

Sovereign Bond Volatility versus Stock Volatility: Evidence from Ghana

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Abstract

In this paper, we examine return volatility in the sovereign domestic/foreign bond and stock markets in Ghana using ratios, correlation, ARCH/GARCH family models. The study considered daily returns covering periods from 1st May 2009 - 31st July 2018. We find that even though the bond market volatility has increased relatively over time, it is less volatile as compared to the stocks. More so, bonds are still an effective diversification medium as a result of nonexistence of trend in the correlation between bond and stock and the ratio of the bond to the stock. We show that the trend in volatility for Ghana Domestic Bond (GDB) and stock markets are negatively significant. Furthermore, we document that the ARCH model can be used to predict future values in the domestic bond return series. However, it cannot be used to predict future values in the Ghana Foreign Bond (GFB) and Stock daily return series.

Keywords: Volatility, Bond Market, Stock Market, Asset Allocation, ARCH, GARCH.

JEL Classification: G11, G17

1 Introduction

Volatility is seen as information flow in several classes of models (Jones, Lamont and Lumsdaine, 1998) and its analysis is crucial to the practice and theory of risk management, asset allocation and asset pricing (Andersen *et al.*, 2001). This has stimulated vibrant and burgeoning research into the return volatility physiognomies of stock and bond markets over three decades now.

Sovereign debt in Sub-Saharan Africa (SSA) over the last decade has witnessed profound changes after having enjoyed a “clean slate” through the Multilateral Debt Relief Initiative (MDRI) and the successors of debt relief under the Heavily Indebted Poor Country (HIPC) initiative (Dafe, Essers and Volz, 2018; Senga, Cassimon and Essers, 2018). In the zeal to boot external financing conditions, mitigate currency mismatches and address the huge infrastructural and social needs. Many ex-HIPC countries have documented a rise in sovereign debt to GDP ratios which has become a changing trend (Dafe, Essers and Volz, 2018).

It is widely believed that there is an exciting investor hunger for SSA bonds and stocks (Senga, Cassimon and Essers, 2018). This is fueled by the global financial crises aftermath of commodity price recovery, and all-time low record of interest rate in developed economies. Presbitero *et al.*, (2016) showed that developing and low-income countries are probably going to issue more international bonds (Eurobonds) should the US interest rate remain low. Notwithstanding the potential advantages of diversified debt, there are also some risks particularly for African countries sovereign Eurobonds (henceforth, foreign bonds). This is because they are denominated in US dollars which could lead to adverse pressure on the exchange rates and country’s foreign reserves when payments are due (Olabisi and Stein, 2015; Senga, Cassimon and Essers, 2018). Studies by Olabisi and Stein (2015) have also documented the high cost of borrowing as part of sovereign debt burden and can contribute to return volatility and future risk of default. Likewise, there have been alarming cases of a deficit in government budgets and instability in the macroeconomic framework since 2014 through to 2016 in Angola, Ghana and Zambia with noticeable consequences on domestic and foreign bond markets (Senga and Cassimon, 2018) which may spillover on other markets like stocks.

Whereas many earlier studies have compared bond and stock market volatility in developed markets. The volatility patterns exhibited in developing and less-income economies has not been broadly studied. In the light of providing such perspective, and convinced that the bond versus stock dispersions are not globally universal. We ask the question: do the bond and stock market volatility in developing markets change over time? More specifically, how is the relative change of the bond to the stock volatility in developing markets? How predictable are the volatility patterns in the bond and stock markets in developing markets? In seeking answers to these questions, we employ dataset from Ghana and analyze intertemporal volatility between sovereign bond returns (domestic and foreign) and stocks return over 9 years.

We focus on Ghana because Moody's has recently affirmed the Government of Ghana's long-term issuer and senior unsecured bond ratings at B3 (Moody's, 2020). Thus, changing the outlook from stable to positive. Therefore, informing on the asset allocation effects between bond and stock markets seems interesting.

The contribution of this study to the existing literature is twofold. First, by comparing and examining bond and stock return volatility within the Ghana market, we sought to give investors intuition into the investing merits and future return predictability of either bonds or stocks relatively. Second, it complements the existing literature which focuses on developed economies (see: Reilly, Wright and Chan, 2000; Johnson and Young, 2002; Jones and Wilson, 2004; Young and Johnson, 2004).

