How to predict large movements in stock prices using the information from derivatives

Kwark, Noe-Keol; Ph.D. Candidate, Hanyang University, School of Business
JUN, Sang-Gyung; Professor, Hanyang University, School of Business
Kang, Hyoung-Goo; Professor, Hanyang University, School of Business

Abstract

This study examines how to predict jumps in stock prices. We used variables such as options-trading information, the futures basis spread, the cross-sectional standard deviation of returns on components in the stock index, and the Korean won-US dollar exchange rate. A stock price jump was defined as a large fluctuation in the stock price that deviated from the distribution thresholds of the stock's past rates of return; a test for significance was performed using a probit model. This empirical analysis showed that the implied volatility spread between at-the-money (ATM) call and put options was a significant predictor for both upward and downward jumps, whereas the volatility skew was less significant. In addition, the predictive value of the futures basis spread was moderately significant for downward stock price jumps. Both the cross-sectional standard deviation of the rates of return on component stocks in the KOSPI 200 and the won-dollar exchange rates were significant predictors for both upward and downward jumps.

Keywords: Stock market jump, probit model, implied volatility, volatility skew, moneyness, basis spread

I. Introduction

Advance information on large stock price changes (termed "stock market jumps" from here on) is useful for stock traders but would be even more useful for options traders who operate with far higher leverage than do stock traders. Forecasts and advance information on stock price jumps are also very valuable because such information could reduce the insurance costs that are incurred when the price of a stock falls in large amount. As such, advance information would be particularly useful for KOSPI200 options, presently the world's most liquid index option product. Since the start of options trading on KOSPI200 in 1997, stock prices in Korea have repeatedly shown a pattern of falls, resulting from unfavorable factors, followed by a rapid rebound. In each of these cases, huge profits and losses related to options investments were reported.

Option trading requires a much quicker response than is necessary for stock trading. Options traders are informed investors who possess more sophisticated information than stock traders on the future movement of stock markets. Therefore, as the predictions of informed options traders will more rapidly affect the derivatives market (such as options) than stock market, informational variables that are related to the derivatives market, and especially to options, are expected to play an important role as explanatory variables in predicting stock price jumps.

The volatility skew of stock options can function as prognostic information for downward jumps in price, as it reflects the fear of large downward jumps in stock markets. If, as suggested by Rubinstein (1994), the volatility skew is a right-downward decline of implied volatility as the exercise price moves from small to large options, the volatility skew would be a very significant factor in determining stock price jumps. According to studies performed by Doran, Peterson, and Tarrant (2007) on the volatility skew of S&P100 options and studies by Kim and Park (2011) on the volatility skew of KOSPI200 options, the option volatility skew is useful to predict negative stock price jumps but relatively ineffective in predicting positive stock price jumps. However, our study reveals that the KOSPI200 options took the shape of a volatility smile rather than the volatility skew that was described by Rubinstein. This finding implies that, in the Korean market, the volatility skew (volatility smile) of KOSPI200 options has limited significance in predicting stock price jumps. Our study shows that, for KOSPI200 options, the volatility skew plays a very limited role in forecasting stock price jumps. Instead, it was significant only for a portion of upward stock jumps.

Aside from the volatility skew, other factors in the option market that can affect stock price jumps include the implied volatility spread between at-the-money (ATM) call and put options, the spread between the implied volatility and the historical volatility, and the put-call ratio. Implicit within the implied volatility spread between ATM call and put options is information regarding future stock price changes and deviations in put-call parity. In our study, the implied volatility spread between ATM call and put options showed very significant results for both upward and downward jumps in stock price.

Information regarding stock price jumps can also be found in places other than option markets. Basis spreads reflect the movements of statistical arbitragers, who are astute and informed investors in the futures markets. An empirical analysis in our study showed that basis spreads provide advance information on stock price jumps. Leading movements of smart money can also exist in stock markets. This information can be captured by the cross-sectional standard deviation of stocks being traded in the market because advance movements on some stocks send an early signal regarding changes in the shape of the earnings distribution of component stocks. Moreover, some macroeconomic variables that play a large role in explaining stock prices can be considered to be the antecedents of stock price jumps. The won-dollar exchange rate is a macroeconomic variable that reflects the characteristics of the Korean economy and that is heavily dependent on foreign trade. Our study shows that fluctuations in the won-dollar exchange rate is a significant explanatory variable with regards to stock price jumps.

The effects of options trading following a stock price jump are valid only for a few days immediately after the jump until the largest option's expiration date. This phenomenon is due to the offsetting effect of the option's time decay. In their study, Doran, Peterson, and Tarrant (2007) used a model in which the effects of the price jump were maintained as being valid for five days and were removed if a price jump occurred in the opposite direction within those five days. However, in our study, we used a more conservative model in which only the day immediately following the jump was used for the analysis. Therefore, the results from our study were able to show whether each explanatory variable presents prognostic information about the day following the stock price jump.

The structure of our research paper is as follows: the next section (II) examines prior research on the prediction of stock price. Section III contains the definitions for the data and the price jumps that are noted in our paper and a summary of the statistical data and the theoretical background research on the 16 explanatory variables that were used in our analysis. Subsequently, in section IV, we present our model and the results from our analysis. Finally, in section V, we present a conclusion.

II. Research in the Existing Literature

In this section, we describe prior studies that have been conducted on the relationship between an option's implied volatility and stock prices. Giot (2005) showed a strong negative correlation between an option's implied volatility index (Chicago Board Options Exchange Market Volatility Index or VIX) and the stock market index; in their 2006 study, Banerjee, Doran, and Peterson (2006) found that implied volatility could forecast short-term stock returns. Chakravary, Gulen, and Mayhew (2004) claimed that price discovery in the options markets was related to the options trade volume, the spread between the stock market and the options markets, and the stock volatility. Korean market research on this topic includes studies by Hong, Ok, and Lee (1998), Kim and Moon (2001), Kim and Hong (2004), Kim (2007), and Lee and Hahn (2007). However, studies that were based only on the trade volumes of stocks and options, the trading value, price, and implied volatility were unable to reach a consensus on whether option market contains embedded, prognostic information on movement in stock markets.

Prior studies have sought to explain the phenomenon of volatility skew. Rubinstein (1994) and Jackwerth and Rubinstein (1996) explained the reasons behind the existence of the volatility skew. Bates (1991, 2000); Bakshi, Cao, and Chen (1997); Jackwerth (2000); and Pan (2002) took the Black-Scholes (1973) model, which assumes a fixed, inherent volatility in underlying assets, and loosened its requirements to create a model with volatility that changes arbitrarily according to changes in asset prices (the stochastic volatility assumption); with this model and with data on negative jump premiums, they explained the volatility skew phenomenon as a property of the implied volatility distribution.

The following studies have claimed that volatility skew is a phenomenon that follows the supply and demand created by options buyers and sellers: Garleanu, Pedersen, and Poteshman (2005) examined the effects of buying pressure from options buyers on options price valuations under real market conditions, where a perfect hedge, the precondition in an options price valuation model, is impossible. Bollen and Whaley (2004) asserted that implied volatility is affected by net buying pressure.

As stated above, no consensus has been reached on the underlying reasons for volatility skew. However, previous studies showed that the appearance of volatility skew reflects market participants' predictions concerning future stock prices, the psychological state of investors following the risks of future stock price fluctuations, the preference for specific options, and the buying trends of options investors. Rather than simply explaining options trade volume and prices, options volatility skew may actually offer greater insight into the price discovery process.

The informational effect of the options volatility skew could be greater at a time of rapid stock market fluctuations than it is during general market situations. Based on this idea, the following studies examined the relationship between the volatility skew and stock prices: Doran, Peterson, and Tarrant (2007) used the daily S&P100 index and options data from 1984-2006 to show that the volatility skew contained prognostic information about stock price jumps, and Doran and Kreiger (2010) claimed that the difference in the implied volatility between ATM call and put options was an important factor in determining stock rate of return.

