Have Stock Markets Become Less Volatile After the Great Recession?

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Abstract

This paper investigates volatility modeling in light of the 2008 global financial crisis. The study was motivated by the measures and regulations introduced by most of the countries following the shock to stabilize their financial markets. The theoretical proposition is that these measures should succeed in reducing volatility which would be modeled differently following the crisis. The adopted ARMA-GARCH process included positive and negative trading volume change to capture the asymmetric effect of trading volume on market volatility for seven international markets. The results indicate that the majority of these markets were not so successful in reducing volatility following the crisis. There is evidence of volatility persistence which dissipates very quickly. Although volatility is modeled differently before and after the crisis, each market is modeled uniquely. The effect of trading volume was found to be asymmetric. Only positive change was a valid predictor. Detailed discussions of the results, implications, and recommendations are provided.

Keywords: stock market volatility, ARCH/GARCH, financial crisis

JEL Classification: G01, G21, G32

1. Introduction

Volatility is a measure of risk that is closely related to return. In theory, higher expected risk is associated with higher expected return. Therefore, one of the factors investors look at when they decide to invest in a stock market is the volatility of returns. This is important for decision makers, especially when making decisions on portfolio selection, hedging, asset pricing… etc. Daily traders (technical analysts) depend, solely, on the movement of the prices and look for up/down volatile moves to position their trades. When deciding on which stock market to invest, large international portfolio investors are concerned about the dispersion of returns, diversification/risk mitigation, correlations of returns, and volatility spillover between the markets. They are concerned because they want to minimize the risk associated with the return they desire to achieve.

To protect traders and investors against misconduct that may lead to extreme volatilities, regulators of stock markets enforce new measures and regulations, especially following major shocks. Mitigation of risks and fair trading are always important targets of any new regulations. All past major crises, including the great depression of 1929, have motivated new laws and regulations to control the financial markets. As of today, a decade has passed from the shock of the 2008 financial crisis. Since then, and to avoid similar depressions and asset devaluation, the world has witnessed numerous global and local reforms. We, therefore, should, conceptually, expect less volatile and more stable markets.

In this paper, we aim to explore this conceptual proposition in the context of the 2008 great recession. We seek answers to particular questions relevant to this proposition. Assuming that the stock markets are being better-controlled and regulated following the crisis, the important question is, have these markets become less volatile? Whether the proposition is confirmed or not, how can volatility be modeled? Is it going to be different? In other words, are the determinants of volatility still the same after the crisis?

Answers to these questions should contribute more to our understanding of the effect of major financial crises on stock markets volatility and for how long it persists. The results of this study should tell us if the evidence can be generalized for all stock markets.

In the next section, the relevant literature will be discussed with the objective to derive the research conceptual framework and hypotheses. An overview of regulatory measures and reforms, following the 2008 crisis in the selected sample stock markets, will be presented. This is followed by a section on the data and methodology where we discuss the scope of our sample stock markets and the method of estimation. The results of the research and discussion will then be presented. The paper ends with a section on the concluding remarks where we highlight the main contribution of the paper, along with the limitations, implications, and recommendations.

2. Literature Review

In statistics, volatility in financial data time series can be defined as the dispersion of rate of returns, typically, measured by the standard deviation or variance. The higher the value of the measure the more volatile (risky) the asset. When dealing with causality, researchers, typically apply regression methods. These methods assume that data should be normally distributed. The nature of the financial data, however, is not. They also assume that the variance of the error term should be homoscedastic (constant over time). If not, then there is a problem of heteroskedasticity. Another essential assumption is that the error term should not exhibit autocorrelation.

A solution to these problems, when investigating volatility, was pioneered by Engle (1982) who introduced the autoregressive conditional heteroskedasticity (ARCH) process where the conditional variance (a measure of volatility) is explained by lagged (previous) error terms. ARCH was then enhanced by Bollerslev (1986) who introduced the Generalized ARCH (GARCH) model where the current conditional variance is a function of the lagged error term and lagged conditional variance. GARCH model was then enhanced further to cater for asymmetry as in EGARCH (Nelson, 1991) and then the nonlinear asymmetric GARCH (NAGARCH) introduced by Engle & Ng (1993). Other versions of GARCH include, but not limited to, the integrated GARCH, the GARCH in mean, the quadratic GARCH of asymmetry, Glosten-Jagannathan-Runkle GARCH, and the threshold GARCH.

Most of the empirical work on ARCH/GARCH modeling revolves around the idea of what determines the observed conditional variance as a measure of market volatility. Up till the writing of this script, Google Scholar internet search engine reports over 24 thousand citations of Engle’s (1982) work and nearly 25 thousand citations of Bollerslev’s (1986) work indicating the enormous reception of ARCH/GARCH process to model volatility. Focusing on the objective of this study, and due to the vast amount of empirical research on volatility using ARCH/GARCH modeling, our discussion is only limited to the literature relevant to the response to financial downturns and regulatory reforms using ARCH/GARCH modeling.

In an attempt to report how volatility responded to a major financial crisis, Holden et al. (2005) utilized both GARCH and TARCH models to study the behavior of stock market returns in Thailand before, during and after the 1997 Asian financial crisis. They found no evidence of significant calendar effects. However, the behavior of returns before, during and after the crisis was found to be significantly different. Within the same region, Chancharoenchai & Dibooglu (2006) used the GARCH in mean to explore volatility spillovers among six Southeast Asian countries around the time of the 1997 Asian financial crisis. They found supporting evidence of their proposition that “*Asian contagion*” which started in Thailand was quickly picked up by neighboring countries. Shamiri & Isa (2009) used a bivariate GARCH model to investigate the transmission of major financial crises and found evidence of volatility spillover from the US towards the markets in South Asia with varying persistence among the different countries. Using a vector autoregressive–EGARCH) model, In et al. (2001) investigated the interdependence and volatility transmission among the Asian stock markets during the 1997-1998 financial crisis and found varying directional transmissions of volatility between the markets. Contagion effect was investigated among East Asian markets by Cho & Parhizgari (2008) using dynamic conditional correlation-GARCH. Evidence of contagion was found. Many other studies were conducted using GARCH models to study the effect of the Asian crisis on volatility including, but not limited to, Pownall & Koedijk (1999), Mittnik et al. (2000), Sim & Zurbruegg (2001), Caporale et al. (2002), Caporale et al. (2003), Choudhry (2005), and Karunanayake et al. (2010). The possible contagion effect of volatility during major crises was also investigated by Celık (2012), Dungeyet et al. (2015), Dimitriouet al. (2013), Kenourgios (2014), Luchtenberg & Vu (2015), Chittedi, K. R. (2015, Hemche et al. (2016), and Bonga-Bonga (2018).

