DEVIATIONS FROM PUT–CALL PARITY AND VOLATILITY PREDICTION: EVIDENCE FROM THE TAIWAN INDEX OPTION MARKET

CHIN-HO CHEN*, HUIMIN CHUNG and SHU-FANG YUAN

This study examines whether deviations from put–call parity are informative about future volatility in the underlying index. Using the difference in implied volatility between call and put options to measure these deviations, we find that deviations from put–call parity predict future volatility. The predictability becomes stronger as option liquidity increases and the liquidity of the underlying index decreases. The results for volatility prediction remain significant even after controlling for implied volatility, information shocks, other information variables on return and volatility used widely in the literature, and short sales constraints. In addition, our results also show that deviations from put–call parity contain information about the future trading volume of options and the underlying index. © 2014 Wiley Periodicals, Inc. Jrl Fut Mark 34:1122–1145, 2014

1. INTRODUCTION

Put–call parity (PCP) is a simple no-arbitrage relation in which the payoff of an asset can be synthetically replicated using a call option, a put option, and a bond. Most empirical studies of violations of PCP find that apparent violations do not always represent tradable arbitrage opportunities because of factors such as transaction costs, dividend payments, the early exercise value of American options, nonsynchronous trades, and margin requirements.[1] Ofek and Richardson (2003), Ofek, Richardson, and Whitelaw (2004), and Shleifer and Vishny (1997) find that violations of PCP may also occur when limits on arbitrage exist, such as those based on short sales constraints and the ability of professional arbitrageurs. The trading activity of informed investors is another potential reason for violations (Cremers & Weinbaum, 2010; Easley, O'Hara, & Srinivas, 1998; Finucane, 1991).

Recent research reports that deviations from PCP can predict asset returns as a consequence of informed trading in the option market. Atilgan (2010), Cremers and Weinbaum (2010), and Finucane (1991) find that PCP deviations predict stock and index returns. Easley et al. (1998) demonstrate that if some informed investors favor trading in

---

Chin-Ho Chen and Huimin Chung are collocated at the Institute of Finance, National Chiao Tung University, Hsinchu, Taiwan. Shu-Fang Yuan is at the Department of Business Administration, Nanhua University, Chiayi County, Taiwan. The authors thank Robert Webb (the editor), Wen-Liang Hsieh, Wei-Peng Chen, and especially an anonymous referee for helpful comments and suggestions.

JEL Classification: G10; G12; G13

*Correspondence author, Institute of Finance, National Chiao Tung University, No. 1001 Ta-Hsueh Road, Hsinchu 30050, Taiwan. Tel: +886-3-5712121 ext. 57075, Fax: +886-3-5733260, e-mail: chinho.rrriver.chen6@gmail.com

Received June 2013; Accepted January 2014

[1]See, for example, Battalio and Schultz (2006), Klemkosky and Resnick (1980), Liu and Longstaff (2000), and Nisbet (1992).

The Journal of Futures Markets, Vol. 34, No. 12, 1122–1145 (2014)

Published online 12 February 2014 in Wiley Online Library (wileyonlinelibrary.com).
DOI: 10.1002/fut.21655

options instead of underlying assets, option prices may contain information about future asset prices. Because of private information, option prices are not fully efficient and deviate from PCP in the direction of the informed investors' private information.[2] However, in practice, volatility trading is popular and options are uniquely suited to investors with private volatility information (Back, 1993). Despite the evidence for the presence of informed volatility trading in the option market (Chang, Hsieh, & Wang, 2010; Ni, Pan, & Poteshman, 2008), much less is known about whether deviations from PCP contain information about future volatility.

This study investigates the extent to which deviations from PCP predict future volatility realized by the underlying index. We adopt deviations from PCP, proposed by Cremers and Weinbaum (2010), to measure the quantity of information and separate the information into positive and negative volatility signals. The deviations are quantified as the difference in implied volatility between call and put options with the same maturity (i.e., volatility spread). Increased (decreased) volatility in the subsequent 2 days following large volatility spreads with positive (negative) information provides evidence on the predictability of volatility by volatility spreads. Findings in this study also suggest that deviations from PCP may be the outcome of volatility information trading.

In addition, a linkage between volatility spreads and trading volume in the option and underlying asset is also examined. If positive (negative) volatility information embedded in volatility spreads is realized in the spot market, the hedging and speculative uses of options arising from increased (decreased) price volatility will lead to a higher (lower) option trading volume because of large (small) potential gains and losses. Similarly, high uncertainty in the underlying asset also affects its trading volume.[3] The volatility-induced change in trading volume implies that volatility spreads and volume are related. Thus, this study further explores the information content of volatility spreads for future volume.[4]

This study analyzes the Taiwan index option (TXO) written on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), which is one of the most liquid index options in the world.[5] Taiwan is the focus of the analysis for two reasons. First, volatility information trading is present in the TXO market. For example, Chang et al. (2010) show that foreign institutional investors and a few individual investors trade on private volatility information in the TXO market.

Second, Taiwan's market has no derivatives to trade volatility. Investors must exploit their volatility information directly in the option market. In the TXO market, volatility trades constructed on an option/futures combination are favored by informed volatility investors (Chang et al., 2010). Thus, as positive (negative) volatility information is realized by buying (selling) a call or put option and hedging by the index futures, the option trades by informed volatility investors may widen the relative position of call and put prices, subsequently leading to a widened volatility spread. This study in the Taiwan market sheds light on many other markets in a similar stage of development.[6]

[2]Although any tradable violation of PCP is expected to be quickly arbitraged away, in the real-world market imperfections and transaction costs may widen the range of the relative position of call and put prices so as not to violate arbitrage restrictions.

[3]Many studies show that a contemporaneous two-way relation exists between volatility and trading volume in the option and underlying asset (Andersen, 1996; Lamoureux & Lastrapes, 1990, 1994; Sarwar, 2003; Sears, 2000; Tauchen & Pitts, 1983).

[4]The authors thank the referee for this insightful suggestion.

[5]On a global scale, the TXO is ranked the fifth most frequently traded index option in 2010. The detailed statistics are available at the World Federation of Exchanges website, http://www.world-exchanges.org/.

[6]For instance, India and Korea have very active index options, the NIFTY 50 index option, and KOPI 200 index option, respectively, but the derivatives for trade the volatility index have yet to be launched.

The results show that volatility spreads with positive and negative information have predictive power with respect to future volatility. In particular, the degree of predictability is stronger when option liquidity is high and liquidity in the underlying index is low, a result consistent with the implication of the Easley et al. (1998) model. In addition, higher rewards for selling volatility following large volatility spreads with negative information also support the notion that deviations from PCP contain information about future volatility.

The predictability of volatility is robust after controlling for implied volatility, information shocks, short sales constraints, and other information variables on return and volatility. The finding that the option market leads the spot market by days, not minutes, provides evidence in support of information discovery in options. In addition, deviations from PCP also contain information about future trading volume. Specifically, following large volatility spreads with positive (negative) information, we find an increase (decrease) in option trading volume, option buy volume, and option sell volume. Similar results are found for trading dollar volume, buy dollar volume, and sell dollar volume of the underlying index.

This study is related to the recent literature showing that option price and volume contain predictive information about asset returns. An, Ang, Bali, and Cakici (2013) and Bali and Hovakimian (2009) use information from the cross-section of options, including the change in call and put implied volatilities, and the realized/implied volatility spread and the call–put implied volatility spread.[7] Bali and Murray (2013), Conrad, Dittmar, and Ghysels (2013), Rehman and Vilkov (2012), and Xing, Zhang, and Zhao (2010) adopt information on cross-sectional risk-neutral skewness.[8] Bollerslev, Tauchen, and Zhou (2009) use the information of implied–realized variance spread and find a positive relation between variance spread and stock market returns. In addition, Pan and Poteshman (2006), Johnson and So (2012), and Roll, Schwartz, and Subrahmanyam (2010) show that option trading volume and the option/stock trading volume ratio predict stock returns.

Other studies focus on predicting option return or price volatility. Goyal and Saretto (2009) find that delta-hedged options with a large positive difference between realized volatility and implied volatility have low average returns. Ni et al. (2008) and Chang et al. (2010) examine the predictive ability of volatility by option trading volume.

The remainder of this study is organized as follows. Section 2 contains a formal development of the method. Section 3 provides a brief description of the empirical data. Section 4 reports the empirical results derived from the models. Finally, Section 5 provides the key results of the study and concluding remarks.

2. METHOD

2.1. Volatility Information Variables

This study's theoretical framework extends the sequential trade model of Easley et al. (1998), allowing investors with private volatility information to trade in options first. In practice, straddles, strangles, and an option/futures combination are the three most commonly used

[7]An et al. (2013) show that stocks with a large increase in call (put) implied volatility have high (low) future returns. Bali and Hovakimian (2009) find a negative relation between realized–implied volatility spread and future stock returns. They also find high future average returns in stocks with large call–put implied volatility spread.

[8]Bali and Murray (2013) find a negative relation between risk-neutral skewness and the skewness asset returns. Rehman and Vilkov (2012) and Xing et al. (2010) find a positive relation between risk-neutral skewness and future stock returns while Conrad et al. (2013) report the opposite relation.

volatility trading strategies (Chaput & Ederington, 2005). This suggests that informed investors who are privy to a positive (negative) volatility signal usually conduct their volatility trades by long (short) straddles, strangles, or an option/futures combination, that is, a long (short) position for a call or put option and a short (long) position for futures. Importantly, as a result of private information, option prices are not fully efficient and deviate from PCP in the direction of the informed investors' private information. Each of the call and put options can carry information about subsequent volatility.

In the model, buying a call (put) in the option/futures strategy is a trade that carries positive volatility information and that raises a call (put) price relative to a put (call) price. Similarly, selling a call (put) that conveys negative volatility information decreases a call (put) price relative to a put (call) price. These trades widen the range of the relative position of call and put prices. A strangle trade based on positive (negative) volatility information, which requires that investors simultaneously buy (sell) both call and put options with different exercise prices to construct an approximately delta-neutral option portfolio, also has a similar effect whereas a straddle trade does not lead to PCP deviations.

This study adopts deviations from PCP, as proposed by Cremers and Weinbaum (2010), to measure the quantity of information. Following Amin, Coval, and Seyhun (2004) and Figlewski and Webb (1993), the deviations are quantified as the call–put implied volatility spread. The rationale is that the PCP for European options equivalently states that the Black–Scholes (1973) implied volatilities of pairs of call and put options are equal, even if option prices do not conform to the Black–Scholes formula. The difference between call and put implied volatilities thus can be interpreted as deviations from model values. However, in practice, deviations caused by informed trading likely occur for options with different exercise prices. The deviations are calculated as the implied volatility spread between call and put options with the same maturity.

