Labuan Bulletin of International Business & Finance
Volume 14 Dec 2016 ISSN 1675-7262
UMS UNIVERSITI MALAYSIA SABAH

MACROECONOMIC VOLATILITY ON STOCK PRICES VOLATILITY DURING GLOBAL FINANCIAL CRISIS IN MALAYSIA

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Abstract

This study examines the impact of macroeconomic volatility on the stock market volatility in Malaysia before and after the Global Financial Crisis (GFC). We attempt to examine the impact of GFC on the relationship between the volatility of macroeconomic and Malaysian stock market volatility. We find that none of the macroeconomic volatility would affect the stock market volatility in the pre-GFC period. Moreover, the volatility of crude oil price is positively and significantly affects the Malaysian stock market volatility during and post-GFC. This implies that Malaysian stock market is sensitive to the crude oil price volatility during and after GFC.

JEL classification: *E44, G12, E3.*
Keywords: *Stock market volatility; Macroeconomic volatility; GARCH; International CAPM; Malaysia.*

1. Introduction

Global Financial Crisis (GFC) in 2008 caused a significant effect on the world economies through the financial market and manufacturing sector. During this period, many Asian countries also experienced downturns in their stock markets and declined in manufacturing, investment, and trade, followed by a slowdown in gross domestic product (GDP) growth rate. According to the Central Bank of Malaysia (2009), the GFC started to affect Malaysia's economy in the fourth quarter of 2008 when exports and manufacturing production declined by 7.4% and 11.1% respectively. Ringgit weakened to RM3.7255 against US dollar on March 2, 2009, and total investment declined significantly by 10.8%. The stock market fell severely, with the Kuala Lumpur Composite Index (KLCI) dropped from 1,445 in December 2007 to the lowest of 838.4 points on March 12, 2009, during the crisis. The impact of GFC was reflected through the declining of most macroeconomic indicators and stock market indices[2].

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[2] Source: Central Bank of Malaysia (2009).

In order to overcome the impact of GFC, the Malaysian Government implemented several policy measures which include lowering the interest rate. The overnight policy rate (OPR) was reduced from 3.25% (January 1, 2009) to 2.00% (February 25, 2009) and base lending rate (BLR) was reduced from 6.72% to 5.51%[3]. Besides that, two stimulus packages totalling RM67 million were announced in November 2008 and in March 2009. These stimulus packages aimed at supporting domestic demand and creating employment opportunities. KLCI rose at the end of March 2009 showing a sign of economy recovery thereafter.

The experience from recent GFC has shown that Malaysia, as a small open economy, is highly integrated with the international movement. The financial liberalisation launched by the Malaysian government in the early 1990s has increased Malaysia's exposure to the international investors and attracted a large amount of portfolio investment into its stock market. Malaysian stock market will encounter a high level of volatility and greater uncertainty in times of crisis. There are empirical studies in the developed market found that the volatility of stock market increases during the crisis (Schwert, 1989; Hamilton and Lin, 1996). An increase in the stock market volatility indicates a riskier environment which would cause investors to get panic and lead to lower investment.

The link between macroeconomic fundamentals and the stock market is clearly shown in financial economic theory. Arbitrage Pricing Theory (APT) provides a theoretical support and states that an asset return is determined by a series of macroeconomic factors. Financial theory suggests that a stock price is the discounted present value of a firm's cash flow. Changes in economic activity would affect the price of stock through the firm's cash flow and required rate of return. Thus, the link between economic activity and stock price should prevail. An increase in the macroeconomic volatility is likely to affect firm's cash flows which will provoke a positive response in the stock market volatility. Hence, this study attempts to examine whether the macroeconomic volatilities, as the underlying fundamental factors, could explain the stock market volatility in Malaysia. What are the fundamental factors that cause stock market volatility in Malaysia?