The rest of the paper proceeds in the following manner. Section 2 provides a brief review of relevant literature. Section 3 defines the data source for the study. Section 4 outlines the methodology employed. Section 5 presents the results of this study with the conclusion presented in section 6.

2 Literature

The literature on stock and bond market volatility has been extensively documented dating back to the 1970s (see e.g., Fisher and Lorie, 1970; Officer, 1973; Sharpe, 1973). Empirically, the evidence about bond market volatility versus stock market volatility is mixed at best. Among the extant works, Reilly, Wright and Chan (2000) found that volatility of the US bond market increased relative to the volatility of the stock market. They further showed that the autoregressive conditional heteroscedasticity (ARCH(1)) model could be employed to predict the bond market volatility but not the stock volatility. Evidence from Swiss and UK markets showed different volatility patterns in bond/stock standard deviations. For example, Young and Johnson (2004) found a negative correlation between bonds and stocks and nonexistence of trend in the bond/stock standard deviations ratio. They again indicated that there was an increase over time in the effectiveness of Swiss bond as diversification vehicles. Their study employed the generalized autoregressive conditional heteroscedasticity (GARCH(1,1)) model. These findings are consistent with evidence by Johnson and Young (2002) who found that over 30-year, the volatility of the UK stock market was about twice the average volatility of the bond market. Jones and Wilson (2004) also found that the relative change in the bond volatility and stock volatility was even more pronounced when inflation was considered.

More recently, Bessembinder (2018) examined the Center for Research in Security Prices (CRSP) database from 1926-2016. He shows that the majority of returns earned on US common stock is less than that of the relative treasury bill return in the long-run horizon. Liu, Wang and Li, (2019) in their findings also revealed that the impact of negative shocks had little effect on US treasury cash market. But causes asymmetric volatility effects in US treasury bond futures market and US stock. Their research used the VEC Copula GJR-GARCH Skewed-Student-t model.

Several studies have shown that bond volatility encrypts valued information concerning the financial market and the state of the economy (Pan and Chan, 2018). Bretscher, Schmid and Vedolin (2016) for example show that the slowdown at the firm level and market future economic activities is positively related to treasury bond volatility. Creal and Wu (2014) also found that higher volatility of treasury bond also leads to a higher rate of unemployment. Arnold and Vrugt (2010) employed the GARCH in their study found that an increase in one standard deviation in macroeconomic uncertainty (measures of real activities, inflation and monetary policy rate) lead to about 20-50 basis points in the volatility of bond market quarterly.

Another applied area of research that has received substantial attention in the literature is the analysis of the properties of volatility indices in international markets. In particular, López (2015) showed that changes in Treasury bond volatility indices were positively correlated with the European equity-based volatility indices and both US non-fixed income and Treasury yield rates. Some interesting facts include a significant dynamic and contemporaneous relationship between international equity-based volatility (see e.g., Åijö, 2008; Konstantinidi, Skiadopoulou and Tzagkaraki, 2008; Siriopoulos and Fassas, 2012), a negative contemporaneous relationship among underlying stock indices return and changes in volatility indices (see e.g., Giot, 2005; Gonzalez and Alfonso, 2009; Whaley, 2009) and the rise or fall of volatility indices following news on macroeconomic fundamentals (see e.g., Castanias II, 1979; Jones,

Lin and Masih, 2005; Rapach, Wohar and Rangvid, 2005; Äijö, 2008; Arnold and Vrugt, 2008; Konstantinidi, Skiadopoulou and Tzagkaraki, 2008; Siriopoulos and Fassas, 2012; Creal and Wu, 2014; Su, Fang and Yin, 2018; Segal, 2019).

While most of the research on bond market volatility has been examined using developed markets, there is some documented literature on stocks volatility in developing markets. For instance, Gbeda and Peprah (2018) found that contrary to the Nairobi Stock Exchange, there is no evidence of conditional volatility in daily prices and return information on the Ghana Stock Exchange. Adjasi (2009) also analyzed the stock price volatility in Ghana based on macroeconomic uncertainty using the EGARCH. He shows that stock volatility resulted from higher interest rates and cocoa price volatility, whilst higher volatility in money supply, oil prices and gold prices reduced stock volatility. Other works on stock market volatility have also been documented (see examples, Alagidede and Panagiotidis, 2006; Frimpong and Oteng-Abayie, 2006; Jaramba and Fadiran, 2009; Angko, 2013; Lin, Wesseh and Appiah, 2014; Saleem *et al.*, 2014; King and Botha, 2015).

