Do options contribute to price discovery in emerging markets?

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Abstract:

We examine the informational role of derivatives in price discovery in Taiwan. After controlling for market cycles, moneyness, and liquidity, we use three different methods to measure the information contents in different trading venues. We find that the trades on futures contribute the most to price discovery. The futures transactions, however, are also the most costly in executing information trading. The information role of options varies with moneyness and market cycles. Options tend be more informative during a downtrend period. This can be partially explained by short-sale constraints. Out-of-the-money options have higher permanent price effects, greater price contributions, and larger information share than other options. It suggests that informed traders are more concerned about option's leverage than its delta or vega. Thus, in examining price discovery in different trading venues, pooling options data irrespective to market cycles and moneyness may affect the empirical results.

1. Introduction

The purpose of this paper is to extend our understanding of information processing among the derivatives and underlying asset markets. We explore the role of price discovery for derivatives in an emerging options market—the Taiwan Stock Index Option market. We compare information contributions among the Taiwan stock spot index (TXI), the index futures (TXF), and the implied index price in the index options (TXO). The tick-by-tick option data is employed to examine the price discovery under different option moneyness and market cycles.

We echo Chakravarty, Gulen, and Mayhew (2004) and extend their study into the Taiwan Stock Index Options market. Our research is related to but different from the literature in two aspects. First, the majority of research focuses on mature option markets. It is intriguing to understand information flow and price discovery in an emerging options market. A typical emerging market usually has different trading regulations from mature markets. It would be informative to examine whether the regulations in a particular emerging market encourage or discourage informed trading in the option market. The Taiwan stock market is unique for its tight short-sale constraints and a 7% daily price change limit. The index derivatives markets by contrast have no short-sale constraints and daily price limits. We would expect these stringent trading regulations in the equity market to steer some informed trading from the equity market to the derivatives market. The results would have important implications for regulators in other emerging markets in terms of regulation and monitoring market activities. In addition, an emerging market should have less insider trading regulations than mature markets. Hence, all else equal, trading in an emerging market provides more profitable opportunities for informed traders. Assuming options are a preferred instrument to capitalize on private information, informed trading should be more prominent in an emerging option market. An understanding of informed trading in an emerging option market could help option market makers better handle adverse selection risk. If informed trading occurs in the option market, this would also give investors signals about future price movements and facilitate regulators monitoring insider trading.

Second, we examine the informational role of options across strike prices under different market cycles. Our empirical tests reveal how the information role of derivatives markets is interacted with different option moneyness and market cycles. The literature indicates that moneyness affects informed traders' choice among different options. De Jong, Koedijk, and Schnitzlein (2001) suggest that informed traders use in-the-money (ITM) options to increase their trading profits because ITM options are more sensitive to underlying equity price changes than other options. Kaul, Nimalendran, and Zhang (2002) argue that at-the-money options (ATM) are more liquid and more sensitive to volatility, and have lower bid-ask spreads than other options. ATM options, thus, are most useful in predicting equity price movements. On the other hand, Chakravarty, Gulen, and Mayhew (2004) show that out-of-the-money (OTM) options play the most significant role in price discovery among of all options, because OTM options provide the highest leverage for investors. Hence, if options' contribution to price discovery varies with option moneyness, pooling all options together could result in mixed findings.

Several studies also show that investors behave differently under different market conditions. Hamilton and Lin (1996) find higher volatility in periods of economic recession. This is reinforced by other findings that volatility levels tend to rise more with negative returns than positive returns (e.g., Bekaert and Wu (2000)). Wood, McInish, and Ord (1985) provide evidence that the equity return generating process differs in bull and bear markets. Lockwood and McInish (1990) find significant more volatile intraday returns during bear markets. If trading in the derivatives markets offers an advantage in trading information because of volatility, short-sale constraints, and price change limits, informed traders should be more active in the derivative markets during a downtrend period.

To assess information flows among the equity, futures, and option markets, we use three different methods— the price effect analysis, the weighted average price contribution analysis, and the information-share analysis. The price effect analysis compares the permanent, temporary, and total price effects of transaction prices in the three markets. We use conventional price impact analysis to estimate the price effects of trades in the multiple-trading environments (e.g., Keim and Madhavan (1996), and Booth, Lin, Martikainen, and Tse (2002)). The weighted average price contribution (WAPC) identifies which trades move price (e.g., Barclay and Warner (1993), Huang (2002)). It examines the venue contributing meaningful price movements and provides a single measure of price leadership. The information-share analysis, closely related to Hasbrouck's work (see, e.g., Hasbrouck (1991, 1995, and 2002)), estimates a trading venue's contribution to price discovery.

Our findings provide several insights about the importance of disentangling options moneyness and market cycles in studying the informational role of options. Consistent with the previous findings based on the mature markets, the Taiwan stock index futures market play the most significant role in price discovery. Trading futures, however, is also most costly in executing informed trades. Although the option market conveys information as well, it accounts less than twenty percent. The test results also indicate that, in the options market, the seller motivated trades are more likely to convey information regarding the true index value than the buyer motivated trades. When we pool all the options data together irrespective of options moneyness and market cycles, the options have lower permanent price effects, contribute less to price discovery, and possess smaller shares of information. When options are classified according to different moneyness and market cycles, OTM options have more impacts on price discovery process, especially during a downtrend period. The finding indicates that option leverage plays an important role in determining which option segments informed traders trade in the options market. Short-sale constraints and price change limit rule in the Taiwan Stock Exchange make options more attractive to informed traders in a bear market. We also find that, regardless of market cycles, ITM options do not contribute to price discovery. Thus, options' sensitivity to underlying asset movements is not a major factor affecting informed trading activities in the emerging market. For robustness results, we also control for liquidity in the option market. Although the price discovery contributions of options tend be positively related to options trading volume, option moneyness still matters.

2. Background and motivation

The information role of derivatives markets in the underlying asset's price discovery process has drawn great attention from academicians and practitioners. The markets with the same underlying asset should be linked by the same set of economic fundamentals. Hence, differences in their information transmission abilities reflect relative information efficiencies. Some market structures may generate larger or more frequent temporary price distortions, or may be prone to error. An analysis of which venue provides more timely and informative prices also enables financial markets to better assess the quality of transaction prices, and trace where informed trades occur. Since transaction prices are widely disseminated, and since they provide input into investors' decisions, the timeliness of information reflected in the prices is important.

Price discovery is the process by which heterogeneous private information or different interpretation of public information is incorporated into equilibrium asset prices through trading in the markets. As such, an asset's unobservable effective value or full-information value is reflected in the transaction prices in the markets. Because the observable prices could be distinct from the full-information value, it is of our interest to examine how the prices in different markets contribute to the price discovery process.

This issue is relevant to information flow, informed trading, and quality of quotes among the markets. If a significant amount of informed trading occurs in the derivatives markets, this has implications for traders watching the signals about the future price movements, and for those engaged in surveillance for illegal insider trading. Also, the role of price discovery for derivatives markets is directly relevant to dealers who are concerned with managing adverse selection risk.

The literature indicates that markets have different information processing ability, though they are governed by the same set of information. If a single financial asset or multiple highly related financial assets are traded on more than one market, each market may be involved in the price discovery process. Nevertheless, these related markets could contribute differently to the price discovery process because of distinct liquidity, transaction costs, leverage effects, restrictions and trade-off pattern between risk and return. Theoretically, market participants should more likely access and assimilate information at the markets with better liquidity, lower trading costs, greater leverage, less restrictions, and more desirable risk and return trade-off pattern. The informational role of the transaction prices in each market, however, could also be influenced by the bid-ask spread, order imbalances, inventory adjustments, and rounding effects, and market cycles, and trading environments. Thus, the price discovery in mature vis-à-vis emerging markets is still an empirical issue. Although the abilities of information processing are judged on the basis of both price discovery and competitive transaction costs, much research has been devoted to the analysis of trading costs while the price discovery process has been relatively less examined.

Price discovery is typically documented by noting the speed at which prices react to new information. Many studies [e.g., Stoll and Whaley (1990) and Chan (1992)] involve the spot and futures markets while paying less attention to the potential information role of options. Stoll and Whaley and Chan find futures lead spot markets in the US market, although there is a feed back relation. International evidence on price discovery function of futures is mixed. Iihara, Kato, and Tokunaga (1996) find that the Japanese Nikkei stock average lags the futures contract. On the other hand, Shyy Vijayraghavan, and Scott-Quinn (1996) report an opposite relation for the French CAC futures and spot.

Given the high leverage nature of options and the built-in downside protection, one may think the options market would be an ideal venue for informed trading. If informed traders prefer to trade in the options market, we would expect to see price discovery in the options market. That is, we would expect at least some new information about the stock price to be reflected in option prices first. Several studies examine the information flow among the spot, futures and options markets. Fleming, Ostdiek, and Whaley (1996) examine the intraday price discovery process among the S&P 500 stock index (SPX), SPX futures, and SPX options in March 1991. Using bivariate analysis, Fleming et al find that index futures lead options and options lead spot, which supports the notion that trading costs and response time are positively correlated. De Jong and Doners (1998) examine Amsterdam European options Exchange using lead–lag regressions and cross-correlation adjusted for irregular trading intervals. De Jong and Doners find futures lead options and attribute these lead-lag patterns to transaction costs.