Under the measure of deviations, a widened volatility spread may be generated by volatility trading based on an option/futures strategy. Nevertheless, volatility trades with a long (short) straddle and strangle tend to drive both call and put options to a relatively higher (or lower) level of implied volatility rather than to produce a larger volatility spread. Since volatility trades through straddles and strangles only account for a small fraction of option trading volume (Chang et al., 2010; Lakonishok, Lee, Pearson, & Poteshman, 2007), the dominant role of volatility trading with an option/futures strategy suggests that the informed volatility trading often results in a widened volatility spread. This widened volatility spread reflects private volatility information.

The information implicit in volatility spreads is separated into positive and negative volatility signals depending on the option implied volatility and the level of PCP on the prior trading day. Buying a call that carries positive volatility information raises implied volatility of calls (V_c) relative to the implied volatility of puts (V_p). Subsequently, the implied volatility of calls rather than the implied volatility of puts deviates more from the prior level of PCP, which is measured by the average implied volatility of call and put options, denoted by OV. The quantity of positive private information implicit in calls on day t (i.e., the volatility spread with positive volatility information) is quantified as

$$VS_b^c = \begin{cases} \left|V_{c,t} - V_{p,t}\right|, & \text{if } V_{c,t} > V_{p,t} \text{ and } \left|V_{c,t} - OV_{t-1}\right| > \left|V_{p,t} - OV_{t-1}\right|, \\ 0, & \text{if otherwise,} \end{cases} \tag{1}$$

where $V_{c,t}$ and $V_{p,t}$ denote the implied volatilities of calls and puts on day t, respectively. OV_{t-1} denotes the level of PCP on day $t-1$, which is the average of V_c and V_p on day $t-1$.

Similarly, buying a put that has positive volatility information raises V_p relative to V_c, leading V_p to deviate more from OV_{t-1}. The quantity of positive private information implicit in puts on day t is quantified as

$$VS_b^p = \begin{cases} \left|V_{c,t} - V_{p,t}\right|, & \text{if } V_{c,t} < V_{p,t} \text{ and } \left|V_{c,t} - OV_{t-1}\right| < \left|V_{p,t} - OV_{t-1}\right|, \\ 0 & \text{if otherwise.} \end{cases} \tag{2}$$

The negative volatility signals are also obtained by abstracting them separately from call and put options. Volatility trades through selling a call lessen V_c relative to V_p, and drive V_c to deviate more from OV_{t-1}. The quantity of negative private information on day t implicit in calls is quantified as

$$VS_s^c = \begin{cases} \left|V_{c,t} - V_{p,t}\right|, & \text{if } V_{c,t} < V_{p,t} \text{ and } \left|V_{c,t} - OV_{t-1}\right| > \left|V_{p,t} - OV_{t-1}\right|, \\ 0, & \text{if otherwise.} \end{cases} \tag{3}$$

Likewise, the quantity of negative private information on day t implicit in puts is quantified as

$$VS_s^p = \begin{cases} \left|V_{c,t} - V_{p,t}\right|, & \text{if } V_{c,t} > V_{p,t} \text{ and } \left|V_{c,t} - OV_{t-1}\right| < \left|V_{p,t} - OV_{t-1}\right|, \\ 0, & \text{if otherwise.} \end{cases} \tag{4}$$

Straddle and strangle trades are more likely to raise or lessen both the implied volatilities of calls and puts and drive them to deviate more from prior level of PCP. The percentage change of level of PCP (ΔOV) is used to gauge the information released by straddle and strangle trades. However, if a strangle trade generates a large deviation from PCP, perhaps arising from a portfolio position in both a call and a put options with a large difference in strike prices, the positive volatility information is incorporated in VS_b^c or VS_b^p whereas the negative information is reflected in VS_s^c or VS_s^p.

2.2. Option Implied Volatility

Without the use of any option-pricing model, this study adopts the approach proposed by Jiang and Tian (2005, 2007) to compute the implied volatilities of call and put options directly from option prices. This method corrects the inherent methodological problem in the Black–Scholes (1973) model for deriving the option-implied volatility, which assumes that the underlying asset's return follows a lognormal distribution that is almost too fat-tailed to be lognormal.

Following the approach of Jiang and Tian (2005, 2007), the model-free implied variance under the assumption of deterministic interest rates is written as

$$2\int_{K_{\min}}^{K_{\max}} \frac{C(\tau,K)/B(0,\tau) - \max[0, S_0/B(0,\tau) - K]}{K^2}\,\mathrm{d}K \approx \sum_{i=1}^{M}[f(\tau,K_i) + f(\tau,K_{i-1})]\Delta K, \tag{5}$$

where S_0 and $C(\tau, K)$ are the asset price and option price, respectively. K is the exercise price. τ denotes the expiration date of option. $B(t, \tau)$ is the time t price of a zero-coupon bound that pays \$1 at time τ. $f(\tau, K_i) = [C(\tau, K_i)/B(0,\tau) - \max(0, S_0/B(0,\tau) - K_i)]/K_i^2$, $\Delta K = (K_{\max} - K_{\min})/M$, and $K_i = K_{\min} + i\Delta K$ for $0 \le i \le M$. The truncation interval $[K_{\min}, K_{\max}]$ denotes the range of available exercise prices, in which $K_{\min}$ and $K_{\max}$ are referred to as left and right truncation points, respectively.

To avoid the bid–ask bounce problem, the midpoint of the quote rather than the transaction price is used to compute the implied volatility (Bakshi, Cao, & Chen, 1997, 2000).

In each day, the implied volatilities at the two nearest maturities are linearly interpolated to obtain the implied volatility at a fixed 22 trading-day horizon, denoted by IV, which is used as a proxy for the implied volatility of the whole option market. For the implied volatility at each contract month, the average implied volatility of calls and puts is first calculated for every 5-minute interval and then averaged across intervals in a day. The 5-minute implied volatility of calls (and puts) is backed out from call (put) prices by using the right-hand side of Equation (5).[9]

Figure 1 shows the plot of implied volatility and volatility spread in the near-month options. The daily implied volatility of puts (V_p) during the time to maturity is found to be frequently above the implied volatility of calls (V_c). Consistent with the findings of Ofek et al. (2004), deviations from PCP are more likely to occur in the direction of puts, which are relatively more expensive than the corresponding calls. The higher implied volatility of puts implies that volatility traders realize their positive private information using a delta-neutral portfolio of a long position in puts and a hedged position in futures. By contrast, a trade that sells calls and buys futures is favored by volatility sellers. These two volatility trading strategies account for 87.71% of the sample. In addition, a higher level of volatility spread during the

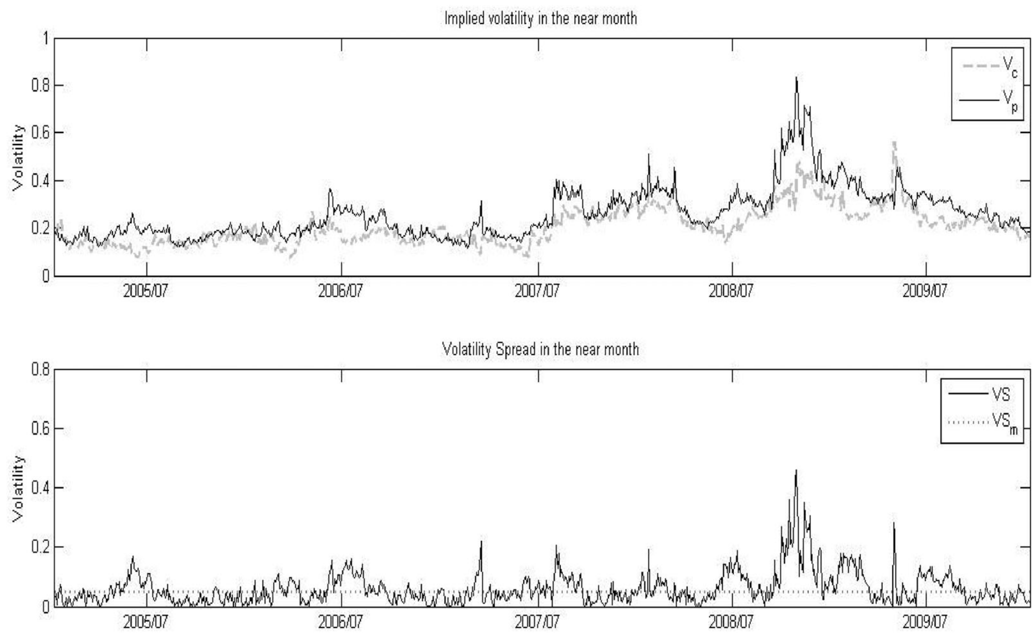

FIGURE 1

Time-series plots of the implied volatilities of near-month options and volatility spreads. This figure depicts the time-series relation between daily implied volatilities of calls and puts (V_c and V_p) in the near-month and volatility spread (*VS*). The time period is from January 1, 2005 through December 31, 2009. V_c and V_p are separately backed out from call and put prices by using Equation (5). *VS* is measured as the size of difference in implied volatilities between call and put options with the same maturity. VS_m is the median of *VS* during the sample period.

[9]The steps are specified as follows. At first, to obtain the not-traded option prices between available exercise prices, a cubic splines method is used to interpolate the Black–Scholes implied volatilities per 20 index points ($\Delta K = 20$). Next, for options with exercise prices beyond the available range, we follow the suggestion of Jiang and Tian (2007) to adjust the slope of the extrapolated segment to match the corresponding slope of the interior segment at the minimum or maximum available exercise price. Finally, the extracted implied volatilities are translated into option prices by using the Black–Scholes model, and the implied volatility is further computed from these option prices.

period of financial crisis in 2008 indicates that larger deviations from PCP are induced by more information flows impounded in the option market. Further, we have similar findings for options in the second month (corresponding figures are not tabulated but are available upon request).

Figure 1 also show that the size of volatility spread changes over time and reverts to its long-term median (VS_m). This positive median (or mean) of volatility spreads likely arises from the widened range between call and put prices due to market imperfection and transaction costs. Facing a mean-reversion volatility spread, the absolute deviations from median rather than the size of volatility spread can better reflect the quantity of volatility information. Thus, the absolute deviations are used from the median, denoted by VSM, as a proxy of volatility information variables. As specified in Section 2.1, VSM_b^c and VSM_b^p indicate the volatility spreads with positive volatility information implicit in call and put options, respectively, and VSM_s^c and VSM_s^p indicate volatility spreads with negative volatility information implicit in call and put options, respectively.

