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SUDDEN CHANGES AND PERSISTENCE IN VOLATILITY OF KOREAN EQUITY SECTOR RETURNS

SANG HOON KANG* · SEONG-MIN YOON**

This study examines the impact of exogenous changes in volatility persistence using the GARCH model with and without shock dummies. For this purpose, we considered five weekly KOSPI 200 sector index series. Using the iterated cumulated sums of squares (ICSS) algorithm, we determined the timing of volatility changes corresponding to major economic and political events, including the 1997 Asian currency crisis, the Russia crisis of 1998, the IT bubble of 2000, the 9/11 terror attack of 2001, the Iraq war of 2003 and the global financial crisis that has been recently affecting nations worldwide. After incorporating these volatility change, volatility persistence in the GARCH model was significantly reduced. This result implies that ignoring exogenous changes overestimates volatility persistence. Thus, incorporating information on exogenous changes in conditional variance will improve the accuracy of volatility forecasting.

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I. INTRODUCTION

Understanding the behaviour of volatility is important for pricing financial assets, implementing hedging strategies, and assessing

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* Department of Business Administration, Pusan National University, Busan 609-735, Korea.
** Corresponding Author: Department of Economics, Pusan National University, Jangjeon2-Dong, Geumjeong-Gu, Busan 609-735, Korea, E-mail: smyoon@pusan.ac.kr, Tel.: +82-51-510-2557, Fax: +82-51- 581-3143.

regulatory proposals to restrict international capital flows. A large number of studies have used the ARCH model of Engle (1982) or the GARCH model of Bollerslev (1986) to describe time varying conditional volatility in stock return data. Many of these studies have found that exogenous changes volatility exhibit high persistence in the GARCH specification (Bollerslev, Chou and Kroner, 1992; Bollerslev and Engle, 1993; Hillebrand, 2005; Baillie and Morana, 2009).

However, it is well known that GARCH class models are unable to incorporate exogenous changes. Lastrapes (1989) and Lamoureux and Lastrapes (1990) found that ignoring such changes would induce persistence in the volatility of stock returns. Thus, including these changes has been known to dramatically reduce the estimates of persistence in GARCH class models. However, their methodology is incapable of identifying when these changes occur which may lead to various biases.

To overcome this problem, empirical studies have suggested various techniques to detect exogenous changes in volatility.[1] For example, Aggarwal, Inclan, and Leal (1999) investigated large sudden shifts in the volatility of 10 emerging markets in Asia and Latin America. They detected when these changes occurred by using the ICSS algorithm of Inclán and Tiao (1994) and then incorporated indicators of when they occurred into a GARCH model. They concluded that a GARCH model with such indicators decreases the estimated persistence of volatility.

More recently, several empirical studies have extended the methodology of Aggarwal, Inclan, and Leal (1999) by using more recent stock market data. For example, Malik and Hassan (2004) detected the

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[1] Hamilton and Susmel (1994) introduced a Markov-switching ARCH model to account for structural/regime changes and thus structural breaks were determined by the data. This model allows for transition probabilities that change with restrictive assumption. Inclán and Tiao (1994) proposed a simple CUSUM test to detect variance changes using the ICSS algorithms. Kokoszka and Leipus (1998, 2000) proposed the ARCH-specific change-point detection method, based on a CUSUM type test. This approach provided good power properties in detecting even small changes in all the GARCH parameters, but suffered size distortions in the persistent GARCH case. Lee, Tokutsu and Kaekawa (2004) considered the problem of testing for a parameter change in regression with ARCH errors following the Inclán and Tiao (1994) approach. Although various applications have been applied, the ICCS method indentified the shifts by properly recognizing outliers which makes it a useful tool for retrospective detection of break points in variances (Malik, Ewing, and Payne, 2005).

timing of changes in volatility for five Dow Jones sector indexes: financial, industrial, consumer, health, and technology. They found that most breaks were associated with global economic and political events rather than sector-specific events and that these breaks increased volatility in most sector series. Malik, Ewing, and Payne (2005) suggested that controlling for exogenous changes in volatility dramatically reduces the persistence of volatility in the Canadian stock market. Hammoudeh and Li (2008) examined the significant reductions in the persistence of volatility for Gulf Cooperation Council (GCC) stock markets. Wang and Moore (2009) investigated the impact of exogenous changes on the persistence of volatility for new European Union members. These studies consistently conclude that incorporating exogenous changes into a GARCH model reduces the persistence of volatility in stock returns.

This study identifies exogenous changes in volatility and their effects on the persistence of volatility for the Korea Composite Price Index 200 (KOSPI 200) sector index series vis-à-vis the following industries: manufacturing, electricity & communication, construction, service, and finance. For this purpose, the ICSS algorithm of Inclán and Tiao (1994) is used to identify the timing exogenous changes, which is then in corporate into a GARCH model to measure their effects on the persistence of volatility.

The reminder of this paper is organised as follows: Section 2 presents the methodologies for the ICSS algorithm and GARCH models. Section 3 describes the characteristics of sample data. Section 4 provides the estimation results of the ICSS algorithm and the GARCH model. The final section provides concluding remarks.

