Effective options trading strategies based on volatility forecasting recruiting investor sentiment

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ARTICLE INFO

ABSTRACT

This study investigates an algorithm for an effective option trading strategy based on superior volatility forecasts using actual option price data for the Taiwan stock market. The forecast evaluation supports the significant incremental explanatory power of investor sentiment 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 sentiment could be further applied in electronic trading and other artificial intelligence decision support systems.

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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 sentiment 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; Li & Kuo, 2008; Poon & Granger, 2003; 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 op-

tion 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 sentiment have an impact on the financial asset price formation process and further influence the variation in returns? Early papers (Fama, 1965; Friedman, 1953) 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 (Baker & Wurgler, 2006, 2007; Brown & Cliff, 2004; Clarke & Statman, 1998; Fisher & Statman, 2000; Han, 2008; Simon & Wiggins, 2001; Solt & Statman, 1988; Wang, 2001). Although sentiment has been applied to portfolio management, fewer studies investigate the relationship between sentiment and market volatility and its application to trading decision

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support (Brown, 1999; Low, 2004; Verma & Verma, 2007; Wang, Keswani, & Taylor, 2006). This motivates us to investigate the effective option trading strategies based on the volatility forecasting model which incorporates the information content of investor sentiment.

The algorithms proposed in this study enhance the performance of option trading and confirm the forecasting ability of investor sentiment 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 sentiment 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.

Taiwan's equity market has long been an indispensable emerging market for international investors. 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. 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 sentiment might be the cause of the price variations. This study therefore proceeds to examine the rapidly-developing Taiwan stock market.

The remainder of this paper is organized as follows. Section 2 discusses the literature focusing on volatility forecasting and the relationship between sentiment, return, and volatility. Section 3 describes the volatility and sentiment proxies. Section 4 outlines the experimental design including the forecasting model, forecasting evaluation and trading strategies. Section 5 reports the results of forecasting performance and simulated trades. Section 6 reviews the conclusions.

2. Literature review

The critical determinants of the performance of many asset management tasks such as risk management, derivatives pricing, options trading, hedging, and asset allocation are all centered on the forecasting of future volatility. Modeling and forecasting market volatility has long been an important issue in finance as well as in econometrics. Blair, Poon, and Taylor (2001) and Poon and Granger (2003) have summarized that volatility forecasting models can be classified in the following four categories: the historical volatility models (HISVOL),[1] the GARCH family, the

options implied standard deviation (ISD) model, and the stochastic volatility model (SV). 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 and 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 (Becker, Clements, & White, 2007; Becker & Clements, 2008; Engle & Gallo, 2006). In addition to the issue of the optimal combination of the multivariate volatility measures, there are other topics examining the possible indicators which could improve the predictive power of forecasting and its application.

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. Sentiment 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 (Baker and Wurgler, 2006; Baker and Wurgler, 2007; Brown and Cliff, 2004; Clarke and Statman, 1998; DSSW, 1990; Fisher and Statman, 2000; Han, 2008; Simon and Wiggins, 2001; Solt and Statman, 1988; Wang, 2001). While less attention is given to the impact of sentiment on the realized volatility or vice versa (Banerjee, Doran, & Peterson, 2007; Brown, 1999; Lee, Jiang, & Indro, 2002; Low, 2004; Verma & Verma, 2007; Wang et al., 2006), 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.

3. Volatility and sentiment proxies

Our analysis is conducted on a daily basis and the study period extends from 2003 to 2007, encompassing a total of 1,240 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.[2] The period used to calculate the future volatility is shaded. The data used in this study are quoted on the Taiwan

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[1] 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).

[2] 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/.