More recently, using the common factor (or implicit efficient price) among cointegrated prices and information sharing techniques, Hasbrouck (1995) and Gonzalo and Granger (1995) develop models to study the contribution of information from different markets trading the same security.[1] Applying these models, Booth, So, and Tse (1999) study information sharing among the spot index, index futures, and index options based on Germany DAX index securities from the period from 1992 to 1994. Using at-the-money options in15-minute intervals, Booth et al find that index futures lead the spot index by 30 minutes and a feedback relation exists between the futures and spot markets. Both the DAX futures and spot index react to information faster than the DAX options. DAX index options contribute only marginally to price discovery. The findings of Booth et al are different from those in Fleming et al. based on the SPX index securities. On the other hand, Chakravarty, Gulen, and Mayhew (2004) show that the contribution of stock option market to price discovery is, on average, about 17% among sixty stock options traded in the Chicago Board Options Exchange from 1988 through 1992. Chakravarty et al also document that information shares vary across option moneyness and stocks.

In brief, the different findings for the informational role of option markets could be attributed to different informational efficiencies in distinct derivatives markets (i.e., the derivatives on DAX and the derivatives on SPX), option moneyness, and market cycles. Thus, how the derivatives contribute to price discovery process in different trading environments is an empirical question. A newly developed derivatives market may have different information processing ability from a mature derivatives market because of regulations, liquidity, and

[1] These methods are also applied in other markets other than derivatives markets. For example, Booth et al. (2002) examines the information shares of upstairs and downstairs markets. Hasbrouck (1995) studies price discovery of the thirty Dow Jones stocks in different stock exchanges. Huang (2002) examines the information sharing of price quotes by electronic communication networks and by trading market makers.

transaction costs. Chan, Chang, Lung (2009) find that short sale constraints and limits on price changes affect the information content in option markets. Chakravarty et al. document that liquidity affects the contribution of option to price discovery. Fleming et al. and Booth et al. (1999) find that transaction costs determine the lead-lag relations among spot, futures, and options markets. Therefore, the informational role of derivatives should vary across different markets.

Option moneyness could also affect the test results on how options contribute to the price discovery of the underlying asset. If informed investors are concerned about option delta and transaction costs, they should prefer to trade in-the-money options. In case that option vega and liquidity play a major role in determining where informed traders trade, at-the-money options should be more attractive to investors. On the other hand, if informed traders are more concerned about leverage effects, they should more likely trade out-of-the-money options. Thus, option moneyness plays an important role in the information processing of options.

Besides the trading environments and options moneyness, market cycles may also influences the test results on the informational role of derivatives. Numerous empirical findings suggest investor behavior is different in bull and bear markets. Given short-sale constraints, a bear market should make it more attractive for informed traders to trade in the derivatives market than in the equity market. Consequently, the empirical findings under different market cycles may not be consistent.

Therefore, we control for market cycles and option moneyness in examining how an emerging derivative market contributes to the price discovery process. To conduct the empirical tests, we measure the informational role in terms of the price effect from the transactions in different trading venues, the weighted average price contribution, and the information share.

3. Data

We use three sets of intraday data (the spot index, index futures and index options) to examine the price discovery process in the Taiwan equity index market. The data source is from the *Taiwan Economic Journal* (TEJ) database from January 2, 2002 to March 19, 2004. The spot index is the Taiwan Stock Exchange Capitalization Weighted Stock Index, which serves as the underlying asset for the futures and the options. The index is reported once a minute at the same second for every minute on the same day. The second is determined daily by the time of the first trade of a component stock within the minute. The futures prices are recorded in ten-second intervals. The time stamp records the trading hour, minute, and second. Regular trading hours for the index futures and the index options run from 8:45 AM to 1:45 PM (Taipei time) and for Taiwan stocks from 9:00 AM to 1:30 PM. To minimize possible measurement errors arising from the different trading hours, we use the futures and options data between the 9:00 AM to 1:30 PM stock trading hours. TEJ records trade-by-trade transactions for the options. The database includes trading time (year, month, date, hour, minute, and second), strike price, expiration date, options transaction price, options type, trading volume, and open interest. The call options and put options are European style. For non-synchronous trading problem, we use data at one-minute intervals to analyze the price discovery process because it is impossible to have price records in the three markets occurring at every point in time.

Although the spot price can be used directly, the index futures and the index options prices are different. It is because each type of derivatives is characterized by more than one contract with contracts having different expiration dates. This problem is solved in the conventional manner by constructing pseudo-price series. In the case of the index futures, this series is developed by splicing together the prices of sequential nearby futures contracts.

The options pseudo-price series is derived by implying the index value from the options price using Black-Scholes option pricing model. The model is specified as:

$$C = S_0\, N(d_1) - Ke^{-rT} N(d_2)$$

$$P = Ke^{-rT} N(-d_2) - S_0\, N(-d_1)$$

$$d_1 = \frac{\ln(S_0 / K) + (r + \sigma^2 / 2)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T} \qquad (1)$$

C is the TXO call options premium, and P is the TXO put options premium. S_0 is the Taiwan Stock Index level, r is the continuously compounded risk free rate, K is the exercise price, $N(\cdot)$ refers to the standard cumulative normal distribution function, σ stands for volatility, and T is time to expiration. d_1 and d_2 are delta for call and put options.

To minimize the measurement error in estimating implied index value, we use a three-step approach. We first estimate the implied volatility and the delta value for each individual option. We then pool the options into different categories according to delta and apply Whaley's (1982) approach of estimating implied volatilities based on the index options in a specific category. The implied volatility for each moneyness category is derived at one-minute intervals. After that, we insert the implied volatility from the previous minute into the option pricing model to calculate the implied index value in each option category.

We use options with maturity of 10 to 90 days and absolute value of delta between 0.02 and 0.98. We exclude options with maturity of less than 10 days or more than 90 days due to position squaring effect and thin trading activities. We also discard options with absolute value of delta lower than 0.02 or higher than 0.98 because of price discreteness. We focus on minute-by-minute implied volatilities as the calculations of implied volatilities for longer time intervals could be affected by non-synchronous trading problem and, thus, contain sizable measurement errors. As options with different moneyness have distinct liquidity, leverage effect, delta (sensitivity to spot price movements), and vega (sensitivity to volatility), we examine the informational role of options across different ranges of options moneyness.

Option market makers view the incoming order flow on all option series, and have the technology to update quotes simultaneously. Thus, information revealed in one series can spread quickly to all other options, making it more difficult to distinguish price discovery across multiple options. We should note that updating of option prices from other option prices is not automatic—it requires an active intervention from a market maker. Also, quotes may be revised not only by market makers, but as a result of public limit orders. Thus, it is common to see option price move first, and the others follow. Although the view may be somewhat clouded, we believe that the differences in estimated information shares across strike prices reflect, at least to some extend, differences in levels of price discovery across OTM, ATM, and ITM options. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02; at-the-money option (ATM) options as options with delta ranging between 0.45 and 0.55; and in-the-money (ITM) options as options with delta ranging between 0.55 and 0.98.

To control for market cycles in examining the role of derivatives in price discovery process, we partition the data into a bull market and a bear market according to the historical data. Figure 1 depicts the index value over the entire sample. In this ex-post study, the bear market is the period from January 02, 2002 through April 29, 2003; the bull market is the period from April 30, 2003 to March 19, 2004.

Insert Figure 1 about here

Table 1 reports descriptive statistics for the Taiwan stock index in equity, futures, and options markets at one-minute intervals. We choose April 30, 2003, as the dividing line between the downtrend and uptrend markets because the Taiwan stock index started moving up on that day. During the entire sample period, one-minute mean return in the equity market is 1.1308×10^{-6} and with a volatility of 0.0010. The equity market in the downtrend period is more volatile than in the uptrend period. This result is consistent with the previous findings that the equity return-generating process differs between downtrend and uptrend markets (Wood, McInish, and Ord, (1985)) and that intraday returns are significantly more volatile during bear markets (Lockwood and McInish, 1990). The means for the futures and option returns are 1.4999×10^{-6} and 1.7370×10^{-6} during the entire sample period. The volatilities for the futures and options show a similar pattern to those for the equity.

Insert Table 1 about here

The derivatives trading activities are presented in Table 2. During the entire sample period, there are 1,850,088 transaction records for call options, and 1,576,167 for puts. On average, the average number of trades per minute is 15 for call options, and 13 for puts. Thus, for the index options, there are 28 trades per minute and the average time span per transaction is less than 3 seconds. Thus, the problem of the infrequent trading is not an issue in the index option markets. These small time spans indicate that the trades are practically simultaneous and suggest that the non-synchronous trading problem within a matched trade should be minimal. It is also worth noting that call options are traded more frequently than put options. Trading volumes also display a similar pattern. This finding is different from other studies in mature options markets where the evidence is that put options are more heavily traded than calls. Bollen and Whaley (2004), for example, show that in S&P 500 index options markets put options account for 55% of overall options trading and call options 45%, because of hedging activities. With respect to the bear and the bull markets, the results share a similar pattern to the entire sample period. Table 2 also shows the trading activities for options across different moneyness. Among ITM and ATM options categories that call options are more heavily traded than put options. For OTM options, the pattern is different. During the entire sample period, average OTM options trading volume per minute is 45 for put options compared to 42 for calls. This pattern is particularly pronounced in the downtrend period. OTM options are about as liquid as ATM options. ITM options have the lowest liquidity.

Insert Table 2 about here

Despite the mean returns and volatilities in the three markets are not identical, their prices should not drift too far apart in the long run for these index securities rely on the same unobservable market fundamentals. With the presence of arbitrage among these markets, the price differences among these markets should be stationary. To examine this possibility, we conduct unit root test based on the Augmented Dickey-Fuller (ADF) method and Johansen's (1988) cointegration tests among the index securities.