Specifically, this study aims to investigate the impact of GFC on the relationship between macroeconomic volatilities and Malaysian stock market volatility. Apart from contributing to the literature on emerging markets, this study also extends the existing relevant studies for Malaysia in a number of ways. First, we consider world excess return as an important factor to influence the stock returns volatility in Malaysia. This is essential as Malaysia is highly integrated with the global capital market after financial liberalisation (Tai, 2007). Second, in addition to the macroeconomic variables used by Zakaria and Shamsuddin (2012) in Malaysia, we add crude oil price volatility as a determinant of stock market volatility. The reason is, as an emerging and oil producing country, Malaysian stock market is sensitive to the change in the price of crude oil (Sadorsky, 2014; Zhu et. al., 2014). Third, contrary to most studies, this research analyses the impact of macroeconomic volatility on stock prices volatility considering the effects of structural breaks. This is

[3] Source: Central Bank of Malaysia (2009).

important as the impact of macroeconomic volatility could vary across different period of time due to structural breaks as highlighted by Chinzara (2011). Previous papers on this topic have failed to take into account the possible structural breaks in their studies.

We proceed by reviewing the currently available literature in Section 2. Section 3 provides a discussion of data and estimation methodology used in our study. Results will be presented in Section 4, and the last section is left for conclusions.

2. Literature Review

The literature on the link between macroeconomic and stock market can be categorised into two classes. The first class focuses on the relation between macroeconomic fundamentals and stock market returns. Using multivariate vector autoregression (VAR), the majority of the studies find that macroeconomic variables affect the stock market. Factors such as interest rate, money supply, exchange rate, inflation rate and industrial production are co-integrated with stock prices and are identified to be important in determining the stock market returns (Mookerjee and Yu, 1997; Kwon and Shin, 1999; Wongbangpo et al, 2002; Azeez and Yonezawa, 2006; Bekhet and Matar, 2013). Due to globalisation, the international factors become increasingly more important which make some authors include oil price changes in their studies. Gjerde and Sættem (1999), for instance, investigate Norwegian market using VAR approach and find that real interest rate and oil price changes affect stock returns. Sadorsky (1999) also documents that oil prices and oil price volatility play a major role in affecting real stock returns.

The second class of studies focuses on the link between macroeconomic volatility and the stock market volatility. The earliest literature on this area has been documented by Schwert (1989) for the United States (US) market. Using monthly data from 1857 to 1987, Schwert (1989) finds weak evidence between stock market volatility and real and nominal macroeconomic volatility like interest rate, inflation rate, the monetary base and industrial production. However, he suggests that stock volatility is more likely to predict future macroeconomic volatility. Chiang and Chiang (1996) also examine stock return volatility for Canada, Japan, Germany and the United Kingdom (UK) and show that the correlation between macroeconomic volatility and stock return volatility is weak. They use exchange rate, M2 money, and industrial production as independent variables in their study. Liljeblom and Stenius (1997) analyse the monthly data for Finland from 1920 to 1991 and find a strong predictive power in both directions, from stock market volatility to macroeconomic volatility and from market economic volatility to stock market volatility. Kearney and Daly (1998) also examine the macroeconomic causes of stock market volatility in Australia. Their results show that conditional volatilities of inflation and interest rate are directly associated with the conditional volatility of the stock market, but the conditional volatilities of industrial production, current account deficit, and money supply show a negative association with stock market volatility.

Moreover, Morelli (2002) documents that the volatility in the macroeconomic variables namely industrial production, real retail sales, money supply, inflation and exchange rates do not explain the volatility in the

UK stock market. The author reports a low explanatory power of macroeconomic volatility to explain stock market volatility, which is a low R2. This result is in line with Schwert (1989) but contrary with Liljeblom and Stenius (1997). On the other hand, Sardosky (2003) has investigated the technology stock returns and finds that the conditional volatility of crude oil price, term premium, and consumer price index significantly influence conditional volatility of technology stock price in the U.S. Beltratti and Monara (2006) examine Standard and Poor 500 returns volatility and find the existence of linkages between macroeconomic and stock market volatility in two directions and the causality direction is stronger from macroeconomic volatility to stock market volatility. The significant variables in their study are the interest rate, money supply growth, output, and inflation volatility. Based on survey data from Survey of Professional Forecasters (SPF), Arnold and Vrugt (2008) provide empirical evidence that stock market volatility is significantly related to the macroeconomic uncertainty over the period of 1969 to 1996. They claim that the macroeconomic uncertainty measures estimated from SPF are more closely related to recessions than the time series based volatility.

