Journal of Applied Finance & Banking, vol. 4, no. 1, 2014, 91-102
ISSN: 1792-6580 (print version), 1792-6599 (online)
Scienpress Ltd, 2014

Macroeconomic Variables Effect on US Market Volatility using MC-GARCH Model

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Abstract

Forecasting equity volatility was thoroughly investigated during the past three decades. The majority based their forecasts on the dynamics of the underlying equity time series. They helped better understand the dynamics of these time series and understand different aspects of volatility. Other models went a step further to include the effect of news announcement on equity volatility. The vast majority ignored the effect of macroeconomic variable or the state of the economy. This paper proposes a volatility-forecasting model that accounts for effect of fundamental macroeconomic variables that reflect the state of the economy. The explanatory variables used measure the stage of business cycle, uncertainty about the fundamental economic variables, and a prediction of the future state of the economy. All these variables have been documented in the empirical literature or in the economic theory to have an effect on equity volatility. Another major contribution is the way volatility is being measured. The proposed model uses MC-GARCH model to measure the long-term volatility without losing much of the relevant information or the characteristics of the volatility time series. This paper also has some policy implications as it shows the relationship between fundamental macroeconomic variables and equity market volatility.

JEL classification numbers: E27, E37, E32, E44.
Keywords: Modified Component GARCH; long-run volatility; macroeconomic effect, Forecasting, Business cycles.

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Article Info: *Received :* September 23, 2013. *Revised :* October 21, 2013.
Published online : January 1, 2014

1 Introduction

During the past three decade a large number of models have been developed to forecast equity volatility. These models attempted to forecast volatility based on three types of information; characteristics of equity time series, effect of news or announcements, and effect of macroeconomic variables. The vast majority of research in this area focused on forecasting volatility based on the characteristics of the equity time series. See for example of work of [1], [2], [3], and [4]. This line of research led to the development of more accurate and sophisticated models to forecast volatility, namely univariate and multivariate GARCH models. [5] provided a survey for the univariate and multivariate GARCH models respectively.

Other researchers attempted to forecast volatility as a reaction to news or announcements. [6] for instance studied the short-term volatility movements as the US macroeconomic information is released. [7] evaluate the forecasting performance of time series models for realized volatility taking into consideration a number of factors including macroeconomic announcements. Other attempts include [8] who found that important political events tend to be associated with sudden jumps in volatility. [9] and [10] who found out that on average the portion of volatility related to world factors is quite small for emerging markets. [11] examined global and local events (social, political, and economic) to assess their effect on volatility in emerging markets. More recent attempts using intra-daily return data include [12], [13], [14] and [15].

These two types of models failed to use other type of available critical information. They ignore the relationship between the state of the economy and the equity volatility, a third category of models incorporate this relationship. These models are relatively scarce. Even the attempts made generally provided weaker relationships than what would be expected. Among the early attempts to incorporate the state of the economy, [16] used leverage and the volatility of industrial production to explain the high volatility during the 1930s. [17] and [18] used the US macroeconomic and microstructural factors to explain the US time varying volatility. Schwert used a long time series data starting from the 19^{th} century to measure the relationship between equity volatility and 3 variables; real and nominal macroeconomic volatility, level of economic activity, and financial volatility. [19] proposed to model equity volatility as a product of both macroeconomic effects and the dynamics of the equity volatility time series. [20] proposed the same idea but used a class of component models that distinguished between short term and secular volatility movements.

Volatility is not just volatility any more. There are conditional and unconditional volatility, short term and long term volatility, static and dynamic volatility. Also, the arrival of new heterogeneous information affects the volatility dynamics with differing frequencies; thus, the equity volatility aggregates numerous independent volatility components [21]. Furthermore, [22] showed that traders with different holding periods could lead to different volatility components. [23] and [24] showed that the actual sample volatility decays much slower than the exponential decay pattern as predicted by the classic GARCH models. Most models distinguish the total conditional variance into short-run, long run variance components and other components, such as seasonal variance component. [25] proposed a two component model that decomposes the total conditional variance into permanent and transitory variance components.

