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Do investor sentiment, weather and catastrophe effects improve hedging performance? Evidence from the Taiwan options market

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ABSTRACT

This study examines the usefulness of incorporating investor sentiment, weather, and catastrophe effects into the benchmark volatility model for an effective hedging strategy in the Taiwan options market. The empirical results indicate that investor sentiment, as measured by the option volatility index (*VIX*) and put-call open interest ratio (*PCO*), and the catastrophic factors of earthquakes (*EQ*) can help explain realized volatility and that the *PCO* has the best predictive ability. Incorporating investor sentiment and weather effects improves the hedging performance of options. *VIX* and changes in cloud cover (ΔCC) have significant improvement level for hedging performance, the highest of which are 0.44% and 5.36%, respectively.

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1. Introduction

Traditional finance theory holds that the stock market is fundamentally rational and, thus, it reflects only economic information relevant to asset pricing (Chang et al., 2008). However, recently, many researchers have found that psychological factors appear to exert significant influence on the trading decisions of investors in financial markets (e.g., Baker and Wurgler, 2007). Moreover, some of the literature demonstrates weather effects on stock returns (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; among many others). Volatility estimation and forecasting are very essential factors of hedging, which is currently considered to be one of the most important investment strategies. In this study, we aim to bridge the gap between options hedging and the information content of investor behavior, weather changes, and catastrophic events. By proposing a volatility model and recruiting the factors of investor sentiment, weather, and catastrophes, we measure the performance of the options hedging strategies of a first-order moving average (MA(1)-type) process in an options model.

In addition to the issue of the optimal combination of multivariate volatility measures[1], other topics examining possible indicators could improve the predictive power of forecasting and its applications. A growing body of literature presents evidence of irrational behavior in stock and options markets. For example, De Long et al. (1990) attempt to substantiate the proposition that noise traders' risks indexed by sentiment influence either the mean or the variance of asset returns. Investor sentiment measurements, such as the option volatility index (*VIX*), market turnover (*TO*), and the put-call open interest ratio (*PCO*), are therefore

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[1] Blair et al. (2001) classify volatility models into the following four categories: historical volatility models (e.g., Bossaerts and Hillion, 1997), the GARCH family (e.g., Yung and Zhang, 2003), the options implied standard deviation model (e.g., Yung and Zhang, 2003) and the stochastic volatility model (e.g., Bakshi et al., 1997).

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proposed to be indicators that could enhance the incremental explanation of asset returns and realized volatility (e.g., Bollen and Whaley, 2004; Sheu and Wei, 2011).

Psychological evidence indicates that numerous factors affect human mood, including the weather, which exerts an inescapable and constant influence (e.g., Huibers et al., 2010). Many finance studies argue that when people feel good as a result of good weather, they hold optimistic opinions of their future prospects (Hirshleifer, 2001). Weather not only affects our daily lives and moods but also decisively influences the trading decisions of investors within the financial markets and four-fifths of global economic activity (Yuan et al., 2006). Some of the literature has noted that market volatility is affected by weather factors, such as cloud cover (*CC*), temperature (*TEMP*) and humidity (*RH*) (e.g., Chang et al., 2008; Symeonidis et al., 2010). Hence, the relationships between weather, mood, and the decision-making processes of investors have been the subject of extensive study.

Additionally, catastrophic events, such as earthquakes, may create huge losses for exposed firms, affecting not only returns but also volatility. Most studies investigate the impact of catastrophes on stock returns (e.g., Shelor et al., 1990; Yamori and Kobayashi, 1999; Carter and Simkins, 2004) and on the volatility (e.g., Thomann, 2013) of the real estate and insurance industries in the US or Japan. Thomann (2013) investigates the impact of natural catastrophes and the September 11th attacks (hereafter, "9-11") on the volatility of US insurance stocks and finds that natural catastrophes increase their volatility.

The motivation to study options hedging performance by employing Taiwan Stock Exchange Capitalization Weighted Stock Index (hereafter, TAIEX) options is enhanced by several characteristics of Taiwan's financial market. First, Taiwan's stock market exhibits a high turnover rate and a high participation rate by individual investors, and several limitations exist on trading activity, including a 7% daily limit on price movement and constraints on short selling.[2] These characteristics are markedly different from those of the major financial markets in the US and Europe. Second, most options and warrants in Taiwan are sold to and traded by individual investors (Chung et al., 2014); individual investors are also more easily affected by market performance than institutional investors and, therefore, are more likely to show investor sentiment (Hsu et al., 2005). These two characteristics imply that investor sentiment and psychological bias may substantially affect trading behavior on the Taiwan stock market (Hsiao et al., 2011). Although Chang et al. (2008) find that the trading activities of individual investors in the Taiwan options market convey no information content, investor sentiment and psychological bias might substantially affect the option volatility and the hedging performance of the Taiwan options market. Last, but not least, due to constraints on short selling in Taiwan, the Taiwan options market provides investors with an important channel for transferring and hedging stock market risk. Thus, observations from the Taiwan options market can provide clear evidence of investor sentiment, weather and catastrophe effects on hedging performance.

Most existing studies examine the relationship between investor sentiment (weather and catastrophe) and stock markets; however, few studies investigate the relationships between investor sentiment, weather, catastrophe and realized volatility and their application to options hedging decisions. The motivation for our study and the questions we set out to answer are as follows: (i) several studies find that investor sentiment, weather, or catastrophes affect volatility (e.g., Saunders, 1993; Bollen and Whaley, 2004; Sheu and Wei, 2011), but which psychological factors more significantly impact the forecasting ability of volatility? (ii) Many studies (e.g., Chang et al., 2008; Symeonidis et al., 2010) use *TEMP*, *RH* and *CC* as weather indicators, but could catastrophic factors such as typhoons and earthquakes, the major natural hazards in Taiwan, also affect the trading activities of investors? In this study, to analyze the effects of a broader range of weather variables on the stock market, we construct multivariate regressions in which realized volatility is linked to the lagged daily historical volatility. This setting implies capturing the autocorrelation of volatility, i.e., the GARCH effect; (iii) Prior studies examine primarily the impact of investor sentiment (weather conditions) on stock returns, and few simultaneously investigate the relationship between investor sentiment, weather, catastrophe, and realized volatility and options hedging decisions. In the present study, we examine the impact of investor sentiment, weather indicators, and catastrophe on the volatility of TAIEX returns and assess the influence of these factors on the performance of TAIEX options hedging strategies, including the delta hedge, delta-gamma hedge and delta-vega hedge methods.

We consider a general option-pricing framework where asset returns are not independent. To capture the autocorrelation of financial asset returns, many classical studies such as Bollerslev (1987) suggest extracting the autocorrelation from the asset returns' first moment in the form of a first-order moving average process (MA(1) process). Liao and Chen (2006) derive the closed-form formula for an MA(Ahn et al., 2007) option on an asset and show that the first-order MA parameter is significant for option values, even when the autocorrelation between asset returns is weak. Hence, we measure the performance of options hedging strategies based on Liao and Chen (2006)'s model.

Our empirical and analytic results support our inclusion of the investor sentiment effect (*VIX* and *PCO*), the weather effect (ΔCC and *RH*), and the catastrophe effect (*EQ*) in the volatility model and options hedging strategies. The best improvement level of the hedging performance in the volatility model was shown during the 2008 financial crisis.

The remainder of this paper is organized as follows. Section 2 reviews the literature and develops our hypothesis. Section 3 presents the research methodology adopted in this study. Section 4 provides a description of the data and the empirical results of the investor sentiment, weather and catastrophe effects on the different volatility models. This section further discusses options hedging performance and investigates the impact of investor sentiment variables and weather on performance. Section 5 provides conclusions to the study.

[2] The Taiwan Stock Exchange has relaxed limits on daily price fluctuations from 7 to 10% since June 1, 2015.

2. Literature and hypothesis

2.1. Investor sentiment

Accompanying the popular viewpoint of behavioral finance, a great number of studies focus on the relationship and the information conveyed between market returns and sentiment (e.g., Baker and Wurgler, 2007; Han, 2008). Moreover, much of the literature, such as Olsen (1998) and Hsu et al. (2005), indicates that investor sentiment will influence market volatility.

Given the lack of surveys of individual investors' decision-making, it is convenient and efficient to employ proxies of investor sentiment computed with timely market data. The conventional measures are summarized as follows: Mayhew and Stivers (2003) employ trading volume; Bollen and Whaley (2004) investigate the put-call open interest ratio (*PCO*); and Sheu and Wei (2011) utilize the ARMS index, market turnover (*TO*), option volatility index (*VIX*), put-call trading volume ratio (*PCV*), and *PCO*.

2.2. Weather effects

Some of the literature further notes that market returns are affected not only by sentiment indicators but also by the weather. The literature empirically finds a so-called 'sunshine effect', as measured by cloud cover (*CC*), which has a significant negative correlation with index and market returns (see Saunders, 1993; Hirshleifer and Shumway, 2003; Yuan et al., 2006; among others). Other studies extend the literature by using additional weather variables: Dowling and Lucey (2008) examine weather effects using *CC*, rain, *RH* and geomagnetic storms; Chang et al. (2006) include *TEMP*, *CC* and *RH*; Theissen (2007) employs *CC*, sunshine, rain and *TEMP*; and Kang et al. (2010) utilize *TEMP* and *RH*. Nevertheless, not all researchers find that weather has a significant impact on stock markets. Goetzmann and Zhu (2005) find no clear relationship between trading by individual investors and local weather after considering liquidity; *CC* is found to have only a limited impact on the stock markets. Kamstra et al. (2003) also report that *CC* and precipitation did not affect NYSE stock returns. Furthermore, based upon the stock indices of 37 countries, Dowling and Lucey (2008) indicate only a weak relationship between *TEMP* and equity returns.

Rather than concentrating on market returns, a recent strand of research has examined the effect of weather on volatility. This particular effect is of great academic and practical interest because unobservable volatility underlies a variety of financial applications in portfolio theory, derivatives pricing, risk management, etc. Kliger and Levy (2003), using S&P 500 index options data, find that a bad mood, proxied by *CC* and precipitation, leads investors to place higher-than-usual probabilities on adverse events. Chang et al. (2008) also find that *CC* and *TEMP* in New York City have a significant positive effect on the intraday volatility of NYSE firms. Kaplanski and Levy (2010) find that *TEMP* is positively related only to the 'perceived' volatility, proxied by the VIX, and not to the 'actual' historical volatility measure. Symeonidis et al. (2010) investigate the relationship between the stock market volatility, which is historical, the implied, realized volatility and the weather, namely *CC*, *TEMP* and precipitation. The results indicate that *CC* is negatively associated with various measures of stock market volatility. Lu and Chou (2012) find that in an order-driven market, environmental impacts on sentiment are likely to affect trading activities but not returns. These authors find that *CC* (*RH*) in China has a significant negative (positive) effect on volatility, while *TEMP* does not have a significant positive effect. Wang et al. (2012) focus on the Taiwan market and conclude that sunshine hours and *TEMP* insignificantly influence stock returns and have a significant impact on stock volatility.

