor Sentiment and Market Index

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Abstract

This dissertation investigates the interaction among implied volatility, investor sentiment and market index from the behavioral finance point of view. The volatility measures and proxies of investor sentiment are constructed and the empirical results and strategy application are analyzed in the emerging Taiwan equity market.

There are three main parts in this study. In the first part, we apply a threshold model (Chan, 1993) to detect the extreme level of investors' sentiment econometrically and investigate the causal relationships between sentiment and returns under different market scenarios. The empirical results show that most of the sentiment measures exhibit a feedback relationship with returns while ignoring different market states. However, sentiment could be a leading indicator if the higher or lower levels of sentiments being distinguished. In the second part, the relationship between the information content implied by the options market-based volatility and the underlying stock index is analyzed through a threshold cointegration model (Hansen and Seo, 2002). Empirical findings show that investors participating in the Taiwan stock market could rebalance their equity portfolios while the implied index derived from the call options takes precedence over the market index. In the last part, an algorithm for effective options trading strategy based on volatility forecasts incorporating investor sentiment is proposed. The forecast evaluation supports the significant incremental explanatory power of investor sentiments in the fitting and forecasting of future volatility in relation to its adversarial multiple-factor model, especially the market turnover and the volatility index which is referred to as the investor fear gauge.

Overall, the asymmetric property of investor sentiment should be incorporated into the interactive analysis between volatility, sentiment and market index. Future research could further investigate the volatility forecasting incorporating the asymmetry of investor sentiment and apply the findings to the actual trading strategies.

Keywords: Implied volatility, Investor sentiment, Volatility forecasting, Threshold model, Causality, Options trading strategy.

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執筆寫下致謝辭的此時，回想起求學生涯的點點滴滴，歷歷在目，心裡是溫暖而踏實的，求學之路峰迴路轉，我的人生與心境都有了不同的體驗，完成論文取得博士學位，是一個里程碑也是另一個開始，感謝這段旅程中陪伴與提攜我的家人、師長與朋友，也期許自己的人生旅程能學以致用，不忘飲水思源。

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Chapter 1. Introduction

The main purpose of this dissertation is to investigate the interaction among implied volatility, investor sentiment and market index from the behavioral finance point of view. An implied index from the options volatility is constructed under the Black-Scholes-Merton options pricing model which could serve as a proxy of the expected index level reflecting the investors' sentiment. The threshold model is applied to examine the extreme regimes of sentiment proxies and the causal relationship between investor sentiment and market index is examined under different market scenarios. Finally the forecasting model considering the information content of investor sentiment is performed and the options trading strategy is proposed. Based on the data of Taiwan stock market covering the period from 2003 to 2007, our results indicate that the information content of investor sentiment could be a leading indicator under overreaction and the strategy incorporating the sentiment proxies outperforms the other competitors.

Early papers (Friedman, 1953; Fama, 1965) argued that noise traders are unimportant in the financial price formation process because trades made by rational arbitrageurs drive prices close to their fundamental values. However, the market anomalies, for example, the under-reaction and overreaction of stock prices, challenge the efficient markets theory. De Long, Shleifer, Summers and Waldmann (DSSW (1990) hereafter) modeled the influence of noise trading on equilibrium prices and motivated empirical attempts to substantiate the proposition that 'noise traders' risks influence price formation'. Barberis, Shleifer and Vishny (1998) present a parsimonious model of investor sentiment. The model is based on psychological evidence and produces both underreaction and overreaction for a wide range of parameter values. If sentiment indicators are risk factors in the time series of returns, they will have the ability to predict the future returns on portfolios, even after appropriately adjusting for other risk factors. These findings support the need for research on the interaction between stock market returns, variation of price formation and indicators of investor sentiment.

Taiwan's equity market has long been an indispensable emerging market for international investors. Index options involving the Taiwan Stock Exchange Capitalization Weighted Stock Index (*TAIEX* index options, abbreviated as TXO) were first traded on December 24, 2001. The *TAIEX* covers all of the listed stocks on the Taiwan Stock Exchange (TWSE) excluding preferred stocks, full-delivery stocks and newly-listed stocks, which are listed for less than one calendar month. The statistical data published in the 2007 annual report of the Futures Industry Association (FIA) show that the trading volume of Taiwan Stock Exchange Capitalization Weighted Stock Index options (TAIEX options) ranks twelfth in the world, which indicates its increasing importance for global asset management.[1] The high trading percentage of individual traders in the Taiwan equity (about 70%) and derivatives (about 50%) markets might also imply that the noise trading or the investor sentiments might be the cause of the price variations. This study therefore proceeds to examine the rapidly-developing Taiwan stock market.

There are three parts in this essay. They present three independent papers, respectively. In the first part of the dissertation, the causal relationships between sentiment and returns under different market scenarios are investigated. In contrast to previous studies that subjectively identify the bullish and bearish markets, we apply a threshold model to detect the extreme level of investors' sentiment econometrically. The empirical results show that most of the sentiment measures exhibit a feedback relationship with returns while ignoring different market states. However, sentiment could be a leading indicator if the higher or lower levels of sentiments were to be distinguished. Among them, the bullish/bearish indicator of ARMS, which is named after its creator, Richard Arms (1989), is a leading indicator if the market is more bearish (in the higher regime). Otherwise, the leading effect of the derivatives market sentiment indicators (the put-call trading volume and option volatility index) is discovered if the market is more bullish (in the lower regime). Our empirical findings further confirm the noise trader explanation that the causal direction would run from investors' sentiment to market behavior.

In the second part, the relationship between the information content implied by the options market-based volatility and the underlying stock index is analyzed through a threshold econometric model. A volatility index in line with the CBOE's new *VIX* is constructed by using intraday data for Taiwan's index options market as the research material. We then derive an implied equity index (*TVII*) from the Taiwan volatility

[1] The FIA is the only association that is representative of all organizations having an interest in the futures market. The FIA has more than 180 corporate members, and reaches thousands of industry participants. Further information may be found on the website http://www.futuresindustry.org/.

index under the Black-Scholes-Merton options pricing scheme. We examine the co-movements and causalities between the *TVII* and the *TAIEX* (Taiwan stock exchange capitalization weighted stock index, *TAIEX*) through the vector error correction model (VECM) and threshold VECM (TVECM) in different market scenarios. The empirical results substantiate the claim that the nonlinear two-regime TVECM provides an appropriate fit for the dynamics between the *TVII* and the *TAIEX*. Investors participating in the Taiwan stock market could rebalance their equity portfolios while the implied index derived from the call options (*TVIIC*) takes precedence over the *TAIEX*.

In the last part, an algorithm for an effective option trading strategy based on superior volatility forecasts using actual option price data for the Taiwan stock market is proposed. The forecast evaluation supports the significant incremental explanatory power of investor sentiments in the fitting and forecasting of future volatility in relation to its adversarial multiple-factor model, especially the market turnover and volatility index which are referred to as the investors' mood gauge and proxy for overreaction. After taking into consideration the margin-based transaction cost, the simulated trading indicates that a long or short straddle 15 days before the options' final settlement day based on the 60-day in-sample-period volatility forecasting recruiting market turnover achieves the best average monthly return of 15.84%. This study bridges the gap between option trading, market volatility, and the signal of the investors' overreaction through the simulation of the option trading strategy. The trading algorithm based on the volatility forecasting recruiting investor sentiments could be further applied in electronic trading and other artificial intelligence decision support systems.

The remainder of this paper is organized as follows. Chapter 1 introduces the dissertation with the organization. Chapter 2 briefly discusses the relevant literature. Chapter 3 outlines the measurements of volatility and investor sentiment. Chapter 4 investigates the interaction between sentiment indicators and stock market returns under different market scenarios. Chapter 5 analyzes the interaction between the implied index from the options and the equity index in Taiwan. Chapter 6 proposes the options trading strategies based on volatility forecasting considering the investor sentiment. Finally, the conclusions drawn from this dissertation are presented in Chapter 7.

Chapter 2. Literature Review

2.1 Volatility Measures and Volatility Forecasting

Volatility is often defined as the (instantaneous) standard deviation (or 'sigma') of the random Wiener-driven component in a continuous-time diffusion model. Volatility is a major parameter in risk management, derivatives pricing, options trading, hedging and asset allocation, and has also been one of the most active and successful areas of research in time series econometrics and economic forecasting in recent decades. Blair, Poon & Taylor (2001) and Poon & Granger (2003) have summarized that volatility forecasting models can be classified in the following four categories: the historical volatility models (HISVOL), the GARCH family, the options implied standard deviation (ISD) model, and the stochastic volatility model (SV).[2]

Over the past decade, several researchers have focused on the univariate analysis of volatility, such as the estimation and properties of volatility (e.g., Engle 1982, Taylor 1986, Bollerslev 1986, Andersen and Bollerslev 1998) and forecasts of volatility (e.g., Fleming et al. 1995, Koopman et al. 2005, Poon and Granger 2005). Other studies have focused on the multivariate analysis. Regardless of what categories of volatility are compared or composed, the main concerns of the forecasting model lie in investigating the possible indicators or properties which could improve the forecasting power and provide incremental information for application. The surveyed paper of Poon & Granger (2003, 2005) indicates that testing the effectiveness of a composite forecast is as important as testing the superiority of the individual models, but this has not been done more often or across different data sets. Multivariate forecasting models that consider the different categories of volatility models, such as the GARCH, historical volatility, stochastic volatility, and option implied volatility models, are constructed and compared hereafter (Engle & Gallo, 2006; Becker, Clements & White, 2007; Becker & Clements, 2008). In addition to the issue of the optimal combination of the multivariate volatility measures, there are other topics

[2] Historical volatility models (HISVOL) include those related to the random walk, historical averages of squared returns or absolute returns. Also included in this category are time series models which are based on historical volatility using moving averages, exponential weights, autoregressive models or fractionally integrated autoregressive absolute returns, etc. All models in the HISVOL group model volatility directly by omitting the goodness of fit of the returns distribution or any other variable such as the options price (Poon & Granger, 2003).

examining the possible indicators which could improve the predictive power of forecasting and its application.

2.2 Volatility and Market Index

Whaley (1993, 2000) and Fleming et al. (1995), for example, find a negative correlation between volatility and the market index. In addition, Copeland and Copeland (1999) show that volatility is a leading indicator of market returns.

Latané and Rendleman (1976), Chiras and Manaster (1978) and Beckers (1981) indicate that, when compared with the earliest methods, volatility which is derived from the options pricing model can be regarded as a good predictor of future volatility. There is also a growing volume of literature on the relationship between volatility and the market index. Wu (2001), Awartani and Corradi (2005) and Bollerslev et al. (2006) have recently claimed that causality between volatility and market index returns can be explained on the basis of the leverage effects (e.g., Black 1976) and volatility feedback (e.g., French et al. 1987).[3] The nature of causality, which may be unidirectional or bi-directional, can be explained jointly by these two indistinguishable effects. Fleming et al. (1995) and Whaley (2000) point out that there is a highly negative correlation and asymmetric relationship between volatility and market index returns. In other words, losses lead to increases in volatility and gains result in decreases, but losses have a far greater impact on traded index volatility than gains. However, this is a direct violation of the predictions of classical finance theory.[4] Montier (2002) claims that the asymmetric effect is just what the prospect theory, as proposed by Kahneman and Tversky (1979) in behavioral finance, would forecast.[5]

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[3] The leverage effect indicates that a drop in the value of equity increases financial leverage, and this makes the equity riskier and thus increases its volatility. Volatility feedback means that if volatility is priced, an anticipated increase in volatility raises the required return on equity. Hence, the leverage effect prescribes a causal nexus from returns to conditional volatility, while volatility feedback prescribes one from conditional volatility to returns.

[4] Markowitz (1952) put forward the portfolio theory and assumed that risk was symmetric and could be expressed in terms of the standard deviation of asset returns.

[5] The prospect theory, proposed by Kahneman and Tversky (1979) in behavioral finance, brings psychology into investors' decisions under uncertainty. It argues that investors have different risk tolerance in the face of gains and losses.

2.3 Investor Sentiment and Market Index

The causal relationships between sentiment indicators and stock market returns are mixed in previous studies. Clarke and Statman (1998) found that the sentiment of newsletter writers, whether bullish or bearish, does not forecast future returns, but that past returns and the volatility of those returns do affect sentiment. Causality would thus run from sentiment to market behavior if the noise trader explanation were to be accepted. However, Brown and Cliff (2004) and Solt and Statman (1988) documented that returns cause sentiment rather than the other way round. Brown and Cliff (2004) used a large number of sentiment indicators to investigate the relationship between sentiment and equity returns and found that returns cause sentiment rather than the opposite being the case. Brown (1999) supported the DSSW theory that irrational investors acting in concert and giving a noisy signal can influence asset prices and generate additional volatility. His tests used volatility instead of returns and his results indicated that deviations from the average level of sentiment are associated with increases in fund volatility only during trading hours. Lee, Jiang and Indro (2002) tested the impact of noise trader risk on the formation of conditional volatility and expected returns. Their empirical results show that sentiment is a systematic risk that is priced. Baker and Wurgler (2006) also indicated that investor sentiment affects the cross-section of stock returns. They found that when beginning-of-period proxies for sentiment are low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks. Wang, Keswani and Taylor (2006) further tested the relationships between sentiment, returns and volatility. They also found strong and consistent evidence that sentiment measures, both in levels and first differences, are Granger-caused by returns. Banerjee, Doran and Peterson (2007) found that future returns are significantly related to both volatility index (VIX) levels and innovations for most portfolios, where the VIX is treated as a proxy variable for sentiment. While the causality test results presented above do not provide evidence of a consistent relationship between noise traders' sentiments and subsequent price movements, it might be possible that a relationship exists, but only in some special market scenarios.

The frame dependence theory, proposed by Shefrin (2000) in behavioral finance, argues that investors' decisions are sensitive to different market scenarios. This motivates us to investigate whether there are dynamic causal relationships between sentiments and returns. Besides considering both positive and negative market scenarios, we infer that investors may exhibit dissimilar behaviors depending on the level of sentiment, and therefore different dynamic relationships may exist between stock market returns and sentiment indicators. Giot (2005) found that for very high (low) levels of the VIX, future returns are always positive (negative). His findings suggested that extremely high levels of the VIX might signal attractive buying opportunities. Banerjee et al. (2007) examined the relationship between returns and the VIX, the proxy variable for sentiment, for different levels of market performance and relatively high or low levels of volatility. Banerjee et al. (2007) defined those returns above and those below the sample median as constituting a 'bull market' and a 'bear market', respectively. Volatilities above the median level of the VIX are said to be in a 'high volatility' period and those below the median in a 'low volatility period'. They provided two analyses, one of the 'bull and bear market' and the other of 'high and low volatility'. Their findings suggested that the market states based on directional movements (positive and negative returns) or volatility levels (above or below the average) do not make a difference. On the contrary, we believe that the results will be misunderstood if the separation of the different market states is defined subjectively.

2.4 Volatility Forecasting and Investor Sentiment

From the behavioral finance point of view, the investors' behavior could be influenced by psychology or by bullish/bearish sentiment proxies (Montier, 2002; Shefrin, 2007). De Long, Shleifer, Summers, & Waldmann (DSSW (1990) hereafter) point out that investors are subject to sentiment and model the influence of noise trading on equilibrium prices. Their study motivates empirical attempts to substantiate the proposition that noise traders' risks indexed by sentiment influence either the mean or variance of asset returns. Sentiments are therefore proposed as one of the indicators which could enhance the incremental explanation of the future volatility.

A large body of literature focuses on the relationship and information content between returns and sentiment (Solt & Statman, 1988; DSSW, 1990; Clarke & Statman, 1998; Fisher & Statman, 2000; Wang, 2001; Simon & Wiggins, 2001; Brown & Cliff, 2004; Baker & Wurgler, 2006; Baker & Wurgler, 2007, Han, 2008).

While less attention is given to the impact of sentiments on the realized volatility or vice versa (Brown, 1999; Lee, Jiang & Indro, 2002; Low, 2004; Wang et al. 2006; Banerjee, Doran & Peterson, 2007; Verma & Verma, 2007), the exact role of sentiment in the price formation process is still a topic worth looking into.

To sum up, the information content of sentiment may be useful for volatility forecasting. However, the precise form in which sentiment will affect or predict volatility is not clear *ex ante*. For this reason, in our empirical analysis the possible sentiment indicators in the Taiwan stock market are constructed by referring to the previous literature, the predictive ability of sentiment to volatility is examined, the forecasting performance of the competitive models is compared, and finally effective option trading strategies are proposed based on the volatility forecasting.

2.5 Related Studies in Taiwan Stock Market

There are some related studies that focus on the Taiwan derivatives market. Lee, Lu and Chiang (2005) compare the characteristics and construction methodology of the volatility indexes across different countries. They find that the volatility index for the *TAIEX* (*VXT*) is a good estimator of future volatility. Besides, the *VXT* has negative and asymmetric relationship with the *TAIEX* and may be a contrarian trading signal when the market plunges. In contrast to Lee et al. (2005), the contribution of our study lies in the econometric analysis of the relationship between the information content of the volatility index and the *TAIEX*. Lee and Yuan (2005) investigate whether the traders' risk preference in the Taiwan stock market can be perceived by the volatility index. They find that investors in the Taiwan stock market tend to hedge the risk perception by put option contracts and the tendency is only remarkable in the bear market. Hsieh, Lee and Yuan (2006) separately construct the call and put implied volatility in the Taiwan Stock Market. Their empirical results show that put implied volatility is more closely linked to the spot index and is more sensitive to the change in the spot index than the call volatility. The strategy based on the information content of the put volatility index also outperforms the benchmark buy-and-hold strategy. In contrast to their study that the put volatility reveals more information content, our study indicates that the implied index derived from call options takes precedence over the underlying *TAIEX*.

Chapter 3. Volatility Measure and Investor sentiment

3.1 Volatility Measures

3.1.1 Future Volatility

In the framework of volatility forecasting, what exactly is forecasted is a key parameter. By referring to Corrado & Miller (2005), we employ the future realized volatility for the next h-days on day t, which is computed as the sample standard deviation of returns over the period from day t+1 through day t+h, and the future volatility is expressed in terms of the percentage annual term.[6] The future realized return standard deviations are expressed as follows:

$$FV_t = \hat{\sigma}_{t;T} = \left(\hat{\sigma}^2_{t;T}\right)^{1/2} = \sqrt{\frac{252}{h-1}\sum_{j=1}^{h}\left[R_{t+j} - \bar{R}_{t,t+h}\right]^2},\ R_{t+j} = \ln\left(\frac{S_{t+j}}{S_{t+j-1}}\right) \tag{3.1}$$

where $\bar{R}_{t,t+h}$ is the mean of the TAIEX return during days $t+j$ to $t+h$, j=1,…h, R_{t+j} represents the TAIEX market returns on day $t+j$, and S_{t+j} and S_{t+j-1} are the daily closing prices of the TAIEX on day $t+j$ and $t+j$-1, respectively. The parameter h corresponds to the h-days-ahead volatility forecasting and it also equals h-days before the settlement day. Under this parameter, h is set as 5, 10, 15 and 20 days which exclude the weekends.

3.1.2 Historical Volatility Models

By referring to Engle & Gallo (2006), we jointly consider the three volatility measures, namely, absolute daily returns (|R|), daily high-low range (HL) and daily realized volatility (RV), as the benchmark forecasting model used in this study and it is simplified as MHV.[7] Both the |R| and the HL are calculated using daily data,[8] and

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[6] By referring to John C. Hull (2006), this study assumes that there are 252 trading days in each year.

[7] A multiple indicators volatility forecasting model jointly considers absolute daily returns (|R|), daily high-low range (HL) and daily realized volatility (RV) as proposed by Engle & Gallo (2006). The three variables have different features relative to one another, the main difference being that the daily return uses information regarding the closing price of the previous trading day, while the high-low spread and the realized volatility are measured on the basis of what is observed during the day. The former takes all trade information into account, and the latter is built on the basis of quotes sampled at discrete intervals.

[8] By taking the price limits in the Taiwan stock market into consideration[8], we transfer the high-low range to the degree of fluctuation relative to the price variation limits for each day. The daily price

the RV is calculated by summing the corresponding five-minute interval squared returns[9] (e.g., Andersen & Bollerslev, 1998; Barndorff-Nielsen & Shephard, 2002, among others), and the variable is expressed in terms of percentage annual terms. The calculations can be expressed as follows:

$$\left|\mathrm{R}_t\right| = \left|\ln\left(\mathrm{S}_t / \mathrm{S}_{t\text{-}1}\right)\right| \tag{3.2}$$

$$\mathrm{HL}_t = \frac{\mathrm{H}_t - \mathrm{L}_t}{\mathrm{S}_{t-1} \times 14\%} \tag{3.3}$$

$$\mathrm{RV}_t = \sqrt{\sum_{i=0}^{n}\left(\ln\frac{\mathrm{S}_{t+i}}{\mathrm{S}_{t+i\text{-}1}}\right)^2} \times \sqrt{252} \tag{3.4}$$

where $|\mathrm{R}_t|$ is absolute daily returns at time t, HL_t is the daily high-low range variation at time t, RV_t is the daily realized volatility at time t, S_t is the closing price on trading date t, $\mathrm{S}_{t\text{-}1}$ is the closing price on the previous trading day, H_t is the highest price on date t, L_t is the lowest price on date t, S_{t+i} is the intraday index level of the i-th interval on trading day t, S_{t+n} represents the closing price on day t, i=0,…, n, and n is the number of time intervals in each day.

3.1.3 Volatility Index

In 1993, the Chicago Board Options Exchange (CBOE) introduced the Volatility Index (VIX) based on the S&P 100 index options, which can be defined as the magnitude of price variations for the next 30 days. In 2003, the CBOE published the new VIX, which is based on the S&P 500 index options prices.[10] The construction of the CBOE's new volatility index incorporates information from the skewness of volatility by using a wider range of strike prices including the out-of-the-money call and put option contracts rather than just the at-the-money series.[11] The new VIX is

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limits on day t in the Taiwan stock market are -7% and +7% of the previous day's closing price. Thus, the maximum price variation on day t would be 14% based on the previous day's closing price.