In the Korean market, Kim and Park (2011) used the daily KOSPI200 index and options data to show, via the same method as Doran, Peterson, and Tarrant(2007), that the options volatility skew contained prognostic information concerning share price jumps in the domestic market. Both Doran, Peterson, and Tarrant (2007) and Kim and Park (2011) claimed that, in cases in which a negative stock jump was predicted, the phenomenon of volatility skew was clearly observed and served as a predictor for the negative stock jumps; however, in the case of positive stock jumps, the phenomenon of options volatility skew was only weakly evident, and it was limited in its predictive value. Additionally, Ok, Lee, and Lim (2009) analyzed KOSPI200 options data from 2002-2007 and showed that the KOSPI200 call and put options both exhibited volatility smiles shapes. The studies described above showed that the options volatility skew provides limited information for rapid stock market fluctuations. Our study is the first to address a more extensive range of informational variables that may be able to predict stock price jumps.

III. Data and Model

1. Data Used

The KOSPI200 options and the KOSPI200 futures market is the world's most liquid and largest market in terms of transaction volume. Research performed on stock price jump models on such a market is of great importance. In our study, we used daily trading data from January 2001-September 2011 (2,665 trading days). We determined the dates of stock price jumps (upwards or downwards) using the KOSPI200's natural log returns and assigned a value of "1" to valid stock jump dates and a value of "0" to those dates without jumps to use as the dependent variables in the probit model[1]. In our study, we treated upwards and downwards jumps in different models. The options data we used were provided by the Korea Exchange (KRX) and the Korea Securities Computing Corporation (KOSCOM), data on the KOSPI200 components and adjusted stock prices were provided by FnGuide, and macroeconomic data such as exchange rates were provided by the Bank of Korea.

2. Definition of Stock Price Jumps

Several different definitions of stock price jumps have been used in previous studies. In one case, a stock price jump was defined as a value exceeding an absolute threshold (critical value) based on the distribution of historical volatility (historical σ) (termed "Historical Deviation (HD) jump" from here on). Doran, Peterson, and Tarrant (2007) defined stock price jumps as "large movements in price that exceed the calculated critical values in a given period" and set the critical value in these cases as "positive or negative daily earnings that exceed the top 5% or 1%."

[1] The probit model is used when the dependent variable Y is a binary variable. In the probit model, Y takes on the form of $\Pr(Y = 1|X) = \Phi(X\beta) + e_t$ towards the influential matrix X of explanatory variables. Here, Φ is the standard normal cumulative distribution, and β is obtained using the maximum likelihood estimation(MLE).

Lee and Mykland (2006) defined a jump (termed "LM jump" from here on) based on earnings that were standardized by the rolling volatility of the prior "k" days. In other words, an earnings variation, controlled for the volatility of a certain "k" days, was established as the guideline, and a jump was defined as a situation in which the earnings exceeded this threshold.

Therefore, an LM jump describes jumps that are independent of volatility at any given point. The test statistic for an LM jump model, $\mathbf{T_t}$, is defined below:

$$\mathbf{T_t} = \frac{\log \mathbf{S_t} - \log \mathbf{S_{t-1}}}{\hat{\boldsymbol{\sigma}}_{\mathbf{t}}} \qquad (1)$$

, where $$\hat{\boldsymbol{\sigma}}_{\mathbf{t}} = \sqrt{\frac{1}{k-2}\sum_{j=t-k+2}^{t-1}\left|\log S_j - \log S_{j-1}\right|\left|\log S_{j-1} - \log S_{j-2}\right|}$$

$$\mathbf{S_t} = \text{Stock price at t}$$

Lee and Mykland (2006) did not offer a definition for k (window size), and Doran, Peterson, and Tarrant (2007) used a k value of either 16 or 30 days and showed that the choice of value had no significant effect on the result. In our study, we used k as 16 days. The definition of a stock price jump used in this study is summarized in Table 1.

INSERT <Table 1> ABOUT HERE

On the basis of the KOSPI200's daily log returns, an HDJump99% (95%) was defined as a positive jump when the returns exceeded the top 1% (5%) during our period of analysis from January 2001–September 2011 and as a negative jump when the returns fell short of the bottom 1% (5%)[2]. An LMJump95% was defined as a positive jump when the returns exceeded the 5% threshold that was set by Lee and Mykland (2006) and as a negative jump when the returns fell short of the bottom 5% threshold. During the 2,665 trading days that were used for analysis, there were 44 positive jumps and 45 negative jumps according to the HDJump99% definition, 103 positive jumps and 126 negative jumps according to the HDJump95% definition, and 59 positive jumps and 75 negative jumps according to the

[2] For the period of analysis from January 2001 to September 2011, the 1% threshold for the KOSPI 200 was ± 0.039771 and the 5% threshold was ± 0.028164. The average of the natural log of the returns during this analysis period was calculated as 0.0005 but was considered to be 0.

LMJump95% definition. Categorizing these data by month, there was a monthly average of 0.7 jumps (HDJump99%), 1.8 jumps (HDJump95%), and 1.0 jump (LMJump95%) in both positive and negative directions.

3. Selection of Explanatory Variables and Theoretical Background

The explanatory variables that were used in our study are summarized in Figure 2. The derivatives that were used as constitutive parameters were the KOSPI200 options and the KOSPI200 futures. Option moneyness was defined as Ke^{-rt}/S_t (where K is the exercise price, S_t is the KOSPI200 index value on day t, and r is the risk free rate, using a 91-day CD interest rate, and T is the remaining maturity), and moneyness intervals were classified according to the standards established by Bakshi and Kapadia (2003). In other words, call options were categorized as deep out-of-the-money (DOTM) in the 1.075-1.125 range, out-of-the-money (OTM) in the 1.025-1.075 range, at-the-money (ATM) in the 0.975-1.025 range, or in-the-money (ITM) in the 0.925-0.975 range; the ranges for put options were 0.875-0.925 for DOTM, 0.925-0.975 for OTM, 0.975-1.025 for ATM, and 1.025-1.075 for ITM.

The value of the implied volatility for each interval was calculated by averaging the implied volatilities of the nearby options with the exercise prices for the corresponding intervals. Therefore, the calculated implied volatility of ATM options is more accurately expressed as the implied volatility of near-the-money (NTM) options. The implied volatilities of the individual options, especially OTM and ITM options, contain many errors (Hentschel, 2003); these errors can be alleviated by averaging the different implied volatilities of the options in the previously mentioned intervals (Doran, Peterson, and Tarrant, 2007). In our study, we used data from the KRX based on a binomial tree model for the implied volatility value of the options. The portions marked with a value of 0.03 in the KRX implied volatility data were considered to be cases in which no solutions were found in the implied volatility calculations using numerical analysis; therefore, these portions were eliminated from our analysis (Ok, Lee, and Lim, 2009). Figure 2 describes each explanatory variable that was used in our model.

INSERT <Table 2> ABOUT HERE

(1) Volatility skews

The call volatility skew (Skew1) and the put volatility skew (Skew2) each show the difference between the implied volatility of the OTM options and the implied volatility of the ATM options. A large volatility skew can be interpreted as a high probability for large fluctuations in stock prices. However, previous analyses on this topic provide little confidence about the influence of the volatility skew on Korean markets. Figure 1 shows the results of the volatility skew analysis on KOSPI 200 options. Panels (A) and (B) are the volatility skew graphs for the calls and the puts, respectively; (a1) and (b1) are the volatility skews of calls and puts as they were calculated during the entire analysis. The classification of intervals for Figure 1 was performed according to the previously mentioned guidelines defined by Bakshi and Kapadia (2003). The solid line in the graph represents the mean and the dotted line represents the median value of the implied volatilities of the options in the corresponding moneyness intervals; (a2) and (a3), and (b2) and (b3) each show the volatility skew of the calls and the puts in the two lower intervals of 2001-2005 and 2006-2011. The shape of the KOSPI 200's volatility skew in Figure 1 is not in the "stock option volatility shape", as stated in Rubinstein (1994), but rather closely resembles the shape of a "volatility smile"; this result is shown throughout the overall interval and for the sub-periods as well.