Based on the psychological evidence for close relationships between weather and mood, individuals tend to behave irrationally in bad weather, demonstrating psychological bias in decision-making. Because no consensus on the relationship between weather and market volatility has been reached, we connect the psychological inference between weather, mood, and investor sentiment and present below the first hypothesis to test the weather effect on market volatility.

Hypothesis 1. There exists a positive (negative) relationship between the volatility of underlying options and weather factors.

2.3. Catastrophe effects

The finance and insurance literature leaves no doubt that man-made and natural catastrophes are of key importance to the property–casualty insurance market and the real estate industry. The catastrophic events most widely considered by researchers when evaluating impacts on stock prices are earthquakes, hurricanes, and 9-11. Shelor et al. (1990) examine the impact of the October 17, 1989, California earthquake on the stock value of firms in the real estate industry. Their findings indicate that there were statistically significant negative stock returns among the firms operating in the San Francisco area. Shelor et al. (1992) find that the Loma Prieta earthquake, which occurred in 1989, had immediate significant and positive effects on the returns of insurance stocks. In the same way, Yamori and Kobayashi (1999) initially attempt to investigate a non-U.S. stock market reaction to a large earthquake and then examined the impact of the 1995 Hanshin-Awaji Earthquake on Japanese insurers' value. They find a significant negative stock price reaction, which contradicts the results for U.S. earthquakes. Studying the impact of Hurricane Andrew, which occurred in 1992, Lamb (1995) finds that property–casualty insurance stocks experienced significant negative effects on the day of the event and the following day. Carter and Simkins (2004) investigate the stock price reaction to 9-

11, and the findings indicate that there were significant negative abnormal returns for the airline stocks studied and smaller negative returns for airfreight firms. In other words, the market reaction was not the same for all airlines.

The other concerns expressed in the literature are of relevance to catastrophic events and stock market risk. Cummins and Lewis (2003) provide evidence that the volatility of insurance stocks increased after Hurricane Andrew and 9-11. Drakos (2004) shows that 9-11 shifted the beta of airline stocks. Furthermore, Patton and Verardo (2012) show that the release of important information leads to significant increases in individual stock betas. Thomann (2013) investigates the impact of the 10 most expensive insured natural catastrophes and the 9-11 attacks on the volatility of US insurance stocks. The results demonstrate that 9-11 shifted the beta of insurance stocks and that almost all natural catastrophes significantly increased the volatility of US insurance stocks, except for Hurricane Hugo in 1989 and the Northridge earthquake in 1994, the latter result conforming to the findings of Cummins and Lewis (2003). Further, these volatility peaks may appear a number of days after a catastrophe. Some studies also demonstrate that a catastrophe can influence the trading activities of investors within financial markets. For example, Blau et al. (2008) show that short selling increased 2 days after the landfall of Hurricane Katrina and that short-selling activity was much more significant around Hurricane Rita.

Based on the literature demonstrating that catastrophes have a significant impact on the stock market, catastrophes can increase the risk of insurer failure for insurers but may provide growth opportunities for strong insurers. Consequently, we argue that catastrophes induce uncertainty and that these events change the probability distribution of stock market returns. Therefore, we present below the second hypothesis to test the catastrophe effect on market volatility.

Hypothesis 2. There exists a positive (negative) relationship between the volatility of underlying options and catastrophe factors.

While there is a large body of literature examining the impact of investor sentiment on stock prices and volatility, few studies investigate how option prices are affected by behavioral biases. Some researchers find evidence that arbitrage in options markets is limited and document obvious misreactions of market participants to information in the options market (see, e.g., Lakonishok et al. (2007) and Han (2008)). Han (2008) suggests that institutional investor sentiment is an important determinant of prices and volatility smile in S&P 500 options market and that the observed mispricing is sentiment-driven. Lemmon and Ni (2010) also suggest that sentiment impacts individual stock options rather than stock index options. In contrast to the conclusions by Han (2008) and Lemmon and Ni (2010); Coakley et al. (2014) find a significant relation between individual investor sentiment and risk-neutral skewness, as estimated from US value and growth stock index options. Szu and Yang (2015) find that the anticipation concerning the change in underlying asset prices of the TAIEX options market is influenced primarily by errors in individual investors' beliefs. The difference in the pre-crisis and crisis period risk-neutral skewness from TAIEX option prices is driven by the aggregate error in individual investors' beliefs. Hence, the empirical evidence of previous studies provided the foundations that investor sentiment can significantly affect option prices, volatility smile and options hedging behaviors.

In light of above-mentioned literature, few studies investigate the relationships between weather, catastrophes, and options hedging decisions. Because the payoffs of stock index option contracts depend on their underlying assets, we expect the option price and its hedging behavior to be affected by weather and catastrophes. Bassi et al. (2013) conduct a series of experiments and indicate that weather may affect financial markets and financial decision making by affecting individual risk tolerance through its effect on mood. The work of Bassi et al. (2013) provides the foundation that weather can significantly affect hedging behaviors. Moreover, using survey and disaggregated trade data, Goetzmann et al. (2015) show weather-based indicators of mood impact perceptions of mispricing and the trading decisions of institutional investors.

Furthermore, some studies indicate that catastrophe would influence the trading activity of option market. For instance, Poteshman (2006) shows an unusually high level of put buying before 9-11. Report of Bank of Japan (2011) also points out the volume of Nikkei 225 put options traded on the Osaka Securities Exchange also marked a record high of approximately 560 thousand contracts after the Great East Japan Earthquake occurred. Hewitt (2012) shows that option strategy will generate abnormal risk-adjusted returns in the post-hurricane period, due to the statistically significant inefficient U.S. market reaction to such events. Since the impacts of catastrophe on option market are significant, some literature concerning the option pricing models incorporate the catastrophe factor into the volatility of asset returns. For instance, Ahn et al. (2007) employ the jump diffusion model to describe the unexpected movements from catastrophic events such as 9-11 or Hurricane Katrina on the pricing of foreign currency options. Thus, it is necessary to incorporate these two factors into the volatility function of option prices. Hypothesis 3 therefore argues that incorporating the effects of investor sentiment, weather, and catastrophes can help predict realized volatility.

Hypothesis 3. Considering the effects of investor sentiment, weather, and catastrophes improves hedging performance.

3. Methodology

3.1. Volatility models

Two types of volatility models are employed in this study. The first type is *Realized volatility* (*RV*), which refers to Corrado and Miller (2005). The *RV* for the next *m* days on day *t* is calculated by the sample standard deviation of returns in the period from

day $t+1$ through $t+m$. The equation is expressed as

$$RV_t = \sqrt{\frac{252}{m-1}\sum_{j=1}^{m}\left(r_{t+j}-\bar{r}_{t,t+m}\right)^2}, \tag{3.1}$$

where m represents the days in the sample period, r_{t+i} is the TAIEX market returns on day $t+j$ and $\bar{r}_{t,t+m}$ is the mean of the TAIEX market returns during days $t+j$ to $t+m$. According to this parameter, m is set as 5, 10, 15 and 20 days.

The second type is *Historical volatility* (*HV*), first proposed by J.P Morgan (1996). The formula for *HV* is analogous to that of *RV*, but the sample period of calculation is different. *HV* employs previous sample prices to forecast the future volatility. In addition, Engle and Gallo (2006) consider absolute daily returns ($|R_t|$) and the daily high-low range (*HL*) to measure volatility. Therefore, we follow this practice and utilize these three variables in the benchmark volatility model. The equations are expressed as follows.

$$|R_t| = \left|\ln\left(\frac{S_t}{S_{t-1}}\right)\right|, \tag{3.2}$$

$$HL_t = \frac{H_t - L_t}{S_{t-1} \times 14\%}, \tag{3.3}$$

where $|R_t|$ represents the absolute daily returns at time t, HL_t represents the daily high-low range variation at time t, S_t represents the TAIEX closing price on day t, S_{t-1} represents the TAIEX closing price at time $t-1$, H_t is the highest TAIEX price on day t, and L_t is the lowest TAIEX price on day t. The daily price change limit in the Taiwan stock market is considered to be 14%, which is -7% and $+7\%$ of the previous day's closing price.

3.2. Variables of investor sentiment, weather, and catastrophe

Based on evidence from previous studies, this paper adopts four types of investor sentiment measures: the volatility index (*VIX*), the put-call trading volume ratio (*PCV*), the put-call open interest ratio (*PCO*), and the market turnover ratio (*TO*). It also adopts three variables for weather: temperature (*TEMP*), relative humidity (*RH*), and cloud cover (*CC*). In addition, this paper considers two kinds of catastrophe factors, typhoons (*TY*) and earthquakes (*EQ*).

The *VIX* was introduced by the Chicago Board Options Exchange (CBOE) in 1993. Olsen (1998) proposes that options-market-based implied volatility can cause expectations about future price changes and can also be deemed an indicator of sentiment. As fear increases, so does the *VIX* level, and thus, the *VIX* is commonly referred to as the "investor fear gauge". In this study, we employ the new version of *VIX* data provided by TAIFEX as an investor sentiment indicator. Moreover, we also employ the put-call ratio calculated by utilizing both trading volume and open interest as follows:

$$PCV = \frac{\text{Total trading volume of puts}}{\text{Total trading volume of calls}} \tag{3.4}$$

$$PCO = \frac{\text{Total open intrest of puts}}{\text{Total open interest of calls}}. \tag{3.5}$$

Similarly to the *VIX*, the *PCV* and *PCO* are regarded by market participants as fear indicators, with higher levels reflecting a more bearish viewpoint. When market participants are bearish, they buy put options to hedge their spot positions or to speculate bearishly. By contrast, a low level of *PCV* (or *PCO*) reflects bullish sentiment with which the demand for put options is relatively low. Finally, *TO* equals the number of shares traded divided by the number of shares listed on the Taiwan Stock Exchange (TWSE).

$$TO = \frac{\text{The number of shares trading}}{\text{The number of shares listed on the TWSE}}. \tag{3.6}$$

Previous literature, e.g., Cooper (1999), and Gervais et al. (2001), note the relationship between trading volume (the numerator of *TO*) and stock market returns, which could provide a trading signal. A high value for *TO* indicates that the market is commanded by irrational investors, implying that the market might be overreacting.

For the weather variables, we follow previous evidence and employ temperature, relative humidity, and cloud cover as the weather factors. In this study, these factors are simplified as *TEMP*, *RH*, and *CC*, respectively. In addition, for the catastrophe variables, this paper considers typhoons (*TY*) and earthquakes (*EQ*) because these two catastrophes are the major natural hazards for Taiwan. If the Central Weather Bureau announced a land alarm for a typhoon or its approach, then we set the dummy of *TY* at one. Additionally, if an earthquake reaches more than six on the Richter magnitude scale, we set the dummy of *EQ* at one.

3.3. Volatility model recruiting factors for investor sentiment, weather, and catastrophe

Considering Engle and Gallo (2006), we employ multiple factors to construct our volatility-forecasting model. Volatility measures involving HV, $|R|$, and HL are used as the benchmark volatility model. The equation is expressed as follows, and it is simplified as a benchmark:

$$RV_t = \beta_0 + \beta_1 HV_{t-1} + \beta_2 |R_{t-1}| + \beta_3 HL_{t-1} + \varepsilon_t, \tag{3.7}$$

where RV_t represents the realized volatility, HV_{t-1}, $|R_{t-1}|$, and HL_{t-1} are the one-day-lagged historical volatility, absolute return, and high-low range for the TAIEX, respectively.