Futures Exchange (TAIFEX), the Taiwan Stock Exchange (TWSE), and in the Taiwan Economic Journal (TEJ).[3]

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 and 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.[4] The future realized return standard deviations are expressed as follows:

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

$$R_{t+j} = \ln\left(\frac{S_{t+j}}{S_{t+j-1}}\right), \tag{1}$$

where $\overline{R}_{t,t+h}$ is the mean of the TAIEX return during days $t + j$ to $t + h$, $j = 1, \ldots, h$, 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 and 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.[5] Both the $|R|$ and the HL are calculated using daily data,[6] and the RV is calculated by summing the corresponding 5 min interval squared returns[7] (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:

$$|R_t| = |\ln(S_t/S_{t-1})|, \tag{2}$$

$$HL_t = \frac{H_t - L_t}{S_{t-1} \times 14\%}, \tag{3}$$

$$RV_t = \sqrt{\sum_{i=0}^{n}\left(\ln\frac{S_{t+i}}{S_{t+i-1}}\right)^2} \times \sqrt{252}, \tag{4}$$

where $|R_t|$ 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, S_{t-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 intra-day index level of the ith interval on trading day t, S_{t+n} represents the closing price on day t, $i = 0, \ldots, n$, and n is the number of time intervals in each day.

3.2. Measuring investor sentiment

3.2.1. ARMS index

ARMS can be interpreted as the ratio of the number of advances to declines standardized by their respective volumes. It is measured as:

$$\text{ARMS}_t = \frac{\#\text{Adv}_t/\text{AdvVol}_t}{\#\text{Dec}_t/\text{DecVol}_t} = \frac{\text{DecVol}_t/\#\text{Dec}_t}{\text{AdvVol}_t/\#\text{Adv}_t}, \tag{5}$$

where $\#\text{Adv}_t$, $\#\text{Dec}_t$, 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. Its creator, Richard Arms, argued that if the average volume in declining (rising) stocks far outweighs the average volume in rising (falling) stocks, then the market is oversold (overbought) and this should be treated as a bullish (bearish) sign.[8]

3.2.2. 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; Gervais, Kaniel, & Mingelgrin, 2001). On the other hand, trading volume, or more generally liquidity, can be viewed as an investor sentiment index (Baker & Stein, 2004; Baker & Wurgler, 2007; Scheinkman & Xiong, 2003). 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).

3.2.3. Investor fear Gauge–Option volatility index (VIX)

Options market-based implied volatility can reflect the expectations with respect to price changes in the future, and it can also be treated as an indicator of sentiment (Olsen, 1998; Whaley, 2000).[9] The greater the fear, the higher the VIX level is, and the volatility index is commonly referred to as the 'investor fear gauge'. The Taiwan volatility index (TVIX) is constructed as a proxy for investor sentiment by adjusting the new revision of the CBOE volatility index published in 2003.[10] In the construction of the Taiwan stock market volatility index, the interest rate is adjusted accordingly and the

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[3] 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/

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

[5] 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 and 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.

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

[7] The latest observations available before the 5 min marks from 09:00 until 13:30 are used to calculate the 5 min returns. We sum the 54 squared intra-day 5 min returns and the previous squared overnight returns to construct the daily realized volatility.

[8] If the index is greater than one, more trading is taking place in declining issues, while if it is less than one, more volume in advancing stocks outpaces the volume in each declining stock.

[9] In 1993, the Chicago Board Options Exchange (CBOE) introduced the original version of the Volatility Index based on the S&P 100 index options (OEX) which can be defined as the magnitude of price variation for the following 30 days. The new version of the Volatility Index published in 2003 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. The new volatility index is more precise and robust than the original version. The fundamental features of the volatility index between the old and new versions, however, remain the same. For details of the index's construction, the interested reader may refer to the white book published by the CBOE in 2003, http://www.cboe.com/micro/vix/vixwhite.pdf

Table 1
Summary statistics.