In the case of bonds, we are not aware of any studies on bond return volatility in Africa. Existing research focuses on regional cases of either foreign bonds (see e.g., Mecagni *et al.*, 2014; Olabisi and Stein, 2015; Gevorkyan and Kvangraven, 2016; Presbitero *et al.*, 2016; Senga, Cassimon and Essers, 2018) or domestic bonds (see e.g., Adelegan and Radzewicz-Bak, 2009; Mu, Phelps, & Stotsky, 2013; Essers, 2014; Dafe, Essers and Volz, 2018). This study analysis volatility conditions in the sovereign bond market and compares it to the stock market in Ghana.

3 Data

For our first dataset, we focus on monthly sovereign bond return volatility computed for both foreign currency and local currency-denominations using daily returns between 1st May 2009 to 31st July 2018 periods from the S&P Ghana Sovereign Bond index and compare their intertemporal deviations with that of the stock return volatility. S&P Ghana Sovereign Bond index was launched in November 2014 as part of S&P Dow Jones Indices which is also a division of S&P Global. All data presented is back-tested before the date of the index lunch. On the other hand, our second data (stock) was sourced from the Ghana Stock Exchange Composite (GSEC) Index which is well specified and fairly comprehensive over the same period. Finally, we explore time-varying heteroscedasticity dynamics for stocks, foreign and domestic bond using daily returns series.

4 Methodology

To examine volatility between the bond and stock markets, we compute 1) 3-month moving standard deviation of the monthly rate of return.¹ 2) discrete standard deviation of the monthly rate of return. 3) ratio of 3-month moving standard deviation of the monthly rate of return for bond relative to the stock. 4) discrete ratio of the monthly standard deviation of the rate of return for bond relative to the stock. 5) 3-month moving correlation between Ghana sovereign bond and stock return. Lastly, we explore volatility clustering properties in daily return series for the Ghana sovereign bond and stock markets over the period measured.

4.1 Stationarity test

To examine the stationarity of the bond and stock daily return series and to evaluate the persistence of shocks, we employ the Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979, Fuller 1976) and Phillips-Perron (PP) test for the null hypothesis of a unit root in the series, contrary to the one-sided alternate stationarity in series. This is because if a series is non-stationary, the asymptotic analysis for the standard assumptions will not be valid or not follow a t-distribution.

4.2 Univariate volatility models

Volatility clustering is a characteristic feature of financial data. This could be interpreted as a clustering of the error term's variance over time. In other words, if the variance tends to be large (small) in one period, it tends to be small (large) in the next. Volatility clustering is indicative of time-varying heteroscedasticity (Engle, 2001). Two well-known models of volatility clustering in literature are the autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982) and Generalized ARCH (GARCH) model of Bollerslev (1986). The study will employ these classical models to analysis volatility clustering in the bond/stock daily series.

The standard ARCH model takes the form:

$$y_t = \phi_0 + \phi_1 y_{t-1} + u_t \quad (1)$$

¹We estimate monthly volatility as the standard deviation of daily return within that month. We also mitigate the effects of possible mechanical return skewness by using log returns.

where y_t = daily stock or bond return, θ_0 = intercept term, θ_1 = lag one period estimated coefficient for stock and bond daily return, and u_t = error term characterized with ARCH, thus, $u_t \sim F(0, \sigma_t^2)$ and for “p” periods of lags

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_p u_{t-p}^2 \quad (2)$$

with $0 \leq \sum_{i=1}^p \alpha_i < 1$ and $\alpha_0, \alpha_i \geq 0$. However, the ARCH(4) specification might be reasonably approximated by a GARCH(1,1). The simplest form is represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 u_{t-2}^2 \quad (3)$$

with $0 \leq \alpha_1 + \beta_1 < 1$ and $\alpha_0, \alpha_1 \geq 0, \beta_1 \geq 0$

5 Result analysis

5.1 Descriptive Statistics

In Table 1, we present the descriptive statistics of the daily returns of the Ghana stock and bond market over the period measured. We show that the average daily returns of the stock, domestic bond and foreign bond markets are 7.715, 5.660 and 5.110 respectively. The daily deviation for stock returns is about 60.42%, while that of the domestic and foreign bonds are about 50.10% and 16.89% respectively. Additionally, in terms of the skewness, the distribution for the stock and domestic bond returns are skewed to the right, while the distribution for the foreign bond return is negatively skewed. Again, we note that the daily stock yield is leptokurtic. Thus, the observations are closer to the mean and more peaked than the normal distribution. However, the domestic bond daily return is platykurtic since the kurtosis value is less than 3. Thus, observations scatter widely about the mean.