To see whether investor sentiment, weather, and catastrophe factors could serve as useful variables, we examine whether they could enhance the forecasts of the RV of TAIEX returns calculated for the next n days on time t. The following is an estimated equation including the level of investor sentiment and weather in the benchmark model.

$$\begin{aligned} RV_t &= \beta_0 + \beta_1 HV_{t-1} + \beta_2 |R_{t-1}| + \beta_3 HL_{t-1} + \gamma_1 IS_{t-1} + \varepsilon_t, \\ RV_t &= \beta_0 + \beta_1 HV_{t-1} + \beta_2 |R_{t-1}| + \beta_3 HL_{t-1} + \gamma_2 WF_{t-1} + \varepsilon_t, \\ RV_t &= \beta_0 + \beta_1 HV_{t-1} + \beta_2 |R_{t-1}| + \beta_3 HL_{t-1} + \gamma_3 CAT_{t-1} + \varepsilon_t, \end{aligned} \tag{3.8}$$

where IS_{t-1} represents investor sentiment measured by VIX, PCV, PCO, and TO; WF_{t-1} represents weather factors measured by $TEMP$, RH, and CC; and CAT_{t-1} represents catastrophe events. The volatility model is simplified as $+VIX$ if the investor sentiment of VIX is included in the benchmark model. $+PCV$, $+PCO$, $+TO$, $+TY$, $+EQ$, $+TEMP$, $+RH$ and $+CC$ are expressed with the same implication. We also consider the first differences for the variables of weather and catastrophes, and the equation is expressed as follows:

$$\begin{aligned} RV_t &= \beta_0 + \beta_1 HV_{t-1} + \beta_2 |R_{t-1}| + \beta_3 HL_{t-1} + \gamma_3 \Delta WF_{t-1} + \varepsilon_t, \\ RV_t &= \beta_0 + \beta_1 HV_{t-1} + \beta_2 |R_{t-1}| + \beta_3 HL_{t-1} + \gamma_3 \Delta CAT_{t-1} + \varepsilon_t, \end{aligned} \tag{3.9}$$

where ΔWF_{t-1} and ΔCAT_{t-1} represent the first differences of variables for weather and catastrophes, respectively. $+\Delta TEMP$, $+RH$, $+\Delta CC$, $+\Delta TY$, and $+\Delta EQ$ represent the change in $TEMP$, RH, CC, TY, and EQ included in the benchmark model, respectively.

In addition, because the weather and catastrophe variables might have significant seasonal patterns, we control for seasonal effects by adding three dummy variables ($S1$, $S2$, and $S3$) representing different seasons. Moreover, the proportion of individual investors decreased significantly while the proportion of institutional investors sharply increased in the Taiwanese stock and options markets during the empirical periods. Changes in market structure would result in changes of trading behaviors of investors. Therefore, we add a 'proportion of trading volume by institutions' variable as a control variable (II) into the main regression to consider the possible influence. The forecasting procedure is conducted through multiple regressions.

3.4. Hedging performance

The performance of various volatility-forecasting models is compared based on the average daily return rate (R_M), which is computed as follows:

$$R_M(\%) = \frac{\frac{1}{n}\sum_{i=1}^{n} PL_{i,M}}{\frac{1}{n}\sum_{i=1}^{n} C_{i,M}} \times 100\% \tag{3.10}$$

where M denotes the various volatility forecasting models, $PL_{i,M}$ denotes the profit-loss of the options hedging strategy for model M in day i, and $C_{i,M}$ denotes the cost of capital involving the transaction costs of the options hedging strategy for model M on day i.

Referring to Bakshi and Kapadia (2003), we apply the gains equation to calculate the profit or loss of the various volatility models. The equation is defined as follows:

$$\begin{aligned} PL_{i,m} = O_{t+\tau} - O_t - \sum_{n=0}^{N-1} CF_{t_n}\left(S_{t_{n+1}} - S_{t_n}\right) - \sum_{n=0}^{N-1} r(O_t - CF_{t_n} S_{t_n})\frac{\tau}{N} \\ -2 \times F_O - N \times F_S - T_O \times (O_t + O_{t+\tau}) - T_S \times \sum_{n=0}^{N-1} S_{t_n}, \end{aligned} \tag{3.11}$$

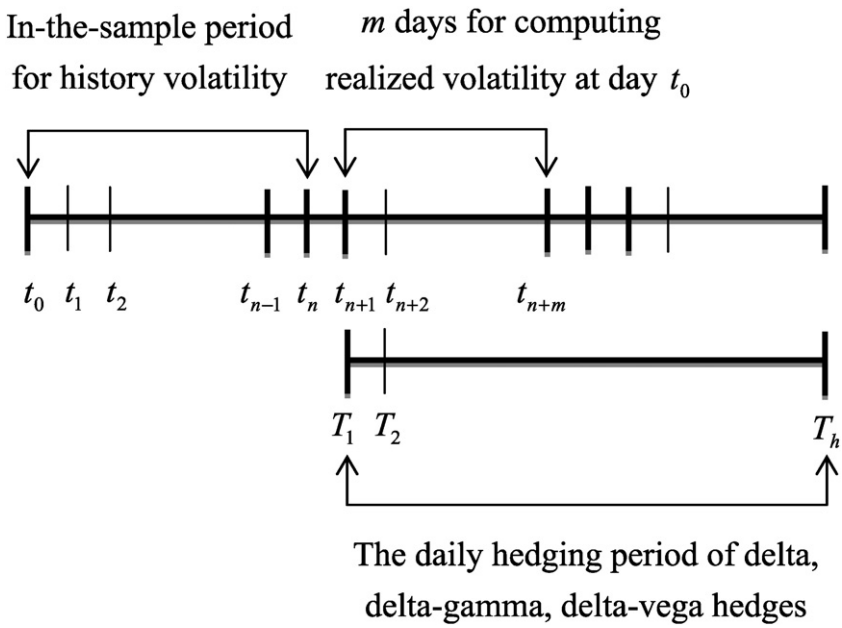

Fig. 1. The framework of volatility forecasting and options hedging strategies.

where CF equals

$$CF = \frac{TSEC\ \ weighted\ \ index \times 50}{The\ \ price\ \ of\ \ future \times 200} \times The\ \ ratio\ \ of\ \ hedge. \tag{3.12}$$

Table 1
Summary statistics.

	Mean	Median	Maximum	Minimum	Std. dev	Skewness	Kurtosis	Jarque-Bera
TAIEX	7416.702	7578.800	9295.200	4089.930	1150.799	−1.114	3.989	295.182***
RV	0.201	0.175	0.700	0.021	0.114	1.264	4.888	494.933***
HV	0.215	0.186	0.514	0.060	0.095	0.919	3.127	168.745***
EWMA	0.202	0.177	0.483	0.056	0.089	0.915	3.124	167.333***
$\|R\|$	0.011	0.007	0.067	0.000	0.010	1.844	7.258	1577.208***
HL	0.101	0.085	0.517	0.023	0.062	2.025	9.372	2833.680***
II	0.287	0.285	0.491	0.126	0.054	0.209	3.118	9.368***
S1	0.226	0.000	1.000	0.000	0.419	1.308	2.711	344.363***
S2	0.254	0.000	1.000	0.000	0.435	1.130	2.278	279.989***
S3	0.262	0.000	1.000	0.000	0.440	1.080	2.167	266.552***
PCV	0.897	0.918	1.638	0.225	0.174	−0.403	3.781	62.653***
PCO	0.967	0.991	1.988	0.286	0.278	−0.013	3.123	0.784***
TO	0.005	0.005	0.017	0.002	0.002	1.394	6.158	882.282***
VIX	25.462	23.440	60.410	13.290	8.949	1.030	3.718	236.512***
TY	0.019	0.000	1.000	0.000	0.138	6.992	49.889	119009.500***
EQ	0.005	0.000	1.000	0.000	0.071	13.994	196.838	1906646.000***
TEMP	23.487	24.000	32.400	9.300	5.432	−0.356	2.114	64.261***
RH	74.394	74.000	96.000	37.000	9.197	−0.153	2.471	18.530***
CC	7.393	7.900	10.000	0.800	2.353	−0.718	2.529	113.562***
ΔTY	(0.018)	0.000	0.000	−1.000	0.132	−7.337	54.827	144223.400***
ΔEQ	(0.005)	0.000	0.000	−1.000	0.071	−13.994	196.838	1906646.000***
$\Delta TEMP$	0.007	0.006	0.723	−0.390	0.115	0.546	7.653	1135.430***
ΔRH	0.007	0.000	0.635	−0.342	0.109	0.409	5.173	268.068***
ΔCC	0.093	0.000	6.100	−1.001	0.591	4.181	31.593	44114.750***

This table presents the descriptive statistics for the data. The in-the-sample period (ISP) covers periods of 30 days; RV forecasts are computed by 5-days-ahead. The data span the period from 2 January 2008 to 21 December 2012, totally 1193 observations.
*** Indicate significance at the 1% levels (one tailed test).

Table 2
Correlation coefficients.

	RV	HV	|R|	HL	II	S1	S2	S3	PCV	PCO	TO	VIX
TAIEX	−0.495**	−0.661**	−0.291**	−0.445**	−0.016	0.010	0.170**	−0.009	0.258**	0.291**	−0.058*	−0.752**
RV		0.605**	0.294**	0.489**	0.201**	0.033	−0.027	0.023	−0.347**	−0.501**	0.092**	0.612**
HV			0.334**	0.521**	0.209**	0.037	−0.037	−0.023	−0.445**	−0.526**	0.150**	0.882**
|R|				0.462**	0.127**	0.030	−0.008	0.012	−0.170**	−0.291**	0.158**	0.377**
HL					0.097**	0.047	−0.013	0.008	−0.260**	−0.356**	0.311**	0.601**
II						−0.052	0.107**	−0.025	−0.223**	−0.538**	−0.521**	0.077**
S1							−0.316**	−0.323**	−0.124**	−.070*	0.142**	0.043
S2								−0.348**	0.116**	0.083**	0.084**	−0.067*
S3									0.006	−0.017	−0.066*	−0.061*
PCV										0.520**	0.010	−0.388**
PCO											0.347**	−0.414**
TO												0.282**
VIX												
TY												
EQ												
TEMP												
RH												
CC												
Δ*TY*												
Δ*EQ*												
Δ*TEMP*												
Δ*RH*												

This table shows the correlation coefficients. The in-the-sample period (ISP) covers periods of 30 days; RV forecasts are computed by 5-days-ahead. The data span the period from 2 January 2008 to 21 December 2012, totally 1193 observations.
*** Indicate significance at the 1% levels (one tailed test).
** Indicate significance at the 5% levels (one tailed test).
* Indicate significance at the 10% levels (one tailed test).

