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ALGORITHMIC TRADING EFFECTS ON KOSPI

Hae-Young Kim[1] and Heon-Yong Jung[2*]
[1] *Ph.D. Candidate, Faculty of Economics & Management, Namseoul University, Cheonan, Korea*
[2] *Professor, Faculty of Economics & Management, Namseoul University, Cheonan, Korea*
[*] *Corresponding author E-mail: gotoyong@nsu.ac.kr*

Abstract: This study examines the impact of algorithmic trading on the Korean stock market using the multivariate EGARCH model. The research period extends from January 2004 to October 2015. Major findings are as follows: First, the increase in program trading value significantly decreased the stock return, but program trading did not have a significant effect on market volatility. Second, the increase in arbitrage program trading value significantly increased the stock market volatility, and the effects have increased in the period after the global financial crisis. Arbitrage program selling had a greater effect on volatility than arbitrage program buying. Third, the increase in non-arbitrage program trading value significantly decreased the stock market volatility. These results were the same both before and after the global financial crisis. When all of these findings are considered, we conclude that program trading did not increased volatility in the Korean stock market. However, the increase in arbitrage program trading value significantly increased the stock market volatility, and the increase in non-arbitrage program trading value significantly decreased the stock market volatility.

Keywords: Algorithmic trading, Arbitrage trading, Non-arbitrage trading, Volatility

I. INTRODUCTION

The rapid developments of IT technology over the past decade have substantially increased the use of algorithmic trading or program trading in global markets. The values of algorithmic trading recently accounts for about 20% of the total values in the Korean stock market. Thus, algorithmic trading may have a significant impact on the stock returns and volatility of the Korean stock market. There are two competing views about the impact of algorithmic trading on the stock returns and volatility of the stock market. The first view is that algorithmic trading can increase the volatility of the stock market by bringing an imbalance in the market due to a sudden increase or decrease in one-way orders. In other words, massive order via algorithmic trading leads to overreaction of stock market participants, which may increase market volatility and destabilizes the stock market. On the other hand, the second view is that algorithmic trading increases the market efficiency by reducing information asymmetry between the two markets through arbitrage between the stock market and futures market. Algorithmic trading plays a role in making the stock market efficient.

Recently, there are many studies on the impact of algorithmic trading but failed the consensus. Furbush (1989) and Harris (1989) examine program trading and stock market crash and find that nonsynchronous trading explains part of the large absolute futures-cash basis during the market crash. Harris *et al.* (1994) examine the effect of program trading on the stock market volatility and find that program trading do not seem to have created major short-term liquidity problems. Choe (1996) examines the effect of program trading in the Korean stock market and finds that program trading does not play significant role as an information messenger but increases market liquidity. Hogan *et al.* (1997) examine the effect of program trading on stock market volatility and find that program trading increases the volatility of the stock market and futures market. Hendershott and

Riordan (2013) examine the role of algorithmic traders in liquidity supply and demand in the 30 Deutsche Aktien Index stocks on the Deutsche Boerse and find that algorithmic traders more actively monitor market liquidity than human traders. Zhou *et al*. (2013) examine algorithmic trading in the Australian stock market and find a significant negative association between the level of algorithmic trading activities in a particular stock and the stock's price swings. Brogaard *et al*. (2014) examine the role of high-frequency traders in price discovery and price efficiency and find that high-frequency traders facilitate price efficiency by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. Hruska & Linnertova (2015) examine the relationship between market liquidity of futures traded on EUREX Exchange and HFT activity on European derivatives markets and find the relevance of the HFT trader's main argument about creating liquidity.

This study extends existing relevant studies by yielding some new evidence for the impact of algorithmic trading on the stock returns and volatility in the Korean stock market. We explore the impact of algorithmic trading on the stock returns and volatility using EGARCH (1, 1)-GED model. This paper is structured as follows. Section 2 describes the data used in this study and models used to examine the impact of algorithmic trading on the stock returns and volatility. Section 3 presents the empirical results. Section 4 is a conclusion in this study.

II. METHODOLOGY

This paper investigates the impact of algorithmic trading on the stock returns and volatility in the Korean stock market. We use the monthly program trading values, arbitrage program trading values, and non-arbitrage program trading values. The data is obtained from the Korea Exchange (KRX). Our sample period is from January 2004 to October 2015.

The descriptive statistics of the variables are as follows. As shown in the standard deviations in Table 1, arbitrage program trading values more fluctuate than non-arbitrage program trading values. The skewness recorded negative values for all variables. The kurtosis are higher than three for KOSPI only. Jaque-Bera values for all variables are rejected a normal distribution at 1% significant level.

