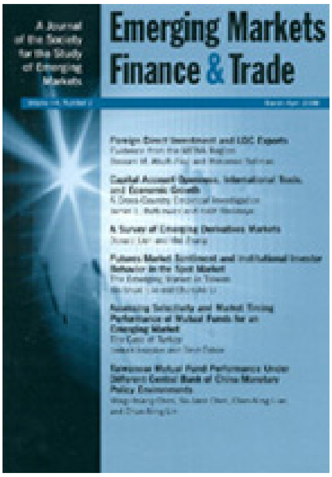


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# Options Trading Based on the Forecasting of Volatility Direction with the Incorporation of Investor Sentiment

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# Options Trading Based on the Forecasting of Volatility Direction with the Incorporation of Investor Sentiment

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*ABSTRACT:* Using options price data on the Taiwanese stock market, we propose an options trading strategy based on the forecasting of volatility direction. The forecasting models are constructed with the incorporation of absolute returns, heterogeneous autoregressive-realized volatility (HAR-RV), and proxy of investor sentiment. After we take into consideration the margin-based transaction costs, the results of our simulated trading indicate that a straddle trading strategy that considers the forecasting of volatility direction with the incorporation of market turnover achieves the best Sharpe ratios. Our trading algorithm bridges the gap between options trading, market volatility, and the information content of investor overreaction.

*KEYWORDS:* HAR-RV model, investor sentiment, market turnover, options trading, volatility forecasting.



The behavioral models related to securities markets suggest the presence of two types of investors, namely, rational arbitrageurs, who are sentiment free, and irrational traders, who are prone to exogenous sentiment. If the trading decisions of such irrational noise traders are based on sentiment, then the measures of such sentiment may have predictive power with regard to asset price behavior.

Evidence is presented in a growing body of literature of the irrational behavior of investors in the stock and options markets, with poor returns from options trades widely attributed to bad market timing, largely due to overreaction among investors to past stock market movements (Bauer et al. 2009). Any filter that could help to improve trading timing by taking into consideration the overreaction of investors is worthy of investigation. The question arises, however, as to how investor sentiment can have an impact on the process of financial asset price formation and further influence variations in returns.

A considerable body of literature already exists on the relationship between returns and sentiment, as well as the information content of this relationship;[1] and although less attention has been paid to the impact of sentiment on realized volatility, or vice versa,[2] the exact role of sentiment is still a topic worthy of examination in the overall price formation process.

In the majority of prior empirical studies examining relationships between sentiment, returns, and volatility, the tendency has been to focus on the American financial market

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(e.g., Christoffersen and Diebold 2006; Wang et al. 2006). Most of the other studies that take direction-of-change forecasting into consideration (e.g., Bekiros and Georgoutsos 2008) also tend to focus on the American financial market.

With respect to emerging markets, Canbas and Kandir (2009), in their investigation of the relationship between investor sentiment and stock returns on the Istanbul Stock Exchange, found that the turnover ratio of the stock market appears to have forecasting potential; however, the forecasting information was not subsequently applied to any simulated trading strategy. There are, in fact, very few studies with a general focus on volatility forecasting or options trading that incorporate investor sentiment. Therefore, in the present study, we attempt to bridge this gap by proposing an algorithm as a trading reference for use in other stock markets.

Taiwan's equity market has long been an indispensable emerging market for international investors; indeed, the statistical data published in the 2010 annual report of the Futures Industry Association reveal that options trading volume in the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) is ranked thirteenth in the world, which clearly indicates its growing importance in global asset management. The high trading proportion by individual traders in Taiwan, at about 70 percent in the equity market and about 50 percent in the derivatives market, also implies that noise trading or investor sentiment may be the root cause of the excessive price variations in the rapidly developing Taiwanese stock market.

The perspective adopted in the present study is not based on an examination of optimal combinations of volatility models or other control variables but, rather, the main purpose of this study is to investigate whether forecasting and trading performance can be improved if the information content of sentiment is taken into consideration in the decision-making process. The algorithm proposed in this study enhances the performance of options trading and confirms the forecasting ability of investor sentiment on future volatility.

## Data Description

The analysis is conducted on a daily basis with the study period running from 2003 to 2007, providing a total sample of 1,240 trading days. The data used in this study are quoted on the Taiwan Futures Exchange (TAIFEX), on the Taiwan Stock Exchange (TSE), and in the *Taiwan Economic Journal* (TEJ).

### *Future Volatility*

In referring to Corrado and Miller (2005), we employ the future realized volatility on day $t$ for the next $h$ days, which we subsequently compute as the standard deviation in the returns of the sample over the period from day $t + 1$ to day $t + h$ ($h = 5$, 10, 15, and 20); future volatility is then expressed in percentage annual terms.[3]

### *Alternative Volatility Measures*

Engle and Gallo (2006) propose the development of a forecasting model under the joint consideration of the absolute daily returns (|R|), the daily high-low range (HL), and the daily realized volatility (RV). Both the |R| and the HL are calculated using daily data;[4] the RV is calculated by summing the squared returns of the corresponding five-minute intervals.[5]

Corsi (2009) proposes use of heterogeneous autoregressive-realized volatility (HAR-RV) proved to be capable of capturing the long memory in volatility by mixing the different realized volatility frequencies. The autoregressive structure in the realized volatility can be written as

$$\text{HAR-RV}_{t+1} = c + \beta^{(d)}\text{RV}_t^{(d)} + \beta^{(w)}\text{RV}_t^{(w)} + \beta^{(m)}\text{RV}_t^{(m)} + w_{t+1}, \quad (1)$$

where $\text{RV}_t^{(d)}$, $\text{RV}_t^{(w)}$, and $\text{RV}_t^{(m)}$, are the respective daily, weekly, and monthly observed realized volatilities. The average of all daily realized volatilities over the previous 5 (22) working days provides the weekly (monthly) realized volatility at time $t$.