[9] The latest observations available before the five-minute marks from 09:00 until 13:30 are used to calculate the five-minute returns. We sum the 54 squared intra-day five-minute returns and the previous squared overnight returns to construct the daily realized volatility.

[10] In March 2004, the CBOE futures exchange (CFE) introduced volatility futures, and volatility options were launched in February 2006. The underlying index is just the VIX published in 2003. The volatility index comprises tradable derivatives. The CBOE new VIX takes into account a wide range of strike prices for the same 30-day maturity, thus freeing its calculation from any specific option pricing model.

[11] For details of the index's construction, the interested reader may refer to the white book publish by the CBOE in 2003. http://www.cboe.com/micro/vix/vixwhite.pdf

not calculated from the Black-Scholes-Merton option pricing model which implies that the calculation is independent of any model. However, the fundamental features of the volatility index between the old and new versions remain the same. Since the new VIX is more precise and robust than the original version, we construct a volatility index for the Taiwan stock market based on the CBOE's last revision of the volatility index.

In the construction of the Taiwan stock market VIX, the interest rate has been adjusted accordingly. The risk-free rate is calculated from the monthly average one-year deposit rates at the Bank of Taiwan, Taiwan Cooperative Bank, First Bank, Hua Nan Bank and Chang Hwa Bank. The CBOE's volatility index (VIX) uses put and call options in the two nearest-term expiration months in order to bracket a 30-day calendar period. With 8 days left to expiration, CBOE's VIX 'rolls' to the second and third contract months in order to minimize pricing anomalies that might occur close to expiration. However, the nearest-term expiration contract usually has high trading volume and the next nearest-term contract usually has low trading volume in the Taiwan options market even if the nearest-term contract is traded on the last trading day. In considering the market structure of liquidity and trading volume for the second and third contract months, we have revised the rollover rule from 8 days to 1 day prior to expiration in constructing the volatility index in Taiwan.

Options market-based implied volatility can reflect the expectations with respect to price changes in the future, and it can be treated as an indicator of sentiment. Olsen (1998) indicated that the volatility index has been viewed as a 'sentiment indicator' in the recent behavioral finance literature and can be regarded as a market indicator of rises and falls in the underlying index. Whaley (2000) and research conducted by the Chicago Board Options Exchange (CBOE) have indicated that the greater the fear, the higher the VIX level is. Therefore, the volatility index is commonly referred to as the 'investor fear gauge'. Baker and Wurgler (2007) also treated option-implied volatility as one of the sentiment measures in investigating the investor sentiment approach. Therefore, the Taiwan stock market volatility index (TVIX) could be one of the volatility measures and one of the sentiment proxy variables in the Taiwan options market.

The hypothesis that volatility could reflect the expectations of future price changes and be treated as an indicator of sentiment is well documented (Whaley 2000, Baker and Wurgler 2006). Research by the Chicago Board of Options Exchange

(CBOE) indicates that, the greater the fear, the higher the Volatility Index (*VIX*) level is. The volatility index is therefore referred to as the "investor fear gauge". Olsen (1998) indicates that the volatility index has been viewed as the "sentiment indicator" in the recent behavioral finance literature and can be a market indicator of rises and falls in index returns in the future.

3.2 The Construction of the Implied Index from the Options Volatility

Whaley (2000) indicates that the volatility index can be expressed as the 'investors' fear gauge'. The *VIX* is also treated as a proxy variable of investor sentiment in recent studies on behavioral finance (Baker and Wurgler, 2007; Banerjee, Doran and Peterson, 2007). Therefore the implied index derived from the *TVIX* can represent the investors' view of the underlying index under a certain level of the *TVIX*. The concept of the implied index proposed in this study from the *TVIX* is expressed below.

Implied volatility is volatility 'implied' from an option price using the Black-Scholes-Merton options pricing model. It can be expressed as $C = Blsprice(S, K, r, T, IV)$, where *C* is the call option price observed in the market. There are five parameters, *S* (underlying index), *K* (exercise price), *r* (risk-free rate), *T* (time to maturity) and *IV* (implied volatility). Here we substitute the volatility parameter as a Taiwan stock market volatility index (*TVIX*) and the implied index from the options volatility index can be derived from the call and put option prices as follows:

$$\begin{aligned} C_{K_i} &= Blsprice(TVIIC_{K_i}, K_i, r, T, TVIX), \\ P_{K_i} &= Blsprice(TVIIP_{K_i}, K_i, r, T, TVIX). \end{aligned} \qquad (3.5)$$

where K_i is the strike price, $i = 1 \cdots X$, *X* is the number of exercise contract traded on day *t*. $TVIIC_{K_i}$ is the implied index derived from the call option at exercise K_i, $TVIIP_{K_i}$ is the implied index derived from the put option at exercise K_i, C_{K_i} is the midpoint of the bid-ask spread of the call option, P_{K_i} is the midpoint of the bid-ask spread of the put option, *r* is the risk-free rate and *T* is the time to maturity. Given *TVIX*, C_{K_i} (P_{K_i}), K_i, *r*, *T* then the *TVII*= g^{-1}(K_i,*r*, *T*, C_{K_i} (P_{K_i}), *TVIX*) is the information derived from the certain level of *TVIX* and we propose it as an implied index from *TVIX* (*TVII*). *TVII* would not be equivalent to the underlying index, the *TAIEX*, in the Taiwan stock market, since the *TVIX* is not derived from the Black-Scholes option pricing model. To construct the $TVIIC$ ($TVIIP$), we calculate the weighted average of $TVIIC_{K_i}$ ($TVIIP_{K_i}$) based on the trading volume of each exercise. The construction is expressed as follows:

$$
\begin{aligned}
&TVIIC = \sum_{i=1}^{N} w_{C,i} \times TVIIC_{Ki},\ w_{C,i} = v_{C,i} / \sum_{i=1}^{N} v_{C,i}, \\
&TVIIP = \sum_{i=1}^{N} w_{P,i} \times TVIIP_{Ki},\ w_{P,i} = v_{P,i} / \sum_{i=1}^{N} v_{P,i}, \\
&TVIIM = \sum_{i=1}^{M} w_i \times TVII_{Ki}, w_i = v_i / \sum_{i=1}^{M} v_i.
\end{aligned}
\tag{3.6}
$$

where N is the number of exercises, M is a $2 \times N$ vector which means that the *TVIIM* contains information content regarding the contracts including the call and put options, K_i is the exercise price, $TVIIC_{K_i}$ is the implied index derived from the call option at exercise K_i, $TVIIP_{K_i}$ is the implied index derived from the put option at exercise K_i, $v_{C,i}$ is the trading volume of the call option at exercise K_i, $v_{P,i}$ is the trading volume of the put option at exercise K_i, v_i is the trading volume of each contract including the call and put options at exercise K_i, $w_{C,i}$ is the weight of the call option at exercise K_i, $w_{P,i}$ is the weight of the put option at exercise K_i, w_i is the weight of each contract including the call and put options at exercise K_i, $TVIIC$ represents the implied index which contains the information content of the call option, $TVIIP$ is the implied index which contains the information content of the put option and $TVIIM$ is the mean effect of $TVIIC$ and $TVIIP$.

3.3 Investor Sentiment

3.3.1 Put-Call Trading Volume and Open Interest Ratios

The put-call trading volume ratio equals the total trading volume of puts divided by the total trading volume of calls (TPCV). Like the TVIX, market participants view the TPCV as a fear indicator, with higher levels reflecting bearish sentiment. When market participants are bearish, they buy put options to hedge their equity positions or to speculate bearishly. By contrast, a low level of TPCV is associated with a lower demand for puts, which reflects bullish sentiment.

The put-call open interest ratios can be calculated using the open interest of options instead of trading volume (TPCO). When the total option interest increases, most of it comes from higher investor demand for TXO puts. Thus the TPCO tends to be higher on days when the total open interest is high.

3.3.2 ARMS Index

The ARMS index is named after its creator, Richard Arms (1989), and is an indicator of bullish or bearish sentiment. The ARMS index on day t is equal to the number of advancing issues scaled by the trading volume (shares) of advancing issues divided by the number of declining issues scaled by the trading volume (shares) of declining issues. It is measured as:

$$ARMS_t = \frac{\#Adv_t / AdvVol_t}{\#Dec_t / DecVol_t} = \frac{DecVol_t / \#Dec_t}{AdvVol_t / \#Adv_t} \tag{3.7}$$

where $\#Adv_t$, $\#Dec_t$, $AdvVol_t$, and $DecVol_t$, respectively, denote the number of advancing issues, the number of declining issues, the trading volume of advancing issues, and the trading volume of declining issues.

ARMS can be interpreted as the ratio of the number of advances to declines standardized by their respective volumes. If the index is greater than one, more trading is taking place in declining issues, while if it is less than one, the average volume of advancing stocks outpaces the average volume of declining stocks. Its creator, Richard Arms, argued that if the average volume of declining stocks far outweighs the average volume of rising stocks, then the market is oversold and this should be treated as a bullish sign. Likewise, he argued that if the average volume of rising stocks far outweighs the average volume of falling stocks, then the market is overbought and this should be treated as a bearish sign.

3.2.3 Market Turnover

Previous studies indicate that there is a relationship between trading volume (the turnover ratio) and stock market returns, and therefore it could be a trading signal (Campbell, Grossman & Wang, 1993; Cooper, 1999; and Gervais, Kaniel, &

Mingelgrin, 2001). On the other hand, trading volume, or more generally liquidity, can be viewed as an investor sentiment index (Scheinkman & Xiong, 2003; Baker & Stein, 2004; Baker & Wurgler, 2007). A high turnover ratio not only indicates that the market is dominated by irrational investors, but also implies that the market might be overreacting. Market turnover is calculated by the ratio of trading volume to the number of shares listed on the TWSE and is simplified as TO in this study. The data are fully quoted in the Taiwan Economic Journal (TEJ).

Chapter 4. Causalities between Sentiment Indicators and Stock Market Returns under Different Market Scenarios

4.1 Introduction

The behavioral models of securities markets regard investors as being of two types: rational arbitrageurs who are sentiment-free and irrational traders who are prone to exogenous sentiment. In considering that investors may either overreact or under-react to extreme levels of sentiment indicators, we examine whether the sentiment indicators are classified according to multiple regimes by using the multivariate threshold model. Since previous studies have usually defined the extreme level subjectively, this paper analyzes the different states more objectively. The causality relationships between stock market returns and sentiment indicators are more significant when the different states are distinguished. The empirical results lead us to conclude that sentiment in both the stock and derivative markets gives rise to distinct lead-lag relationships with returns.

The analysis is conducted on a daily basis and the sentiment indicators used in this study include the TXO put-call trading volume ratio (TPCV), the TXO put-call open interest ratio (TPCO), the option market volatility index (TVIX) and the ARMS index. Our major focus of concern is on whether the causal relationship between sentiment and returns differs when investors' sentiment is at an extreme level identified optimistically by the threshold model. Our major findings suggest that there is nonlinearity in the sentiment indicators. The causality between sentiment and returns leads to different results when the sentiment index is at an extremely high or low level, or else reflects a typical regime. In the ordinary market scenario, there is low negative correlation as well as bi-directional causality. When the market overacts, the sentiment indicators Granger cause the returns. Among them, the ARMS index Granger causes the stock returns in the median and higher regimes, while the sentiment indicators in the derivatives market Granger cause the returns in the median and lower regimes. Our empirical findings further confirm the noise trader explanation that the causal direction runs from sentiment to market behavior.

To sum up, we apply the threshold model to examine the threshold effect of the sentiment indicators. Higher and lower regimes of sentiment indicators will be detected objectively. Therefore, the causality relationship needs to be tested for different market scenarios.

4.2 Data

The daily sentiment indicators used consist of the TXO put-call trading volume ratio (TPCV), the TXO put-call open interest ratio (TPCO), the TXO volatility index (TVIX) and the TAIEX ARMS index. To do this, we use data that are fully quoted on the Taiwan Futures Exchange (TAIFEX) and the Taiwan Stock Exchange (TSE). The study period extends from 2003 to 2006, encompassing 993 trading days. Table 1 contains summary statistics of all the variables discussed in the study. The returns display excess kurtosis, negative skewness and almost no serial correlation. The contemporaneous relationships among many measures of investor sentiment and market returns depicted in Table 2 are shown to be strong. Figure 1 shows the daily evolution of the TAIEX and returns from 2003 to 2006. Figure 2 is the daily evolution of the sentiment indices from 2003 to 2006.

Table 1 Summary Statistics of Investor Sentiment and TAIEX

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Autocorrelation			
					ρ_1	ρ_2	ρ_3	ρ_4
TAIEX	6,030.7580	732.2869	-0.4379	3.2624	0.9850	0.9700	0.9550	0.9410
R	0.0006	0.0120	-0.3855	6.3835	0.0390	-0.0110	0.0250	-0.0420
TVIX	20.7318	5.4899	0.9942	3.9072	0.9710	0.9530	0.9390	0.9230
TPCV	0.7835	0.1669	0.8043	4.3116	0.4640	0.3470	0.2820	0.2280
TPCO	0.9307	0.2597	1.1246	5.2412	0.9410	0.8720	0.8010	0.7370
ARMS	0.7168	0.3820	9.0595	175.3529	0.1190	0.0690	0.0010	-0.0120
ΔTVIX	-0.0029	1.2995	1.2845	16.4393	-0.2030	-0.0490	0.0360	-0.0510
ΔTPCV	0.0004	0.1729	-0.0767	4.3869	-0.3920	-0.0550	-0.0050	-0.0220
ΔTPCO	0.0004	0.0885	-3.0162	35.3451	0.0870	0.0250	-0.0670	-0.0420
ΔARMS	-0.0010	0.5087	-0.9781	91.5070	-0.4700	0.0110	-0.0320	0.0110

Notes: This table presents the summary statistics for the return on the Taiwan stock exchange capitalization weighted stock index (TAIEX) and various sentiment measures, namely, the Taiwan volatility index (TVIX), the put-call volume ratio (TPCV), the put-call open interest ratio (TPCO) and the ARMS ratio. The period covers 1/2/2003 to 12/29/2006.

Table 2 Contemporaneous Correlations of Investor Sentiment and TAIEX

	R	TVIX	TPCV	TPCO	ARMS	ΔTVIX	ΔTPCV	ΔTPCO	ΔARMS
TAIEX	0.0442	-0.4035***	0.0559*	0.2024***	-0.0282	0.0016	0.0007	-0.006	0.0035
R		-0.0885***	-0.2773***	0.1509***	-0.3542***	-0.2537***	-0.2622***	0.3703***	-0.2635***
TVIX			-0.0759**	-0.1974***	0.1028***	0.1197***	-0.0006	-0.0406	-0.0117
TPCV				0.0345	0.1476***	0.0667**	0.5179***	-0.146***	0.021
TPCO					-0.162***	0.0395	-0.0036	0.1704***	0.0222
ARMS						0.0316	0.0404	-0.1609***	0.6638***
ΔTVIX							0.0674**	-0.0431	-0.0285
ΔTPCV								-0.1509***	0.0486
ΔTPCO									-0.0596*

Notes: The pairwise correlations are for selected variables used in the analysis. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

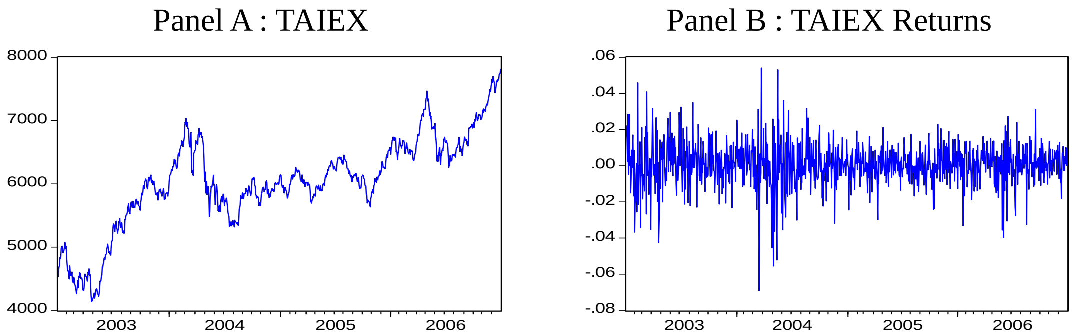


Figure 1 Daily Evolution of the TAIEX and TAIEX Returns

Notes: This figure shows the daily evolution of the TAIEX and TAIEX returns from 2003 to 2006. TAIEX represents the Taiwan stock exchange capitalization weighted stock index. TAIEX returns are calculated as the logarithmic difference in the daily TAIEX, i.e., $R_t = \ln S_t - \ln S_{t-1}$, where R_t represents the TAIEX market returns on day t, and S_t and S_{t-1} are the daily closing prices of the TAIEX on day t and t-1, respectively.

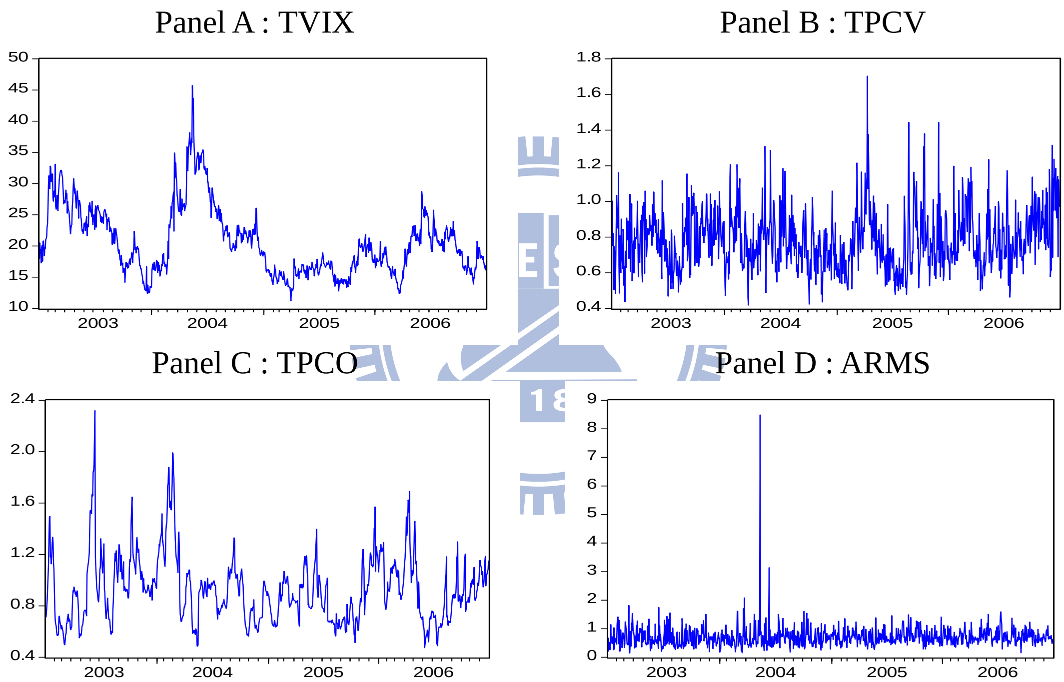


Figure 2 Daily Evolution of the Sentiment Indices

Notes: This figure shows the daily investor sentiments during 2003 to 2006. The Taiwan volatility index (TVIX) is calculated using daily data quoted on the Taiwan Futures Exchange (TAIFEX) and the Taiwan Stock Exchange (TWSE). The method used to construct the TVIX refers to the essence of the last revision of the volatility index of the CBOE and the interest rate, and the rollover rule is revised accordingly. The ARMS, put-call trading volume ratio (TPCV) and put-call open interest ratio (TPCO) are calculated using daily data quoted on the TWSE and TAIFEX.

4.3 Research Design

4.3.1 Causality Tests

We test for Granger causality between sentiment and returns by estimating bivariate VAR models (Granger, 1969, 1988; Sims, 1972). The Granger causality tests examine whether the lags of one variable enter the equation to determine the dependent variables, assuming that the two series (sentiment index and stock market return) are covariance stationary and the error items are i.i.d. white noise errors.

We estimate the models using both levels and changes in sentiment measures since it is not easy to determine which specification should reveal the primary effects of sentiment. For example, suppose investor sentiment decreases from very bullish to bullish. One might anticipate a positive return due to the still bullish sentiment, but on the other hand, since sentiment has decreased, it is also possible for someone to expect a reduction in the return. The general model we use here can be expressed as follows:

$$\begin{aligned} R_t &= c_1 + \sum_{p=1}^{L} a_{1p} R_{t-p} + \sum_{p=1}^{L} b_{1p} Senti_{t-p} + \varepsilon_{1t} \ , \\ Senti_t &= c_2 + \sum_{p=1}^{L} a_{2p} R_{t-p} + \sum_{p=1}^{L} b_{2p} Senti_{t-p} + \varepsilon_{2t} \ , \end{aligned} \tag{4.1}$$

where R_t denotes the stock market returns and $Senti_t$ represents the sentiment levels or the sentiment changes. The sentiment indices include TVIX, TPCV, TPCO and ARMS. In the bivariate Granger causality tests, the returns do not Granger cause the sentiment measures if the lagged values R_{t-p} do not enter the $Senti_t$ equation. Similarly, the returns do not Granger cause the sentiment measures if all the a_{2p} equal zero as a group based on a standard F-test. Meanwhile, the sentiment measures do not Granger cause the returns if all the b_{1p} equal zero.