The goal of this paper is to develop a model that utilizes information provided by the state of the economy. The proposed model integrates the effect of fundamental macroeconomic variables into the volatility-forecasting model. Another key improvement in this model is the way volatility is defined. The proposed model utilizes a newly developed class of the component GARCH, namely Modified Component GARCH (MC-GARCH), developed by [26]. The MC-GARCH provides a superior filtration that filters out the short-term volatility from the time-varying long run conditional variance. This paper further explores the policy implications of establishing the relationship between the equity markets volatility and macroeconomic variables.

We proceed in this study as follows: In section 2, the variables used are described along with the process of selecting them and their sources. Then the methodology and the proposed model are discussed followed by the data used. Section 3 presents the empirical results and their interpretations. In section 4 the conclusion is presented.

2 Data and Methodology

2.1 Methodology

The purpose of this paper is to find out which macroeconomic variables has significant effect on the long run volatility of market portfolio. We use the S&P 500 index as the proxy for market portfolio. It is needless to say that empirical results are significantly affected by the employed methodologies. Therefore, it is indispensable to examine the effectiveness of alternative methodologies before we draw any conclusions about the topic.

It is well known that the popular methodologies to filter the long run volatility are the [19] and [25]. [26] modify the Engle and Lee model and show their modified model captures the long run volatility better. This study uses the daily returns from the S&P 500 index and average the filtered daily long run volatility for each year. We compare the empirical results using the annualized long run volatilities from Engle and Rangel model and Cho and Elshahat model. [3] The empirical findings will be discussed with the results from the better-performed methodology.

[26] identify the two main conditions of coefficients of the [25] model under which the long-run variance component is not filtered from the total conditional variance. These two mal-adjustment conditions are caused by the innovation term in the long run variance equation in Engle and Lee model. Hence, Cho and Elshahat redefine the innovation in the long run variance based on the definition of innovation in time series as stated in [27]. Specifically, Cho and Elshahat's modified component GARCH model (MC-GARCH hereafter) model is as follows:

$$r_t = E[r_t] + e_t \tag{1}$$

with

$$e_t = \sqrt{h_t} v_t \tag{2}$$

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[3]This paper does not specify the [19] model. Only the empirical results from their model will be discussed.

$$h_t = q_t + \alpha_1\left(e_{t-1}^2 - q_{t-1}\right) + \beta_1\left(h_{t-1} - q_{t-1}\right) \tag{3}$$

$$q_t = w + \phi\left(h_{t-1} - q_{t-1}\right) + \rho q_{t-1} \tag{4}$$

Note that the long run variance equation in (4) is different from that in the [25] model as shown below:

$$q_t = w + \phi\left(e_{t-1}^2 - h_{t-1}\right) + \rho q_{t-1} \tag{5}$$

The methodology to examine the macroeconomic determinants of the long run volatility is regression analysis. The dependent and independent variables are all annual values for the regression analysis.

2.2 Data

It is worth mentioning again here that volatility is not just volatility. After three decades of volatility research and development it became a fact that not any measure of oscillation is the correct measure of volatility. A major contribution of this paper is the attention paid to measuring the dependent variable of the proposed model. The dependent variable used is the long run volatility using the daily returns on S&P500 index. Specifically,

$$r_t = 100\left(\ln\left(P_t\right) - \ln\left(P_{t-1}\right)\right) \tag{6}$$

The long run volatility is measured using the MC-GARCH model. While the principle of multiple components is widely accepted, there is neither a clear agreement on how to specify the dynamics of each of the components nor an agreement on the filtering method. The MC-GARCH is found to provide a long run forecast without losing much of information available. The use a model that filters too much information simply would fail to capture an existing effect. The estimated daily long run volatilities are annualized by average each year to be used in regression analysis.

There are many potential macroeconomic variables that affect the long run market volatility. In this paper we use the [19] model as a benchmark to compare our results. To make a fair comparison, the same variables used by [19] are used in this research. The variables used are inspired by prior empirical research or economic theory. The variables are intended to measure the following; the effect of business cycles, the uncertainties about fundamentals, and prediction of economic factors or future states of the economy. [19] tested their model using a sample that covers different countries, developed and under developed. Thus, they used control variables to control for the market development level and economy size. These two categories are out of the scope of this paper, as our focus is only on the US market.