### *ARMS Index*

The ARMS index can be interpreted as the ratio of the number of advances to declines standardized by their respective volume. Its creator, Richard Arms (1989), suggested 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 regarded as a bullish (bearish) sign.

### *Market Turnover*

Trading volume, or more generally, liquidity, can be viewed as an investor sentiment index.[6] Market turnover is calculated as the ratio of trading volume to the number of shares listed on the TSE; this is simplified as TURN in this study. A high TURN not only indicates that the market is dominated by irrational investors but also implies that the market may be overreacting.

### *Options Volatility Index*

Options market–based implied volatility may reflect expectations of future price changes, and it may also be regarded as an indicator of sentiment (Whaley 2000). The greater the fear, the higher the volatility index (VIX) level, and thus the VIX is commonly referred to as the investor fear gauge. The Taiwan volatility index (TVIX)[7] is constructed as a proxy for investor sentiment by adjusting the new revision of the Chicago Board Options Exchange (CBOE) VIX published in 2003.[8]

### *Put-Call Trading Volume and Open Interest Ratios*

The put-call trading volume ratio (TPCV) is the sum of the total trading volume of puts divided by the total trading volume of calls. The put-call open interest ratio (TPCO) can be calculated using the open interest of options instead of trading volume. When market participants are in a bearish mood, they will buy put options to hedge their spot positions or to engage in bearish speculation.

## Summary Statistics

Table 1 provides the descriptive statistics and the autocorrelation coefficients related to the data.[9] The future volatility in Table 1 is calculated over the next 15 days. The series of log future volatilities has high autocorrelations with a first-lag correlation of 0.971. The other volatility measures are also found to have high autocorrelations except for the absolute

**Table 1. Summary statistics**

| | | | | | Autocorrelation | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Mean | Standard deviation | Skewness | Kurtosis | Lag 1 | 2 | 3 | 4 |
| FV | 17.6541 | 7.5752 | 1.5026 | 5.197 | 0.9754 | 0.9508 | 0.9232 | 0.8931 |
| HV | 17.5957 | 7.5288 | 1.5357 | 5.3476 | 0.975 | 0.9493 | 0.9211 | 0.8898 |
| \|R\| | 0.8612 | 0.856 | 2.1499 | 9.7432 | 0.0646 | 0.1393 | 0.1561 | 0.1048 |
| HL | 8.8358 | 4.8139 | 1.7839 | 7.4517 | 0.3764 | 0.3211 | 0.3402 | 0.2999 |
| HAR-RV | 16.7241 | 4.9765 | 1.2487 | 4.9401 | 0.9433 | 0.9223 | 0.8919 | 0.8632 |
| LogFV | 2.7943 | 0.3788 | 0.5687 | 2.9325 | 0.971 | 0.9427 | 0.9141 | 0.8836 |
| LogHV | 2.7918 | 0.3766 | 0.5801 | 2.9911 | 0.9706 | 0.9413 | 0.9121 | 0.8805 |
| LogHL | 2.0557 | 0.4872 | 0.241 | 3.0939 | 0.3844 | 0.3453 | 0.3357 | 0.3042 |
| LogHAR-RV | 2.7776 | 0.274 | 0.5361 | 2.7605 | 0.9488 | 0.9323 | 0.9071 | 0.8811 |
| LogTVIX | 3.0109 | 0.262 | 0.4624 | 2.4677 | 0.9724 | 0.9546 | 0.9405 | 0.9231 |
| TPCV | 0.8067 | 0.1776 | 0.7308 | 3.8638 | 0.4993 | 0.3853 | 0.3534 | 0.292 |
| TPCO | 0.9452 | 0.2439 | 1.0018 | 5.3609 | 0.9391 | 0.8687 | 0.7962 | 0.7327 |
| ARMS | 0.7092 | 0.2919 | 1.9941 | 13.6045 | 0.1139 | 0.0836 | –0.0028 | 0.0003 |
| TURN | 0.8131 | 0.3449 | 1.5275 | 5.6631 | 0.8723 | 0.8276 | 0.7959 | 0.7601 |
| ΔLogTVIX | 0.0005 | 0.0598 | 0.8937 | 8.9417 | –0.1906 | –0.0684 | 0.0683 | –0.0454 |
| ΔTPCV | 0.0001 | 0.178 | 0.0215 | 4.3276 | –0.3859 | –0.0816 | 0.0298 | –0.0106 |
| ΔTPCO | 0.0001 | 0.0847 | –2.9717 | 35.5607 | 0.0778 | 0.0196 | –0.0716 | –0.0419 |
| ΔARMS | 0.0004 | 0.3883 | –0.2457 | 9.3561 | –0.482 | 0.0305 | –0.05 | 0.0084 |
| ΔTURN | 0.0002 | 0.1744 | 0.5468 | 13.3611 | –0.3212 | –0.051 | 0.0174 | –0.0298 |