	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[***]
$\triangle$TVIX	0.0085	−0.0649	12.5563	−7.3052	1.4006	1.4741	16.2863	9453.84[***]
$\triangle$TPCV	0.0002	−0.0056	0.6863	−0.7872	0.1775	0.0219	4.3419	92.01[***]
$\triangle$TPCO	0.0001	0.0013	0.3551	−1.1324	0.0844	−2.9814	35.8413	56865.73[***]
$\triangle$ARMS	−0.0002	0.0018	7.0135	−7.6913	0.4915	−0.8733	86.4724	355795.5[***]
$\triangle$TO	0.0001	−0.0040	1.7295	−1.0063	0.1739	0.5457	13.4042	5585.96[***]

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). $\triangle$TVIX, $\triangle$TPCV, $\triangle$TPCO, $\triangle$ARMS and $\triangle$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.
[***] Indicate significance at the 1% levels.

roll-over rule is revised to one day prior to expiration in light of the market structure in Taiwan.[11]

3.2.4. 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 spot positions or to speculate bearishly. By contrast, a low level of TPCV is associated with a lower demand for puts, which would reflect 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 put options. Thus, the TPCO tends to be higher on days when the total open interest is high.

3.3. Summary statistics

Table 1 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 leptokurticity relative to the normal distribution. Fig. 1 shows the original evolution of the future volatility and sentiment indices from 2003 to 2007. The correlation coefficient matrix is presented in Table 2. 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).

4. Experimental design

4.1. 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:

$$V_t = C_1 + \sum_{p=1}^{L} \alpha_{1p} V_{t-p} + \sum_{p=1}^{L} \beta_{1p} SI_{t-p} + \varepsilon_{1t},$$

$$SI_t = C_2 + \sum_{p=1}^{L} \alpha_{2p} V_{t-p} + \sum_{p=1}^{L} \beta_{2p} SI_{t-p} + \varepsilon_{2t}, \tag{6}$$

where V_t denotes the future volatility and SI_t is the sentiment index. The levels of (SI_t) and changes ($\triangle SI_t$) 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 $\alpha_{2p} = 0$ ($\beta_{1p} = 0$) as a group based on a standard F-test.

4.2. Regression-based forecast efficiency test

By following and extending Engle and Gallo (2006) and Poon and Granger (2003, 2005), 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.

$$FV_t = \beta_0 + \beta_1 HL_{t-1} + \beta_2 |R_{t-1}| + \beta_3 RV_{t-1} + \varepsilon_t, \tag{7}$$