In the recent years, similar studies have been focused on emerging markets. The study in Latin American countries has been conducted by Abugri (2008). The author shows that volatility of stock market returns is affected by macroeconomic shocks, and global factors (like Morgan Stanley Capital International (MCSI) and the US Treasury bill) appear to be more important than domestic variables in explaining stock returns across emerging markets. Adjasi (2009) analyses the Ghana Stock Exchange and finds higher volatility in cocoa price, and interest rate increases the volatility of stock prices while higher volatility in gold prices, oil prices, and money supply reduces the volatility of stock prices. The latest study is found in South Africa by Chinzara (2011). This author reports positive volatility spillovers from the Treasury bill rate, the exchange rate and the gold price, and negative volatility spillovers from inflation. For the related study in Malaysia, to the best of our knowledge, the only relevant study is Zakaria and Shamsuddin (2012). They use industrial production index (IPI), consumer price index (CPI), interest rates, exchange rate and money supply and show a weak relationship between stock market volatility and macroeconomic volatilities from January 2000 to June 2012.

In summary, the relationship between macroeconomic volatility and stock market volatility is confirmed as mixed. Some authors in the developed markets document the relationship as weak (Schwert, 1989 and Morelli, 2002), but some report it as strong (Chiang and Chiang, 1996; Liljeblom and Stenius, 1997; Sardosky, 2003; Abugri, 2008). Nevertheless, all the above studies have included a different set of macroeconomic variables. There seems to be no standard set of macroeconomic variables are documented. The variables that are commonly used in the empirical studies include interest rate, CPI, industrial production, money supply, and exchange rate. The exceptional variables are oil price and gold price which are employed by Adjasi (2009) and Chinzara (2011).

3. Data and Methodology

3.1 Data

Considering Malaysia as an oil producing country, our study takes into account a set of common variables as stated above and crude oil price as independent variables. Table 1 summarises the definition for each variable. The natural logarithm is taken to transform the variables into the rate of return or growth rate. Monthly data covering the period from January 2001 to December 2014 are collected. We determine the breakpoint of KLCI using Zivot-Andrew unit root test and separate the sample period into two sub-sample periods, i.e. pre-GFC (from January 2001 to March 2009) and post-GFC (from April 2009 to December 2014).

Table 1: Definition of data.

Variables	Measures	Source
Malaysia stock market return (*RKLCI*)	$\Delta \ln(KLCI)$	Central Bank of Malaysia
Change in exchange rate (*REXR*)	$\Delta \ln(RM/USD)$	Central Bank of Malaysia
Money supply growth (*RMS*)	$\Delta \ln(M2)$	Central Bank of Malaysia
Industrial production growth (*RIP*)	$\Delta \ln(IPI)$	Central Bank of Malaysia
Inflation rate (*RCPI*)	$\Delta \ln(CPI)$	Central Bank of Malaysia
Change in crude oil price (*RCOP*)	Δ ln (Brent crude oil price)	U.S. Energy Information Administration
World return (*RMSCI*)	$\Delta \ln(MSCI)$	*MSCI* Global Equity Indexes
World risk-free rate (*WRF*)	US 3-month Treasury Bill (annual rate)	Board of Governors of the Federal Reserve System

Autoregressive conditional heteroscedasticity (ARCH) and generalised autoregressive conditional heteroscedasticity (GARCH) models that introduced by Engle (1982) and Bollerslev (1986) have been widely used in the studies of conditional volatility of the stock market and macroeconomic variables. Liljeblom and Stenius (1997) use GARCH(1,1) to estimate the conditional volatility of stock return, growth rates of CPI, industrial production, money supply and changes in the terms of trade. Morelli (2002) uses GARCH(1,1) to estimate the conditional volatility of the stock market and exchange rate, and ARCH(1) to estimate the conditional volatility of industrial production, inflation, real retail sales and M1 money supply. Chiang and Doong (1999) use GARCH(1,1)-M to model the monthly stock excess return based on the real and financial volatility.