This preliminary analysis shows that the variables Skew1 and Skew2, representing the volatility skew of the KOSPI 200 options, might not have great significance. The specific values of the volatility skews are noted in panels (C) and (D).

INSERT <Figure 1> ABOUT HERE

(2) Implied volatility spreads between ATM calls and puts

Imvol_Spread shows the spread between the implied volatilities of call and put options (ATM call implied volatility-ATM put implied volatility). However, more accurately, it describes the implied volatility spread of calls and puts that are calculated as NTM, which in turn is calculated by averaging the implied volatilities of the options in the moneyness intervals. Doran and Krieger(2010) argued that embedded within this variable is information about future stock price fluctuations and the deviation of put-call parities.

(3) The spread of average implied volatility and historical volatility of Call or Put options

For the average implied volatility of call and put options, we used data that were calculated using KRX's method. KRX calculates average implied volatility using the weighted average of nearby options' trade volumes (Yoo, 2010). The historical volatility of calls (puts) is calculated as a yearly volatility that is rolled every 90 days. When a large change in stock price is forecasted, the average implied volatility of the options moves in advance of the historical volatility, thus causing a larger spread between the two. Vol_Spread1 and Vol_Spread2 show the "average implied volatility of call options - historical volatility of call options" and the "average implied volatility of put options - historical volatility of put options", respectively.

(4) Trading unit price of options and Open interest

Price1 and Price2 designate the transaction costs of options as calculated by dividing the options trading value by the options trading volume ("call option transaction costs (100,000 won)/call option trade volume" and "put option transaction costs (100,000 won)/put option trade volume"). As options traders who have advance information on stock market jumps increase their trading of OTM options, which have comparatively large leverage, the trading unit price of the options will decrease. For the same reason, as options traders with advance knowledge on stock market jumps expand their reserves of OTM options, OpenInterest1 (open interest of call options) and OpenInterest2 (open interest of put option) increases.

(5) Futures basis spread

The basis spread of futures can provide advance information on stock market jumps by reflecting the movements of probabilistic arbitragers, who are savvy and informed investors in the futures market. If the market is efficient, there is no opportunity for index arbitrage. However, even a movement of the futures basis spread within a band of improbable index arbitrage still reflects the directions of the arbitragers' changes and thus provides information on stock market fluctuations.

(6) Stock market and Macroeconomic Factors

Even in the stock market, there are advance movements by smart money. Such information can be captured by cross-sectional moments of the stocks being traded in the market because advance movements by certain stocks can give early warnings as to changes in the component stocks' distribution of rates of returns. Stdev shows the cross-sectional standard deviation of log returns on a given day for the 200 constituents of the KOSPI 200.

The Korean won-US dollar exchange rate has significant explanatory power as a macroeconomic variable and reflects the characteristics of the Korean economy that depend heavily on foreign trade. This exchange rate may also provide a meaningful explanation for stock market jumps.

Table 3 shows a summary of statistics for the explanatory variables, including the mean, standard deviation, median, minimum value, 25th percentile, 75th percentile, and the maximum value of each explanatory variable. For the values of Currency1, Currency2, and Currency3, which are the log return volatilities for the exchange rates, we used the value of the log return volatility as calculated by the probit analysis; however, as the resulting value was too small, we present the value multiplied by 100 as a percentage in Table 3. Table 4 shows a matrix of correlation coefficients using the explanatory variables. Specifically, the correlation coefficients between the related call and put option variables show that the correlation coefficient was 0.599 between Skew1 and Skew2, 0.766 betweenVol_Spread1 andVol_Spread2, and 0.603 between OpenInterest1 andOpenInterest2. The correlation coefficient between Price1 and Price2 is high, with a value of 0.492. For each analysis of upward or downward jumps using the probit model, we picked from two combinations of variables; the combination of call option-related variables (Skew1, Vol_Spread1, OpenInterest1, and Price1) was distinguished from the combination of put option-related variables (Skew2, Vol_Spread2, OpenInterest2, and Price2).

INSERT <Table 3> ABOUT HERE

INSERT <Table 4> ABOUT HERE

IV. Model and Empirical Analysis Results

In our study, we configured the analysis model according to the type and the direction of the jump. We applied a one-day time differential to all of the explanatory variables in the model. In other words, the explanatory variables precede the dependent variable by 1 day to predict one-day future returns.

Using each jump as a dependent variable, we first configured a probit model using all of the explanatory variables and then estimated the model using the maximum likelihood estimation (MLE). Next, we reconfigured the model using only the significant or meaningful variables, and we estimated the coefficients again. The resulting models are shown below from (2) to (7), and the results from each model are summarized in Table 5, Table 6, and Table 7.

$$\begin{aligned}\mathbf{Prob(D_t = 1) = \Phi(\alpha + \beta_1 Skew1_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread1_{t-1}}\\ \mathbf{+\beta_4 OpenInterest1_{t-1} + \beta_5 Price1_{t-1} + \beta_6 p/c\_Ratio_{t-1}}\\ \mathbf{+\beta_7 BasisSpread_{t-1} + \beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1}}\\ \mathbf{+\beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t}\end{aligned} \quad (2)$$

$$\begin{aligned}\mathbf{Prob(D_t = 1) = \Phi(\alpha + \beta_1 Skew1_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Price1_{t-1}}\\ \mathbf{+\beta_4 p/c\_Ratio_{t-1} + \beta_5 Stdev_{t-1} + \beta_6 Currency1_{t-1}) + e_t}\end{aligned} \quad (3)$$

INSERT <Table 5> ABOUT HERE

Table 5 shows the estimated results from the HD upward jump model. The results (2) were estimated by using all of the explanatory variables and an upward jump as the dependent variable, and the results (3) were estimated by taking only the significant and meaningful explanatory variables from (2) to reconstruct the model. In addition, Table 5 presents the results after the process was executed on HD99% upward jumps and HD95% upward jumps to verify the model's robustness. Noted in the table are the estimated coefficient values followed by the Z value (within the parentheses). For the HD upward jump, statistical significance was found for the "ATM call implied volatility – ATM put implied volatility" (Imvol_Spread), the "put/call ratio" (p/c_ratio), the "cross-sectional standard deviation of the KOSPI200 components' log returns" (Stdev), and the "won/dollar exchange rates' log return volatility" (Currency1).

$$\begin{aligned}\mathbf{Prob(D_t = 1)} = \mathbf{\Phi(\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{t-1}}\\ \mathbf{+\beta_4 OpenInterest2_{t-1} + \beta_5 Price2_{t-1} + \beta_6 p/c\_Ratio_{t-1}}\\ \mathbf{+\beta_7 BasisSpread_{t-1} + \beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1}}\\ \mathbf{+\beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t}\end{aligned} \tag{4}$$

$$\begin{aligned}\mathbf{Prob(D_t = 1)} = \mathbf{\Phi\,(\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{t-1}}\\ \mathbf{+\beta_4 OpenInterest2_{t-1} + \beta_5 BasisSpread_{t-1} + \beta_6 Stdev_{t-1}}\\ \mathbf{+\beta_7 Currency1_{t-1} + \beta_8 Currency2_{t-1}) + e_t}\end{aligned} \tag{5}$$