Prior to empirical analysis, it is necessary to test whether the time-series data is stationary via a unit root test. In general, each time-series variable is known to be a non-stationary process. The stationarity of the variables need to be teste prior to analysis of time-series data. The Schwart information criterion-based Augmented Dickey Fuller (ADF) test and the Phillips-Perron (PP) test were

Table 1
Descriptive Statistics

	Mean	*Maximum*	*Minimum*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J-B*
KOSPI	0.0064	0.1268	-0.2631	0.0554	-0.8465	6.3301	82.5751*
PT	16.9234	17.8477	15.4625	0.5738	-0.7731	2.4494	15.9377*
PT(B)	16.2047	17.1890	14.7206	0.5723	-0.7483	2.5663	14.3659*
PT(S)	16.2465	17.1190	14.8159	0.5952	-0.8230	2.5206	17.3887*
APT	15.2165	16.7383	12.7388	0.8467	-0.7992	2.8325	15.2830*
APT(B)	14.4856	16.2256	11.9239	0.8884	-0.7830	2.9209	14.5484*
APT(S)	14.4990	15.8681	12.1542	0.9019	-0.7953	2.6247	14.4763*
NPT	16.5959	17.7777	14.7665	0.7583	-0.7274	2.3953	14.6856*
NPT(B)	15.8747	17.0838	13.9779	0.7517	-0.6959	2.4507	13.2460*
NPT(S)	15.9226	17.0854	14.0487	0.7814	-0.8131	2.5611	16.7861*

Notes: KOSPI, PT, PT(B), PT(S), APT, APT(B), APT(S), NPT, NP (B) and NPT(S) each represent Korea composite stock price index, program trading value, buy program trading value, sell program trading value, arbitrage program trading value, buy arbitrage program trading value, sell arbitrage program trading value, non-arbitrage program trading value, buy non-arbitrage program trading value, and sell non-arbitrage program trading value. * indicate a significance level of 1%.

used to perform unit root tests. Test run for level and first difference cases, with two lags applied. As shown in Table 2, the test results of all variables do not reject the null hypothesis that all variables have a unit root, but the test results of first-differenced variables reject the null hypothesis when both the ADF test and the PP test. Accordingly, the log-differenced variables for all variables are confirmed to have stationary time-series at a significance level of 1%. Based on the test results, this study used first-differenced variables. In addition, the Johansen cointegration test was performed to see whether there is a cointegration relation between the first-differenced variables. The lags of cointegration were set to two based on Schwart information criterion, and the results showed that there is a cointegration relation at a significance level of 1%, proving a long-term relation between the variables. Due to the results, this study adopt the GARCH-family model developed by Bollerslev (1986) and Nelson (1991) for analysis. The AIC, BIC, and HQIC information criteria-based analyses were performed to determine a suitable model

Table 2
Unit Root Test Results

	ADF		*KPSS*	
	Level	*1st Difference*	*Level*	*1st Difference*
KOSPI	-1.4289	-11.5758*	-1.7843	-11.6296*
PT	-1.4477	-11.5883*	-1.8073	-19.6090*
PT(B)	-1.4583	-11.8422*	-2.3982	-19.9040*
PT(S)	-1.6229	-12.5486*	-2.3580	-24.8243*
APT	-0.9075	-17.5417*	-1.2670	-17.7970*
APT(B)	-1.0751	-12.5967*	-2.2301	-23.4337*
APT(S)	-1.2082	-12.2086*	-2.4742	-23.3930*
NPT	-1.2646	-12.3959*	-1.4498	-19.3818*
NPT(B)	-1.1896	-11.1714*	1.3157	-18.4854*
NPT(S)	-1.5484	-13.8270*	-1.9722	-21.2499*

Notes: KOSPI, PT, PT(B), PT(S), APT, APT(B), APT(S), NPT, NPT(B) and NPT(S) each represent Korea composite stock price index, program trading value, buy program trading value, sell program trading value, arbitrage program trading value, buy arbitrage program trading value, sell arbitrage program trading value, non-arbitrage program trading value, buy non-arbitrage program trading value, and sell non-arbitrage program trading value . * indicate a significance level of 1%.

to examine the volatility-trading volume relation, and the results showed that the EGARCH (1, 1)-GED model would be most suitable. Accordingly, this study uses that model to examine the impact of algorithmic trading on the Korean stock market. Ljung-Box Q-statistics analysis performed to identify the volatility clustering properties of all variables, and the properties were found to be significant and suitable for the GARCH model.