3.2 Measuring Stock Market Volatility

The model in this study is unique as compared to previous related studies because we estimate the stock market excess return using international capital asset pricing model (CAPM) to show the integration between Malaysian stock market with the international market. This model has been introduced by Solnik (1977) and Stehle (1977). It is widely examined by other researchers in the study of international portfolio of stock excess return (Harvey 1994; Buckberg, 1995 and Gerard et *al*., 2003). Harvey (1994) provides statistical tests of the single-factor model to explore emerging market returns in relation to global risk. He finds evidence that Malaysia has a significant beta which shows a relation between Malaysian market return and world market excess return. Buckberg's (1995) test of conditional international CAPM reveals that Malaysia is one of the emerging markets that integrated with the global market. Following this, we employ single-factor international CAPM to estimate KLCI excess return and then calculate the volatility of KLCI using ARCH(1) model. The model takes the form:

$$RKLCI_t - WRF_t = a + b(RKLCI_{t-1} - WRF_{t-1}) + c(RMSCI_t - WRF_t) + \varepsilon_{KLCI,t} \tag{1}$$

$$\varepsilon_{KLCI,t} \sim N(0, \sigma^2_{KLCI,t})$$

$$\sigma^2_{KLCI,t} = \omega_{KLCI} + \alpha_{KLCI}\varepsilon^2_{KLCI,t-1} \tag{2}$$

where RKLCI represents Malaysian stock market return, RMSCI represents world market return, and WRF represents world risk-free rate. $\alpha_{KLCI}\varepsilon^2_{KLCI,t-1}$ is the residual with zero mean and conditional variance ($\sigma^2_{KLCI,t}$).

3.3 Measures of Macroeconomic Volatility

We employ ARCH(1) to estimate the volatility of inflation rate and industrial production whereas the volatility of money supply, exchange rate, and crude oil price are estimated using GARCH(1,1). The conditional mean equation will follow equation (3) while the conditional variance equation of ARCH(1) or GARCH(1,1) follow equations (4) and (5), respectively.

$$RX_t = a_X + b_X RX_{t-1} + \varepsilon_{X,t} \tag{3}$$

$$\varepsilon_{X,t} \sim N(0, \sigma^2_{X,t})$$

$$\sigma^2_{X,t} = \omega_X + \alpha_X \varepsilon^2_{X,t-1} \tag{4}$$

or

$$\sigma^2_{X,t} = \omega_X + \alpha_X \varepsilon^2_{t-1} + \beta_X \sigma^2_{X,t-1} \tag{5}$$

In equation (3), the macroeconomic variables (RX_t) is regressed on its own lagged which follows AR(1) process. a_X is intercept and $\varepsilon_{X,t}$ is residual term which is distributed as $N(0, \sigma^2_{X,t})$. $\varepsilon^2_{X,t-1}$ represents the ARCH term and $\sigma^2_{X,t-1}$ represents the GARCH term.

3.4 Methodology

Our analysis is carried out in two stages. First, the relationship between the conditional volatility of KLCI and macroeconomic variables is examined using

Granger causality test. This test determines whether the conditional volatility of macroeconomic variables causes the conditional volatility of KLCI and vice versa. We use first difference data volatility series for the causality test. Second, multiple regression analysis is performed to test the relationships of the macroeconomic conditional volatilities on the conditional KLCI conditional volatility. The regression model is given as in equation (6).

$$VKLCI_t = a + b_1 VCPI_t + b_2 VIP_t + b_3 VMS_t + b_4 VEXR_t + b_5 VCOP_t + \varepsilon_t \tag{6}$$

where $VKLCI_t$ represents the volatility of stock market, $VCPI_t$ represents the volatility of inflation, VIP_t represents the volatility of industrial production growth, VMS_t represents the volatility of money supply growth, $VEXR_t$ represents the volatility of exchange rate growth, and $VCOP_t$ represents the volatility of crude oil price growth. We use this model for pre- and post-GFC periods.

4. Empirical Results and Discussion

Before proceeding to estimate the volatility of stock return and macroeconomic variables, we employ three stationary tests: Augmented Dickey-Fuller (*ADF*) (Dickey and Fuller, 1981), Phillip-Perron (*PP*) (Phillips and Perron, 1988) and Zivot-Andrews (*ZA*) (Zivot and Andrews, 1992) to detect unit root of all data. The results are shown in Table 2. The *ADF* and *PP* unit root tests results indicate that the series are *I*(1). In addition to *ADF* and *PP* unit root tests, we use the *ZA* test to detect the possible existence of structural breaks in the time series. We use *ZA* model 1 which allows for a break in the intercept, and model 3 which allows for a break in the intercept and slope to perform the analysis[4]. Two observations are presented. First, consistent with the *ADF* and *PP* tests, the *ZA* test indicates that all series follow *I*(1) process. Secondly, all series show breakpoints during the GFC years of 2007-2009. Important note from the second observation, we use the KLCI breakpoint (2009M4) that identified by ZA test to divide our sample into pre-GFC and post-GFC periods. This breakpoint is also consistent with the second stimulus package announced by the government in March 2009 to overcome the impact of GFC in the country.