Using market data for 153 years (from the year 1834 to 1987), Schwert (1989) used a process similar to ARCH showed that market volatility increases during financial crises and increases after stock prices fall. The same researcher (Schwert, 2011), used monthly, daily, and intraday data for over 125 years to show that, unlike previous recessions, the 2008 global financial crisis was preceded by high volatility, particularly among financial sector stocks.

When dealing with stock market data, volatility is, typically, measured by the variance derived from a mean equation as a function of its lagged squared error (ARCH effect) and its lagged variance (GARCH effect). However, in the mean equation or the variance equation, researchers have been including variables that are closely associated with the market rate of return. For example, Kin et al. (2005), in their study on the volume-volatility relationship in the Korean market after the 1997 crisis, included the MA (1) in the mean equation. Granger model was applied to test for causality between the trading volume and volatility reporting a significant bidirectional effect. Al Rjoub (2011) used dummy variables in the mean and variance equations to investigate volatility in the Jordanian stock market during particular crises. He found that it behaved differently during the different crises. Angabini & Wasiuzzaman (2011) included ARIMA effects in the mean equation and no additional variables in the variance equation to study the impact of the 2008 global financial crisis on the volatility of the Malaysian stock market. Ali & Afzal (2012) included ARMA (p, q) in the mean equation in addition to a dummy variable investigate the effect of the 2008 global financial crisis on the Pakistani and Indian stock markets. To measure volatility, they used EGARCH model and found that it had a stronger response to negative shocks. Considering the effect of the same crisis, Sakthivel et al. (2014) reported similar findings for the Indian market alone. Amit & Bammi (2016) investigated the volatility of the Indian stock market before, during, and after the 2008-2009 global crisis. They did not include any additional variables in the model. Their results showed significantly different reactions to negative and positive news with prominent leverage effect during downturns.

In terms of volatility persistence, many researchers investigated the effect of including additional variables in the mean and variance equations of the GARCH process. For example, Ali Ahmed et al. (2005) included the trading volume in the variance equation to investigate volatility in the Malaysian stock market during a crisis. They found evidence of leverage effect and that the inclusion of volume in the variance equation reduced persistence. Their findings were inconsistent with the results reported by Lamoureux & Lastrapes (1990) but endorsed those reported by Majand & Yung (1991) and Huang Yong (2001). Chandra & Rajib (2010), employed ARMA (1, 1) in the mean equation, and symmetric contemporaneous and lagged volume interchangeably in the EGARCH model to study the volatility persistence in an emerging futures market. They reported two important results. The first is that negative shocks increase volatility more than positive shocks. The second is that the inclusion of contemporaneous and lagged trading volume lowers volatility persistence.

3. The Research Conceptual Framework

To conclude on the reviewed literature, it appears that there is evidence of the effect of financial crises on stock market volatility. There is also evidence of the contagiousness of volatility and spillover from larger stock markets. However, the evidence on volatility persistence is inconclusive. Moreover, the more the variables added to the variance equation, the lower the persistence value as measured by the sum of ARCH and GARCH coefficients. The evidence on the asymmetric effect of lagged volatility is also inconclusive. Due to the evident association between trading volume and volatility reported by the literature, we propose the inclusion of the asymmetric effect of volume in the variance equation before and after the crisis. To the best of our knowledge, this particular issue is not investigated before.

Conceptually, the generalized autoregressive conditional heteroskedasticity method and its variants are widely applied for modeling stock market volatility. To formulate the mean equation of the GARCH model, we consider the lagged returns (autoregression) and lagged moving averages as predictors of stock market returns. This is known as an ARMA process. Initially, the first lag of the squared error (news of market volatility) and variance (lagged volatility) are considered as the predictors of the variance equation. Based on specific selection criteria to come up with a better model fit, additional lags may be considered. Therefore, we proposed a mean equation where the rate of return is a function of ARMA. We also propose a variance equation where today's variance is a function of lagged news of the market volatility and lagged volatility in addition to the positive and negative change in volume. The reason for introducing the volume variables is to learn more about the volatility response to the increase versus the decrease in the trading volume.

In this paper, our investigation is limited to seven stock markets in the USA, France, Hong Kong, Jakarta, Mexico, and Kuwait representing four different continents. It is believed that these countries have taken measures to regulate their stock markets in response to the 2008 global financial crisis.

4. Overview of the Reforms in the Selected Countries

Following the 1929 stock market crash, the US enforced the Securities Act in 1933 and the Securities Exchange Act of 1934. By the end of the decade, it was amended to regulate over-the-counter markets. It was further amended in 1964. Major new rules were introduced in 1988 to deal with fraud cases. In the year 2000, the SEC issued the Regulation Fair Disclosure. In response to the 2008 financial crisis, the US enforced the Dodd–Frank Wall Street Reform and Consumer Protection.

In France, financial markets are regulated by the European Act (SEA) in 1986, which was amended in the wake of the 2008 global financial shock in addition to the Credit Default Swaps regulation and European Market Infrastructures Regulation.

In Hong Kong, and in response to the 1987 stock market crash, the Securities and Futures Commission (SFC) was set up the following year. The financial environment was improved following the establishment of the Central Clearing and Settlement System (CCASS) in 1992 and the Automatic Order Matching and Execution System (AMS) in 1993. Following the 1997 Asian financial shock, the Hong Kong monetary authority improved the transparency of the currency board system to regulate the market. In 2002, the Securities and Futures Ordinance regulation was enforced by the legislative council. In response to 2008 crisis and in cooperation with mainland China, Hong Kong government introduced a range of measures, to lessen its impact, including loan guarantee programs, bank deposits guarantee with no-ceiling and injecting more liquidity in the market.

In Indonesia, and in response to the 2008 crisis, a stimulus package of Rp73.3 trillion was provided for the year 2009 to mitigate the risk of the global financial crisis. The country also reacted with a set of local market policies to regulate the market focusing on tax reforms.

