Can Derivative Information Predict Stock Price Jumps?

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ABSTRACT

This study examines the predictability of jumps in stock prices using options-trading information, the futures basis spread, the cross-sectional standard deviation of returns on components in the stock index, and exchange rates. A stock price jump was defined as a large fluctuation in the stock price that deviated from the distribution thresholds of the past rates of return. This empirical analysis shows that the implied volatility spread between 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 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

1. INTRODUCTION

Predictability of large stock price changes (termed "stock price jumps" from here on) has been a significant issue to capital market participants. Stock price jumps would be an important consideration especially to options traders, who operate with far higher leverage than do stock traders. With reliable predictability of negative stock price jumps could derivatives traders reduce the insurance costs. Since the start of options trading on KOSPI200 in 1997, stock prices in Korean market have repeatedly shown a pattern of falls, resulting from unfavorable factors, followed by a rapid rebound. Huge profits and losses related to options trading were reported in each of those cases.

Option trading requires a much quicker response than does stock trading. Options traders are informed investors who possess more sophisticated information than stock traders on the future short-term movement of stock markets. Since 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 predictive information for downward jumps in stock price, as it reflects the fear of large downward jumps in stock markets. 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 and would be a 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 limited role in predicting stock price jumps. Instead, it was significant only in explaining a portion of upward stock jumps.

Aside from the volatility skew, we can think of other explanatory variables in the option market that can affect stock price jumps. These variables 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. The implied volatility spread between ATM call and put options would implicitly reflect information regarding future stock price changes and possible deviations in put-call parity (Bali and Hovakimian, 2009; Doran and Kreiger, 2010). In our study, the implied volatility spread between ATM call and put options showed a very significant power in predicting both upward and downward jumps in stock price.

Clues on stock price jumps can also be found in other than option markets. Basis spreads may 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 have predictability 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 return; advance movements on some stocks send an early signal regarding entire market such as the changes in the shape of the earnings distribution of stocks. Moreover, some macroeconomic variables can be considered as antecedents of stock price jumps. The won-dollar exchange rate is a macroeconomic variable that reflects the characteristics of the Korean economy, which 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 structure of our research paper is as follows: Section II examines prior research on the prediction of stock price. Section III describes data and variables of the analysis. It provides a summary statistics and the theoretical background on the 16 explanatory variables that were used in our analysis. Subsequently, in section IV, we present our model and results of our analysis. Finally, in section V, we present a conclusion.

2. LITERATURE REVIEW

In this section, we describe prior studies that have been conducted on the relationship between option's implied volatility and stock prices. Giot (2005) showed a strong negative correlation between options' implied volatility index (Chicago Board Options Exchange Market Volatility Index or VIX) and the stock market index. Banerjee, Doran, and Peterson (2006) also 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 trading volume, the spread between the stock market and the options markets, and the stock volatility. Hong, Ok, and Lee (1998), Kim and Moon (2001), Kim and Hong (2004), Kim (2007), and Lee and Hahn (2007) researched on this topic using KOSPI200 options. These studies focus on rather smaller number of variables such as trading volumes, price, and implied volatility than our study does. They do not reach a consensus on whether option market contains embedded, predictive 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) loosened the Black-Scholes (1973) model's assumption of a fixed, inherent volatility in underlying assets. With the assumption of stochastic volatility and negative jump premiums, they explained the volatility skew phenomenon as a property of the implied volatility distribution.

Several studies focus on the institutional explanations about volatility skew. These studies claimed that volatility skew results from the supply and demand created by options buyers and sellers. They loosen the assumption of perfect hedge of option valuation models. Garleanu, Pedersen, and Poteshman (2005) examined the effects of options traders' buying pressure on options prices under real market conditions, such as imperfect hedging. Bollen and Whaley (2004) asserted that implied volatility is affected by net buying pressure.

Other important explanations are: market participants' predictions concerning future stock prices, the psychological state of investors about the risks of future stock price fluctuations, the preference for specific options, and the buying trends of options investors. These studies propose that options volatility skew may actually provide more information contents on the price discovery process than options trading volume and prices.

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 predictive information about stock price jumps. 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.

Kim and Park (2011), using the daily KOSPI200 index and options data, showed that the options volatility skew contained predictive information on share price jumps. Doran, Peterson, and Tarrant (2007) and Kim and Park (2011) claimed that, 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, 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 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.