4.3.2 Causality Relationship under Different Market Scenarios

We examine the causality relationship under the positive and negative market return scenario. The model may alternatively be written as:

$$\begin{cases} R_t = c_{11} + \sum_{p=1}^{L} a_{11p} R_{t-p} + \sum_{p=1}^{L} b_{11p} Senti_{t-p} + \varepsilon_{11t} \\ Senti_t = c_{12} + \sum_{p=1}^{L} a_{12p} R_{t-p} + \sum_{p=1}^{L} b_{12p} Senti_{t-p} + \varepsilon_{12t} \end{cases} , \text{ if } R_t \geq 0 \tag{4.2}$$

$$\begin{cases} R_t = c_{21} + \sum_{p=1}^{L} a_{21p} R_{t-p} + \sum_{p=1}^{L} b_{21p} Senti_{t-p} + \varepsilon_{21t} \\ Senti_t = c_{22} + \sum_{p=1}^{L} a_{22p} R_{t-p} + \sum_{p=1}^{L} b_{22p} Senti_{t-p} + \varepsilon_{22t} \end{cases} , \text{ if } R_t < 0 \tag{4.3}$$

where $R_t \geqq 0$ represents the positive return scenario and $R_t < 0$ is the negative return scenario. The threshold variable of the return is also substituted as a sentiment variable. There are three scenarios examined in the following study, the extremely high sentiment (top 20%), the extremely low sentiment (bottom 20%) and the typical sentiment group (median 60%).

4.3.3 The Oversold and Overbought Scenarios Identified by the Threshold Model

A two-regime version of the threshold autoregressive (TAR) model developed by Tong (1983) is expressed as follows:

$$y_t = I_t\left[\theta_{10} + \sum_{i=1}^{p}\theta_{1i}y_{t-i}\right] + (1-I_t)\left[\theta_{20} + \sum_{i=1}^{p}\theta_{2i}y_{t-i}\right] + \varepsilon_i,\ I_t = \begin{cases}1, & if\ y_{t-1} \geq \gamma \\ 0, & if\ y_{t-1} < \gamma\end{cases} \tag{4.4}$$

where y_t is the series of interest, θ_{1i} and θ_{2i} are the coefficients to be estimated, i=1…p, p is the order of the TAR model, γ is the value of the threshold, and I_t is the Heaviside indicator function. One problem with Tong (1983)'s model is that the threshold may not be known. When γ is unknown, Chan (1993) shows how to obtain a super-consistent estimate of the threshold parameter. The general form of Chan's model can be described as:

$$y_t = \begin{cases}\theta_{10} + \theta_{11}y_{t-1} + \cdots + \theta_{1p}y_{t-p} + c_1e_t, & if\ y_{t-d} < \gamma \\ \theta_{20} + \theta_{21}y_{t-1} + \cdots + \theta_{2p}y_{t-p} + c_2e_t, & if\ y_{t-d} \geq \gamma\end{cases} \tag{4.5}$$

For a TAR model, the procedure is to order the observations from the smallest to the largest such that $y_1 < y_2 < y_3 \ldots < y_T$. For each value of y_i, let $\gamma = y_i$, and let the Heaviside indicator be set according to this potential threshold in order to estimate a TAR model. The regression equation with the smallest residual sum of squares contains a consistent estimate of the threshold. Chan (1993) indicates that each data point within the band has the potential to be the threshold. However, it may be inefficient to examine the threshold effect of each value. Therefore, we adopt the grid search method whereby n sample points within the estimation period are selected to test the threshold effect and we set n equal to 100. In order to classify the oversold and overbought regimes, we apply the threshold test twice in the above and below average levels of each sentiment indicator. The highest and lowest 10 percent of the values are excluded from the search to ensure an adequate number of observations on each side of the threshold.

4.4 Empirical Results and Analysis under Different Market Scenarios

The lag lengths of the TAIEX returns and sentiment indices are determined before the causality test is performed. The numbers of lagged terms in the VAR models are decided parsimoniously by the Akaike information criterion (AIC) and the Schwarz criterion (SC). Table 3 presents the general causality tests. The results show that there is a feedback relationship between returns and sentiment, in both levels and first differences, and including TVIX and ARMS. As for the other two derivatives market sentiment indicators, TPCV and TPCO, these have no leading effect.

The positive and negative market return scenarios indicate whether the market returns are greater than zero or not. The results of these Granger-causality tests are presented in Table 4. The TVIX Granger causes returns when the return is greater than zero. However, the sentiment indicators are Granger-caused by returns while the return is smaller than zero. In short, TVIX could be a leading indicator while the market returns are positive.

The other situations with which we are concerned in this study are whether the sentiment is grouped in the top 20% or the bottom 20%. Most of the results, which are presented in Table 5, show that there is no distinct causal relationship between sentiment and returns although the TVIX and TPCV Granger cause returns while in the bottom 20%. Considering that the critical values of the overreaction scenarios are determined subjectively, the feedback relationship may be mixed.

Finally, there is the causality test between the returns and sentiment indicators in the extreme levels of investor sentiment that are determined by the threshold model. The threshold tests for each sentiment indicator are presented in Table 6 and the percentages for each regime classified by threshold model are shown in Table 7. The threshold tests show that the higher regime of TVIX and the lower regime of ARMS are not significant. Besides, the other sentiment indicators give rise to significant critical values of the higher and lower regimes that can represent the oversold and overbought situations.

Table 3 General Causality Tests between Returns and Sentiment

Sentiment	Hypothesis			
	H_{01}	H_{02}	H_{03}	H_{04}
TVIX	2.7533 (0.0642)*	3.9627 (0.0193)**	4.3919 (0.0364)**	6.4175 (0.0115)**
TPCV	0.0196 (0.9806)	0.9918 (0.3713)	0.1901 (0.9031)	6.4853 (0.0002)***
TPCO	0.4045 (0.5249)	51.7436 (<0.0001)***	3.0538 (0.0809)*	30.2449 (<0.0001)***
ARMS	4.8131 (0.0083)***	19.369 (<0.0001)***	2.5839 (0.0173)**	9.0376 (<0.0001)***

Notes: The numbers of lagged terms in the VAR models are decided parsimoniously by the Akaike information criterion (AIC) and the Schwarz criterion (SC). H_{01}: Granger-noncausality from sentiment to returns, i.e., sentiment does not cause returns. H_{02}: Granger-noncausality from returns to sentiment, i.e., returns do not cause sentiment. H_{03}: Granger-noncausality from changes in sentiment to returns, i.e., changes in sentiment do not cause returns. H_{04}: Granger-noncausality from returns to changes in sentiment, i.e., returns do not cause changes in sentiment. Values in the table and the parentheses are F test statistics and p-values, respectively. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4 Causality Tests between Returns and Sentiment – Considering the Positive and Negative Market Return Scenarios

Sentiment	Hypothesis			
	H_{01}	H_{02}	H_{03}	H_{04}
Panel A Positive Return				
TVIX	33.5609 (<0.0001)***	0.4766 (0.6212)	3.8761 (0.0495)**	0.0607 (0.8056)
TPCV	0.4318 (0.6496)	2.1598 (0.1164)	1.0806 (0.3568)	5.9478 (0.0005)***
TPCO	4.9796 (0.0261)**	15.1619 (0.0001)***	0.782 (0.377)	7.5925 (0.0061)***
ARMS	13.4788 (<0.0001)***	9.4277 (0.0001)***	4.7919 (0.0001)***	5.8443 (<0.0001)***
Panel B Negative Return				
TVIX	23.7999 (<0.0001)***	4.9421 (0.0075)***	0.0029 (0.9569)	9.9774 (0.0017)***
TPCV	1.2442 (0.2891)	0.2446 (0.7831)	0.8122 (0.4876)	2.5514 (0.0551)*
TPCO	2.2443 (0.1348)	61.2698 (<0.0001)***	0.118 (0.7314)	42.7464 (<0.0001)***
ARMS	0.5613 (0.5708)	11.2781 (<0.0001)***	1.3231 (0.2451)	4.7347 (0.0001)***

Notes: This table presents the causality tests between returns and sentiment considering the positive and negative market return scenarios. The numbers of lagged terms in the VAR models are decided parsimoniously by the Akaike information criterion (AIC) and the Schwarz criterion (SC). H_{01}: Granger-noncausality from sentiment to returns, i.e., sentiment does not cause returns. H_{02}: Granger-noncausality from returns to sentiment, i.e., returns do not cause sentiment. H_{03}: Granger-noncausality from changes in sentiment to returns, i.e., changes in sentiment do not cause returns. H_{04}: Granger-noncausality from returns to changes in sentiment, i.e., returns do not cause changes in sentiment. Values in the table and the parentheses are F test statistics and p-values, respectively. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5 Causality Tests between Returns and Sentiment – Sentiments Grouped at the Top, Median and Bottom Levels

Sentiment	Hypothesis			
	H_{01}	H_{02}	H_{03}	H_{04}
Panel A Top 20% of the sentiment				
TVIX	3.8314 (0.0233)**	8.6299 (0.0003)***	0.0076 (0.9308)	56.8343 (<0.0001)***
TPCV	1.943 (0.1461)	0.8829 (0.4152)	1.4031 (0.2432)	1.9424 (0.1242)
TPCO	0.4743 (0.4918)	2.7216 (0.1006)	0.0001 (0.9938)	0.2948 (0.5877)
ARMS	1.4385 (0.2398)	3.3526 (0.037)**	1.1535 (0.3333)	2.6497 (0.0173)**
Panel B Median of the sentiment				
TVIX	2.686 (0.069)*	8.3332 (0.0003)***	0.0053 (0.9417)	4.2173 (0.0405)**
TPCV	1.4351 (0.2389)	1.0379 (0.3548)	1.5621 (0.1975)	1.7258 (0.1605)
TPCO	28.2164 (<0.0001)***	25.3552 (<0.0001)***	0.701 (0.4028)	27.3828 (<0.0001)***
ARMS	13.3482 (<0.0001)***	3.2147 (0.0409)**	7.4548 (<0.0001)***	0.6305 (0.7059)
Panel C Bottom 20% of the sentiment				
TVIX	0.3011 (0.7404)	3.3127 (0.0385)**	3.6214 (0.0585)*	0.7986 (0.3726)
TPCV	10.5245 (<0.0001)***	1.7001 (0.1854)	4.4979 (0.0045)***	1.8991 (0.1312)
TPCO	20.0555 (<0.0001)***	16.3919 (0.0001)***	0.7241 (0.3959)	0.7776 (0.379)
ARMS	0.3037 (0.7384)	1.7525 (0.1761)	2.1734 (0.0474)**	5.4883 (<0.0001)***

Notes: This table presents causality tests between returns and sentiment considering the sentiments grouped at the top, median and bottom levels. The numbers of lagged terms in the VAR models are decided parsimoniously by the Akaike information criterion (AIC) and the Schwarz criterion (SC). H_{01}: Granger-noncausality from sentiment to returns, i.e., sentiment does not cause returns. H_{02}: Granger-noncausality from returns to sentiment, i.e., returns do not cause sentiment. H_{03}: Granger-noncausality from changes in sentiment to returns, i.e., changes in sentiment do not cause returns. H_{04}: Granger-noncausality from returns to changes in sentiment, i.e., returns do not cause changes in sentiment. Values in the table and the parentheses are F test statistics and p-values, respectively. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6 Threshold Test

	Upper regime			Lower regime		
Sentiment	Threshold Value	F test statistic	p-value	Threshold Value	F test statistic	p-value
TVIX	22.3673	0.3000	(0.5459)	17.9989	3.4807	(0.0293)**
TPCV	0.9612	8.3180	(0.0003)***	0.7377	6.3779	(0.0018)***
TPCO	1.1807	7.0289	(0.0009)***	0.7633	10.7162	(<0.0001)***
ARMS	1.0648	5.0219	(0.0038)***	0.5045	1.7117	(0.12)
ΔTVIX	0.9236	8.5034	(0.0002)***	-1.2803	10.3877	(<0.0001)***
ΔTPCV	0.1876	11.7296	(<0.0001)***	-0.1243	4.8070	(0.0084)***
ΔTPCO	0.0345	4.1566	(0.0159)**	-0.0223	7.7502	(0.0005)***
ΔARMS	0.3477	103.4980	(<0.0001)***	-0.0896	87.9864	(<0.0001)***

Notes: This table presents the threshold tests. The upper regime is the regime above the average level of the sentiment indicators. The lower regime is the regime below the average level of the sentiment indicators. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 7 Percentage of Each Regime Classified by Threshold Model

	Higher Regime	Typical Regime	Lower Regime
TVIX			39%
TPCV	14%	42%	44%
TPCO	14%	57%	29%
ARMS	10%		
ΔTVIX	15%	74%	10%
ΔTPCV	13%	68%	19%
ΔTPCO	24%	50%	26%
ΔARMS	15%	46%	39%

Notes: This table presents the percentages of different regimes classified by the threshold model. The higher regime is the regime above the higher threshold which is above the average level of the sentiment indicators. The lower regime is the regime below the lower threshold which is below the average level of the sentiment indicators. The typical regime is the regime between the higher and lower thresholds of the sentiment indicators. The blank of the higher regime and typical regime of TVIX indicates that the threshold test is not significant in the upper regime of the TVIX level. The blank of the lower regime and typical regime of ARMS indicates that the threshold test is not significant in the lower regime of the ARMS level.

The results of the causality relationship in the oversold and overbought situations are shown in Table 8. We can find that the market sentiment indicator, ARMS, leads returns while in the upper regime. Both the equity market and derivatives market sentiment indicators, ARMS and TPCV, Granger cause returns in the median regime. In the lower regime, only the sentiment indicators in the derivatives market, TVIX and TPCV, Granger cause returns. From these findings, we can conclude that the equity or derivatives markets sentiment indicators perform differently in terms of the lead-lag relationship between returns while the sentiments are in the higher, median or lower regimes. Our study suggests that investors can adjust their portfolios by analyzing the sentiment indicators for different scenarios.

Table 8 Causality Tests between Returns and Sentiment - Application of the Multivariate Threshold Model

Sentiment	Hypothesis			
	H_{01}	H_{02}	H_{03}	H_{04}
Panel A Upper regime (above the higher threshold)				
TVIX				
TPCV	0.7388 (0.4796)	1.1357 (0.3243)	0.5386 (0.6567)	0.7615 (0.5178)
TPCO	0.0732 (0.7871)	0.5083 (0.4771)	0.0589 (0.8084)	0.0922 (0.7616)
ARMS	3.4356 (0.0364)**	0.8965 (0.4115)	1.5796 (0.1574)	3.0123 (0.0085)***
Panel B Typical regime (between the two thresholds)				
TVIX				
TPCV	5.7821 (0.0033)***	0.1239 (0.8835)	2.3032 (0.0759)*	3.1818 (0.0235)**
TPCO	29.5417 (<0.0001)***	39.5976 (<0.0001)***	1.4719 (0.2256)	16.3007 (0.0001)***
ARMS				
Panel C Lower regime (below the lower threshold)				
TVIX	4.4883 (0.0118)**	5.8011 (0.0033)***	3.8007 (0.0541)*	0.5805 (0.4479)
TPCV	7.0184 (0.001)***	1.3517 (0.2599)	4.4569 (0.0048)***	1.6189 (0.1865)
TPCO	10.7606 (0.0012)***	18.2885 (<0.0001)***	0.8613 (0.3542)	0.4873 (0.4858)
ARMS				

Notes: This table presents the causality tests between returns and sentiment by applying the multivariate threshold model. The numbers of lagged terms in the VAR models are decided parsimoniously by the Akaike information criterion (AIC) and the Schwarz criterion (SC). H_{01}: Granger-noncausality from sentiment to returns, i.e., sentiment does not cause returns. H_{02}: Granger-noncausality from returns to sentiment, i.e., returns do not cause sentiment. H_{03}: Granger-noncausality from changes in sentiment to returns, i.e., changes in sentiment do not cause returns. H_{04}: Granger-noncausality from returns to changes in sentiment, i.e., returns do not cause changes in sentiment. The blank spaces for the causality tests in the higher regime of the TVIX, the typical regime of TVIX and ARMS, and the lower regime of ARMS indicate that the threshold test is not significant in that scenario. Therefore, the causality tests are not examined in these scenarios. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

4.5 Sub-Conclusions

In this paper, we have examined the causal relationship between investors' sentiment and stock market returns. The difference between this paper and the previous literature is that we identify the extreme level of sentiment econometrically by using the threshold model. Our analysis is conducted in three steps by using equity market data. We first construct the sentiment indicators in the equity and derivatives markets including the ARMS index, option volatility index, put-call trading volume ratio and put-call open interest ratio. We then examine the threshold of the sentiment indicators to test whether the sentiment could be classified into oversold, overbought and ordinary regimes. Finally, we investigate the relationships and causal directions for the different market scenarios.

The empirical results show that the causal relationships between the sentiment indicators and returns are mixed if the market scenario is not classified according to investors' sentiments. The TVIX Granger causes returns in the scenario that returns are greater than zero. Although previous studies (Simon and Wiggins, 2001; Giot, 2005) define the top 20% and bottom 20% as the extreme levels of sentiment, the causality information is still mixed. The linearity test of sentiment shows that the threshold effect is significant except in the higher regime of TVIX and the lower regime of ARMS in levels. When the threshold level is decided objectively, we find that ARMS Granger causes returns in the upper regimes. The sentiment indicators in the derivatives market including TPCV and TVIX Granger cause returns in the typical and lower levels. ARMS (TPCV and TVIX) could be the leading indicator if the market is more bearish (bullish). In conclusion, ARMS (sentiments in the derivatives market) will lose the leading effect in the overbought (oversold) scenario.

We find that the causality relationship is confused if the market scenarios are not taken into account. A leading characteristic of the sentiment indicators would be captured if the extreme scenarios were to be identified. Our empirical findings confirm the noise trader explanation that the causality would run from sentiment to market behavior. The results also support the view that accurate models of prices and expected returns need to assign a prominent role to investor sentiment.

This study is limited to the assumptions of the overreaction regime identified by the upper or lower thresholds of the sentiment indicators. Other econometric methodology, for example the smooth transition autoregressive (STAR) model that is viewed as a generalization of a nonlinear model, could be applied in further research to capture the transition process from bullish regimes to bearish regimes or vice versa. Besides, the information content of the investors' overreaction could be applied to the trading strategy or other portfolio management for further research.

Chapter 5. Interaction between the Implied Index from the Options Volatility and the Equity Index in Taiwan

5.1 Introduction

With the growing importance of modeling and predicting asset volatility in modern finance, the relevance of implied volatility as a rational forecast of future realized volatility and the information content of implied volatility with regard to historical volatility are two important research topics. Some studies have focused on the link between implied volatility and future realized volatility, while others have focused on the volatility forecasting performance by incorporating the *VIX* information. The frontier models of conditional heteroskedasticity are widely employed in this line of research for analyzing the mutual predictability between future realized volatility and options implied volatility. These two categories of research reveal different features of the relationships among returns, realized volatilities and implied volatilities. There are, however, only a small number of studies that deal with the possible relationship between implied volatility and future changes in stock indexes or returns. This probably stems from the belief that financial markets are efficient, and so implied volatility cannot provide relevant information as to whether stock prices are going up or down. The lack of a simultaneous analysis of the equity index level and the information level implied by the *VIX* is not, however, a major cause for concern. From another point of view, however, the opinions of non-academic market participants often lead to the conclusion that the *VIX* can be interpreted as a gauge of investor sentiment by analyzing the correlation between the *VIX* and its underlying equity index (*IDX*) through traditional technical analysis. When examining the relationship between the *VIX* and the *IDX*, an issue arises with regard to the different integration orders for the two time series. The equity index is always characterized by the property of nonstationarity. However, the standard Augmented Dickey Fuller tests for the *VIX* often show that the unit root hypothesis is rejected, although the degree of persistence in the series is very high. The practitioners' rationale is that very high implied volatility levels occur during periods of financial turmoil when investors are believed to be overreacting and hence selling financial assets indiscriminately to raise cash or control losses.

Previous academic research does not prove that practitioners believe that there is a direct relationship between the *VIX* and IDX. Hence there is a need to construct a methodology to solve both the different integration orders of the stock index and the *VIX* time series, and to analyze the relationship between the information content implied by the *VIX* and the underlying stock index under a reasonable econometric system. This motivates us to develop an implied equity index from the volatility index (*VII*) under the Black-Scholes-Merton options pricing model as an input for performing the co-movement analysis between the *VII* and the stock index (*IDX*). By holding to the view put forward in previous studies that volatility is a sentiment indicator, we verify the premise that investors exhibit distinct kinds of behavior depending on the level of volatility, and that different dynamic relationships therefore exist between *VIX* and underlying equity index in the high/low sentiment regime. In order to obtain a substantive answer to this issue, we apply the threshold cointegration model to examine possible nonlinear co-movements between the information content of volatility and the market index.

In this paper, we construct a volatility index for the Taiwan equity market (*TVIX*) in line with the CBOE's new *VIX* using intraday data for the Taiwan index options market. We then propose an implied equity index from the Taiwan volatility index (*TVII*) under the Black-Scholes-Merton options pricing scheme as an input for performing the co-movement analysis between the *TVII* and the stock index of the Taiwan stock exchange (*TAIEX*).

This paper examines the co-movements between the *TVII* (the equity index implied from the options' volatility index) and the *TAIEX* (its underlying stock index) using the vector error correction model (VECM) and threshold vector error correction model (TVECM). The causalities for positive and negative stock market returns at different deviation levels classified by the thresholds of the error correction terms are analyzed. To explore the nonlinear dynamics between the *TVII* and *TAIEX* under different deviation levels, we apply the threshold VECM of Hansen and Seo (2002) to construct a two-regime TVECM for performing the empirical tests. We examine whether there is a threshold for deviations between the *TVII* and the *TAIEX* to distinguish the different co-movement relationships. We then investigate whether there are possible lead/lag causalities between the *TVII* and the *TAIEX* under positive and negative stock market returns conditions in the VECM and TVECM schemes.

The empirical results substantiate the claim that the nonlinear two-regime TVECM model provides an appropriate fit for the dynamics between the *TVII* and the *TAIEX*. The linear causality tests based on the VECM show that the *TVII* from calls (*TVIIC*) Granger causes the *TAIEX* under a positive market return. The causality tests based on the TVECM show that no matter how high or low the deviation of the co-movement is, the *TVIIC* Granger causes the *TAIEX*, while in a typical regime of deviation between the *TVII* and the *TAIEX*, the *TVIIC* leads the *TAIEX* under both positive and negative stock market returns conditions. This indicates that the information content from call options in Taiwan does serve as a leading indicator for the underlying equity index. Investors participating in the Taiwan stock market could adjust their equity portfolios while the *TVIIC* takes precedence over the *TAIEX*.