The ADF test of unit root is specified as:

$$\Delta p_{t,j} = \beta_1 \, p_{t-1,j} + \beta_2 \, p_{t-2,j} + \ldots + \beta_j \, p_{t-m,j} + \varepsilon_t, \qquad (2)$$

where $\Delta p_{t,j}$ is the price changes at time t in market j. The optimal number of lags, m, is chosen based on Akaike information criterion (AIC). The ADF unit root test specifies β_1=0 as the null hypothesis and the critical values for the t-tests are based on Dickey and Fuller (1979). Table 3 provides the test results. Given the large number of estimates, we report only the number of optimal lags and t-statistics. The test results indicate that the optimal number of lags and the t-statistic for different index securities are not identical. For price levels (log prices), the null hypothesis of unit root is not rejected for all the three securities. It suggests that the prices are nonstationary. However, for the price changes, all the null hypotheses of unit root are rejected. Therefore, the price changes in the three markets are stationary and informative.

Insert Table 3 about here

Given all the index securities' price levels follow are I(1) and informative, we need to examine if they share common information regarding the true value of the index. The Johansen's maximum likelihood methodology is applied in this study. This approach uses the rank of the coefficient matrix in a vector autoregression (VAR) model to identify whether or not the price levels are cointegrated and detect the number of cointegrating vectors. The VAR model in this study is specified as:

$$\begin{pmatrix} p_{1,t} \\ p_{2,t} \\ p_{3,t} \end{pmatrix} = A_0 + A_1 \begin{pmatrix} p_{1,t-1} \\ p_{2,t-1} \\ p_{3,t-1} \end{pmatrix} + A_2 \begin{pmatrix} p_{1,t-2} \\ p_{2,t-2} \\ p_{3,t-2} \end{pmatrix} + \ldots + A_q \begin{pmatrix} p_{1,t-q} \\ p_{2,t-q} \\ p_{3,t-q} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}. \qquad (3)$$

A_0 is a (3×1) drift vector. A_1, A_2, …, A_q are (3×3) coefficient matrices, and q is the number of order the time series. $(\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t})'$ is a stationary vector process with zero mean and contemporaneous covariance matrix Σ. $\varepsilon_{1,t}$, $\varepsilon_{2,t}$, and $\varepsilon_{3,t}$ are serially independent. Define A as:

$$A = I_3 + A_1 + A_2 + \ldots A_q, \qquad (4)$$

where I_3 is the (3×3) identity matrix and A_1 A_2, ...A_q are specified in Equation (3). According to Johansen (1988), the rank of matrix A determines whether the three price series are cointegrated and the number of cointegrating vectors. Two test statistics, λ_{trace} and λ_{max}, are used in Johansen's methodology. They are:

$$\lambda_{trace}(r) = -N \times [\sum_{i=r+1}^{R} ln(1-\hat{\lambda}_i)] \qquad (5)$$

$$\lambda_{max}(r, r+1) = -N \times [ln(1-\hat{\lambda}_{r+1})]. \qquad (6)$$

R stands for the number of prices in different markets, N is the observation numbers, and $\hat{\lambda}$ refers to the eigenvalue in the test. $\lambda_{trace}(r)$ is to test the null hypothesis that the number of cointegrating vectors is not greater than r; $\lambda_{max}(r, r+1)$ examines the null hypothesis that the number of cointegrating vectors is equal to r against the alternative hypothesis that the number is equal to $r+1$. In this study, r is 0, 1, or 2. The number of lag, q, in Equation (3) is selected by the Schwarz information criterion (SIC).[2] Critical values of λ_{trace} and λ_{max} are based on Johansen and Juselius (1990). Table 4 presents the test results. According to the test statistics of $\lambda_{trace}(r)$, for all the periods, the null hypothesis of $r=0$ is rejected. It suggests that the three prices are cointegrated. However, we fail to reject the null hypothesis of $r\leq 2$ in all the cases. This finding indicates that the order of cointegration for the three prices is two and the three markets are influenced by one common set of information.

Insert Table 4 about here

In sum, according to the test results from Tables 3 and 4, we find that the prices are nonstationary, but the first differences of the price levels are stationary for the index value, index futures, and implied prices in options. Moreover, the test results show that the three securities are cointegrated with two cointegrating vectors. It suggests that the three securities are governed by one common set of information and share a long-run equilibrium. Given the findings, we proceed to examine the informational role of these three securities in the following sections.

4. Methods

To analyze the information role of the three markets in the price discovery process, we conduct three tests—the price impact analysis, the weighted price contribution analysis, and the information share analysis. These three approaches address the same issue in different perspectives. The price impact analysis examines the information content of trading activities. A market with more informed trading should contribute more to price discovery than a market with more uninformed trading. The weighted price contribution analysis investigates the source

[2] The selection for the number of lags is subjective. In this study, we find the results are similar when different criterions and lags are employed.

of price movements from different trading venues. A venue provides more sources of price movements should be more likely to have a price leadership. The information share analysis studies the portion of price discovery from different markets. It identifies the venue giving the most timely and informative trades.

4.1 The price impact analysis

The price impact analysis assesses the difference in pricing by comparing the permanent, temporary, and the total price effects of transactions in the equity, futures, and options markets. These effects are estimated based on the methodology used in Holthausen, Leftwich, and Mayers (1987). The permanent price effect of a transaction is utilized to estimate a change in value resulting from new innovation or information content in the trading activity. On the other hand, the temporary price effect measures a transitory impact caused by the bid-ask bounce, short term order imbalances, inventory adjustments, and other market frictions. The transitory effect is usually measured by the extent of price reversal following the transaction. The total price effect of a transaction captures the size of price concession. It is calculated based on the difference between the transaction price and the previous trade price. Explicitly, the total price effect reflects the price change needed to absorb the transaction in the market. When informed traders are more likely to use certain venue, the venue should contain more information. Consequently, the market should have a greater permanent price effect and a smaller temporary price effect than other markets. Nevertheless, the venue conveying more informed trades may not have larger total price effect than other markets. The market with higher total price effect should be more costly to informed investors.

Following previous studies (i.e., Keim and Madhavan (1996), Booth et al. (2002)), we estimate the price effects based on buyer-motivated and seller-motivated transactions. Similar to Lee and Ready (1990), Booth et al. (2002), and Chan, Cheng, and Lung. (2004), we define a buyer-motivated transaction as the trade with a price higher than the previous trade price. A seller-motivated transaction is the trade with a price lower than the previous trade. For the spot, futures indices, and call options, the classification for a seller- or buyer-motivated trade is straightforward. However, it is slightly different for put options. A buyer-motivated trade in put options has a negative effect on the implied index value, because put option premiums are negatively related to the underlying asset's price. Therefore, in this study, a buyer-motivated transaction on put options is the trade with an implied price lower than the previous trade price, and vice versa for a seller-motivated transaction.

We exclude the transaction with a price equal to the previous trade. The permanent effect, the temporary effect and the total effect are estimated as follows:

$$\textit{Permanent price effect} = p_{t+\kappa} - p_{t-l} \quad (7)$$

$$\textit{Temporary price effect} = p_t - p_{t+\kappa} \quad (8)$$

$$\textit{Total price effect} = \textit{Permanent effect} + \textit{Temporary effect} = p_t - p_{t-l}, \quad (9)$$

where p_t is the transaction price at time t, p_{t-l} is the price of the l^{th} trade before the trade at time t, and $p_{t+\kappa}$ is the transaction price of the κ^{th} trade after the trade at time t. In this setting, p_{t-l} is assumed to be the equilibrium price before the trade at time t, and $p_{t+\kappa}$ serves as the equilibrium price after the trade at time t. Thus, the difference between these two equilibrium prices should be the permanent effect attributed to fundamental information during the time period. The price change from time t to time t+κ captures the transitory effect cause by factors other than fundamental information. The total effect in the market is the sum of the impacts from fundamental information and non-fundamental factors. For a buyer (seller) -motivated transaction, a positive (negative) temporary effect in Equation (8) indicates a price reversal. Hence, based on a buyer (seller) -motivated transaction, the larger (smaller) the temporary effect, the less informative of the transaction tends to be. In this methodology, the selection of l and κ in the price impact analysis is subjective. It depends on how fast the information flows and how responsive of the market to the trade. This study chooses l = 12 and κ=6.[3] In the price effect estimation, we pool together the index value occurred in all three markets in sequence of their recording time. Specifically, for a trade in options market at time t, the price at t-l and t + κ could be from the equity or the futures market.