3. DATA AND MODEL

3.1 Data

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.

3.2 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%."

Lee and Mykland (2006) defined a jump (termed "LM jump" from here on) based on rates of return that were standardized by the rolling volatility of the prior "k" days. In other words, a rate of return, 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 rate of return 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, T_t, is defined below:

[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 $\Pr(Y = 1|X) = \Phi(X\beta) + e_t$ with X of explanatory variables. Here, Φ is the standard normal cumulative distribution, and β is obtained using the maximum likelihood estimation (MLE).

$$T_t = \frac{\log S_t - \log S_{t-1}}{\hat{\sigma}_t} \quad (1)$$

where

$$\hat{\sigma}_t = \sqrt{\frac{1}{k-2}\sum_{j=t-k+2}^{t-1} |\log S_j - \log S_{j-1}||\log S_{j-1} - \log S_{j-2}|}$$

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

Lee and Mykland (2006) did not offer a definition for k (window size). 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.

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. 2,665 trading days were used for this analysis. 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.

Table 1. Stock Market Jumps and Frequency of Jumps

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

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]. 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 the analysis, there were 44 positive jumps and 45 negative jumps according to the HDJump99% definition. There were 103 positive jumps and 126 negative jumps according to the HDJump95% definition. Using LMJump95% definition, we found 59 positive jumps and 75 negative jumps. Categorizing these data by month, there was a monthly average of 0.7 jumps of HDJump99%, 1.8 jumps of HDJump95%, and 1.0 jump of LMJump95% in both positive and negative directions.

3.3 Selection of Explanatory Variables

The explanatory variables that were used in our study are summarized in Table 2. The derivatives that were used as constitutive parameters were the KOSPI200 options and the KOSPI200 futures. Option moneyness was defined as Ke^{-rt}/St (where K is the exercise price, S_t is the KOSPI200 index value on day t, and r is the risk free rate, defined as 91-day CD interest rate, and T is the remaining maturity). Following Bakshi and Kapadia (2003), 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

[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.

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. Hentschel (2003) report that the implied volatilities of the individual options, especially OTM and ITM options, contain many errors. These errors can be alleviated by averaging the different implied volatilities of the options in the 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 marked values of 0.03 in the KRX implied volatility data are the cases in which no solutions were found in the implied volatility calculations using numerical analysis. Therefore, these observations were eliminated from our analysis (Ok, Lee, and Lim, 2009). Table 2 describes each explanatory variable that was used in our model.

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. 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.

Table 2. Explanatory Variables Used in This Analysis

	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	Currency1	Korean won/US dollar exchange rates' log returns
15	Currency2	Japanese yen/US dollar exchange rates' log returns
16	Currency3	Chinese yuan US dollar exchange rates' log returns