5.2 Methodology

5.2.1 Application of the Threshold VECM

In the framework of different threshold econometric models, some studies apply one threshold to separate the adjustment process into two regimes (e.g., Balke and Fomby 1997, Enders and Granger 1998, Hansen and Seo 2002), whereas others apply two thresholds to separate it into three regimes (e.g., Obstfeld and Taylor 1997, Serra and Goodwin 2003, Seo 2003). Among them, Hansen and Seo (2002) propose a method that implements the maximum likelihood estimation (MLE) of the threshold model.[12] The algorithm involves a joint grid search over the threshold and the cointegrating vector. Hansen and Seo (2002) also develop the SupLM test for the presence of the threshold effect and simulate the rejection regimes by using the bootstrapping method.

The model under study is the following version:

$$\Delta x_t = \begin{cases} A_1' X_{t-1}(\beta) + u_t & \text{if } w_{t-1}(\beta) \le \gamma , \\ A_2' X_{t-1}(\beta) + u_t & \text{if } w_{t-1}(\beta) > \gamma , \end{cases} \tag{5.1}$$

where x_t is a p-dimensional I(1) time series which is cointegrated with one $p \times 1$ cointegrating vector β, and $w_t(\beta) = \beta' x_t$ denotes the I(0) error-correction term.

[12] The programs and data which compute estimates and test, and replicate the empirical work reported in Hansen & Seo (2002), are available at http://www.ssc.wisc.edu/~bhansen/.

The regressor $X_{t-1}(\beta)=[1,\ w_{t-1},\ \Delta x_{t-1},\ \Delta x_{t-2},\ldots,\Delta x_{t-l}]$ is a $k\times 1$ and A is a $k\times p$ coefficient matrix where $k=p\times l+2$ and l is the lag length. The error u_t is assumed to be a vector martingale difference sequence (MDS) with finite covariance matrix $\Sigma=E(u_t u_t')$. In this study we set the error correction term to be $w_t(\beta)=TVII_t-\beta\times TAIEX_t$ where $TVII_t$ and $TAIEX_t$ represent the natural logarithms and γ is the threshold parameter. This may alternatively be written as:

$$\Delta x_t = A_1' X_{t-1}(\beta) d_{1t}(\beta,\gamma) + A_2' X_{t-1}(\beta) d_{2t}(\beta,\gamma) + u_t \tag{5.2}$$

where $d_{1t}(\beta,\gamma)=1(w_{t-1}(\beta)\le\gamma),\ d_{2t}(\beta,\gamma)=1(w_{t-1}(\beta)>\gamma)$ and $1(\cdot)$ denotes the indicator function.

We propose estimating eq.(5.1) using maximum likelihood estimation under the assumption that the errors u_t are iid Gaussian and the concentrated Gaussian likelihood function is proposed as follows:

$$\begin{aligned} Ln(\beta,\gamma) &= Ln(\hat{A}_1(\beta,\gamma),\hat{A}_2(\beta,\gamma),\hat{\Sigma}(\beta,\gamma),\beta,\gamma) \\ &= -\frac{n}{2}\log|\hat{\Sigma}(\beta,\gamma)| - \frac{np}{2}. \end{aligned} \tag{5.3}$$

We extend a grid search over the two-dimensional space (β,γ) to find the MLE of the cointegration vector ($\hat{\beta}$) and the threshold (γ_1) as the minimizers of $\log|\hat{\Sigma}(\beta,\gamma)|$. The threshold only exists if $0<P(w_{t-1}\le\gamma)<1$ or the model is simplified to a linear cointegration model.

In accordance with the threshold test of Hansen and Seo (2002), the long-term equilibrium can be divided into two regimes when the coefficient matrix in each regime is significantly different. The hypothesis is as follows:

$$\begin{aligned} H_0 &: \Delta x_t = A' X_{t-1}(\beta) + u_t \\ H_1 &: \Delta x_t = A_1' X_{t-1}(\beta) d_{1t}(\beta,\gamma) + A_2' X_{t-1}(\beta) d_{2t}(\beta,\gamma) + u_t \end{aligned} \tag{5.4}$$

Let H_0 denote the class of linear VECM models and H_1 denote the class of two-regime threshold models. These models are nested, and the restriction H_0

denotes the class of models in H_1 which satisfies $A_1 = A_2$. When β and γ are unknown, the statistic is evaluated at point estimates obtained under H_0. The null estimate of β is $\tilde{\beta}$ which is the estimated cointegration vector of the linear error correction model, but there is no estimate of γ under H_0, so there is no conventionally defined LM statistic. The statistic is adjusted as

$$\text{SupLM}_{\gamma} = \sup_{\gamma_L \le \gamma \le \gamma_U} \text{LM}(\tilde{\beta}, \gamma). \tag{5.5}$$

For this test, the search region $[\gamma_L, \gamma_U]$ is set and $\tilde{w}_{t-1} = w_{t-1}(\tilde{\beta})$ so that γ_L is the $\pi_0 = 0.05$ percentile of the $\tilde{w}_{t-1}$ and γ_U is the $1-\pi_0 = 0.95$ percentile. Given that asymptotic critical values of the sampling distribution of the SupLM statistic cannot in general be tabulated, a residual bootstrap algorithm as well as a fixed-regressor experiment are performed.

5.2.2 Causality Tests

The research scheme of this study is that we want to investigate the co-movement and causality between the implied index from the option volatility index (*TVII*) and the underlying index in the Taiwan stock market (*TAIEX*). The general Granger causality tests used in this study are described as shown below.

As Granger (1988) pointed out, if there is cointegration among variables, there is causality among them at least in one direction. Thus, Granger-causality tests are used to examine the nature of such relationships. However, the model should take into account the information provided by the cointegrated properties of the variables. The model we use here can be expressed as an error correction model (ECM) as follows:

$$\begin{aligned} \Delta TVII_t &= c_1 + \alpha_1 w_{t-1} + \sum_{p=1}^{L} a_{1p} \Delta TVII_{t-p} + \sum_{p=1}^{L} b_{1p} \Delta TAIEX_{t-p} + \varepsilon_{1t}, \\ \Delta TAIEX_t &= c_2 + \alpha_2 w_{t-1} + \sum_{p=1}^{L} a_{2p} \Delta TVII_{t-p} + \sum_{p=1}^{L} b_{2p} \Delta TAIEX_{t-p} + \varepsilon_{2t}, \end{aligned} \tag{5.6}$$

where w_{t-1} denotes the error correction term and *TVII* represents three indexes including *TVIIM*, *TVIIC* and *TVIIP*. In a cointegrated system, the *TVII* does not Granger cause the *TAIEX* if the lagged values $\Delta TVII_{t-p}$ do not enter the $\Delta TAIEX$

equation and if the *TAIEX* does not respond to the deviation from the long-run equilibrium. Similarly, the *TVII* does not Granger cause the *TAIEX* if all the $a_{2p} = 0$ and if $\alpha_2 = 0$ as a group based on standard F-tests. In addition, the *TAIEX* does not Granger cause the *TVII* if all the $b_{1p} = 0$ and if $\alpha_1 = 0$.

Furthermore we examine the causality relationship under positive and negative stock market returns. The model may alternatively be written as:

$$\begin{cases} \Delta TVII_t = c_{11} + \alpha_{11} w_{t-1} + \sum_{p=1}^{L} a_{11p} \Delta TVII_{t-p} + \sum_{p=1}^{L} b_{11p} \Delta TAIEX_{t-p} + \varepsilon_{11t} \\ \Delta TAIEX_t = c_{12} + \alpha_{12} w_{t-1} + \sum_{p=1}^{L} a_{12p} \Delta TVII_{t-p} + \sum_{p=1}^{L} b_{12p} \Delta TAIEX_{t-p} + \varepsilon_{12t} \end{cases}, \text{ if } \Delta TAIEX_{t-1} \geq 0$$

$$\begin{cases} \Delta TVII_t = c_{21} + \alpha_{21} w_{t-1} + \sum_{p=1}^{L} a_{21p} \Delta TVII_{t-p} + \sum_{p=1}^{L} b_{21p} \Delta TAIEX_{t-p} + \varepsilon_{21t} \\ \Delta TAIEX_t = c_{22} + \alpha_{22} w_{t-1} + \sum_{p=1}^{L} a_{22p} \Delta TVII_{t-p} + \sum_{p=1}^{L} b_{22p} \Delta TAIEX_{t-p} + \varepsilon_{22t} \end{cases}, \text{ if } \Delta TAIEX_{t-1} < 0$$

(5.7)

where $\Delta TAIEX_{t-1} \geq 0$ represents the positive stock market returns and $\Delta TAIEX_{t-1} < 0$ is the negative stock market returns scenario.

If the empirical results show that the threshold cointegration is significant, which means that the deviation of the *TVII* and the *TAIEX* can be classified into higher and typical standards, we then examine the causality relationship mentioned above for different deviation levels. There are therefore different kinds of empirical results if we combine the co-movements with the causality analysis. In the linear VECM, the causality tests would be proceeded in general case (presented in eq.(5.6)) and positive/negative return scenario (as in eq.(5.7)). In the threshold VECM, there are also general causality tests in the higher and typical regime of w_{t-1}. The positive and negative returns conditions are further distinguished in different deviation regimes to analyze the causality relationship. In summary, the causality tests are examined while the co-movements between the *TVII* and the *TAIEX* are in the higher (typical) deviation levels and positive (negative) return conditions.

5.3 Empirical Results and Analysis

5.3.1 Data

The fifteen-minute volatility index of the Taiwan stock market (*TVIX*) is constructed by adapting the last revision of the volatility index (*VIX*) of the CBOE in 2003; to do this, we use high frequency data which are fully quoted on the Taiwan Futures Exchange (*TAIFEX*) and the Taiwan Stock Exchange Corporation (*TWSE*). The study period extends from 2003 to 2005, for a total of 746 trading days. The interest rate is adjusted accordingly,[13] and in light of the market structure in Taiwan, the roll-over rule is revised to one day prior to expiration. Figure 3 shows the original evolution of the *TVIX* and the *TAIEX* from 2003 to 2005 and the correlation coefficient is -0.4066.

The trading hours of the *TAIEX* are 9:00 a.m. to 1:30 p.m. and those of the options market are 8:45 a.m. to 1:45 p.m. Due to the restrictions on the cointegration analysis, the paired data are maintained during the same trading hours as the *TAIEX*, and the sample consists of 13,428 observations from January 2, 2003 to December 30, 2005. Figure 4 shows the original evolution of the implied index *TVII* (*TVIIM*, *TVIIC* and *TVIIP*) and the *TAIEX* from 2003 to 2005. In our empirical study, the *TVIIM*, *TVIIC*, *TVIIP* and *TAIEX* are both in natural logarithms. Table 9 provides the descriptive statistics. The skewness and kurtosis measures indicate that both series exhibit leptokurticity relative to the normal distribution.

[13] The risk-free rate is calculated from the monthly average deposit rate for one year at the Bank of Taiwan, Taiwan Cooperative Bank, First Bank, Hua Nan Bank and Chang Hwa Bank.

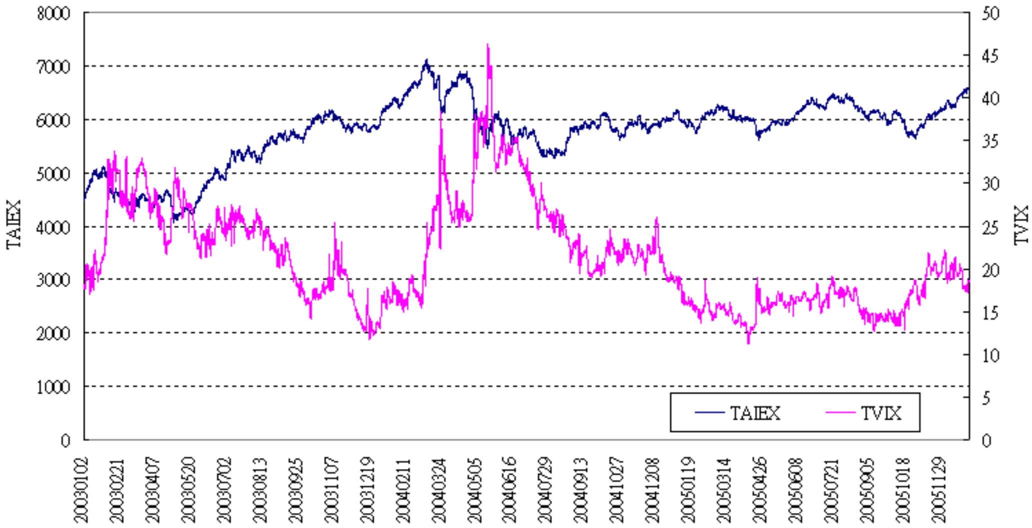


Figure 3 Fifteen-minute Evolution of the *TAIEX* and the Taiwan Volatility Index

Notes: *TAIEX* represents the Taiwan stock exchange capitalization weighted stock index. The Taiwan volatility index (*TVIX*) is calculated using fifteen-minute intraday data quoted on the Taiwan Futures Exchange (TAIFEX) and the Taiwan Stock Exchange (TWSE). The construction method of the *TVIX* refers to the essence of the last revision of the volatility index of the CBOE and the interest rate; the rule of roll-over is revised accordingly.

Table 9 Summary Statistics of the *TAIEX*, *TVIIC*, *TVIIP* and *TVIIM*

	Raw Data			
	TAIEX	*TVIIC*	*TVIIP*	*TVIIM*
Mean	5765.892	5754.601	5770.257	5762.429
Median	5904	5899.179	5904.01	5921.084
Maximum	7123	7276.496	7146.41	7209.053
Minimum	4063	4103.887	4095.347	4112.76
Std. Dev.	615.0564	617.6386	607.2023	610.9517
Skewness	-0.8872	-0.8403	-0.8876	-0.8726
Kurtosis	3.327	3.3756	3.3315	3.3605
Jarque-Bera	1821.374(0.00)***	1659.241(0.00)***	1824.8(0.00)***	(0.00)***
	ln natural logarithms			
	TAIEX	*TVIIC*	*TVIIP*	*TVIIM*
Mean	8.6535	8.6515	8.6545	8.653
Median	8.6834	8.6826	8.6834	8.6863
Maximum	8.8711	8.8924	8.8744	8.8831
Minimum	8.3097	8.3197	8.3176	8.3219
Std. Dev.	0.1135	0.1141	0.1119	0.1127
Skewness	-1.1343	-1.1057	-1.1326	-1.1258
Kurtosis	3.6847	3.703	3.6928	3.704
Jarque-Bera	3141.562(0.00)***	3012.368(0.00)***	3139.531(0.00)***	3113.879(0.00)***

Notes: *TAIEX* represents the Taiwan stock exchange capitalization weighted stock index. *TVIIC* is the implied index derived from the call option. *TVIIP* is the implied index derived from the put option. *TVIIM* is the mean of *TVIIC* and *TVIIP*. The period covers 2003/1/2 to 2005/12/30. *** indicates significance at the 1% level.

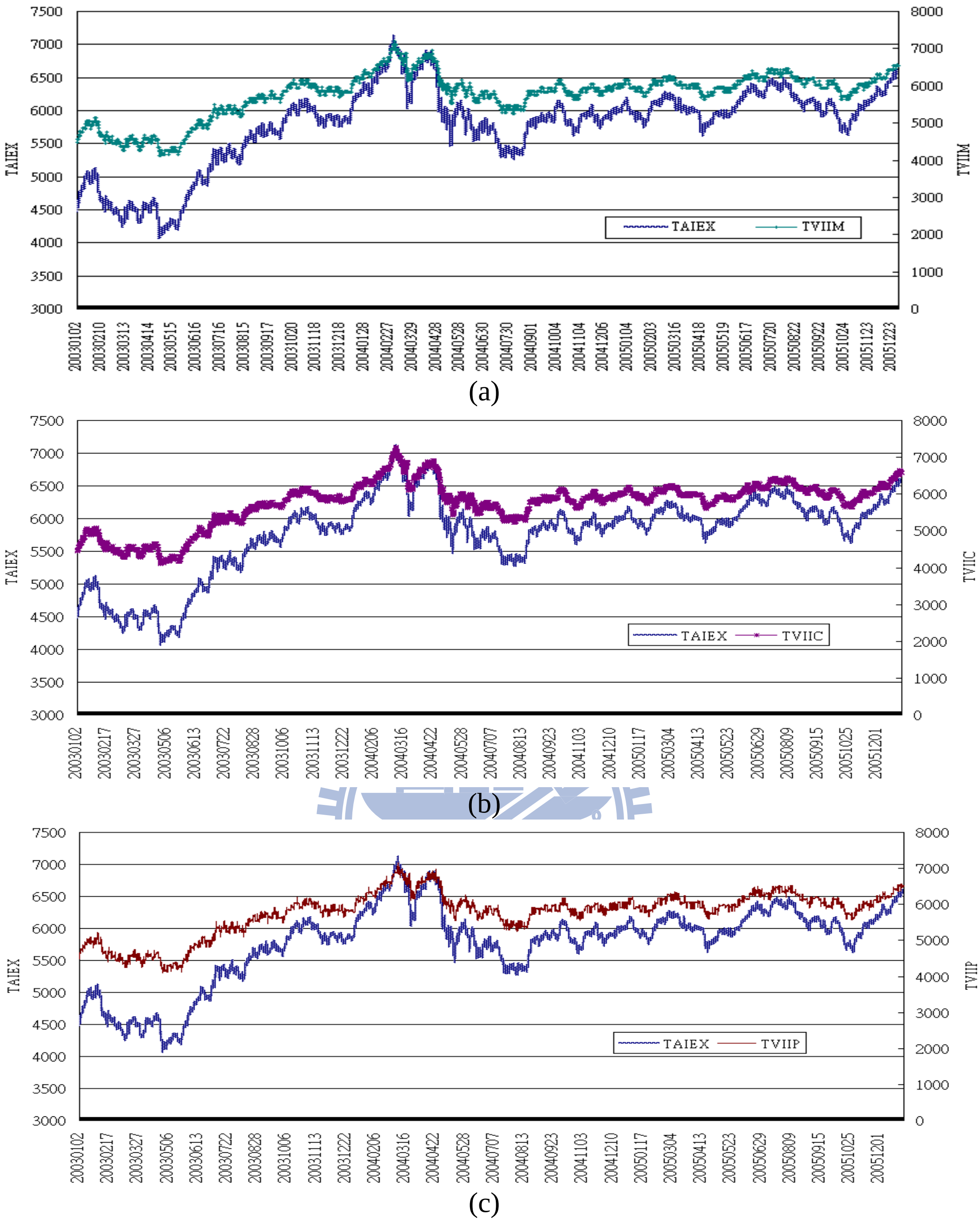


Figure 4 Fifteen-minute Evolution of the *TAIEX* and the Implied Index from the Taiwan Volatility Index

Notes: *TAIEX* represents the Taiwan stock exchange capitalization weighted stock index. The Implied Index is derived from the call and put option prices and the parameter of volatility is substituted by *TVIX*. *TVIIC* is the implied index derived from the call option. *TVIIP* is the implied index derived from the put option. *TVIIM* is the mean of *TVIIC* and *TVIIP*. The Taiwan volatility index (*TVIX)* is calculated using fifteen-minute intraday data quoted on the Taiwan Futures Exchange (TAIFEX) and the Taiwan Stock Exchange (TWSE). The construction method of the *TVIX* refers to the essence of the last revision of the volatility index of the CBOE and the interest rate; the rule of roll-over is revised accordingly.

5.3.2 Cointegration Tests

To test whether the series are stationary, we employ the ADF, PP and KPSS tests. The unit root tests are presented in Table 10. The results show that both the *TVII* (*TVIIM*, *TVIIC*, *TVIIP*) and *TAIEX* series are I(1),[14] which is the first condition for cointegration. The ADF and PP unit root tests show that the *TVIX* rejects the unit root at the 10% significance level, although the KPSS test results indicate that the *TVIX* rejects the stationary hypothesis. The results support the argument mentioned in the introduction that the *VIX* and its underlying index exhibit different integration orders, and also provides the motivation to further investigate the relationship between the information content of the *VIX* and the underlying equity index by constructing the *TVII*.

Table 10 Unit Root Tests

	TAIEX	*TVIX*	*TVIIC*	*TVIIP*	*TVIIM*
			Level		
ADF	-2.1259	-2.8394*	2.0423	-2.4959	-2.1486
PP	-2.1363	-2.6963*	-2.0997	0.5624	-2.2982
KPSS	11.8052***	7.7176***	11.5004***	0.9429***	11.8797***
			lst Difference		
ADF	-197.4229***	-52.1682***	-142.9328***	-63.8146***	-70.8196***
PP	-197.4107***	-250.9513***	-196.5994***	-302.7922***	-331.6444***
KPSS	0.1152	0.0402	0.1168	0.0307	0.0959

Notes: *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

The lag length of *TVII* and *TAIEX* is determined to be 4 parsimoniously based on the AIC and the SIC. The Engle-Granger (1987) cointegration test results show that the error correction terms, w_{t-1}, of the *TVII* and *TAIEX* are stationary and, hence, the *TVII* and *TAIEX* series are cointegrated. Johansen's (1991) cointegration test indicates that the co-movement between the *TVII* and the *TAIEX* is significant at the 5% level based on the trace test and the max-eigenvalue test.[15] The co-movement between the *TVII* and the *TAIEX* can reflect the degree of deviation between the investors' view and the real value of *TAIEX*. The great deviation between the *TVII* and the *TAIEX* can

[14] The exogenous variables in the unit root model include the trend and intercept.
[15] The Johansen cointegration test includes the intercept term.

also reflect the investors' behavior in terms of overreaction or underrreaction. We also examine the cointegration relationship using the Johansen (1991) VAR framework.

5.3.3 Threshold Cointegration Test

We test the hypothesis of linearity against the threshold-type of non-linearity with the application of the SupLM test given by (4.5). We calculate the p-values using both the fixed-regressor and a residual bootstrap with 5,000 simulation replications. The estimations of the thresholds and the test results are shown in Table 11.