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[11] The risk-free rate is calculated from the monthly average one-year deposit rate 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 eight 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. The nearest-term expiration contract, however, 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 liquidity and trading volume of the second and third contract months, we revised the roll-over rule from eight days to one day prior to expiration.
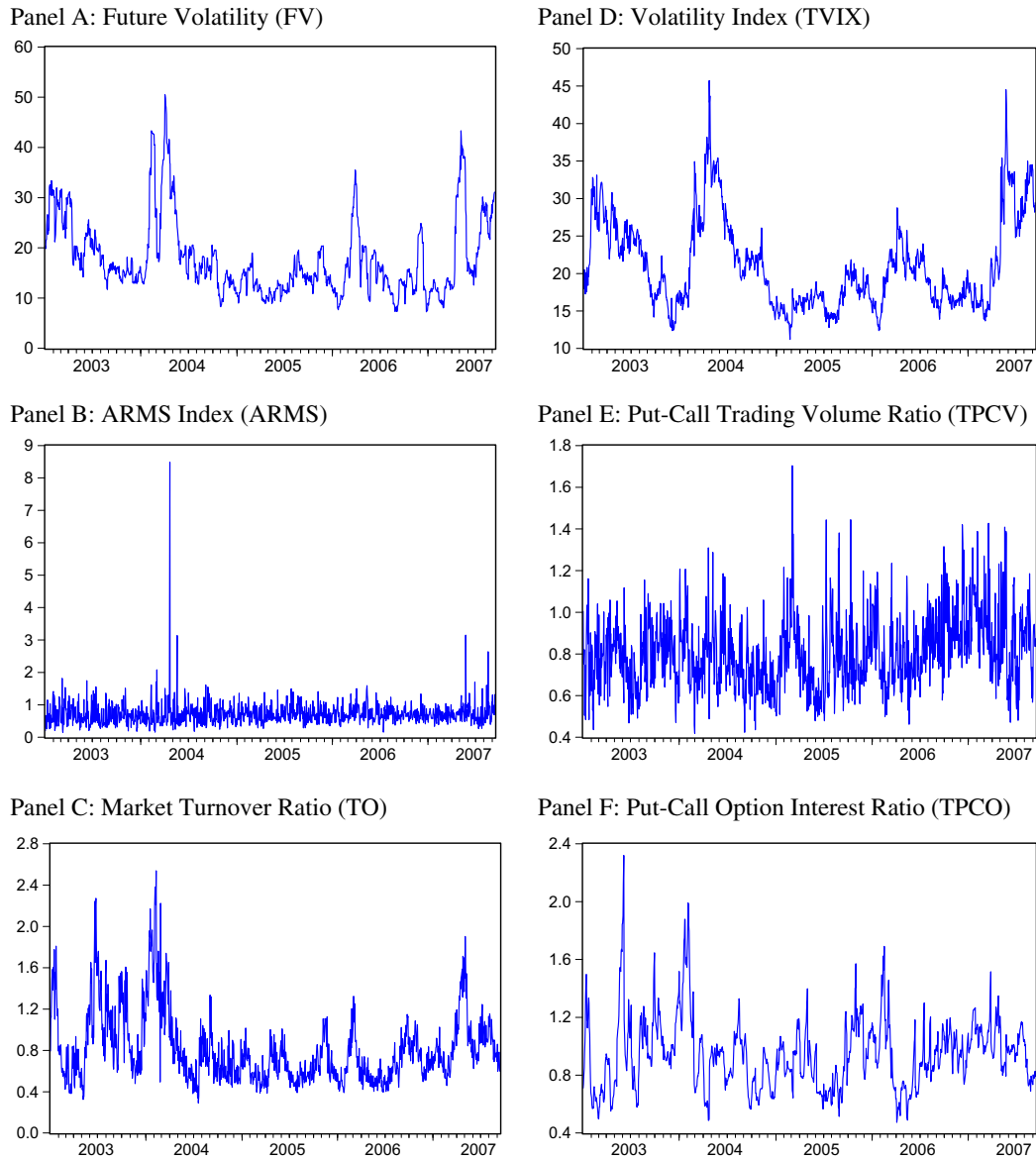
Panel A: Future Volatility (FV)

Panel D: Volatility Index (TVIX)

Panel B: ARMS Index (ARMS)

Panel E: Put-Call Trading Volume Ratio (TPCV)

Panel C: Market Turnover Ratio (TO)

Panel F: Put-Call Option Interest Ratio (TPCO)

Fig. 1. Daily evolution of future volatility and sentiment indices from 2003 to 2007. 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.

where FV_t is the future volatility measure, and HL_{t-1}, $|R_{t-1}|$ and RV_{t-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:

$$FV_t = \beta_0 + \beta_1 HL_{t-1} + \beta_2|R_{t-1}| + \beta_3 RV_{t-1} + \gamma SI_{t-1} + \varepsilon_t, \tag{8}$$

where SI_{t-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:

$$FV_t = \beta_0 + \beta_1 HL_{t-1} + \beta_2|R_{t-1}| + \beta_3 RV_{t-1} + \gamma\Delta SI_{t-1} + \varepsilon_t, \tag{9}$$

for the case where lagged three historical volatility defines the benchmark model MHV and $\triangle SI_{t-1}$ stands for the differences of sentiment. +$^\triangle$TVIX represents the MHV recruiting the changes in TVIX and so does the +$^\triangle$TPCV, +$^\triangle$TPCO, +$^\triangle$ARMS and +$^\triangle$TO.

4.3. 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

Table 2
Correlation coefficients.

	FV	HV	RV	|R|	HL	TVIX	TPCV	TPCO	ARMS	TO	$\triangle$TVIX	$\triangle$TPCV	$\triangle$TPCO	$\triangle$ARMS	$\triangle$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***
$\triangle$TVIX												0.1228***	-0.0385	-0.0039	0.1567***
$\triangle$TPCV													-0.1354***	0.035	-0.1331***
$\triangle$TPCO														-0.0405	0.152***
$\triangle$ARMS															0.0568***

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 $\triangle$TVIX, $\triangle$TPCV, $\triangle$TPCO, $\triangle$ARMS and $\triangle$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.