Table 1 Descriptive statistics of daily returns of Ghana stocks and bond market between May 2009 to July 2018

	Stock	GDB	GFB
Observation	2,277	2,406	2,406
Minimum	6.8459	4.6057	4.6057
Maximum	13.6234	6.5729	5.4493
Mean	7.7146	5.6604	5.1101
Std. Dev.	0.6042	0.5010	0.1689
Variance	0.3650	0.2510	0.0285
Skewness	1.1587	0.1567	-0.5744
Kurtosis	7.8086	2.1241	3.2198

Authors' Computation, using STATA 14.2.

Note: GDB= Ghana Domestic Bond, GFB = Ghana Foreign Bond

5.2 Analysis of monthly Ghana Domestic Bond (GDB) market volatility

Panel A in Figure 1 displays the plot of a 3-month moving standard deviation of monthly return for GDB from May 2009 - July 2018 periods. We see that there are some significant peaks at about 4.9% in August 2009, increasing significantly to about 7.0% in September 2009 and then declines slightly to about 3.7% in December 2009. Return volatility peaked up again at about 4.9% rising to 5.2% in April 2010 and May 2010 respectively. January 2013 recorded the most substantial volatility peak in domestic bond return when about 8.6% volatility was reached. There are also noticeable volatile peaks at about 8.0%, 6.7% and 5.2 in December 2012, November 2012 and March 2013 respectively. August 2013 saw the lowest volatility return, with some sluggish trough at about 0.2%-0.3% from May 2011 – July 2011. The test for 9-year trend in the GDB volatility is negatively significant at a 1% confidence level ($t = -2.74$). Implying that GDB volatility seems to be decreasing. The list of the summary statistics of the ten lowest and highest volatility range for the GDB is shown in Table 2. The current mean of monthly standard deviation yield is about 0.7%, while the GDB annual standard deviation of monthly return is about 5.7%.

Table 2 Summary Statistics for Ghanaian Sovereign Bond and Stock market return indexes: Monthly Standard Deviations of Daily Returns: 1st May 2009-31st July 2018**A. High Volatility**

Domestic Bond Market		Foreign Bond Market		Stock Market	
Months	Monthly Std. Dev. (%)	Months	Monthly Std. Dev. (%)	Months	Monthly Std. Dev. (%)
Jan-13	3.080	Jul-15	8.694	Oct-11	142.313
Jul-09	2.795	Sep-14	7.586	Mar-11	141.923
Sep-14	2.135	Mar-17	4.085	Jun-09	11.126
May-12	2.129	Aug-15	3.614	May-09	5.961
Feb-14	2.106	Feb-14	3.532	Jan-18	5.842
Jun-09	1.809	Aug-14	3.446	Jul-17	5.389
Oct-09	1.546	Jan-13	2.954	Mar-13	4.816
Mar-10	1.484	Jul-09	2.711	Feb-13	4.558
Jul-12	1.425	Mar-15	2.695	Oct-09	4.476
Jan-10	1.415	Apr-12	2.655	Jun-18	3.364