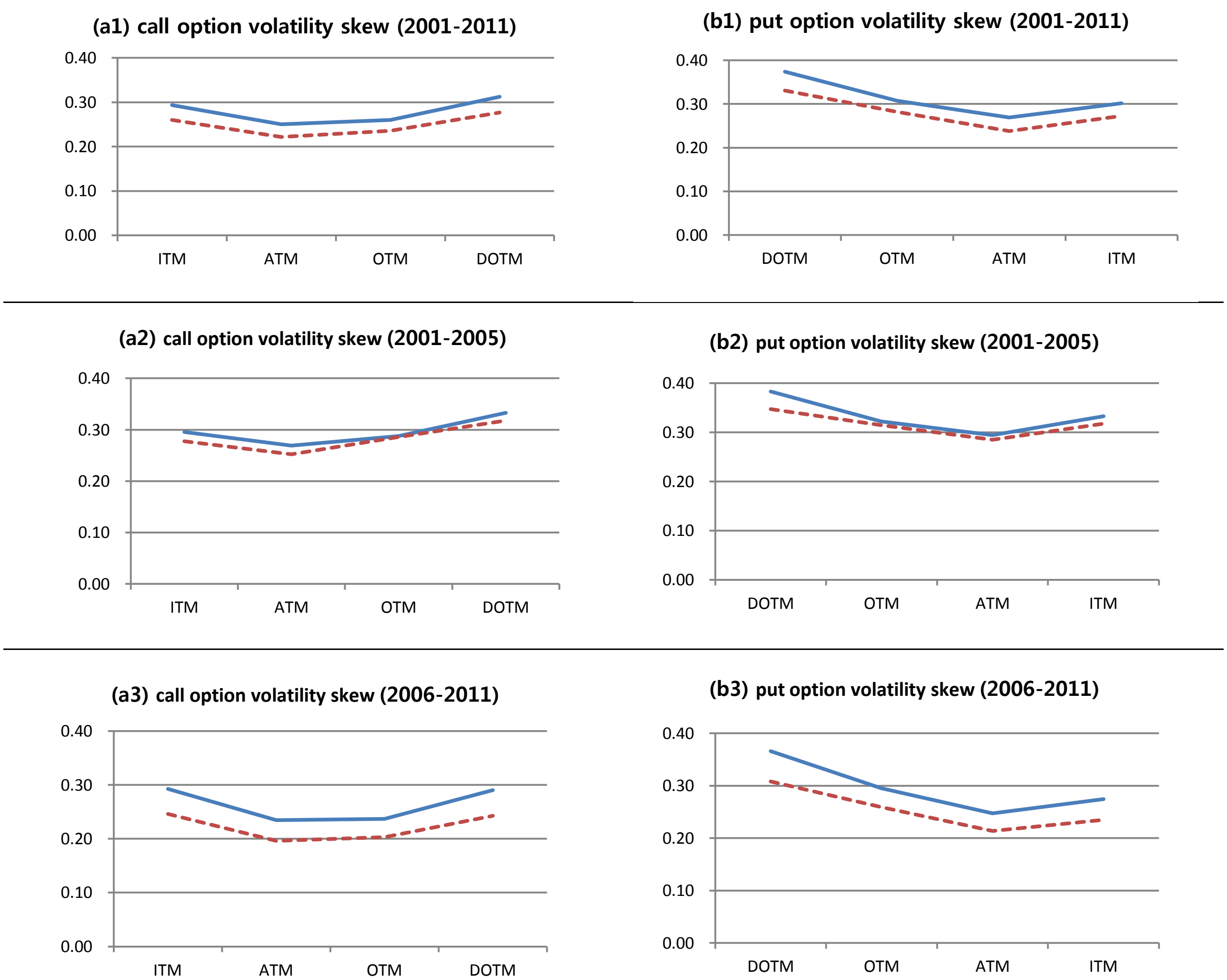
3.3.1 Volatility Skews

The call volatility skew (Skew1) and the put volatility skew (Skew2) show the difference between the implied volatility of the OTM options and that of the ATM options. A large volatility skew can be interpreted as a high probability for large fluctuations in stock prices. However, our preliminary analyses suggest 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. Part (A) and (B) are the volatility skew graphs for the calls and the puts, respectively. Graph (a1) and (b1) are the volatility skews of calls and puts during the entire period. 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. Graph (a2) and (a3), and (b2) and (b3) each show the volatility skew of the calls and the puts in the two sub-periods of 2001-2005 and 2006-2011.

We can observe that 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). The shape rather closely resembles that of a "volatility smile". This result is consistent for the overall period and for the two 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).

In Figure 1, 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. (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 specific values of the volatility skews are noted in panels (C) and (D).

(A) Call Option Volatility Skew **(B) Put Option Volatility Skew**



(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

Figure 1. Volatility Skew of KOSPI200 Options

3.3.2 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.

3.3.3 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.

3.3.4 Unit Prices And Open Interest

Price1 and Price2 represent average unit prices of options, measured by dividing the options trading value by the trading volume for calls and puts, respectively. Because OTM options have comparatively large leverage, options traders would increase their trading of OTM options with lower prices when they predict stock price jumps. Then the values of Price1 and Price2 will be lowered near stock price jumps. For the same reason, as options traders with advance knowledge on stock market jumps increase their reserves of OTM options, OpenInterest1 (open interest of call options) and OpenInterest2 (open interest of put option) will increases.

3.3.5 Futures Basis Spread

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. If the market is efficient, there is no opportunity for index arbitrage. However, even a movement of the futures basis spread within a band with no arbitrage, it still reflects the directions of the arbitragers' changes and thus provides information on stock market fluctuations.

3.3.6 Stock Market Factors 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 stock returns. Advance movements of certain stocks can give early signals of changes in the distribution 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 influences heavily the Korean capital market as well as real businesses. It also reflects the characteristics of the Korean economy that depend heavily on foreign trade. Thus exchange rate may aprovide 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. Currency1, Currency2, and Currency3 are the log return volatilities for the exchange rates. Since the original values of Currency1, Currency2, and Currency3 are too small, we report values in percentage in Table 3. We, however, used the original values of the log return volatility in the probit analysis.