* Indicate significance at the 10% levels.
** Indicate significance at the 5% levels.
*** Indicate significance at the 1% levels.

days ahead ($h = 5, 10, 15, 20$), which are days used to calculate the future volatility in Eq. (1). The idea of the volatility forecasting could be presented in the following framework in Fig. 2.

In the context of this idea of volatility forecasting, T_0 is the date of option trading based on the volatility forecasting recruiting investor sentiment. 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.

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 to 2007 period. In order to select the 'best' model which gives the most accurate forecasts, the forecasting error for different competitive models is measured by using the mean absolute percentage error (MAPE) referred to by Gospodinov, Gavala, and Jiang (2006) and Poon and Granger (2003, 2005). The MAPE is scale independent and may be defined as follows:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} |1 - \widehat{FV}_{i,M}/FV_i|, \tag{10}$$

where $\widehat{FV}_{i,M}$ 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 to 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 $+^{\triangle}$TVIX, $+^{\triangle}$TPCV, $+^{\triangle}$TPCO, $+^{\triangle}$ARMS and $+^{\triangle}$TO. The algorithm of volatility forecasting recruiting investor sentiment is then evaluated through the simulation of the option trading strategy.

4.4. 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
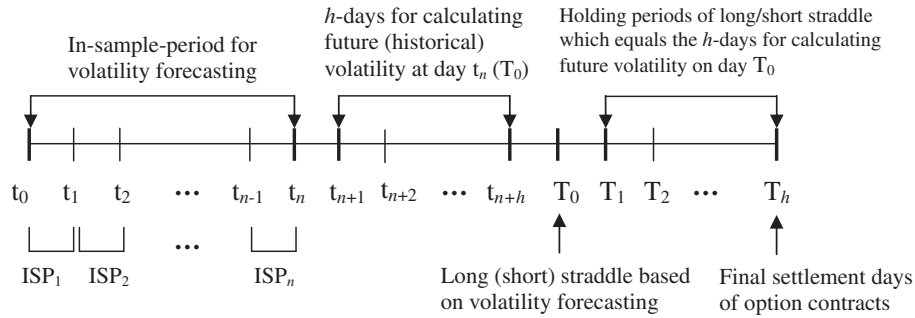
Fig. 2. The framework of volatility forecasting. T_0 is the date of the long or short straddle based on the volatility forecasting recruiting investor sentiment. T_h is the final settlement day of the option contracts. T_1 to T_h is the holding period of the long or short straddle and it equals h days 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.

support for other hybrid option trading strategies.[12] The strike price of the straddle selected in this study is the at-the-money call and put option contracts on the trading day (for example, T_0 in Fig. 2). 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 Fig. 2 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 Fig. 3.

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.[13] The cost of capital is calculated by the transaction cost and the maximum margin requirement during the

holding period if the trading strategies are short straddle.[14] 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:

$$R_M(\%) = \frac{\frac{1}{n}\sum_{i=1}^n PL_{i,M}}{\frac{1}{n}\sum_{i=1}^n C_{i,M}} \times 100\%, \qquad (11)$$

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

5. Results of simulated trades

5.1. Causality test

The results of the Granger causality tests using future volatility and investor sentiment are presented in Table 3. 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 sentiment should be considered in future volatility forecasting.

5.2. 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 sentiment based on regression analysis. Whether or not the levels or the first differences of the investor sentiment are able to enhance forecasting

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

[13] 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. 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 15 min 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 15 min 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.