INSERT <Table 6> ABOUT HERE

Table 6 shows the estimated results of the HD downward jump model shown in (4) and (5). For the HD downward jump, statistical significance was found for the "ATM call implied volatility – ATM put implied volatility" (Imvol_Spread), the "average implied volatility of put options-historical volatility of call options" (Vol_Spread2), the "open interest put options" (OpenInterest2), the "futures market basis-theoretical basis" (BasisSpread), the "cross-sectional standard deviation of the KOSPI200 components' log returns" (Stdev), the "won/dollar exchange rates' log return volatility" (Currency1), and the "Japanese yen/dollar exchange rates' log return volatility" (Currency2).

$$\begin{aligned}\mathbf{Prob(D_t = 1)} = \mathbf{\Phi(\alpha + \beta_1 Skew1_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread1_{t-1}}\\ \mathbf{+\beta_4 OpenInterest1_{t-1} + \beta_5 Price1_{t-1} + \beta_6 p/c\_Ratio_{t-1}}\\ \mathbf{+\beta_7 BasisSpread_{t-1} + \beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1}}\\ \mathbf{+\beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t}\end{aligned} \tag{6}$$

$$\begin{aligned}\mathbf{Prob(D_t = 1)} = \mathbf{\Phi(\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{t-1}}\\ \mathbf{+\beta_4 OpenInterest2_{t-1} + \beta_5 Price2_{t-1} + \beta_6 p/c\_Ratio_{t-1}}\end{aligned}$$

$$+\boldsymbol{\beta_7 BasisSpread_{t-1}} + \boldsymbol{\beta_8 Stdev_{t-1}} + \boldsymbol{\beta_9 TermSpread_{t-1}}$$
$$+\boldsymbol{\beta_{10} Currency1_{t-1}} + \boldsymbol{\beta_{11} Currency2_{t-1}} + \boldsymbol{\beta_{12} Currency3_{t-1}}) + \mathbf{e_t} \quad (7)$$

INSERT <Table 7> ABOUT HERE

Table 7 shows the estimated results of the LM upward and downward jump models shown in (6) and (7). For the LM upward jump model, statistical significance was observed for the "ATM call implied volatility – ATM put implied volatility" (Imvol_Spread), the "open interest call option" (OpenInterest1), the "transaction costs of the call options/the call option trade volume" (Price1), the "futures market basis-theoretical basis"(BasisSpread), the "won/dollar exchange rates' log return volatility" (Currency1), and the "Japanese yen/dollar exchange rates' log return volatility" (Currency2). For the LM downward jump model, statistical significance was observed for the "put/call ratio" (p/c_ratio), the "futures market basis-theoretical basis"(BasisSpread), the "won/dollar exchange rates' log return volatility" (Currency1), the "Japanese yen/dollar exchange rates' log return volatility" (Currency2), and the "Chinese yuan/dollar exchange rates' log return volatility" (Currency3). According to the results of the empirical analysis of the LM Jump model, the "ATM call implied volatility – ATM put implied volatility" (Imvol_Spread) has a relatively weaker significance than it does in the HD jump model. These findings can be attributed to the calculations that were used for the LM jump model. As the LM Jump model adjusts for a rolling implied volatility during a period of k days (the denominator in equation (1) can be seen as a demeaned volatility with a mean value of 0), the explanatory aspect of the implied volatility is offset during the jump calculation process.

In general, the explanatory variables that were significant across almost all of the various upward and downward jumps were the "ATM call implied volatility – ATM put implied volatility" (Imvol_Spread), the "cross-sectional standard deviation of KOSPI200 components' log returns" (Stdev), the "futures market basis-theoretical basis "(BasisSpread), and the "won/dollar exchange rates' log return volatility" (Currency1). The explanatory variables that were related to options, such as the "put/call ratio" (p/c_ratio), the "average implied volatility of put options - historical volatility of put options" (Vol_Spread2), and the "open interest of put options" (OpenInterest2), were significant for certain models and had explanatory value.

From the above empirical analysis of stock market jumps in the KOSPI200, we found a number of significant results. These results were not found in previous studies and are thus notable. First, the implied volatility spread between the ATM call and put options (Imvol_Spread) was significant in both HD upward and downward jumps. The signs of the estimated coefficients are negative in upward jumps and positive in downward jumps; therefore, Imvol_Spread explains a large jump in stock prices if the implied volatility of the ATM puts becomes relatively larger, and it explains a large fall if the implied volatility of the ATM calls becomes relatively larger. In other words, if the options prices fall to one side, the possibility of a technical upward jump or a rapid fall in stock prices seems to increase. However, the volatility skew was found to not have significant explanatory value for stock market jumps. This result can be attributed to the fact that the volatility skew of the KOSPI200 options market is in the shape of a volatility smile.

Second, the smaller is the futures basis spread (BasisSpread), the greater the possibility of a negative jump in stock prices. This observation shows that the basis spread of futures can provide advance information on stock market jumps by reflecting the movements of statistical arbitragers, who are savvy and informed investors in the futures market. However, the futures basis spread was not significant in explaining positive stock market jumps.

Third, as the cross-sectional standard deviation of the KOSPI200 components' returns became larger, the possibility of a positive or negative stock market jump became significantly larger as well. This shows that information on leading movements of smart money in stock markets can be captured by the cross-sectional standard deviation of the stocks that are being traded in this market because advance movements on some stocks send an early signal as to changes in the shape of the distribution of component stock returns.

Fourth, as the won/dollar exchange rate (Currency1) decreases, the probability of a positive stock market jump increases, and when the Currency1 increases, so does the probability of a negative jump. The won/dollar exchange rate, which reflects the characteristics of the Korean economy that depend strongly on foreign trade, has a very strong explanatory value in predicting stock price jumps. However, the Japanese yen/dollar exchange rate was only significant for negative jumps when the rate decreased.

V. Conclusions

Advance information on large changes or jumps in the stock market is very important to stock traders and especially so to options traders. The type of stock market jump can be defined according to how much the distribution thresholds of past stock market returns used, and our research defined jumps based on historical deviation (HD; Doran, Peterson, and Tarrant, 2007) and LM standards (Lee and Mykland, 2006). Our empirical analysis revealed the following significant results.

First, the implied volatility spread between the ATM call and put options (Imvol_Spread) was significant for both HD upward and downward jumps. However, the volatility skew did not show significant explanatory value for stock market jumps. Second, the smaller the futures basis spread (BasisSpread), the larger the likelihood of a negative jump in stock prices. However, the futures basis spread did not significantly explain positive stock market jumps. Third, as the cross-sectional standard deviation of the KOSPI200 components' returns became larger, the likelihood of a positive or negative stock market jump increased significantly. Fourth, as the won/dollar exchange rate (Currency1) decreased, the likelihood of a positive stock market jump increased, whereas the likelihood of a negative jump increased as the won/dollar exchange rate increased. However, the Japanese yen-dollar exchange rate was only significant for negative jumps when the rate decreased. The above results were not found in previous studies and are thus of great importance.

We could not verify the robustness of our model by sub-dividing a period into two periods because the relatively short history of the KOSPI200 options market did not provide a sufficient number of stock market jumps. However, considering that the results were consistent and significant for several types of jumps, we can presume that our analysis had sufficient significance as well.

In the future, we can consider conducting studies using the KOSPI200 options market's high-frequency data. With such research, we expect to get even more immediate prognostic information on stock market jumps. In addition, we could use our model to design a trading strategy and evaluate the profits therein.

References

Banerjee R., Doran J., Peterson D., 2006, Implied Volatility and Future Portfolio Returns, Journal of Banking and Finance, 31, 3183-3199.