2.3. Model Specifications

2.3.1. Volatility prediction by volatility spreads

If informed investors do trade on private volatility information in the option market first, their private information would be subsequently reflected in the spot market. We can expect that an increase in subsequent volatility will follow volatility spreads with a positive signal (VSM_b), and a decrease in subsequent volatility will follow volatility spreads with a negative signal (VSM_s). The empirical model is specified as

$$RV_t = \alpha + \beta_1 VSM_{b,t-j} + \beta_2 VSM_{s,t-j} + \beta_3 \Delta OV_{t-j} + \beta_4 IV_{t-1} + \beta_5 IS_{t-1} + \varepsilon_t, \qquad (6)$$

where RV_t denotes the realized volatility of underlying index on day t, which is calculated as the difference of the intraday highest and lowest prices divided by the closing price.[10] VSM_b is the volatility spread with positive volatility information embedded in both call and put options, $VSM_b^c$and VSM_b^p, respectively. VSM_s denotes the volatility spread with negative volatility information involving VSM_s^c and VSM_s^p.

Three control variables are considered in Equation (6). IV_{t-1} denotes the implied volatility of the whole option market on day $t-1$, which the literature, in general, finds to be best predictor for future volatility. This variable controls for publicly available information already contained in the option prices. ΔOV_{t-j} controls the effect of straddle and strangle trades on day $t-j$ for future volatility, where OV is the average implied volatility of call and put options. IS_{t-1} indicates the information shocks on day $t-1$, which may lead to persistence in volatility.[11] This variable is incorporated in the return caused by the information flows to capture the dynamic impact of news on volatility. The information shocks are calculated as absolute return innovations by applying the AR(1) model to the daily return.

The regression in Equation (6) is estimated separately for different values of j, from 1 to k, to capture the potential predictive power of volatility spreads for future realized volatility. In addition, the asymptotic t-statistics of estimated parameters are calculated by using Newey and West's (1987) autocorrelation correction.

[10]Based on the same realized volatility measure, Alizadeh, Brandt, and Diebold (2002) find that the results are robust to several alternative definitions of realized volatility.

[11]Evidence of volatility changes due to information shocks is provided by Andersen (1996), who shows that return volatility dynamics is governed by information flows, and Chen and Ghysels (2010), who find that both very good news and bad news increase volatility, with the latter having a more serve impact.

Unlike investors with positive information about asset prices who only choose to buy calls, an investor with a positive volatility signal can buy either calls or puts due to the positive values of vega in both. The calls and puts can thus carry positive information about subsequent volatility. To further test whether the directional volatility information is reflected in both calls and puts, a predictive regression of volatility spreads with the positive and negative information implicit separately in calls and puts on future volatility is run as

$$RV_t = \alpha + \beta_1 VSM^c_{b,t-j} + \beta_2 VSM^p_{b,t-j} + \beta_3 VSM^c_{s,t-j} + \beta_4 VSM^p_{s,t-j} + \beta_5 \Delta OV_{t-j} + \beta_6 IV_{t-1} + \beta_7 IS_{t-1} + \varepsilon_t, \tag{7}$$

where VSM^c_b and VSM^p_b (VSM^c_s and VSM^p_s) denote the volatility spreads with positive (negative) volatility information implicit separately in calls and puts.

2.3.2. *Interaction between predictability in volatility and liquidity*

In the Easley et al. (1998) model, the documented predictability is pronounced for the specific condition under which informed trades in options should occur more frequently. The condition is satisfied as options have higher liquidity relative to the underlying assets. This implication is tested to determine whether the predictability in volatility for relatively liquid options with relatively illiquid underlying index can be improved. A liquid dummy variable (D) to control the level of liquidity in both options and the underlying index is included into Equation (8) to analyze the influence of liquidity on the degree of predictability in volatility as

$$RV_t = \alpha + \beta_1 VSM_{b,t-j} + \beta_2 D_{t-j}{}^{*} VSM_{b,t-j} + \beta_3 VSM_{s,t-j} + \beta_4 D_{t-j}{}^{*} VSM_{s,t-j} + \beta_5 \Delta OV_{t-j} + \beta_6 IV_{t-1} + \beta_7 IS_{t-1} + \varepsilon_t. \tag{8}$$

For daily option liquidity ($QSPR$) of each contract month, the average of percentage quoted spread of calls and puts in every 5-minute interval is first calculated and then averaged across intervals in a day, in which the percentage quoted spread in calls (and puts) is equally weighted across all individual call (put) options. As for the percentage quoted spread of individual call (put) option, it is calculated as the difference between ask and bid prices dividing the mid-quote. In addition, the liquidity of underlying index is gauged by the logarithmic daily trading volume of the underlying index (ILiq). Under these measures of liquidity, option liquidity increases as the QRSP decreases whereas liquidity in the underlying index decreases as the ILiq decreases.

2.3.3. *Predictability by controlling for other information variables*

To examine further whether the predictability is robust after controlling for short sales constraints and other information variables about return and volatility, several control variables, each of which may have some influence on the volatility prediction, are added to the following regression model:

$$RV_t = \alpha + \beta_1 VSM^c_{b,t-j} + \beta_2 VSM^p_{b,t-j} + \beta_3 VSM^c_{s,t-j} + \beta_4 VSM^p_{s,t-j} + \beta_5 \Delta OV_{t-j} + \beta_6 IV_{t-1} + \beta_7 IS_{t-1} + \sum_{i=1}^{4} \gamma_i RV_{t-i} + \psi_1 OIV_{t-j} + \psi_2 DV_{t-j} + \psi_3 IDV_{t-j} + \psi_4 FV_{t-j} + \psi_5 SBL_{t-j} + \varepsilon_t, \tag{9}$$

where RV_{t-i} for $i=1, 2, \ldots, 4$ is the i-day lagged volatility used to control for the volatility clustering and possible patterns (Lakonishok et al., 2007). IDV_{t-j} refers to the logarithmic trading volume of the underlying asset on day $t-j$. FV_{t-j} is the logarithmic open interest of underlying index futures on day $t-j$.

OIV is the put–call ratio of options used to proxy for informed directional information trades. Empirical studies show that investors trade on private directional information in the option market (e.g., Ahn, Kang, & Ryu, 2008; Chakravarty, Gulen, & Mayhew, 2004; Chang, Hsieh, & Lai, 2009; Easley et al., 1998; Pan & Poteshman, 2006). The put–call ratio of options widely used as a proxy for private information is adopted to control for the potential impact of directional information trades on future volatility. *OIV* is calculated as the open-interest put contracts divided by summing the open-interest put and call contracts.

DV is the option demand for volatility used to proxy for informed volatility trading. In addition to trading on directional information, informed investors may also trade on volatility information in the option market, as reported in Ni et al. (2008) and Chang et al. (2010). The possible influence of informed volatility trading on future volatility is controlled by using order imbalances weighted by the Black–Scholes vega across all options to proxy the option demand for volatility (*DV*).[12]

Following Chordia, Roll, and Subrahmanyam (2008), the order imbalance is calculated as the difference between the number of buyer-initiated and seller-initiated trades divided by the total number of trades within every 5-minute interval, in which the Lee and Ready's (1991) algorithm is used to classify each option trade as buyer initiated or seller initiated. For daily order imbalance, the order imbalance is first calculated for every 5-minute interval by weighting order imbalances across all options according to the Black–Scholes vega and then averaged across intervals in a day.

SBL is a security borrowing and lending fee in the stock-lending market used to proxy for short sales constraints. Several studies argue that deviations from PCP may arise in the presence of short sales constraints on the underlying stocks (Lamont & Thaler, 2003; Ofek & Richardson, 2003; Ofek et al., 2004). Bali and Hovakimian (2009) find that the deviations caused by short sales constraints may reflect the expected future price change of the underlying stock. The possible influence of the difficulty of selling short the underlying index on volatility is controlled by using *SBL* to proxy short sales constraints. That is, a high *SBL* fee rate in stock-lending market makes shorting the stocks costly for the borrower of the stocks and can thus be interpreted as a signal of short sale constraints.[13] The *SBL* fee rate of the Taiwan Top 50 Tracker Fund, which is an exchange-traded fund, is used to proxy for the short sales constraints on the whole stock market.[14]

[12]The order imbalance is widely used in the literature as a proxy for the nonmarket maker net demand. Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004) use order imbalance to measure both direction and degree of buying or selling pressure. Bollen and Whaley (2004) gauge the net demand using order imbalance between the number of buyer-initiated and seller-initiated trades.

[13]In June 2003, the TWSE launched a centralized SBL system to meet the needs of qualified institutional investors while TWSE serves as an intermediary. This SBL system provides three types of transactions: fixed-rate, competitive bid, and negotiated transaction. This study adopts a competitive bid as a proxy of short sales constraints because the SBL fee rate is determined by the bids and offers quoted by the borrower and the lender.

[14]The Taiwan Top 50 Tracker Fund (0050), which is managed by Polaris International Securities and Investment Trust Company Ltd, uses full replication to track the performance of the TWSE Taiwan Top 50 Index. The fund's constituents are selected from the top 50 listed stocks on the TWSE by market weight, after meeting the criteria to be included in the index. The fund allows investors to invest in all 50 constituents with a single investment and is adjusted quarterly to closely reflect the index and market.

2.3.4. *Volume prediction by volatility spreads*

The unexpected variation in volatility may generate a change in trading volume of options and the underlying index (Andersen, 1996; Lamoureux & Lastrapes, 1990, 1994; Sarwar, 2003; Sears, 2000; Tauchen & Pitts, 1983). The contemporaneous and lagged relation between price volatility and trading volume implies that volatility spreads with private information about future volatility and trading volume are related. This study further explores the information content of volatility spreads with positive and negative information for future option trading volume and trading dollar volume in the underlying index.

The daily option trading volume in the near and second month (*OPVOL*) is examined as a consequence of options with the best liquidity and largest trading volume. The *OPVOL* is further separated into signed buy volume ($OPVOL_{buy}$) and signed sell volume ($OPVOL_{sell}$) by using the Lee and Ready's (1991) algorithm. For daily trading dollar volume in the underlying index, we use trading dollar volume (*IDVOL*) of dealers, securities investment trust companies, and foreign investors as a proxy and further separate *IDVOL* into buy dollar volume ($IDVOL_{buy}$) and sell dollar volume ($IDVOL_{sell}$).[15] This method is followed because the underlying index of TXO, a stock market index for companies traded on the TWSE, is not traded directly whereas these three types of investors account for almost all trading volume in the Taiwanese spot market.