$O_{t+\tau}$ is the closing price of an option at maturity, O_t is the closing price of an option at the beginning, CF_{t_n} is the future hedging contracts, N is the number of hedging contracts from the beginning to the end, τ is the days from the beginning to the end divided by 252, r is the constant risk-free interest rate, F_O is the option fee, F_S is the underlying asset's fee, T_O is the tax rate for the option, and T_S is the tax rate for the underlying asset.

4. Data and empirical results

4.1. Data description

Our analysis employs daily data between 2008 and 2012, including a total of 1260 trading days. We exclude data on investor sentiment or weather if there is a missing value; thus, 1193 samples in total are utilized in this study. The target for measuring market turnover is selected by the option with the largest trading volume. We divide TAIEX options into three groups and two periods, which are in-the-money, at-the-money, out-of-the-money, near-month and next-near-month. We adopt the daily closing price of the TAIEX, absolute daily returns (|*R*|), daily high-low range (*HL*), market turnover (*TO*) data, and the proportion of trading volume by institutions (*II*) from the Taiwan Economic Journal (TEJ) database. The TAIEX options, put-call trading volume ratio (*PCV*), put-call open interest ratio (*PCO*), and the option volatility index (*VIX*) data are available from the Taiwan Futures Exchange (TAIFEX). All of our weather and catastrophe data, namely, temperature (*TEMP*), humidity (*RH*), cloud cover (*CC*) in Taipei, earthquakes (*EQ*) and typhoons (*TY*), are from the Central Weather Bureau of Taiwan.

Fig. 1 presents the volatility forecasting framework and options hedging strategies. In this study, hedging is conducted every day, and terms T_1 to T_h represent the hedging period of the delta, delta-gamma and delta-vega hedges, where h is equal to the number out-of-the-sample. Our regression of *RV* on the first lagged variables involve |*R*|, *HL*, *HV*, four investor sentiments, and five weather measurements; thus, terms t_0 to t_n are the in-the-sample period (ISP) for estimating the coefficients of the *RV* model. Here, n denotes the ISP covering 30, 60 and 90 days.

4.2. Summary statistics and empirical results

Table 1 presents the descriptive statistics for the data. The sample mean for all variables is positive. By comparing the standard deviation, we find the maximum degree of dispersion is for the TAIEX, the second is for the weather factor of *RH*, and the third is for the investor sentiment of *VIX*. With regard to the descriptive statistics of skewness and kurtosis, we discover that the TAIEX and the weather factors (*TEMP*, *RH* and *CC*) exhibit negative skewness; all variables cannot pass the goodness-of-fit test matching normal distribution.

The correlation coefficient matrix is shown in Table 2. The correlations between *RV* and investor sentiment are significant at the 5% level, in which the *PCV* and the *PCO* are negatively correlated with the *RV*, but *TO* and *VIX* are positively correlated. No

TY	EQ	TEMP	RH	CC	ΔTY	ΔEQ	ΔTEMP	ΔRH	ΔCC
0.005***	0.005	−0.018	0.032	0.034	0.002	−0.005	0.015	−0.007	0.008
−0.017	−0.052**	0.017	−0.026	−0.029	0.012	0.057	0.014	−0.006	−0.019
−0.025	−0.029	−.002	0.008	0.014	0.014	0.026	−0.011	0.009	−0.006
−0.022	0.007	0.004	0.032	0.018	−0.021	0.003	−0.027	0.041	0.038
−0.007	−0.014	0.027	0.002	0.002	0.022	0.014	−0.019	0.032	0.024
0.043	−0.053	0.132**	0.034	0.051	−0.050	0.053	−0.021	0.009	−0.002
−0.076**	−0.010	−0.600**	0.193**	0.144**	0.072*	0.010	0.049	0.000	−0.009
0.002	−0.014	0.173**	−0.032	0.084**	0.005	0.014	0.037	0.011	−0.006
0.138**	0.011	0.644**	−0.205**	−0.309**	−0.138**	−0.011	−0.042	−0.005	0.016
−0.005	0.027	0.077**	−0.048	−0.016	0.014	−0.001	0.008	−0.035	−0.021
−0.001	0.036	−0.021	−0.073*	−0.057	0.012	−0.034	0.021	−0.012	0.023
−0.047*	0.010	−0.136**	−0.050	−0.024	0.049	−0.016	0.007	0.005	0.020
−0.054*	−0.011	−0.026	−0.001	−0.001	0036	0.013	−0.011	0.019	0.007
	−0.010	0.131**	−0.017	−0.054	0.019	0.010	−0.016	−0.004	0.004
		0.029	−0.029	−0.008	0.010	0.005	0.030	−0.048	−0.011
			−0.336**	−0.405**	−0.123**	−0.027	0.150**	−0.038	0.015
				0.650**	−0.004	0.007	−0.186**	0.403**	−0.007
					−0.009	0.009	−0.299**	0.280**	0.223**
						−0.010	0.023	−0.043	−0.064*
							0.009	−0.023	0.008
								−0.227**	−0.189**
									0.346**

significant correlation is seen between market volatility and weather factors, providing a first impression opposing Hypothesis 1. The insignificantly positive direction of association for *TEMP* and *RV* is consistent with Lu and Chou (2012). However, *RH* is significantly negatively correlated with *PCO*, and *TEMP* is significantly negatively correlated with *TO* and positively correlated with *PCV*. It appears that evidence exists of a linkage between weather factors and investor sentiment. Next, we focus on the catastrophe variables. Only *EQ* is significantly associated with *RV*, and the correlation is negative. It is likely that people have pessimistic moods and are less willing to trade in the market when an earthquake is occurring, leading to low realized volatility. In addition, *TY* is also negatively correlated with *TO* and *VIX*. No significant correlations are discovered between *RV* and the changes in variables for weather and catastrophes. Finally, for the controlling variables, the correlations between the institutional proportion (*II*) and investor sentiment are significant, and the correlations between seasonal dummies and weather factors are also significant. Thus, controlling for the seasonal effects and the changes in the Taiwan financial market structure is meaningful.

Before analyzing the forecast estimations by different volatility models, we first examine the dependencies for *RV* with respect to proxies of investor sentiment, weather, and catastrophes based on multiple analyses. Table 3 represents the results of multiple regressions for *RV* and provides the incremental contribution of each additional factor based on the benchmark volatility model. All the coefficients of *HL*, $|R|$, and *HV* in the benchmark model exhibit significant explanatory ability for market volatility, and the controlling variables *II* and *S3* are also significant. However, when we use the variables of investor sentiment, weather, and catastrophes, the increment in the adjusted R^2 of most models is positive, that is, these variables (except *CC*) enhance the forecasting power for market volatility. Among the 9 models with recruiting variables, all the variables for investor sentiment and *EQ* produce significant coefficients. Therefore, we provide clear evidence supporting Hypothesis 2 and conclude that considering an *EQ* catastrophe is helpful in forecasting market volatility. Nevertheless, the explanatory power of models $+VIX$ and $+PCO$ are higher than that of model $+EQ$, i.e., the indicators of investor sentiment offer better forecasts of volatility than the catastrophe factor.

The forecast evaluation of the various volatility models is compared using the mean absolute percentage error (MAPE). The 15 forecasting models include the benchmark volatility model and other volatility models separately by recruiting the levels and changes in the variables of investor sentiment, weather, and catastrophes, namely, $+PCV$, $+PCO$, $+TO$, $+VIX$, $+TY$, $+EQ$, $+TEMP$, $+RH$, $+CC$, $+\Delta TY$, $+\Delta EQ$, $+\Delta TEMP$, $+\Delta RH$ and $+\Delta CC$. The ISP covers periods of 30, 60 and 90 days; *RV* forecasts are computed by *m*-days-ahead, where *m* is 5, 10, 15 and 20 trading days. Again, for space considerations, the *m*-days-ahead forecasting errors of the various volatility models with multiple and stepwise regression analyses are omitted, and we show only the results for minimum MAPE with multiple regression analysis in Table 4. With multiple regression analysis, the average MAPE of the 20-days-ahead forecasts (DAF) ranges from 0.0486 to 0.05 according to an ISP of between 30 and 90 days. Compared with the 20-DAF, the average MAPE of other *m*-DAF ranges from 0.0543 to 0.093. The mean of MAPE indicates that, regardless of the ISP, the 20-DAF could be characterized by better forecasting ability.

It is noted that, no matter what the *m*-day-ahead or the ISP or the year is, all of the mean MAPEs are smaller than 0.1. This implies that the models provide good measures of prediction accuracy for forecasting volatility. Interestingly, we also find that among yearly data, the mean MAPE of 2008 is almost larger than other years and the MAPE of 2012 is the smallest. In 2008, financial markets worldwide were affected by the subprime mortgage crisis. Hence, our results present a larger forecasting error in 2008, which appears to imply that the impacts of multiple factors on trading activity are more evasive when an extreme financial event occurs. Because multiple regression analysis can observe the forecasting error of each volatility model, we additionally

Table 3
Estimation results of the regression based forecast efficiency test with multiple regression analysis