Bakshi G., Cao C., Chen Z., 2000, Pricing and hedging long-term options, Journal of Econometrics, 94(1/2), 277-318

Bakshi G., Kapadia N., 2003, Delta-hedged gains and the negative market volatility risk premium: Review of Financial Studies, 16(2), 527-566

Bates D., 1991, The crash of '87: Was it expected? The evidence from options markets, Journal of Finance, 46(3), 1009-1044

Bates D., 2000, Post-'87 crash fears in the SandP500 futures options market, Journal of Econometrics, 94(1/2), 181-238

Black F., Scholes M., 1973, The pricing of options and corporate liabilities, Journal of Political Economy, 81 (3), 637-659

Bollen N., Whaley R., 2004, Does net buying pressure affect the shape of implied volatility functions? The Journal of Finance, 59(2), 711–753

Chakravarty S., Gulen H., Mayhew S., 2004, Informed trading in stock and option markets, Journal of Finance, 59(3), 1235-1257

Doran J.S., Krieger K., 2010, Implications for asset returns in the implied volatility skew, Financial Analysis Journal, 66(1), 65-76

Doran J.S., Peterson D.R., Tarrant B.C., 2007, Is there information in the volatility skew? The Journal of Futures Markets, Vol. 27, Mo. 10, 921-959

Evans R., Geczy C., Musto D., Reed, A., 2005, Failure is an option: Impediments to short selling and options prices, Review of Financial Studies, 22 (5), 1955-1980

Garleanu N., Pedersen L.H., Poteshman A., 2009, Demand-based option Pricing, The Review of Financial Studies, 22 (10), 4259-4299

Giot P., 2005, On the relationships between implied volatility indices and stock index Returns, Journal of Portfolio Management, 31 (3), 92-100.

Hentschel L., 2003, Errors in implied volatility estimation, The Journal of Financial and Quantitative Analysis, 38, 779-810

Hong S., Ok J., Lee Y., 1998, A Review of Interactions among Index Futures, Index Options and Stocks, Korea Derivatives Association, Seminar in Fall, 113-149

Jackwerth, J.C. and M. Rubinstein, 1996, Recovering probability distributions from option prices, Journal of Finance ,51 (5), 1611-1631

Jackwerth, J.C., 2000, Recovering risk aversion from option prices and realized returns, Review of Financial Studies, 13(2), 433-451

Kim S., 2007, Information Contents of Call-Put Options Trading Value Ratio, Korean Journal of Futures and Options, 15(2), 31-53

Kim S., Hong C., 2004, The Relationship between Stock and Option Markets: An Empirical Analysis Using Implied Stock Prices, Korean Journal of Financial Studies, 33(3), 95-122

Kim C., Moon K., 2001, A Study on the Lead-Lag Effects among the Stocks, Futures and Options in Korean Markets, The Korean Journal of Financial Management, 18(1), 129-

Kim T., Park J., 2006, Measuring Implied Volatility for Predicting Realized Volatility, The Korean Journal of Financial Engineering, 5(2),1-25

Kim S., Park H., 2011, Forecasting the Jumps of Stock Index Using Volatility Skew, Korean Finance Association Seminar (Session #19)

Lee J. H., Hahn D. H., 2007, Lead-Lag Relationship between Return and Volume in the KOSPI200 Spot and Option Markets, Korean Journal of Futures and Options, 15(2),121-143

Lee J., Kwon T., 2006, The Information Content and Volatility Transfer Effect of Implied Volatility on KOSPI200 Returns, The Korean Journal of Financial Engineering, 5(1), 41-59

Lee S, Mykland P., 2006, Jumps in real-time financial markets: A new nonparametric test and jump dynamics, Review of Financial Studies (Univ. of Chicago) 21 (6), 2535-2563

Ok K., Lee S., Lim S., 2009, A Study on the Deterministic Factors of Volatility Smile in KOSPI200 Options Market, Korean Association of Financial Engineering, Seminar in Fall

Pan J., 2002, The jump-risk premia implicit in options: evidence from an integrated time-series study, Journal of Financial Economics, 63(1), 3–50

Rubinstein, M.E. 1994, Implied Binomial Trees, Journal of Finance, 69(3), 771-818

Yoo S., 2010, Enhancing the Prediction Power of Realized Volatility Using Volatilities of Other Financial Markets, The Journal of Eurasian Studies. Vol. 7, No. 4

Vijh A. M., 1990, Liquidity of the CBOE Equity Options, Journal of Finance, 45(4), 1157-1179. Banerjee R., Doran J., Peterson D., 2006, Implied Volatility and Future Portfolio Returns, Journal of Banking and Finance, 31, 3183-3199.

<Table 1> Stock Market Jumps and Frequency of Jumps

On the basis of the KOSPI 200's daily log returns, an HDJump99% (95%) was defined as a positive jump when the returns exceeded the top 1% (5%) during our period of analysis from January 2001-September 2011 and was defined as a negative jump when the returns fell short of the bottom 1% (5%). An LMJump95% was defined as a positive jump when the returns exceeded the 5% threshold that was set by Lee-Mykland (2006) and was defined as a negative jump when the returns fell short of the bottom 5% threshold. During the 2,665 trading days that were used for this analysis, there were 44 positive jumps and 45 negative jumps according to the HDJump99% definition, 103 positive jumps and 126 negative jumps according to the HDJump95% definition, and 59 positive jumps and 75 negative jumps according to the LMJump95% definition. For the period of analysis from January 2001- to September 2011, the 1% threshold for the KOSPI 200 was ±0.039771 and the 5% threshold was ±0.028164. The average of the natural log of the returns during this analysis period was calculated as 0.0005 but was considered to be 0

Jump Type	+/-	Number of Days with a Jump (Weight)	Sum of Days with a Jump (Weight)
HDJump99%	+Jump -Jump	**44 (1.65%)** **45 (1.69%)**	**89 (3.34%)**
HDJump95%	+Jump -Jump	**103 (3.86%)** **126 (4.73%)**	**229 (8.59%)**
LMJump95%	+Jump -Jump	**59 (2.21%)** **75 (2.81%)**	**134 (5.02%)**