In Table 3, 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.

Table 3. Summary Statistics of Explanatory Variables

	Explanatory variables	Average	Standard deviation	Median	Minimum	25th percentile	75th 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	Currency1 (%)	-0.0030	0.7678	-0.0239	-13.2431	-0.3010	0.2509	10.2290
15	Currency2 (%)	-0.0150	0.7012	-0.0086	-6.3738	-0.3947	0.3769	5.7649
16	Currency3 (%)	-0.0097	0.0862	0.0000	-2.0322	-0.0136	0.0029	0.8606

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 one of two combinations of variables. That is, the combination of call option-related variables (Skew1, Vol_Spread1, OpenInterest1, and Price1) was not used together with that of put option-related variables (Skew2, Vol_Spread2, OpenInterest2, and Price2) in the analysis.

The correlation coefficients between the related call and put variables was calculated and is shown in Table 4. 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).

Table 4. Matrix of Correlation Coefficients Between Explanatory Variables

	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	**Open Interest1**	0.145	0.200	-0.069	0.229	0.223	1.000										
7	**Open Interest2**	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	**Basis Spread**	-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	**Term Spread**	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	**Currency1**	-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	**Currency2**	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	**Currency3**	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

4. EMPIRICAL ANALYSIS

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 set up a probit model using all of the explanatory variables and then estimated the model using the maximum likelihood estimation (MLE). Next, we re-estimated the model using only the significant or meaningful variables. 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.

$$\begin{aligned}\mathrm{Prob}(D_t = 1) = \Phi(&\alpha + \beta_1 \mathrm{Skew1}_{t-1} + \beta_2 \mathrm{Imvol\_Spread}_{t-1} + \beta_3 \mathrm{Vol\_Spread1}_{t-1} \\ &+\beta_4 \mathrm{OpenInterest1}_{t-1} + \beta_5 \mathrm{Price1}_{t-1} + \beta_6 \mathrm{p/c\_Ratio}_{t-1} \\ &+\beta_7 \mathrm{BasisSpread}_{t-1} + \beta_8 \mathrm{Stdev}_{t-1} + \beta_9 \mathrm{TermSpread}_{t-1} \\ &+\beta_{10} \mathrm{Currency1}_{t-1} + \beta_{11} \mathrm{Currency2}_{t-1} + \beta_{12} \mathrm{Currency3}_{t-1}) + e_t\end{aligned} \quad (2)$$

$$\begin{aligned}\mathrm{Prob}(D_t = 1) = \Phi(&\alpha + \beta_1 \mathrm{Skew1}_{t-1} + \beta_2 \mathrm{Imvol\_Spread}_{t-1} + \beta_3 \mathrm{Price1}_{t-1} \\ &+\beta_4 \mathrm{p/c\_Ratio}_{t-1} + \beta_5 \mathrm{Stdev}_{t-1} + \beta_6 \mathrm{Currency1}_{t-1}) + e_t\end{aligned} \quad (3)$$

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. The results (3) were estimated by taking only the significant and meaningful explanatory variables from (2) to reconstruct the model. The process was executed separately 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 Imvol_Spread ("ATM call implied volatility – ATM put implied volatility"), p/c_ratio ("put/call ratio"), Stdev ("cross-sectional standard deviation of the KOSPI200 components' log returns"), and Currency1 ("won/dollar exchange rates' log return volatility").

A probit model using HD upward jumps and all of the explanatory variables and then estimated the model using the maximum likelihood estimation, was confugured. 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).

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

$$\mathrm{Prob}(D_t=1)=\Phi(\alpha+\beta_1\mathrm{Skew1}_{t-1}+\beta_2\mathrm{Imvol}_{\mathrm{Spread}_{t-1}}+\beta_3\mathrm{Vol}_{\mathrm{Spread1}_{3_{t-1}}}+\beta_4\mathrm{OpenInterest1}_{t-1}+\beta_5\mathrm{Price1}_{t-1}+\beta_6\mathrm{p/c\_Ratio}_{t-1}+\beta_7\mathrm{BasisSpread}_{t-1}+\beta_8\mathrm{Stdev}_{t-1}+\beta_9\mathrm{TermSpread}_{t-1}+\beta_{10}\mathrm{Currency1}_{t-1}+\beta_{11}\mathrm{Currency2}_{t-1}+\beta_{12}\mathrm{Currency3}_{t-1})+e_t \quad (2)$$