4.2 The weighted average price contribution analysis

The weighted average price contribution (WAPC) is to remove the effects of transitory price movements by averaging price movements over time. In the literature, the WAPC has been applied to identify which trades drive price movement in a single market (i.e., Barclay and Warner (1993)). It can also capture the price contribution during certain trading period of time (i.e., Cao, Ghysels, and Hatheway (2000)) and the price leadership among various price quoting systems (i.e., Huang (2002)). This study uses the WAPC to trace the source of price movements driven by the transactions in different venues. After pooling all the transaction prices from different venues, we calculate the WAPC as follows:

[3] The selection for the trade span is subjective and dependent on the trade-by-trade data. In this study, we choose l = 12 and κ=6, because we find no significant price movements nine transactions before and five transactions after a transaction. As we vary both l and κ from 3 up to 20, the test results are qualitatively similar. However, the wider the span, the more noise tends to occur.

$$WAPC_i = \sum_{h=1}^{D} \frac{\Delta p_{h,i}}{\Delta p_h} \times W_h \qquad (10)$$

$$W_h = \frac{|\Delta p_h|}{\sum_{h=1}^{D} |\Delta p_h|} \qquad (11)$$

where Δp_h is the price change during time h, and $\Delta p_{h,i}$ refers to the sum of price changes attributed from market i during time h. A price change is credited to the venue that initiates the immediate next transaction. For instance, if the first transaction price occurs in the futures market and the very next trade is from the options market, the source of price movement between these two transactions is credited to the contribution from the options market. Therefore, $\frac{\Delta p_{h,i}}{\Delta p_h}$ measures the proportion of price movement attributed to market i during time h. W_h serves as a weight estimated by the contribution of the absolute price change during time h to the cumulative absolute price change during the entire trading day. Thus, WAPC reveals "who is driving the price movements" and captures the source of price changes from different venues. To calculate the WAPC, this study aggregate all the TXI, TXF, and TXO together in sequence of their recording time. In this manner, the WAPC provides a single measure of price leadership. However, it tends to inflate the informational role of those trading venue with more transaction records in the sample data.

4.3 The informational share analysis

To explore the information shares contributed from different trading venues, we follow Hasbrouck's (1995) method. We estimate the contribution to price discovery for securities traded in respective markets. The method can also be generalized to the case of different securities that share the same underlying asset. In this paper, the equity value, futures prices, and implied prices in the options market are linked by arbitrage. Since the three price series are cointegrated, the information share approach of Hasbrouck can be used to measure each market's relative contribution to price discovery. The information share analysis assumes that the prices from the three markets share a common random walk component referred to as the efficient price. The information share of a market is measured as that market's contribution to the total variance of the common random-walk component.

From the view of time series, the informational share analysis starts from Equation (3). Given the three price series are cointegrated and the number of cointegrated vector is one (as reported in Table 4), based on the Granger Representation Theorem, Equation (3) can be written in vector error correction form (VECM):

$$\begin{pmatrix} \Delta p_{1,t} \\ \Delta p_{2,t} \\ \Delta p_{3,t} \end{pmatrix} = A \begin{pmatrix} p_{1,t-1} \\ p_{2,t-1} \\ p_{3,t-1} \end{pmatrix} + B_1 \begin{pmatrix} \Delta p_{1,t-1} \\ \Delta p_{2,t-1} \\ \Delta p_{3,t-1} \end{pmatrix} + \ldots + B_{q-1} \begin{pmatrix} \Delta p_{1,t-q+1} \\ \Delta p_{2,t-q+1} \\ \Delta p_{3,t-q+1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}, \qquad (12)$$

where A is specified in Equation (4). $(\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t})'$ and q are these as those in Equation (3). B_1, …, B_{q-1} are (3×3) parameter matrices. For the purpose of the informational share analysis, it is more convenient to restate Equation (12) in its infinite order vector moving average form (VMA):

$$\begin{pmatrix} \Delta p_{1,t} \\ \Delta p_{2,t} \\ \Delta p_{3,t} \end{pmatrix} = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix} + C_1 \begin{pmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{pmatrix} + C_2 \begin{pmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{pmatrix} + \ldots, \qquad (13)$$

where $C_1, C_2, \ldots$ are (3×3) parameter matrices. In this three variable VMA, by aggregating all the parameters in Equation (13), we can measure the permanent impact of new information on the true index value. Specifically, given

$$C = I_3 + \sum_{k=1}^{\infty} C_k \,, \qquad (14)$$

The permanent impact of time t innovations on the index value, Φ, should be equal to:

$$\Phi = C \times \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}. \qquad (15)$$

Thus, the variance-covariance matrix of the permanent impact can be written as:

$$Var(\Phi) = \Phi\, \Phi' = C\, \Sigma\, C', \qquad (16)$$

where Σ is the diagonal covariance matrix of innovations as specified in Equation (3), as we assume that $\varepsilon_{1,t}$, $\varepsilon_{2,t}$, and $\varepsilon_{3,t}$ are assumed to be uncorrelated. If we decompose the variances of these permanent impacts on the diagonal of $Var(\Phi)$, the information share attributed from a trading venue is measured by each market's contribution to the total variance of the permanent impacts. It is:

$$IS_i = C_i^2\, \Sigma_{ii} \,/\, Var(\Phi), \qquad (17)$$

where IS_i is the information share of market i and Σ_{ii} is the variance of ε_i.

However, if the innovations are correlated, we cannot directly apply Equation (17) to compute the information share. This question can be solved by a Cholesky Factorization of the variance covariance matrix of innovations. Σ can be rewritten as:

$$\Sigma = X \times X'$$

$$X = \begin{pmatrix} x_{11} & 0 & 0 \\ x_{21} & x_{22} & 0 \\ x_{31} & x_{32} & x_{33} \end{pmatrix}, \qquad (18)$$

where X is a lower-diagonal (3×3) matrix. The correlated innovations in the markets can be rewritten as:

$$\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix} = \mathrm{X} \times \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix} \qquad (19)$$

where $(e_{1,t}, e_{2,t}, e_{3,t})'$ is a vector of uncorrelated zero mean unit variance random variables, in which $e_{1,t}$, $e_{2,t}$, and $e_{3,t}$ are orthogonalized innovations. Through the expression in Equation (19), the correlated innovations in the markets, ε_t, are restructured as linear combinations of the orthogonalized innovations. Thus, the order of the innovations in the vector ε_t affects the estimated innovation value. For example, when the innovation from market 1 is ordered first in ε_t, $\varepsilon_{1,t} = x_{11} e_{1,t}$, which is determined by its own orthogonalized innovation. However, if it is ordered the last,

$\varepsilon_{1,t} = x_{31} e_{1,t} + x_{32} e_{2,t} + x_{33} e_{3,t}$, which is determined by all three orthogonalized innovations. Therefore, in calculating the information share of a trading venue, the order of innovations from different venues can affect the test results, if the innovations are highly correlated.

Combining equations (15) and (19), we obtain:

$$\Phi = C \times X \times \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix}, \qquad (20)$$

and the variance-covariance matrix of the permanent impact becomes:

$$Var(\Phi) = C \times X \times \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix} \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix}' X'C' \qquad (21)$$

Equation (21) shows that the permanent impact of time t innovations on the index value is determined by the coefficients in the VMA model, the lower triangular matrix from the Cholesky factorization of Σ, and the orthogonalized innovations. The calculation for the information share is in the same manner as specified in Equation (17). Because the order of the innovations from different venues plan a role in determining the information share, we estimate the upper and lower bounds of the information share for each market by rotating the positions of the innovations in Equation (19).

5. Results

5.1 Test results from the price impact analysis

Table 5 reports the estimates of price effects in the equity, futures, and options markets. Panel 5A reports the test results for the entire sample period, Panel 5B, for the downtrend period, and Panel 5C for the uptrend period. In Panel 5A, for the buyer-motivated transactions, the permanent price effects are 3.92×10^{-6}, 4.18×10^{-6}, and 1.98×10^{-6} for the equity, futures, and options markets, respectively. All of them are positive. It suggests the buyer-motivated transactions in all the three markets containing positive information about the true value of the index. The futures market has the largest permanent price effect. This finding indicates that the transactions in the futures market contain more information about the true index value than other markets. The trade in the options market also conveys the information, but it is not as much as that in the futures or equity market. On the other hand, the temporary effect for the option market is larger than that in other markets. It suggests that the trade in the option market has a larger price reversal and less informative.

Interestingly, on average, we find that the futures market tends to have the largest total price effect. As shown in Panel 5A for the buyer-motivated trades, the total price effects are 2.27×10^{-6}, 2.94×10^{-6}, and 1.75×10^{-6} for the equity, futures, and options markets, respectively. It implies that informed trading in the futures is more costly than informed trading in the option market.

For the seller-motivated transactions in Panel 5A, the results show a similar pattern to those for the buyer-motivated trades. The transaction in the futures market has the largest size of the permanent effect, -3.77×10^{-6}, and the equity market, the second, -2.89×10^{-6}. For the trade in the option market, it is intriguing to note that a seller-motivated trade contains more information than a buyer-motivated transaction. For example, the magnitude of the permanent effect in the options market is 2.47×10^{-6} which is about 66% (2.47 / 3.77) of the effect in the futures market based on a seller-motivated transaction, while it is 1.98×10^{-6} according to a buyer-motivated trade.

The test results for the bear market are reported in Panel 5B, and the bull market, in Panel 5C. In general, these two panels reveal similar findings to Panel 5A. Nevertheless, comparing the results in the bear and the bull markets, we find that informed trading in the options market is more active in the bear market than in the bull market. For instance, based on a seller-motivated transaction, the permanent effect of the option market is -3.11×10^{-6} in the bear market as shown in Panel 5B, whereas it is -2.00×10^{-6} during the bull market in Panel 5C. Based on the temporary price effects, we find a similar conclusion. These results could be attributed to short sale constraints which make the option market more attractive to informed traders in a bear market.

To investigate the possible impact of moneyness on the informational role of options, we conduct the price effect tests for options in different moneyness categories. Table 6 presents the test results under different market trends. To save space, we only report the test results for options during the downtrend and uptrend markets, while omit the test results for equity and futures and truncate the results for the entire sample period. Panel 6A reports the results for the downtrend period and Panel 6B for the uptrend period.