The volatility spreads with positive and negative information are used separately to test for the predictability in *OPVOL*, $OPVOL_{buy}$, and $OPVOL_{sell}$ (and *IDVOL*, $IDVOL_{buy}$, and $IDVOL_{sell}$). Each of them is individually included in the following regression model:

$$\begin{aligned} VOL_t = {} & \alpha + T_{t-1} + \beta_1 VSM^c_{t-j} + \beta_2 VSM^p_{t-j} + \beta_3 FV_{t-j} + \beta_4 IDV_{t-j} + \beta_5 IS_{t-j} \\ & + \sum_{i=1}^{4} \gamma_i VOL_{t-i} + \varepsilon_t, \end{aligned} \tag{10}$$

where VSM^c_{t-j} and VSM^p_{t-j} denote either volatility spreads with positive information (VSM^c_b and VSM^p_b) or negative information (VSM^c_s and VSM^p_s) on day $t-j$ of calls and puts, respectively. *VOL* is either of *OPVOL*, $OPVOL_{buy}$, or $OPVOL_{sell}$ (and *IDVOL*, $IDVOL_{buy}$, or $IDVOL_{sell}$). T is a linear time trend used to control for the time effect.

Figure 2 presents the time-series trading volume and trading dollar volume. The graph shows a slightly negative time trend in option trading volume (*OPVOL*), signed buy volume ($OPVOL_{buy}$), and signed sell volume ($OPVOL_{sell}$) in the left part of figure but a slightly positive time trend in trading dollar volume (*IDVOL*), buy dollar volume ($IDVOL_{buy}$), and sell dollar volume ($IDVOL_{sell}$) in the right part of figure.

3. DATA DESCRIPTION

The intraday data on the TXO, which is traded on the Taiwan Futures Exchange (TAIFEX),[16] are obtained from the Taiwan Economic Journal (TEJ) database. The data contain quote and trade files of options. We extract transaction prices and volumes for every trade from the trade

[15]Dealers are defined by dealers' proprietary account and securities investment trust companies mean domestic mutual funds managed by securities investment trust companies. Foreign investors are defined by regulations governing investment in securities by overseas Chinese and foreign nationals and regulations governing securities investment and futures trading in Taiwan by Mainland area investors.

[16]The TAIFEX introduced the European style TXO on December 24, 2001, which is written on the TAIEX. The contract matures on the third Wednesday of the delivery month. The contract months involve five contracts with different maturities in the nearby month, the next 2 calendar months, and the following 2 quarterly months.

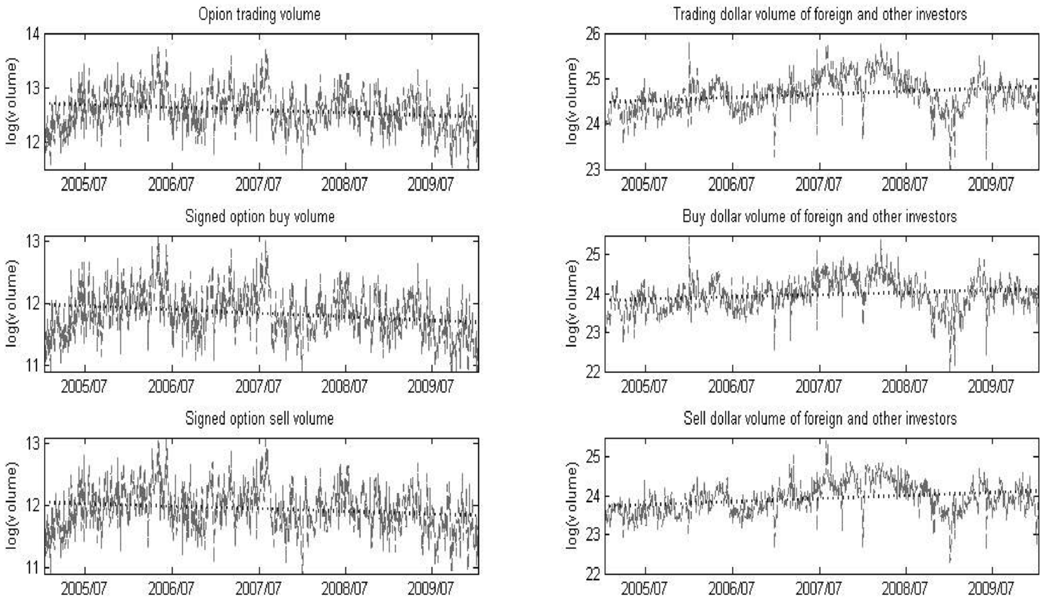

FIGURE 2

Time-series plots of trading volume and trading dollar volume. This figure depicts the time-series option trading volume, signed option buy volume, and signed option sell volume in the left of figure and trading dollar volume, buy dollar volume, and sell dollar volume of foreign and other investors in the right part of figure. The time period is from January 1, 2005 through December 31, 2009. The dotted line indicates a linear time trend for trading volume and trading dollar volume.

file, and the bid and ask prices from the quote file for January 1, 2005 through December 31, 2009. The daily open interest of index option and futures is collected from TAIFEX database covering the period from January 1, 2005 through December 31, 2009. Daily closing prices, highest prices, lowest prices, and volume of Taiwan stock index for January 1, 2005 through December 31, 2009 and the 3-month time deposit of postal saving system for the risk-free interest rate are obtained from TEJ database. In addition, the security borrowing and lending fee of the Taiwan Top 50 Tracker Fund, and the trading dollar volume, buy dollar volume, and sell dollar volume of dealers, securities investment trust companies, and foreign investors are collected from the TWSE database.

Several data filters are applied to select the final sample. First, options with quote price less than 0.1, the minimum tick size, are excluded from the sample. These prices do not reflect true option value. Next, options with less than 5 trading days remaining to maturity are eliminated from the sample due to potential liquidity concerns. Finally, options violating the PCP boundary conditions are deleted from the sample. These options are significantly undervalued and have negative Black–Scholes implied volatilities.

A nonsynchronic question occurs because the conventional trading time periods for Taiwanese stock and option markets differ slightly, running weekdays from 9:00 a.m. to 1:30 p.m. and from 8:45 a.m. to 1:45 p.m., respectively. Battalio and Schultz (2006) find that such nonsynchronicity can lead observations to violate PCP where none exists. To resolve the possible concern for nonsynchronicity, the daily volatility spreads and realized volatility are calculated by using the data of options and underlying index with the same trading time period on the day, formed on the trading time of TAIEX stock market from 9:00 a.m. to 1:30 p.m.

Table I presents the summary statistics of common variables used for the empirical analysis. On average, the implied volatility (IV) is slightly above the realized volatility (RV) by

TABLE I
Summary Statistics of Common Variables

	Mean	*Std*	*Median*	*Skewness*	*Kurtosis*	*Min*	*Max*
RV	0.2203	0.1401	0.1834	2.0535	9.2118	0.0476	1.1394
VSM_b^c	0.0052	0.0232	0.0000	6.9835	73.4701	0.0000	0.3290
VSM_b^p	0.0181	0.0393	0.0000	4.5710	32.6352	0.0000	0.4116
VSM_s^c	0.0156	0.0308	0.0000	3.7149	23.8299	0.0000	0.3139
VSM_s^p	0.0035	0.0153	0.0000	4.4929	23.2038	0.0000	0.1108
ΔOV	−0.0023	0.0648	0.0010	−0.0899	6.8997	−0.3416	0.3161
IV	0.2312	0.0864	0.2112	1.2508	4.8280	0.1241	0.6363
IS	0.0099	0.0103	0.0069	2.1273	8.6657	0.0000	0.0675
OIV	0.4600	0.0715	0.4668	−0.4317	2.7751	0.2619	0.6342
DV	−0.0295	0.0311	−0.0278	−1.1871	13.1943	−0.3376	0.0717
IDV	15.1756	0.3146	15.1742	0.2683	2.8982	14.3222	16.1610
FV	10.7190	0.2278	10.7037	0.3489	2.8192	10.0905	11.3621
$QSPR_1$	0.0319	0.0191	0.0281	0.7615	3.0750	0.0035	0.0971
$QSPR_2$	0.0415	0.0259	0.0373	0.9279	3.7221	0.0054	0.1366
SBL	0.0379	0.0022	0.0380	−0.5901	2.0368	0.0320	0.0400

Note. This table presents the summary statistics of the common variables, including realized volatility (*RV*), four volatility spreads with positive and negative volatility information respectively implicit in calls and puts (VSM_b^c, VSM_b^p, VSM_s^c, and VSM_s^p), percentage change of option-implied volatility (ΔOV), implied volatility (*IV*), information shock (*IS*), option put–call ratio (*OIV*), option demand for volatility (*DV*), logarithmic trading volume of the underlying index (*IDV*), logarithmic open interest of the underlying index futures (*FV*), option liquidity in the near-month ($QSPR_1$), option liquidity in the second-month ($QSPR_2$), and short sales constraints (*SBL*).

109 basis points, with average annualized volatilities of 0.2312 and 0.2203, respectively. This positive spread between implied volatility and actual volatility (i.e., volatility risk premium) compensates liquidity providers and motivates them to accept the unhedgeable risks of options, as described by Bollen and Whaley (2004) and Gârleanu, Pedersen, and Poteshman (2009). The volatility spreads with positive (negative) information implicit separately in calls and puts, VSM_b^c and VSM_b^p (VSM_s^c and VSM_s^p), average 0.0052 and 0.0181 (0.0156 and 0.0035), respectively, and are positively skewed and exhibit leptokurtosis. Overall, the put–call ratio (*OIV*) is below 0.5 (0.4600), showing that the open-interest position on calls is relatively higher than that of puts.

The correlation coefficients between realized volatility and implied volatility and between realized volatility and information shock are 0.6236 and 0.4941, respectively. The positive relation between information shock and realized volatility provides evidence that return volatility is driven by information inflows (Andersen, 1996; Chen & Ghysels, 2010). In addition, a negative correlation coefficient of −0.2469 between *IV* and volatility demand (*DV*) indicates that the high level of implied volatility can generate more demand for selling volatility.