<Table 2> Explanatory Variables Used in This Analysis

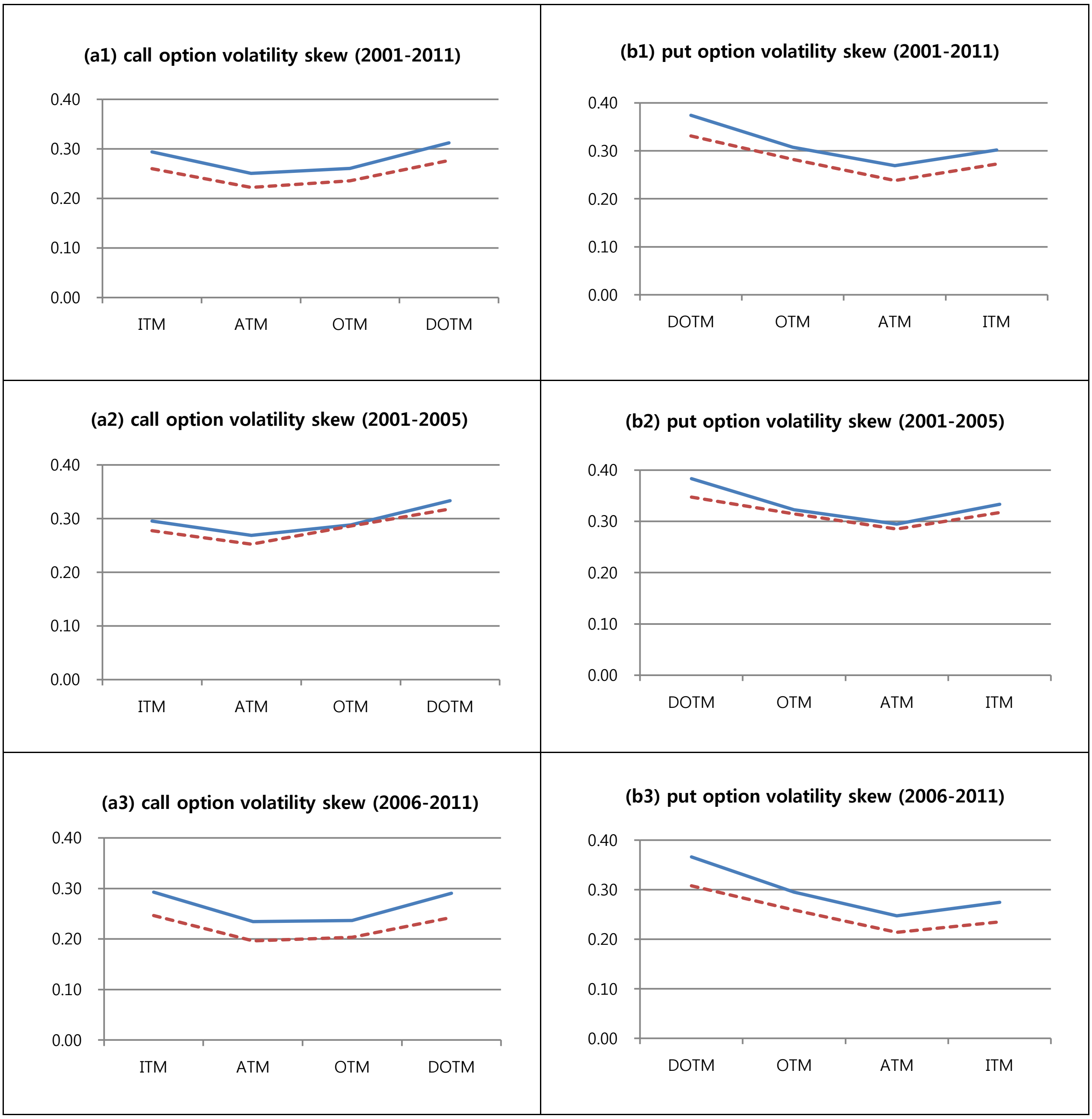
The derivatives that were used as constitutive parameters were the KOSPI200 Options and the KOSPI200 Futures. Option moneyness was defined as Ke^{-rT}/S_t (where K is the exercise price, St is the KOSPI 200 index value on day t, and r is the risk free rate, using a 91-day CD interest rate, and T is the remaining maturity). Moneyness intervals were classified for call options as DOTM (1.075-1.125), OTM (1.025-1.075), ATM (0.975-1.025), or ITM (0.925-0.975); put options were categorized as DOTM (0.875-0.925), OTM (0.925-0.975), ATM (0.975-1.025), or ITM (1.025-1.075). In our study, we used data from KRX based on a binomial tree model for the implied volatility value of options. The value of the implied volatility for the moneyness interval was calculated by averaging the implied volatilities of nearby options with the exercise prices at the corresponding intervals. The calculated implied ATM volatility is more accurately expressed as the implied volatility of NTM options. For the average implied volatility of call and put options, we used data calculated using KRX's method (KRX calculates the average implied volatility using the weighted average of the trade volumes of nearby options). The historical volatility of calls (puts) is calculated as a yearly volatility, rolled every 90 days. Price1 and Price2 designate the trading unit costs of call and put options, respectively. Stdev is the cross-sectional standard deviation for log returns on a given day for the 200 components of the KOSPI 200. A one-day time differential was applied to all of the explanatory variables in the model (in other words, the explanatory variables lead the dependent variable by 1 day).

	Explanatory variables	Descriptions
1	Skew1	Volatility skew of call options (OTM call – ATM call)
2	Skew2	Volatility skew of put options (OTM put–ATM put)
3	Imvol_Spread	Implied volatility of ATM calls – Implied volatility of ATM puts
4	Vol_Spread1	Average implied volatility of calls – Historical volatility of calls
5	Vol_Spread2	Average implied volatility of puts – Historical volatility of puts
6	OpenInterest1	Open interest of call options (100,000 contracts)
7	OpenInterest2	Open interest of put options (100,000 contracts)
8	Price1	Trading value (100,000 won)/ Trading volume of call option
9	Price2	Trading value (100,000 won)/ Trading volume of put option
10	p/c_Ratio	put/call ratio(based on Trading volume)
11	BasisSpread	Futures Market basis – Theoretical basis (pt)
12	Stdev	Cross-sectional standard deviation of the natural log returns of component stocks in KOSPI200
13	TermSpread	3-year treasury bond yields – CD interest rate
14	Currrency1	Korean won/US dollar exchange rates' log returns
15	Currrency2	Japanese yen/US dollar exchange rates' log returns
16	Currrency3	Chinese yuan US dollar exchange rates' log returns

<Figure 1> Volatility Skew of KOSPI200 Options

Panels (A) and (B) are volatility skew graphs for calls and puts, respectively. Option moneyness was defined as Ke^{-rt}/S_t (where K is the exercise price, St is the KOSPI200 index value on day t, and r is the risk free rate, using a 91-day CD interest rate, and T is the remaining maturity). Moneyness intervals were classified for call options as DOTM (1.125-1.175), OTM (1.075-1.125), ATM (1.025-1.075), and ITM (0.975-1.025); put options were categorized as DOTM (0.875-0.925), OTM (0.925-0.975), ATM (0.975-1.025), and ITM (1.025-1.075). We used data from KRX based on a binomial tree model for the implied volatility value of options. The value of the implied volatility for the moneyness interval was calculated by averaging the implied volatilities of nearby options with the exercise prices at the corresponding intervals. The solid line in the graph represents the mean and the dotted line represents the median for the implied volatilities of the options for the corresponding moneyness intervals.

(A) call option volatility skew **(B)**put option volatility skew



<Figure 1> Volatility Skew of KOSPI200 Options (continued)

(a1) and (b1) are the volatility skews of calls and puts as they were calculated during the entire analysis. The solid line in the graph represents the mean and the dotted line represents the median of the implied volatilities of the options for the corresponding moneyness intervals. (a2), (a3) and (b2), (b3) each show the volatility skew of calls and puts during the two sub-periods of 2001-2005 and 2006-2011. The KOSPI200's volatility skew in Figure 1 is not in the "stock option volatility shape" described by Rubinstein (1994), but rather, it closely resembles a "volatility smile"; this result is shown for 2001-2005 and 2006-2011 as well. The specific values of the volatility skews are noted in panels (C) and (D).

(C) Call option volatility skew (Average of the implied volatilities of the options for each corresponding interval)

Category	Period	ITM	ATM	OTM	DOTM
Mean	2001-2011	0.2939	0.2505	0.2604	0.3122
	2001-2005	0.2954	0.2690	0.2880	0.3332
	2006-2011	0.2926	0.2345	0.2367	0.2905
Median	2001-2011	0.2600	0.2220	0.2355	0.2768
	2001-2005	0.2775	0.2523	0.2860	0.3180
	2006-2011	0.2463	0.1963	0.2032	0.2425

(D) Put option volatility skew (Average of the implied volatilities of the options for each corresponding interval)

Category	Period	DOTM	OTM	ATM	ITM
Mean	2001-2011	0.3742	0.3077	0.2692	0.3020
	2001-2005	0.3833	0.3225	0.2947	0.3331
	2006-2011	0.3660	0.2949	0.2472	0.2744
Median	2001-2011	0.3310	0.2820	0.2380	0.2725
	2001-2005	0.3475	0.3145	0.2850	0.3175
	2006-2011	0.3078	0.2589	0.2136	0.2350

<Table 3> Summary Statistics of Explanatory Variables

The mean, standard deviation, median, minimum value, 25th percentile, 75th percentile, and maximum value of each explanatory variable are shown. For the values of Currency1, Currency2, and Currency3, which are the log return volatilities for the exchange rates, we used the value of the log return volatility as calculated by the probit analysis; however, as the resulting value was too small, we present the value multiplied by 100 as a percentage in this table.