According to the buyer-motivated transactions in Panel 6A, OTM options have a larger permanent price effect than ITM options. For instance, the permanent effect of OTM call options is 2.76×10^{-6}, while it is -0.13×10^{-6} for ITM call options. It indicates that the transactions on OTM options are more informative. Option's leverage influences where informed traders trade in the options market. Comparing calls and puts, we find that a buyer-motivated call option tends to have a larger permanent effect in size than a buyer-motivated put option. For example, the permanent effect for ATM calls is 2.17×10^{-6}, whereas it is -1.26×10^{-6} for ATM puts. As discussed in Section 4.1, a buyer-motivated put is actually initiated by a put option seller. This suggests that, on average, a put option seller during the downtrend is less informed.

The findings based on seller-motivated trades in Panel 6A are different from those for buyer-motivated transactions. OTM put options have the larger size of permanent effect. This suggests that a seller-motivated trade on OTM puts is more informative than a buyer-motivated trade on puts during the downtrend period. For instance, the permanent effect for a seller-motivated OTM put options is -6.35×10^{-6} in Panel 6A, while it is it is 1.91×10^{-6} for a buyer-motivated put.

The test results based on the uptrend period, as shown in Panel 6B, are distinct from those in Panel 6A. Based on the buyer motivated transactions, OTM call options have the largest size of permanent effect among all the options. For example, the permanent effect for a buyer-motivated OTM call is 5.65×10^{-6}, while it is 2.43×10^{-6} for a buyer-motivated call. This finding implies that, during the bull market, informed traders are more likely to buy OTM calls, instead to sell OTM put options. It is also worth noting that ITM options tend have a larger temporary effect. For instance, a buyer-motivated ITM put has a temporary effect of 2.15×10^{-6}. This finding implies that liquidity trading during the bull market is often to occur on ITM put options.

To examine the impact of liquidity on the informational role of options, we classify the options trades into five liquidity groups according to option's trading volume. Group one includes the transactions with trading volume equal to or below 20^{th} percentile, group two, from 20^{th} to 40^{th} percentile, and so on. Within each group, the options transactions also divided according to their moneyness. Table 7 reports the test results. To save space, we only show the test results based on OTM put options in this table. The results on ITM and ATM options are available upon request. Panel 7A is for the downtrend period, and Panel 7B is for the uptrend period. In general, the findings in each group are similar to those reported in Table 6. We also find that liquidity is positively related to the permanent price effects. For instance, in Panel 7A for the seller-motivated trades on OTM put options during the bear market, the permanent effects range from -8.91×10^{-6} in Group five to -2.17×10^{-6} for Group one. On the other hand, the temporary price effects are inversely related to liquidity. Based on the seller-motivated trades, for instance, the temporary price effect is -2.11×10^{-6} for the lowest liquidity group, whereas it is 0.13×10^{-6} for the highest liquidity group.

5.2 Test results from the weighted average price contribution analysis

The average of the daily WAPC is reported in Table 8. During the entire sample period, the mean estimates are 36.2%, 45.56%, and 18.24% for the equity, futures, and option markets, respectively. The futures market has the highest mean WAPC and post the most informative transactions. Although the WAPC estimate for the equity market is higher than that for the option market, it is much lower than the estimate for the futures market. The test results during the uptrend and downtrend markets indicate a similar conclusion. For the trades in the options market, however, the WAPC from the option market is higher in the downtrend market than in the uptrend period. This shows that the options transactions are more informative in the bear market, which confirms the findings based on the price impact analysis in Section 5.1.

We also apply the WAPC analysis for the options transactions in the three different moneyness categories. The WAPC calculation is repeated for the implied prices from ITM, ATM and OTM options separately. Table 9 shows the test results. Because the test results for TXI and TXF are similar to those in Table 8, we only report the WAPC estimates for options. Regardless of market cycles and option types, we find that OTM options have the highest WAPC and ITM options, the lowest. For example, during the downtrend period for put options, the WAPC for OTM put options is 23.43%. It is only 1.39% for ITM puts. This suggests that OTM options tend to contribute more price discovery than other options. It also indicates that option's leverage effect plays a more important role than its vega or delta in determining informed trading in the option market.

Although, as reported in Tables 8 and 9, the market cycles and moneyness affect the informational role of options, the impact of liquidity on the test results has not been addressed. To examine whether a higher WAPC for OTM is solely attributed to higher trading volume, we conduct the following test:

$$WAPC_{Ratio,t} = \alpha + \beta \times VOL_{Ratio,t} + \varepsilon_t \tag{22}$$

$$WAPC_{Ratio,t} = \frac{WAPCforOTM}{WAPCforATM}, \frac{WAPCforOTM}{WAPCforITM}, or \frac{WAPCforATM}{WAPCforITM}$$

$$VOL_{Ratio} = \frac{OTM\,(OptionsTradingVolume)}{ATM\,(OptionTradingVolume)},$$

$$\frac{OTM\,(OptionsTradingVolume)}{ITM\,(OptionTradingVolume)},\ or$$

$$\frac{ATM\,(OptionsTradingVolume)}{ITM\,(OptionTradingVolume)}$$

In Equation (22), the ratio of WAPC between any two different moneyness groups is regressed on the ratio of their trading volume. If β is positive and significant, and α is not different from zero, high WAPC estimates for OTM are purely attributed to liquidity. If it is not the case, option's moneyness affects the information content in the option market. The test results are presented in Table 10. During the downtrend period, all the intercepts are statistically significant. Although most of the β estimates are positive, only one of them is statistically significant at 10% level. Thus, liquidity cannot fully explain the WAPC differences among ITM, ATM, and OTM options. For the uptrend market, the test results show a similar pattern with only one β estimate significant at 5% level. Thus, moneyness does matter.

As discussed in Section 4.2, the WAPC provides a single measure of price leadership. The futures market leads other markets. Nevertheless, we cannot solely rely on the WAPC to explain the contribution of a trading venue to price discovery. In this study, the WAPC for options could be inflated because options have more transaction records than other securities in this study. On the other hand, the price contribution from the equity is potentially underestimated. In the following section, we further conduct the information share analysis to examine the contribution of a trading venue to the price innovations.

5.3 Test results from the information share analysis

To examine the information shares contributed from the TXI, TXF, and TXO, the information share analysis requires the three price series occur at the same transaction time and trade at regular intervals. Ideally, to reduce the impact of the correlated price innovations and to better reflect the price updating sequence among the markets, the models should be estimated with second by second sampling intervals. However, for the transactions data, it is not possible that all the TXI, TXF, and TXO records occur at the same time for each single second. Thus, the data preparation for the information share analysis is different from that in Sections 5.1 and 5.2.

To deal with the non-synchronous trading problem, this study uses minute-by-minute time intervals in conducting information share analysis. At the start of each trading day, as soon as an equity index observation is reported, the most recent trades for the futures and options markets are acquired to form the first matched price set for the first trading minute. This matched price set is saved and a new matched price set is formed in the same manner for the second minute on the trading day. To minimize the impact of data staleness on the test, we eliminate those matched price set with prices recording more than fifteen seconds apart. For instance, if an index futures transaction is reported at 9:10:58 (hh:mm:ss), while the matched options is traded at 9:10:42, the matched prices are sixteen seconds apart and, thus, the price set is discarded in the information share calculation. As discussed in Section 3, the average trading time span are ten, four, and five seconds for the futures, calls, puts, respectively. It suggests that the trades are practically simultaneous. In all the specifications of the information share analysis, vector autoregression lags up to 60 minutes are used. To keep the estimations manageable, similar to Hasbrouck (1995) and Chakravarty et al. (2004), we use polynomial distributed lags. Information share bounds are computed each day using intraday transactions data. Since an estimate of the information share's standard error is difficult to obtain, we follow Hasbrouck and

Chakravarty et al. by using daily variation in the information share to determine the statistical significance of the estimates.[4]

As discussed in Section 4.3, when price innovations across markets are not independent, the information share is not uniquely defined. We can only compute a range of information shares instead of a point estimate. The upper and lower bounds of this range are obtained by trying all alternative rotations in Equation (19). We report our findings in Table 11 based on the means of lower bounds and higher bounds. During the entire sample period, the information shares are 43.86%, 46.69%, and 9.46%, for the equity, futures and options markets, respectively. Similar to the findings in Sections 5.1 and 5.2, the futures market contributes the most to price discovery and the options market the least. It indicates that the transactions on futures contain more timely and informative prices than the trades on options. As the entire sample period is divided into the downtrend and uptrend, the options market still has less contribution than the futures market regardless of the market cycles. However, the transactions on options tend to be more informative during the downtrend period than during the uptrend period. The information share of the options market during the bear market is 10.48%. It is 8.04% during the bull market. It shows again that options are relatively more attractive to informed traders in the downtrend period. This can be partially explained by short-sale constraints and the price change limit rule in the Taiwan Stock Exchange.

The information shares from the options across moneyness are presented in Table 12. To save space, we only report the information shares for options across moneyness. Regardless of the market cycles, OTM options tend to have the highest information share among all the options. On the other hand, the transactions for ITM options are less informative, particularly in

[4] Alternatively, as discussed in Grammig, Melvin, and Schlag (2005), a bootstrap methodology can also be applied in determining the statistical significance.

the bear market. For instance, during the downtrend sample period, the information share of OTM put options is 14.62%, whereas it is 11.26% for ATM puts and 1.21 for ITM put options. It is also intriguing to note that the information share for OTM puts is higher than that when all the options are lumped together. For example, during the downtrend, the information share is 10.48% in Table 11, while it is 14.62% for OTM put options in Table 12. It indicates that the test results for the informational role of options may not be clear if all the options are aggregated irrespective to the impact of moneyness.