*Notes:* This table presents the summary statistics for various volatility measures and sentiment proxies, namely, the future volatility (FV), the historical volatility (HV), the heterogeneous autoregressive model of the realized volatility (HAR-RV), the absolute return (|R|), the high–low range (HL), the Taiwan volatility index (TVIX), the put-call trading volume ratio (TPCV), the put-call open interest ratio (TPCO), the ARMS ratio, and the market turnover ratio (TURN). ΔTVIX, ΔTPCV, ΔTPCO, ΔARMS, and ΔTURN represent the first difference changes in the individual sentiment index. The period covers January 2, 2003, to November 22, 2007.

return. The model used to check the Ljung-Box statistics gives Q(10) = 8.9882 (0.533) for the standardized residual when we use the first lag of future volatility. There is no serial correlation for the fitted model if we incorporate the first lag of future volatility. The levels and the first differences of all of the sentiment indicators exhibit a skewed and leptokurtic pattern. We find that all levels of the sentiment indicators, except for the ARMS index, have substantial positive autocorrelations, whereas the first differences have significant negative first-lag autocorrelations except for the TPCO.[10]

The correlation coefficient matrix is presented in Table 2, from which we can see that the TVIX has a substantial positive correlation with the volatility measures between 0.33 and 0.81. As regards the TPCO, TPCV, and ARMS, we find that the correlations are more substantial for the level data than for the change data. Besides, the TPCO has more substantial correlations with volatility measures than the TPCV. As for the TURN, there is evidence of nonnegligible correlation between the volatility measures for both the level and change data.

### Granger Causality Test

We test for Granger causality between sentiment and future volatility through the estimation of bivariate vector autoregressive models. The models are estimated using both the levels and changes in the sentiment measures, because the specifications that will reveal the primary effects of sentiment are not so easy to determine. The results of the Granger causality tests are presented in Table 3.[11] The results reveal a clear feedback relationship between future volatility and sentiment in levels, including TPCO and TURN. Otherwise, the levels (first differences) in TVIX and ARMS (TVIX, TPCV, and TPCO) are caused by future volatility. Our findings suggest that investor sentiment in relation to TPCO and TURN should be taken into consideration in forecasting future volatility.

### Regression-Based Forecasting Efficiency Tests

We continue to determine whether those sentiment measures found to have causal effects can subsequently be used for volatility forecasting. The forecasting models are constructed with the incorporation of multiple factors for the Taiwanese stock market by following and extending Poon and Granger (2003) and Engle and Gallo (2006). We expect to find that the error terms in the regressions are strongly serially correlated, and we thereby compute the standard errors in the regression model using heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimators (Newey and West 1987).

To determine whether the alternative volatility measures can be incorporated into the benchmark forecasting model of multiple historical volatility model (MHV), we compare the incremental adjusted $R^2$; the model producing the highest increment in the adjusted $R^2$ will serve as the MHV. This is expressed as

$$\mathrm{FV}_t = \beta_0 + \beta_1 \mathrm{FV}_{t-1} + \sum_i \beta_{1+i} \mathrm{Vol}_{i,t-1} + \varepsilon_t, \tag{2}$$

where $\mathrm{FV}_t$ is the future volatility measure, and $\mathrm{Vol}_{i,t-1}$ represents the one-day lag volatility measures, including the HAR-RV, HL, and |R|.

We present the investigation of MHV in Panel A in Table 4. We find that model (5) in Panel A produces the highest increment of the adjusted $R^2$ of 0.0109 percent (94.4452 percent minus 94.4343 percent). The benchmark MHV used in this study therefore incorporates the first lag of future volatility, HAR-RV, and |R|.

## Table 2. Correlation coefficients

**Panel A: Level data of investor sentiment**

| Variable | TVIX | TPCV | TPCO | ARMS | TURN |
|---|---|---|---|---|---|
| FV | 0.6324*** | –0.0268 | –0.0397 | 0.0549* | 0.3434*** |
| HV | 0.7581*** | –0.0852*** | –0.2619*** | 0.0455 | 0.0703** |
| \|R\| | 0.3303*** | 0.0672** | –0.0971*** | 0.0944*** | 0.1827*** |
| HL | 0.5107*** | –0.0026 | –0.0974*** | 0.1139*** | 0.309*** |
| HAR-RV | 0.8114*** | –0.1485*** | –0.1204*** | 0.0491* | 0.2693*** |

**Panel B: Change data of investor sentiment**

| Variable | ΔTVIX | ΔTPCV | ΔTPCO | ΔARMS | ΔTURN |
|---|---|---|---|---|---|
| FV | 0.0615** | 0.0036 | –0.0678** | 0.0126 | –0.0451 |
| HV | –0.0271 | –0.0179 | 0.0282 | –0.0009 | –0.0539* |
| \|R\| | 0.1475*** | 0.0008 | –0.0151 | –0.0602** | 0.2532*** |
| HL | 0.1716*** | –0.0097 | –0.0892*** | –0.0491* | 0.2344*** |
| HAR-RV | –0.0167 | –0.018 | –0.0242 | 0.0069 | –0.0907*** |

*Notes:* The correlations are between the sentiment variables and the volatility measures. Panel A presents the level data for the sentiment variables, and Panel B shows the change data for the sentiment variables. The volatility measures are the future volatility (FV), the historical volatility (HV), the heterogeneous autoregressive model of the realized volatility (HAR-RV), the absolute return (|R|), and the high–low range (HL). The sentiment proxies are the Taiwan volatility index (TVIX), the put-call trading volume ratio (TPCV), the put-call open interest ratio (TPCO), the ARMS ratio, and the market turnover ratio (TURN). The symbols ΔTVIX, ΔTPCV, ΔTPCO, ΔARMS, and ΔTURN represent the first difference changes in the individual sentiment index. We transfer the logarithm of FV, HV, HAR-RV, HL, and TVIX. The period covers January 2, 2003, to November 22, 2007, and the period used to calculate the future volatility is shaded. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