The real GDP growth rate is used to measure the stage of the business cycle. Our hypothesis here is the negative relationship between volatility and the business cycle [28]. That is to say that during recession volatility is expected to be higher. [29] and [30] documented the empirical regularity that risk-premia are counter cyclical. To measure the uncertainty or the volatility of the fundamental macroeconomic variables and their effect on the equity market volatility, we used the volatility of three macroeconomic variables; real GDP, short term interest rates and exchange rates. For instance, [31] used stochastic volatility models of macroeconomic variables to forecast volatility; [32] documented that equity market volatility are affected by inflation and earnings uncertainty.

The level of inflation is used as a predictor of the future state of the economy as it is a major goal for any central bank. Inflation level is associated with any monetary policy decision and future economic growth as documented by the economic theory. Here we add one more independent variable, which is the growth rate of M2. The main macroeconomic effect of growth of M2 is related to inflation. The CPI reflects two different sources of inflation: monetary inflation and structural (non-monetary) inflation. Hence, it is meaningful to separate the effect of monetary inflation on the long run market volatility by including the growth rate of M2. The growth rates of M2 are annual values.

We use the three-month Treasury bill rate as [32] short-term interest rate and the dollar index as the exchange rate. Both variables are downloaded from the federal funds reserve website. The inflation rate is defined as the annual growth of CPI (consumer price index). The inflation rate is the growth rate of CPI using December CPI values of each year. Inflation is downloaded from the Bureau of Labor statistics (BLS) Web site. The dollar index is calculated using the exchange rates of six major currencies: the British pound, Canadian dollar, euro, Japanese yen, Swedish krona and Swiss franc. This index was initiated in 1973 with a base of 100 and the dollar index calculated is relative to this base.

Following [19], all the annualized volatility values of monthly short term interest, exchange rate, GDP and inflation are computed by MA(1). Using the monthly data the annual standard deviations of residuals of MA(1) models are computed.

3 Empirical Results

3.1 Performance of Alternative Methodologies

Before discussing the results of regression analysis on the U.S. macroeconomic determinants of the long run market volatility, we compare the performance of the alternative methodologies. Figure 1 shows the estimated total volatility and the filtered long run volatilities from Engle and Rangel and Cho and Elshahat models. Since the Engle and Rangel model use spline method, the filtered long run volatility seems to lose the innovations in the long run volatility series. Without reflection of innovations in long run volatility, it is possible that important macroeconomic variables may lose the explanatory power for the long run market volatility. The small value of R square of Engle and Rangel in Table 1 indicates that the long run variance from their model loses important macroeconomic information that affect the market uncertainty. In addition to the small R square, there is only one macroeconomic variable that significantly affect the long run market volatility obtained from the Engle and Rangel's model.

For the comparison purpose, we also use the total conditional variance (h_t) as the dependent variable to examine how the macroeconomic variables affect the annualized. We should expect that there are few macroeconomic variables that determine the total volatility because the total volatility (h_t) contains short-term volatility component in it. In accordance with this expectation, only two independent macroeconomic variables have statistically significant explanatory power.

Figure 1 shows that unlike the long run volatility from Engle and Rangel model, that from

Cho and Elshahat model captures the innovations in the long run volatility process. The estimation results in Table 1 also prove that the filtered long run volatility using Cho and Elshahat model better reflect the macroeconomic effects. Put differently, most of macroeconomic variables are statistically significant with the expected signs of coefficients. Hence, the regression results are discussed using the results from [26] model.