Table 11 Tests for the Threshold Effect

		$TVIIM_\gamma$	$TVIIC_\gamma$	$TVIIP_\gamma$
Threshold estimate(γ)		0.0781	-0.0275	0.1893
Cointegrating vector estimate(β)		0.9918	1.0031	0.9799
SupLM		70.5369**	38.7306**	75.4462**
Fixed regressor bootstrap	p-value	0.0000	0.1200	0.0000
	5% critical value	40.8631	43.9873	38.2280
Residual bootstrap	p-value	0.0000	0.0000	0.0000
	5% critical value	36.8632	32.2586	39.5073

Notes: $TVIIM_\gamma$ represents the threshold effect of the error correction term between *TVIIM* and *TAIEX*. $TVIIC_\gamma$ represents the threshold effect of the error correction term between *TVIIC* and *TAIEX*. $TVIIP_\gamma$ represents the threshold effect of the error correction term between *TVIIP* and *TAIEX*. ** indicates significance at the 5% level.

The results exhibit clear evidence of the threshold effect at the 5% level. The threshold effect ($TVIIM_\gamma$, $TVIIC_\gamma$, $TVIIP_\gamma$) shows that there are two regimes in the long-run relationship between the '*TVIIM* and *TAIEX*', '*TVIIC* and *TAIEX*' and '*TVIIP* and *TAIEX*' which we refer to as the higher and the typical deviation regimes. Table 12 to Table 14 show the results of the estimated threshold VECM developed here.

Table 12 Estimation of the Threshold VECM between *TVIIM* and *TAIEX*

Model:

$$\Delta TVIIM_t = c_1 + \alpha_1 w_{t-1} + \sum_{p=1}^{L} a_{1p}\Delta TVIIM_{t-p} + \sum_{p=1}^{L} b_{1p}\Delta TAIEX_{t-p} + \varepsilon_{1t}, w_{t-1} \le \gamma$$

$$\Delta TAIEX_t = c_2 + \alpha_2 w_{t-1} + \sum_{p=1}^{L} a_{2p}\Delta TVIIM_{t-p} + \sum_{p=1}^{L} b_{2p}\Delta TAIEX_{t-p} + \varepsilon_{2t}, w_{t-1} \le \gamma$$

$$\Delta TVIIM_t = c_3 + \alpha_3 w_{t-1} + \sum_{p=1}^{L} a_{3p}\Delta TVIIM_{t-p} + \sum_{p=1}^{L} b_{3p}\Delta TAIEX_{t-p} + \varepsilon_{3t}, w_{t-1} > \gamma$$

$$\Delta TAIEX_t = c_4 + \alpha_4 w_{t-1} + \sum_{p=1}^{L} a_{4p}\Delta TVIIM_{t-p} + \sum_{p=1}^{L} b_{4p}\Delta TAIEX_{t-p} + \varepsilon_{4t}, w_{t-1} > \gamma$$

Coefficient	Regime 1($w_{t-1}(\beta) > \gamma$)		Regime 2($w_{t-1}(\beta) \le \gamma$)	
	$\Delta TAIEX_t$	$\Delta TVIIM_t$	$\Delta TAIEX_t$	$\Delta TVIIM_t$
$\alpha_i\,(w_{t-1})$	-3.0000	-0.2697	-0.0026	-0.1742
	(-0.0862)	(-2.3943)**	(-0.4521)	(-16.2542)***
C_i	-0.0003	-0.0194	0.0002	0.0125
	(-0.0449)	(-2.1683)**	(0.5320)	(16.4601)***
$\rho_{i1}\,(\Delta TVIIM_{t-1})$	-0.0398	-0.3718	0.0015	-0.3195
	(-1.8102)*	(-7.9688)***	(0.1905)	(-17.7802)***
$\rho_{i2}\,(\Delta TVIIM_{t-2})$	-0.0369	-0.2400	-0.0023	-0.2015
	(-1.7665) *	(-4.9454)***	(-0.2839)	(-11.8194)***
$\rho_{i3}\,(\Delta TVIIM_{t-3})$	-0.0255	-0.1068	0.0143	-0.0874
	(-1.4944)	(-2.6099)***	(1.7330)*	(-5.7052)***
$\rho_{i4}\,(\Delta TVIIM_{t-4})$	-0.0243	-0.1382	0.0176	-0.0315
	(-1.0972)	(-3.4395)***	(2.8232)***	(-2.4704)**
$\beta_{i1}\,(\Delta TAIEX_{t-1})$	-0.0069	-0.3133	-0.0976	0.2171
	(-0.1594)	(-4.1942)***	(-7.0644)***	(9.9950)***
$\beta_{i2}\,(\Delta TAIEX_{t-2})$	0.0595	-0.1761	-0.0043	0.1597
	(1.3545)	(-2.3689)**	(-0.3120)	(7.0245)***
$\beta_{i3}\,(\Delta TAIEX_{t-3})$	-0.0220	-0.1275	-0.0177	0.0729
	(-0.6629)	(-2.0339)**	(-1.3867)	(3.4772)***
$\beta_{i4}\,(\Delta TAIEX_{t-4})$	-0.0060	0.1107	-0.0005	0.0556
	(-0.1552)	(1.6642)*	(-0.0432)	(2.8745)***

Notes: The fifteen-minute paired data from 2003/1/2 to 2005/12/30 make up 13,428 observations. *TAIEX* represents the Taiwan capitalization weighted stock index. *TVIIM* represents the mean of *TVIIC* and *TVIIP*. The error correction term (w_t) represents the long-run relationship between the *TVIIM* and *TAIEX*, and $w_{t,TVIIM} = TVIIM_t - 0.9918 \times TAIEX_t$. γ is the threshold from the threshold VECM. In this empirical study, the *TVIIM* and *TAIEX* are both in natural logarithms. $\Delta TVIIM_t = TVIIM_t - TVTIM_{t-1}$; and $\Delta TAIEX_t = TAIEX_t - TAIEX_{t-1}$. C_i represents the intercept. w_{t-1} represents the error correction term between the *TVIIM* and *TAIEX* at t-1 and can be viewed as the adjustment of the long-term equilibrium. α_i shows the expected change in $\Delta TVIIM_t$ ($\Delta TAIEX_t$) per unit change in w_{t-1} , assuming all other independent variables are held fixed. $\Delta TVIIM_{t-p} = TVIIM_{t-p} - TVIIM_{(t-p)-1}$; $\Delta TAIEX_{t-p} = TAIEX_{t-p} - TAIEX_{(t-p)-1}$. p is the lag length, p=1, 2, …L, L=4. ρ_{ip} and β_{ip} are the coefficients of $\Delta TVIIM_{t-p}$ and $\Delta TAIEX_{t-p}$, respectively, and each shows the expected variation in the current *TVIIM* and *TAIEX*($\Delta TVIIM_t$, $\Delta TAIEX_t$) per unit change in the variation in *TVIIM* and *TAIEX* in lag p ($\Delta TVIIM_{t-p}$, $\Delta TAIEX_{t-p}$), assuming all other independent variables are held fixed. i =1,2,3,4 represents the regression function of $\Delta TVIIM_t$ and $\Delta TAIEX_t$ in different regimes. The values in parentheses are t-statistics. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 13 Estimation of the Threshold VECM between *TVIIC* and *TAIEX*

Model:

$$\Delta TVIIC_t = c_1 + \alpha_1 w_{t-1} + \sum_{p=1}^{L} a_{1p} \Delta TVIIC_{t-p} + \sum_{p=1}^{L} b_{1p} \Delta TAIEX_{t-p} + \varepsilon_{1t}, w_{t-1} \le \gamma$$

$$\Delta TAIEX_t = c_2 + \alpha_2 w_{t-1} + \sum_{p=1}^{L} a_{2p} \Delta TVIIC_{t-p} + \sum_{p=1}^{L} b_{2p} \Delta TAIEX_{t-p} + \varepsilon_{2t}, w_{t-1} \le \gamma$$

$$\Delta TVIIC_t = c_3 + \alpha_3 w_{t-1} + \sum_{p=1}^{L} a_{3p} \Delta TVIIC_{t-p} + \sum_{p=1}^{L} b_{3p} \Delta TAIEX_{t-p} + \varepsilon_{3t}, w_{t-1} > \gamma$$

$$\Delta TAIEX_t = c_4 + \alpha_4 w_{t-1} + \sum_{p=1}^{L} a_{4p} \Delta TVIIC_{t-p} + \sum_{p=1}^{L} b_{4p} \Delta TAIEX_{t-p} + \varepsilon_{4t}, w_{t-1} > \gamma$$

Coefficient	Regime 1($w_{t-1}(\beta) > \gamma$)		Regime 2($w_{t-1}(\beta) \le \gamma$)	
	$\Delta TAIEX_t$	$\Delta TVIIC_t$	$\Delta TAIEX_t$	$\Delta TVIIC_t$
$\alpha_i\,(w_{t-1})$	0.0302	0.0052	0.0016	-0.0145
	(2.1850)**	(0.3794)	(0.2461)	(-2.2055)**
C_i	0.0007	0.0000	0.0001	-0.0004
	(2.2161)**	(0.0724)	(0.2756)	(-1.6878)*
$\rho_{i1}\,(\Delta TVIIC_{t-1})$	0.2817	-0.0057	0.2318	0.0205
	(5.8564)***	(-0.1121)	(7.0799)***	(0.6505)
$\rho_{i2}\,(\Delta TVIIC_{t-2})$	0.1403	0.0476	0.0514	-0.0257
	(4.0400)***	(1.3881)	(2.0180)**	(-1.0066)
$\rho_{i3}\,(\Delta TVIIC_{t-3})$	0.0456	-0.0155	0.0789	0.0572
	(1.3611)	(-0.4944)	(3.3919)***	(2.5682)**
$\rho_{i4}\,(\Delta TVIIC_{t-4})$	0.0746	0.0436	-0.0142	-0.0030
	(2.5059)**	(1.5329)	(-0.3709)	(-0.0964)
$\beta_{i1}\,(\Delta TAIEX_{t-1})$	-0.3252	-0.0043	-0.2686	-0.0277
	(-7.5537)***	(-0.1006)	(-8.3301)***	(-1.0102)
$\beta_{i2}\,(\Delta TAIEX_{t-2})$	-0.1359	-0.0286	-0.0630	0.0111
	(-3.9662)***	(-0.8383)	(-2.5434)**	(0.4638)
$\beta_{i3}\,(\Delta TAIEX_{t-3})$	-0.0867	-0.0013	-0.0459	-0.0120
	(-2.6705)***	(-0.0457)	(-1.9103)*	(-0.5491)
$\beta_{i4}\,(\Delta TAIEX_{t-4})$	-0.0812	-0.0312	0.0252	0.0213
	(-2.9608)***	(-1.1851)	(0.7599)	(0.7778)

Notes: The fifteen-minute paired data from 2003/1/2 to 2005/12/30 make up 13,428 observations. *TAIEX* represents the Taiwan capitalization weighted stock index. *TVIIC* represents the implied index derived from the call option. The error correction term (w_t) represents the long-run relationship between the *TVIIC* and *TAIEX*, and $w_{t,TVIIC} = TVIIC_t - 1.0031 \times TAIEX_t$. γ is the threshold from the threshold VECM. In this empirical study, the *TVIIC* and *TAIEX* are both in natural logarithms. $\Delta TVIIC_t = TVIIC_t - TVTIC_{t-1}$; and $\Delta TAIEX_t = TAIEX_t - TAIEX_{t-1}$. C_i represents the intercept. w_{t-1} represents the error correction term between the *TVIIC* and *TAIEX* at t-1 and can be viewed as the adjustment of the long-term equilibrium. α_i shows the expected change in $\Delta TVIIC_t$ ($\Delta TAIEX_t$) per unit change in w_{t-1}, assuming all other independent variables are held fixed. $\Delta TVIIC_{t-p} = TVIIC_{t-p} - TVIIC_{(t-p)-1}$; $\Delta TAIEX_{t-p} = TAIEX_{t-p} - TAIEX_{(t-p)-1}$. p is the lag length, p=1, 2, …L, L=4. ρ_{ip} and β_{ip} are the coefficients of $\Delta TVIIC_{t-p}$ and $\Delta TAIEX_{t-p}$, respectively, and each shows the expected variation in the current *TVIIC* and *TAIEX*($\Delta TVIIC_t$, $\Delta TAIEX_t$) per unit change in the variation in *TVIIC* and *TAIEX* in lag p ($\Delta TVIIC_{t-p}$, $\Delta TAIEX_{t-p}$), assuming all other independent variables are held fixed. i =1,2,3,4 represents the regression function of $\Delta TVIIC_t$ and $\Delta TAIEX_t$ in different regimes. The values in parentheses are t-statistics. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 14 Estimation of the Threshold VECM between *TVIIP* and *TAIEX*

Model:

$$\Delta TVIIP_t = c_1 + \alpha_1 w_{t-1} + \sum_{p=1}^{L} a_{1p} \Delta TVIIP_{t-p} + \sum_{p=1}^{L} b_{1p} \Delta TAIEX_{t-p} + \varepsilon_{1t}, w_{t-1} \le \gamma$$

$$\Delta TAIEX_t = c_2 + \alpha_2 w_{t-1} + \sum_{p=1}^{L} a_{2p} \Delta TVIIP_{t-p} + \sum_{p=1}^{L} b_{2p} \Delta TAIEX_{t-p} + \varepsilon_{2t}, w_{t-1} \le \gamma$$

$$\Delta TVIIP_t = c_3 + \alpha_3 w_{t-1} + \sum_{p=1}^{L} a_{3p} \Delta TVIIP_{t-p} + \sum_{p=1}^{L} b_{3p} \Delta TAIEX_{t-p} + \varepsilon_{3t}, w_{t-1} > \gamma$$

$$\Delta TAIEX_t = c_4 + \alpha_4 w_{t-1} + \sum_{p=1}^{L} a_{4p} \Delta TVIIP_{t-p} + \sum_{p=1}^{L} b_{4p} \Delta TAIEX_{t-p} + \varepsilon_{4t}, w_{t-1} > \gamma$$

Coefficient	Regime 1($w_{t-1}(\beta) > \gamma$)		Regime 2($w_{t-1}(\beta) \le \gamma$)	
	$\Delta TAIEX_t$	$\Delta TVIIP_t$	$\Delta TAIEX_t$	$\Delta TVIIP_t$
α_i (w_{t-1})	-0.0126	-0.0848	-0.0024	-0.2115
	(-0.4133)	(-1.1094)	(-0.7110)	(-19.4703)***
C_i	0.0026	0.0130	0.0005	0.0371
	(0.4458)	(0.8816)	(0.7791)	(19.5967)***
ρ_{i1} ($\Delta TVIIP_{t-1}$)	-0.0254	-0.4547	-0.0053	-0.3012
	(-2.9032)***	(-11.8348)***	(-1.2383)	(-18.0928)***
ρ_{i2} ($\Delta TVIIP_{t-2}$)	-0.0296	-0.3195	-0.0027	-0.1821
	(-3.4143)***	(-7.8644)***	(-0.6525)	(-11.7026)***
ρ_{i3} ($\Delta TVIIP_{t-3}$)	-0.0108	-0.1479	0.0029	-0.0861
	(-1.3964)	(-3.9533)***	(0.6659)	(-6.1541)***
ρ_{i4} ($\Delta TVIIP_{t-4}$)	-0.0087	-0.1531	0.0061	-0.0326
	(-1.1734)	(-4.5938)***	(1.6074)	(-2.7127)***
β_{i1} ($\Delta TAIEX_{t-1}$)	-0.0403	0.3931	-0.0837	0.2006
	(-1.1097)	(4.6395)***	(-6.4141)***	(6.2959)***
β_{i2} ($\Delta TAIEX_{t-2}$)	0.0449	0.1203	-0.0012	0.1541
	(1.5729)	(1.3778)	(-0.0917)	(4.6679)***
β_{i3} ($\Delta TAIEX_{t-3}$)	0.0141	0.1428	-0.0102	0.0755
	(0.5339)	(1.7221)*	(-0.8981)	(2.3529)**
β_{i4} ($\Delta TAIEX_{t-4}$)	-0.0115	0.1862	0.0083	0.0491
	(-0.4594)	(2.5338)**	(0.7672)	(1.5427)

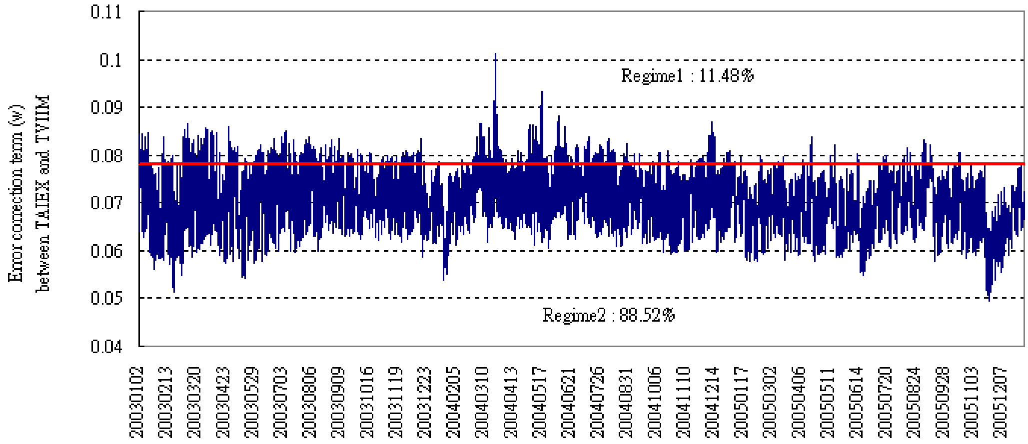
Notes: The fifteen-minute paired data from 2003/1/2 to 2005/12/30 make up 13,428 observations. *TAIEX* represents the Taiwan capitalization weighted stock index. *TVIIP* represents the implied index derived from the put option. The error correction term (w_t) represents the long-run relationship between the *TVIIP* and *TAIEX*, and $w_{t,TVIIP} = TVIIP_t - 0.9799 \times TAIEX_t$. γ is the threshold from the threshold VECM. In this empirical study, the *TVIIP* and *TAIEX* are both in natural logarithms. $\Delta TVIIP_t = TVIIP_t - TVTIP_{t-1}$; and $\Delta TAIEX_t = TAIEX_t - TAIEX_{t-1}$. C_i represents the intercept. w_{t-1} represents the error correction term between the *TVIIP* and *TAIEX* at t-1 and can be viewed as the adjustment of the long-term equilibrium. α_i shows the expected change in $\Delta TVIIP_t$ ($\Delta TAIEX_t$) per unit change in w_{t-1} , assuming all other independent variables are held fixed. $\Delta TVIIP_{t-p} = TVIIP_{t-p} - TVIIP_{(t-p)-1}$; $\Delta TAIEX_{t-p} = TAIEX_{t-p} - TAIEX_{(t-p)-1}$. p is the lag length, p=1, 2, …L, L=4. ρ_{ip} and β_{ip} are the coefficients of $\Delta TVIIP_{t-p}$ and $\Delta TAIEX_{t-p}$, respectively, and each shows the expected variation in the current *TVIIP* and *TAIEX*($\Delta TVIIP_t$, $\Delta TAIEX_t$) per unit change in the variation in *TVIIP* and *TAIEX* in lag p ($\Delta TVIIP_{t-p}$, $\Delta TAIEX_{t-p}$), assuming all other independent variables are held fixed. i =1,2,3,4 represents the regression function of $\Delta TVIIP_t$ and $\Delta TAIEX_t$ in different regimes. The values in parentheses are t-statistics. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.3.4 Concept of Thresholds

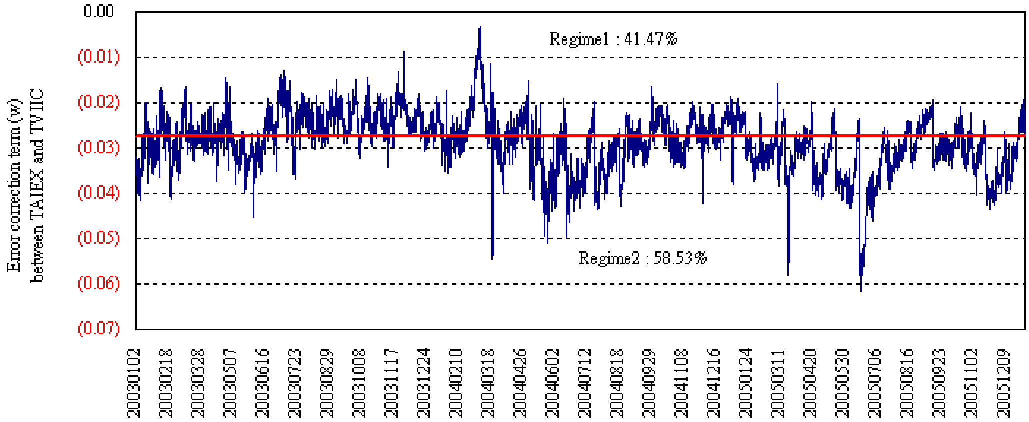
The implied index is constructed to represent the information content of the volatility index. Since the volatility index is one of the proxy variables for the sentiment indicators, the implied index could also reflect the investors' emotional differentials. The error correction term (w_{t-1}) is the spread of the *TVII* and the *TAIEX*. The higher deviation level between the *TVII* and the *TAIEX* could be explained as the investors' overreaction regime. If the financial markets are efficient, the implied index derived from the *TVIX* cannot provide relevant information as to whether stock prices are going up or down. The spread or the deviation level of the *TVII* and the *TAIEX* might be due to the inefficient or overreacting behavior of market participants.

Figure 5 shows the fifteen-minute evolution of the error correction term and the threshold effects. Panel (a) in Figure 5 is the evolution of the error correction term between the *TVIIM* and the *TAIEX*. Panel (b) in Figure 5 is the evolution of the error correction term between the *TVIIC* and the *TAIEX*. Panel (c) in Figure 5 is the evolution of the error correction term between the *TVIIP* and the *TAIEX*.