Out of the six countries, Mexico is the closest to the US regarding the location and economic integration, especially after enforcing the NAFTA agreement in 1994. When the 2008 shock burst in the US market, it was immediately picked up by the Mexican market. It led, almost immediately, to assets liquidations, currency depreciation, extreme stock prices volatility and scarcity of liquid assets. In response, and to reduce volatility, the central bank of Mexico began injecting US dollars in the economy. To maintain more stability in the economy, it also arranged foreign currency swap line with the US Federal Reserve. Furthermore, by the end of 2008 and the beginning of 2009, new macroeconomic and fiscal policies were introduced to withstand the effect of the crisis.

For Kuwait, the Kuwait stock exchange was struck hard by the crisis, losing, quickly, over 70% of its value. Before the crisis, the price index recorded over 14 thousand points compared to the current 6 thousand points indicating the long-lasting drastic effect of the crisis. In response, Kuwait worked on a new regulatory package and created the Capital Markets Authority (CMA) to control and supervise all affairs of current and future capital markets to ensure fair trading, fight misconduct, and enforce proper corporate governance. In 2010, the CMA, as well as a new company law, was enforced. Moreover, parallel with the enforcement of CMA, it started the process of demutualization of its stock exchange. However, the demutualized stock market is yet to be operational.

Most of the measures enforced after the crisis had positive short-run effects in alleviating the risks of the 2008 financial shock. How effective these measures to maintain, long lasting, less volatile stock markets, this is a question to be answered by this research.

5. Data & Methodology

As mentioned earlier, and confined only by our limited access to historical prices, the data was gathered from Yahoo Finance, for seven stock markets; S&P 500, Nasdaq, CAC 40, Jakarta, Hang Seng, Mexico, and Kuwait for the period from the beginning of January, 2001 (when available) to the 19th of September, 2016. The data is divided into two sets representing the two periods before and after the 2008 crisis.

Based on the research conceptual framework, we select a GARCH process to model volatility as it is known of its ability to cater for the two main violations of OLS assumptions: error term heteroskedasticity and autocorrelation. In this paper, we use GRACH (with some variations) as the main process to model volatility in the time series of market returns. Each stock market is modeled individually for each data set.

GARCH process consists of two equations, the mean equation, and the variance equation. As proposed, the mean equation is estimated as an ARMA process using the maximum likelihood function. The error variance is derived from it and used as the dependent variable, representing volatility, in the variance equation. Typically, the mean equation following the ARMA (*p*, *q*) process can be written with or without additional explanatory variables as

$$r_t = \delta + \sum_{i=1}^{p} \emptyset_i r_{t-1} + \sum_{j-1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

Where $\boldsymbol{r_t}$ is the natural log of the stock market index rate of return at time $\boldsymbol{t}$, δ is constant, p and q are lag terms, $\emptyset$ and θ are the coefficients for AR and MA respectively and, ε is the error term. The variance equation can be written as

$$h_t = w + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j-1}^{q} \beta_j h_{t-j} + \gamma_1 v_t^+ + \gamma_2 v_t^- \quad (2)$$

Where $\boldsymbol{h_t}$ is the variance today derived from equation (1) representing volatility. α and β are coefficients, $\boldsymbol{\varepsilon_{t-i}^2}$ is the lagged information on the market return and $\boldsymbol{h_{t-j}}$ is the lagged volatility. γ_1 and γ_2 are coefficient for the effect of positive change in trading volume (v_t^+) and the effect of negative change in trading volume (v_t^-).

For each data set, the process is applied to each stock market. We apply the AIC model selection test to choose the appropriate model for each market and each data set.

Three conditions have to be satisfied prior to GARCH estimation:

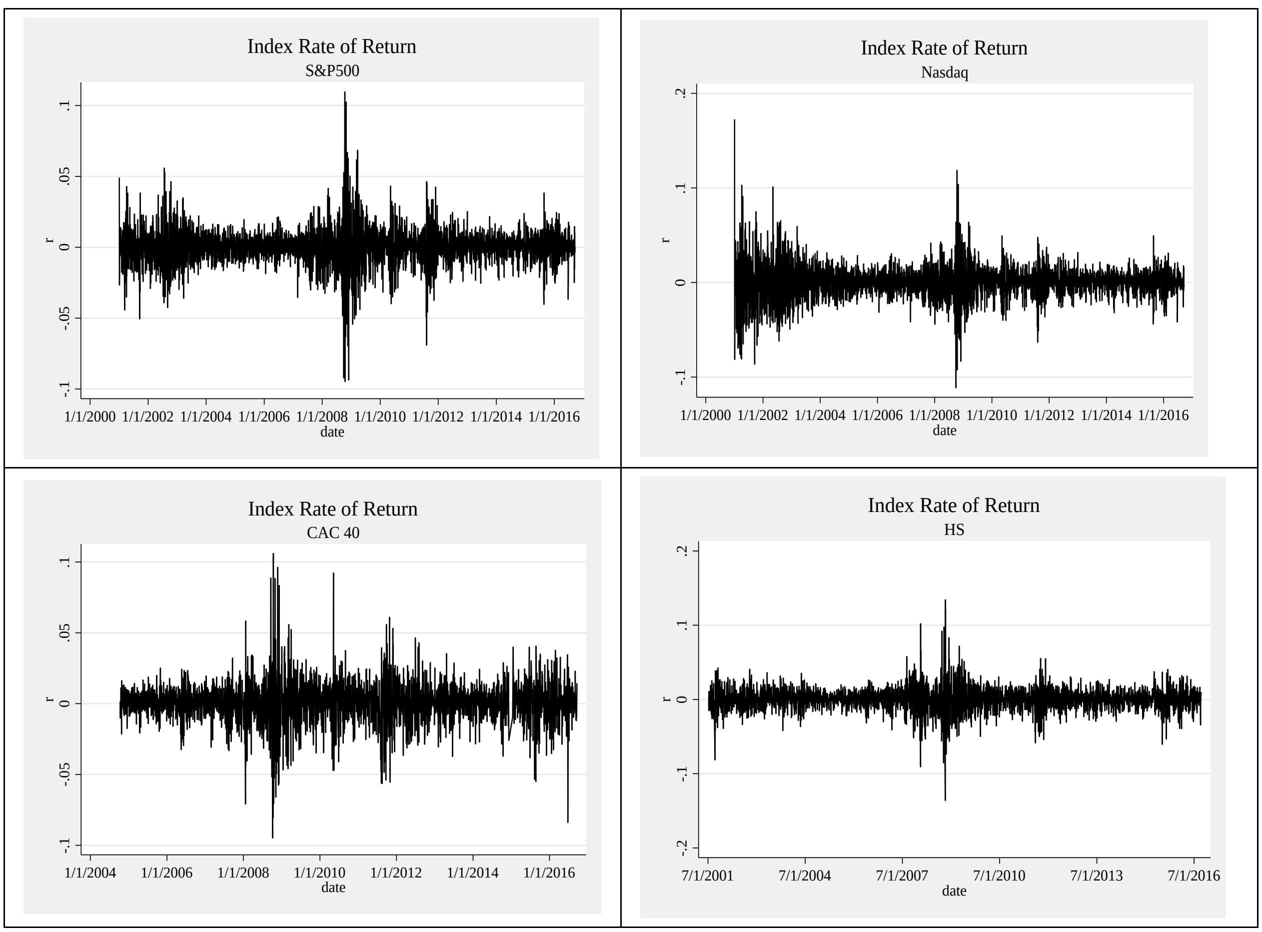
(1) There should be evidence of data volatility clustering. That is; a period of high volatility is followed by a period of high volatility and a period of low volatility is followed by a period of low volatility and changing over time.