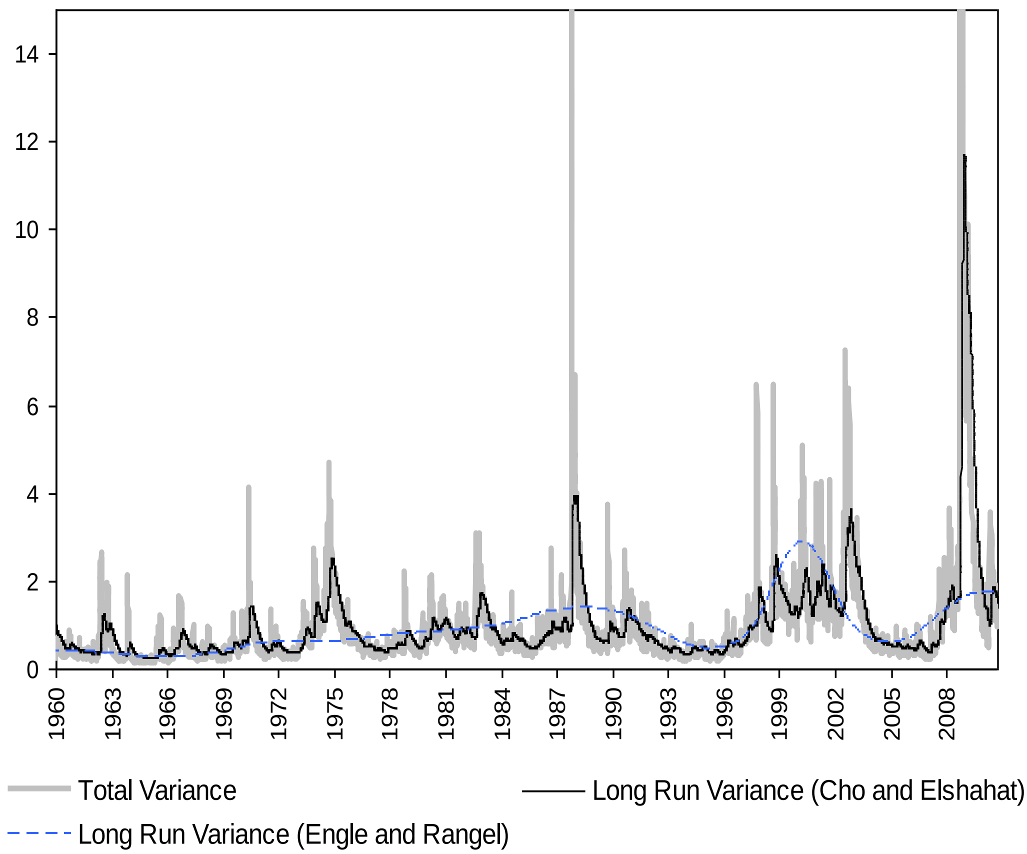

Figure 1: Filtered long run volatilities

The total volatility contains both the temporary component and long run components. The long run volatilities are estimated using two different models from Engle and Rangel (2008) and Cho and Elshahat (2011). The estimated values of total volatility larger than 15 is trimmed for the better visibility of the filtered long run volatilities. For the GARCH models the returns on S&P500 index are used. Specifically:

$$r_t = 100\left(\ln\left(P_t\right) - \ln\left(P_{t-1}\right)\right) \tag{6}$$

Because the percentage returns (as shown by multiplication by 100 in (6)) are used, the scale of the estimated volatilities is large.

Table one shows the results of the model proposed. Using the same independent macroeconomic variables, three different models yield different results mainly because they use different dependent variable. The three models use volatility as the dependent variable, but measured differently. Our model provides a strong forecasting power without losing much information. The estimated daily long run volatilities are annualized by average each year. Grgdp = Growth rate of real GDP, Irate = Short term interest rate. * represents the statistical significance at or less than the 10% critical value.

Table 1: Results of regression analysis

Dependent variable		Long variance (q_t) (Cho&Elshahat)		Long variance (q_t) (Engle&Rangel)		Total Conditional variance (h_t)	
Independent variable		Coeff.	t Value	Coeff.	t Value	Coeff.	t Value
	Intercept	-5.886	**-2.04***	-4.585	**-2.05***	-3.512	-1.04
(1)	Log nominal GDP	0.736	**2.59***	0.580	**2.63***	0.487	1.47
(2)	Growth rate real GDP	-0.289	**-3.76***	-0.062	-1.04	-0.305	**-3.39***
(3)	Annual inflation rate	0.017	0.25	0.003	0.05	-0.057	-0.69
(4)	Growth rate of M2	-0.050	-0.95	0.047	1.15	-0.005	-0.09
	Growth rate of M2 lagged by 1 year	0.148	**3.04***	0.048	1.27	0.120	**2.10***
(5)	Volatility of grgdp	0.983	**2.52***	0.510	1.68	0.648	1.42
(6)	Volatility of dollar index	0.347	**1.85***	0.186	1.27	0.226	1.03
(7)	Volatility of irate	-1.419	-0.96	-0.626	-0.55	0.209	0.12
	Volatility of irate lagged by 3 month	-3.139	-1.66	0.249	0.17	-3.123	-1.41
	Volatility of irate lagged by 6 month	3.407	**2.90***	-0.163	-0.18	2.072	1.50
(8)	Volatility of inflation rate	-1.068	-0.92	-1.363	-1.52	0.557	0.41
	R-Square	0.68		0.436		0.633	
	N	37		37		37	