	Benchmark	Recruiting investor sentiment levels				Recruiting weather factors levels					Recruiting weather factors changes				
	(+HV)	+PCV	+PCO	+TO	+VIX	+TY	+EQ	+TEMP	+RH	+CC	+Δ*TY*	+Δ*EQ*	+Δ*TEMP*	+Δ*RH*	+Δ*CC*
C	0.012	0.089	0.179	−0.021	−0.027	0.012	0.013	0.025	−0.001	0.015	0.012	0.013	0.012	0.012	0.012
	(1.146)	(5.032)***	(8.944)***	(−1.331)	(−2.275)**	(1.104)	(1.192)	(1.637)	(−0.047)	(1.221)	(1.101)	(1.192)	(1.127)	(1.145)	(1.166)
HV	0.562	0.516	0.471	0.553	0.326	0.561	0.562	0.562	0.562	0.562	0.562	0.562	0.562	0.562	0.561
	(24.041)***	(20.971)***	(19.327)***	(23.547)***	(7.632)***	(24.010)***	(24.019)***	(24.047)***	(24.049)***	(24.030)***	(24.035)***	(24.024)***	(24.032)***	(24.026)***	(24.0116)***
|*R*|	0.435	0.435**	0.273	0.390	0.312	0.428	0.439	0.427	0.430	0.437	0.444	0.437	0.439	0.438	0.440
	(2.170)**	(2.196)	(1.407)	(1.946)*	(1.574)	(2.136)**	(2.185)**	(2.124)**	(2.139)**	(2.177)**	(2.211)**	(2.177)**	(2.186)**	(2.181)**	(2.1931)**
HL	0.340	0.333	0.305	0.308	0.258	0.341	0.340	0.342	0.340	0.340	0.338	0.340	0.340	0.340	0.340
	(9.122)***	(9.036)***	(8.457)***	(7.948)***	(6.684)***	(9.143)***	(9.114)***	(9.174)***	(9.131)***	(9.115)***	(9.081)***	(9.117)***	(9.129)***	(9.125)***	(9.132)***
II	0.116	0.084	−0.089	0.195	0.172	0.118	0.114	0.122	0.114	0.116	0.118	0.114	0.116	0.116	0.116
	(3.314)***	(2.405)**	(-2.236)**	(4.407)***	(4.873)***	(3.381)***	(3.275)***	(3.463)***	(3.275)***	(3.331)***	(3.379)***	(3.275)***	(3.331)***	(3.315)***	(3.312)***
S1	0.002	0.009	−0.001	−0.001	0.006	0.002	0.002	−0.00008	0.002	0.003	0.002	0.002	0.002	0.002	0.002
	(0.466)	(0.006)	(−0.101)	(-0.141)	(1.139)	(0.456)	(0.455)	(−0.016)	(0.383)	(0.485)	(0.456)	(0.455)	(0.417)	(0.466)	(0.460)
S2	0.007	0.015	0.012	0.003	0.012	0.007	0.007	0.010	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(1.382)	(1.827)*	(2.470)**	(0.604)	(2.275)**	(1.437)	(1.373)	(1.728)*	(1.430)	(1.379)	(1.425)	(1.373)	(1.338)	(1.385)	(1.379)
S3	0.015	0.015	0.014	0.014	0.021	0.016	0.015	0.021	0.016	0.015	0.016	0.015	0.015	0.015	0.015
	(2.991)**	(2.994)***	(2.886)***	(2.795)***	(4.113)***	(3.148)***	(2.989)***	(2.989)***	(3.089)***	(2.786)***	(3.136)***	(2.989)***	(2.989)***	(2.989)***	(2.996)***
PCV		−0.064													
		(-5.383)***													
PCO			−0.087												
			(−9.686)***												
TO				3.293											
				(2.903)***											
VIX					0.003										
					(6.536)***										
TY						−0.019					0.019				
						(−1.437)					(1.361)				
EQ							−0.019					0.019			
							(−1.717)*					(0.730)			
TEMP								−0.001					0.013		
								(−1.169)					(0.833)		
RH									0.00001					-0.007 (-	
									(0.855)					0.417)	
CC										0.0001					−0.002
										(−0.453)					(−0.749)
Adj. R2	55.00%	56.31%	59.20%	55.30%	59.52%	55.02%	57.37%	55.02%	55.02%	54.99%	55.00%	55.01%	55.00%	54.99%	55.00%
IR Adj. R2		1.31%	4.20%	0.30%	4.52%	0.02%	2.37%	0.02%	0.02%	−0.01%	0.00%	0.01%	0.00%	-0.01%	0.00%

This table shows the estimation results of the regression based forecast efficiency test with multiple regression analysis. The in-the-sample period (ISP) covers periods of 30 days; RV forecasts are computed by 20-days-ahead. The data span the period from 2 January 2008 to 3 December 2012, totally 1179 observations.
Parentheses denote the t value.
*** Indicate significance at the 1% levels (one tailed test).
** Indicate significance at the 5% levels (one tailed test).
* Indicate significance at the 10% levels (one tailed test).

Table 4
Forecast evaluations of volatility models for 20-days-ahead forecasts of realized volatility with multiple regression analysis using MAPE.

ISP	Year	Benchmark	Recruiting investor sentiment levels				Recruiting weather levels					Recruiting weather changes					Mean	Total average
		(+*HV*)	+*PCV*	+*PCO*	+*TO*	+*VIX*	+*TY*	+*EQ*	+*TEMP*	+*RH*	+*CC*	+Δ*TY*	+Δ*EQ*	+Δ*TEMP*	+Δ*RH*	+Δ*CC*		
30	2008	0.0661	0.0667	0.0620	0.0696	0.0686	0.0689	0.0688	0.0718	0.0708	0.0683	0.0689	0.0689	0.0688	0.0690	0.0691	0.0684	
	2009	0.0467	0.0451	0.0443	0.0465	0.0452	0.0465	0.0466	0.0448	0.0451	0.0470	0.0465	0.0465	0.0460	0.0463	0.0463	0.0460	
	2010	0.0461	0.0471	0.0467	0.0473	0.0437	0.0476	0.0478	0.0458	0.0467	0.0483	0.0477	0.0478	0.0479	0.0476	0.0475	0.0470	
	2011	0.0476	0.0477	0.0441	0.0471	0.0462	0.0474	0.0475	0.0480	0.0463	0.0474	0.0473	0.0475	0.0460	0.0476	0.0476	0.0470	
	2012	0.0348	0.0353	0.0352	0.0335	0.0337	0.0344	0.0348	0.0323	0.0332	0.0360	0.0345	0.0348	0.0353	0.0346	0.0346	0.0345	0.0486
60	2008	0.0662	0.0647	0.0609	0.0670	0.0699	0.0665	0.0663	0.0668	0.0750	0.0664	0.0664	0.0663	0.0665	0.0662	0.0664	0.0668	
	2009	0.0489	0.0474	0.0472	0.0492	0.0452	0.0490	0.0492	0.0486	0.0470	0.0490	0.0492	0.0491	0.0487	0.0491	0.0491	0.0484	
	2010	0.0470	0.0469	0.0469	0.0468	0.0430	0.0468	0.0471	0.0464	0.0450	0.0469	0.0470	0.0471	0.0468	0.0470	0.0470	0.0465	
	2011	0.0453	0.0475	0.0427	0.0466	0.0470	0.0468	0.0468	0.0465	0.0533	0.0468	0.0467	0.0468	0.0455	0.0468	0.0468	0.0468	
	2012	0.0379	0.0375	0.0367	0.0363	0.0332	0.0370	0.0374	0.0374	0.0317	0.0371	0.0371	0.0374	0.0375	0.0375	0.0374	0.0366	0.0490
90	2008	0.0697	0.0682	0.0630	0.0702	0.0706	0.0698	0.0695	0.0711	0.0753	0.0698	0.0695	0.0695	0.0696	0.0697	0.0698	0.0697	
	2009	0.0505	0.0495	0.0510	0.0499	0.0477	0.0511	0.0511	0.0496	0.0482	0.0509	0.0512	0.0512	0.0506	0.0511	0.0511	0.0503	
	2010	0.0428	0.0426	0.0429	0.0426	0.0402	0.0425	0.0428	0.0412	0.0403	0.0424	0.0428	0.0428	0.0429	0.0425	0.0425	0.0423	
	2011	0.0474	0.0496	0.0444	0.0486	0.0475	0.0488	0.0488	0.0490	0.0523	0.0489	0.0487	0.0488	0.0475	0.0489	0.0489	0.0485	
	2012	0.0413	0.0400	0.0384	0.0391	0.0350	0.0402	0.0405	0.0387	0.0339	0.0400	0.0402	0.0405	0.0416	0.0402	0.0401	0.0393	0.0500
	Mean	0.0492	0.0491	0.0471	0.0493	0.0478	0.0496	0.0497	0.0492	0.0496	0.0497	0.0496	0.0497	0.0494	0.0496	0.0496		

This table shows the forecast evaluations of volatility models for 20-days-ahead forecasts of realized volatility using MAPE. The in-the-sample period (ISP) covers periods of 30, 60 and 90 days. This table provides the MAPE of each volatility model recruiting investor sentiment levels, weather level and weather changes year by year (2008–2012) based on different ISP.

calculate the average MAPE of the various volatility models of *m*-DAF. From the results, we see that the average MAPE of the volatility model adding *PCO* has the minimum value, which implies the best predictive ability.

4.3. Hedging performance

The various volatility models are employed as options hedging strategies, and the hedging performances of the various models are compared. Because the TAIEX is unable to trade in practice, we employ TAIEX futures to hedge because they are the most common alternative products for investors. The daily closing prices for TAIEX futures are from TAIFEX. The transaction cost, including the transaction fee and transaction tax, is considered. The option transaction fee is calculated as NT$6 per trade; further, the futures transaction fee is NT$12. The option transaction tax per contract is 0.1% of the contract value multiplied by the premium and multiplier, while the futures transaction tax per contract is 0.002%.

We apply the moneyness range of Goyal and Saretto (2009) to classify our options data into three categories: options close to in-the-money (ITM), at-the-money (ATM) and out-of-the-money (OTM), with moneyness in the ranges of 1.025-1.05, 0.975-1.025 and 0.975–0.95, respectively. The hedging performance of each volatility model is evaluated based on the average daily return. We exclude deep ITM and deep OTM options data because the trading volume is relatively small and/or the daily closing price of zero is too high.

We employ the delta, delta-gamma, and delta-vega hedging performance of near-month call and put options for 5, 10, 15, and 20-DAF and ISP covering 30-, 60-, and 90-day forecasts of *RV* with multiple regression analysis to rank the top three volatility models. We also display the average returns of the corresponding DAF period with the ISP and the benchmark volatility model. For space considerations, we exhibit the top three delta-gamma hedging performances of the volatility forecasting models in

Table 5
Top three delta-gamma hedging performance of volatility forecasting models.