(2) The error term is to be heteroskedastic

(3) There should be evidence of autocorrelation (ARCH effect)

6. Pre-estimation Diagnostics

To check volatility clustering, we use a plot of the market rate of return against time. Figure 1 below exhibits the patterns of change in index rate of return for the seven sample markets showing the volatility clustering with the evident burst of the 2008 global financial crisis starting around the mid of the year almost simultaneously for all the markets.



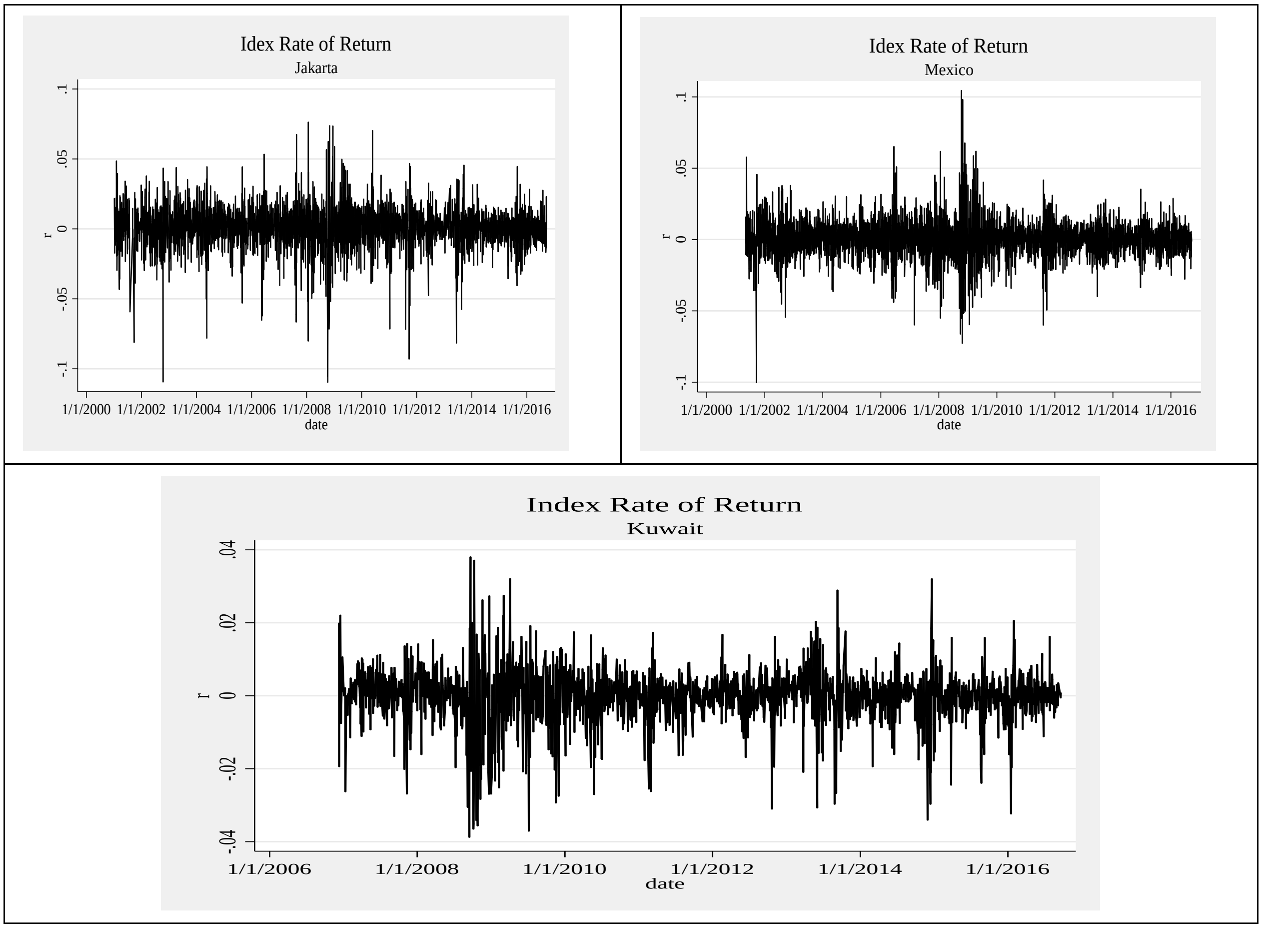


Figure 1. Examples of volatility clustering

For the more developed (and maybe more efficient markets) of the US, France and Hong Kong, the clustering is more synchronized than the other less developed market of Kuwait, Mexico, and Indonesia. Interestingly, the more developed market show smother shorter post-crisis spikes and more smooth variability of return changes compared to the other group indicating their ability to absorb the great shock better. These observations are yet to discuss thoroughly following the estimation of the econometric models. The less smoother spikes for the other markets may be an indication of more market volatility and persistence following the shock.

To examine the heteroskedasticity problem, the white's test is applied. The null hypothesis *H*o: error term is homoscedastic against *H*a: unrestricted heteroskedasticity exists. Autocorrelation is tested using the LM test for ARCH with a null hypothesis of no-autocorrelation.

A summary of pre-estimation tests of heteroskedasticity and autocorrelation is presented in Table 1.