4. EMPIRICAL RESULTS

4.1. Predictability in Volatility

Table II shows the results of volatility prediction by volatility spreads with positive and negative information. The volatility spreads are calculated separately from the near-month and second-month options with the corresponding results reported in the left part and in the right

TABLE II
Volatility Prediction by Volatility Spreads

	VSM calculated from near-month options				*VSM calculated from second-month options*			
	1		*2*		*1*		*2*	
j	*Coeff.*	*t*	*Coeff.*	*t*	*Coeff.*	*t*	*Coeff.*	*t*
α	−0.0003	−0.37	−0.0002	−0.22	−0.0003	−0.35	−0.0003	−0.42
$VSM_{b,t-j}$	0.0146	1.53	0.0252	2.35**	0.0122	1.03	0.0113	0.87
$VSM_{s,t-j}$	−0.0058	−0.49	−0.0192	−2.04**	0.0017	0.14	0.0119	0.76
ΔOV_{t-j}	−0.0041	−1.12	−0.0104	−2.05**	−0.0019	−0.40	0.0001	0.01
IV_{t-1}	0.0567	13.17***	0.0554	14.31***	0.0564	13.07***	0.0557	13.47***
IS_{t-1}	0.0815	1.95*	0.1009	2.32**	0.0845	2.01**	0.0891	2.07**
Adj. R^2	0.3911	—	0.4044	—	0.3884	—	0.3885	—

$$RV_t = \alpha + \beta_1 VSM_{b,t-j} + \beta_2 VSM_{s,t-j} + \beta_3 \Delta OV_{t-j} + \beta_4 IV_{t-1} + \beta_5 IS_{t-1} + \varepsilon_t$$

Note. This table represents the estimation results of the prediction regression, shown in Equation (6), of lagged volatility spreads with positive and negative information on volatility. The regression is separately estimated for different values of *j*, from 1 to 2, to capture the potential predictive power of volatility spreads for future realized volatility. The volatility spreads are calculated respectively from near-month and second-month options with the corresponding results reported in the left part and in the right part of table. The volatility spreads are used to measure the quantity of volatility information and are further separated into positive and negative signals. $VSM_{b,t-j}$ and $VSM_{s,t-j}$ denote volatility spreads with positive and negative volatility information on day $t-j$, respectively. RV_t is the realized volatility, which is calculated as the difference of the intraday highest and lowest prices divided by the closing price on day *t*. IV_{t-1} is implied volatility for the whole option market on day $t-1$. ΔOV_{t-j} is used to control the effect of the straddle and strangle trades on day $t-j$ for future volatility, in which *OV* is the average implied volatility of call and put options. IS_{t-1} denotes the absolute return innovations controlled for the impact of information flows on day $t-1$. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. ***, **, and * indicate that *t* values are significant at the 0.01, 0.05, and 0.1 level, respectively.

part of Table II, respectively. The left part of the table shows that the coefficients of volatility spreads with positive (negative) information, VSM_b (VSM_s), are all positive (negative) in each regression and are significant at 2 days ahead with *t* values of 2.35 (−2.04).[17] This positive (negative) relation from lagged volatility spreads with positive (negative) information to volatility indicates that deviations from PCP have some degree of predictive power for future volatility. This result also provides evidence for informed volatility trading in the TXO market, consistent with the finding of Chang et al. (2010) who examine the predictive ability of volatility by option trading volume.

The coefficients of lagged *IV* and information flows (*IS*) are all significant and positive, with the former having a more pronounced influence on realized volatility (all coefficients are at the 1% significance level). Consistent with the majority of prior empirical evidence, implied volatility is a better predictor of future volatility due to private information about the volatility brought into option prices through the trading process. A positive impact of information flows on volatility shows that return volatility is governed by information inflows, as described in Andersen (1996) and Chen and Ghysels (2010). In particular, these results provide no evidence of significant and positive ΔOV coefficients, used as a proxy for the effect of straddle and strangle trades on future volatility. The result that volatility spreads rather than ΔOV provide strong predictive power on volatility supports the findings of Chang et al. (2010) that volatility traders often adopt an option/future strategy within Taiwan's option market.

[17]To save space, Tables II, III, and VI only report the predictive results within two days because the results for the key variable, volatility spreads, are either weak or insignificant for $j = 3$ and 4.

The right side of Table II shows no evidence to support the predictability of volatility spreads to predict future volatility. One likely reason is that options in the second-month (with average liquidity of 0.0415 shown in Table I) are less liquid relative to the near-month options (with average liquidity of 0.0319), whereas informed traders are more likely to trade in options with more liquidity.[18] Thus, the subsequent analysis focuses only on the near-month options.

To further test whether the directional (positive or negative) volatility information is reflected in both call and put options, four volatility spreads, which carry positive and negative volatility information separately implicit in calls and puts, are adopted to run the predictive regression model in Equation (7). Table III reports the results.

Table III shows that both lagged volatility spreads with positive information separately abstracted from calls and puts are positively related to volatility in the subsequent 2 days and are especially significant for the 2-day-ahead volatility. This finding is supported by a significantly positive coefficient of VSM_b^c at 2 days ahead (with $t = 3.74$) and significantly positive coefficients of VSM_b^p within 2 days (with $t = 1.67$ and 1.65). Similarly, volatility spreads with negative information, VSM_s^c and VSM_s^p, embedded in calls and puts have significant predictive power on the 2-day-ahead volatility (with $t = -1.83$ and -1.97). Accordingly, for each of four volatility spreads, predictability lasts at least 2 days into the future, which provides evidence that call and put options may contain same-directional information about future volatility.

TABLE III
Volatility Prediction by Controlling for Other Information Variables

	1		*2*	
j	*Coeff.*	*t*	*Coeff.*	*t*
α	−0.0001	−0.19	−0.0003	−0.36
$VSM_{b,t-j}^c$	0.0039	0.50	0.0303	3.74***
$VSM_{b,t-j}^p$	0.0189	1.67*	0.0229	1.65*
$VSM_{s,t-j}^c$	−0.0058	−0.42	−0.0200	−1.83*
$VSM_{s,t-j}^p$	−0.0007	−0.06	−0.0179	−1.97**
ΔOV_{t-j}	−0.0042	−1.16	−0.0103	−2.01**
IV_{t-1}	0.0559	11.65***	0.0560	13.06***
IS_{t-1}	0.0821	1.94*	0.0995	2.26**
Adj. R^2	0.3924	—	0.4047	—

$$RV_t = \alpha + \beta_1 VSM_{b,t-j}^c + \beta_2 VSM_{b,t-j}^p + \beta_3 VSM_{s,t-j}^c + \beta_4 VSM_{s,t-j}^p + \beta_5 \Delta OV_{t-j} + \beta_6 IV_{t-1} + \beta_7 IS_{t-1} + \varepsilon_t$$

Note. This table represents the estimation results of the prediction regression, shown in Equation (7), of lagged volatility spreads with private information implicit in calls and puts on realized volatility. The regression is separately estimated for different values of *j*, from 1 to 2, to capture the potential predictive power of volatility spreads for future volatility. The volatility spreads are used to measure the quantity of volatility information and are further separated into positive and negative signals. VSM_b^c and VSM_b^p (VSM_s^c and VSM_s^p) denote volatility spreads with positive (negative) information separately implicit in calls and puts on day $t-j$, respectively. RV_t is the realized volatility on day *t*. IV_{t-1} is implied volatility for the whole option market on day $t-1$. ΔOV_{t-j} is used to control the effect of the straddle and strangle trades on day $t-j$ for future volatility. IS_{t-1} denotes the absolute return innovations used to control for the impact of information flows on day $t-1$. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. ***, **, and * indicate that *t* values are significant at the 0.01, 0.05, and 0.1 level, respectively.

[18]The average daily trading volumes of near-month and second-month options are 319,749 and 27,387 contracts for January 1, 2005 through December 31, 2009, respectively.

4.2. Predictability in Volatility and Liquidity

This study considers three cases of different levels of liquidity in both options and the underlying index, which is determined by a liquidity dummy variable D, including D ($QSPR < 50\%$, ILiq $< 50\%$), D ($QSPR < 30\%$, ILiq $< 30\%$), and D ($QSPR < 15\%$, ILiq $< 15\%$). In Case 1, D ($QSPR < 50\%$, ILiq $< 50\%$) indicates that options are liquid and its underlying index is illiquid. In Case 2, D ($QSPR < 30\%$, ILiq $< 30\%$) represents higher liquidity in the options and lower liquidity in the underlying index. In Case 3, D ($QSPR < 15\%$, ILiq $< 15\%$) indicates the best liquidity in options and the worst liquidity in the underlying index. D_t equals 1 if both the QRSP and ILiq are below the $k\%$ of the sample on day t, and zero otherwise, in which $k = 50$, 30, and 15 for Case 1, Case 2, and Case 3, respectively. Panels A–C of Table IV reports the results for Cases 1–3.

TABLE IV
Interaction Between Predictability in Volatility and Liquidity

	1		*2*		*3*	
j	*Coeff.*	*t*	*Coeff.*	*t*	*Coeff.*	*t*
Panel A: Case 1 is D (QRSP < 50%, ILiq < 50%)						
β_1	0.0040	0.41	0.0225	2.77***	−0.0033	−0.34
β_2	0.0282	1.67*	0.0063	0.38	0.0064	0.45
β_3	0.0091	0.93	−0.0209	−1.55	0.0135	0.98
β_4	−0.0381	−3.08***	0.0039	0.24	0.0142	0.58
Adj. R^2	0.4027	—	0.4047	—	0.3917	—
Panel B: Case 2 is D (QRSP < 30%, ILiq < 30%)						
β_1	0.0065	0.69	0.0272	2.61***	−0.0056	−0.51
β_2	0.0491	2.60***	−0.0112	−0.81	0.0280	2.49**
β_3	0.0074	0.78	−0.0196	−1.58	0.0158	1.17
β_4	−0.0478	−3.40***	0.0025	0.14	0.0093	0.28
Adj. R^2	0.4085	—	0.4049	—	0.3940	—
Panel C: Case 3 is D (QRSP < 15%, ILiq < 15%)						
β_1	0.0080	0.81	0.0239	2.30**	−0.0047	−0.47
β_2	0.0712	7.64***	0.0142	1.72*	0.0478	5.39***
β_3	−0.0037	−0.30	−0.0194	−1.79*	0.0209	1.82*
β_4	−0.0284	−2.34**	−0.0002	−0.01	−0.0209	−1.72*
Adj. R^2	0.4035	—	0.4048	—	0.3963	—

$$RV_t = \alpha + \beta_1 VSM_{b,t-j} + \beta_2 D^* VSM_{b,t-j} + \beta_3 VSM_{s,t-j} + \beta_4 D^* VSM_{s,t-j} + \beta_5 \Delta OV_{t-j} + \beta_6 IV_{t-1} + \beta_7 IS_{t-1} + \varepsilon_t$$

Note. This table represents the estimation results of the prediction regression, shown in Equation (8), in different levels of liquidity in both options and the underlying index. The regression is separately estimated for different values of j, from 1 to 3, to capture the potential predictive power of volatility spreads for future realized volatility (RV). This study considers three cases of different liquidity levels, which is determined by a liquidity dummy D, involving D ($QSPR < 50\%$, ILiq $< 50\%$), D ($QSPR < 30\%$, ILiq $< 30\%$), and D ($QSPR < 15\%$, ILiq $< 15\%$); the results are separately reported in Panels A–C, respectively. In Case 1, a liquidity dummy variable D ($QSPR < 50\%$, ILiq $< 50\%$) indicates that options are liquid and its underlying index is illiquid. In Case 2, a dummy variable D ($QSPR < 30\%$, ILiq $< 30\%$) represents higher liquidity in options and lower liquidity in the underlying index. In Case 3, D ($QSPR < 15\%$, ILiq $< 15\%$) indicates the best liquidity in options and the worst liquidity in the underlying index. D_t is equal to 1 if both the QRSP and ILiq are below the $k\%$ of the sample on day t, and zero otherwise, in which k is 50, 30, and 15, respectively corresponding to the three cases. $QSPR$ denotes option liquidity in the near month and ILiq is the liquidity of underlying index. IV_{t-1} is implied volatility on day $t-1$. ΔOV_{t-j} and IS_{t-1} control the effect of the straddle and strangle trades and the impact of information flows on day $t-1$ for future volatility, respectively. For brevity, only the β_1, β_2, β_3, and β_4 are reported. Newey–West standard errors are used to calculate the t-statistics of the estimated parameters. ***, **, and * indicate that t values are significant at the 0.01, 0.05, and 0.1 level, respectively.