II. METHODOLOGY

In accordance with the work of Inclán and Tiao (1994), this study identifies exogenous changes in volatility with the ICSS algorithm and then estimates the $\text{GARCH}(1,1)$ model with and without sudden change dummies.

2.1. Detecting Points of Exogenous Change in Volatility

The ICSS algorithm is utilised to identify periods of exogenous changes volatility in stock returns. It assumes that the conditional variance of a time series is stationary over an initial period of time until a exogenous change occurs as the result of an unpredictable event; the variance is then predicted to become stationary again until another such change occurs. This process is repeated over time, generating a time series of observations with an unknown number of exogenous changes in the variance.

Let $\{\varepsilon_t\}$ denote an independent time series with zero mean and unconditional variance σ_t^2. The variance in each interval is given by σ_j^2, $j = 0,1,\ldots,N_T$, where N_T is the total number of variance changes in T observations and $1 < K_1 < K_2 < \ldots < K_{N_T} < T$ are the set of change points. Then, the variance over N_T intervals is defined as follows:

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < K_1 \\ \sigma_1^2, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_T}^2, & K_{N_T} < t < T \end{cases} . \tag{1}$$

A cumulative sum of squares is utilised to determine the number of changes in variance and the point in time at which each variance shift occurs. The cumulative sum of squares from the first observation to the k^{th} point in time is expressed as follows:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 , \qquad \text{where } k = 1,\ldots,T . \tag{2}$$

Define the statistic D_k as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \qquad \text{where } D_0 = D_T = 0 \tag{3}$$

and C_T is the sum of the squared residuals from the whole sample period. Note that if there are no changes in variance, the D_k statistic will oscillate around zero (i.e., if D_k is plotted against k, it will resemble a horizontal line). However, if there are one or more changes in variance, the statistical values will drift up or down from zero. In this context, significant changes in variance are detected using the critical values obtained from the distribution of D_k under the null hypothesis of constant variance. If the maximum absolute value of D_k is greater than the critical value, the null hypothesis of homogeneity can be rejected. Define k^* to be the value at which $\max_k |D_k|$ is reached, and if $\max_k \sqrt{(T/2)}|D_k|$ exceeds the critical value, k^* is used as the time point at which a variance change in the series occurs. The term $\sqrt{(T/2)}$ is required for standardisation of the distribution.

In accordance with the study of Inclán and Tiao (1994), the critical value of 1.358 is the 95$^{\text{th}}$ percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$.[2] Therefore, upper and lower boundaries can be established at ± 1.358 in the D_k plot. An exogenous change in variance is defined to be one that exceeds these boundaries. However, if the series harbour multiple change points, the D_k function alone is not sufficiently powerful to detect the changes at different intervals. To address this issue, Inclán and Tiao (1994) modified an algorithm that employs the D_k function to systematically search for changes at different times in a series. The algorithm works by evaluating the D_k function over different time periods, and those different periods are determined by breakpoints that are identified by the D_k plot.

2.2. GARCH Model with Sudden Change Dummies

Following the seminal work of Engle (1982), consider a stock return series y_t and the associated prediction error $\varepsilon_t = y_t - E_{t-1}[y_t]$, where $E_{t-1}[\cdot]$ is the expectation of the conditional mean on the information set at time $t-1$. The GARCH(1,1) model of Bollerslev (1986) is as follows:

[2] See Table 1 illustrated in the study of Inclán and Tiao (1994, p. 914).

$$y_t = \mu + \varepsilon_t\,,\;\; \varepsilon_t = z_t\sqrt{h_t}\,,\;\; z_t \sim N(0,1)\,, \tag{4}$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}\,, \tag{5}$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, which ensure the conditional variance (h_t) is positive, and $(\alpha + \beta) < 1$ are introduced for covariance stationarity. In the GARCH model, the sum of α and β quantifies the persistence of exogenous changes in conditional variance. A common empirical finding is that the sum of α and β is very close to one, implying that exogenous changes are expected to be infinitely persistent, corresponding to the integrated GARCH (IGARCH) process.

The above model can be rewritten by decomposing the squared resiudals into its own conditional expection (h_t) and an innovation term (υ_h), as:

$$\varepsilon_t^2 = h_t + \upsilon_t\,. \tag{6}$$

If the model is correctly specified, then the unpredictable error υ_t should be orthogonal to h_t and serially uncorrelated (Engle and Bollerslev, 1986). If the unconditional variance exits, then we arrive at the following equation:

$$\varepsilon_t^2 = \sigma^2 + \upsilon_t + \theta_1\upsilon_{t-1} + \theta_2\upsilon_{t-2} + \cdots + \theta_k\upsilon_{t-k} + \cdots\,, \tag{7}$$

where σ^2 is unconditional variance and is equal to $\omega/(1-\alpha-\beta)$ in this case. Here, θ_i is a non-linear function of the ARCH and GARCH parameter. In Equation (7), ε_t^2 represents the degree to which unpredictable exogenous changes in variance persist over time. If $\theta_k (= \partial\varepsilon_t^2 / \partial\upsilon_{t-k})$ remains large as k increases, then shocks will have greater persistence. The dynamic response function can be constructed and shows the relationship between θ and the horizon k.