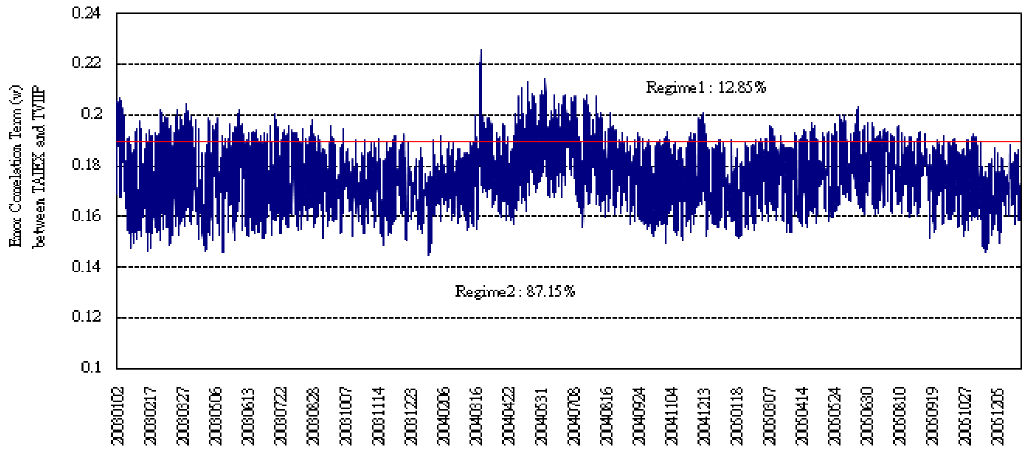
The concept of thresholds in the error correction term can be expressed as the critical level which divides the deviation of the *TVII* and the *TAIEX* into two regimes to capture the higher and typical deviation regimes. Take the evolution of the error correction term between *TVIIM* and *TAIEX* as an example (Figure 5 (a)). The higher regime (with 11.48% of the observations) occurs when $TVIIM > 0.0781 + 0.9918 \times TAIEX$, which indicates that the deviation between the *TVII* and the *TAIEX* is at the higher level. The second regime (with 88.52% of the observations), where $TVIIM \leq 0.0781 + 0.9918 \times TAIEX$, by contrast describes the typical regime.



(a)



(b)



(c)

Figure 5 Fifteen-minute Evolution of the Error Correction Term between the *TVII* and *TAIEX*

Notes: *TAIEX* represents the Taiwan stock exchange capitalization weighted stock index. *TVIIC* is the implied index derived from the call option. *TVIIP* is the implied index derived from the put option. *TVIIM* is the mean of *TVIIC* and *TVIIP*. $w_{t,TVIIM} = TVIIM_t - \beta \times TAIEX_t$ is the error correction term between the *TVIIM* and the *TAIEX*. $w_{t,TVIIC} = TVIIC_t - \beta \times TAIEX_t$ is the error correction term between the *TVIIC* and the *TAIEX*. $w_{t,TVIIP} = TVIIP_t - \beta \times TAIEX_t$ is the error correction term between the *TVIIP* and the *TAIEX*. The line in each plot is the threshold effect of the error correction term.

5.3.5 Correlation Coefficients and Causality Tests

The correlation coefficients and causality between the *TVII* and *TAIEX* are presented in Table 15 and Table 16. Table 15 presents the empirical results that describe the linear-type VECM and Table 16 presents the results for the threshold-type VECM. The correlation coefficients show that the co-movement between the *TVII* (*TVIIM*, *TVIIC* and *TVIIP*) and the *TAIEX* is close.

Causality tests using the linear-type VECM show that bi-directional Granger-causality exists between the *TVII* and the *TAIEX* under the negative returns scenario. Besides, the *TVIIC* Granger causes the *TAIEX* under the positive returns condition. There are different causality results for the threshold-type VECM. The *TAIEX* leads the *TVIIC* under a negative returns scenario when the deviation between the *TVIIC* and the *TAIEX* is in a higher regime. It implies that the signal of information content of call (*TVIIC*) is weak while there is bad news or overreaction. However, we find that the *TVIIC* leads the *TAIEX* when the deviation is in the typical regime no matter what the positive or negative market returns condition is. On the contrary, the causality relationship between the *TVIIM*, *TVIIP* and *TAIEX* in the threshold-type VECM is one of feedback or one where the *TAIEX* leads, which implies that the *TVIIM* and *TVIIP* contribute less information than the *TVIIC*. Our empirical results support the view that there is more information content in the call option in the Taiwan derivatives market.

Table 15 Correlation Coefficient and Causality Tests of the *TVII* and *TAIEX* in a Linear VECM

	Correlation Coefficient	Null Hypothesis	General Condition			Positive Returns			Negative Returns		
			F statistics	P-value	Causal relationship	F statistics	P-value	Causal relationship	F statistics	P-value	Causal relationship
TVIIM	0.9986	H_0: *TAIEX* does not Granger cause *TVIIM*	50.8044	0.0000**	*TAIEX* leads	37.5710	0.0000**	Feedback	42.8357	0.0000**	Feedback
		H_0: *TVIIM* does not Granger cause *TAIEX*	1.8350	0.1191		218.8572	0.0000**		183.8675	0.0000**	
TVIIC	0.9984	H_0: *TAIEX* does not Granger cause *TVIIC*	0.4748	0.7543	*TVIIC* leads	0.4961	0.7386	*TVIIC* leads	2.6618	0.0309**	Feedback
		H_0: *TVIIC* does not Granger cause *TAIEX*	56.7731	0.0000**		2.7366	0.0272**		2.9154	0.0201**	
TVIIP	0.9946	H_0: *TAIEX* does not Granger cause *TVIIP*	22.8284	0.0000**	Feedback	14.7517	0.0000**	Feedback	16.3322	0.0000**	Feedback
		H_0: *TVIIP* does not Granger cause *TAIEX*	3.2182	0.0119**		288.0876	0.0000**		214.7205	0.0000**	

Notes: *TVIIC* is the implied index derived from the call option. *TVIIP* is the implied index derived from the put option. *TVIIM* is the mean of *TVIIC* and *TVIIP*. ** indicates significance at the 5% level.

Table 16 Correlation Coefficient and Causality Tests of the *TVII* and *TAIEX* in a Threshold VECM

	Regime	Correlation Coefficient	Null Hypothesis	General Condition			Positive Returns			Negative Returns		
				F statistics	P-value	Causal relationship	F statistics	P-value	Causal relationship	F statistics	P-value	Causal relationship
TVIIM	$w_{t-1} > \gamma$	0.9990	H_0: *TAIEX* does not Granger cause *TVIIM*	6.2582	0.0000**	*TAIEX* leads	5.1234	0.0004**	Feedback	5.9204	0.0000**	Feedback
			H_0: *TVIIM* does not Granger cause *TAIEX*	1.0230	0.3941		34.8793	0.0000**		15.8301	0.0000**	
	$w_{t-1} \leq \gamma$	0.9998	H_0: *TAIEX* does not Granger cause *TVIIM*	40.1867	0.0000**	Feedback	30.0058	0.0000**	Feedback	28.9867	0.0000**	Feedback
			H_0: *TVIIM* does not Granger cause *TAIEX*	3.0936	0.0148**		135.5057	0.0000**		204.4008	0.0000**	
TVIIC	$w_{t-1} > \gamma$	0.9991	H_0: *TAIEX* does not Granger cause *TVIIC*	0.6354	0.6372	*TVIIC* leads	2.5695	0.0361**	Feedback	2.5942	0.0347**	*TAIEX* leads
			H_0: *TVIIC* does not Granger cause *TAIEX*	25.6223	0.0000**		4.2674	0.0019**		2.2798	0.0583	
	$w_{t-1} \leq \gamma$	0.9996	H_0: *TAIEX* does not Granger cause *TVIIC*	1.2913	0.2709	*TVIIC* leads	2.1603	0.0708	*TVIIC* leads	2.3124	0.0552	*TVIIC* leads
			H_0: *TVIIC* does not Granger cause *TAIEX*	34.1182	0.0000**		4.4725	0.0013**		5.3597	0.0003**	
TVIIP	$w_{t-1} > \gamma$	0.9963	H_0: *TAIEX* does not Granger cause *TVIIP*	5.8568	0.0001**	Feedback	3.4306	0.0084**	Feedback	5.7813	0.0001**	Feedback
			H_0: *TVIIP* does not Granger cause *TAIEX*	3.1673	0.0133**		68.4223	0.0000**		26.3488	0.0000**	
	$w_{t-1} \leq \gamma$	0.9991	H_0: *TAIEX* does not Granger cause *TVIIP*	17.0817	0.0000**	*TAIEX* leads	12.8334	0.0000**	Feedback	11.5899	0.0000**	Feedback
			H_0: *TVIIP* does not Granger cause *TAIEX*	1.9546	0.0985		149.8097	0.0000**		208.5894	0.0000**	

Notes: *TVIIC* is the implied index derived from the call option. *TVIIP* is the implied index derived from the put option. *TVIIM* is the mean of *TVIIC* and *TVIIP*. ** indicates significance at the 5% level.

5.4 Sub-Conclusions

This paper investigates the relationship between the information content of the volatility index and its underlying equity index in the emerging Taiwan stock market. We construct a volatility index for the Taiwan equity market (*TVIX*) in line with the the CBOE's new *VIX* by using intraday data for the Taiwan index options market. We then derive an implied equity index from the Taiwan volatility index (*TVII*) under the Black-Scholes-Merton options pricing scheme as an input for performing the co-movement analysis between the *TVII* and the stock index of the Taiwan stock exchange (*TAIEX*). The co-movements between the *TVII* (the equity index implied from the options' volatility index) and the *TAIEX* (its underlying stock index) are investigated through the VECM and TVECM models. The lead-lag causalities between the *TVII* and *TAIEX* under positive and negative stock market returns conditions are also analyzed.

The empirical results substantiate the claim that the nonlinear two-regime TVECM model provides an appropriate fit for the dynamics between the *TVII* and the *TAIEX*. The causality tests based on the TVECM show that no matter what the deviation between the *TVIIC* and the *TAIEX* is, the *TVIIC* Granger causes the *TAIEX* if the positive and negative returns conditions are ignored, while in a typical deviation regime for the TVECM, the *TVIIC* leads the *TAIEX* under both positive and negative returns scenarios. These findings indicate that the information content implied by the call options in Taiwan does serve as a leading indicator for the underlying equity index under certain circumstances. On the contrary, the leading information of call is weak while investors' fear gauge is in the higher regime. Investors participating in the Taiwan stock market could rebalance their equity portfolios while the *TVIIC* takes precedence over the *TAIEX*.

The differences between this paper and previous studies are that: (1) it derives an implied index from the options volatility index for the Taiwan stock market (*TVII*) and makes the cointegration analysis between the *TVII* and the *TAIEX* possible; (2) it examines the causalities between the *TVII* and the *TAIEX* for positive and negative stock market returns at extreme and typical co-movement deviation regimes which are classified by the thresholds of the error correction terms; (3) it demonstrates from the causality tests based on the TVECM that in the typical deviation regime, the *TVIIC* Granger causes the *TAIEX* under both positive and negative market returns conditions; and (4) it confirms that the *TVII* from call options contribute more information content than those from put options.

Chapter 6. Effective Options Trading Strategies Based on Volatility Forecasting Incorporating Investor Sentiment

6.1 Introduction

This study bridges the gap between option trading and the information content of investor overreaction by proposing an algorithm for volatility forecasting recruiting investor sentiments through the simulation of an option trading strategy. The mechanisms or factors which could filter out the noise and enhance the performance of trading are practical and theoretical issues in the areas of finance, decision support and artificial intelligence (Engle, Hong, Kane & Noh, 1993; Poon & Granger, 2003; Li & Kuo, 2008; Rada, 2008). Among the filters used in option trading, volatility forecasting is one of the key criteria that could be applied in the decision process. The optimal choice of an appropriate model for predicting future volatility is closely related to the question of how the prediction performance of a model can be measured. Since there is no certain measure of the 'true' value, comparing the forecasting performance is usually considered to be straightforward when the volatility model is applied to option trading strategies. A growing body of literature presents evidence of irrational behavior in the stock and option markets. The poor performance of option trades has been attributed to bad market timing due to overreaction to past stock market movements (Bauer, Cosemans & Eichholtz, 2009). The filter which could improve the trading timing by taking into consideration the investors' overreaction is worth noting.

How could sentiments have an impact on the financial asset price formation process and further influence the variation in returns? Early papers (Friedman, 1953; Fama, 1965) argued that noise traders are unimportant in the financial asset price formation process because trades made by rational arbitrageurs drive prices close to their fundamental values. On the other hand, market anomalies, for example, the underreaction and overreaction of stock prices, challenge the efficient markets theory. The behavioral models of securities markets posit two types of investors: rational arbitrageurs who are sentiment-free and irrational traders who are prone to exogenous sentiment. If such irrational noise traders base their trading decisions on sentiment, then measures of it may have predictive power for asset price behavior.

The investor sentiment proxies have proved to be an asset pricing factor for which there exists a causal relationship between sentiment and market return (Solt & Statman, 1988; Fisher & Statman, 2000; Wang, 2001; Clarke & Statman, 1998; Simon & Wiggins, 2001; Brown & Cliff, 2004; Baker & Wurgler, 2006; Baker & Wurgler, 2007, Han, 2008). Although sentiment has been applied to portfolio management, fewer studies investigate the relationship between sentiment and market volatility and its application to trading decision support (Brown, 1999; Low, 2004; Wang et al. 2006; Verma & Verma, 2007). This motivates us to investigate the effective option trading strategies based on the volatility forecasting model which incorporates the information content of investor sentiments.

The algorithms proposed in this study enhance the performance of option trading and confirm the forecasting ability of investor sentiments in relation to future volatility. The trading performance of our model has proved to be significantly superior to its non-sentiment adversarial counterparts. The empirical results show that sentiment proxies do enhance the forecasting of future volatility. The long (short) straddle based on a positive (negative) change in volatility forecasting including the sentiment level of the 'turnover ratio (TO)' achieves an average monthly return of 15.84%. The point of view adopted in this study does not lie in examining the optimal combination of volatility models or other control variables. The main purpose of this study is to investigate whether the forecasting and trading performance could be improved if the information content of sentiment were to be considered in the decision process.

This study makes the following contributions to the existing literature. First, a volatility forecasting model that includes investor sentiments is constructed in order to bridge the gap between price variation and the signal of the investors' overreaction. Second, an effective option trading algorithm is proposed based on the volatility forecasting model and it could further be applied in the electronic trading platforms.

6.2 Data Description

Our analysis is conducted on a daily basis and the study period extends from 2003 to 2007, encompassing a total of 1,236 trading days. The volatility forecasting and trading strategies are constructed based on the settlement day occurring once a month and there are 59 settlement days between January 16, 2003 and November 22, 2007.[16] The period used to calculate the future volatility is shaded. The data used in this study are quoted on the Taiwan Futures Exchange (TAIFEX), the Taiwan Stock Exchange (TWSE), and in the Taiwan Economic Journal (TEJ).[17]

Table 17 provides the descriptive statistics for the data. Since the forecasting evaluation in the following empirical results indicates that the 15-day-ahead forecasting model is superior to the other *h*-day-ahead models, the related summary statistics and data evolution of future volatility on day *t* is calculated by the next 15 days. The skewness and kurtosis measures indicate that both series exhibit

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[16] The historical settlement day and related settlement information for the TAIEX options are summarized on the website of the Taiwan Futures Exchange, http://www.taifex.com.tw/.

[17] The details regarding the Taiwan Futures Exchange (TAIFEX), the Taiwan Stock Exchange (TWSE) and the Taiwan Economic Journal (TEJ) may be found at http://www.taifex.com.tw/, http://www.twse.com.tw and http://www.finasia.biz/ensite/.

leptokurticity relative to the normal distribution. Figure 6 shows the original evolution of the future volatility and sentiment indices from 2003 to 2007. The correlation coefficient matrix is presented in Table 18. The correlation coefficients between the future volatility and sentiment levels (changes) are significant at the 1% level except for TPCV (changes in TPCV and ARMS).

Table 17 Summary Statistics of Volatility and Investor Sentiment

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TAIEX	6504.2890	6222.0500	9809.8800	4140.0000	1215.7490	0.6979	3.2398	102.36***
FV	17.8022	15.4949	50.5001	7.2590	7.5988	1.4355	4.9049	605.91***
HV	17.7252	15.4949	50.5001	7.2590	7.5306	1.4762	5.0985	669.70***
RV	19.4296	16.5348	149.1987	5.3144	11.6781	3.2478	23.8796	24405.68***
|R|	0.8640	0.6267	6.9123	0.0005	0.8555	2.1291	9.6516	3183.77***
HL	8.8569	7.5760	38.8611	0.9747	4.8137	1.7726	7.3910	1625.62***
TVIX	21.1433	19.6371	45.7164	11.1995	5.9369	0.9567	3.4276	196.21***
TPCV	0.8065	0.7877	1.7033	0.4189	0.1772	0.7273	3.8667	146.34***
TPCO	0.9436	0.9339	2.3189	0.4740	0.2433	1.0164	5.3931	503.24***
ARMS	0.7192	0.6657	8.4857	0.1468	0.3687	8.5484	165.8623	1368755***
TO	0.8122	0.7233	2.5380	0.2904	0.3434	1.5395	5.7221	862.06***
∆TVIX	0.0085	-0.0649	12.5563	-7.3052	1.4006	1.4741	16.2863	9453.84***
∆TPCV	0.0002	-0.0056	0.6863	-0.7872	0.1775	0.0219	4.3419	92.01***
∆TPCO	0.0001	0.0013	0.3551	-1.1324	0.0844	-2.9814	35.8413	56865.73***
∆ARMS	-0.0002	0.0018	7.0135	-7.6913	0.4915	-0.8733	86.4724	355795.5***
∆TO	0.0001	-0.0040	1.7295	-1.0063	0.1739	0.5457	13.4042	5585.96***

Notes: This table presents the summary statistics for the Taiwan stock exchange capitalization weighted stock index (TAIEX), various volatility measures and sentiment proxies, namely, the future volatility (FV), historical volatility (HV), realized volatility (RV), the absolute return (|R|), the high-low range (HL), the Taiwan volatility index (TVIX), the put-call volume ratio (TPCV), the put-call open interest ratio (TPCO), the ARMS ratio and the market turnover ratio (TO). ∆TVIX, ∆TPCV, ∆TPCO, ∆ARMS and ∆TO represent the first difference changes in the individual sentiment index. The period covers January 16, 2003 to November 22, 2007 and the period used to calculate the future volatility is shaded. The *, **, and *** symbols indicate significance at the 10%, 5% and 1% levels, respectively.

Table 18 Correlation Coefficients of Volatility and Investor Sentiment

	FV	HV	RV	|R|	HL	TVIX	TPCV	TPCO	ARMS	TO	△TVIX	△TPCV	△TPCO	△ARMS	△TO
TAIEX	-0.0002	-0.1624***	-0.0527*	-0.0546*	-0.1738***	0.0055	0.2089***	0.2006***	-0.0052	0.1369***	0.016	0.0008	-0.0108	0.0041	-0.0042
FV		0.5045***	0.4047***	0.2808***	0.4391***	0.6309***	-0.0046	-0.0573**	0.0953***	0.3372***	0.0817***	0.0046	-0.0741***	0.0063	-0.0538*
HV			0.4431***	0.2549***	0.4179***	0.7915***	-0.0819***	-0.2679***	0.0844***	0.064**	-0.0374	-0.0136	0.0313	-0.0129	-0.0475*
RV				0.6121***	0.4543***	0.5217***	-0.0225	-0.0732**	0.1266***	0.2638***	0.1435***	-0.0494*	-0.0234	0.0788***	0.1677***
|R|					0.5808***	0.3509***	0.0617**	-0.0992***	0.1538***	0.1815***	0.1603***	0.0018	-0.0155	0.0879***	0.2529***
HL						0.524***	0.0329	-0.131***	0.1364***	0.2856***	0.2175***	0.0109	-0.098***	0.0288	0.2551***
TVIX							-0.0642**	-0.1981***	0.1296***	0.1456***	0.1211***	0.0011	-0.0412	-0.0043	-0.0341
TPCV								0.0656**	0.1263***	-0.1051***	0.1183***	0.5002***	-0.127***	0.0286	-0.0844***
TPCO									-0.1625***	0.5519***	0.0429	-0.0043	0.1727***	0.02	0.036
ARMS										-0.0809***	0.0296	0.0116	-0.1278***	0.6655***	-0.0235
TO											0.1484***	-0.0259	0.0233	0.0383	0.2529***
△TVIX												0.1228***	-0.0385	-0.0039	0.1567***
△TPCV													-0.1354***	0.035	-0.1331***
△TPCO														-0.0405	0.152***
△ARMS															0.0568**

Notes: The pairwise correlations are for selected variables used in the analysis. TAIEX is the Taiwan stock exchange capitalization weighted stock index. There are various volatility measures and sentiment proxies, namely, the future volatility (FV), historical volatility (HV), realized volatility (RV), the absolute return (|R|), the high-low range (HL), the Taiwan volatility index (TVIX), the put-call volume ratio (TPCV), the put-call open interest ratio (TPCO), the ARMS ratio and the market turnover ratio (TO). The symbols △TVIX, △TPCV, △TPCO, △ARMS and △TO represent the first difference changes in the individual sentiment index. The period covers January 16, 2003, to November 22, 2007 and the period used to calculate the future volatility is shaded. The *, **, and *** symbols indicate significance at the 10%, 5% and 1% levels, respectively.