To examine the impact of option liquidity on the analysis, we classify daily information share estimates into five groups based on liquidity for different moneyness. The liquidity of options market on each day is measured by total trading volume of options on the day. Group one includes the days with liquidity equal to or below 20^{th} percentile, group two, from 20^{th} to 40^{th} percentile, and etc. Table 13 reports the results. Similar to other tables, we only present the test results for OTM put options only. We find that high liquidity groups tend to have higher information shares than low liquidity groups. Thus, the information role of options is positively related to liquidity. For instance, during the downtrend period, OTM puts in Group five has an information share of 16.93%. OTM puts in Group one has only 2.63% of information share. The uptrend period shows a similar pattern.

6. Conclusion

We examine the informational role of options in an emerging derivatives market, the Taiwan Stock Index option market. After controlling for market cycles, option moneyness, and liquidity, we document new empirical evidence regarding the information processing ability and trading behavior among the equity, futures, and option markets linked by the same set of fundamental information. We conduct the price effect analysis, the weighted price contribution analysis, and the information share analysis. These three methods enable us to analyze the informational contents of trades among the three markets. Each approach reveals the informational role of derivatives from a different angle.

The price effect analysis shows the quality of transaction prices by comparing the permanent, temporary, and total price effects. The weighted price contribution analysis relies on the percentage of price movements driven by different trades among the three markets. It detects "which market is moving first". Therefore, the weighted price contribution measures the price leadership. The information share analysis traces the price innovations attributed to different markets. It is relevant to a trading venues' information content regarding the unknown effect price.

Our results indicate that, regardless of market cycles, the futures market has the largest permanent price effect, highest weighted average price contribution, and the largest information share. Thus, the trades on futures are the main driving force for in the price discovery process. The futures market is the price leader. It contains the greatest amount of information. However, it also has the highest total price effect. This finding suggests that the informed trades in the futures market is more costly than in the options market.

According to the three analyses, we also find that the options market contributes to price discovery as well. Nevertheless, in comparison with the futures trades, the transactions on options are less essential in price driving, have lower permanent price effects, and contribute less to price innovations. Interesting, the empirical results suggest that the information content of options varies as market conditions change. During the downtrend period, options have greater permanent price effects, higher weighted average price contributions, and larger information shares. Thus, the option market during the downtrend period is relatively more preferred trading venue for the informed traders. This can be partially explained by short-sale constraints and the price change limit rule in the Taiwan Stock Exchange.

As options are classified into different moneyness, the test results also reveal that, irrespective of market cycles, OTM options have the highest permanent price effect, greatest price contribution, and largest information share among all the options. This finding is more pronounced for OTM call options during the uptrend and OTM puts during the downtrend period. The findings suggest that option leverage outweighs its delta and vega in determining where informed traders trade. On the other hand, ITM options are not informative. The results are robust with respect to different market liquidity. Liquidity is positively related to the informational role of options, but it cannot fully explain the whole story. Moneyness does matter in informed trading. Finally, we also show that, in examining the price discovery in different trading venues, pooling options data irrespective to market cycles and moneyness may affect the empirical results.

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Table 1
The descriptive statistics for TXI, TXF, and TXO

This table presents descriptive statistics for Taiwan index returns in one-minute interval for TXI, TXF, and TXO. In this ex-post study, the entire sample is divided into two subperiods. Downtrend market runs from January, 2002 to April, 2003, and uptrend market runs from May, 2003 to March, 2004. We choose April 2003 as the dividing line between the downtrend and uptrend markets because the Taiwan stock index started moving up in April 2003

	Obs.	Mean (10^{-6})	Std.	Min	Max
Entire period (01/02/2002~03/19/2004)					
TXI	120,954	1.1308	0.0010	-0.0463	0.0331
TXF	120,954	1.4999	0.0012	-0.0354	0.0362
TXO	120,954	1.7370	0.0017	-0.0516	0.0413
Downtrend (01/02/2002~04/29/2003)					
TXI	69,692	-4.0635	0.0011	-0.0463	0.0331
TXF	69,692	-3.5682	0.0013	-0.0354	0.0362
TXO	69,692	-4.5109	0.0020	-0.0516	0.0413
Uptrend (04/30/2003~03/19/2004)					
TXI	51,262	8.1926	0.0008	-0.0155	0.0193
TXF	51,262	8.3902	0.0008	-0.0190	0.0274
TXO	51,262	10.2311	0.0013	-0.0234	0.0312

Table 2
The trading activities for the Taiwan Index Options across moneyness

This table presents trading activities for Taiwan stock index options. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02; at-the-money option (ATM) options as options with delta ranging between 0.45 and 0.55; and in-the-money (ITM) options as options with delta ranging between 0.55 and 0.98.

Call options								
	All		ITM		ATM		OTM	
Transactions	Number	per. minute	Number	per. minute	Number	per. minute	Number	per. minute
The entire sample period	1,850,088	15	278,221	2	894,090	7	677,777	6
The downtrend period	466,171	7	60,629	1	261,231	4	144,311	2
The uptrend period	1,383,917	27	217,592	4	632,859	12	533,466	10
Trading volume	Number	per. minute	Number	per. minute	Number	per. minute	Number	per. minute
The entire sample period	11,134,540	92	1,223,131	10	4,836,003	36	5,075,406	42
The downtrend period	2,115,801	30	217,299	3	695,124	8	1,203,378	17
The uptrend period	9,018,739	176	1,005,832	20	4,140,879	73	3,872,028	76
Put options								
	All		ITM		ATM		OTM	
Transactions	Number	per. minute	Number	per. minute	Number	per. minute	Number	per. minute
The entire sample period	1,576,167	13	137,833	1	687,685	6	750,649	6
The downtrend period	369,641	5	42,732	1	165,450	2	161,459	2
The uptrend period	1,206,526	24	95,101	2	522,235	10	589,190	11
Trading volume	Number	per. minute	Number	per. minute	Number	per. minute	Number	per. minute
The entire sample period	9,778,435	81	644,523	5	3,748,251	31	5,385,661	45
The downtrend period	1,640,688	24	216,897	3	531,395	8	892,396	13
The uptrend period	8,137,747	159	427,626	8	3,216,856	63	4,493,265	88

Table 3
The Augmented Dickey-Fuller unit root test for the TXI, TXF, and TXO

$$\Delta p_{t,j} = \beta_1 p_{t-1,j} + \beta_2 p_{t-2,j} + \ldots + \beta_j p_{t-m,j} + \varepsilon_t, \quad (2)$$

This table reports the results of the Augmented Dickey-Fuller unit root tests for the equity, futures, and implied prices in options. $p_{t,j}$ is a log price. $\Delta p_{t,j}$ is the first difference of the log price. The optimal number of lags, m, is chosen based on Akaike information criterion (AIC). The ADF unit root test specifies β_1=0 as the null hypothesis and the critical values for the t-tests are based on Dickey and Fuller (1979). "# of lags" refers to the number of lags used in the test.

	TXI		TXF		TXO	
Index level (Log price)						
	# of lags	t-statistic	# of lags	t-statistic	# of lags	t-statistic
The entire sample period	16	0.95	11	0.95	13	0.95
The downtrend period	19	0.93	14	0.93	16	0.93
The uptrend period	13	0.91	8	0.91	12	0.91
Price change (Return)						
	# of lags	t-statistic	# of lags	t-statistic	# of lags	t-statistic
The entire sample period	15	-69.25	12	-69.25	15	-69.25
The downtrend period	16	-29.51	16	-29.51	11	-29.51
The uptrend period	14	-36.13	10	-36.13	9	-36.13

Note: The critical value of 1% in the test is -2.58, 5% is -1.95, and 10% is -1.62.

Table 4
The cointegration tests for the TXI, TXF, TXO at index level during the entire sample period

$$\lambda_{trace}(r) = -N \times [\sum_{i=r+1}^{R} ln(1-\hat{\lambda}_i)] \qquad (5)$$

$$\lambda_{max}(r, r+1) = -N \times [ln(1-\hat{\lambda}_{r+1})] \qquad (6)$$

This table reports the results of Johansen cointegration tests for the equity, futures, and implied prices in options. R stands for the number of prices in different markets, N is the observation numbers, and $\hat{\lambda}$ refers to the eigenvalue in the test. $\lambda_{trace}(r)$ is to test the null hypothesis that the number of cointegrating vectors is not greater than r; $\lambda_{max}(r, r+1)$ examines the null hypothesis that the number of cointegrating vectors is equal to r against the alternative hypothesis that the number is equal to $r+1$. In this study, r is 0, 1, or 2. The number of lag, q, in Equation (3) is selected by the Schwarz information criterion (SIC). Critical values of λ_{trace} and λ_{max} are based on Johansen and Juselius (1990).