Explanatory variables		Average	Standard deviation	Median	Minimum	25^{th} percentile	75^{th} percentile	Maximum
1	Skew1	0.0101	0.0578	-0.0047	-0.1900	-0.0174	0.0133	0.4175
2	Skew2	0.0389	0.0562	0.0255	-0.3560	0.0117	0.0448	0.3760
3	Imvol_Spread	-0.0188	0.0553	-0.0150	-0.7935	-0.0450	0.0104	0.3350
4	Vol_Spread1	-0.0011	0.0586	-0.0050	-0.2230	-0.0300	0.0230	0.4550
5	Vol_Spread2	0.0356	0.0710	0.0310	-0.2090	-0.0030	0.0660	0.9200
6	OpenInterest1	17.5477	7.4575	16.8478	1.1938	11.9554	22.4755	44.9594
7	OpenInterest2	18.0178	7.8060	17.7530	1.1535	12.0556	22.8700	54.7844
8	Price1	0.7789	0.3192	0.6881	0.2254	0.5586	0.9362	3.9563
9	Price2	0.8840	0.7337	0.6877	0.3079	0.5478	1.0027	11.8274
10	p/c_Ratio	0.9269	0.2627	0.9019	0.2337	0.7660	1.0538	3.7563
11	BasisSpread	-0.4132	0.6754	-0.4000	-5.7300	-0.8000	0.0000	6.2800
12	Stdev	0.0268	0.0070	0.0258	0.0142	0.0222	0.0301	0.1175
13	TermSpread	0.0051	0.0059	0.0041	-0.0167	0.0009	0.0085	0.0214
14	Currrency1 (%)	-0.0030	0.7678	-0.0239	-13.2431	-0.3010	0.2509	10.2290
15	Currrency2 (%)	-0.0150	0.7012	-0.0086	-6.3738	-0.3947	0.3769	5.7649
16	Currrency3 (%)	-0.0097	0.0862	0.0000	-2.0322	-0.0136	0.0029	0.8606

<Table 4> Matrix of Correlation Coefficients Between Explanatory Variables

We calculated the correlation coefficients between the related call and put variables. The correlation coefficient was 0.599 between Skew1 and Skew2, 0.766 between Vol_Spread1 and Vol_Spread2, 0.603 between OpenInterest1 and OpenInterest2, and 0.492 between Price1 and Price2. For each analysis of upward or downward jumps using the probit model, we picked from two combinations of variables; the combination of call option-related variables (Skew1, Vol_Spread1, OpenInterest1, and Price1) was distinguished from the combination of put option-related variables (Skew2, Vol_Spread2, OpenInterest2, and Price2).

Explanatory variables		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**Skew1**	1.000															
2	**Skew2**	0.599	1.000														
3	**Imvol_Spread**	-0.290	0.277	1.000													
4	**Vol_Spread1**	-0.140	-0.058	0.058	1.000												
5	**Vol_Spread2**	-0.048	-0.176	-0.450	0.766	1.000											
6	**OpenInterest1**	0.145	0.200	-0.069	0.229	0.223	1.000										
7	**OpenInterest2**	0.144	0.332	0.128	-0.025	-0.035	0.603	1.000									
8	**Price1**	-0.355	-0.150	0.148	0.156	0.033	-0.331	-0.162	1.000								
9	**Price2**	-0.237	-0.106	-0.110	0.448	0.426	-0.020	-0.217	0.492	1.000							
10	**p/c_Ratio**	0.013	0.016	0.020	-0.138	-0.131	-0.142	0.096	0.227	-0.226	1.000						
11	**BasisSpread**	-0.100	0.233	0.510	0.053	-0.284	0.063	0.175	0.029	-0.081	0.045	1.000					
12	**Stdev**	-0.001	-0.100	-0.074	0.284	0.227	-0.075	-0.211	0.113	0.236	-0.085	-0.050	1.000				
13	**TermSpread**	0.080	0.014	0.025	-0.159	-0.218	-0.073	0.176	0.082	-0.193	0.147	-0.053	-0.102	1.000			
14	**Currrency1**	-0.001	0.015	0.023	-0.011	-0.043	0.016	-0.016	0.005	-0.000	-0.008	0.022	-0.057	-0.037	1.000		
15	**Currrency2**	0.031	0.013	0.008	-0.017	-0.017	0.004	-0.009	-0.035	-0.033	-0.026	-0.015	0.004	0.011	-0.049	1.000	
16	**Currrency3**	0.017	-0.020	-0.031	0.004	0.013	0.002	-0.017	-0.024	-0.003	0.012	-0.009	0.036	0.051	0.003	0.027	1.000

<Table 5> HD Upward (+) Jump Model and Estimated Results

We configured a probit model using HD upward jumps and all of the explanatory variables and then estimated the model using the maximum likelihood estimation. All of the explanatory variables for upward jumps were used in the construction of model (2); we then reconfigured the model using only the significant or meaningful variables from that model to build the model (3). This process was undertaken on HD99% upward jumps and HD95% upward jumps to verify the model's robustness. Noted in the table are the estimated coefficient values followed by the Z-values (in parentheses). The probit model is used when the dependent variable Y is a binary variable. In the probit model, Y takes on the form of $\Pr(Y = 1|X) = \Phi(X\beta) + e_t$ towards the influential matrix X of explanatory variables. Here, Φ is the standard normal cumulative distribution, and β is obtained using the maximum likelihood estimation (MLE).

$$\mathbf{Prob}(\mathbf{D_t = 1}) = \boldsymbol{\Phi}(\boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{Skew1_{t-1}} + \boldsymbol{\beta_2}\mathbf{Imvol\_Spread_{t-1}} + \boldsymbol{\beta_3}\mathbf{Vol\_Spread1_{3_{t-1}}} + \boldsymbol{\beta_4}\mathbf{OpenInterest1_{t-1}} + \boldsymbol{\beta_5}\mathbf{Price1_{t-1}} + \boldsymbol{\beta_6}\mathbf{p/c\_Ratio_{t-1}} + \boldsymbol{\beta_7}\mathbf{Basis}\mathrm{Spread}_{\mathbf{t-1}} + \boldsymbol{\beta_8}\mathbf{Stdev_{t-1}} + \boldsymbol{\beta_9}\mathbf{TermSpread_{t-1}} + \boldsymbol{\beta_{10}}\mathbf{Currency1_{t-1}} + \boldsymbol{\beta_{11}}\mathbf{Currency2_{t-1}} + \boldsymbol{\beta_{12}}\mathbf{Currency3_{t-1}}) + \mathbf{e_t} \qquad (2)$$

$$\mathbf{Prob}(\mathbf{D_t = 1}) = \boldsymbol{\Phi}(\boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{Skew1_{t-1}} + \boldsymbol{\beta_2}\mathbf{Imvol\_Spread_{t-1}} + \boldsymbol{\beta_3}\mathbf{Price1_{t-1}} + \boldsymbol{\beta_4}\mathbf{p/c\_Ratio_{t-1}} + \boldsymbol{\beta_5}\mathbf{Stdev_{t-1}} + \boldsymbol{\beta_6}\mathbf{Currency1_{t-1}}) + \mathbf{e_t} \qquad (3)$$