To investigate the dynamic role of program trading in the Korean stock market, we consider program trading values, arbitrage program trading values, and non-arbitrage program trading values. We also analyze the effect of each trading on the return and volatility of the Korean stock market by dividing each trading buy and sell trading again. Model for examine the dynamic role of program trading is as follows.

$$KOSPI_t = a_0 + b_1 PT_t + \varepsilon_t \tag{1}$$

$$\ln h_t = a_1 + \beta \ln(\sigma_t^2) + \gamma \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \delta \frac{\varepsilon_{t-1}}{h_{t-1}} + c_1 \ln \varepsilon_{PT_t}^2 \tag{2}$$

Where, $KOSPI_t$ indicates the KOSPI index at time t. α_0 and a_1 are constant terms. b_1 represents a parameter of program trading value at time t. And c_1 represents the parameter of the log values of the square of the residual of program trading value at time t. Parameter γ and δ denote leverage effects. This means if γ is a positive value, the conditional variance increases when the size of market innovation is larger than expected; if δ is a negative value, it indicates the presence of an asymmetric volatility effect.

III. EMPIRICAL RESULTS

Table 3 shows the effects of program trading on the index returns and volatilities of KOSPI. In the Korean stock market, the increase in program trading value significantly decreased the stock return. These results were the same both before and after the global financial crisis, but its effects have increased in the period after the global financial crisis. However, program trading did not have a significant effect on market volatility.

Table 3
The Effects of Program Trading on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.3182***	-0.1588	0.7549***
b_1	-0.0185***	-0.0115*	-0.0431***
a_1	0.4499	0.8720	0.5175**
β	0.9963***	0.9374***	0.9412***
γ	-0.0919	-0.0405	-0.0341
δ	-0.1054	-0.1124	0.2318**
c_1	-0.0239	0.5228	0.1939
$\overline{R^2}$	0.0783	0.0695	0.0827
Log-L	231.29	217.15	249.66

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 4
The Effects of Program Buying on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.3737***	0.0588	1.0153***
b_1	0.0226	-0.0029	0.0609
a_1	0.2649	-1.6460***	-1.8448***
β	0.9926***	0.9040	0.9621***
γ	-0.1032	-0.0420	-0.0226
δ	-0.1105	-0.2569	0.0907
c_1	-0.0144	0.4697	0.2292
$\overline{R^2}$	0.0621	0.0587	0.1160
Log-L	232.99	175.42	253.40

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 5
The Effects of Program Selling on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.0588	-0.2185	0.0336
b_1	-0.0029	0.0155	-0.0016
a_1	-0.6461***	-1.3966***	-1.8361***
β	0.9473***	0.9434***	0.8991***
γ	-0.0420	0.0504	-0.0745
δ	-0.2569	-0.0067	-0.1765
c_1	0.4697	-0.1326	0.0280
$\overline{R^2}$	0.0786	0.0710	0.0745
Log-L	175.42	173.92	169.21

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 4 and Table 5 show the effects of program buying and selling on the index returns and volatilities of KOSPI. Table 4 shows that the increase in program buying did not have significant effect on the return and volatility. Table 5 also shows that the increase in program selling did not have significant effect on the return and volatility. In the Korean stock market, program trading did not have a significant effect on the stock return and volatility.

Table 6 shows the effects of arbitrage program trading on the index returns and volatilities of KOSPI. The increase in arbitrage program trading value significantly increased the stock market volatility. These results were the same both before and after the global financial crisis, but the effects have increased in the period after the global financial crisis. Table 7 and Table 8 show the effects of arbitrage program buying and selling on the index returns and volatilities of KOSPI. Table 7 shows that the increase in arbitrage program buying significantly increased stock market volatility. Table 8 also shows that the increase in arbitrage program selling significantly increased volatility. However, arbitrage program selling had a greater effect on volatility than arbitrage program buying, and these effects have increased in the period after the global financial crisis.