Lastrapes (1989) and Lamoureux and Lastrapes (1990) have argued that the GARCH model tends to overestimate the persistence in volatility when exogenous changes are prevalent but not respresented in the measure of conditional variance. Thus, From Equation (5), we modify the $\text{GARCH}(1,1)$ model with multiple exogenous changes that are identified via the ICSS algorithm as follows:

$$h_t = \omega + d_1 D_1 + \cdots + d_n D_n + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{8}$$

where $D_1, \ldots, D_n$ are indicator variables that take a value of one when an exogenous change in conditional variance occurs and take a value of zero elsewhere.

III. DATA

3.1. KOSPI 200 Sector Index

The data sets used in this study consist of the KOSPI 200 sector index series vis-a-vis the following industries: manufacturing, electricity & communication, construction, service, and finance.[3] KOSPI 200 is a capitalisation–weighted index that consists of 200 blue chip stocks listed on the Korea Exchange (KRX). Its constituent shares represent approximately 70–80% of the total domestic market capitalisation.

The data sets consist of the weekly Friday closing prices of KOSPI 200 from January 5, 1990 to March 27, 2010 (1,055 observations) and the last year of data (50 observations) is used to evaluate out-of-sample volatility forecasts. For non-trading Fridays, the closing prices of the preceding Thursdays were used. The use of weekly prices in the analysis, instead of daily higher frequency prices, eliminates or significantly reduces potential bias, such as the bid–ask effect and biases from non–trading days, among others.

3.2. Descriptive Statistics and Unit Root Tests

The price series were converted into the nominal percentage return series for all sample indices, i.e., $y_t = 100 \times \ln(P_t / P_{t-1})$ for $t = 1, 2, \ldots, T$, where y_t is the returns of each index at time t, P_t is the current index, and P_{t-1} is the index of previous day.

[3] All sample index data were obtained from the database of Korea Exchange (KRX).

[Table 1] Descriptive Statistics and Unit Root Tests

	Manufacturing	Electricity & Communication	Construction	Service	Finance
Panel A: Descriptive statistics					
Mean	0.111	0.089	-0.073	-0.060	-0.114
S.D.	4.624	4.684	6.642	5.322	5.939
Max.	24.90	23.47	48.87	22.88	31.10
Min.	-24.65	-24.57	-45.47	-29.68	-35.33
Skew.	-0.186	0.254	0.216	-0.279	0.028
Kurt.	7.101	6.639	10.92	6.610	6.403
J-B	709.58***	564.77***	2632.13***	558.26***	484.59***
$Q_s(12)$	262.89***	277.33***	77.39***	183.05***	243.79***
$Q_s(24)$	336.12***	391.44***	124.83***	287.74***	384.20
Panel B: Unit root tests					
ADF	-34.07***	-34.63***	-31.91***	-31.75***	-34.05***
PP	-34.01***	-34.51***	-31.91***	-31.77***	-33.97***
KPSS	0.088	0.058	0.195	0.132	0.094***

Notes: The Jarque and Bera (J-B) corresponds to the test statistic for the null hypothesis of normality in sample return distribution. The Ljung-Box test statistics, $Q_s(n)$, check for the serial correlation of the squared return residuals for up to n^{th} order. Mackinnon's 1% critical value is -3.435 for ADF and PP tests. The critical value for the KPSS test is 0.739 at the 1% significance level. *** indicates a rejection of the null hypothesis at the 1% significance level.

Table 1 shows the descriptive statistics and the results of the unit root test for all sample returns (from January 5, 1990 to March 27, 2009). As shown in Panel A of Table 1, the returns for the manufacturing and electricity & communication sectors showed positive means, while the rest (i.e., construction, service, and finance) were negative. The standard deviations (S.D.) of sample returns were much higher than the mean. Based on the values of skewness (Skew.), excess kurtosis (Kurt.), and the Jarque-Bera (J-B) statistics, we can determine that all of the return series followed a leptokurtic distribution, which has a higher peak and fatter tail than a normal distribution. The Ljung-Box Q statistics, $Q_s(n)$, for the squared return series were extremely high, indicating the rejection of the null hypothesis of no serial correlation.

Additionally, the Panel B of Table 1 provides the results of three types of unit root test: the augmented Dickey-Fuller (ADF), Phillips-Peron (PP), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS). The null hypothesis of ADF and PP tests is that a time series contains a unit root, whereas KPSS test has the null hypothesis of a stationary process. As the data in Table 1 indicates, large negative values for ADF and PP test statistics reject the null hypothesis of a unit root, whereas the KPSS test statistic does not reject the null hypothesis of stationarity with a significance level of 1%. Thus, as the results indicate, all return series are a stationary process.