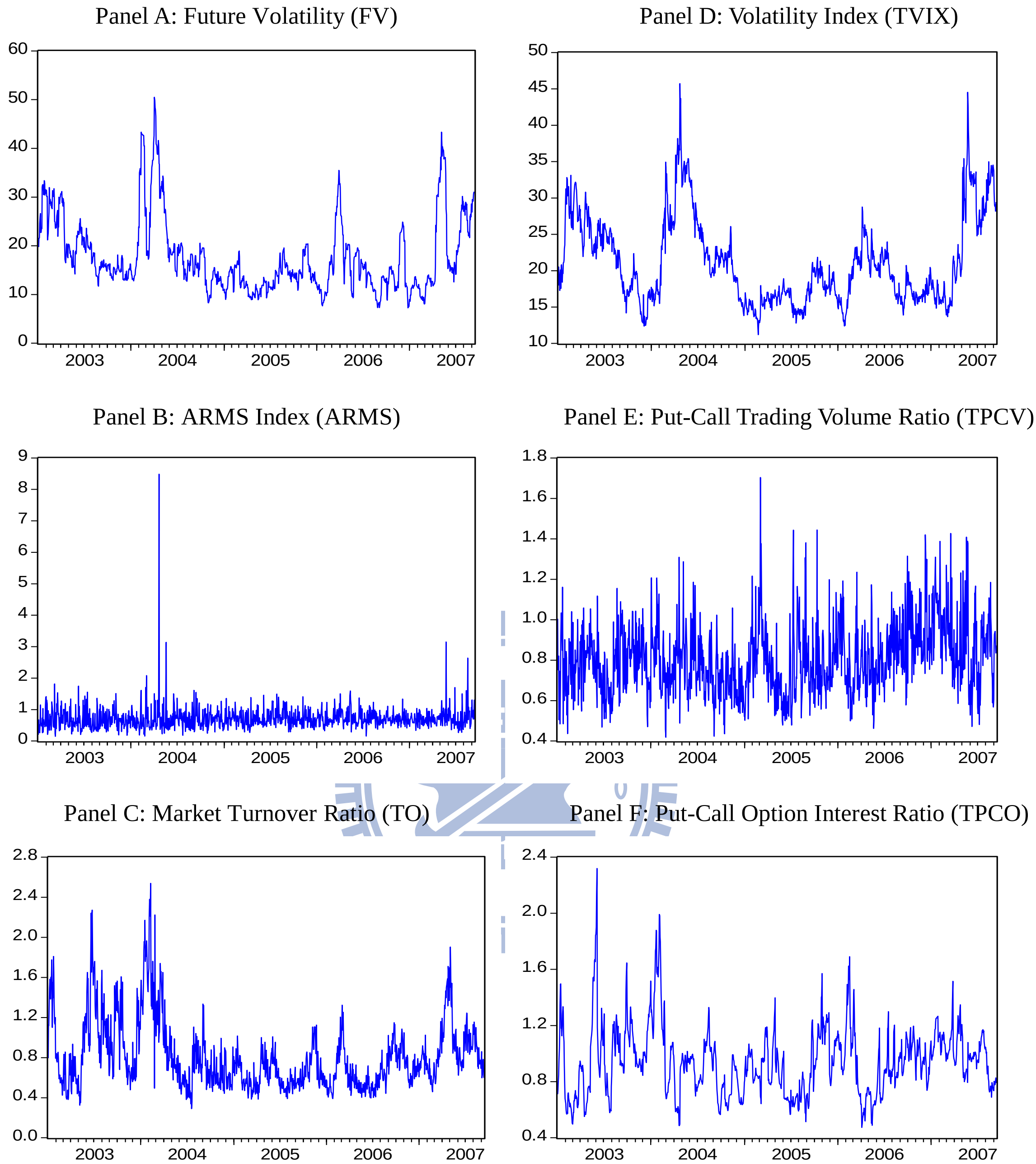

Figure 6 Daily Evolution of Future Volatility and Sentiment Indices

Notes: FV is the future volatility of the next *h*-day TAIEX return on day *t*. The Taiwan volatility index (TVIX) is calculated using daily data quoted on the Taiwan Futures Exchange (TAIFEX) and the Taiwan Stock Exchange (TWSE). The method used to construct the TVIX refers to the essence of the last revision of the volatility index of the CBOE and the interest rate, and the roll-over rule is revised accordingly. The put-call trading volume ratio (TPCV), put-call open interest ratio (TPCO), ARMS and market turnover ratio (TO) are calculated using daily data quoted on the TAIFEX and TWSE.

6.3 Experimental Design

6.3.1 Causality Test

We test for Granger causality between sentiment and future volatility by estimating bivariate vector autoregressive (VAR) models (Granger, 1969; Sims, 1972). We estimate the models using both levels and changes in sentiment measures since it is not easy to determine which specification should reveal the primary effects of sentiment. For example, suppose that investor sentiment decreases from very bullish to bullish. One might anticipate a positive return due to the still bullish sentiment, but on the other hand, since sentiment has decreased it is also possible for someone to expect a reduction in the return. The general model we use here can be expressed as follows:

$$\begin{aligned} \mathrm{V}_t &= c_1 + \sum_{p=1}^{L} a_{1p}\mathrm{V}_{t-p} + \sum_{p=1}^{L} b_{1p}\mathrm{SI}_{t-p} + \varepsilon_{1t} \ , \\ \mathrm{SI}_t &= c_2 + \sum_{p=1}^{L} a_{2p}\mathrm{V}_{t-p} + \sum_{p=1}^{L} b_{2p}\mathrm{SI}_{t-p} + \varepsilon_{2t} \ , \end{aligned} \tag{6.1}$$

where V_t denotes the future volatility and SI_t is the sentiment index. The levels of (SI_t) and changes ($\Delta\mathrm{SI}_t$) in sentiment are both examined in the causality test. The sentiment indices include TVIX, TPCV, TPCO, ARMS and TO. Volatility (the sentiment measure) does not Granger cause the sentiment measure (volatility) if all $a_{2p} = 0$ ($b_{1p} = 0$) as a group based on a standard *F*-test.

6.3.2 Regression-based Forecast Efficiency Test

By following and extending Poon & Granger (2003, 2005) and Engle & Gallo (2006), we employ multiple factors to build up our volatility forecasting model in Taiwan. Three historical volatility measures including HL, RV and |R| are used as the benchmark forecasting model as shown in the following equation and it is simplified as MHV.

$$\mathrm{FV}_t = \alpha_0 + \alpha_1 \mathrm{HL}_{t-1} + \alpha_2 |\mathrm{R}_{t-1}| + \alpha_3 \mathrm{RV}_{t-1} + \varepsilon_t \tag{6.2}$$

where FV_t is the future volatility measure, and $\mathrm{HL}_{t\text{-}1}$, $|\mathrm{R}_{t\text{-}1}|$ and $\mathrm{RV}_{t\text{-}1}$ are the one-day lag high-low range, absolute return and realized volatility for the TAIEX, respectively. To see whether sentiment indicators could serve as useful forecasting variables, we therefore decided to examine whether they could enhance forecasts of the future volatility of TAIEX returns computed from the next *h*-days on day *t*. The following equation is estimated when the level of sentiment indicators is included in the benchmark MHV model with three historical volatility measures:

$$\mathrm{FV}_t = \alpha_0 + \alpha_1 \mathrm{HL}_{t-1} + \alpha_2 |\mathrm{R}_{t-1}| + \alpha_3 \mathrm{RV}_{t-1} + \gamma \mathrm{SI}_{t-1} + \varepsilon_t, \tag{6.3}$$

where $\mathrm{SI}_{t\text{-}1}$ represents the sentiment level and includes the TVIX, TPCV, TPCO, TO, and ARMS index. The forecasting model will be simplified as +TVIX if the sentiment proxy of TVIX is included in MHV. +TPCV, +TPCO, +ARMS and +TO are presented as the same proposition. When the first differences of the sentiment indicators are included, the regression equation is specified as:

$$\mathrm{FV}_t = \alpha_0 + \alpha_1 \mathrm{HL}_{t-1} + \alpha_2 |\mathrm{R}_{t-1}| + \alpha_3 \mathrm{RV}_{t-1} + \gamma \Delta \mathrm{SI}_{t-1} + \varepsilon_t, \tag{6.4}$$

for the case where lagged three historical volatility defines the benchmark model MHV and $\Delta \mathrm{SI}_{t\text{-}1}$ stands for the differences of sentiment. +ΔTVIX represents the MHV recruiting the changes in TVIX and so does the +ΔTPCV, +ΔTPCO, +ΔARMS and +ΔTO.

6.3.3 Forecast Evaluation

According to previous related studies, there is no certain rule for selecting the in- and out-of-sample ranges. We therefore apply the dynamic sample range selection procedure to select the in-sample ranges, which can be as short as 30 days or as long as 120 days. Then the parameters obtained within the data from the initial in-sample period are inserted in the relevant forecasting formulas. Volatility forecasts are then obtained for the subsequent h trading days ahead (h=5, 10, 15, 20), which are days used to calculate the future volatility. The idea of the volatility forecasting could be presented in the following framework in Figure 7.

In the context of this idea of volatility forecasting, T_0 is the date of option trading based on the volatility forecasting recruiting investor sentiments. T_h is the final settlement day of the option contracts, and T_1 to T_h are the holding periods of the option strategy and are equal to the h days for calculating the future volatility at T_0. Future volatility is regressed on the first lagged variables such as HL, |R|, RV and other sentiment proxies; therefore, t_0 to t_n is the in-sample-period for estimating the coefficients of the volatility forecasting model. In this model, n represents the in-sample-period used in this study covering 30, 60, 90, and 120 days. t_{n+1} to t_{n+h} are the periods used to calculate the future volatility on day t_n. Consequently, the future volatility on day t_1 is calculated by the following t_2 to t_{h+1} days.

The next h-days future volatility at day T_0 could be predicted by using the estimated coefficients and the lagged related variables on day t_{n+h} in Fig. 2. The future volatility, used as the trading filter of the option trading strategies proposed in this study, is then compared with the h-day historical volatility that we can capture on day T_0. The historical volatility on day T_0 is calculated based on the last h-day index return during t_{n+1} to t_{n+h}. Different volatility forecasting models are estimated once a month by using the same group parameters, namely, the *h*-day forecast and the *n*-day in-sample-period, and the predicted value of the future volatility is derived.

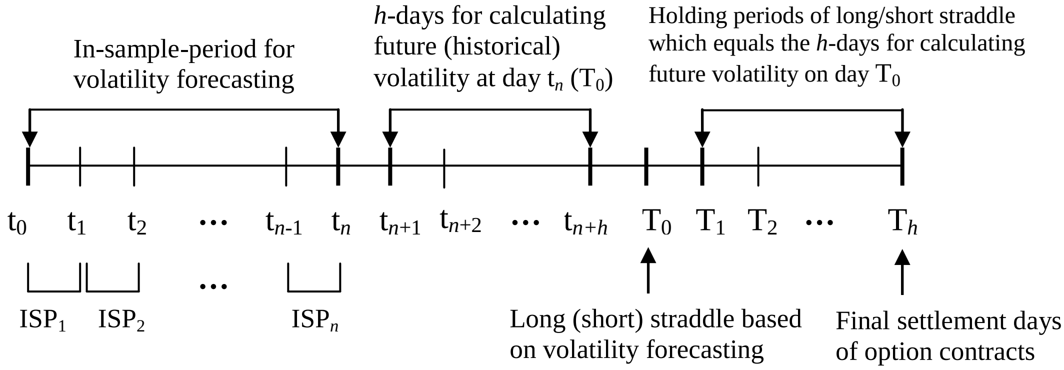

Figure 7 The Framework of Volatility Forecasting

Notes: T_0 is the date of the long or short straddle based on the volatility forecasting recruiting investor sentiments. T_h is the final settlement day of the option contracts. T_1 to T_h is the holding period of the long or short straddle and it equals *h* days for calculating the future volatility at T_0. We regress future volatility on the first lagged variables including the high-low range, absolute return, realized volatility and other sentiment proxies, and therefore t_0 to t_n is the in-sample-period for estimating the coefficients of the volatility forecasting model. In this model, *n* represents the in-sample-period used in this study covering 30, 60, 90, and 120 days. The terms t_{n+1} to t_{n+h} are the periods used to calculate the future (historical) volatility at day t_n (T_0). Consequently, the future volatility at day t_1 is calculated by the following t_2 to t_{h+1} days.

Once the forecasting models are constructed, we then compare the models that best fit our series. The forecasting error is calculated after all the predicted future volatility is obtained during the 2003-2007 period. In order to select the ‘best’ model which gives the most accurate forecasts, the forecasting error for different competitive models is measured. Popular evaluation measures used in the literature include mean error (ME), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE), Theil-U statistic and LINEX. Instead of comparing the alternative evaluation measures, this study focuses on comparing the forecasting error between alternative forecasting models. By referring to Poon & Granger (2003, 2005) and Gospodinov, Gavala & Jiang (2006), this study applies the mean absolute percentage error (MAPE). The MAPE is scale independent and may be defined as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} |1 - \hat{\mathrm{FV}}_{i,M} / \mathrm{FV}_i| \tag{6.5}$$

where $\hat{\mathrm{FV}}_{i,M}$ is the predicted value based on the volatility forecasting model M, FV_i is the realized future volatility for month i calculated on day t which is h days before the final settlement day of the option contracts, n is the number of months during the study period 2003-2007, excluding the last month for the calculation of future volatility and n equals 59. The benchmark model is simplified as MHV and the other forecasting model including the sentiment proxies based on MHV can be separately expressed as +TVIX, +TPCV, +TPCO, +ARMS and +TO. If the changes in each sentiment proxy are considered, it could be expressed as +ΔTVIX, +ΔTPCV, +ΔTPCO, +ΔARMS and +ΔTO. The algorithm of volatility forecasting recruiting investor sentiments is then evaluated through the simulation of the option trading strategy.

6.3.4 Options Trading Strategies

One of the applications of volatility forecasting is to serve as a reference for the direction of future volatility. Engle et al. (1993) propose that the direction of predicted volatility change can be used for constructing trading strategies such as straddles. A combination of calls and puts could be adopted as an option trading strategy while investors have expectations regarding the movement in the underlying index. The algorithm of the effective option trading strategy proposed in this study is simulated based on a long (short) straddle and the algorithm can also be the decision support for other hybrid option trading strategies.[18] The strike price of the straddle selected in

[18] If an investor feels that the underlying index will move significantly, he could create a straddle by buying both a put and a call with the same expiration date and the same strike prices. If the stock price is close to this strike price at the expiration of the options, the long (short) straddle leads to a loss

this study is the at-the-money call and put option contracts on the trading day (for example, T_0 in Figure 7). A large price movement implies that there is uncertainty as to whether there will be an increase or a decrease, and the volatility could be at the higher level and vice versa. The long (short) straddle is simulated while the increasing or positive (decreasing or negative) change in volatility is predicted.

In this study, the option trading strategies are simulated to compare the performance of the volatility forecasting model in terms of whether the sentiment indicators are considered or not. The long (short) straddle is set up on date T_0 in Figure 7 which is *h* days before the final settlement day if the direction of the predicted future volatility change is upward (downward) on that day. The benchmarks of the trading strategy are based on the long (short) straddle without any filter on date T_0, *h* days before the final settlement day. The historical volatility calculated by the last *h*-day standard deviation of return on date T_0 is treated as the benchmark when comparing the upward (downward) movement in the predicted volatility change. The algorithm of the effective option trading strategies based on the volatility forecasting is shown in Figure 8.

The volatility trading strategies are constructed by using the TAIEX option (TXO) *h* days before the final settlement day and holding it until the cash settlement. The transaction cost is taken into consideration and includes the transaction fees, transaction tax and settlement tax.[19] The cost of capital is calculated by the

(profit). If there is a sufficiently large move in either direction, however, a significant profit (loss) will result in a long (short) straddle.

[19] The transaction fee is calculated as NT$50 per contract. The transaction tax per contract is 0.1% of the contract value which is multiplied by the premium and multiplier. The settlement tax is 0.01% of the settlement contract value which is calculated by the final settlement price and multiplier[19]. The transaction tax and the settlement tax are rounded to integrals. The multiplier of the Taiwan Stock Exchange Capitalization Weighted Stock Index option (TAIEX option, TXO) is NT$50 per index point. The final settlement price for each contract is computed from the first fifteen-minute volume-weighted average of each component stock's price in the TAIEX on the final settlement day. For those component stocks that are not traded during the beginning fifteen-minute interval on the final settlement day, their last closing prices are applied instead. For more detailed information, the reader should refer to the Taiwan Futures Exchange (TAIFEX) website www.taifex.com.tw.

transaction cost and the maximum margin requirement during the holding period if the trading strategies are short straddle.[20] On the other hand, the cost of capital if the trading strategies are long straddle is summed up by the transaction cost and the premiums. The performance of different forecasting models is compared based on the average monthly rate of return, R(%), which is calculated as:

$$\mathrm{R}_M(\%) = \frac{\frac{1}{n}\sum_{i=1}^{n}\mathrm{PL}_{i,M}}{\frac{1}{n}\sum_{i=1}^{n}\mathrm{C}_{i,M}} \times 100\% \tag{6.6}$$

where M represents different forecasting models, and $\mathrm{PL}_{i,M}$ ($\mathrm{C}_{i,M}$) represents the profit–loss (cost of capital including transaction costs) of the option trading strategy for model M in month i.

[20] The margining requirements for stock options in the Taiwan derivatives market could be summarized as follows. Margin of short call or put = 100% of option market value + max (A - out-of-the-money amount, B). A and B are fixed amounts as announced by the TAIFEX (or a percentage of margin required by the TAIEX futures contracts. Margin of straddle or strangle positions = max (margin requirement for call, margin requirement for put) + option market value of call or put (depending on which margin requirement is less).

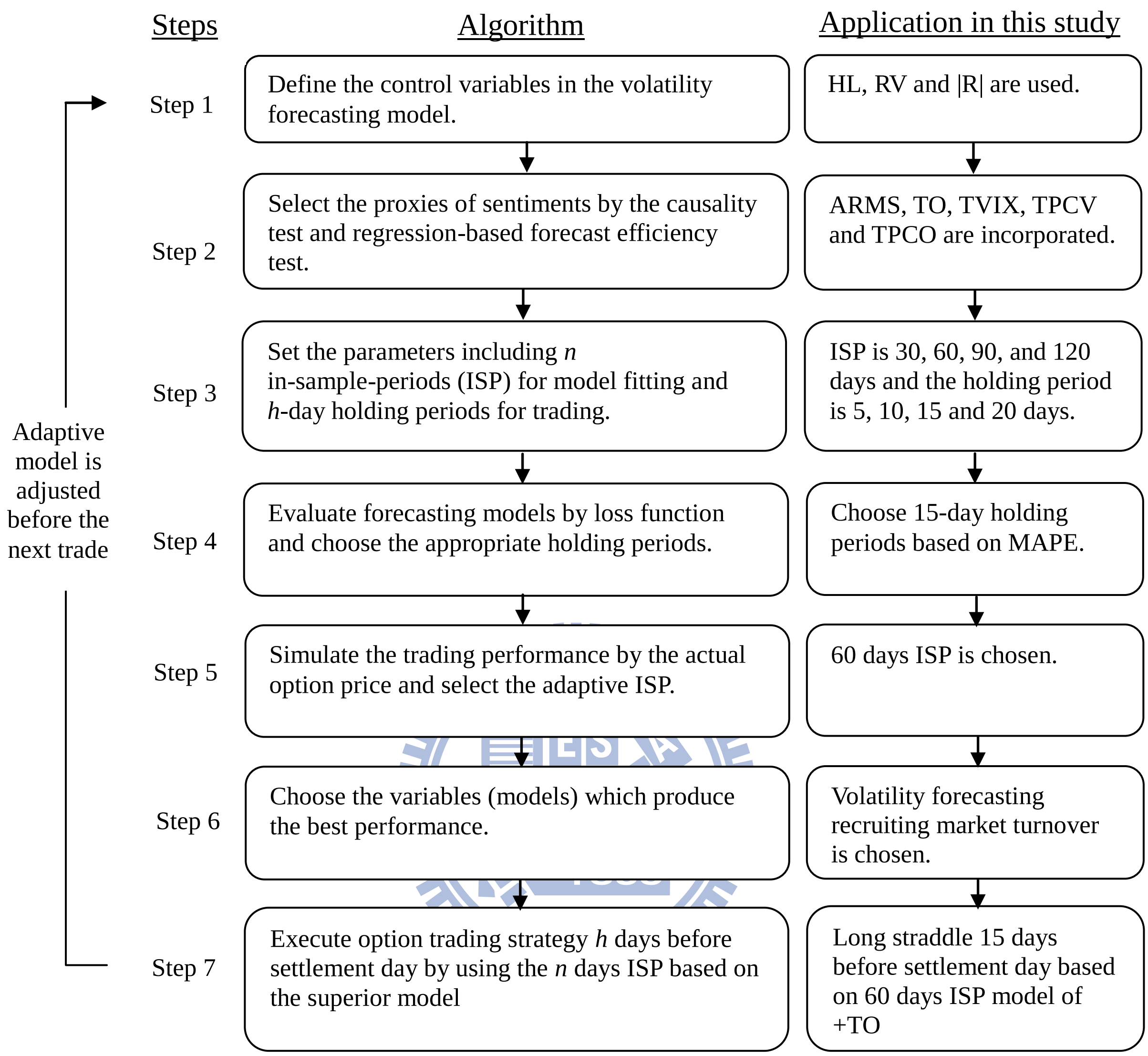

Figure 8 The Algorithm of the Effective Option Trading Strategies

6.4 Results of Simulated Trades

6.4.1 Causality Test

The results of the Granger-causality tests using future volatility and investor sentiments are presented in Table 19. The lag lengths of the future volatility and sentiment indices are determined parsimoniously before performing the causality test by the Akaike information criterion (AIC) and the Schwarz criterion (SC). The optimal number of lags depends on the pair of variables used in the causality tests; it varies between 1 and 3 for the sentiment levels and between 1 and 16 for the sentiment changes. The results show that there is a feedback relationship between future volatility and sentiment in levels and first differences, including TVIX, ARMS and Turnover. Otherwise, the first differences of TPCV and TPCO are caused by future volatility. Our findings suggest that the investor sentiments should be considered in future volatility forecasting.