	Null Hypothesis	Alternative Hypothesis	Test value	P-value
λ_{Trace}				
	r=0	r>0	1635.81	<0.0001
	r<=1	r>1	71.92	<0.0001
	r<=2	r>2	0.85	>0.0500
λ_{Max}				
	r=0	r=1	891.65	<0.0001
	r=1	r=2	549.88	<0.0001
	r=2	r=3	0.62	>0.0500

Table 5
The price effect analysis for the TXI, TXF, and TXO

Permanent price effect = $p_{t+\kappa} - p_{t-l}$ (7)
Temporary price effect = $p_t - p_{t+\kappa}$ (8)
Total price effect = Permanent effect + Temporary effect = $p_t - p_{t-l}$, (9)

This table shows the test results of the price effect analysis for the equity, futures, and implied prices in options. $p_{t,}$ is a log price. The permanent price effect, temporary effect, and total price effect are calculated based on equations (7), (8) and (9), respectively. p_t is log of transaction price at time t, p_{t-l} is log of price of the lth trade before the trade at time t, and $p_{t+\kappa}$ is log of transaction price of the κth trade after the trade at time t. This study chooses l = 12 and κ=6. In the price effect estimation, we pool together the index value occurred in all three markets in sequence of their recording time. Specifically, for a trade in options market at time t, the price at t-l and t + κ could be from the equity or the futures market.

Panel 5A: The entire sample period

	The buyer-motivated transactions			The seller-motivated transactions		
	TXI	TXF	TXO	TXI	TXF	TXO
The permanent price effect (10^{-6})	3.92	4.18	1.98	-2.89	-3.77	-2.47
The temporary price effect (10^{-6})	-1.65	-1.24	-0.23	0.70	0.34	-0.24
The total price effect (10^{-6})	2.27	2.94	1.75	-2.19	-3.43	-2.71

Panel 5B: The downtrend sample period

	The buyer-motivated transactions			The seller-motivated transactions		
	TXI	TXF	TXO	TXI	TXF	TXO
The permanent price effect (10^{-6})	2.91	3.15	2.37	-2.98	-6.71	-3.11
The temporary price effect (10^{-6})	-0.90	-0.82	-0.45	0.05	2.47	0.50
The total price effect (10^{-6})	2.01	2.33	1.92	-2.93	-4.24	-2.61

Panel 5C: The uptrend sample period

	The buyer-motivated transactions			The seller-motivated transactions		
	TXI	TXF	TXO	TXI	TXF	TXO
The permanent price effect (10^{-6})	5.01	5.29	1.77	-2.73	-3.93	-2.00
The temporary price effect (10^{-6})	-2.46	-1.69	-0.11	0.77	1.18	0.94
The total price effect (10^{-6})	2.55	3.60	1.66	-1.96	-2.75	-1.06

Table 6
The price effect analysis for options across moneyness

Permanent price effect = $p_{t+\kappa} - p_{t-l}$ (7)
Temporary price effect = $p_t - p_{t+\kappa}$ (8)
Total price effect = Permanent effect + Temporary effect = $p_t - p_{t-l}$, (9)

This table shows the test results of the price effect analysis for the implied prices in options across moneyness. p_t, is a log price. The permanent price effect, temporary effect, and total price effect are calculated based on equations (7), (8) and (9), respectively. p_t is log of transaction price at time t, p_{t-l} is log of price of the lth trade before the trade at time t, and $p_{t+\kappa}$ is log of transaction price of the κth trade after the trade at time t. This study chooses $l = 12$ and κ=6. In the price effect estimation, we pool together the index value occurred in all three markets in sequence of their recording time. Specifically, for a trade in options market at time t, the price at t-l and t + κ could be from the equity or the futures market. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02; at-the-money option (ATM) options as options with delta ranging between 0.45 and 0.55; and in-the-money (ITM) options as options with delta ranging between 0.55 and 0.98.

Panel 6A: The downtrend sample period

	Call options					
	The buyer-motivated transactions			The seller-motivated transactions		
	ITM	ATM	OTM	ITM	ATM	OTM
The permanent price effect (10^{-6})	-0.13	2.17	2.76	1.06	-3.45	-4.01
The temporary price effect (10^{-6})	1.03	-0.12	-0.29	-2.28	-0.86	-0.65
The total price effect (10^{-6})	0.9	2.05	2.47	-1.22	-4.31	-4.66
	Put options					
	The buyer-motivated transactions			The seller-motivated transactions		
	ITM	ATM	OTM	ITM	ATM	OTM
The permanent price effect (10^{-6})	0.05	1.26	1.91	-1.22	-2.91	-6.35
The temporary price effect (10^{-6})	1.01	0.37	0.11	-1.05	0.87	0.69
The total price effect (10^{-6})	1.06	1.63	2.02	-2.27	-2.04	-5.66

Panel 6B: The uptrend sample period

	Call options					
	The buyer-motivated transactions			The seller-motivated transactions		
	ITM	ATM	OTM	ITM	ATM	OTM
The permanent price effect (10^{-6})	1.31	3.37	5.65	-0.71	-2.05	-1.56
The temporary price effect (10^{-6})	1.96	-1.87	-1.06	-1.08	-0.66	0.73
The total price effect (10^{-6})	3.27	1.5	4.59	-1.79	-2.71	-0.83
	Put options					
	The buyer-motivated transactions			The seller-motivated transactions		
	ITM	ATM	OTM	ITM	ATM	OTM
The permanent price effect (10^{-6})	-0.61	1.79	2.43	-0.39	-2.89	-3.62
The temporary price effect (10^{-6})	2.15	0.24	0.97	0.74	1.2	1.31
The total price effect (10^{-6})	1.54	2.03	3.4	0.35	-1.69	-2.31

Table 7
The impact of liquidity on the price effect analysis for OTM put options

Permanent price effect = $p_{t+\kappa} - p_{t-l}$ (7)
Temporary price effect = $p_t - p_{t+\kappa}$ (8)
Total price effect = Permanent effect + Temporary effect = $p_t - p_{t-l}$, (9)

This table shows the test results of the price effect analysis for the implied prices in OTM put options across five groups of liquidity. p_t, is a log price. The permanent price effect, temporary effect, and total price effect are calculated based on equations (7), (8) and (9), respectively. p_t is log of transaction price at time t, p_{t-l} is log of price of the lth trade before the trade at time t, and $p_{t+\kappa}$ is log of transaction price of the κth trade after the trade at time tIn the price effect estimation, we pool together the index value occurred in all three markets in sequence of their recording time. Specifically, for a trade in options market at time t, the price at t-l and t + κ could be from the equity or the futures market. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02. Group one includes the transactions with trading volume equal to or below 20th percentile, group two, from 20th to 40th percentile, and so on.

Panel 7A: The downtrend sample period					
	The buyer-motivated transactions				
	Group 1	Group 2	Group 3	Group 4	Group 5
	<=20th percentile	20th ~ 40th percentile	40th ~ 60th percentile	60th ~ 80th percentile	>80th percentile
The permanent price effect	1.01	0.78	2.15	3.02	2.97
The temporary price effect	1.31	1.09	-0.75	-1.02	-0.31
The total price effect	2.32	1.87	1.40	2.00	2.66
	The seller-motivated transactions				
	Group 1	Group 2	Group 3	Group 4	Group 5
	<=20th percentile	20th ~ 40th percentile	40th ~ 60th percentile	60th ~ 80th percentile	>80th percentile
The permanent price effect	-2.17	-3.05	-6.81	-8.74	-8.91
The temporary price effect	-2.11	-1.45	0.71	0.29	0.13
The total price effect	-4.28	-4.50	-6.10	-8.45	-8.78
Panel 7B: The uptrend sample period					
	The buyer-motivated transactions				
	Group 1	Group 2	Group 3	Group 4	Group 5
	<=20th percentile	20th ~ 40th percentile	40th ~ 60th percentile	60th ~ 80th percentile	>80th percentile
The permanent price effect	0.78	2.01	1.94	2.71	2.65
The temporary price effect	3.26	2.52	1.25	-0.71	-1.14
The total price effect	4.04	4.53	3.19	2.00	1.51
	The seller-motivated transactions				
	Group 1	Group 2	Group 3	Group 4	Group 5
	<=20th percentile	20th ~ 40th percentile	40th ~ 60th percentile	60th ~ 80th percentile	>80th percentile
The permanent price effect	-0.69	-1.45	-4.01	-3.78	-4.59
The temporary price effect	-1.28	0.75	2.16	-0.63	-1.29
The total price effect	-1.97	-0.70	-1.85	-4.41	-5.88

Table 8
The means of the daily weighted average price contribution for the TXI, TXF, and TXO

$$WAPC_i = \sum_{h=1}^{D} \frac{\Delta p_{h,i}}{\Delta p_h} \times W_h \qquad (10)$$

$$W_h = \frac{|\Delta p_h|}{\sum_{h=1}^{D} |\Delta p_h|} \qquad (11)$$

This table reports the test results of the weighted average price contribution for the equity, futures, and implied prices in options. Δp_h is the price change during time h, and $\Delta p_{h,i}$ refers to the sum of price changes attributed from market i during time h. A price change is credited to the venue that initiates the immediate next transaction. The WAPC is calculated based on equations (10) and (11). $\frac{\Delta p_{h,i}}{\Delta p_h}$ measures the proportion of price movement attributed to market i during time h. W_h serves as a weight estimated by the contribution of the absolute price change during time h to the cumulative absolute price change during the entire trading day. To calculate the WAPC, this study aggregate all the TXI, TXF, and TXO together in sequence of their recording time.