As reported in Panel A of Table IV, the coefficients for β_2 and β_4 are significant at 1 day ahead with t values of 1.67 and -3.08, respectively, but are only significant for β_1 at 2 days ahead with a t value of 2.77. The greater number of significant coefficients on β_2 and β_4 indicates that the predictive ability of volatility improves on relatively liquid options with a relatively illiquid underlying index. The results in Panel B are similar to those of Panel A except that volatility spread with a positive signal (β_2) has additional predictive ability at 3 days ahead (evidenced by the t-value of 2.49).

Compared with Panels A and B, the increased number of significant coefficients on β_2 and β_4 (from two to three) shows that predictability increases as option liquidity increases and liquidity in the underlying index decreases. Specifically, when liquidity in the options is at its best and liquidity of its underlying index is at its worst, as shown in Panel C, predictability becomes stronger. This finding is supported by the five significant coefficients for β_2 and β_4, that is, significant β_2 coefficients at 1, 2, and 3 days ahead with $t = 7.64$, 1.72, and 5.39, respectively, and significant β_4 coefficients at 1 and 3 days ahead with $t = -2.34$ and -1.72, respectively. These results support the implication of Easley et al.'s (1998) model that predictability is stronger in options with high liquidity and an underlying asset with low liquidity.

4.3. Volatility Trades Formed on Levels of Volatility Spreads

If deviations from PCP are driven by informed volatility trading, investors can profit from observed large volatility spreads due to the preceding private volatility information embedded in volatility spreads. To test this conjecture, we construct a trading simulation of selling volatility with a delta-neutral option/futures strategy formed on levels of volatility spreads. The rewards for selling volatility are separated into two classes based on the daily volatility spreads with a negative signal (VSM_s) at the spot market closing time (1:30 p.m.): volatility spreads below 75% of the sample and volatility spreads over 75% of the sample.

To conduct the trading simulation, each call and put option in the near month is assumed to be sold at the midpoint price of quotes at the option closing time (1:45 p.m.). Further, price risk is dynamically hedged every 30 minutes to maintain the delta-neutrality of the option positions in the subsequent four trading days by buying (selling) |delta| units of the underlying futures in the case of a call (put).[19] The daily delta-hedged gains for writing an option (call/put) are given as

$$\pi_{t,t+1} \equiv C_t - C_{t+1} + \sum_{k=0}^{n-1} \Delta_{t_k}(F_{t_{k+1}} - F_{t_k}) + \sum_{k=0}^{n-1} r_k (C_t - \Delta_{t_k} F_{t_k}) \frac{1}{n}, \tag{11}$$

where the risk-free interest rate, r_k, and option delta, Δ_{tk}, are updated on a 30-minute basis. n, the hedged discretely times during 1 day, is set to 9. The rebalancing frequency, $1/n$, is set to 30 minutes. C_t and F_t are the mid-quotes of option and futures at the time t, respectively.

In the trading simulation, all the transaction costs are ignored because our focus is on the predictability of volatility. If volatility spreads are informative about future volatility, the largest profit for selling volatility should occur at the 2-day ahead window rather than at other days, as suggested by the results in Tables II and III, which show that the private volatility information is often incorporated into market prices at the 2-day ahead interval.

[19]The delta is calculated by constructing on the Black–Scholes model, in which the implied volatility on day t is used to forecast the realized volatility on day $t + 1$. In addition, every TXO can be hedged only by a quarter of TXF contract because the multipliers for the futures and options contracts are NT$200 and NT$50 per index point, respectively.

Table V provides the average of daily delta-hedged gains in the subsequent four trading days from applying the volatility spread trading strategy to index options for January 1, 2005 through December 31, 2009. Panels A and B report the profits of the two classes, volatility spreads over 75% of the sample (with 236 observations) and below 75% of the sample (with 708 observations), respectively. For each class, the delta-hedged gains are grouped into three categories by option moneyness: in-the-money ($m < 0.975$), at-the-money ($0.975 \leq m \leq 1.025$), and out-the-money ($m > 1.025$). The option moneyness is defined as $m = K/S\,e^{r\tau}$, where K is strike price and S is underlying index price. The measure unit for hedged gains is an index point, with each index point valued at NT$50.

Panel A of Table V shows that almost all the average delta-hedged gains for calls and puts are positive in the three moneyness groups, with the puts having large delta-hedged gains. The larger delta-hedged gains for puts likely arise from the fact that the average implied volatility of puts (0.2603) is higher than the average implied volatility of calls (0.2082) at the time of selling index options. Thus, volatility sellers can capture more profits from puts because the targeted profits are roughly the size of spread between implied volatility and realized volatility.

The sum of average delta-hedged gains of calls and puts in the subsequent 4 days, shown in the last column of Table V, are all positive with values of 74.18, 138.18, 23.83, and 76.44, respectively. Specifically, the largest profit, 138.18, occurs at 2-day ahead, the day predicted by volatility spreads with private information as the day that informed volatility information is often incorporated in the spot market (see Tables II and III).

By contrast, the average delta-hedged gains for calls and puts, as shown in Panel B of Table V, are smaller and more negative. Only the sum of the average delta-hedged gain at

TABLE V

Performance of Selling Volatility Formed on Levels of Volatility Spreads

	Out-the-money ($m > 1.025$)			*At-the-money* ($0.975 \leq m \leq 1.025$)			*In-the-money* ($m < 0.975$)			
Day	*C*	*P*	*C + P*	*C*	*P*	*C + P*	*C*	*P*	*C + P*	*Total*
Panel A: Volatility spreads over 75% of the sample ($VSM_b \geq 75\%$)										
1	16.41	−16.89	−0.48	16.19	21.90	38.08	13.47	23.10	36.57	74.18
2	16.23	45.24	61.47	18.46	23.95	42.41	7.58	26.73	34.30	138.18
3	13.92	7.53	21.45	8.38	40.75	49.14	−82.84	36.09	−46.75	23.83
4	16.36	47.08	63.45	17.42	33.73	51.14	−59.07	20.91	−38.16	76.44
Panel B: Volatility spreads below 75% of the sample ($VSM_b < 75\%$)										
1	12.99	−5.61	7.39	10.79	27.44	38.24	−55.79	25.55	−30.24	15.39
2	13.46	−40.51	−27.05	10.23	27.85	38.08	−77.44	21.58	−55.86	−44.82
3	15.07	−72.21	−57.14	18.68	18.20	36.88	−16.30	11.84	−4.46	−24.72
4	12.64	−99.22	−86.58	16.92	23.24	40.16	−32.09	17.50	−14.60	−61.01

Note. This table represents the performance of selling volatility formed on the levels of volatility spreads with negative information (VSM_s). Panel A and Panel B, respectively, report the profits of two classes, volatility spreads over the 75% of the sample (with 236 observations) and below the 75% of the sample (with 708 observations). For each class, the delta-hedged gains (π) are grouped into three categories by option moneyness (m): in-the-money options ($m < 0.975$), at-the-money options ($0.975 \leq m \leq 1.025$), and out-the-money options ($m > 1.025$). The option moneyness is defined as $m = K/S\,e^{r\tau}$, where K is strike price, r is risk-free interest rate, and S is underlying index price. For each of three categories, the average daily delta-hedged gains are calculated in the subsequent 4 days. Each of call and put options in the near-month is assumed to be sold at the midpoint prices of quotes at the close time of options. Further, price risk is dynamically hedged every 30 minutes to keep delta-neutral of option positions. The delta-hedged gains of every option are calculated each day. In addition, the unit of measurement for delta-hedged profits is an index point, which is valued at NT$50 per index point.

1-day ahead, 15.39, is positive. A comparison of the results in Panels A and B shows higher profits for selling volatility following large volatility spreads and again confirms that deviations from PCP contain information about future volatility.

4.4. Incremental Predictive Ability of Volatility Spreads

Table VI provides the results of the prediction regression for realized volatility by adding several control variables in Equation (9), including lagged RVs, option put–call ratio (*OIV*),

TABLE VI

Volatility Prediction by Controlling for Short Sales Constraints and Other Information Variables

	1		*2*	
j	*Coeff.*	*t*	*Coeff.*	*t*
α	−0.0062	−0.32	−0.0096	−0.50
$VSM^c_{b,t-j}$	0.0066	0.82	0.0305	3.87***
$VSM^p_{b,t-j}$	0.0200	1.66*	0.0180	1.18
$VSM^c_{s,t-j}$	−0.0110	−0.89	−0.0255	−2.43**
$VSM^p_{s,t-j}$	−0.0022	−0.23	−0.0215	−2.22**
ΔOV_{t-j}	−0.0047	−1.23	−0.0108	−2.10**
IV_{t-1}	0.0462	7.12***	0.0469	6.85***
IS_{t-1}	0.0489	0.98	0.0742	1.38
RV_{t-1}	0.0717	1.34	0.0541	0.99
RV_{t-2}	0.0655	1.55	0.0404	0.93
RV_{t-3}	0.0579	1.21	0.0490	1.04
RV_{t-4}	−0.0134	−0.31	0.0181	0.44
OIV_{t-j}	−0.0025	−0.52	−0.0042	−0.85
DV_{t-j}	0.0187	3.25***	0.0153	1.97**
IDV_{t-j}	−0.0003	−0.18	−0.0003	−0.19
FV_{t-j}	0.0010	0.88	0.0016	1.35
SBL_{t-j}	−0.0149	−0.13	−0.0745	−0.74
Adj. R^2	0.4084	—	0.4179	—

$$RV_t = \alpha + \beta_1 VSM^c_{b,t-j} + \beta_2 VSM^p_{b,t-j} + \beta_3 VSM^c_{s,t-j} + \beta_4 VSM^p_{s,t-j} + \beta_5 \Delta OV_{t-j} + \beta_6 IV_{t-1} + \beta_7 IS_{t-1}$$
$$+\sum_{i=1}^{4}\gamma_i RV_{t-i} + \psi_1 OIV_{t-j} + \psi_2 DV_{t-j} + \psi_3 IDV_{t-j} + \psi_4 FV_{t-j} + \psi_5 SBL_{t-j} + \varepsilon_t$$