**Table 3. Granger causality tests between future volatility and sentiment**

| | Hypothesis | | | |
|---|---|---|---|---|
| **Sentiment** | $H_{01}$ | $H_{02}$ | $H_{03}$ | $H_{04}$ |
| TVIX | 1.5542 | 28.5388*** | 1.0304 | 8.5552*** |
| | (0.2118) | (<0.0000) | (0.3572) | (0.0002) |
| TPCV | 0.2125 | 0.6487 | 0.827 | 3.3449*** |
| | (0.8086) | (0.5229) | (0.508) | (0.0098) |
| TPCO | 10.9057*** | 7.1029*** | 0.0026 | 4.8691** |
| | (0.001) | (0.0078) | (0.9592) | (0.0275) |
| ARMS | 0.8646 | 5.2884** | 0.9302 | 0.5952 |
| | (0.3526) | (0.0216) | (0.4721) | (0.7344) |
| TURN | 9.1336*** | 4.6052*** | 2.8021* | 0.9986 |
| | (<0.0000) | (0.0033) | (0.0611) | (0.3687) |

*Notes:* The numbers of lagged terms in the vector autoregression 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). We transfer the logarithm of future volatility (FV) and the TVIX. Values in the table and the parentheses are $F$-test statistics and $p$-values, respectively. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

To determine whether the sentiment indicators could serve as useful forecasting variables, we examine whether they could enhance the forecasting of future volatility in the TAIEX returns. The examination is expressed as follows:

$$\mathrm{FV}_t = \beta_0 + \beta_1 \mathrm{FV}_{t-1} + \beta_2 \mathrm{HAR\text{-}RV}_{t-1} + \beta_3 \left|\mathrm{R}_{t-1}\right| + \gamma \mathrm{SI}_{t-1} + \varepsilon_t, \tag{3}$$

where $\mathrm{SI}_{t-1}$ represents the sentiment indicators considering the level and first differences that have been determined as having the significant causal effects.

Panel B in Table 4 summarizes the explanatory power of sentiment when the level and changes in TPCO and TURN are incorporated into the MHV. We find that a positive significant increment is discernible in the adjusted $R^2$ of the models incorporating +TPCO, +TURN, and +ΔTURN. As the TPCO or TURN rises and the market overreacts more, there is a corresponding rise in future volatility.

### Volatility Forecasting and the Evaluation of Forecasting Performance

The volatility forecasting is constructed based on settlement days occurring once a month; thus there were a total of 59 settlement days during the period under examination from January 2, 2003, to November 22, 2007. According to prior related studies, no certain rule currently exists for selection of the in-sample and out-of-sample ranges for volatility forecasting. We therefore apply the dynamic in-sample ranges, which can be set as 30, 60, 90, and 120 days. The parameters obtained within the data from the in-sample period are inserted into the relevant forecasting formulae. The volatility forecasts are then obtained for the subsequent $h$ trading days ahead ($h$ = 5, 10, 15, and 20).

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

**Panel A: Explanatory power of alternative volatility measures**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| C | 0.0776*** | 0.0474* | 0.0815*** | 0.0734*** | 0.0541* | 0.0511* | 0.0772*** | 0.055* |
| | (3.7734) | (1.6968) | (3.8895) | (3.4992) | (1.8854) | (1.8161) | (3.5934) | (1.9117) |
| $\lvert R_{t-1} \rvert$ | | | 0.0047* | | 0.004 | | 0.0031 | 0.0031 |
| | | | (1.7676) | | (1.4744) | | (1.0208) | (1.0119) |
| $HAR\text{-}RV_{t-1}$ | | 0.0205 | | | 0.0182 | 0.0159 | | 0.0159 |
| | | (1.51) | | | (1.3133) | (1.1147) | | (1.1081) |
| $HL_{t-1}$ | | | | 0.0091 | | 0.0065 | 0.0064 | 0.0038 |
| | | | | (1.4579) | | (0.9805) | (0.8832) | (0.4992) |
| $FV_{t-1}$ | 0.9723*** | 0.9627*** | 0.9695*** | 0.9672*** | 0.9614*** | 0.9612*** | 0.9667*** | 0.9608*** |
| | (130.0486) | (92.0364) | (125.5027) | (115.3562) | (91.7347) | (91.2928) | (114.443) | (91.0122) |
| Adj. $R^2$ (percent) | 94.4343 | 94.4425 | 94.4399 | 94.4406 | 94.4452 | 94.4428 | 94.4397 | 94.4420 |
| IR Adj. $R^2$ (percent) | | 0.0082 | 0.0057 | 0.0063 | 0.0109 | 0.0085 | 0.0054 | 0.0077 |