[14] 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).
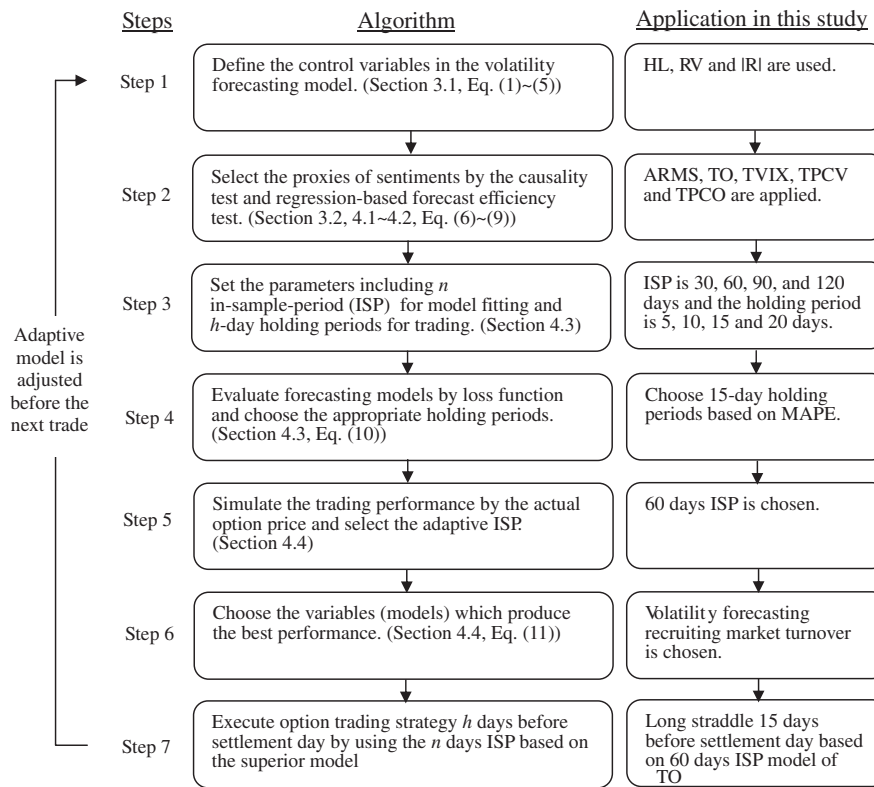
Steps	Algorithm	Application in this study
Step 1	Define the control variables in the volatility forecasting model. (Section 3.1, Eq. (1)~(5))	HL, RV and |R| are used.
Step 2	Select the proxies of sentiments by the causality test and regression-based forecast efficiency test. (Section 3.2, 4.1~4.2, Eq. (6)~(9))	ARMS, TO, TVIX, TPCV and TPCO are applied.
Step 3	Set the parameters including n in-sample-period (ISP) for model fitting and h-day holding periods for trading. (Section 4.3)	ISP is 30, 60, 90, and 120 days and the holding period is 5, 10, 15 and 20 days.
Step 4	Evaluate forecasting models by loss function and choose the appropriate holding periods. (Section 4.3, Eq. (10))	Choose 15-day holding periods based on MAPE.
Step 5	Simulate the trading performance by the actual option price and select the adaptive ISP. (Section 4.4)	60 days ISP is chosen.
Step 6	Choose the variables (models) which produce the best performance. (Section 4.4, Eq. (11))	Volatility forecasting recruiting market turnover is chosen.
Step 7	Execute option trading strategy h days before settlement day by using the n days ISP based on the superior model	Long straddle 15 days before settlement day based on 60 days ISP model of TO

Adaptive model is adjusted before the next trade

Fig. 3. The algorithm of the effective option trading strategies.

Table 3
Granger causality tests between future volatility and sentiment.

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

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 does 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 does not cause changes in sentiment. Values in the table and the parentheses are F-test statistics and p-values, respectively.
[*] Indicate significance at the 10% levels.
[**] Indicate significance at the 5% levels.
[***] Indicate significance at the 1% levels.

power is examined based on the benchmark MHV forecasting model in Eq. (7). From Table 4, 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 (+△TO) 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 (+△TVIX, +△TPCV, +△TPCO, +△ARMS and +△TO). 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 5. 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.