Note. This table represents the estimation results of prediction regression, shown in Equation (9), for realized volatility by controlling on short sales constraints and other information variables. The regression is separately estimated for different values of *j*, from 1 to 2, to capture the potential predictive power of volatility spreads for future volatility. The volatility spreads are used to measure the quantity of volatility information and are further separated into positive and negative signals. $VSM^c_{b,t-j}$ and $VSM^p_{b,t-j}$ ($VSM^c_{s,t-j}$ and $VSM^p_{s,t-j}$) denote volatility spreads with positive (negative) signals separately implicit in calls and puts on day $t-j$. A security borrowing and lending fee in the stock-lending market is used to proxy the short sales constraints (*SBL*). OIV_{t-1} and DV_{t-1} are the put–call ratio of options and option demand for volatility separately used to proxy for informed directional trades and informed volatility trades. IDV and *FV* are logarithmic trading volume of the underlying index and logarithmic open interest of the underlying index futures, respectively. RV_t is the realized volatility on day *t*. IV_{t-1} is implied volatility for the whole option market on day $t-1$. ΔOV_{t-j} is used to control the effect of the straddle and strangle trades on day $t-j$ for future volatility. IS_{t-1} denotes the absolute return innovations used to control for the impact of information flows on day $t-1$. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. ***, **, and * indicate that *t* values are significant at the 0.01, 0.05, and 0.1 level, respectively.

volatility demand (*DV*), logarithmic trading volume of the underlying index (*IDV*), logarithmic open interest of underlying index futures (*FV*), and short sales constraints (*SBL*). The results show that volatility spreads with positive and negative information implicit in calls and puts continue to predict 1- and 2-day-ahead volatility. This result also indicates that deviations from PCP contain incremental information beyond implied volatility and other information variables about return and volatility used widely in the literature.

The option demand for volatility (*DV*) calculated from option trading volume has significant predictive power for realized volatility in the subsequent 2 days. This result is consistent with Ni et al. (2008) and Chang et al. (2010) who find that option trading volume contains future volatility information. In addition, the predictability continues to last at least 2 days after controlling for short sales constraints, suggesting that the difficulty of selling the underlying stocks short has less influence on the predictability of volatility by deviations from PCP. The finding that the option market leads the spot market by days, not minutes, also provides evidence in support of information discovery in options.

4.5. Volume Prediction by Volatility Spreads

Table VII presents the results of the predictive regression for $OPVOL$, $OPVOL_{buy}$, and $OPVOL_{sell}$. The results of volume prediction by volatility spreads with positive and negative volatility information are reported in Panels A and B, respectively. Panel A shows that the coefficients of volatility spreads with positive information implicit in calls and puts (VSM_b^c and VSM_b^p, respectively) are all positive in each regression for option trading volume ($OPVOL$), signed buy volume ($OPVOL_{buy}$), and signed sell volume ($OPVOL_{sell}$). Specifically, the volatility information abstracted from puts has a significantly positive effect on $OPVOL$, $OPVOL_{buy}$, and $OPVOL_{sell}$ at 2-day ahead interval (respectively, with t values of 3.46, 3.29, and 3.59) whereas the significant and positive effect from the volatility information implicit in calls occurs at 1-day ahead (with t values of 1.99, 2.03, and 1.91, respectively).

This positive relation from lagged volatility spreads to volume indicates that volatility spreads have forecasting ability for option trading volume and option buy and sell volume. The possible cause is that when an unexpected increase in market volatility is realized—exactly as the volatility forecast by volatility spreads with positive information shown in Tables II, III, and VI—the hedging and speculative uses of option not only enlarge option buy and sell volume but also increase option trading volume because of large potential gains and losses associated with greater volatility. This result also implies a positive volume–volatility relation, consistent with Sarwar (2003) and Sears (2000) who cite a positive relation between volatility and option trading volume.

Panel B of Table VII shows a relatively weak negative relation from lagged volatility spreads to volume: Most of the coefficients for volatility spreads with negative information are negative, whereas only the volatility information abstracted from calls has a significant effect on $OPVOL$, $OPVOL_{buy}$, and $OPVOL_{sell}$ at 2 days ahead. A possible explanation for this result is that a decrease in market volatility predicted by volatility spreads with negative information reduces option buy and sell volume and option trading volume because of the limited use of options for hedging and speculation. In addition, the coefficients of T are all significantly negative in Panels A and B, indicating a negative time trend for $OPVOL$, $OPVOL_{buy}$, and $OPVOL_{sell}$. Results of a positive (negative) volatility-induced change in option trading volume following large volatility spreads with positive (negative) information provide evidence that deviations from PCP are informative about future trading volume in options.

Table VIII reports similar but relatively weak prediction results for $IDVOL$, $IDVOL_{buy}$, and $IDVOL_{sell}$. Panel A shows that volatility spreads with positive information implicit in calls and puts also have some forecasting ability for trading dollar volume ($IDVOL$), buy dollar

TABLE VII
Predictability in Option Trading Volume by Volatility Spreads

	OPVOL		$OPVOL_{buy}$		$OPVOL_{sell}$	
j	1	2	1	2	1	2
Panel A: Volatility spread with positive information						
T	−0.0701 (−2.76***)	−0.0578 (−2.53**)	−0.0368 (−2.86***)	−0.0307 (−2.65***)	−0.0336 (−2.67***)	−0.0272 (−2.40**)
$VSM^c_{b,t-j}$	1.2781 (1.99**)	0.8053 (1.14)	0.6452 (2.03**)	0.3755 (1.05)	0.6336 (1.91*)	0.4307 (1.22)
$VSM^p_{b,t-j}$	0.2833 (0.60)	1.5675 (3.46***)	0.1576 (0.64)	0.7631 (3.29***)	0.1286 (0.55)	0.8048 (3.59***)
Adj. R^2	0.3445	0.3453	0.3583	0.3587	0.3264	0.3274
Panel B: Volatility spread with negative information						
T	−0.0764 (−3.17***)	−0.0537 (−2.37**)	−0.0398 (−3.25***)	−0.0284 (−2.46**)	−0.0368 (−3.09***)	−0.0254 (−2.28**)
$VSM^c_{s,t-j}$	0.5642 (1.11)	−1.8250 (−2.82***)	0.3044 (1.14)	−0.8533 (−2.61***)	0.2545 (1.02)	−0.9696 (−3.00***)
$VSM^p_{s,t-j}$	−1.2784 (−0.82)	−2.4502 (−1.46)	−0.6014 (−0.76)	−1.1399 (−1.40)	−0.6783 (−0.87)	−1.3167 (−1.51)
Adj. R^2	0.3442	0.3462	0.3579	0.3591	0.3261	0.3289

$$VOL_t = \alpha_0 + \alpha_1 T_{t-1} + \beta_1 VSM^c_{t-j} + \beta_2 VSM^p_{t-j} + \beta_3 FV_{t-j} + \beta_4 IDV_{t-j} + \beta_5 IS_{t-j} + \sum_{i=1}^{4} \gamma_i VOL_{t-i} + \varepsilon_t$$

Note. This table represents the estimation results of prediction regression, shown in Equation (10), for option trading volume by controlling on a linear time trend (*T*), logarithmic open interest of the index futures (*FV*), logarithmic trading volume of the underlying index (*IDV*), the impact of information flows (*IS*), and four lagged option trading volume. The regression is estimated for different values of *j*, from 1 to 2, to capture the potential predictive power of volatility spreads for future volume. Volatility spreads with positive information and negative information are used separately to test for the predictability in *OPVOL*, $OPVOL_{buy}$, and $OPVOL_{sell}$. The results of volume prediction by volatility spreads with positive and negative information are reported in Panel A and Panel B, respectively. VSM^c_{t-j} and VSM^p_{t-j} denote either volatility spreads with positive information (VSM^c_b and VSM^p_b) or negative information (VSM^c_s and VSM^p_s) on day $t-j$ of calls and puts, respectively. *VOL* is either of *OPVOL*, $OPVOL_{buy}$, or $OPVOL_{sell}$. *OPVOL* denotes the option trading volume in the near and second month. $OPVOL_{buy}$ and $OPVOL_{sell}$ are the signed buy and sell volume of options, respectively. *T* is a linear time trend used to control for the time effect. For brevity, only α_1, β_1, and β_2 are reported. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. ***, **, and * indicate that *t* values (in parentheses) are significant at the 0.01, 0.05, and 0.1 level, respectively.

TABLE VIII
Predictability in Trading Dollar Volume by Volatility Spreads

	IDVOL		$IDVOL_{buy}$		$IDVOL_{sell}$	
j	1	2	1	2	1	2
Panel A: Volatility spread with positive information						
T	0.0008 (0.13)	0.0048 (0.79)	0.0031 (0.44)	0.0080 (1.13)	−0.0026 (−0.37)	0.0017 (0.23)
$VSM^c_{b,t-j}$	0.6211 (2.48**)	0.7794 (1.88*)	0.4875 (1.39)	0.5404 (1.04)	0.8259 (3.20***)	0.8850 (2.00***)
$VSM^p_{b,t-j}$	0.0703 (0.29)	0.3648 (1.24)	0.1959 (0.87)	0.3352 (1.12)	0.0332 (0.10)	0.3319 (0.95)
Adj. R^2	0.6099	0.6090	0.5157	0.5135	0.6103	0.6071
Panel B: Volatility spread with negative information						
T	0.0012 (0.19)	0.0058 (0.90)	0.0045 (0.65)	0.0092 (1.22)	−0.0033 (−0.46)	0.0026 (0.35)
$VSM^c_{s,t-j}$	−0.3643 (−1.58)	−0.9820 (−4.03***)	−0.6873 (−2.74***)	−0.9660 (−3.20***)	−0.2861 (−0.93)	−0.9271 (−3.67***)
$VSM^p_{s,t-j}$	0.4448 (0.70)	−0.1527 (−0.31)	0.1799 (0.23)	−0.3073 (−0.59)	0.3047 (0.55)	0.0701 (0.11)
Adj. R^2	0.6097	0.6115	0.5171	0.5165	0.6088	0.6085

$$VOL_t = \alpha_0 + \alpha_1 T_{t-1} + \beta_1 VSM^c_{t-j} + \beta_2 VSM^p_{t-j} + \beta_3 FV_{t-j} + \beta_4 IDV_{t-j} + \beta_5 IS_{t-j} + \sum_{i=1}^{4} \gamma_i VOL_{t-i} + \varepsilon_t$$