**Panel B: Explanatory power of sentiment**

| | (1) +TPCO | (2) +TURN | (3) +ΔTPCO | (4) +ΔTURN |
|---|---|---|---|---|
| C | 0.0082 | 0.0602** | 0.0542* | 0.05* |
| | (0.2553) | (2.071) | (1.8901) | (1.7147) |
| $TPCO_{t-1}$ | 0.0386*** | | | |
| | (3.5044) | | | |

| | | | | |
|---|---|---|---|---|
| $TURN_{t-1}$ | | 0.0392*** | | |
| | | (4.5626) | | |
| $\Delta TPCO_{t-1}$ | | | −0.0028 | |
| | | | (−0.1101) | |
| $\Delta TURN_{t-1}$ | | | | 0.0158 |
| | | | | (1.117) |
| $\|R_{t-1}\|$ | 0.0048* | 0.0025 | 0.004 | 0.003 |
| | (1.7345) | (0.973) | (1.4745) | (1.0357) |
| $HAR\text{-}RV_{t-1}$ | 0.0232* | 0.0149 | 0.0182 | 0.0198 |
| | (1.7149) | (1.1036) | (1.3151) | (1.413) |
| $FV_{t-1}$ | 0.9595*** | 0.9515*** | 0.9614*** | 0.9616*** |
| | (97.6506) | (101.1627) | (92.0716) | (91.7629) |
| Adj. $R^2$ (percent) | 94.5012 | 94.5519 | 94.4406 | 94.4454 |
| IR Adj. $R^2$ (percent) | 0.0560 | 0.1067 | −0.0046 | 0.0002 |
| *F*-test | 13.2944 | 24.6663 | 0.0086 | 1.0441 |

*Notes:* This table shows the incremental contribution of investor sentiment to future volatility (FV). Panel A presents the explanatory power of alternative volatility measures. Panel B shows the explanatory power of sentiment incorporating the benchmark model, model (5) in Panel A, producing the highest incremental adjusted $R^2$ of 0.0109 percent. The FV is calculated for the next 15 days on day *t*. Investor sentiment includes the put-call open interest ratio (TPCO) and the market turnover ratio (TURN), which has significant causal effects as shown in Table 3. +TPCO and +TURN represent the volatility forecasting, respectively, including the sentiment level for TPCO and TURN based on the multiple historical volatility model (MHV), which incorporates the first lag of future volatility, the heterogeneous autoregressive model of the realized volatility (HAR-RV), and the absolute return ($|R|$). Two volatility measures are regarded as the control variables, namely, the heterogeneous autoregressive model of the realized volatility (HAR-RV) and the absolute return (|R|). We transfer the logarithm of future volatility (FV), historical volatility (HV), HAR-RV, and the TVIX. IR Adj. $R^2$ in Panel B is the incremental adjusted $R^2$ relative to the benchmark model, model (5) in Panel A. The forecasting model incorporating sentiment levels or changes may refer to models (1) to (4) in Panel B individually. The values in the parentheses are the *t*-test statistics. The *F*-test examines the incremental explanatory power of sentiment levels or changes. *, **, and *** symbols denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

The predictive accuracy of different models is statistically tested to compare the forecast errors of different models by using Diebold and Mariano's sign test (Diebold and Mariano 1995; Muñoz et al. 2007). Let $\hat{\sigma}_t^i$ and $\hat{\sigma}_t^j$ be two sets of forecasts for the volatility $\sigma_t$ from models *i* and *j*, respectively. The loss differential is calculated by using the loss function defined in Equations (4) to (6) as

$$d = \left( \left(\hat{\sigma}_t\right)^2 - \left(\hat{\sigma}_t^i\right)^2 \right)^2 - \left( \left(\hat{\sigma}_t\right)^2 - \left(\hat{\sigma}_t^j\right)^2 \right)^2. \tag{4}$$

The loss differential is simply the difference between the two forecast errors obtained from models *i* and *j*, respectively. The hypothesis test could be $H_0 : E(d_t) = 0$ and $H_1 : E(d_t) \neq 0$. Assuming that $d_t$ ~ independent and identically distributed, then the test statistic is

$$S = \sum_{t=1}^{N} I_+\left(d_t\right), \text{ where } I_+\left(d_t\right) + \begin{cases} 1 & \text{if } d_t > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

Following Diebold and Mariano (1995), the large sample Studentized version of an exact finite sample test, the sign test, is asymptotically normal:

$$S_a = \frac{\mathrm{S} - 0.5N}{\sqrt{0.25N}} \sim N\left(0,1\right). \tag{6}$$

The comparisons of the loss differentials between forecasting models are shown in Table 5. The forecasting models are not equivalent with regard to forecasting performance when the values in Panel B in Table 4 are significant. We calculate the "percentage of the significance" as a percentage of the number of times the comparison is significant divided by the number of times that a comparison is made. The percentage of the significance at the 10 percent level for the model comparison between MHV versus +TPCO (MHV versus +TURN) is 62.5 percent (50 percent). However, it is relatively low in the case of the forecasting model incorporating sentiment changes.

Once the estimated models are proved to be statistically different, we then select the model that best fits our series. We use the mean absolute percentage error (MAPE) to measure the forecasting error for different competitive models (Poon and Granger 2003). The MAPE, which is scale independent, is defined as follows:

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| 1 - \widehat{\mathrm{FV}}_{i,M} \,/\, \mathrm{FV}_i \right|, \tag{7}$$

where $\widehat{\mathrm{FM}}_{i,M}$ is the predicted value based on the volatility forecasting model, *M*; $\mathrm{FV}_i$ is the realized future volatility for month *i*; and *n* is the number of forecasts (in our case *n* equals 59, the number of settlement days).

In addition to the point forecast–oriented error metrics, such as the MAPE, we compare the ranking of models based on the directional accuracy of the alternative volatility forecasting models by using regression and logit analysis, simplified as DA and DALogit. The directional accuracy (DA) is measured as a percentage of the number of times the correct direction of the volatility is forecast based on the regression analysis divided by the number of times that a forecast is made (Maris et al. 2007). DALogit is the directional accuracy based on the logit analysis.