IV. EMPIRICAL RESULTS

4.1. Exogenous Changes in Volatility

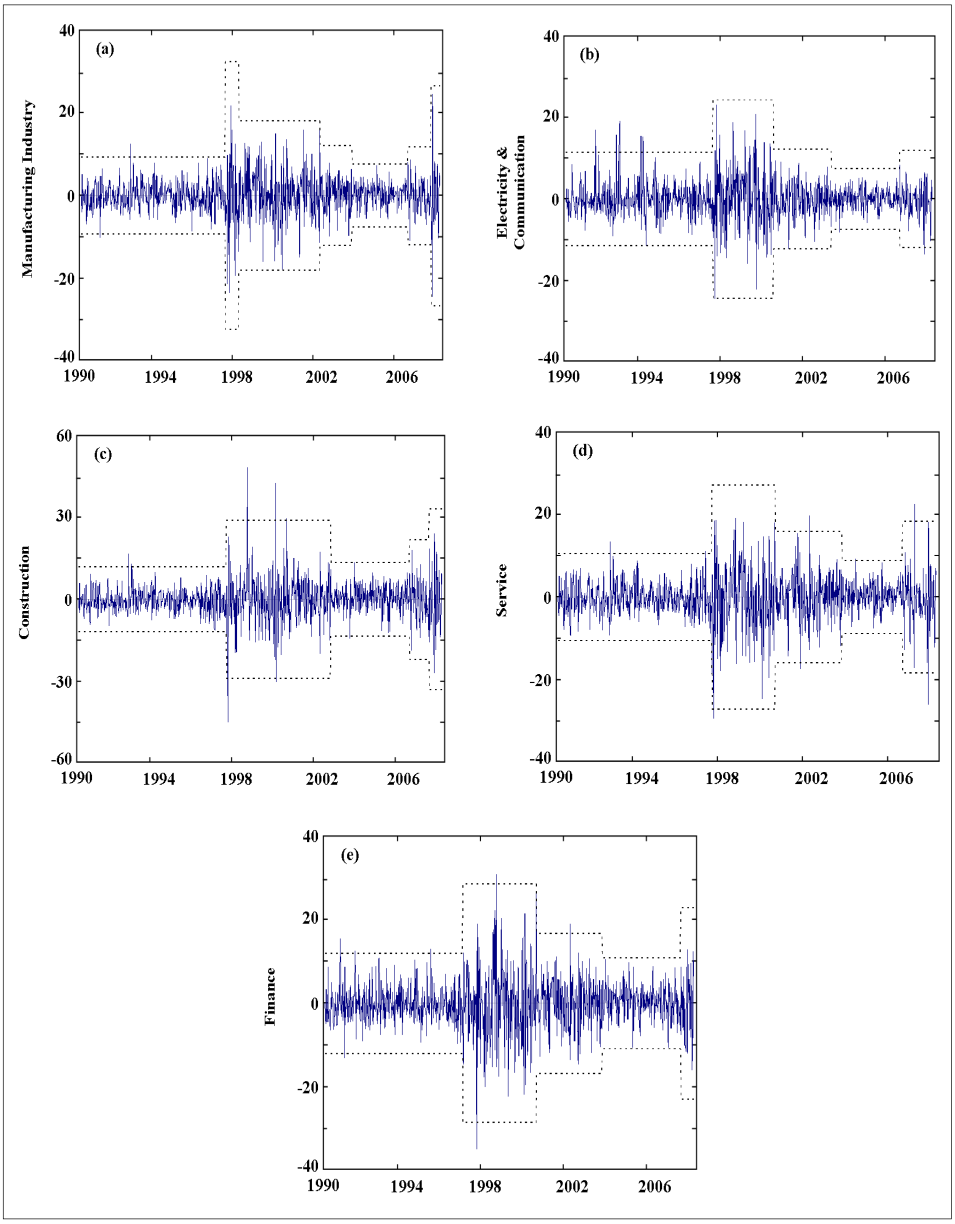
The ICSS algorithm calculates standard deviations between exogenous changes to determine the number of such changes. Figure 1 illustrates the returns for the five sector index series with exogenous changes and ±3 standard deviations. Table 2 indicates the periods of exogenous changes in volatility as identified by the ICSS algorithm. The manufacturing industry sector series had six such changes corresponding to seven distinct volatility “regimes”, while the other sector series (i.e., electricity & communication, construction, service, and finance) had four exogenous changes and five volatility “regimes”.

Looking at Figure 1 and Table 2, all series returns had similar occurrence of exogenous changes in volatility, corresponding with global economic and political events.[4] With respect to the manufacturing industry, the first significant increase in volatility occurred after the Asian currency crisis of 1997. Under the IMF bailout program implemented on November 21, 1997, many Korean financial policies and regulations were reformed, which caused greater uncertainty and volatility initially. This

[4] Volatility decreases mean that the market returns to a tranquil period; our explanation only considers volatility increases.

increase in volatility continued up to the end of 1998 because of subsequent crises in Russia and Brazil. The Russian crisis had triggered

[Figure 1] Weakly Sector Returns: (a) Manufacturing Industry, (b) Electricity & Communication, (c) Construction, (d) Service, (e) Finance



Note: Bands (dot lines) are at ±3 standard deviations where change points are estimated by the ICSS algorithm.