Table 19 Granger Causality Tests between Future Volatility and Sentiment

	Hypothesis			
Sentiment	H_{01}	H_{02}	H_{03}	H_{04}
TVIX	2.4547	51.6341	3.2512	8.1191
	(0.0863)*	(<0.0000)***	(<0.0000)***	(<0.0000)***
TPCV	1.3686	1.7635	0.5565	3.7608
	(0.2508)	(0.1523)	(0.6943)	(0.0048)***
TPCO	15.0029	9.0404	0.283	5.8677
	(0.0001)***	(0.0027)***	(0.5949)	(0.0156)**
ARMS	15.0695	7.203	2.8509	4.597
	(<0.0000)***	(0.0008)***	(0.0001)***	(<0.0000)***
Turnover	12.6873	7.6378	3.3182	7.1091
	(<0.0000)***	(<0.0000)***	(0.0103)**	(<0.0000)***

Notes: The numbers of lagged terms in the VAR models are decided parsimoniously by the Akaike information criterion (AIC) and the Schwarz criterion (SC). H_{01}: Granger-noncausality from sentiment to future volatility; i.e., sentiment does not cause future volatility. H_{02}: Granger-noncausality from future volatility to sentiment; i.e., future volatility do not cause sentiment. H_{03}: Granger-noncausality from changes in sentiment to future volatility; i.e., changes in sentiment do not cause future volatility. H_{04}: Granger-noncausality from future volatility to changes in sentiment, i.e.; future volatility do not cause changes in sentiment. Values in the table and the parentheses are F-test statistics and p-values, respectively. The *, **, and *** symbols indicate significance at the 10%, 5%, and 1% levels, respectively.

6.4.2 Volatility Forecasting Recruiting Sentiment Indicators

Before analyzing the forecast evaluations among different forecasting models, we first examine the dependencies for future volatility in relation to proxies of investor sentiments based on regression analysis. Whether or not the levels or the first differences of the investor sentiments are able to enhance forecasting power is examined based on the benchmark MHV forecasting model in equation (6.2). From Table 20, the MHV model including the high-low range, absolute return, and realized volatility are significant explanations of future volatility. We also find that the increment in the adjusted R^2 of model +TVIX and +TO (+ΔTO) is positive while the levels (changes) are recruited in the forecasting model. The turnover ratio, regardless of whether the levels or changes are considered, consistently enhances the benchmark models in a statistically significant manner. As the turnover ratio rises and the market overreacts more, future volatility rises.

The forecast evaluation of different forecasting models is compared by the MAPE. The forecasting models cover the benchmark MHV model and the other competitive forecasting models separately by recruiting sentiment levels (changes) such as +TVIX, +TPCV, +TPCO, +ARMS and +TO (+ΔTVIX, +ΔTPCV, +ΔTPCO, +ΔARMS and +ΔTO). The in-sample-period (ISP) covers periods of 30, 60, 90, and 120 days. The *h*-day-ahead forecasting errors of different models are summarized in Table 21. In this study, the *h* day represents the 5-, 10-, 15- and 20- trading days which are the periods between the option trading day and the option contracts' final settlement day.

Table 20 Estimation Results of the Regression-Based Forecast Efficiency Test

	Benchmark	Recruiting Sentiment Levels					Recruiting Sentiment Changes				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	MHV	+TVIX	+TPCV	+TPCO	+ARMS	+TO	+ΔTVIX	+ΔTPCV	+ΔTPCO	+ΔARMS	+ΔTO
Constant	9.8247	1.6617	9.1747	9.2440	9.7013	7.8437	9.7900	9.8158	9.8614	9.8193	9.2482
	(23.8263)***	(2.7743)***	(10.9499)***	(10.4524)***	(18.7864)***	(14.8861)***	(23.5105)***	(23.7838)***	(23.8639)***	(23.7847)***	(22.4539)***
TVIX		0.5796					-0.0738				
		(17.4845)***					(-0.6042)				
TPCV			0.7946					0.4736			
			(0.8911)					(0.5965)			
TPCO				0.5679					-2.8031		
				(0.7422)					(-1.2894)		
ARMS					0.1961					-0.1137	
					(0.3972)					(-0.3124)	
TO						3.2081					-7.6012
						(5.933)***					(-7.5378)***
RV	0.2139	0.0936	0.2153	0.2147	0.2137	0.1987	0.2143	0.2149	0.2141	0.2141	0.2153
	(11.9966)***	(5.3087)***	(12.028)***	(12.0176)***	(11.9734)***	(11.1578)***	(12.0084)***	(11.9988)***	(12.0091)***	(11.9958)***	(12.3025)***
|R|	-1.161	-0.6151	-1.1756	-1.1621	-1.163	-1.0801	-1.1606	-1.1663	-1.15	-1.1602	-0.9437
	(-4.4723)***	(-2.5818)***	(-4.5193)***	(-4.4759)***	(-4.4779)***	(-4.2033)***	(-4.4699)***	(-4.4891)***	(-4.4288)***	(-4.468)***	(-3.6806)***
HL	0.6186	0.3545	0.6175	0.6224	0.6175	0.5764	0.6213	0.618	0.6135	0.6186	0.6531
	(14.9476)***	(8.7371)***	(14.912)***	(14.9229)***	(14.883)***	(13.8799)***	(14.9254)***	(14.9225)***	(14.757)***	(14.9428)***	(15.9763)***
Adj. R^2	30.91%	42.80%	30.90%	30.89%	30.87%	32.49%	30.88%	30.88%	30.94%	30.87%	33.44%
IR Adj. R^2		11.89%	-0.01%	-0.02%	-0.04%	1.58%	-0.03%	-0.03%	0.03%	-0.04%	2.53%

Notes: This table shows the incremental contribution of investor sentiments for future volatility (FV). The FV is calculated for the next 15 days on day *t*. The investor sentiments include the Taiwan volatility index (TVIX), the put-call volume ratio (TPCV), the put-call open interest ratio (TPCO), the ARMS ratio and the market turnover ratio (TO). Three volatility measures are considered as the control variables, including realized volatility (RV), the absolute return (|R|) and the high-low range (HL). Sentiment levels and changes are both examined in the regression-based forecast efficiency test. *IR* is the incremental adjusted R^2 relative to the benchmark model. The benchmark MHV model and forecasting model recruiting sentiment indicators could refer to models (1) to (11) individually. The values in the parentheses are the *T*-test statistics. The *, **, and *** symbols indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 21 Forecast Evaluation of Volatility Models for *h*-day ahead Forecasts of Future Volatility Using *MAPE*

ISP	Benchmark (1) MHV	Recruiting Sentiment Levels (2) +TVIX	(3) +TPCV	(4) +TPCO	(5) +ARMS	(6) +TO	Recruiting Sentiment Changes (7) +ΔTVIX	(8) +ΔTPCV	(9) +ΔTPCO	(10) +ΔARMS	(11) +ΔTO	Mean
5-day ahead forecasting												
30	0.4118	0.4676	0.4232	0.4613	0.4220	0.4477	0.4150	0.4215	0.4203	0.4265	0.4194	0.4306
60	0.4216	0.4158	0.4220	0.4417	0.4330	0.4296	0.4200	0.4228	0.4311	0.4272	0.4150	0.4254
90	0.4009	0.4053	0.4044	0.3943	0.4059	0.4183	0.3941	0.4039	0.3996	0.4069	0.3955	0.4026
120	0.4033	0.3823	0.4092	0.3993	0.4106	0.3958	0.4018	0.4060	0.3996	0.4084	0.3962	0.4011
10-day ahead forecasting												
30	0.3026	0.3591	0.3038	0.4168	0.3020	0.3776	0.3067	0.3015	0.2977	0.3055	0.3061	0.3254
60	0.2842	0.3053	0.2723	0.3319	0.2899	0.3235	0.2857	0.2761	0.2866	0.2863	0.2822	0.2931
90	0.2793	0.2954	0.2692	0.3035	0.2842	0.3093	0.2801	0.2756	0.2775	0.2798	0.2677	0.2838
120	0.2996	0.2870	0.2981	0.3215	0.3004	0.3297	0.3026	0.2967	0.2974	0.2986	0.2853	0.3015
15-day ahead forecasting												
30	0.3116	0.3998	0.3093	0.3423	0.3133	0.3005	0.3092	0.3136	0.3082	0.3059	0.3176	***0.3210***
60	0.2733	0.3460	0.2674	0.3118	0.2699	0.2989	0.2699	0.2744	0.2736	0.2709	0.2771	***0.2848***
90	0.2610	0.3176	0.2536	0.2832	0.2644	0.2885	0.2619	0.2633	0.2617	0.2622	0.2648	***0.2711***
120	0.2688	0.2926	0.2665	0.2924	0.2681	0.2764	0.2678	0.2681	0.2700	0.2693	0.2646	***0.2731***
20-day ahead forecasting												
30	0.3053	0.3738	0.3170	0.3987	0.3118	0.3162	0.3049	0.3138	0.3099	0.3046	0.3009	0.3234
60	0.2796	0.3677	0.2883	0.3273	0.2906	0.2845	0.2797	0.2859	0.2836	0.2755	0.2777	0.2946
90	0.2817	0.3599	0.2941	0.3194	0.2915	0.2997	0.2808	0.2834	0.2825	0.2816	0.2745	0.2954
120	0.2824	0.3316	0.2885	0.3200	0.2872	0.2867	0.2837	0.2841	0.2820	0.2823	0.2721	0.2910

Notes: This table presents the forecast evaluation of different volatility forecasting models based on the mean absolute percentage error (MAPE). The loss function is calculated by equation (6.5) which is a function of actual future volatility and the forecast of future volatility based on different models. Model (1) in Table 5 is the benchmark volatility forecasting model based on multivariate historical volatility measures, realized volatility (RV), the absolute return (|R|) and the high-low range (HL), and is simplified as MHV. Model (2) to Model (6) (Model (7) to Model (11)) in Table 5 are volatility forecasting models recruiting levels (changes) in investor sentiment. +TVIX represents the volatility forecasting based on the MHV and the sentiment proxy of TVIX is included as are the other symbols. The volatility forecasts are obtained for the subsequent *h*-days ahead (*h* equals 5, 10, 15 and 20). The in-sample-period (ISP) is set as 30, 60, 90 and 120 days. The boldface and italics are the average MAPE for the 15-day ahead forecasting model which is smaller than the other *h*-days ahead forecasting models.

The average MAPE values of 15-day-ahead forecasts range from 0.32 to 0.27 according to the in-sample-period of between 30 and 120 days. In contrast to the 15-day-ahead forecasting, the average MAPE of the other *h*-day ahead forecasting ranges from 0.43 to 0.29. The mean of MAPE in Table 21 indicates that regardless of what the in-sample-period is, the 15-day-ahead forecasts could be characterized by a better forecasting ability. The comparisons between the values of loss functions in the 15-day-ahead forecasts further show that most of the forecasting models recruiting the investor sentiments are superior to the benchmark historical volatility model. To sum up, the forecast evaluation proposes that investor sentiments should be integrated into volatility forecasting.

6.4.3 Application of the Trading Strategies

Previous forecast evaluations indicate that the 15-day-ahead forecasting model generally outperforms the other *h*-day-ahead volatility forecasting. We then propose the option trading strategies based on the 15-day-ahead predicted change in future volatility. The competitive volatility forecasting models are applied to the option trading strategies and the performances of different models are compared. The option strategies are traded based on the predictive ability of sentiment levels of (changes in) the future volatility and the results are shown in Table 22. The long (short) straddle is traded while positive (negative) future volatility changes are predicted. The benchmark trading strategies are the long and short straddle without any decision support. Panel A (Panel B) in Table 22 depicts the monthly rate of return of the long (short) straddle traded 15 days before the options final settlement day based on different volatility models.

Table 22 Performance of Option Trading Strategy

ISP	Benchmark	Recruiting Sentiment Levels					Recruiting Sentiment Changes					Without any decision support
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
	MHV	+TVIX	+TPCV	+TPCO	+ARMS	+TO	+ΔTVIX	+ΔTPCV	+ΔTPCO	+ΔARMS	+ΔTO	
Panel A: Performance of long straddle based on the decision support of volatility forecasting (%)												
30	14.86	9.40	14.03	12.94	13.30	23.19	14.86	14.86	14.86	13.26	13.83	9.12
60	8.86	15.40	14.62	18.18	8.86	***28.07***	16.97	8.86	8.86	8.86	***19.46***	
90	17.49	5.91	9.24	17.85	17.18	15.77	9.79	17.49	17.49	15.97	15.19	
120	10.95	0.70	15.90	7.14	13.37	11.09	10.95	15.27	10.95	17.01	9.10	
Panel B: Performance of short straddle based on the decision support of volatility forecasting (%)												
30	-0.58	-4.04	-1.52	-1.82	-1.80	1.91	-0.58	-0.58	-0.58	-0.58	-1.84	-4.15
60	-4.47	-0.69	-1.85	1.19	-4.47	***3.61***	0.78	-4.47	-4.47	-4.47	***1.45***	
90	1.21	-6.07	-4.31	1.49	1.35	-0.80	-4.00	1.21	1.21	-0.19	-1.02	
120	-3.41	-7.80	-0.68	-5.10	-2.19	-3.63	-3.41	-1.41	-3.41	-0.71	-4.36	

Notes: This table presents the performance of the option trading strategy for options traded 15 days before the final settlement day based on different volatility forecasting models. Panel A (Panel B) summarizes the monthly rate of return (%) for a long (short) straddle referring to equation (6.6). Model (1) in Table 6 is the benchmark volatility forecasting model based on multivariate historical volatility measures, realized volatility (RV), the absolute return (|R|) and the high-low range (HL), and is simplified as MHV. Model (2) to Model (6) (Model (7) to Model (11)) in Table 6 are volatility forecasting models' recruiting levels of (changes in) investor sentiments. +TVIX represents the volatility forecasting based on the MHV, and the sentiment proxy of TVIX is included as are the other symbols. The in-sample-period (ISP) is set as 30, 60, 90 and 120 days. Values in boldface and italics are long or short strategies which produce the best average monthly rate of return (%) based on MHV recruiting levels of or changes in investor sentiments.

The performance of each model is evaluated based on the monthly rate of return by referring to equation (6.6). For space considerations, the cumulative profit-loss and cost of capital of each model are omitted but are available from the authors upon request. The trading performance of the forecasting model that recruits the sentiment index results in a better average rate of return compared to the benchmark MHV model, especially when the in-sample period is 60 days. Most of the performance of the long straddle strategy that is based on alternative models, including the benchmark MHV model, is superior to the benchmark strategy of the long straddle without any filter, although not all of the strategies traded based on different sentiment integrated models and in-sample periods outperform the benchmark strategy. The performance of the short straddle based on the volatility forecasting, however, does not consistently present a better rate of return than the benchmark strategy for the short straddle without any filter. The trading performance concludes that the short straddle 15 days before the final settlement day based on the +TO model, the forecasting model based on the MHV recruiting level of the turnover ratio, gives rise to a monthly rate of return of 3.61%, which is better than the risk-free rate. The long straddle 15 days before the final settlement day based on +TO (+ΔTO) further produces a monthly rate of return of 28.07% (19.47%) while the levels (changes) are considered. The effective option trading strategy suggests that a long (short) straddle based on the positive (negative) changes of volatility forecasting including the sentiment level of the 'turnover ratio (TO)' achieves the average monthly return of 15.84%.

6.5 Sub-Conclusions

The algorithm of option trading strategies based on volatility forecasting is evaluated in this study. The difference between this paper and the previous literature is that we construct a volatility forecasting model that recruits the investor sentiments. The contribution of this study is that the algorithm of the effective option trading strategy proposed is based on a superior model. We also bridge the gap between investor sentiments and the decision support system from a behavioral finance point of view.

The algorithm is established by means of the following steps. First, possible sentiment proxies for the equity and derivatives markets are collected such as the volatility index which is a proxy for the investors' fear gauge, put-call trading volume ratio, put-call open interest ratio, market turnover ratio and the ARMS index. Second, the causal relationship between investor sentiments and future volatility is examined to confirm the predicted ability of sentiment indicators. Third, the multiple-factor forecasting model is built up by including each sentiment indicator based on the benchmark forecasting model (MHV), including absolute daily returns, daily high-low range and daily realized volatility. Fourth, the forecasting ability of competitive models is compared and the forecast evaluation is measured by the regression-based forecast efficiency test and the mean absolute percentage error (MAPE). The parameters used in the option trading strategy, including the in-sample-period and the holding period, are identified in this step. Finally, we simulate the option trading strategies based on the predicted future volatility change. An effective multiple-factor volatility forecasting model that recruits the sentiment indicators from the stock and derivatives markets is presented.

The causality and the regression based forecast efficiency tests support the view that the sentiment proxies of market turnover and the volatility index include levels and changes that can help predict future volatility. The algorithm for the option trading strategies is supposed to long (short) straddle 15 days before the final settlement days of the option contract based on a 60-day in-sample-period volatility forecasting model. Volatility forecasting that recruits market turnover is the best filter and the average monthly return is about 28.07% (3.61%) for a long (short) straddle, which implies an average monthly return of 15.84% considering the margin based transaction cost. An effective option trading strategy that refers to a predicted positive (negative) change in future volatility that recruits market turnover is suggested in this study.

In conclusion, our empirical findings agree with the noise trader explanation that the causality runs from sentiment to market behavior. The results also support the view that the forecasting models of volatility need to assign a prominent role to investor sentiments. We posit that proxies of investor sentiments support the decision to engage in option trading, and that the trading algorithm based on the volatility forecasting recruiting investor sentiments can be further applied in the electronic trading platforms and other artificial intelligence decision support systems.

Chapter 7. Conclusions

The frame dependence theory proposed by Shefrin (2000, 2005) in behavioral finance argues that investors' sentiments and decisions are sensitive to different market scenarios. In contrast to the previous studies which respectively emphasize on the relationship between investor sentiment and stock market returns, volatility and market index, or volatility forecasting considering the stock market return, this study investigates the interaction among implied volatility, investor sentiment and market index from the behavioral finance point of view in the emerging Taiwan equity market.

The dissertation investigates the nonlinear co-movement and causalities between the implied volatility, investor sentiment and market index from different dimensions. We propose that the options trading strategy constructed based on the volatility direction forecasting incorporating the investor sentiment outperforms the alternative models. Our results reveal that the property of investor sentiment which could capture the overreaction in the stock market should be considered in the volatility forecasting, portfolio management and options trading strategy.

In summary, the essays of this dissertation provide some insights into the information content of investor sentiment, emphasize on the nonlinear relationship between sentiment, implied volatility and the market index and the improvement of volatility forecasting by incorporating sentiment proxies. Future research could further investigate the volatility forecasting incorporating the asymmetry of investor sentiment and apply the findings to the actual trading strategies.

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The Application of Information Sentiments to the Warning Model of Abnormal Return and Portfolio Management (with Yang-Cheng Lu and Chien-Wei Chang)

The Spillover Effect of the Volatility Index on Underlying Equity Returns: Evidence from Asian Emerging Markets (with Her-Jiun Sheu)

The Application of Financial News-Corpus Mining to the Warning Model for Corporate Financial Distress (with Yang-Cheng Lu)

Stealth Trading, Aggressiveness of Trades and Investor Types: Evidence from the Emerging Taiwan Equity Market (with Yang-Cheng Lu and Chien-Wei Chang)

Does stealth trading behavior and price manipulation reveal in the institutional investors in the Taiwan stock market? (with Yang-Cheng Lu)

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Teaching Experiences

Lecturer in the Finance Department, Ming Chuan University
Feb. 2008 ~ Jul. 2010

Working Experiences

Researcher, Polaris Securities Corporation
Jul. 2004 ~ Dec. 2005

Researcher, Capital Futures Corporation
Jul. 2002 ~ May. 2004

Working Experiences on Research Program

International Portfolio Analysis with the Consideration of Volatility, Spillover Effect and Information Flow (NSC-96-2416 -H-009 -020- MY3)
Aug. 2007 ~ Jul. 2010, National Science Council, Taipei, Taiwan

A Text Mining Based Artificial Intelligence System on the Prediction of Corporate Default Probability and Investor Sentiment Derived Abnormal Returns (98-EC-17-A-29-S2-0147)
Jun. 2009 ~ May. 2010, Department of Industrial Technology (DoIT) of the Ministry of Economic Affairs (MOEA), Taiwan

信用結構型金融商品風險管理與結算制度集中化管理之可行性分析-從美國次貸風暴事件剖析
Nov. 2008 ~ Jun. 2009, 中華民國證券商業同業公會

不同類型投資人委託資訊與成交揭示資訊之透明度與優勢資訊內涵-以臺灣證券交易所掛牌交易公司逐筆資料解析
May. 2007 ~ Nov. 2007, 中華民國證券商業同業公會

指數期貨與現貨價格之預測-水準門檻誤差修正模型之運用 (NSC-95-2416 -H-130 -013)
Aug. 2006 ~ Jul. 2007, National Science Council, Taipei, Taiwan

企業危機發生機率預警模型

Jun. 2005 ~ Jan. 2006, 銘傳大學財務金融所暨時報資訊股份有限公司共同發展研究計畫

Other Publications

盧陽正、王麗惠、方豪、魏裕珍、張健偉 (2007)。債券市場理論與實務翻譯（Fabozzi, F., Bond Markets: Analysis and Strategies, 7th ed., 2007）。台北市：雙葉書廊。

Honors, Grants and Scholarships

Traveling Grant for the International Symposium on Finance and Accounting (ISFA), Japan (2010), Granted by National Science Council (Grant Number: NSC-99-2922-I-009-102), Taipei, Taiwan

Traveling Grant for the 4th International Conference on Asia-Pacific Financial Markets, Korea (2009), Granted by Ministry of Education (Grant Number: 09D250), Taipei, Taiwan

Traveling Grant for the International Symposium on Finance and Accounting (ISFA), Malaysia (2009), Granted by National Science Council (Grant Number: NSC-98-2922-I-009-068), Taipei, Taiwan

Outstanding Research Award of the Global Conference on Business and Finance (2009), Costa Rica

Traveling Grant for the First Asia Conference on Financial Engineering and Markets, Hong Kong, (2008), Granted by Ministry of Education (Grant Number: 08D137), Taipei, Taiwan

Research Scholarship (Aug. 2006 ~ Jul. 2008) Granted by the National Science Council, Taipei, Taiwan

Master’s Thesis Award (2002), A Multi-Stage Real Option Approach on the Evaluation of the On Line Game Company - Case Study for NCsoft, Granted by the National Science Council