Volatility as a Leading Indicator for Composite Stock Index Investment

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Abstract

This paper proposes systematic investment strategies for composite stock index using volatility index of KOSPI (VKOSPI) as a leading indicator. Systematic strategies adopt a monitoring system that is widely used to detect abnormality of production line, and employed to decide when to take a position as well as what position out of long and short should be taken. It is accomplished by monitoring whether VKOSPI touches the control limit lines. Computational experiments using KOSPI (Korea Composite Stock Price Index) 200 for recent three years are conducted to show the excellent performance of the proposed investment strategies under systematic monitoring framework in terms of rate of return.

Keywords : Leading Indicator, Monitoring, Stock Index Investment, Systematic Framework

1. Introduction

The volatility of an underlying asset is a quantitative measure of risk and is used as an important indicator for investment strategy. Volatility measures the gap between a point and the average of past data: high volatility of an asset on the stock market entails corresponding risks. In other words, under the same rate of return for the same period, an asset whose volatility was lower than another asset can be deemed to be more stable. However, the fact that volatility is high may turn out to be an opportunity in the derivatives market. For example, under the same conditions of rate of return within an equal period, exercise price and expiration date, the price of an option whose volatility is the highest is also in general the highest¹.

An accurate calculation of volatility is needed in order for it to be utilized as an effective investment indicator; therefore, since April 13, 2009 the Korea Exchange (KRX) has been providing the volatility index of KOSPI200 (VKOSPI) and past VKOSPI to January 2, 2003 which is also offered using the same calculation method. In the United States, since 2003, the Chicago Board Options Exchange (CBOE) has been providing Volatility Index (VIX) derived from option prices without a pricing model. Generally, VIXs operate on the prediction of investment indicators and on a hedge strategy of market risk based on

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the fact that they are negatively correlated with underlying assets². Volatility indices for derivatives investment are usually used as a qualitative reference parameter. It is difficult, however, during a qualitative investment process relying on the volatility index, to recognize objectively the top or bottom of the current volatility index. An extremely high volatility in a certain period as a result of instant variables that are difficult to predict could be exposed to the risk of loss³⁻⁵.

Therefore, this study intends to propose an effective investment strategy using a volatility index and a quantitative system. First, whether a negative correlation exists between the KOSPI200 index which is being traded in KRX and VKOSPI will be analyzed, and a quantitative system will be developed to implement this relationship into the investment strategy. In other words, an investment strategy for the KOSPI200 index will be built by applying a control chart in the field of Statistical Quality Control (SPC), which is used to recognize the existence of quality errors in the production, to monitor VKOSPI values. In addition, a strategy in accordance with the difference of VKOSPI will be discussed. In order to verify the function of the proposed investment strategies for KOSPI200 index which use VKOSPI, factors such as rates of return and the number of trade transactions from January 2009 to December 2011 will be compared and analyzed.

2. Existing Research

Existing research about volatility are mostly about enhancing the accuracy of the volatility calculation and about the prediction of future stock price via volatility: they demonstrate a relative lack in derivatives investment strategy using the volatility of underlying assets⁶⁻⁸. Especially as there is a restraint, even in worksite operation, when using volatility indices, in terms of when to make a quantitative decision about whether to buy or sell, the indices are generally used as a reference only⁹.

From representative research to date, there is comparative research using historical volatilities, the GARCH model, and implied volatilities with regard to the prediction outcome of underlying asset prices. In¹⁰⁻¹² have shown that implied volatility outweighs historical volatility in prediction performance. Reference¹³ has verified whether implied volatility is better in prediction than historical volatility by using SandP100 index options recorded from Mar 1983 to Mar 1987. As a result, in¹³ has proved that when predicting implied volatility, an error occurs dependently of the option's strike price and expiration date and has attributed the reason to the method of inversely calculating the implied volatility using the Black-Scholes pricing model. Reference¹⁴ has shown that the rates of return of the SandP100 and the Nasdaq100 and their implied volatility indices, VIX and VXN, have a statistically significant negative correlation. In³ has revealed that unlike the model-driven predictions of rate of return based on historical volatility, implied volatility has a market-driven predictability and contains information on jump activation in the rate of return.

In¹⁵ has proved the existence of volatilities' asymmetry among stock price indices of eight countries including South Korea and the United States, using the GJR-GARCH model. In¹⁶ in particular, investigated the predictability of VKOSPI, implied volatilities, and historical volatilities through correlation and regression analyses of the realized volatility of KOSPI200: according to the results, VKOSPI had the highest predictability. Meanwhile, a control chart has been applied to the stock portfolio management problem, and has proved that the portfolio management methodology using a control chart is better in terms of the rate of return than the real stock price indices such as KRX, AMEX and NYSE¹⁷.