The evaluation of the forecasting performance shown in Table 6 covers +TPCO and +TURN, which are found to have the significant causal effects of sentiment and to further indicate the significant different forecasting performance based on the sign test. The ranking of the models in Table 6 is based on the average of the 16 ranking values using the forecasting evaluation between +TPCO and +TURN. When we take into account the

**Table 5. Diebold and Mariano's sign test**

| | Incorporating sentiment levels | | Incorporating sentiment changes | |
|---|---|---|---|---|
| ISP | MHV versus +TPCO | MHV versus +TURN | MHV versus +ΔTPCO | MHV versus +ΔTURN |
| 5-day-ahead forecasting | | | | |
| 30 | –1.9528* | –2.9943*** | 0.1302 | –0.1302 |
| 60 | –1.6925* | –1.6925* | –1.6925* | 0.3906 |
| 90 | –2.734*** | –1.1717 | –0.6509 | 0.9113 |
| 120 | –1.1717 | 0.6509 | –0.9113 | 0.6509 |
| 10-day-ahead forecasting | | | | |
| 30 | –2.734*** | –1.4321 | –0.1302 | 0.9113 |
| 60 | –1.6925* | –3.7755*** | –0.3906 | 0.3906 |
| 90 | –0.6509 | –2.2132** | 0.1302 | 0.3906 |
| 120 | 0.3906 | –1.6925* | –0.3906 | –0.3906 |
| 15-day-ahead forecasting | | | | |
| 30 | –2.734*** | –1.6925* | 0.9113 | –0.9113 |
| 60 | –2.734*** | –0.9113 | –0.3906 | 0.3906 |
| 90 | –0.6509 | –1.4321 | 0.1302 | 1.1717 |
| 120 | 0.3906 | –1.1717 | –0.9113 | 0.1302 |
| 20-day-ahead forecasting | | | | |
| 30 | –2.4736** | –0.6509 | –2.2132** | 0.3906 |
| 60 | –3.7755*** | –1.9528* | –1.4321 | –1.1717 |
| 90 | –2.734*** | –0.9113 | –0.1302 | –2.2132** |
| 120 | –1.4321 | –1.6925* | 0.1302 | –1.4321 |
| Significance | | | | |
| 1 percent | 37.50 | 12.50 | 0.00 | 0.00 |
| 5 percent | 43.75 | 18.75 | 6.25 | 6.25 |
| 10 percent | 62.50 | 50.00 | 12.50 | 6.25 |

*Notes:* This table presents the comparison of forecasting performance calculated from Equation (4), and finally the sign test is performed in Equation (6). +TPCO and +TURN represent the volatility forecasting based on the multiple historical volatility model (MHV), which incorporates the first lag of future volatility, the heterogeneous autoregressive model of the realized volatility (HAR-RV), and the absolute return ($|R|$). +ΔTPCO and +ΔTURN represent the volatility forecasting, respectively, including the sentiment changes for TPCO and TURN based on the MHV. "MHV versus +TPCO" is the comparison of forecast errors obtained from MHV and +TPCO. The other comparisons are obtained from MHV and the volatility forecasting model incorporating the sentiment level or sentiment changes. 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 values in the table are the $Z$-values. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

ranking of the MAPE and DALogit statistics, the performance of the forecasting model incorporating TURN appears to be superior to the performance of the forecasting model incorporating TPCO.

## Options Trading Strategies

The options trading strategies proposed in the present study are constructed by a long (short) straddle $h$ days prior to the final settlement day if the direction of the predicted change in future volatility is upward (downward) compared with the historical volatility

**Table 6. Ranking of models**

| | MAPE | DA | DALogit |
|---|---|---|---|
| +TPCO | 1.5625 | 1.25 | 1.5 |
| +TURN | 1.4375 | 1.5 | 1.4375 |

*Notes:* +TPCO and +TURN represent the volatility forecasting based on the multiple historical volatility model (MHV) and the sentiment proxies for TPCO and TURN, respectively. MAPE is the forecast evaluation of volatility models based on the mean absolute percentage error. The directional accuracy (DA) is measured as a percentage of the number of times the correct direction of the volatility is forecast based on the regression analysis divided by the number of times that a forecast is made. DALogit is the directional accuracy based on the logit analysis. The ranking of models is the average ranking of the forecasting model by using parameters with different in-sample period and *h*-day-ahead forecasting. The in-sample period covers 30-, 60-, 90-, and 120-day periods, with *h* days representing 5, 10, 15, and 20 trading days, the periods between the option trading day and the final settlement day of the options contract.



calculated based on the last *h*-day index return, and then holding the option until the cash settlement. The transaction costs considered in the study include the transaction fees, transaction tax, and settlement tax.[12] If the trading strategies are based on a "short straddle," then the cost of capital is calculated as the transaction costs and the maximum margin requirement during the holding period;[13] conversely, if the trading strategies are based on a "long straddle," then the cost of capital is summed up by the transaction costs and the premiums.