Table 1. A summary of the pre-estimation tests

		White test		LM ARCH Lag(1)	
Market	Dataset	χ^2 (2)	***P-value***	χ^2 (1)	***P-value***
S&P500	Before Crisis	22.05	0.0000	98.718	0.0000
	After Crisis	14.43	0.0007	69.198	0.0000
Nasdaq	Before Crisis	15.15	0.0005	59.313	0.0000
	After Crisis	24.74	0.0000	60.207	0.0000
CAC40	Before Crisis	6.57	0.0374	13.453	0.0002

	After Crisis	88.31	0.0000	3.965	0.0465
Jakarta	Before Crisis	15.38	0.0005	56.262	0.0000
	After Crisis	9.84	0.0073	21.470	0.0000
HS	Before Crisis	34.22	0.0000	218.204	0.0000
	After Crisis	151.46	0.0000	19.151	0.0000
Mexico	Before Crisis	28.62	0.0000	55.225	0.0000
	After Crisis	29.02	0.0000	10.663	0.0011
Kuwait	Before Crisis	0.59	0.7461[1]	64.610	0.0000
	After Crisis	49.32	0.0000	75.889	0.0011

[1] *Alternatively, Cameron & Trivedi's decomposition of IM test is significant*

The resulting tests shown in Table 1 reject the null hypotheses of homoscedasticity and no-autocorrelation for all the sample stock markets exhibiting the problems of heteroskedasticity and autocorrelation. As all pre-conditions are satisfied, the process is good to go with GARCH estimations.

7. Model Estimation and Discussion of the Results

The ARCH family regression results for the seven markets are presented in Tables 2 to 8 as follows.

Table 2. S&P500: Results of ARCH family regression

Variable		***Before crisis***			***After crisis***		
		Coef.	z	P > |z|	Coef.	z	P > |z|
ARMA	$\emptyset_1$	-.0902	-1.89	0.058*	-.1486	-2.73	0.006***
	θ_1	-.5798	-15.13	0.000***	-.4993	-10.27	0.000***
Volume	γ_1	4.9980	5.80	0.000***	3.3241	2.65	0.008***
	γ_2	23.3707	1.12	0.265	1.5154	0.29	0.768
ARCH	α_1	.3349	5.77	0.000***	.4341	5.52	0.000***
	β_1	.3941	6.32	0.000***	.4437	4.24	0.000***
Volatility persistence	$\alpha + \beta$	0.73			0.87		

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

Table 2 shows that the ARMA process, significantly, explains the rate of return behavior for the S&P 500 stock market before and after the crisis. GARCH (1, 1) is the proper determinant of its volatility before and after the crisis. Only the positive change in trading volume seems to have a positive and significant effect on volatility for this market, indicating an asymmetric effect of trading volume on volatility. Volatility persistence appeared to have increased after the crisis indicated by the value of 0.87 compared to 0.73 before the crisis against the expectation. The conclusion on the S&P 500 stock market is that volatility is not modeled differently after the crisis and there is no evidence of reduced persistence. However, the relatively low value of persistence represented by the β coefficient only (below 0.75), shows relatively acceptable volatility movements lasting for a short period of time.

Table 3. NASDAQ: Results of ARCH family regression

Variable		*Before crisis* Coef.	z	P > |z|	*After crisis* Coef.	z	P > |z|
ARMA	$\emptyset_1$	-.0414	-0.82	0.413	-.1382	-2.49	0.013**
	θ_1	-.6339	-16.06	0.000***	-.5029	-10.13	0.000***
Volume	γ_1	.1066	0.07	0.945	1.4584	2.60	0.009***
	γ_2	60.4378	1.03	0.302	404.499	0.49	0.626
ARCH	α_1	.4956	6.72	0.000***	.3334	5.35	0.000***
	β_1	.3634	7.59	0.000***	.5285	10.88	0.000***
Volatility persistence	$\alpha + \beta$	0.86			0.86		

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

Table 3 shows that, while ARMA process explained the changes in the rate of return for the NASDAQ after the crisis, only MA (1) component found to be a significant determinant before the crisis. Similar to the S&P 500 market, the volatility of NASDAQ is only affected by the positive changes in the trading volume indicating the asymmetry effect of volume. Total persistence has not changed which. However, the low value of the β coefficient alone may be an indication of a relatively stable long run trading environment. Volatility modeling after the crisis exhibited a slight change in the mean equation only.

Table 4. CAC40: Results of ARCH family regression

Variable		*Before crisis* Coef.	z	P > |z|	*After crisis* Coef.	z	P > |z|
ARMA	$\emptyset_1$	-.0745	-1.20	0.229	-.0320	-0.50	0.616
	θ_1	-.5617	-11.01	0.000***	-.5542	-9.88	0.000***
Volume	γ_1	.8257	0.32	0.751	2.7249	3.55	0.000***
	γ_2	101.390	0.13	0.900	.2087	0.05	0.960
ARCH	α_1	.0860	2.12	0.034**	.2619	4.96	0.000***
	α_7	.3606	5.55	0.000***	.1380	3.95	0.000***
	β_1	.4597	6.55	0.000***	.4668	4.88	0.000***
Volatility persistence	$\alpha + \beta$	0.90			0.87		

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

The outcome in Table 4 indicates that only the MA (1) component of the ARMA process is a valid determinant of the change in the rate of return for the CAC 40 stock market. Volatility was found to be a function of ARCH (1), ARCH (7) and GARCH (1) before and after the crisis indicating the effect of pervious market volatility information long memory on market volatility. Similar to the previous two markets, the volatility is only influenced by positive changes in the trading volume confirming, again, the asymmetry effect. Volatility persistence appeared to have decreased slightly after the crisis and maybe confirming the effectiveness of the reforms. The results show no changes to how volatility is modeled.