Table 3 shows the results of Granger causality tests. For the pre-GFC period, there is no significant causality either from macroeconomic volatility to stock market volatility or from stock market volatility to macroeconomic

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[4] ZA model 1: $\Delta y_t = c + \alpha y_{1-t} + \beta t + \lambda DU_T + \sum_{j=1}^{k} \delta_j \Delta y_{t-j} + \varepsilon_t$

ZA model 3: $\Delta y_t = c + \alpha y_{1-t} + \beta t + \lambda DU_T + \gamma DT_t + \sum_{j=1}^{k} \delta_j \Delta y_{t-j} + \varepsilon_t$

where DU_t is a dummy variable for mean shift at each possible break-time (TB) which takes the value of one if t > TB and zero otherwise. Meanwhile, DT_t represents a dummy variable for time shift which equals to t – TB if t > TB and zero otherwise. The null hypothesis tests the series contains a unit root with drift against the alternative hypothesis that the series is stationary with one-time break in the intercept at an unknown breakpoint (model 1) or the series is stationary with one-time break in the intercept and slope at an unknown breakpoint (model 3).

volatility. Meanwhile, for the post-GFC period, the volatility of inflation rate, exchange rate and change in crude oil price significantly Granger causes the volatility of stock market at 10% significant level or more. The volatility of industrial production growth and money supply growth do not Granger cause the volatility of stock market. No causality moving from stock market volatility to macroeconomic volatility is detected for the post-GFC period.

Table 2: Unit root test.

	ADF (intercept)		PP (intercept)		ZA (intercept)		ZA (intercept and trend)	
	Level	First difference	Level	First difference	Level (TB)	First difference (TB)	Level (TB)	First difference (TB)
KLCI	-0.36	-11.44*	-0.57	-11.55*	-3.83*** (2008m1)	-11.81* (2009m4)	-4.11*** (2008m6)	-11.92* (2009m4)
MSCI	-1.17	-10.85*	-1.24	-10.96*	-5.86*** (2008m6)	-11.49* (2007m11)	-5.81*** (2008m6)	-11.45** (2007m11)
CPI	0.39	-8.62*	0.65	-8.65*	-4.24** (2008m4)	-9.63* (2008m8)	-4.28 (2005m8)	-9.60* (2008m8)
IPI	-1.22	-3.53*	-1.44	-33.86*	-5.29*** (2008m9)	-7.66** (2008m2)	-4.98*** (2008m9)	-7.95*** (2008m2)
MS	3.19	-11.54*	3.04	-11.70*	-4.45*** (2011m9)	-12.74*** (2004m8)	-3.92*** (2011m9)	-12.81** (2007m3)
EXR	-1.41	-11.95*	-1.42	-11.93*	-2.28** (2006m10)	-12.46** (2005m1)	-3.41*** (2010m3)	-12.51*** (2007m9)
COP	-2.00	-7.89*	-1.85	-7.94*	-3.31** (2009m9)	-8.17 (2008m7)	-3.76* (2011m2)	-8.30** (2009m1)

Note: (***), (**) and (*) indicate significant at 1%, 5% and 10% levels, respectively.

Table 3: Granger causality between stock market volatility and macroeconomic volatility.