Note. This table represents the estimation results of prediction regression, shown in Equation (10), for trading dollar volume by controlling on a linear time trend (T), logarithmic open interest of the index futures (FV), logarithmic trading volume of the underlying index (IDV), the impact of information flows (IS), and four lagged trading dollar volume. The regression is estimated for different values of j, from 1 to 2, to capture the potential predictive power of volatility spreads for future volume. Volatility spreads with positive information and negative information are used separately to test for the predictability in $IDVOL$, $IDVOL_{buy}$, and $IDVOL_{sell}$. The results of volume prediction by volatility spreads with positive and negative information are reported in Panel A and Panel B, respectively. VSM^c_{t-j} and VSM^p_{t-j} denote either volatility spreads with positive information ($VSM^c_{b,t-j}$ and $VSM^p_{b,t-j}$) or negative information ($VSM^c_{s,t-j}$ and $VSM^p_{s,t-j}$) on day $t-j$ of calls and puts, respectively. VOL is either of $IDVOL$, $IDVOL_{buy}$, or $IDVOL_{sell}$. $IDVOL$, $IDVOL_{buy}$, and $IDVOL_{sell}$ indicate the trading dollar volume, buy dollar volume, and sell dollar volume of the underlying index, respectively. T is a linear time trend used to control for the time effect. For brevity, only α_1, β_1, and β_2 are reported. Newey–West standard errors are used to calculate the t-statistics of the estimated parameters. ***, **, and * indicate that t values (in parentheses) are significant at the 0.01, 0.05, and 0.1 level, respectively.

volume ($IDVOL_{buy}$), and sell dollar volume ($IDVOL_{sell}$) in the underlying index, with strong predictability from the positive volatility information abstracted from calls. The significant coefficients for $IDVOL_{sell}$ (with t values of 3.20 and 2.00, respectively) rather than $IDVOL_{buy}$ (with t values of 1.39 and 1.04, respectively) indicate that a rise in market uncertainty leads foreign and other investors to sell more stocks for their risk management and optimal portfolio choice, thus generating a higher trading dollar volume.

Nonetheless, as shown in Panel B of Table VIII, a significant negative relation only exists between volatility spreads with negative information implicit in calls and the trading dollar volume, buy dollar volume, and sell dollar volume of the underlying index. The forecasting ability from volatility spreads to trading dollar volume provides evidence that deviations from PCP contain information about future trading dollar volume in the underlying index.

5. CONCLUSIONS

This study investigates the predictability of volatility by deviations from PCP in the Taiwan market, where the index option is actively traded and volatility trading is frequent. We adopt deviations from PCP to measure the quantity of volatility information and separate the information into positive and negative signals. The deviations are calculated as the implied volatility spread between call and put options with the same maturity. In addition, the information content of volatility spreads for future volume is also examined.

The finding of an increased (decreased) volatility in the subsequent days following large volatility spreads with positive (negative) information indicates that informed investors trade on volatility information in the option market first, and subsequently their private information is reflected in the underlying index. This result not only provides evidence for the forecasting ability of volatility by volatility spreads but also supports the presence of volatility information trading in the TXO market. In particular, the degree of predictability is stronger in options with high liquidity and an underlying asset with low liquidity.

Predictability is robust after controlling for implied volatility, information shocks, other information variables on return and volatility used widely in the literature, and short sales constraints. In addition, deviations from PCP also contain information about future volume, as evidenced by the finding of an increase (decrease) in the option trading volume and trading dollar volume in the underlying index following large volatility spreads with positive (negative) information.

REFERENCES

Ahn, H.-J., Kang, J., & Ryu, D. (2008). Informed trading in the index option market: The case of KOSPI 200 options. Journal of Futures Markets, 28, 1118–1146.

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. Journal of Finance, 57, 1047–1091.

Amin, K., Coval, J., & Seyhun, N. (2004). Index option prices and stock market momentum. Journal of Business, 77, 835–873.

An, B-J., Ang, A., Bali, T. G., & Cakici, N. (2013). The joint cross selection of stocks and options. NBER Working Paper No. 19590, Cambridge, MA.

Andersen, T. G. (1996). Return volatility and trading volume: An information flow interpretation of stochastic volatility. Journal of Finance, 51, 169–204.

Atilgan, Y. (2010). Deviations from put–call parity and earnings announcement returns. Working paper.

Back, K. (1993). Asymmetric information and options. Review of Financial Studies, 6, 435–472.

Bakshi, G., Cao, C., & Chen, Z. (1997). Empirical performance of alternative option pricing models. Journal of Finance, 52, 2003–2049.

Bakshi, G., Cao, C., & Chen, Z. (2000). Pricing and hedging long-term options. Journal of Econometrics, 94, 277–318.

Bali, T. G., & Hovakimian, A. (2009). Volatility spreads and expected stock returns. Management Science, 55, 1797–1812.

Bali, T. G., & Murray, S. (2013). Does risk-neutral skewness predict the cross-section of equity option portfolio returns? Journal of Financial and Quantitative Analysis, forthcoming.

Battalio, R., & Schultz, P. (2006). Options and the Bubble. Journal of Finance, 61, 2071–2102.

Black, F., & Scholes, M. S. (1973). The pricing of options and corporate liabilities. Journal of Political Economy, 81, 637–654.

Bollen, N. P. B., & Whaley, R. E. (2004). Does net buying pressure affect the shape of implied volatility functions? Journal of Finance, 59, 711–754.

Bollerslev, T., Tauchen, G. E., & Zhou, H. (2009). Expected stock returns and variance risk premia. Review of Financial Studies, 22, 4463–4492.

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). Informed trading in stock and option markets. Journal of Finance, 59, 1235–1257.

Chang, C.-C., Hsieh, P.-F., & Lai, H.-N. (2009). Do informed option investors predict stock returns? Evidence from the Taiwan stock exchange. Journal of Banking and Finance, 33, 757–764.

Chang, C.-C., Hsieh, P.-F., & Wang, Y.-H. (2010). Information content of options trading volume for future volatility: Evidence from the Taiwan options market. Journal of Banking and Finance, 34, 174–183.

Chaput, J. S., & Ederington, L. H. (2005). Volatility trade design. Journal of Futures Markets, 25, 243–279.

Chen, X., & Ghysels, E. (2010). News—good or bad—and its impact on volatility predictions over multiple horizons. Review of Financial Studies, 24, 46–81.

Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Order imbalance, liquidity and market returns. Journal of Financial Economics, 65, 111–130.

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. Journal of Financial Economics, 87, 249–268.

Chordia, T., & Subrahmanyam, A. (2004). Order imbalance and individual stock returns: Theory and evidence. Journal of Financial Economics, 72, 485–518.

Conrad, J., Dittmar, R. F., & Ghysels, E. (2013). Ex ante skewness and expected stock returns. Journal of Finance, 68, 85–124.

Cremers, M., & Weinbaum, D. (2010). Deviations from put–call parity and stock return predictability. Journal of Financial and Quantitative Analysis, 45, 335–367.

Easley, D., O'Hara, M., & Srinivas, P. (1998). Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance, 53, 431–465.

Figlewski, S., & Webb, G. (1993). Options, short sales, and market completeness. Journal of Finance, 48, 761–777.

Finucane, T. J. (1991). Put–call parity and expected returns. Journal of Financial and Quantitative Analysis, 26, 445–457.

Gârleanu, N., Pedersen, L. H., & Poteshman, A. M. (2009). Demand-based option pricing. Review of Financial Studies, 22, 4259–4299.

Goyal, A., & Saretto, A. (2009). Cross-section of option returns and volatility. Journal of Financial Economics, 94, 310–326.

Jiang, G., & Tian, Y. (2005). Model-free implied volatility and its information content. Review of Financial Studies, 18, 1305–1342.

Jiang, G., & Tian, Y. (2007). Extracting model-free volatility from option prices: An examination of the VIX index. Journal of Derivatives, 14, 1–26.

Johnson, T. L., & So, E. C. (2012). The option to stock volume ratio and future returns. Journal of Financial Economics, 106, 262–286.

Klemkosky, R. C., & Resnick, B. G. (1980). An ex ante analysis of put–call parity. Journal of Financial Economics, 8, 363–378.

Lakonishok, J., Lee, I., Pearson, N. D., & Poteshman, A. M. (2007). Option market activity. Review of Financial Studies, 20, 813–857.

Lamont, O., & Thaler, R. (2003). Can the market add and subtract? Mispricing in tech stock carve-outs. Journal of Political Economy, 111, 227–268.

Lamoureux, C. G., & Lastrapes, W. D. (1990). Heteroskedasticity in stock return data: Volume versus GARCH effects. Journal of Finance, 45, 221–229.

Lamoureux, C. G., & Lastrapes, W. D. (1994). Endogenous trading volume and momentum in stock-return volatility. Journal of Business and Economic Statistics, 12, 253–260.

Lee, C., & Ready, M. (1991). Inferring trade direction from intradaily data. Journal of Finance, 46, 733–746.

Liu, J., & Longstaff, F. A. (2000). Losing money on arbitrage: Optimal dynamic portfolio choice in markets with arbitrage opportunities. Review of Financial Studies, 17, 611–641.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance martrix. Econometrica, 55, 703–708.
Ni, S. X., Pan, J., & Poteshman, A. M. (2008). Volatility information trading in the option market. Journal of Finance, 63, 1059–1091.
Nisbet, M. (1992). Put–call parity theory and an empirical test of the efficiency of the London traded options market. Journal of Banking and Finance, 16, 381–403.
Ofek, E., & Richardson, M. (2003). Dotcom Mania: The rise and fall of internet stock prices. Journal of Finance, 58, 1113–1136.
Ofek, E., Richardson, M., & Whitelaw, R. (2004). Limited arbitrage and short sales restrictions: Evidence from the options markets. Journal of Financial Economics, 74, 305–342.
Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. Review of Financial Studies, 19, 871–908.
Rehman, Z., & Vilkov, G. (2012). Risk-neutral skewness: Return predictability and its sources. Working Ppaper.
Roll, R., Schwartz, E., & Subrahmanyam, A. (2010). The relative trading activity in options and stock. Journal of Financial Economics, 96, 1–17.
Sarwar, G. (2003). The interrelation of price volatility and trading volume of currency options. Journal of Futures Markets, 23, 681–700.
Sears, S. M. (2000). Equity options trading takes defensive turn as players react to stock market declines. Wall Street Journal, 19, C16.
Shleifer, A., & Vishny, R. (1997). The limits of arbitrage. Journal of Finance, 52, 35–55.
Tauchen, G. E., & Pitts, M. (1983). The price variability-volume relationship on speculative markets. Econometrica, 51, 485–505.
Xing, Y., Zhang, X., & Zhao, R. (2010). What does individual option volatility smirks tell us about future equity returns? Journal of Financial Quantitative Analysis, 45, 641–662.