Moneyness	DAF	ISP	Call					Put				
			Volatility Model			Return (%)		Volatility Model			Return (%)	
			Top 1	Top 2	Top 3	Our	Benchmark	Top 1	Top 2	Top 3	Our	Benchmark
In-the-money	5	30	*VIX*	Δ*CC*	Δ*TEMP*	46.38	46.29	*PCO*	*TO*	Δ*EQ*	32.32	32.03
$1.05>\frac{S}{K}>1.025$ (Call)		60	Δ*CC*	Δ*RH*	Δ*TEMP*	46.06	45.90	*RH*	*PCO*	*TEMP*	32.89	32.27
		90	Δ*CC*	*TY*	Δ*TEMP*	60.70	46.02	*RH*	*PCO*	*TEMP*	33.04	32.21
	10	30	*CC*	*TEMP*	*TO*	48.73	45.23	*VIX*	*PCO*	*PCV*	32.29	31.62
$0.975>\frac{S}{K}>0.95$ (Put)		60	*CC*	Δ*CC*	Δ*TEMP*	45.88	45.79	*PCO*	*TEMP*	*VIX*	32.90	32.66
		90	*VIX*	*TO*	Δ*CC*	46.07	45.73	*PCO*	*TEMP*	Δ*TY*	32.73	32.46
	15	30	*CC*	*TO*	Δ*TEMP*	45.66	45.51	*TEMP*	*PCO*	*VIX*	33.13	32.81
		60	*RH*	*TEMP*	*VIX*	46.29	45.64	*PCO*	*CC*	*EQ*	32.92	32.72
		90	*RH*	*TEMP*	*TO*	46.13	45.74	*PCO*	*CC*	Δ*RH*	32.98	32.71
	20	30	*TEMP*	*VIX*	*RH*	45.91	45.66	*PCO*	*CC*	Δ*TY*	33.08	32.93
		60	*RH*	*VIX*	*TO*	46.86	45.78	*PCO*	Δ*RH*	Δ*TY*	33.19	32.98
		90	*RH*	*VIX*	*TEMP*	46.37	45.65	*PCO*	Δ*TY*	Δ*EQ*	32.90	32.67
At-the-money	5	30	*VIX*	Δ*CC*	Δ*TEMP*	45.39	45.28	*PCO*	*TO*	Δ*EQ*	35.54	35.24
$1.025>\frac{S}{K}>0.975$		60	Δ*CC*	Δ*RH*	Δ*TEMP*	45.02	44.75	*RH*	*PCO*	*TEMP*	36.01	35.38
		90	Δ*CC*	*TY*	Δ*TEMP*	60.34	45.01	*RH*	*PCO*	*TEMP*	36.22	35.37
	10	30	*CC*	*TEMP*	*TO*	48.03	44.42	*VIX*	*PCO*	*PCV*	35.47	34.80
		60	*CC*	Δ*CC*	Δ*TEMP*	44.81	44.72	*PCO*	*TEMP*	*VIX*	36.02	35.78
		90	*VIX*	*TO*	Δ*CC*	45.05	44.67	*PCO*	*TEMP*	Δ*TY*	35.91	35.65
	15	30	*CC*	*TO*	Δ*TEMP*	44.62	44.41	*TEMP*	*PCO*	*VIX*	36.13	35.81
		60	*RH*	*TEMP*	*VIX*	45.25	44.57	*PCO*	*CC*	*EQ*	36.03	35.83
		90	*RH*	*TEMP*	*TO*	45.07	44.66	*PCO*	*CC*	Δ*RH*	36.11	35.85
	20	30	*TEMP*	*VIX*	*RH*	44.83	44.57	*PCO*	*CC*	Δ*TY*	36.04	35.89
		60	*RH*	*VIX*	*TO*	45.77	44.65	*PCO*	Δ*RH*	Δ*TY*	36.23	36.02
		90	*RH*	*VIX*	*TEMP*	45.33	44.59	*PCO*	Δ*TY*	Δ*EQ*	36.05	35.82
Out-the-money	5	30	*VIX*	Δ*CC*	Δ*TEMP*	44.67	44.57	*PCO*	*TO*	Δ*EQ*	33.67	33.36
$0.975>\frac{S}{K}>0.95$ (Call)		60	Δ*CC*	Δ*RH*	Δ*TEMP*	44.32	44.23	*RH*	*PCO*	*TEMP*	34.17	33.53
		90	Δ*CC*	*TY*	Δ*TEMP*	59.89	44.31	*RH*	*PCO*	*TEMP*	34.37	33.53
	10	30	*CC*	*TEMP*	*TO*	47.50	43.85	*VIX*	*PCO*	*PCV*	33.84	33.16
$1.05>\frac{S}{K}>1.025$ (Put)		60	*CC*	Δ*CC*	Δ*TEMP*	44.09	44.00	*PCO*	*TEMP*	*VIX*	34.14	33.90
		90	*VIX*	*TO*	Δ*CC*	44.35	43.95	*PCO*	*TEMP*	Δ*TY*	34.07	33.80
	15	30	*CC*	*TO*	Δ*TEMP*	43.89	43.68	*TEMP*	*PCO*	*VIX*	34.30	33.98
		60	*RH*	*TEMP*	*VIX*	44.55	43.88	*PCO*	*CC*	*EQ*	34.18	33.98
		90	*RH*	*TEMP*	*TO*	44.33	43.93	*PCO*	*CC*	Δ*RH*	34.23	33.97
	20	30	*TEMP*	*VIX*	*RH*	44.07	43.81	*PCO*	*CC*	Δ*TY*	34.21	34.05
		60	*RH*	*VIX*	*TO*	45.02	43.89	*PCO*	Δ*RH*	Δ*TY*	34.32	34.11
		90	*RH*	*VIX*	*TEMP*	44.61	43.87	*PCO*	Δ*TY*	Δ*EQ*	34.19	33.96

This table shows hedging performance of volatility forecasting models on MA(Ahn et al., 2007)-type option model. The delta and gamma of MA (Ahn et al., 2007)-type option model is $N(d_1')$ and $(1/\sqrt{2\pi}s\sigma_t)\exp(-d_1'^2)$, $\sigma_t = RV_t * \sqrt{[(1+\beta)^2(\tau-h)+h]}$. $d_1' = \ln(s/k)+(r\tau+0.5\sigma_t^2)/\sigma_t$. s is the underlying asset; k is the exercise price. r is the risk-free interest rate. The coefficient β represents the impact of the past shock and is the estimated as -0.025 by using the data of September 1, 2007 to December 31, 2007. τ is the time to maturity and $h>0$ is a fixed, but arbitrary small constant.

Table 5. We illustrate five aspects of the empirical results, including the DAF period, the ISP, volatility models, moneyness of call and put options, option class, and hedging methods.

From the point of view of the DAF period and the ISP, the results for the delta, delta-gamma and delta-vega hedging performance of call and put options are the same. For the volatility models, we compare 15 types of volatility forecasting models, including the benchmark volatility model and the volatility model adding investor sentiment, weather, and catastrophes. The results of the DAF period and the ISP cover different days, and the forecasting volatility models are different. For call options, the hedging performances of the volatility models when adding the levels of *VIX*, *CC*, *RH*, and *TEMP* and the changes of *CC* (ΔCC) are better than the others, regardless of the moneyness and hedging strategies we employed. The top-performing call options for 5-days-ahead and 10-days-ahead are found by adding *VIX*, *CC*, and ΔCC, while the top-performing call options for 15-days-ahead and 20-days-ahead are found by adding *RH*, *CC*, and *TEMP*.

The results of using put options to hedge are different from those of using call options. The results indicate that the hedging performances of put options in the volatility models when adding the levels of *PCO*, *VIX*, *RH*, and *TEMP* are better than the others, regardless of the moneyness and hedging strategies we employed. Interestingly, comparing the top-performing call and put options, we find that the same variables include *VIX*, *RH*, and *TEMP*. In summary, if we observe the top hedging performance in each group, we find that the levels of *VIX*, *PCO*, *RH*, and changes of *CC* are the most important factors. We further compare the hedging performance on the MA(1)-type option model with the on Black-Scholes (BS) option model shown in Table 6. The results show that the performance of ATM and OTM (ITM) call or put options on MA(1)-type option model is higher (lower) than those on BS option model. Furthermore, similar to the results of ATM and OTM put options on the MA(1)-type option model, adding the levels of *PCO*, *VIX*, *RH*, and *TEMP* can enhance hedging performance.

Although from Table 5 we cannot find significant differences between the average returns from our volatility models and the returns from the benchmark model, we find that some of the factors of investor sentiment and weather could play important roles in options hedging performance. We further provide the best improvement level for the volatility models recruiting investor

Table 6
Top three delta-gamma hedging performance of volatility forecasting models.

Moneyness	DAF	ISP	Call					Put				
			Volatility model			Return (%)		Volatility model			Return (%)	
			Top 1	Top 2	Top 3	Our	Benchmark	Top 1	Top 2	Top 3	Our	Benchmark
In-the-money	5	30	*RH*	*VIX*	*TEMP*	62.59	60.88	*VIX*	ΔCC	*TEMP*	58.56	58.40
$1.05>\frac{S}{K}>1.025$ (Call)		60	ΔRH	ΔCC	ΔTY	62.06	61.99	ΔCC	ΔRH	$\Delta TEMP$	57.77	57.67
		90	ΔCC	*TY*	*EQ*	80.68	61.94	ΔCC	*TY*	*EQ*	77.49	57.63
	10	30	*CC*	*TEMP*	*TO*	68.99	61.30	*CC*	*TEMP*	*TO*	65.62	57.41
$0.975>\frac{S}{K}>0.95$ (Put)		60	*CC*	ΔCC	*PCV*	61.49	61.27	*CC*	ΔCC	*PCV*	57.06	56.74
		90	*VIX*	*TO*	ΔCC	61.92	61.17	*VIX*	*TO*	ΔCC	57.60	56.83
	15	30	*CC*	*TO*	*PCV*	61.01	60.87	*CC*	*TO*	*PCV*	56.65	56.52
		60	*RH*	*TEMP*	*VIX*	62.54	61.01	*RH*	*TEMP*	*VIX*	58.30	56.59
		90	*CC*	*TO*	*PCV*	61.01	60.85	*RH*	*TEMP*	*TO*	57.59	56.54
	20	30	*TEMP*	*RH*	*VIX*	61.42	60.77	*TEMP*	*VIX*	*RH*	57.07	56.34
		60	*RH*	*VIX*	*TO*	63.47	60.93	*RH*	*VIX*	*TO*	59.28	56.43
		90	*RH*	*VIX*	*TO*	63.47	60.93	*RH*	*VIX*	*TEMP*	58.35	56.44
At-the-money	5	30	*PCO*	ΔTY	*EQ*	31.82	31.57	*PCO*	*TO*	ΔEQ	28.63	28.17
$1.025>\frac{S}{K}>0.975$		60	*RH*	*VIX*	*TEMP*	31.87	30.90	*RH*	*PCO*	*VIX*	29.70	28.67
		90	*RH*	*PCO*	*VIX*	32.16	30.85	*RH*	*PCO*	*VIX*	30.02	28.66
	10	30	*VIX*	*PCV*	*PCO*	32.69	31.92	*VIX*	*PCO*	*PCV*	30.65	29.78
		60	*TEMP*	*PCO*	*VIX*	31.62	31.35	*TEMP*	*PCO*	*VIX*	29.47	29.16
		90	*PCO*	*TEMP*	ΔTY	31.57	31.29	*PCO*	*TEMP*	ΔTY	29.45	29.14
	15	30	*TEMP*	*PCO*	*VIX*	32.11	31.62	*TEMP*	*PCO*	*VIX*	30.00	29.48
		60	*PCO*	*CC*	*EQ*	31.75	31.55	*PCO*	*CC*	*EQ*	29.64	29.39
		90	*TEMP*	*PCO*	*VIX*	32.11	31.62	*PCO*	*CC*	*VIX*	29.64	29.33
	20	30	*CC*	*PCO*	ΔTY	31.88	31.70	*CC*	*PCO*	ΔTY	29.76	29.57
		60	*PCO*	ΔRH	ΔTY	31.79	31.38	*PCO*	ΔRH	ΔTY	29.67	29.39
		90	*PCO*	ΔRH	ΔTY	31.79	31.43	*PCO*	ΔTY	*EQ*	29.74	29.46
Out-the-money	5	30	*PCO*	ΔTY	*EQ*	19.55	19.14	*PCO*	*TO*	ΔEQ	15.26	14.68
$0.975>\frac{S}{K}>0.95$ (Call)		60	*RH*	*VIX*	*TEMP*	19.57	17.82	*RH*	*VIX*	*TEMP*	16.82	15.23
		90	*RH*	*PCO*	*VIX*	20.18	17.86	*RH*	*PCO*	*VIX*	17.35	15.22
	10	30	*VIX*	*PCO*	*PCV*	20.25	18.38	*VIX*	*PCO*	*PCV*	17.58	15.93
$1.05>\frac{S}{K}>1.025$ (Put)		60	*TEMP*	*VIX*	*PCO*	19.23	18.72	*TEMP*	*PCO*	*VIX*	16.51	16.03
		90	*PCO*	*TEMP*	ΔTY	19.08	18.65	*PCO*	*TEMP*	ΔTY	16.36	15.95
	15	30	*TEMP*	*PCO*	*VIX*	20.03	19.12	*TEMP*	*PCO*	*VIX*	17.29	16.44
		60	*PCO*	*CC*	*EQ*	19.38	19.01	*PCO*	*CC*	*EQ*	16.65	16.32
		90	*TEMP*	*PCO*	*VIX*	20.03	19.12	*PCO*	*CC*	*VIX*	16.73	16.31
	20	30	*CC*	*PCO*	*EQ*	19.65	19.32	*CC*	*PCO*	ΔTY	16.93	16.62
		60	*PCO*	ΔRH	ΔTY	19.58	19.16	*PCO*	ΔRH	ΔTY	16.84	16.45
		90	*PCO*	ΔRH	ΔTY	19.58	19.13	*PCO*	ΔTY	*EQ*	16.80	16.42

This table shows hedging performance of volatility forecasting models on BS option model. The delta and gamma of BS option model is $N(d_1)$ and $(1/\sqrt{2\pi}s\sigma_t)\exp(-d_1^2)$,$\sigma_t = RV_t * \sqrt{\tau}$.$d_1 = \ln(s/k) + (r\tau + 0.5\sigma_t^2)/\sigma_t$.$s$ is the underlying asset; k is the exercise price. r is the risk-free interest rate. τ is the time to maturity.