[Table 2] Sudden Changes in Volatility as Detected by the ICSS Algorithm

Series	S.D.	Time period	Events
Manufacturing Industry	3.0961	5 January 1990- 19 September 1997	
	9.8639	26 September 1997- 12 June 1998*	Asian currency crisis; Russia crisis
	6.0669	19 June 1998- 18 October 2002*	IT industry bubbles; 9/11 terror attack
	4.0871	22 October 2002- 2 July 2004	
	2.4769	9 July 2004- 29 June 2007	
	3.0985	6 July 2007- 26 September 2008	
	9.1077	2 October 2008- 27 March 2009*	Global financial crisis
Electricity & Communication	3.8754	5 January 1990- 19 September 1997	
	7.8911	26 September 1997- 24 November 2000*	Asian currency crisis; Russia crisis; IT industry bubbles
	3.9867	1 December 2000- 5 December 2003*	9/11 terror attack; the invasion of Iraq; huge credit card debt
	2.3726	12 December 2003- 6 July 2007	
	4.1178	13 July 2007- 27 March 2009*	Global financial crisis
Construction	4.0730	5 January 1990- 24 October 1997	
	9.3928	31 October 1997 2 May 2003*	Asian currency crisis; IT industry bubbles; 9/11 terror attack; the invasion of Iraq
	4.4228	9 May 2003- 29 June 2007	
	7.3404	7 July 2007- 11 July 2008*	The US sub-prime mortgage crisis
	11.594	18 July 2008- 27 March 2009*	Global financial crisis

[Table 2] (Continued) Sudden Changes in Volatility as Detected by the ICSS Algorithm

Series	S.D.	Time period	Events
Service	3.5473	5 January 1990- 24 October 1997	
	8.6608	31 October 1997- 12 January 2001*	Asian currency crisis; Russia crisis; IT industry bubbles
	5.4946	19 January 2001- 4 June 2004	
	2.8801	11 June 2004- 29 June 2007	
	6.6795	6 July 2007- 27 March 2009*	Global financial crisis
Finance	4.0857	5 January 1990- 7 March 1997	
	9.9575	14 March 1997- 5 January 2001*	Asian currency crisis; Russia crisis; IT industry bubbles
	5.7119	12 January 2001- 11 June 2004	
	3.6083	18 June 2004- 11 July 2008	
	7.7111	18 July 2008- 27 March 2009*	Global financial crisis

Notes: The bold types indicate the largest value of standard deviation among the time period for sudden changes in volatility. * denotes period of increased volatility. Time periods detected by ICSS algorithm.

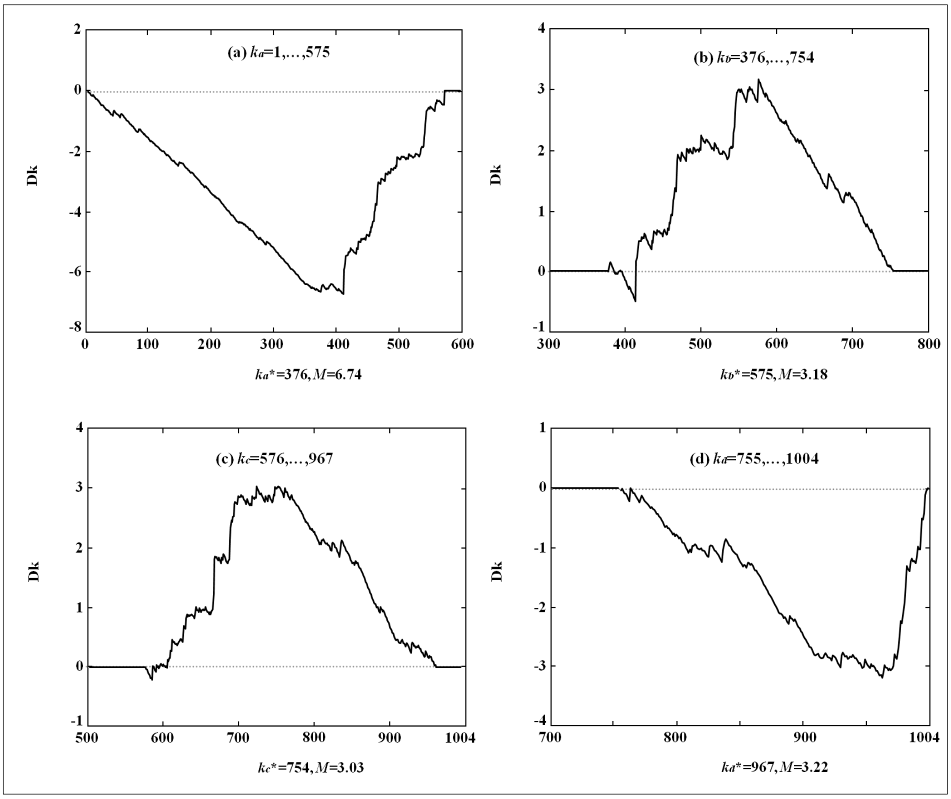
the decrease in oil prices and caused a global recession. The second volatility increase during 2000-2002 occurred after IT stock prices fell and the 9/11 terror attack occurred. The last exogenous change was due to the recent global financial crisis.