As described above, applying quantitative methodology to derivatives investment using the volatility of underlying assets has not been adequately investigated to date. Therefore, this research analyzes the correlation between the volatility index and underlying assets, and proposes its applicability by implementing the results into the strategy development of KOSPI200 investment along with the SPC chart, which is one of the traditional quality control techniques for production system.

The structure of this paper is as follows: Section three analyses the correlation between VKOSPI and KOSPI200 and Section four describes the basic concept on SCP chart and its application to the investment strategies for KOSPI200 index. Experimental design and analyses for experiment results will be given in Section five. Lastly, Section six presents the conclusion.

3. Correlation between KOSPI200 and VKOSPI

VKOSPI, as provided by the KRX, reflects the market-expected values of future volatilities implied in the option price whose underlying asset is based on the KOSPI200 index, and the information transparency and objectivity are guaranteed in that they are officially calculated by the KRX. The volatility index, in particular, has a negative correlation with the underlying asset index, and this is known to be attributable to the contrarian psychology of investors toward options. For example, when the index of an underlying asset increases beyond a certain level, call option buyers tend to achieve profit below an appropriate price due to their mental unease from thinking that an additional increase is unlikely and by contrast, call option sellers tend to enforce selling due to the confidence that a further increase is improbable. Owing to this fact, the option price loses its dynamics for additional increase (change), and consequently the volatility index decreases.

This research has analyzed the correlation between VKOSPI of the domestic market and the KOSPI200 index to check the existence of negative correlation. In August 2011, especially, it can be noted that due to the European financial crisis, KOSPI200 plummeted while VKOSPI soared.

As shown in Table 1, the correlation between the KOSPI200 index and VKOSPI is -0.804 on average from January 2009 to May 2012. This means that an increase (a decrease) in the KOSPI200 index results in a decrease (an increase) in VKOSPI: this can be used as a useful indicator for an investment strategy of futures and options whose underlying asset is the KOSPI200 index. The

Table 1.	Correlation between KOSPI200 and	
VKOSPI		

Year	2009	2010	2011	2012
Correlation	-0.933	-0.521	-0.901	-0.864

correlation in 2010, however, was -0.521, which is relatively small. In chapter 5, the effects of such a correlation on the performance of the investment strategy shall also be discussed.

However, in order to effectively implement such negative correlation into an investment strategy, it is crucial to decide the trade timing of KOSPI200 index derivatives by recognizing the existence of the market top or bottom of VKOSPI. In order to do this, a system that quantitatively tells whether the current VKOSPI value is the top or bottom is needed. Thus, a methodology will be discussed in the next chapter which enters VKOSPI into the control chart used to manage the quality standard and utilizes it in the investment strategy for KOSPI200 index.

4. Systematics Stragety for KOSPI200 Index Investment

4.1 Investment Strategy with VKOSPI

A control chart is a statistical quality control technique that checks whether or not a process is in a stable state. It is used for maintaining production process by swiftly recognizing the cause of quality change and taking a series of actions. That is to say, a control chart is a methodology to manage the quality level by marking the quality measure that represents the condition of the process with a dot on chart and to decide statistical control limit lines (upper and lower limits) on which a decision can be made to discriminate an abnormal diffusion from coincidental one. If the quality measure of a product falls below 40, the process can be interpreted as being at an abnormal situation.

This study monitors VKOSPI values by marking dots on the control chart and takes positions on KOSPI200 index when the dotted line touches either control limit line by regarding it as an abnormal situation of volatility. The equations for UCL and LCL are as follows:

$$UCL = \eta + k\sigma \tag{1}$$

$$LCL = \eta - k\sigma \tag{2}$$

Where,

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\eta is the mean of VKOSPI.
\sigma is the standard deviation of VKOSPI.
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k is a decision parameter on UCL and LCL (0 < k < 1).

The value of *k* in equations 1 and 2 is a decision parameter that decides control limits and according to the value, the trade timing and rate of return of the entire trade are affected. The derivation there of will be discussed in chapter 5.1. Mean (η) and standard deviation (σ) are calculated from the past 1-year data, and are to be renewed annually at the beginning of the year.

Figure 1 illustrates the decision process of trade timing and position according to the traditional control chart methodology that uses real VKOSPI data of a specific period as mentioned above. Basically, when VKOSPI touches upward either UCL or LCL, it takes a selling position (short position; S.No.) and when it touches downward either limit, then a buying position (long position; L.No.) is taken (here, 'No' represents an identification number). Besides taking a trading position, it conducts cash settlement via the reverse action in order to minimize the risk exposure. For example, in (a) Figure 1, VKOSPI touches upward the UCL, so the short position (S.1) is taken and in (b), VKOSPI touches downward the UCL, so the long position (L.1) is taken while S.1 is being settled at the same time. Likewise, in (c), VKOSPI touches downward the LCL, so there is no another new long position while holding L.1 taken since (d). In such a way, the trading position and timing of KOSPI200 index can be quantitatively decided by monitoring the VKOSPI values dotted on control chart and the control limit lines, UCL and LCL.