Table 7
Best improvement level of volatility forecasting model.

Option	Hedging method	DAF	ISP	Moneyness	Volatility model	Return (%)		Improvement (%)
						Volatility model (Ahn et al., 2007)	Benchmark model (Baker and Wurgler, 2007)	(Ahn et al., 2007)-(Baker and Wurgler, 2007)
Panel A: Top one improvement level of volatility models recruiting investor sentiments.								
2008								
Call	Delta	10	90	ITM	*VIX*	5.58	5.45	0.13
	Delta-gamma	10	90	OTM	*VIX*	9.89	9.76	0.13
	Delta-vega	10	90	ITM	*VIX*	10.27	10.13	0.14
Put	Delta	10	30	ATM	*VIX*	2.54	2.13	0.41
	Delta-gamma	10	30	ITM	*VIX*	2.73	2.30	0.43
	Delta-vega	10	30	ITM	*VIX*	2.94	2.50	0.44
2009								
Call	Delta	5	30	ITM	*VIX*	3.59	3.54	0.05
	Delta-gamma	15	30	OTM	*PCO*	7.20	7.13	0.07
	Delta-vega	15	30	ITM	*PCO*	6.39	6.33	0.06
Put	Delta	10	30	ITM	*VIX*	1.52	1.40	0.12
	Delta-gamma	10	30	OTM	*VIX*	6.30	6.19	0.11
	Delta-vega	10	30	OTM	*VIX*	6.34	6.23	0.11
2010								
Call	Delta	20	60	ITM	*VIX*	5.82	5.75	0.07
	Delta-gamma	10	90	ATM	*VIX*	9.22	9.11	0.11
	Delta-vega	10	90	OTM	*VIX*	9.10	9.01	0.09
Put	Delta	5	30	ITM	*PCO*	3.34	3.18	0.16
	Delta-gamma	5	30	OTM	*PCO*	7.54	7.38	0.16
	Delta-vega	5	30	OTM	*PCO*	7.57	7.40	0.17
2011								
Call	Delta	20	60	ITM	*VIX*	6.13	6.03	0.1
	Delta-gamma	20	60	OTM	*VIX*	9.53	9.43	0.1
	Delta-vega	20	60	OTM	*VIX*	9.65	9.55	0.1
Put	Delta	10	30	ITM	*VIX*	3.51	3.43	0.08
	Delta-gamma	10	30	OTM	*VIX*	7.32	7.24	0.08
	Delta-vega	10	30	OTM	*VIX*	7.36	7.28	0.08
2012								
Call	Delta	10	90	ITM	*VIX*	5.88	5.78	0.1
	Delta-gamma	10	90	OTM	*VIX*	8.54	8.44	0.1
	Delta-vega	10	90	OTM	*VIX*	8.60	8.50	0.1
Put	Delta	5	60	ITM	*VIX*	3.05	3.02	0.03
	Delta-gamma	5	30	OTM	*TO*	6.34	6.30	0.04
	Delta-vega	5	30	ATM	*TO*	6.20	6.16	0.04
Panel B: Top one improvement level of volatility models recruiting weather.								
2008								
Call	Delta	5	90	ITM	ΔCC	10.69	5.54	5.15
	Delta-gamma	5	90	OTM	ΔCC	15.21	9.85	5.36
	Delta-vega	5	90	OTM	ΔCC	15.15	9.79	5.36
Put	Delta	5	90	ATM	*RH*	2.73	2.56	0.17
	Delta-gamma	5	90	ITM	*RH*	3.04	2.86	0.18
	Delta-vega	5	90	ITM	*RH*	3.12	2.93	0.19
2009								
Call	Delta	5	90	ITM	ΔCC	4.90	3.54	1.36
	Delta-gamma	5	90	ITM	ΔCC	7.87	6.35	1.52
	Delta-vega	5	90	ITM	ΔCC	7.76	6.23	1.53
Put	Delta	5	90	ITM	*RH*	1.53	1.45	0.08
	Delta-gamma	5	90	OTM	*RH*	6.38	6.30	0.08
	Delta-vega	5	90	OTM	*RH*	6.35	6.27	0.08
2010								

Table 7 *(continued)*

Option	Hedging method	DAF	ISP	Moneyness	Volatility model	Return (%)		Improvement (%)
						Volatility model (Ahn et al., 2007)	Benchmark model (Baker and Wurgler, 2007)	(Ahn et al., 2007)-(Baker and Wurgler, 2007)
Call	Delta	5	90	ITM	ΔCC	8.09	5.88	2.21
	Delta-gamma	5	90	OTM	ΔCC	11.65	9.14	2.51
	Delta-vega	5	90	OTM	ΔCC	11.60	9.09	2.51
Put	Delta	5	90	ITM	*RH*	3.47	3.30	0.17
	Delta-gamma	5	90	OTM	*RH*	7.69	7.50	0.19
	Delta-vega	5	90	OTM	*RH*	7.71	7.52	0.19
2011								
Call	Delta	5	90	ITM	ΔCC	9.04	6.19	2.85
	Delta-gamma	5	90	OTM	ΔCC	12.72	9.58	3.14
	Delta-vega	5	90	OTM	ΔCC	12.74	9.59	3.15
Put	Delta	5	90	ITM	*RH*	3.45	3.26	0.19
	Delta-gamma	5	90	OTM	*RH*	7.31	7.10	0.21
	Delta-vega	5	90	OTM	*RH*	7.30	7.09	0.21
2012								
Call	Delta	5	90	ITM	ΔCC	8.49	5.84	2.65
	Delta-gamma	5	90	OTM	ΔCC	11.47	8.50	2.97
	Delta-vega	5	90	OTM	ΔCC	11.54	8.57	2.97
Put	Delta	5	90	ITM	*RH*	3.25	3.08	0.17
	Delta-gamma	5	90	ATM	*RH*	6.50	6.31	0.19
	Delta-vega	5	90	ATM	*RH*	6.32	6.13	0.19

This table shows top one improvement level of volatility models recruiting weather on MA(1)-type option model. The delta, gamma and vega of MA(1)-type option model is $N(d_1')$,$(1/\sqrt{2\pi}s\sigma_t)\exp(-d_1'^2)$, and $(s/\sqrt{2\pi})\exp(-d_1'^2)$,respectively. $\sigma_t = RV_t * \sqrt{[(1+\beta)^2(\tau-h)+h]}$. $d_1' = \ln(s/k) + (r\tau + 0.5\sigma_t^2)/\sigma_t$. s is the underlying asset; k is the exercise price. r is the risk-free interest rate. The coefficient β represents the impact of the past shock and is the estimated as -0.025 by using the data of September 1, 2007 to December 31, 2007. τ is the time to maturity and $h>0$ is a fixed, but arbitrary small constant.

sentiment and weather factors year by year, as shown in Panel A and Panel B of Table 7, respectively. Among the volatility models recruiting the investor sentiment factors, adding the levels of *VIX* or *PCO* often provides the best improvement level for hedging performance. For example, in 2008, regardless of the hedging strategies we employ, the hedging performance of the volatility model adding *VIX* for put options illustrates a good improvement level, and the highest is 0.44%. In addition, in 2010, regardless of the hedging strategies we employ, the highest improvement level for hedging performance of put options is 0.17% for the volatility model recruiting the *PCO*. Furthermore, we compare the hedging performance in each year. We find that, in 2008, 10-days-ahead and an ISP covering 30 days of put options has the highest reversion in hedging performance.

From Panel B, we discover that the hedging performance for 5-days-ahead and an ISP covering 90 days for volatility models recruiting weather factors have the best improvement level. Regardless of the hedging strategies we employ, the hedging performance of volatility model adding the change of *CC* (ΔCC) for call options provides a good improvement level during our empirical period, with the highest being 5.36% in 2008. In addition, when using the *RH* for put options, the highest improvement level is 0.21% in 2011. Using the perspective of behavioral finance to explain the relationship between change in *CC* (or *RH*) and volatility, it is likely that when a change in *CC* (or *RH*) is large enough to cause investors to feel impatient or upset, investors reduce trading to avoid making poor decisions. Such behavior would lead to decrease market volatility and thereby affect hedging performance. On the contrary, when the change in *CC* (or *RH*) is relatively small and thus causes investors to be in good mood, investors increase trading and cause higher market volatility.

From these results, we find that volatility models considering investor sentiment and weather can indeed improve hedging performance. Overall, we provide clear evidence supporting Hypothesis 3 and conclude that investor sentiment (*VIX* and *PCO*) and weather ($\Delta CC$and *RH*) is helpful to enhance the hedging performance in the Taiwan options market.

If we observe only the hedging performance of the moneyness of options, we discover that regardless of the values for DAF and ISP, of which volatility forecasting models are employed, of which years are considered, and of what hedging methods we use, the performance of ITM options is the best and that of OTM options is the worst. This result appears to be reasonable because OTM options are cheaper, such that investors are willing to take a risk and pursue returns and may not have an incentive to hedge. In summary, considering transaction costs, the hedging performance of OTM options is the worst.

Comparing the performance of call options with put options, we find that, regardless of the DAF period, ISP, the volatility models, the years, and the hedging methods employed, call options perform better than put options. For the hedging methods, in terms of total average returns, the performance of call options for the delta-gamma method is better than that for delta-vega, although the difference is not large. The delta hedging method has the worst performance. In addition, the delta-vega hedging performance of put options is the best, and the delta performance is also the worst. These results are consistent with the

previous literature. To sum up, the delta-gamma and delta-vega hedging have a good ability to capture price fluctuations and are more efficient than delta hedging.

5. Conclusions

To some extent, all human activities will inevitably be influenced by sentiment and the atmospheric environment, and indeed, investor sentiment, weather and catastrophes appear to affect people's decision-making processes, such as their options hedging activities. Nevertheless, the extant literature focuses on the relationship between the options markets and investor sentiment (or weather and catastrophes). The contribution of this study is that it bridges the gap between the information content of investor behavior, weather, and catastrophe effects and hedging strategies in the TAIEX options market.