$$\mathrm{Prob}(D_t=1)=\Phi(\alpha+\beta_1\mathrm{Skew1}_{t-1}+\beta_2\mathrm{Imvol\_Spread}_{t-1}+\beta_3\mathrm{Price1}_{t-1}+\beta_4\mathrm{p/c\_Ratio}_{t-1}+\beta_5\mathrm{Stdev}_{t-1}+\beta_6\mathrm{Currency1}_{t-1})+e_t \quad (3)$$

	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	Open Interest1	-0.0090	(-0.83)			0.0010	(0.130		
8	Price1	-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	Basis Spread	-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	Currency1	-31.7106	(-3.62)***	-32.9920	(-3.87)***	-40.6627	(-5.91)***	-40.7668	(-6.03)***
15	Currency2	7.7887	(0.88)			6.3638	(0.95)		
16	Currency3	57.1851	(0.55)			15.8004	(0.26)		

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

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 Imvol_Spread ("ATM call implied volatility – ATM put implied volatility"), Vol_Spread2 ("average implied volatility of put options-historical volatility of call options"), OpenInterest2 ("open interest put options"), BasisSpread ("futures market basis-theoretical basis"), Stdev ("cross-sectional standard deviation of the KOSPI200 components' log returns"), Currency1 ("won/dollar exchange rates' log return volatility"), and Currency2 ("Japanese yen/dollar exchange rates' log return volatility").

$$\begin{aligned}\mathrm{Prob}(D_t=1)=\Phi(\alpha&+\beta_1\mathrm{Skew2}_{t-1}+\beta_2\mathrm{Imvol\_Spread}_{t-1}+\beta_3\mathrm{Vol\_Spread2}_{t-1}\\&+\beta_4\mathrm{OpenInterest2}_{t-1}+\beta_5\mathrm{Price2}_{t-1}+\beta_6\mathrm{p/c\_Ratio}_{t-1}\\&+\beta_7\mathrm{BasisSpread}_{t-1}+\beta_8\mathrm{Stdev}_{t-1}+\beta_9\mathrm{TermSpread}_{t-1}\\&+\beta_{10}\mathrm{Currency1}_{t-1}+\beta_{11}\mathrm{Currency2}_{t-1}+\beta_{12}\mathrm{Currency3}_{t-1})+e_t\end{aligned} \quad (4)$$

$$\begin{aligned}\mathrm{Prob}(D_t=1)=\Phi\,(\alpha&+\beta_1\mathrm{Skew2}_{t-1}+\beta_2\mathrm{Imvol\_Spread}_{t-1}+\beta_3\mathrm{Vol\_Spread2}_{t-1}\\&+\beta_4\mathrm{OpenInterest2}_{t-1}+\beta_5\mathrm{BasisSpread}_{t-1}+\beta_6\mathrm{Stdev}_{t-1}\\&+\beta_7\mathrm{Currency1}_{t-1}+\beta_8\mathrm{Currency2}_{t-1})+e_t\end{aligned} \quad (5)$$

A probit model was configuerd 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).

Table 6. HD Downward (-) Jump Model and Estimated Results

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

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

	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	**Open Interest2**	-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	**Basis Spread**	-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	**Currency1**	35.8487	(4.91)***	35.9411	(5.14)***	43.8496	(7.58)***	44.6739	(7.82)***
15	**Currency2**	-35.4850	(-4.31)***	-35.5070	(-4.37)***	-16.8391	(-2.78)***	-17.3495	(-2.90)***
16	**Currency3**	-12.5349	(-0.20)			108.7335	(1.91)*		

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

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 Imvol_Spread ("ATM call implied volatility – ATM put implied volatility"), OpenInterest1 ("open interest call option"), Price1 ("average unit price of call options"), BasisSpread ("futures market basis-theoretical basis"), Currency1 ("won/dollar exchange rates' log return volatility"), and Currency2 ("Japanese yen/dollar exchange rates' log return volatility").