Explanatory variables		HD Upward Jump (99%) Model Estimated Values						HD Upward Jump (95%) Model Estimated Values					
	Intercept	-1.6693	(-3.10)	***	-2.1765	(-5.07)	***	-2.6491	(-7.43)	***	-2.6686	(-9.57)	***
1	**Skew1**	-3.3471	(-1.55)		-4.2949	(-1.88)	*	-0.8553	(-0.79)		-1.0576	(-0.98)	
3	**Imvol_Spread**	-3.5560	(-2.91)	***	-3.9985	(-3.57)	***	-2.7125	(-2.95)	***	-3.0246	(-3.67)	***
4	**Vol_Spread1**	1.6173	(1.33)					0.0630	(0.07)				
6	**OpenInterest1**	-0.0090	(-0.83)					0.0010	(0.130				
8	**Price1l**	-0.6297	(-1.92)	*	-0.3964	(-1.38)		0.0781	(0.43)		0.0796	(0.47)	
10	**p/c_Ratio**	-0.9321	(-2.70)	***	-1.0487	(-3.15)	***	-0.3761	(-1.84)	*	-0.4295	(-2.15)	**
11	**BasisSpread**	-0.0102	(-0.10)					-0.0519	(-0.65)				
12	**Stdev**	28.5784	(3.54)	***	35.6724	(4.71)	***	35.4252	(5.23)	***	37.1667	(5.99)	***
13	**TermSpread**	-19.6546	(-1.44)					-11.2327	(-1.30)				
14	**Currrency1**	-31.7106	(-3.62)	***	-32.9920	(-3.87)	***	-40.6627	(-5.91)	***	-40.7668	(-6.03)	***
15	**Currrency2**	7.7887	(0.88)					6.3638	(0.95)				
16	**Currrency3**	57.1851	(0.55)					15.8004	(0.26)				

Level of significance: *** 0.01 **0.05 *0.1

<Table 6> HD Downward (−) Jump Model and Estimated Results

We configured a probit model using HD downward jumps and all of the explanatory variables and then estimated the model using the maximum likelihood estimation. All of the explanatory variables for downward jumps were used in the construction of the model (4); we then reconfigured the model using only the significant or meaningful variables from that model to build the model (5). This process was undertaken on HD99% downward jumps and HD95% downward jumps to verify the model's robustness. Noted in the table are the estimated coefficient values followed by the Z-values (in parentheses).

$$\mathbf{Prob(D_t = 1) = \Phi(\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{3_{t-1}} + \beta_4 OpenInterest2_{t-1} + \beta_5 Price2_{t-1} + \beta_6 p/c\_Ratio_{t-1} + \beta_7 BasisSpread_{t-1}} \\ \mathbf{+\beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1} + \beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t} \quad (4)$$

$$\mathbf{Prob(D_t = 1) = \Phi\ (\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{t-1} + \beta_4 OpenInterest2_{t-1} + \beta_5 BasisSpread_{t-1} + \beta_6 Stdev_{t-1}} \\ \mathbf{+\beta_7 Currency1_{t-1} + \beta_8 Currency2_{t-1}) + e_t} \quad (5)$$

	Explanatory variables	**HD** Downward Jump (99%) Model Estimated Values						**HD** Downward Jump (95%) Model Estimated Values					
	intercept	-2.8407	(-7.17)	***	-2.7086	(-8.63)	***	-2.2455	(-7.98)	***	-2.3408	(-10.51)	***
2	**Skew2**	1.5151	(1.25)		1.56101	(1.32)		0.6409	(0.73)		0.7255	(0.84)	
3	**Imvol_Spread**	3.2346	(2.41)	**	3.41714	(2.55)	**	2.3395	(2.35)	**	2.3636	(2.43)	**
5	**Vol_Spread2**	2.2825	(2.01)	**	2.1772	(2.39)	**	1.0425	(1.34)		1.5931	(2.44)	**
7	**OpenInterest2**	-0.0210	(-1.97)	**	-0.0217	(-2.17)	**	-0.0126	(-1.81)	*	-0.0155	(-2.35)	**
9	**Price2**	-0.0250	(-0.28)					0.0342	(0.56)				
10	**p/c_Ratio**	0.2444	(1.15)					-0.1036	(-0.61)				
11	**BasisSpread**	-0.2272	(-2.30)	**	-0.2288	(-2.35)	**	-0.2234	(-2.94)	***	-0.2085	(-2.83)	***
12	**Stdev**	17.8895	(2.22)	**	19.0431	(2.41)	**	23.3642	(3.97)	***	24.1244	(4.15)	***
13	**TermSpread**	-12.9491	(-1.05)					-7.2995	(-0.89)				
14	**Currrency1**	35.8487	(4.91)	***	35.9411	(5.14)	***	43.8496	(7.58)	***	44.6739	(7.82)	***
15	**Currrency2**	-35.4850	(-4.31)	***	-35.5070	(-4.37)	***	-16.8391	(-2.78)	***	-17.3495	(-2.90)	***
16	**Currrency3**	-12.5349	(-0.20)					108.7335	(1.91)	*			

Level of significance: *** 0.01 **0.05 *0.1

<Table 7> LM Jump Model and Estimated Results

We configured a probit model using LM jumps and explanatory variables and then estimated the model using the maximum likelihood estimation. All of the explanatory variables for LM upward jumps were used in the construction of the model (6); we then reconfigured the model using only the significant or meaningful variables from that model. All of the explanatory variables for LM downward jumps were used in the construction of the model (7); we then reconfigured the model using only the significant or meaningful variables from that model. Noted in the table are the estimated coefficient values followed by the Z-values (in parentheses).

$$\mathbf{Prob(D_t = 1)} = \mathbf{\Phi(\alpha + \beta_1 Skew1_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread1_{3_{t-1}} + \beta_4 OpenInterest1_{t-1} + \beta_5 Price1_{t-1} + \beta_6 p/c\_Ratio_{t-1} + +\beta_7 BasisSpread_{t-1}} \\ \mathbf{+\beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1} + \beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t} \quad (6)$$

$$\mathbf{Prob(D_t = 1)} = \mathbf{\Phi(\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{3_{t-1}} + \beta_4 OpenInterest2_{t-1} + \beta_5 Price2t_{t-1} + \beta_6 p/c\_Ratio_{t-1} + \beta_7 BasisSpread_{t-1}} \\ \mathbf{+\beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1} + \beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t} \quad (7)$$

Explanatory variables		**LM Upward Jump (95%)**						**LM Downward Jump (95%)**					
	intercept	-1.5870	(-3.93)	***	-1.4027	(-5.60)	***	-2.3983	(-6.78)	***	-2.3960	(-12.70)	***
1	**Skew1**	0.9243	(0.99)		1.0430	(1.15)							
2	**Skew2**							-1.7663	(-1.22)		-0.9012	(-0.78)	
3	**Imvol_Spread**	-1.9120	(-1.86)	*	-2.0519	(-2.07)	**	2.1122	(1.57)		1.4124	(1.19)	
4	**Vol_Spread1**	0.9226	(0.83)										
5	**Vol_Spread2**							0.9014	(0.90)				
6	**OpenInterest1**	-0.0250	(-2.87)	***	-0.0238	(-2.85)	***						
7	**OpenInterest2**							0.0103	(1.26)				
8	**Price1**	-0.4677	(-2.02)	**	-0.3306	(-1.49)							
9	**Price2**							-0.0063	(-0.07)				
10	**p/c_Ratio**	0.3161	(1.43)					0.4018	(2.24)	**	0.3847	(2.27)	**
11	**BasisSpread**	0.1785	(2.01)	**	0.1902	(2.19)	**	-0.1920	(-2.03)	**	-0.1724	(-1.92)	*
12	**Stdev**	-0.9831	(-0.12)					-7.8657	(-0.91)				
13	**TermSpread**	6.8027	(0.68)					1.7912	(0.19)				
14	**Currrency1**	-26.4808	(-3.77)	***	-25.5649	(-3.82)	***	34.3088	(5.18)	***	33.4218	(5.39)	***
15	**Currrency2**	17.0170	(2.10)	**	16.0615	(2.03)	**	-27.3634	(-3.85)	***	-27.1777	(-3.93)	***
16	**Currrency3**	-0.3320	(-0.01)					132.8158	(2.12)	**	133.3649	(2.11)	**

Level of significance: *** 0.01 **0.05 *0.1