We calculate the Sharpe ratio (Sharpe 1994) for performance comparison, because reporting the returns from options trading does not provide us with any information on the associated risks. The Sharpe ratio is a measure of the excess return per unit of risk in an investment asset or a trading strategy. The ratio is defined as follows:

$$S_M = \frac{R_M - R_f}{\sigma_M} = \frac{E\left[R_{i,M} - R_f\right]}{\sqrt{\operatorname{var}\left[R_{i,M} - R_f\right]}}, \tag{8}$$

where $R_{i,M}$ represents the monthly returns of the different forecasting model $M$ in month $i$, the profits/losses divided by the cost of capital; $R_f$ is the risk-free rate; $E[R_{i,M} - R_f]$ is the expected value of the excess returns; and $\sigma_M$ is the standard deviation.

The simulated trade results are presented in Table 7, with Panel A (Panel B) presenting the Sharpe ratios for the long (short) straddle traded *h*-days prior to the final settlement day of the options based on different volatility forecasting models. The benchmark trading performance is a long (short) straddle with no forecasting support. The comparisons of the average Sharpe ratios between MHV and alternative forecasting models of Model (2) to Model (5) in Panel A in Table 7 reveal that the trading strategies based on +TPCO, +TURN, and +ΔTURN are found to outperform the MHV model, which is consistent with the regression-based forecast efficiency test found in Table 4.

From the trading performance examined here, we suggest that the long (short) straddle strategy 15 days prior to the final settlement day based on +TURN (the forecasting model based on the MHV model incorporating the levels of market turnover) with a 30-day in-sample period provides a Sharpe ratio of 36.7 percent (18.42 percent). This would therefore seem to suggest that investors could adopt a long or short straddle based on

**Table 7. Sharpe ratios of options trading strategy (in percent)**

| | | Incorporating sentiment levels | | Incorporating sentiment changes | | |
|---|---|---|---|---|---|---|
| ISP | (1) MHV | (2) +TPCO | (3) +TURN | (4) +ΔTPCO | (5) +ΔTURN | Benchmark |
| Panel A: Performance of long straddle | | | | | | |
| 5-day-ahead forecasting | | | | | | |
| 30 | 1.31 | 0.84 | 11.03 | –0.50 | 3.03 | 6.02 |
| 60 | 1.02 | 0.85 | –3.08 | 5.97 | 4.48 | |
| 90 | 1.88 | 2.27 | 4.72 | 5.33 | 1.36 | |
| 120 | 11.07 | 11.07 | 9.44 | 6.71 | 5.93 | |
| 10-day-ahead forecasting | | | | | | |
| 30 | –7.81 | –3.31 | 3.13 | –7.81 | –3.26 | –2.15 |
| 60 | –0.74 | –0.33 | 6.04 | –0.74 | –1.52 | |
| 90 | –0.33 | –2.73 | 2.70 | –0.33 | –0.33 | |
| 120 | –0.33 | –0.33 | 2.70 | –0.33 | –1.10 | |
| 15-day-ahead forecasting | | | | | | |
| 30 | 29.82 | 27.85 | **36.70** | 33.10 | 31.19 | 9.70 |
| 60 | 27.46 | 27.46 | 31.49 | 27.46 | 27.46 | |
| 90 | 27.46 | 31.19 | 27.46 | 27.46 | 27.46 | |
| 120 | 31.19 | 31.19 | 31.19 | 31.19 | 31.19 | |
| 20-day-ahead forecasting | | | | | | |
| 30 | 21.24 | 22.60 | 14.96 | 21.24 | 19.11 | 5.11 |
| 60 | 17.39 | 18.00 | 21.56 | 14.30 | 17.39 | |
| 90 | 17.39 | 19.11 | 18.00 | 14.30 | 17.39 | |
| 120 | 17.39 | 18.00 | 17.39 | 17.39 | 17.39 | |
| Average | 12.21 | 12.73 | 14.71 | 12.17 | 12.32 | 4.67 |

*(continues)*

**Table 7. Continued**

| | | Incorporating sentiment levels | | Incorporating sentiment changes | | |
|---|---|---|---|---|---|---|
| **ISP** | **(1) MHV** | **(2) +TPCO** | **(3) +TURN** | **(4) +ΔTPCO** | **(5) +ΔTURN** | **Benchmark** |
| Panel B: Performance of short straddle | | | | | | |
| 5-day-ahead forecasting | | | | | | |
| 30 | −23.38 | −24.26 | −6.94 | −27.01 | −20.11 | −16.36 |
| 60 | −24.03 | −24.47 | −31.36 | −16.39 | −17.88 | |
| 90 | −22.32 | −21.59 | −18.92 | −16.12 | −23.20 | |
| 120 | −6.33 | −6.33 | −9.69 | −14.04 | −15.45 | |
| 10-day-ahead forecasting | | | | | | |
| 30 | −12.05 | −6.57 | 0.22 | −12.05 | −6.09 | −5.29 |
| 60 | −3.89 | −3.08 | 5.28 | −3.89 | −4.93 | |
| 90 | −3.08 | −6.75 | 1.08 | −3.08 | −3.08 | |
| 120 | −3.08 | −3.08 | 1.08 | −3.08 | −4.14 | |
| 15-day-ahead forecasting | | | | | | |
| 30 | 6.47 | 8.08 | **18.42** | 14.68 | 7.27 | −18.12 |
| 60 | 4.01 | 4.01 | 7.51 | 4.01 | 4.01 | |
| 90 | 4.01 | 7.27 | 4.01 | 4.01 | 4.01 | |
| 120 | 7.27 | 7.27 | 7.27 | 7.27 | 7.27 | |
| 20-day-ahead forecasting | | | | | | |
| 30 | 6.07 | 7.95 | −2.91 | 6.07 | 2.43 | −11.70 |
| 60 | 0.84 | 0.87 | 6.19 | −3.16 | 0.84 | |
| 90 | 0.84 | 2.43 | 0.87 | −3.16 | 0.84 | |
| 120 | 0.84 | 0.87 | 0.84 | 0.84 | 0.84 | |
| Average | −4.24 | −3.59 | −1.07 | −4.07 | −4.21 | −12.87 |