Table 5. Jakarta: Results of ARCH family regression

Variable		*Before crisis* Coef.	z	P > |z|	*After crisis* Coef.	z	P > |z|
ARMA	$\emptyset_1$	-.0396	-0.32	0.750	-.2470	-1.88	0.061*
	θ_1	-.4836	-4.15	0.000***	-.2396	-1.82	0.069*
Volume	γ_1	2.0548	1.76	0.079*	1.3200	2.98	0.003***
	γ_2	-1.6994	-1.34	0.179	-1.0672	-2.62	0.009***
ARCH	α_1	.2354	3.83	0.000***	.1118	1.66	0.098*
	β_1	.6483	5.79	0.000***	.2977	0.96	0.335
Volatility persistence	$\alpha + \beta$	0.88			0.41		

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

The analysis of the volatility of the Jakarta stock market shows that only the MA (1) component of the ARMA process explains the changes in return of the mean equation before the crisis. After the crisis, however, the ARMA process shows an insignificant effect at the 5% level. The GARCH (1, 1) process does explain volatility before the crisis. After the crisis, however, it does show a significant effect at the 5% level. Interestingly, and for this stock market only, the positive and negative changes in the trading volume are the only explanatory variables with significant effects indicating symmetric properties. The drastic drop in persistence is logically explained by the disappearance of the effect of lagged variance and lagged news on volatility. The volatility model has also changed after the crisis.

Table 6. HS: Results of ARCH family regression

Variable		*Before crisis* Coef.	z	P > |z|	*After crisis* Variable	Coef.	z	P > |z|
ARMA	$\emptyset_1$	-.1444	-1.79	0.073*	$\emptyset_1$	-.1125	-1.33	0.182
	θ_1	-.4694	-6.19	0.000***	θ_1	-.4932	-6.19	0.000***
Volume	γ_1	1.4264	1.16	0.244	γ_1	1.6978	1.88	0.060*
	γ_2	2.977	0.33	0.742	γ_2	-.3599	-0.62	0.536
ARCH	α_1	.2212	3.50	0.000***	α_1	.1292	3.11	0.002***
	α_4	-.2254	-0.75	0.456	α_5	.1754	3.87	0.000***
	α_{14}	.2567	4.22	0.000***	α_{20}	.0695	2.66	0.008***
	β_1	.5397	2.97	0.003***	β_1	1.3002	6.48	0.000***
	β_2	-.0033	-0.01	0.991	β_2	-1.0086	-3.06	0.002***
Volatility persistence	$\alpha + \beta$	1.01				0.67		

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

For the Hang Seng market, the mean equation did not indicate a significant change after the crisis. That is, only MA (1) component of the ARMA process is a valid explanatory variable for the changes in index rate of return. As for the ARCH effect, it seems that there is long memory of the effect of the lagged news on volatility as indicated by the significant values of ARCH (1) and then ARCH (14). After the crisis, the memory is getting longer as indicated by significant values of ARCH (1), ARCH (5), and then ARCH (20). The GARCH effect has also changed after the crisis. Before the crisis, only the effect of GARCH (1) was significant. After the crisis, however, GARCH (1) and GARCH (2) were both significant regressorr of the market volatility. Trading volume is not a determinant of volatility for this market. The model has changed after the crisis regarding the mean equation as well as the variance equation. Total persistence has dropped after the crisis.

Table 7. Mexico: Results of ARCH family regression

Variable		***Before crisis***			***After crisis***		
		Coef.	z	P > |z|	Coef.	z	P > |z|
ARMA	$\emptyset_1$	.0707	1.76	0.079*	.0568	2.07	0.038**
	θ_1						
Volume	γ_1	.6173	3.02	0.003***	.5952	3.20	0.001***
	γ_2	8.0016	2.68	0.007***	42.4943	1.23	0.219
ARCH	α_1	.2188	4.51	0.000***	.2148	5.15	0.000***
	β_1	.3220	5.10	0.000***	.5071	10.62	0.000***
Volatility persistence	$\alpha + \beta$	0.54			0.72		

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

For the Mexican market, only the AR (1) component of the ARMA process is valid to model the mean equation. It was significant at the 5% level after the crisis only. The GARCH (1, 1) model is the proper process for the variance equation. It had a significant positive effect on volatility before and after the crisis. Positive and negative changes in the trading volume had a significant effect on volatility before the crisis. However, only positive changes in the trading volume had a positive effect after the crisis.

Interestingly, the negative changes in volume before the crisis had a positive effect on volatility. That is, a further decrease in trading volume motivated higher market volatility. The model had changed in the mean equation and the variance equation. This market has witnessed an increase in volatility persistence after the crisis indicating the ineffectiveness of any reforms to mitigate long run market risk.

Table 8. Kuwait: Results of ARCH family regression

Variable		***Before crisis***			***After crisis***		
		Coef.	z	P > |z|	Coef.	z	P > |z|
ARMA	$\emptyset_1$	.1931	1.53	0.126	-.0253	-0.37	0.715
	θ_1	-.6639	-6.83	0.000***	-.4906	-8.15	0.000***
Volume	γ_1	1.178	1.99	0.047**	1.2944	1.42	0.154
	γ_2	.5802	0.51	0.611	15.6300	0.55	0.586
ARCH	α_1	.9946	3.05	0.002***	.4138	5.90	0.000***

	β_1	.0699	0.92	0.359	.4598	7.16	0.000***
Volatility persistence	$\alpha + \beta$		-			0.87	

** Significant @ 10%, ** significant @ 5%, *** significant @ 1%*

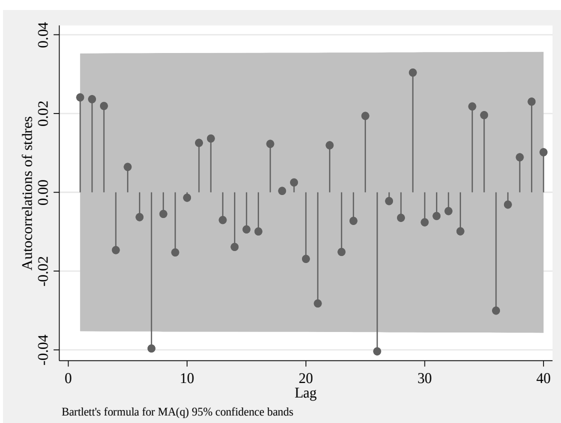
The results of the ARCH family estimation in Table 8 show that only the MA (1) component of the ARMA process is significant before and after the crisis for Kuwait stock exchange. The lagged changes in the rate of return do not explain the current rate of return. The lagged volatility does not explain current volatility before the crisis. It is, however, explained by the lagged news of the market. The high value of the ARCH coefficient indicates that volatility is less persistent and spiker. This result is supported by the insignificant value of GARCH, which indicates that the previous-day-volatility does not explain current market volatility. The post-crisis volatility is affected significantly by ARCH (1) and GARCH (1). In terms of the effect of the trading volume, it appears that only its positive change is a significant determinant of volatility before the crisis. Although the model has not changed after the crisis, apparently, the determinants in the mean equation and variance equation have. The results show that the volatility persistence, measured only by βcoefficient (because it was insignificant before the crisis) has increased after the crisis rejecting our theoretical proposition.