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 5 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 sentiment are superior to the benchmark historical volatility model. To sum up, the forecast evaluation proposes that investor sentiment should be integrated into volatility forecasting.

5.3. 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 pre-

Table 4
Estimation results of the regression-based forecast efficiency test.

	Benchmark	Recruiting sentiment levels					Recruiting sentiment changes				
	(1) MHV	(2) +TVIX	(3) +TPCV	(4) +TPCO	(5) +ARMS	(6) +TO	(7) +$\triangle$TVIX	(8) +$\triangle$TPCV	(9) +$\triangle$TPCO	(10) +$\triangle$ARMS	(11) +$\triangle$TO
Constant	9.8247 (23.8263)***	1.6617 (2.7743)***	9.1747 (10.9499)***	9.2440 (10.4524)***	9.7013 (18.7864)***	7.8437 (14.8861)***	9.7900 (23.5105)***	9.8158 (23.7838)***	9.8614 (23.8639)***	9.8193 (23.7847)***	9.2482 (22.4539)***
TVIX		0.5796 (17.4845)***					−0.0738 (−0.6042)				
TPCV			0.7946 (0.8911)					0.4736 (0.5965)			
TPCO				0.5679 (0.7422)					−2.8031 (−1.2894)		
ARMS					0.1961 (0.3972)					−0.1137 (−0.3124)	
TO						3.2081 (5.933)***					−7.6012 (−7.5378)***
RV	0.2139 (11.9966)***	0.0936 (5.3087)***	0.2153 (12.028)***	0.2147 (12.0176)***	0.2137 (11.9734)***	0.1987 (11.1578)***	0.2143 (12.0084)***	0.2149 (11.9988)***	0.2141 (12.0091)***	0.2141 (11.9958)***	0.2153 (12.3025)***
$|R|$	−1.161 (−4.4723)***	−0.6151 (−2.5818)***	−1.1756 (−4.5193)***	−1.1621 (−4.4759)***	−1.163 (−4.4779)***	−1.0801 (−4.2033)***	−1.1606 (−4.4699)***	−1.1663 (−4.4891)***	−1.15 (−4.4288)***	−1.1602 (−4.468)***	−0.9437 (−3.6806)***
HL	0.6186 (14.9476)***	0.3545 (8.7371)***	0.6175 (14.912)***	0.6224 (14.9229)***	0.6175 (14.883)***	0.5764 (13.8799)***	0.6213 (14.9254)***	0.618 (14.9225)***	0.6135 (14.757)***	0.6186 (14.9428)***	0.6531 (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%

This table shows the incremental contribution of investor sentiment for future volatility (FV). The FV is calculated for the next 15 days on day t. The investor sentiment 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)–(11) individually. The values in the parentheses are the T-test statistics.
*** Indicate significance at the 1% levels.

Table 5
Forecast evaluation of volatility models for h-day-ahead forecasts of future volatility using MAPE.

ISP	Benchmark	Recruiting sentiment levels					Recruiting sentiment changes					Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
	MHV	+TVIX	+TPCV	+TPCO	+ARMS	+TO	+△TVIX	+△TPCV	+△TPCO	+△ARMS	+△TO	
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	0.3591	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

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 Eq. (10) 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. Models (2)–(6) (Models (7)–(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.

Table 6
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	+△TVIX	+△TPCV	+△TPCO	+△ARMS	+△TO	
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	

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 Eq. (11). 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. Models (2)–(6) (Models (7)–(11)) in Table 6 are volatility forecasting models' recruiting levels of (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 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 sentiment.

dictive ability of sentiment levels of (changes in) the future volatility and the results are shown in Table 6. 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 6 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.

The performance of each model is evaluated based on the monthly rate of return by referring to (11). 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-period 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 (+$^\Delta$TO) 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. 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 sentiment. 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 sentiment 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 sentiment 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 sentiment. We posit that proxies of investor sentiment support the decision to engage in option trading, and that the trading algorithm based on the volatility forecasting recruiting investor sentiment can be further applied in the electronic trading platforms and other artificial intelligence decision support systems.

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