Like the manufacturing industry, the electricity & communication sector experienced increased volatility at the end of September 1997 due to the Asian currency crisis, and subsequently due to the crises in Russia and Brazil. Another exogenous volatility change occurred after the 9/11 terror attack in US, and the Iraq war, and a domestic liquidity crisis. The breakout of the Iraq war on March 3, 2003 induced the lowest price on record for 2003. Domestic credit card companies experienced a liquidity crisis at the end of November 2003. A fourth volatility change was due to the recent US financial crisis in 2008.

The construction sector experienced volatility changes corresponding to the 1997 Asian currency crisis, the US financial crisis during 2008, and the subsequent recent global financial crisis during 2008-2009. Unlike other sectors, the impact of the recent global financial crisis to the volatility was much stronger than that of the 1997 Asian crisis.

Both the service and finance sectors exhibited similar exogenous changes corresponding to the 1997 Asian currency crisis and the recent global financial crisis. Interestingly, exogenous changes in volatility in the finance sector occurred in 1997 six months before those in other sectors due to the financial problems of Korea's business conglomerates that became apparent in March 1997.

[Figure 2] D_k Plot for KOSPI 200 Finance Sector Index



Notes: Critical value is ± 1.358. M indicates absolute ($\max_k \sqrt{(T/2)}|D_k|$) in each D_k plot.

Figure 2 reports the use of the ICSS algorithm with KOSPI 200 finance sector index series having four variance changes Figure 1(e).[5] We cut series into four parts according to change points: the first part $(1 \le k_a \le 575)$, the second part $(376 \le k_b \le 754)$, the third part $(576 \le k_c \le 967)$, and the last part $(755 \le k_d \le 1{,}004)$. Figure 2(a) shows a possible change at $k_a^* = 376$ because the calculated value of M (absolute ($\max_k \sqrt{(T/2)}\left|D_k\right|$)) exceeds the critical value. Next, subsequent beaks are observed at $k_b^* = 575$ (Figure 2(b)), $k_c^* = 754$ (Figure 2(c)) and $k_d^* = 967$ (Figure 2(d)).

As a result, most significant changes in volatility in the KOSPI 200 sector index series were associated with exogenous global economic and political events rather than sector specific events. In fact, all of the five sector series experienced a similar exogenous change. As argued by Engle, Ito, and Lin (1990), volatility in one financial market is transmitted to other markets like 'a meteor shower'. Thus, an exogenous event can affect different sectors simultaneously and cause similar changes in volatility.

4.2. GARCH Estimation, Persistence, and Exogenous Changes in Volatility

The next step is to incorporate these volatility changes into the standard GARCH model. Table 3 reports the estimation results from the GARCH(1,1) model with and without dummy variables for exogenous changes in volatility. In the GARCH model without dummy variables, index returns for all of the sectors showed high persistence in volatility, because the sum of the estimated GARCH parameters $(\alpha + \beta)$ was close to one (especially for the construction sector), which represents the IGARCH effect. This implies that exogenous changes have a permanent impact on volatility.

However, the inclusion of dummy variables for exogenous changes dramatically reduced persistence of the conditional variance in all index returns. The finance sector showed the largest decline in volatility

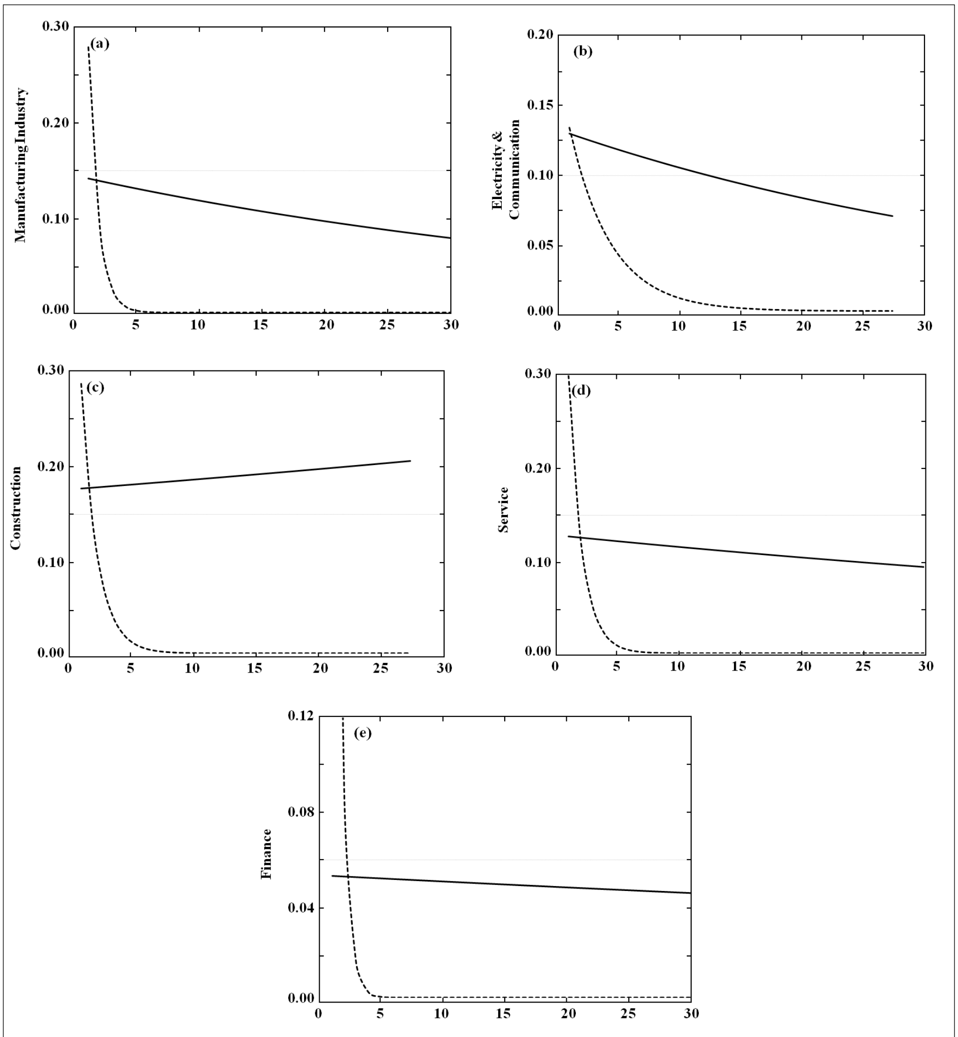
[5] For saving space, we do not report the D_k plot of all cases here, but all are available on request.