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

$$\begin{aligned} Prob(D_t = 1) = \Phi(&\alpha + \beta_1 Skew2_{t-1} + \beta_2 Imvol\_Spread_{t-1} + \beta_3 Vol\_Spread2_{t-1} \\ &+\beta_4 OpenInterest2_{t-1} + \beta_5 Price2_{t-1} + \beta_6 p/c\_Ratio_{t-1} \\ &+\beta_7 BasisSpread_{t-1} + \beta_8 Stdev_{t-1} + \beta_9 TermSpread_{t-1} \\ &+\beta_{10} Currency1_{t-1} + \beta_{11} Currency2_{t-1} + \beta_{12} Currency3_{t-1}) + e_t \end{aligned} \quad (7)$$

For the LM downward jump model, statistical significance was observed for p/c_ratio ("put/call ratio"), BasisSpread ("futures market basis-theoretical basis"), Currency1 ("won/dollar exchange rates' log return volatility"), Currency2 ("Japanese yen/dollar exchange rates' log return volatility"), and Currency3 ("Chinese yuan/dollar exchange rates' log return volatility").

According to the results of the empirical analysis of the LM Jump model, Imvol_Spread ("ATM call implied volatility – ATM put implied volatility") 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. Thus, 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 Imvol_Spread ("ATM call implied volatility – ATM put implied volatility"), Stdev ("cross-sectional standard deviation of KOSPI200 components' log returns"), BasisSpread ("futures market basis-theoretical basis“), and Currency1 (“won/dollar exchange rates’ log return volatility”). The explanatory variables that were related to options, such as the p/c_ratio (“put/call ratio”), Vol_Spread2 (“average implied volatility of put options - historical volatility of put options”), and OpenInterest2 (“open interest of put options”) were significant only for some models.

A profit model was configured 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).

Table 7. LM Jump Model and Estimated Results

$$\mathrm{Prob}(D_t = 1) = \Phi\,(\alpha + \beta_1 \mathrm{Skew1}_{t-1} + \beta_2 \mathrm{Imvol}_{\mathrm{Spread}_{t-1}} + \beta_3 \mathrm{Vol}_{\mathrm{Spread1}_{3_{t-1}}} + \beta_4 \mathrm{OpenInterest1}_{t-1} + \beta_5 \mathrm{Price1}_{t-1} + \frac{\beta_6 p}{c_{\mathrm{Ratio}_{t-1}}} + \beta_7 \mathrm{BasisSpread}_{t-1} + \beta_8 \mathrm{Stdev}_{t-1} + \beta_9 \mathrm{TermSpread}_{t-1} + \beta_{10} \mathrm{Currency1}_{t-1} + \beta_{11} \mathrm{Currency2}_{t-1} + \beta_{12} \mathrm{Currency3}_{t-1}) + e_t \quad (6)$$

$$\mathrm{Prob}(D_t = 1) = \Phi(\alpha + \beta_1 \mathrm{Skew2}_{t-1} + \beta_2 \mathrm{Imvol}_{\mathrm{Spread}_{t-1}} + \beta_3 \mathrm{Vol}_{\mathrm{Spread2}_{3_{t-1}}} + \beta_4 \mathrm{OpenInterest2}_{t-1} + \beta_5 \mathrm{Price2t}_{t-1} + \beta_6 \mathrm{p/c\_Ratio}_{t-1} + \beta_7 \mathrm{BasisSpread}_{t-1} + \beta_8 \mathrm{Stdev}_{t-1} + \beta_9 \mathrm{TermSpread}_{t-1} + \beta_{10} \mathrm{Currency1}_{t-1} + \beta_{11} \mathrm{Currency2}_{t-1} + \beta_{12} \mathrm{Currency3}_{t-1}) + e_t \quad (7)$$

	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	**Currency1**	-26.4808	(-3.77)***	-25.5649	(-3.82)***	34.3088	(5.18)***	33.4218	(5.39)***
15	**Currency2**	17.0170	(2.10)**	16.0615	(2.03)**	-27.3634	(-3.85)***	-27.1777	(-3.93)***
16	**Currency3**	-0.3320	(-0.01)			132.8158	(2.12)**	133.3649	(2.11)**

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

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. 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, the increase in implied volatility of the ATM puts predicts a positive jump in stock prices, and the decrease in implied volatility of the ATM puts predicts a negative jump. In other words, if the options prices move 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 of the KOSPI200 options market takes 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 becomes 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 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. 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 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.

5. 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 the distribution thresholds of past stock market returns. 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 any 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.

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

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