*Notes:* This table presents the Sharpe ratios of the options trading strategy for options traded before the final settlement day based on different volatility forecasting models. Panel A (Panel B) summarizes the Sharpe ratios for a long (short) straddle referring to Equation (8). Model (1) in Table 7 is the benchmark volatility forecasting model based on heterogeneous autoregressive model of the realized volatility (HAR-RV) and the absolute return (|R|) and is simplified as MHV. Model (2) to Model (3) (Model (4) to Model (5)) are volatility forecasting models incorporating 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 are long or short strategies that produce the best Sharpe ratios based on MHV incorporating investor sentiment.

directional volatility forecasting with the incorporation of information content based on investor sentiment, particularly the market turnover.

As a check for robustness, we simulate the performance of a long or short straddle while also taking into consideration the predicted magnitude of the directional volatility forecast. We divide the absolute positive and negative predicted magnitudes into three regimes, the top (30 percent), median (40 percent), and bottom (30 percent) regimes, and find that the profits/losses in the higher regime of the magnitude of absolute positive (negative) predicted volatility is not always superior to that in the lower regime. These simulations therefore reveal that trading performance may not necessarily be superior when the predicted magnitude is taken into consideration.

## Conclusions

The information content of sentiment may be of considerable use in forecasting volatility; however, an ex ante understanding of the precise form in which sentiment can affect or predict volatility remains elusive. In this paper we refer to the literature for the construction of the potential sentiment indicators for the empirical analysis. We then examine the predictive ability of sentiment on volatility, compare the forecasting performance of the comparative models, and finally propose options trading strategies based on volatility forecasting.

From our empirical results, trading performance appears to be superior to its non-sentiment adversarial counterparts that incorporate the HAR-RV and absolute return. A long (short) straddle trading strategy, based on a positive (negative) change in volatility forecasting, and incorporating the sentiment level within the turnover ratio, achieves the best Sharpe ratios.

Our empirical findings are in line with the noise trading theory that causality runs from sentiment to market behavior. Our results also provide support for the view that investor sentiment should be assigned a prominent role in the construction of volatility forecasting models.

## Notes

1. Examples include Baker and Wurgler (2006, 2007), Brown and Cliff (2004), Clarke and Statman (1998), De Long et al. (1990), Fisher and Statman (2000), Han (2008), Simon and Wiggins (2001), and Solt and Statman (1988).

2. See Banerjee et al. (2007), Brown (1999), Lee et al. (2002), Low (2004), Verma and Verma (2007), and Wang et al. (2006).

3. Following Hull (2006), we make the assumption of a total of 252 trading days in each year.

4. By taking into consideration the price limits in the Taiwanese stock market, 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 Taiwanese stock market are –7 percent and +7 percent of the closing price on the previous day; thus, the maximum price variation on day $t$ would be 14 percent based on the previous day's closing price.

5. See, among others, Engle and Gallo (2006) and Wang et al. (2006). The latest observations available before the five-minute intervals from 09:00 until 13:30 are used to calculate the five-minute returns. The 54 squared intraday five-minute returns and the previous squared overnight returns are summed to construct the daily realized volatility.

6. Refer to Baker and Stein (2004) and Baker and Wurgler (2007).

7. In the construction of the TVIX, the interest 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, and the rollover rule is revised to one day prior to expiration in light of Taiwan's market structure.

8. The construction of the CBOE's new VIX incorporates information on 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. Interested readers should see the white paper published by the CBOE in 2003 for comprehensive details of the construction of the index, available at www.cboe.com/micro/vix/vixwhite.pdf.

9. We transfer the logarithm of volatility measures, essentially because the log form is much closer to the normal distribution than the original variable (Andersen et al. 2001).

10. The volatility measures and sentiment time series appear to be stationary, and all reject the unit root null hypothesis at the 1 percent level. The unit root null hypothesis is based on the augmented Dickey-Fuller test, with lags varying between 1 and 15.

11. The lag lengths of the future volatility and sentiment indices are determined parsimoniously prior to performing the test under the Akaike information criterion (AIC) and the Schwarz criterion (SC). The optimal number of lags, which is dependent on the pair of variables used in the causality tests, varies between 1 and 3 for the sentiment levels, and between 1 and 6 for changes in sentiment.

12. The transaction fee is calculated as NT$50 per contract. The transaction tax per contract is 0.1 percent of the contract value, which is multiplied by the premium and multiplier. The settlement tax is 0.01 percent 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. For more detailed information, see the Taiwan Futures Exchange (TAIFEX) Web site at www.taifex.com.tw.

13. The margin requirements for the TAIEX options (TXOs) are summarized as follows. The margin for a short call or put = 100 percent of the option market value + max (A – out-of-the-money amount, B). Out-of-the-money amount of call = max ((exercise price – underlying index price) × 50, 0). Out-of-the-money amount of put = max ((underlying index price – exercise price) × 50, 0). A and B are fixed amounts as announced by the TAIFEX. The margin for a "straddle" or "strangle" position = max (margin requirement for call, margin requirement for put) + option market value of the call or put (depending on which margin requirement is less).



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