Figure 1. Sytematic investment procedure with VOKSPI.

4.2 Investment Strategy with the Difference of VKOSPI

In consideration that not only VKOSPI but also the change rate of VKOSPI could be an investment indicator to predict the market movement, this study defines the daily changes in VKOSPI (= $VKOSPI_{i^{th}Day} - VKOSPI_{(i-1)^{th}Day}$) as the difference of VKOSPI. And, it proposes an investment strategy using the same methodology as with traditional control chart.

5. Experimental Results and Analysis

5.1 Experimental Design

In this study, in order to verify the rate of return and the applicability of the four proposed investment strategies: of a traditional control chart (V-TC) using VKOSPI, and of a traditional control chart (DV-TC) using difference of VKOSPI, the KOSPI200 index data from January 2, 2009 to December 29, 2011 and VKOSPI from January 2, 2008 to December 29, 2011 were collected for the experiment. Here, the handling commission was set at 0.004%. The experimental design is shown in Table 2. In this experiment, the decision parameter k, which is used to decide control limit lines, was established through a preparatory experiment for the convenience of the entire experiment. Namely, the average rates of return in 2011 obtained by varying k from 0.1 to 1 at an interval of 0.1 were compared and consequently 0.7 was determined as the final value of k.

5.2. Results and Analysis

Table 3 shows the number of trade transactions, rates of return, the means, and the standard deviations of the four investment methodologies. Figure 2 compares the yearly rates of return of each strategy. From the perspective of

Table 2.	Experimental	settings
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Factors	Values	
Derivatives for investment	KOSPI200 index	
Transaction cost	0.004%	
Data	VKOSPI, KOSPI200 index	
Investment strategies	V-TC, DV-TC	
Target period	3 years (2009.01.02~2011.12.29)	

 Table 3. Analysis of proposed strategies interms of number of trading and rate of returns

Proposed strategies			# of trading	Rate of return (%)
V-TC	Year	2009	48	14.7
		2010	14	17.1
		2011	44	26.6
	Mean		35.3	19.5
	Standard deviation		18.6	6.4
DV-TC	Year	2009	66	50.1
		2010	164	11.6
		2011	292	18.6
	Mean Standard deviation		174.0	26.8
			113.3	20.2



Figure 2. Performance comparison between strategies.

the number of transactions, VKOSPI has a specific directionalnature, and this is the corresponding result because VKOSPI moves in a direction and lingers. However, we cannot find significant correlation between the number of transactions and rate of return. This explains that the number of transactions was not necessarily proportional to the rate of return, and that tuning the value of k could be rather more effective.

In the case of the V-TC strategy, the mean is 19.5% and the standard deviation is 6.5, which is a relatively steady result compared to the others. However, the restraint of investment opportunity due to sluggish transactions could lead to the risk of getting stuck in a downturn when the position taken in the past tends toward loss rather than profit. Meanwhile, the DV-TC strategy has a relatively high standard deviation, 20.2, compared to V-TC, but the number of transactions is higher than V-TC. In 2011, for example, the number for DV-TC was 292 while that for V-TC was 44. It has been revealed that the negative correlation between KOSPI200 and VKOSPI discussed in Chapter 3 did not affect the experiment result.

6. Conclusion

This study has proposed a quantitative investment strategy using VKOSPI, which is provided by the KRX, using a quantitative system. First, it demonstrated the negative correlation which exists between VKOSPI and the KOSPI200 index, which is traded on the KRX. In order to apply this relationship to investment strategy, a trade strategy for the KOSPI200 index investment was developed by implementing a control chart, which is used by the quality control division to check the process quality in monitoring VKOSPI values. Further, to enhance the efficiency of the investment, two investment strategies were proposed including control chart in which pairs of control limits were used, and the difference of VKOSPI, which is a new investment indicator. In order to verify the strategies presented in this research, comparisons and analyses were performed on the basis of the data from the most recent three years (from January 2009 to December 2011) relating these to the rates of return from the KOSPI200 index and the rates of return attained by each strategy. For the future studies, the optimum value of k, which is a decision parameter of control limit lines, will be investigated via its sensitivity analysis and joint strategy development will be undertaken that analyzes the complementary relationship between the two strategies.

7. Acknowledgment

This research was supported by a 2015 Research Grant from Sangmyung University.

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