The results presented in this article underscore the significant correlation between market volatility and investor sentiment levels (such as *PCO* and *VIX*). No significant correlation between market volatility and weather factors exists, whereas we present evidence of linkage between weather factors and investor sentiment. When there is high substantial humidity (typhoon) during bad weather, *PCO* (*VIX*) is significantly reduced. Our results also indicate that the catastrophe levels of earthquakes can help predict realized volatility. It may be that earthquakes are a major natural catastrophe hazard in Taiwan, and an increasing catastrophe frequency causes people to be pessimistic and thus influences their trading activity. We also conclude that the investor sentiment level and weather level effects are more essential to the improvement level for hedging performance when extreme financial events occur. Considering the improvement level for hedging performance, we find that *VIX*, *PCO* and changes in cloud cover (ΔCC) and *RH* have good improvement level, with the highest at 0.44%, 0.17%, 5.36%, and 0.21%, respectively.

The purpose of this study is to discuss the utility of using investor sentiment, weather, and catastrophe effects when considering volatility and options hedging strategies. To avoid the complications of volatility and the options hedging model, we employ the fundamental options hedging strategies of the MA(1)-type option model. Further research could extend this research to other various volatility forecasting models, such as EGARCH, TGARCH, etc. In addition, we employ only specific factors of investor sentiment and weather, while in reality, there are other diverse proxies, for example, investor sentiment from the ARMS index and the advance decline ratio (ADR), as well as the weather factors of precipitation and wind speed; these could be employed in future research.

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References

Ahn, C., Cho, D.C., Park, K., 2007. The pricing of foreign currency options under jump-diffusion processes. J. Futur. Mark. 27, 669–695.
Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21, 129–151.
Bakshi, G., Kapadia, N., 2003. Delta-hedged gains and the negative market volatility risk premium. Rev. Financ. Stud. 16, 527–566.
Bakshi, G., Cao, C., Chen, Z., 1997. Empirical performance of alternative option pricing models. J. Financ. 52, 2003–2049.
Bank of Japan, 2011. Responses to the Great East Japan Earthquake by Payment and Settlement Systems and Financial Institutions in Japan. BOJ Report and Research Papers. Payment and Settlement Systems Department, Bank of Japan, Tokyo.
Bassi, A., Colacito, R., Fulghieri, P., 2013. 'O Sole Mio: an experimental analysis of weather and risk attitudes in financial decisions. Rev. Financ. Stud. 26, 1824–1852.
Blair, B., Poon, S.H., Taylor, S.J., 2001. Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high frequency index returns. J. Econ. 105, 5–26.
Blau, B., Van Ness, R., Wade, C., 2008. Capitalizing on catastrophe: short selling insurance stocks around hurricanes Katrina and Rita. J. Risk Insur. 75, 967–996.
Bollen, N., Whaley, R., 2004. Does net buying pressure affect the shape of implied volatility functions? J. Financ. 59, 711–754.
Bollerslev, T., 1987. A conditionally heteroskedastic time series model for speculative prices and rates of return. Rev. Econ. Stat. 69, 542–547.
Bossaerts, P., Hillion, P., 1997. Local parametric analysis of hedging in discrete time. J. Econ. 81, 243–272.
Carter, D.A., Simkins, B.J., 2004. The market's reaction to unexpected, catastrophic events: the case of airline stock returns and the September 11th attacks. Q. Rev. Econ. Finance 44, 539–558.
Chang, T., Nieh, C.C., Yang, M.J., Yang, T.Y., 2006. Are stock market returns related to the weather effects? Empir. Evid. Taiwan, Physica A 364, 343–354.
Chang, S., Chen, S., Chou, R., Lin, Y., 2008. Weather and intraday patterns in stock returns and trading activity. J. Bank. Financ. 32, 1754–1766.
Chung, S.-L., Liu, W.-R., Tsai, W.-C., 2014. The impact of derivatives hedging on the stock market: evidence from Taiwan's covered warrants market. J. Bank. Financ. 42, 123–133.
Coakley, J., Dotsis, G., Liu, X., Zhai, J., 2014. Investor sentiment and value and growth stock index options. Eur. J. Finance 20, 1211–1229.
Cooper, M., 1999. Filter rules based on price and volume in individual security overreaction. Rev. Financ. Stud. 12, 901–935.
Corrado, C.J., Miller, T.W., 2005. The forecast quality of CBOE implied volatility indexes. J. Futur. Mark. 25, 339–373.
Cummins, J. David, Lewis, C.M., 2003. Catastrophic events, parameter uncertainty and the breakdown of implicit long-term contracting: the case of terrorism insurance. J. Risk Uncertain. 26, 2–3.
De Long, J.B., Shleifer, A., Summers, L.G., Waldmann, R.J., 1990. Noise trader risk in financial markets. J. Polit. Econ. 98, 703–738.
Dowling, M., Lucey, B., 2008. Robust global mood influences in equity pricing. J. Multinational Financ. Manage. 18, 145–164.
Drakos, K., 2004. Terrorism-induced structural shifts in financial risk: airline stocks in the aftermath of the September 11th terror attacks. Eur. J. Polit. Econ. 20, 435–446.
Engle, R.F., Gallo, G.M., 2006. A multiple-indicators model for volatility using intra-daily data. J. Econ. 131, 3–27.
Gervais, S., Kaniel, R., Mingelgrin, D.H., 2001. The high-volume return premium. J. Financ. 56, 877–919.
Goetzmann, W.N., Zhu, N., 2005. Rain or shine: where is the weather effect? Eur. Financ. Manage. 11, 559–578.
Goetzmann, W.N., Kim, D., Kumar, A., Wang, Q., 2015. Weather-induced mood, institutional investors, and stock returns. Rev. Financ. Stud. 28, 73–111.
Goyal, A., Saretto, A., 2009. Cross-section of option returns and volatility. J. Financ. Econ. 94, 310–326.
Han, B., 2008. Investor sentiment and option prices. Rev. Financ. Stud. 21, 387–414.

Hewitt, E.R., 2012. Examining Market Response Following Hurricane Landfall: Does the U.S. Stock Market React Efficiently to Hurricanes? Economics Honors Projects. Paper 45.
Hirshleifer, D., 2001. Investor psychology and asset pricing. J. Financ. 56 (4), 1533–1597.
Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. J. Financ. 58, 1009–1032.
Hsiao, H.-F., Hsu, C.-Y., Li, C.-A., Hsu, A.-C., 2011. The relationship between managerial sentiment, corporate investment and firm value: evidence from Taiwan. Emerg. Markets Finance and Trade 47 (2), 99–111.
Hsu, H., Kuo, W.H., Cheng, N.C., 2005. The interrelationship between investor sentiment index and stock price volatility: evidence from the Taiwan stock market. Taiwan Bank. Finance Q. 6 (3), 107–121.
Huibers, M., de Graaf, L., Peeters, F., Arntz, A., 2010. Does the weather make us sad? Meteorological determinants of mood and depression in the general population. Psychiatry Res. 180 (2-3), 143–146.
Kamstra, M.J., Kramer, L.A., Levi, M.D., 2003. Winter blues: a SAD stock market cycle. Am. Econ. Rev. 93, 324–333.
Kang, S.H., Jiang, Z.H., Lee, Y.J., Yoon, S.M., 2010. Weather effects on the returns and volatility of the Shanghai stock market. Physica A 389, 91–99.
Kaplanski, G., Levy, H., 2010. Sentiment and stock prices: the case of aviation disasters. J. Financ. Econ. 95, 174–201.
Kliger, D., Levy, O., 2003. Mood-induced variation in risk preferences. J. Econ. Behav. Organ. 52, 573–584.
Lakonishok, J., Lee, I., Pearson, N., Poteshman, A., 2007. Option market activity. Rev. Financ. Stud. 20, 813–857.
Lamb, R.P., 1995. An exposure-based analysis of property-liability insurer stock values around hurricane Andrew. J. Risk Insur. 62 (1), 111–123.
Lemmon, M.L., Ni, S.X., 2010. The Effects of Investor Sentiment on Speculative Trading and Prices of Stock and Index Options. Working Paper.
Liao, S.L., Chen, C.C., 2006. The valuation of European options when asset returns are autocorrelated. J. Futur. Mark. 26, 85–102.
Lu, J., Chou, R.K., 2012. Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. J. Empir. Finance 19, 79–93.
Mayhew, S., Stivers, C., 2003. Firm-level stock return dynamics, option volume, and the information content of implied volatility. J. Futur. Mark. 23, 615–646.
Morgan, J.P., 1996. RiskmetricsTM—Technical Document. fourth ed. Global Research, Morgan Guaranty Trust Company, New York.
Olsen, R.A., 1998. Behavioral finance and its implications for stock-price volatility. Financ. Analysts J. 54, 10–18.
Patton, A., Verardo, M., 2012. Does beta move with news? Firm-specific information flows and learning about profitability. Rev. Financ. Stud. 25 (9), 2789–2839.
Poteshman, A.M., 2006. Unusual option market activity and the terrorist attacks of September 11, 2001. J. Bus. 79, 1703–1726.
Saunders, J., 1993. Stock prices and the Wall Street weather. Am. Econ. Rev. 83, 1337–1345.
Shelor, R.M., Anderson, D.C., Cross, M.L., 1990. The impact of the California earthquake on real estate firms' stock value. J. Real Estate Res. 5, 335–340.
Shelor, R.M., Anderson, D.C., Cross, M.L., 1992. Gaining from loss: property-liability insurer stock values in the aftermath of the 1989 California earthquake. J. Risk Insur. 59, 476–488.
Sheu, H.J., Wei, Y.C., 2011. Effective options trading strategies based on volatility forecasting recruiting investor sentiment. Expert Syst. Appl. 38, 585–596.
Symeonidis, L., Daskalakis, G., Markellos, R.N., 2010. Does the weather affect stock market volatility? Physica A 389, 91–99.
Szu, W.-M., Yang, W.-R., 2015. Influence of individual investor sentiment on Taiwan option prices during 2007–2010 financial crisis. Manag. Financ. 41 (5), 437–464.
Theissen, E., 2007. An analysis of private investors' stock market return forecast. Appl. Financ. Econ. 17, 35–43.
Thomann, C. J., 2013. The impact of catastrophes on insurer stock volatility, J. Risk Insur., 80(1), 65-94, 2013.
Wang, Y.M., Li, C.A., Lin, C.F., 2012. Investor sentiment of lottery stock — evidence from the Taiwan Stock Market. Investment Manage. Financ. Innov. 9 (2), 203–207.
Yamori, N., Kobayashi, T., 1999. Is it true that insurers benefit from a catastrophic event? Market reactions to the Hanshin-Awaji earthquake. Pacific Basin Working Paper Series, No: PB99-04. Francisco, Federal Reserve Bank of San.
Yuan, K., Zheng, L., Zhu, Q., 2006. Are investors moonstruck? Lunar phases and stock returns. J. Empir. Finance 13, 1–23.
Yung, H.H.M., Zhang, H., 2003. An empirical investigation of the GARCH option pricing model: hedging performance. J. Futur. Mark. 23, 1191–1207.