[Table 3] GARCH$(1,1)$ Parameters with and without Dummy Variables for exogenous changes in Volatility

Series	α	β	$(\alpha+\beta)$		$Q_s(12)$	$Q_s(24)$	$LM(5)$	LL	AIC	SBIC
Manufacturing Industry	0.139 (0.018)	0.841 (0.022)	0.980		14.04 [0.372]	21.06 [0.635]	0.674 [0.643]	–2834.57	5.6548	5.6744
Electricity & Communication	0.127 (0.016)	0.846 (0.018)	0.973		8.205 [0.830]	15.51 [0.905]	0.493 [0.782]	–2849.73	5.6847	5.7044
Construction	0.177 (0.017)	0.828 (0.025)	1.005		3.550 [0.990]	9.945 [0.995]	0.335 [0.892]	–3197.92	6.3783	6.3979
Service	0.129 (0.031)	0.865 (0.027)	0.990		11.56 [0.564]	21.68 [0.598]	1.247 0.285]	–2977.55	5.9393	5.9589
Finance	0.052 (0.011)	0.943 (0.016)	0.995		16.25 [0.879]	15.87 [0.893]	7.499 [0.823]	–3097.10	6.1774	6.1970
Series	**α**	**β**	**$(\alpha+\beta)$**	**Persistence decline**	**$Q_s(12)$**	**$Q_s(24)$**	**$LM(5)$**	**LL**	**AIC**	**SBIC**
Manufacturing Industry	0.079 (0.034)	0.203 (0.342)	0.282	0.698	11.44 [0.491]	19.95 [0.700]	0.971 [0.434]	–2782.91	5.5655	5.6194
Electricity & Communication	0.104 (0.021)	0.674 (0.092)	0.778	0.195	19.15 [0.085]	30.72 [0.162]	0.262 [0.934]	–2817.57	5.6306	5.6747
Construction	0.148 (0.036)	0.366 (0.135)	0.514	0.491	7.467 [0.825]	18.69 [0.768]	0.780 [0.564]	–3151.37	6.2955	6.3396
Service	0.126 (0.053)	0.293 (0.244)	0.419	0.571	5.162 [0.952]	12.99 [0.966]	0.358 [0.877]	–2939.74	5.8739	5.9180
Finance	0.088 (0.035)	0.081 (0.333)	0.169	0.826	4.885 [0.962]	13.82 [0.951]	0.339 [0.889]	–3059.58	6.1127	6.1567

Notes: The Ljung–Box test statistic, $Q_s(n)$, checks the serial correlation of squared residual series. $LM(5)$ test statistic checks the remaining ARCH effects in estimated residuals. AIC is the Akaike information criterion and SBIC is the Schwarz Bayesian information criterion. *LL* refers to log–likelihood. P–values are in brackets and standard errors are in parenthesis.

[Figure 3] Dynamic impulse response functions: (a) Manufacturing Industry, (b) Electricity & Communication, (c) Construction, (d) Service, (e) Finance



Notes: The dynamic impulse response function shows the persistence in volatility from a standardized unit shock and plots $\theta_k (= \partial \varepsilon_t^2 / \partial \upsilon_{t-k})$ against horizon k. The response function for the GARCH model is given by the solid line and the response function for the GARCH with exogenous changes is given by dashed line.

persistence with 0.826, while the electricity & communication sector showed the smallest decline in volatility persistence with 0.195. Thus, these results are consistent with the view of Aggarwal, Inclan, and Leal (1999), Malik and Hassan (2004), Hammoudeh and Li (2008), and Wang and Moore (2009): they argued that the standard GARCH model overestimates persistence in volatility when ignoring exogenous changes in conditional variance.