Table 6
The Effects of Arbitrage Program on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	-0.0212	0.3032	0.0458
b_1	0.0020	-0.0183	-0.0030
a_1	-2.9811***	-1.2409***	-1.2703***
β	0.9023***	0.9068***	0.9546***
γ	-0.0398	0.0291	-0.0556
δ	-0.1806	-0.1091	-0.2311
c_1	1.1866***	0.0593***	0.5668***
$\overline{R^2}$	0.1137	0.0997	0.1020
Log-L	261.18	227.99	255.96

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 7
The Effects of Arbitrage Program Buying on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.0018	0.3750***	0.0595**
b_1	0.0007	0.0238	0.0041
a_1	-2.8001***	-1.1597***	-3.0305***
β	0.9849***	0.9378***	0.9645***
γ	-0.0277	-0.0204	-0.2057
δ	-0.1775	-0.2049	-0.2224
c_1	1.1846***	0.6007***	0.5922***
$\overline{R^2}$	0.0947	0.0714	0.0827
Log-L	234.20	247.79	225.94

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 8
The Effects of Arbitrage Program Selling on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	-0.0930*	-0.0244**	-0.0116
b_1	0.0071	0.0032	0.0010
a_1	-1.9034**	-1.2413**	-1.7482***
β	0.9211***	0.9568	0.9376***
γ	-0.0081	-0.0586	-0.0845
δ	-0.1395	-0.0249	-0.1489
c_1	0.6337**	0.0895**	0.4469***
$\overline{R^2}$	0.1057	0.0975	0.0902
Log-L	228.26	219.02	215.54

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 9
The Effects of Non-Arbitrage Program on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.1838**	-0.0423	0.5483***
b_1	-0.0107	0.0035	-0.0317
a_1	0.6252***	-1.6274***	4.2815***
β	0.9851***	0.9410***	0.9034***
γ	-0.1225	-0.0804	-0.4639
δ	-0.0344	-0.1167	-0.0671
c_1	-0.0378**	-0.5118**	-0.2684***
$\overline{R^2}$	0.1158	0.0915	0.0978
Log-L	230.89	217.45	218.48

Note: *, ** and *** indicate a significance level -0.0116**of 10%, 5% and 1% respectively.

Table 10
The Effects of Non-Arbitrage Program Buying on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.1910**	-0.0423	0.5993**
b_1	0.0116	0.0035	0.0361
a_1	0.6274***	0.2743*	2.9915***
β	0.9864***	0.9404***	0.9248***
γ	-0.1199	-0.1084	-0.3291
δ	-0.0243	-0.1667	0.0559
c_1	-0.0393***	-0.5118**	-0.1991***
$\overline{R^2}$	0.1176	0.0852	0.0902
Log-L	231.27	217.46	223.67

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 11
The Effects of Non-Arbitrage Program Selling on KOSPI

	Total Period	*Before Crisis*	*After Crisis*
a_0	0.1657**	-0.0758	0.3273
b_1	-0.0101*	-0.0062	-0.0196
a_1	0.4515**	-1.5584***	1.6465
β	0.9917***	0.9704***	0.9472***
γ	-0.1018	-0.0269	-0.1622
δ	-0.0771	-0.1496	-0.2536
c_1	-0.0267**	-0.1466*	-0.5985**
$\overline{R^2}$	0.1123	0.0951	0.0924
Log-L	230.18	215.33	214.51

Note: *, ** and *** indicate a significance level of 10%, 5% and 1% respectively.

Table 9 shows the effects of non-arbitrage program trading on the index returns and volatilities of KOSPI. The increase in non-arbitrage program trading value significantly decreased the stock market volatility. These results were the same both before and after the global financial crisis. Table 10 and Table 11 show the effects of non-arbitrage program buying and selling on the index returns and volatilities of KOSPI. Table 10 shows that the increase in arbitrage program buying significantly decreased stock market volatility. Table 11 also shows that the increase in arbitrage program selling significantly decreased market volatility.

IV. CONCLUSION

This study examines the impact of algorithmic trading on the stock returns and volatility in the Korean stock market using EGARCH (1, 1)-student's t model. Our sample period is from January 2004 to October 2015.

The findings are as follows. First, the increase in program trading value significantly decreased the stock return, but program trading did not have a significant effect on market volatility.

Second, the increase in arbitrage program trading value significantly increased the stock market volatility, and the effects have increased in the period after the global financial crisis. Arbitrage program selling had a greater effect on volatility than arbitrage program buying.

Third, the increase in non-arbitrage program trading value significantly decreased the stock market volatility. These results were the same both before and after the global financial crisis

When all of these findings are considered, we conclude that program trading did not increased volatility in the Korean stock market. However, the increase in arbitrage program trading value significantly increased the stock market volatility, and the increase in non-arbitrage program trading value significantly decreased the stock market volatility.

When all of these findings are considered, we suggest that policy makers of Korean stock market will need to take a policy that arbitrage program trading does not increase foreign market volatility.

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