	TXI		TXF		TXO	
	WAPC mean	Std.	WAPC mean	Std.	WAPC mean	Std.
The entire sample period	36.20%	12.96%	45.56%	17.32%	18.24%	8.39%
The downtrend period	34.29%	9.83%	46.40%	20.19%	19.31%	8.28%
The uptrend period	38.83%	14.76%	44.40%	15.48%	16.77%	10.45%

Table 9
The means of the daily weighted average price contribution for options across moneyness

$$WAPC_i = \sum_{h=1}^{D} \frac{\Delta p_{h,i}}{\Delta p_h} \times W_h \qquad (10)$$

$$W_h = \frac{|\Delta p_h|}{\sum_{h=1}^{D} |\Delta p_h|} \qquad (11)$$

This table reports the test results of the weighted average price contribution for the implied prices in options across moneyness. Δp_h is the price change during time *h*, and $\Delta p_{h,i}$ refers to the sum of price changes attributed from market *i* during time *h*. A price change is credited to the venue that initiates the immediate next transaction. The WAPC is calculated based on equations (10) and (11). $\frac{\Delta p_{h,i}}{\Delta p_h}$ measures the proportion of price movement attributed to market *i* during time *h*. W_h serves as a weight estimated by the contribution of the absolute price change during time *h* to the cumulative absolute price change during the entire trading day. To calculate the WAPC, this study aggregate all the TXI, TXF, and TXO together in sequence of their recording time. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02; at-the-money option (ATM) options as options with delta ranging between 0.45 and 0.55; and in-the-money (ITM) options as options with delta ranging between 0.55 and 0.98.

The downtrend period

	ITM		ATM		OTM	
	WAPC mean	Std.	WAPC mean	Std.	WAPC mean	Std.
Call options	2.51%	4.66%	15.61%	9.24%	18.08%	10.59%
Put options	1.39%	4.01%	20.17%	11.58%	23.43%	9.87%

The uptrend period

	ITM		ATM		OTM	
	WAPC mean	Std.	WAPC mean	Std.	WAPC mean	Std.
Call options	1.83%	2.92%	18.25%	10.09%	20.64%	12.33%
Put options	0.44%	0.79%	9.57%	6.72%	12.09%	7.87%

Table 10
The impact of liquidity on the weighted average price contribution ratio among different moneyness

$$WAPC_{Ratio,t} = \alpha + \beta \times VOL_{Ratio,t} + \varepsilon_t \qquad (22)$$

$$WAPC_{Ratio,t} = \frac{WAPCforOTM}{WAPCforATM}, \frac{WAPCforOTM}{WAPCforITM}, or \frac{WAPCforATM}{WAPCforITM}$$

$$VOL_{Ratio} = \frac{OTM(OptionsTradingVolume)}{ATM(OptionTradingVolume)}, \frac{OTM(OptionsTradingVolume)}{ITM(OptionTradingVolume)}, or \frac{ATM(OptionsTradingVolume)}{ITM(OptionTradingVolume)}$$

This table reports the regression test results for the impact of liquidity on the weighted average price contribution in the option market. $WAPC_{Ratio,t}$ is the WAPC ratio at time t. VOL_{Rati} is option trading volume ration at time t. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02; at-the-money option (ATM) options as options with delta ranging between 0.45 and 0.55; and in-the-money (ITM) options as options with delta ranging between 0.55 and 0.98.

	The downtrend period							
	Call options				Put options			
	Alpha	p-value	Beta	p-value	Alpha	p-value	Beta	p-value
OTM to ATM	0.28	<0.001	-0.87	0.98	1.63	<0.001	2.65	0.54
OTM to ITM	0.46	<0.001	1.28	0.14	2.07	<0.001	4.97	0.18
ATM to ITM	0.09	<0.001	1.66	0.08	2.90	<0.001	3.68	0.44
	The uptrend period							
	Call options				Put options			
	Alpha		Beta		Alpha		Beta	
OTM to ATM	0.83	<0.001	1.27	0.71	0.71	<0.001	0.7589	0.46
OTM to ITM	2.68	<0.001	3.10	0.21	1.55	<0.001	3.253	0.05
ATM to ITM	6.51	<0.001	2.00	0.16	2.10	<0.001	6.041	0.34

Table 11
The means of the daily information shares for the TXI, TXF, and TXO

$$IS_i = C_i^2 \Sigma_{ii} / Var(\Phi) \qquad (17)$$

This table reports the means of lower bounds and higher bounds in the information share analysis for the equity, futures, and implied prices in options. IS_i is the information share of market i and Σ_{ii} is the variance of ε_i . The calculation is discussed in Section 4.3. This study uses minute-by-minute time intervals in conducting information share analysis. At the start of each trading day, as soon as an equity index observation is reported, the most recent trades for the futures and options markets are acquired to form the first matched price set for the first trading minute. This matched price set is saved and a new matched price set is formed in the same manner for the second minute on the trading day. To minimize the impact of data staleness on the test, we eliminate those matched price set with prices recording more than fifteen seconds apart. Information share bounds are computed each day using intraday transactions data. Since an estimate of the information share's standard error is difficult to obtain, the analysis follows Hasbrouck and Chakravarty et al. in using daily variation in the information share to determine the statistical significance of the estimates. Because price innovations across markets are usually dependent, the information share is not uniquely defined. This study computes a range of information shares instead of a point estimate. The upper and lower bounds of this range are obtained by trying all alternative rotations in Equation (19).

	TXI		TXF		TXO	
	IS mean	Std.	IS mean	Std.	IS mean	Std.
The entire sample period	43.86%	15.36%	46.69%	21.55%	9.46%	5.86%
The downtrend period	41.89%	17.11%	47.63%	23.06%	10.48%	6.42%
The uptrend period	46.57%	13.69%	45.39%	19.72%	8.04%	5.76%

Table 12
The means of the daily information shares for options across moneyness

$$IS_i = C_i^2 \Sigma_{ii} / Var(\Phi) \qquad (17)$$

This table reports the means of lower bounds and higher bounds in the information share analysis for the implied prices in options across moneyness. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02; at-the-money option (ATM) options as options with delta ranging between 0.45 and 0.55; and in-the-money (ITM) options as options with delta ranging between 0.55 and 0.98. IS_i is the information share of market *i* and Σ_{ii} is the variance of ε_i. The calculation is discussed in Section 4.3. This study uses minute-by-minute time intervals in conducting information share analysis. At the start of each trading day, as soon as an equity index observation is reported, the most recent trades for the futures and options markets are acquired to form the first matched price set for the first trading minute. This matched price set is saved and a new matched price set is formed in the same manner for the second minute on the trading day. To minimize the impact of data staleness on the test, we eliminate those matched price set with prices recording more than fifteen seconds apart. Information share bounds are computed each day using intraday transactions data. Since an estimate of the information share's standard error is difficult to obtain, the analysis follows Hasbrouck and Chakravarty et al. in using daily variation in the information share to determine the statistical significance of the estimates. Because price innovations across markets are usually dependent, the information share is not uniquely defined. This study computes a range of information shares instead of a point estimate. The upper and lower bounds of this range are obtained by trying all alternative rotations in Equation (19).

The downtrend period

	ITM		ATM		OTM	
	IS mean	Std.	IS mean	Std.	IS mean	Std.
Call options	0.57%	5.36%	8.59%	5.68%	7.03%	6.26%
Put options	1.21%	7.55%	11.26%	6.70%	14.62%	8.19%

The uptrend period

	ITM		ATM		OTM	
	IS mean	Std.	IS mean	Std.	IS mean	Std.
Call options	2.05%	4.24%	9.29%	6.41%	11.08%	5.45%
Put options	0.03%	2.71%	6.39%	6.15%	4.26%	3.61%

Table 13
The impact of liquidity on the information shares for OTM put options

$$IS_i = C_i^2\, \Sigma_{ii} / Var(\Phi) \qquad (17)$$

This table shows the test results of the information share analysis for the implied prices in OTM put options across five groups of liquidity. We define out-of-the-money (OTM) options as options with delta ranging between 0.45 and 0.02. The liquidity of options market on each day is measured by total trading volume of options on the day. Group one includes the days with liquidity equal to or below 20th percentile, group two, from 20th to 40th percentile, and etc. IS_i is the information share of market i and Σ_{ii} is the variance of ε_i. The calculation is discussed in Section 4.3. This study uses minute-by-minute time intervals in conducting information share analysis. At the start of each trading day, as soon as an equity index observation is reported, the most recent trades for the futures and options markets are acquired to form the first matched price set for the first trading minute. This matched price set is saved and a new matched price set is formed in the same manner for the second minute on the trading day. To minimize the impact of data staleness on the test, we eliminate those matched price set with prices recording more than fifteen seconds apart. Information share bounds are computed each day using intraday transactions data. Since an estimate of the information share's standard error is difficult to obtain, the analysis follows Hasbrouck and Chakravarty et al. in using daily variation in the information share to determine the statistical significance of the estimates. Because price innovations across markets are usually dependent, the information share is not uniquely defined. This study computes a range of information shares instead of a point estimate. The upper and lower bounds of this range are obtained by trying all alternative rotations in Equation (19).

The downtrend period			
		IS mean	Std.
Group 1	<=20th percentile	2.63%	2.07%
Group 2	20th ~ 40th percentile	1.95%	2.56%
Group 3	40th ~ 60th percentile	12.79%	6.24%
Group 4	60th ~ 80th percentile	13.35%	5.71%
Group 5	>80th percentile	16.93%	7.61%

The uptrend period			
		IS mean	Std.
Group 1	<=20th percentile	1.09%	2.26%
Group 2	20th ~ 40th percentile	0.74%	2.71%
Group 3	40th ~ 60th percentile	2.72%	3.10%
Group 4	60th ~ 80th percentile	5.53%	3.80%
Group 5	>80th percentile	4.11%	3.65%

Figure 1
The Taiwan Stock Index during the entire sample period

This figure depicts Taiwan stock index spot levels in one-minute interval from January 2002 through March 2004.