Table 3 shows the accuracy of model specification using several diagnostic tests. The insignificance of $LM(5)$ statistic, Ljung–Box $Q_s(12)$, and $Q_s(24)$ tests indicate that the GARCH model without dummy variables was well–specified. Nevertheless, the GARCH model with dummy variables performed better than the one without dummy variables, as indicated by the lower values of Schwarz Bayesian information criterion (SBIC) and Akaike information criterion (AIC).

Figure 3 shows the dynamic response functions in Equation (7) for the five sector index, up to a forecast horizon of 30 weeks. The response function for the GARCH model is given by the solid line and the response function for the GARCH with exogenous changes is given by dashed line. In each case, the GARCH model without exogenous changes shows slow decay of the impulse response functions as k increases, whereas the GARCH model with exogenous changes represents rapid decay of the response functions. Thus, ignoring exogenous changes tends to overestimate the persistence in volatility.

Our findings provide an important implication for risk managers. Since major exogenous events may lead to increases in the persistence of volatility, this impact distorts risk-returns trade-off. In particular, risk managers generally consider over–predictions of volatility differently than under–predictions using Value-at-Risk (VaR) analysis. Thus, proper accounting for exogenous changes in volatility is important for calculating VaR accurately and determining optimal portfolio allocations.

4.3. Out-of-Sample Forecasts

In this section, we further investigate the forecasting ability of the GARCH model with/without exogenous changes. In accordance with the relevant literature (Brailsford and Faff, 1996; Brooks and Persand, 2003; Degiannakis, 2004), daily ex post volatility (variance) was measured by the squared returns $(\sigma_t^2 = r_t^2)$. To measure forecasting accuracy, we calculated the mean of absolute errors (MAE) and the root mean squared errors ($RMSE$) as follows:

$$MAE = \frac{1}{T}\sum_{i=1}^{T}\left|\sigma_{f,t}^{2} - \sigma_{a,t}^{2}\right|,$$

$$RMSE = \left[\frac{1}{T}\sum_{i=1}^{T}(\sigma_{f,t}^{2} - \sigma_{a,t}^{2})^{2}\right]^{1/2}, \tag{9}$$

in which T is the number of forecasting data points and $\sigma_{f,t}^{2}$ denotes the volatility forecast for day t, whereas $\sigma_{a,t}^{2}$ signifies actual volatility on day t.

[Table 4] Forecast Evaluation

	Manufacturing Industry		Electricity & Communication		Construction	
	MAE	*RMSE*	*MAE*	*RMSE*	*MAE*	*RMSE*
Without indicators	2.031	2.531	1.938	2.471	4.573	6.563
With indicators	2.002	2.508	1.946	2.465	3.619	4.787
	Service		Finance			
	MAE	*RMSE*	*MAE*	*RMSE*		
Without indicators	2.055	2.551	4.231	5.861		
With indicators	2.047	2.544	4.228	5.860		

The forecast evaluation of the 50 one-step-ahead forecasts generated from the GARCH (1,1) model with/without exogenous changes is reported in Table 4. Smaller forecasting error statistics reflect the superior forecasting ability of a given model. An overall evaluation indicates that the GARCH model with indicators for exogenous changes provides relatively good forecasts of volatility whereas those models without these indicators seem to be a poor alternative. Thus, the results of one-step-ahead forecasting analysis suggest that the volatility models with exogenous changes provide excellent out-of-sample predictability.

V. CONCLUSIONS

This study examines dates of exogenous changes in volatility through the ICSS algorithm and examines the effect of these changes on the persistence in volatility using the GARCH model. For this purpose, we used five weekly KOSPI 200 sector index series, namely manufacturing, electricity & communication, construction, service, and finance.

Using the ICSS algorithm, we detected when the changes in volatility occurred, corresponding to major economic and political events, including the 1997 Asian currency crisis, the Russia crisis of 1998, the IT bubble of 2000, the 9/11 terror attack of 2001, the Iraq war of 2003, and the global financial crisis of 2008-2009. After incorporating these indicators, we found that the persistence in volatility $(\alpha+\beta)$ in the GARCH model was significantly reduced. This result implies that ignoring exogenous changes overestimates the persistence in volatility. In addition, out-of-sample analysis confirms that volatility models that incorporate exogenous changes provide more accurate one-step-ahead volatility forecasts than their counterparts without exogenous changes. Thus, incorporating information on exogenous changes in conditional variance may improve the accuracy of estimating the persistence in volatility.

Our findings suggest that major economic and political events tend to overestimate the persistence in volatility, leading to potential errors by risk managers in interpreting Value-at-Risk (VaR). For example, risk managers build minimum capital requirement based on the VaR. When ignoring exogenous changes in volatility, the over-prediction of volatility persistence might lead to misevaluate the VaR and the amount of capital necessary for safety. Thus, proper accounting for exogenous changes in volatility forecasting is important for accurately estimating the VaR and for optimally allocating funds among assets and capital.

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