8. Post-Estimation Diagnostics

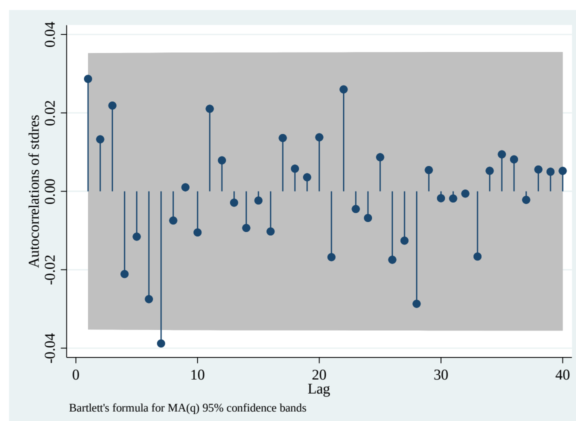
For the post-estimation diagnostics, we show in figure 2 the autocorrelgram of the squared returns for all seven markets showing the absence of significant autocorrelations.

Autocorrelation …

Panel 1: S&P 500

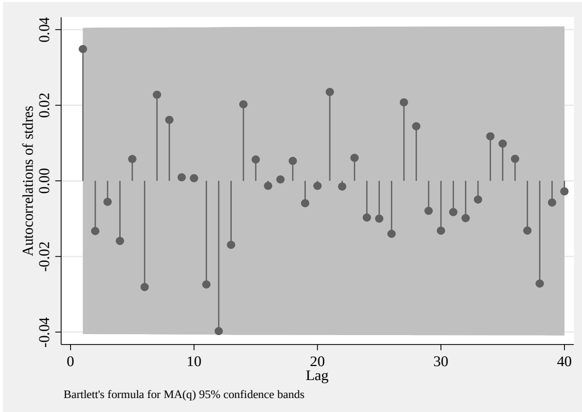


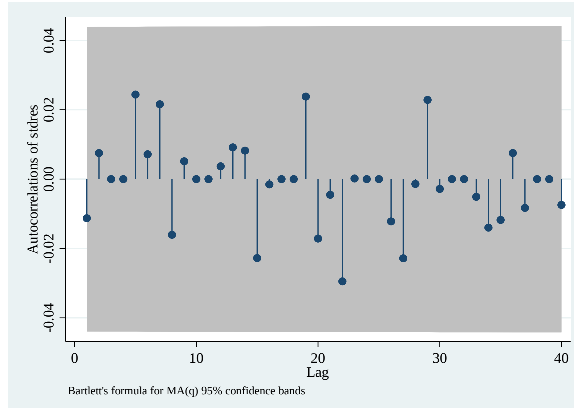
Panel 2: NASDAQ



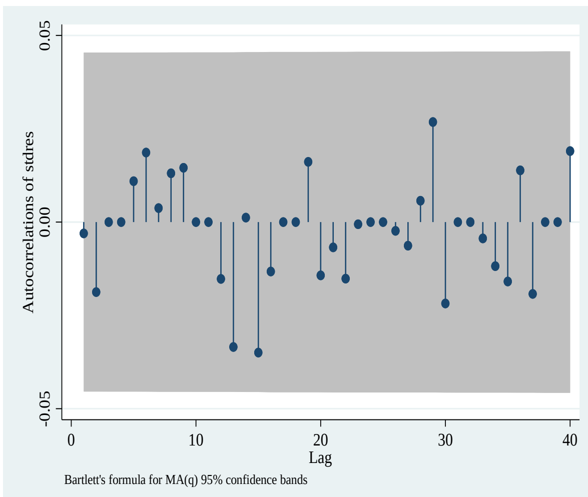
Panel 3: CAC40

Panel 4: HS

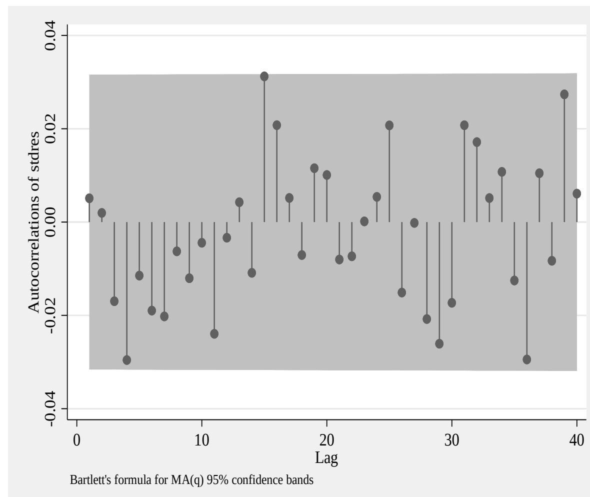




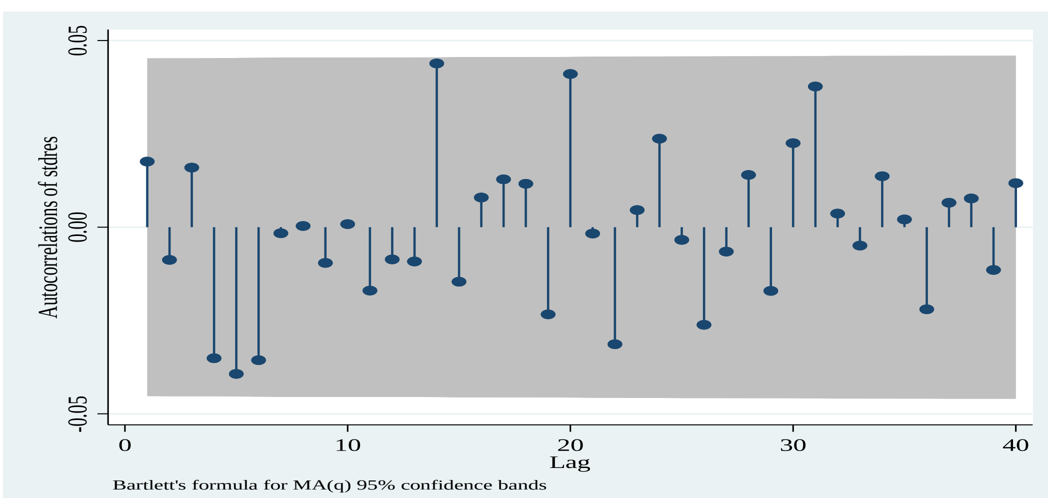
Panel 5: Jakarta



Panel 6: Mexico



Panel 7: Kuwait



Furthermore, we report the tests for heteroskedasticity and white noise for the S&P 500 as an example. Before the crisis, the heteroskedasticity test of χ^2 (1) with a score = 0.017 has a P-value=0.8965. The white noise test using the Portmanteau (Q) statistic = 36.9867 with a P-Vale > χ^2 (40) = 0.6067. Similar conclusions were reported for the other six markets. After the crisis, the heteroskedasticity test of χ^2 (1) score is 1.376 with a P-value=0.2408. The white noise test using the Portmanteau (Q) statistic is 35.3319 with a P-Vale > χ^2 (40) = 0.6802. A similar conclusion was reported for each of the other six markets. The post-estimation diagnostic indicate that all individual models for each data set is well specified.

Table 9. Summary of the results

		ARCH effect		*GARCH effect*		*Volume effect*		
Market	***Crisis***	$\emptyset_1$	θ_1	α_1	β_1	γ_1	γ_2	***Persistence***
S&P500	*Before*	✓-	✓-	✓+	✓+	✓+		↑
	After	✓-	✓-	✓+	✓+	✓+		
Nasdaq	*Before*		✓-	✓+	✓+			-
	After	✓-	✓-	✓+	✓+	✓+		
CAC40	*Before*		✓-	✓+, ***L7*** +	✓+			↓
	After		✓-	✓+, ***L7*** +	✓+	✓+		
Jakarta	*Before*		✓-	✓+	✓+	✓+		↓
	After	✓-	✓-	✓+		✓+	✓	
H S	*Before*	✓-	✓-	✓+, ***L14*** +	✓+			↓
	After		✓-	✓+, ***L5+, L20+***	✓+, ***L2 -***	✓+		
Mexico	*Before*	✓+		✓+	✓+	✓+	✓+	↑
	After	✓+		✓+	✓+	✓+		
Kuwait	*Before*		✓-	✓+		✓+		↑
	After		✓-	✓+	✓+			

In general, our results indicate that the inclusion of ARMA effects in the mean equation, the extra lags in the variance equation to come up with a better fit for some of the markets, and the trading volume variables have contributed to the reduced volatility persistence. This result is consistent with the results of some of the previous studies which argued that the more variables added to the model the less the value of the volatility persistence (see for example Lamoureux & Lastrapes, 1990, Chandra Pati & Rajib, 2010, Louhichi, 2011) but contradicts with the results found by Naik & Padhi (2014) and Naik et al. (2018).

The proposition that the crisis has motivated new regulations and reforms leading to lower volatility (as measured by the persistence value) is confirmed only for the Jakarta stock market. Interestingly, Jakarta is the only market that has witnessed insignificant volatility effects in response to the 2008 global financial crisis indicating possible long run market stability. It is also the only market that witnessed significant symmetric effect of trading volume on the market volatility (the negative change in volume is significant at the 10% level).

Despite the slight increase in the effect of lagged volatility after the crisis, the low values of the coefficients < 0.75 (although significant) indicate very low persistence (measured by the value of β only), indicating its fast dissipation, possibly, because of the introduction of the new of rules and regulations following the crisis to stabilize the stock markets.

There is evidence for a decreased total volatility persistence (measured by the value of $\alpha + \beta$ coefficients) after the crisis for three out of the seven markets, indicating a faster dissipation of volatility, probably caused by the increased control and the introduction of new rules and reforms. The other three markets of S&P 500, Mexico, and Kuwait witnessed increased level of persistence in volatility. However, this persistence is not very high. Only the NASDAQ exhibited unchanged levels of volatility persistence.