Pre-GFC: 2001M1-2009M3			Post-GFC: 2009M4-2014M12		
Direction of causality	*F*-statistic	Results	Direction of causality	*F*-statistic	Results
$VCPI \rightarrow VKLCI$	1.160	$VCPI \not\leftrightarrow VKLCI$	$VCPI \rightarrow VKLCI$	1.716*	$VCPI \rightarrow VKLCI$
$VKLCI \rightarrow VCPI$	1.500		$VKLCI \rightarrow VCPI$	0.813	
$VIPI \rightarrow VKLCI$	0.638	$VIPI \not\leftrightarrow VKLCI$	$VIPI \rightarrow VKLCI$	0.733	$VIPI \not\leftrightarrow VKLCI$
$VKLCI \rightarrow VIPI$	0.775		$VKLCI \rightarrow VIPI$	1.376	
$VMS \rightarrow VKLCI$	0.574	$VMS \not\leftrightarrow VKLCI$	$VMS \rightarrow VKLCI$	1.169	$VMS \not\leftrightarrow VKLCI$
$VKLCI \rightarrow VMS$	0.306		$VKLCI \rightarrow VMS$	0.402	
$VEXR \rightarrow VKLCI$	0.702	$VEXR \not\leftrightarrow VKLCI$	$VEXR \rightarrow VKLCI$	2.056**	$VEXR \rightarrow VKLCI$
$VKLCI \rightarrow VEXR$	1.227		$VKLCI \rightarrow VEXR$	0.280	
$VCOP \rightarrow VKLCI$	0.983	$VCOP \not\leftrightarrow VKLCI$	$VCOP \rightarrow VKLCI$	2.534**	$VCOP \rightarrow VKLCI$
$VKLCI \rightarrow VCOP$	0.821		$VKLCI \rightarrow VCOP$	0.648	

Note: (**) and (*) indicate significant at 5% and 10% levels, respectively.

The results of the regression analysis are shown in Table 4. The results for model (6) show a low value of R^2 in the pre-GFC period. The macroeconomic variables do not affect stock market volatility in the pre-GFC period which is demonstrated by the insignificant F-statistic. However, the results improve significantly during and after GFC. The model shows a better fit with a higher value of R^2 (15.56%). The impact of macroeconomic volatility on stock market volatility appears to be significant in the post-GFC period indicated by the significant F-statistic.

Table 4: Estimated results from regression of stock market volatility.

	Pre-GFC: 2001M1-2009M3					
Variables	Model (6)		Model (6a)		Model (6b)	
	Coefficient	Statistic	Coefficient	Statistic	Coefficient	Statistic
VBLR						
VCPI	-0.0816	-0.1312	-0.0769	-0.1235	-0.0843	-0.1358
VIPI	-0.2776	-1.0934				
VMS	1.0110	0.6850	1.0705	0.7250		
VEXR	-0.7877	-1.0059	-0.8010	-1.0219	-0.8097	-1.0358
VCOP	0.0163	1.1214	0.0141	0.9776	0.0154	1.0764
C	0.0016	3.9408***	0.0012	5.2419***	0.0013	9.2167***
R-squared		0.0342		0.0215		0.0159
F-statistic		0.6447		0.5060		0.5019
Q(12)		18.1820		20.6090*		18.7550*
Q^2 (12)		8.0590		7.6768		7.5185
	Post-GFC: 2009M4-2014M12					
Variables	Model (6)		Model (6a)		Model (6b)	
	Coefficient	Statistic	Coefficient	Statistic	Coefficient	Statistic
VBLR						
VCPI	6.3738	1.1767	6.5150	1.2108	6.3462	1.1838
VIPI	-0.0533	-0.5470				
VMS	1.4750	0.7848	1.4744	0.7888		
VEXR	0.0914	0.4373	0.1081	0.5253	0.1551	0.7901
VCOP	0.0241	2.6833***	0.0245	2.7534***	0.0262	3.0544***
C	0.0008	3.0275***	0.0007	3.4129***	0.0008	4.3974***
R-squared		0.1556		0.1516		0.1433
Adjusted R-squared		0.0886		0.0985		0.1038
F-statistic		2.3214*		2.8583**		3.6248**
Q(12)		4.9258		5.2449		5.0013
Q^2 (12)		2.9968		2.8192		2.6074

Note: (***), (**) and (*) indicate significant at 1% , 5% and 10% levels, respectively.

Nevertheless, none of the macroeconomic variable volatility shows significant impact on the stock market volatility in the pre-GFC period. In the post-GFC period, only crude oil price volatility significantly and positively affects the stock market volatility. This result is consistent with the finding of Granger causality test as well. The impacts of individual macroeconomic volatility are quite consistent before and after the GFC. Only for the volatility of inflation rate and exchange rate which show a change in the sign of its coefficient from negative to positive but these variables are insignificant.