3.2 Macroeconomic Determinants of the Long Run Market Volatility

The estimation results in Table 1 are very good given the small number of observations. The number of observations (number of years) is 37. The reason for the small number of observations is due the independent variable, Dollar Index. Unlike other variables, the values of Dollar Index are available from 1973. The effective number of independent variables for the regression is 8: (1) Log nominal GDP, (2) growth rate of real GDP, (3) Inflation rate, (4) Growth rate of (lagged) M2, (5) volatility of real GDP, (6) volatility of exchange rate (dollar index), (7) volatility of (lagged) short term interest rate, and (8) volatility of inflation rate. Among these eight independent variables, six variables determine the long run market volatility statistically significantly. The two inflation variables (3) and (8) are insignificant.

The rationale of using nominal GDP as independent variables is to examine which of the leverage effect and diversification effects dominates on the long run market volatility as the size of the U.S. economy grows bigger. Results in Table 1 shows that the leverage effect dominates the diversification, as the size of U.S. economy grows bigger. This result is also observed in [19]. [17] and [28] show that economic recession is the most important factor that affects the US stock-return volatility. Our results also support their results in that the long run market volatility increases as the real economic activities diminish. The results without Argentina sample in [19] also support this result.

It is well known that the stock can be a perfect hedge against inflation only if prices and costs increase uniformly and hence a firm passes on all increased costs to its buyers. However, inflation is rarely uniform in affecting prices and costs. As a result, inflation increases earning volatility and hence reduces value. We expect to find the negative relation between the long run market volatility and these inflation variables (3) Inflation rate and (8) volatility of inflation rate).

However, results show that these two inflation variables are not significant. The explanatory power of volatility of inflation rate disappear when other explanatory variables are included, especially, growth rate of real GDP, the regression model. Also the correlation coefficient in Table 3 shows that there is significant positive relation of inflation volatility to the long run stock return volatility as shown by 34.4%. The level of inflation rate does not have any explanatory power for the long run volatility. The reason can be that level of inflation may be adjusted into prices and costs in the long run. Hence, only uncertainty in inflation rate causes the increase in long run volatility.

This table shows the estimation results of Cho and Elshahat's (2011) modified component GARCH model. In the following model, h_t represents the total volatility and q_t the long run volatility. * represents the statistical significance at or less than the 10% critical value. MC-GARCH model is specified as follows:

$$r_t = E[r_t] + e_t \tag{1}$$

with

$$e_t = \sqrt{h_t}\, v_t \tag{2}$$

$$h_t = q_t + \alpha_1\left(e_{t-1}^2 - q_{t-1}\right) + \beta_1\left(h_{t-1} - q_{t-1}\right) \tag{3}$$

$$q_t = w + \phi\left(h_{t-1} - q_{t-1}\right) + \rho q_{t-1} \tag{4}$$

Table 2: The estimation results of long run volatility

	Coefficient	**t Value**
ALPHA1	0.078	**14.94***
BETA1	0.877	**53.96***
W	0.002	**3.59***
RHO	0.998	**1141.26***
PHI	0.019	**2.50***
N	2,777	
LOGLIK	-15,592	

Table three shows the correlation coefficients for the variables used in the regression analysis. To compute the correlation coefficients, the same number of observations (37) that was used for the regression analysis was used. The computed correlation coefficients are multiplied by 100 in the table. **Grgdp = Growth rate of real GDP, Irate = Short term interest rate.** *represents the statistical significance at or less than the 10% critical value.