Except for Kuwait stock exchange, volatility of the sample stack markets, after the crisis, is positively affected by the positive change in trading volume. After the crisis, however, negative change in trading volume was found to affect volatility negatively only for the stock market of Jakarta. Furthermore, except for the Mexican market, the negative effect of the trading volume did not have significant effect on volatility.

9. Concluding Remarks

In this paper, the determinants of stock market volatility in the presence of a major financial crisis are investigated. In light of the measures, rules, and regulation enforced by the relevant countries to mitigate the damaging effect of the 2008 crisis, the objective was to investigate how volatility responded to these measures. The stock market volatility is modeled by ARMA-GARCH process. Positive and negative changes in trading volume were added to the variance equation of the model as exogenous proxies for contradicting information arrival for a possible explanation of the stock market volatility.

In line with most of the previous research, ARMA (1, 1) process was found robust in explaining changes in the rate of the return. Although additional GARCH lags were added for few cases to come up with a better model fit, the GARCH (1, 1) was found robust in explaining variability in volatility for the majority of the cases. Additionally, only positive change in trading volume was found robust in contributing to the explanation of volatility changes for all the markets. Except for a single case, negative changes in trading volume was found to have no influence on volatility variability.

The results of this research indicate that stock market volatility, before and after the crisis, for all the stock markets is modeled differently. The results also indicate that, except for S&P 500, volatility, before and after the crisis, for each individual country is modeled differently. These results may be indicative of the individual uniqueness of financial market settings for each stock exchange lending support to some of the previous research. This is, probably, the only possible generalization derived from these results.

In terms of persistence, three markets witnessed an increased, but rather short-lived, volatility persistence after the crisis. Another three witnessed a decrease which may be indicative of how successful the measures that were taken to stabilize these markets. Again, no possible generalization can be derived from the results except the individual uniqueness of individual markets settings.

The results of investigating the asymmetric effect of trading volume in the variance equation are probably the distinctive contribution of this paper implying an important contribution to the existing literature, at least for this sample of markets. This implication may be undermined by the relatively small size of market. Accordingly, further research to include a wider sample would be greatly appreciated. It is also believed that other variables can be added to the variance equation to explain variability in market volatility.

The paper also lends some implications and recommendations for regulators and business managers. For markets that still suffer from instability after the crisis, they probably need to reconsider reviewing their measures and regulations. The fact that only the positive change in trading volume is a predictor of volatility, investment managers are advised to use it as an important signal to decide on their trading positions as big changes in trading volume lead to more volatility and risk.

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