The results of this paper compare well with other related works in developed markets that show weak evidence of macroeconomic volatility to explain stock market volatility. Schwert (1989) reports 2.2 - 5% of R^2 in the US and Morelli (2002) confirms 4.4% in the UK although Liljeblom and Stenius (1997) show 16% - 67% in Finland. Additionally, Chinzara (2011) highlights that the total macroeconomic volatility only explains 25% of the variation in South African stock market volatility if structural breaks are not taken into account but it improves to 80% when structural breaks are considered.

Particularly, the volatility of crude oil price is an important influence on stock market volatility in Malaysia. Those authors that include crude oil price volatility as a determinant are Sadorsky (2003), Adjasi (2009) and Chinzara (2011). All of these papers find crude oil price volatility has a significant impact on stock market volatility. Our results show a significant positive coefficient of crude oil price volatility which is in line with the findings documented by Chinzara (2011) in South Africa but contradict with Adjasi (2009). Sadorsky (2003), however, does not report the sign of the relationship.

The significant and positive coefficient of crude oil price volatility during and after the GFC indicates that an increase in the crude oil price volatility will lead to higher stock market volatility in Malaysia. Crude oil price volatility does not seem to have a significant impact before 2008 due to the government control over the price of petroleum in Malaysia, and the stock market is less sensitive to the crude oil price changes. As part of government's subsidy rationalisation program, fuel subsidy has been gradually removed, and the price of petrol has been adjusted several times since 2008. This has rendered the exposure of Malaysian firms to more volatile world crude oil price, and firms become more sensitive to crude oil price fluctuations. As an oil-exporting country, when the price of crude oil decreases, it is a signal of bad news and leading to reduce investors' confidence in corporate earnings which in turn affect stock market negatively and increase in its volatility. During and after GFC, the world crude oil price shows greater volatility than before GFC. This might be the reason why Malaysian stock market volatility is significantly and positively affected by the volatility of crude oil price after the GFC.

4.1 Robustness Check

To assess the robustness of the multiple regression results, we employ the following additional models. In model (6a) the conditional volatility of industrial production is excluded, and model (6b) excludes the volatility of money supply. We exclude these two variables because they are found to be less volatile. These tests allow us to determine which variables should be included to obtain the best model in predicting the Malaysian stock market volatility.

$$VKLCI_t = a + b_2 VCPI_t + b_4 VMS_t + b_5 VEXR_t + b_6 VCOP_t + \varepsilon_t \tag{6a}$$

$$VKLCI_t = a + b_4 VCPI_t + b_5 VEXR_t + b_6 VCOP_t + \varepsilon_t \quad (6b)$$

In general, our model is robust as the results of the regression analysis remain consistent across different models. The regression models are less well defined in the pre-GFC period. However, it performs better in the post-GFC period indicated by the high value of R^2 and significant F-statistic.

5. Conclusion

This study examines the impact of 2008 GFC on the relationship between macroeconomic volatility and stock market volatility. Monthly data spanning from January 2001 to December 2014 is divided into pre- and post-GFC periods. To consider the effect of a global factor, the world excess return is included in the conditional mean equation of ARCH(1) to estimate the conditional volatility of stock market excess return. ARCH(1) is used to model the conditional volatility of inflation and industrial production growth whereas GARCH(1,1) for money supply, exchange rate, and crude oil price.

Granger causality tests show no evidence that the macroeconomic volatility causes the volatility of the stock market for the pre-GFC period. Nevertheless, the causality of the inflation rate, exchange rate, and crude oil price volatility are significant in the post-GFC period. The 2008 GFC has altered the influence of macroeconomic volatility on the Malaysian stock market volatility. It is also evident through the regression analysis that Malaysian stock market volatility is weakly explained by the volatility of macroeconomic variables before the GFC, where no macroeconomic volatility is found to affect significantly affect Malaysian stock market volatility during this period. However, the influence of macroeconomic volatility on stock market volatility has been strengthened during and after the GFC. The volatility of crude oil price is the only variable that shows the significant positive impact on Malaysian stock market volatility.

Overall, the findings of this paper have provided some empirical evidence that macroeconomic volatility has an influence on stock prices volatility during and after GFC. More attention should be given to crude oil price volatility. Malaysia as an oil exporting country, its stock market is subject to greater influence in the world oil market. A prudent economic policy is needed to reduce the negative impact of crude oil price volatility besides sustaining the country's economic growth.

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