Table 3: Correlation coefficients

	Long run volatility	Log GDP	Growth rate of real GDP	Annual inflation rate	Growth rate of M2 lag by 1 year	Volati. of grgdp	Volati. of dollar index	Volati. of irate/ lagged by 3 mon/lagged by 6 mon.
Log nominal GDP	33.5							
Growth rate of real GDP	**-40.4***	-10.2						
Annual inflation rate	-22.4	**-73.7***	-14.9					
Growth rate of M2 lagged by 1 year	15.1	**-47.7***	15.8	31.9				
Volatility of grgdp	10.2	**-51.6***	-21.1	**58.0***	**37.8***			
Volatility of dollar index	23.5	-13.7	-9.7	6.7	24.1	17.7		
Volatility of irate/ lagged by 3 month/ lagged by 6 month	-9.0 -4.0 1.3	**-51.0*** **-47.3*** **-49.9***	**-39.2*** **-45.4*** **-36.3***	**65.6*** **59.6*** **54.5***	**27.4*** 23.8 25.6	**67.3*** **63.7*** **61.3***	**36.2*** **35.3*** **34.7***	
Volatility of inflation rate	**34.4***	13.0	**-56.0***	-0.2	15.8	**31.5***	3.1	24.2 23.7 20.8
Growth rate of M2	2.1	**-43.9***	1.9	19.2	**56.4***	**37.9***	11.2	**34.5*** **33.4*** **44.4***

We add new empirical findings about the effect of M2 on the long run volatility. As mentioned earlier, the growth of M2 can cause monetary inflation in the long run. Then, we should expect that the lagged growth rate of M2 should increase the uncertainty in earnings. In accordance with this expectation, there is significant positive correlation between lagged growth rate of M2 and volatility of real GDP as shown by 37.8%. Regression results also show that the lagged growth rate of M2 significantly increases the long run volatility.

Volatilities of fundamentals are important factors that affect the market volatility. As done in [19], we include the volatilities of real GDP, exchange rate (dollar index), interest rate and inflation rate. As expected these uncertainty in fundamentals significantly increase the long run market volatility. Unlike [19], we find that volatility of interest rate lagged by two quarters increases the market volatility.

4 Conclusion

This paper provides evidence that the fundamental macroeconomic variables and the state of the economy have a significant effect on the equity market's volatility. The authors' justification for the mixed results in the literature or non-significant relations are due to the use of contaminated volatility measures. Some of the measures of conditional volatility do not filter noise, and just use the total conditional volatility. The existences of too much noise obviously affect the relationship. Other models filter too much information and leave a long-term volatility measure that is unable to capture existing relations. The proposed model provides a model that can forecast long-term volatility without filtering out relevant information. In this paper, the proposed model is compared to the spline-GARCH model proposed Engle and Rangel 2008 and to the total conditional volatility. The results reached showed that the proposed model offers a stronger explanatory power and forecasting ability for equity volatility.

The results reached in this paper provide valuable insights for the policy makers, as it provide evidence of significant relationships between some fundamental macroeconomic variables and the equity market volatility. Starting with the effect of the business cycle as measured by the growth rate of real GDP, unlike the results reached by [19] our results are consistent with the economics literature that shows a significant negative relationship between the business cycle and the equity market volatility. Thus, our model expects volatility to be higher during recessions, consistent with [28] and [29].

To reflect the uncertainty about the fundamental macroeconomic variables, we used the volatility of three variables; real GDP, short-term interest rates, and exchange rate index. Consistent with the economic theory and the empirical literature, these three variables showed significant positive relationship with long-term equity volatility using the proposed model and no significant relationship using the Engle and Rangel Spline-GARCH model. This finding is just intuitive. As these macroeconomic variables become more volatility, the risk premia for equity securities will become more volatility, and thus the risk of the equity market volatility increase. The third explanatory variable used as a predictor of future state was the level of inflation. Consistent with the literature, our model showed a positive relationship between annual inflation rate and the equity market volatility, but the relation was not statistically significant. Even though our model did not result in a significant relation, it resulted in stronger relation as compared to the results reached by [19].

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