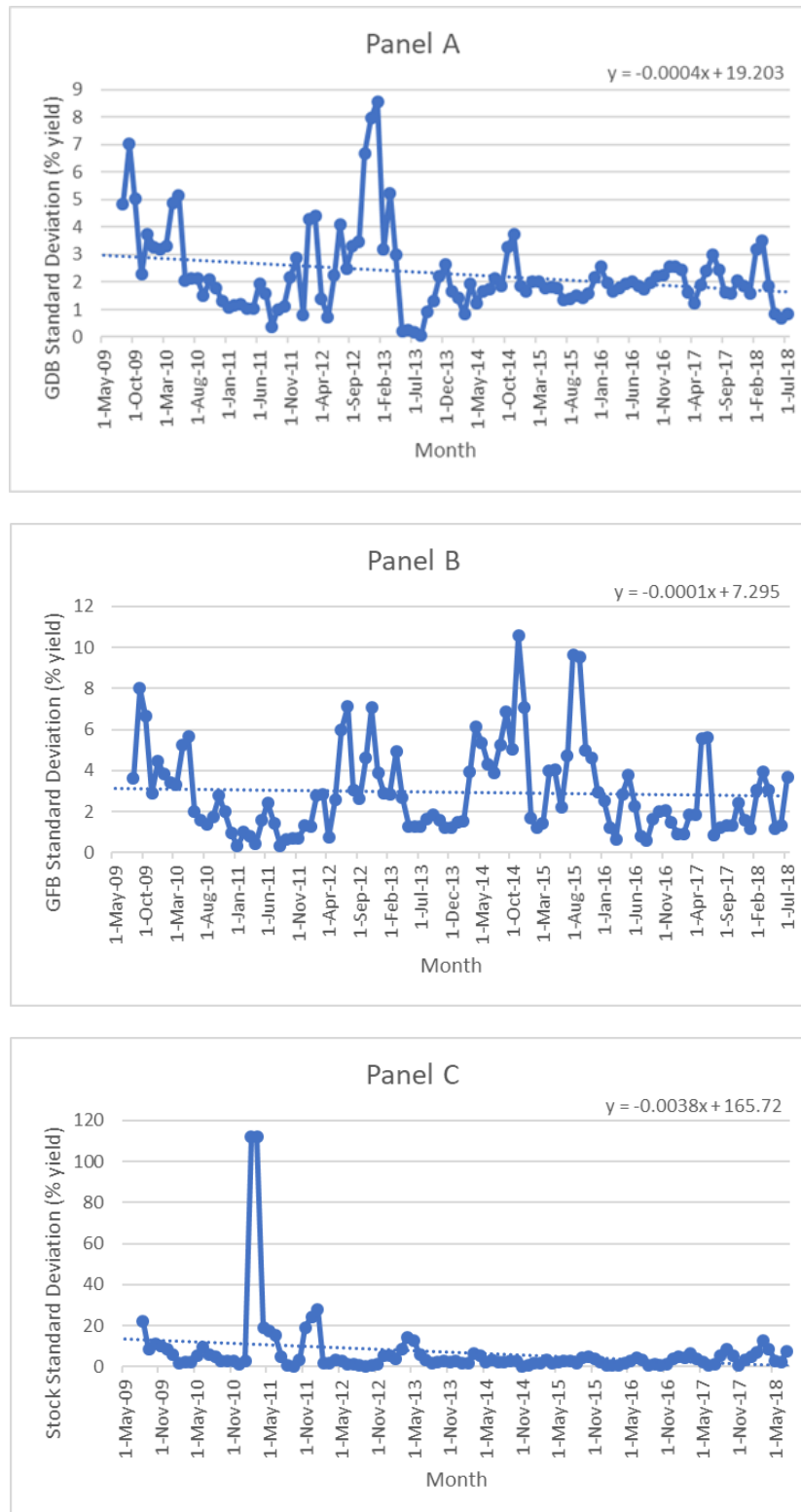
B. Low Volatility

Domestic Bond Market		Foreign Bond Market		Stock Market	
Months	Monthly Std. Dev. (%)	Months	Monthly Std. Dev. (%)	Months	Monthly Std. Dev. (%)
Dec-11	0.179	May-10	0.116	Nov-13	0.228
May-18	0.190	Nov-10	0.249	Jul-16	0.292
Nov-11	0.193	Dec-12	0.271	Jan-16	0.323
Feb-18	0.196	Apr-18	0.309	Oct-15	0.352
Oct-11	0.215	Feb-12	0.315	Jan-12	0.353
Feb-11	0.238	Oct-10	0.320	Jun-15	0.360
Aug-13	0.244	Dec-11	0.322	Aug-12	0.380
Mar-12	0.263	Jun-12	0.325	Dec-13	0.387
Jul-14	0.275	Feb-13	0.332	Feb-15	0.388
Apr-18	0.282	Apr-15	0.358	Sep-12	0.408

C. Statistics for Entire Period: May 2009- July 2018

Domestic Bond Market (%)	Foreign Bond Market (%)	Stock Market (%)
Mean of Monthly Standard Deviations (N=111) 0.716	1.310	4.085
Mean of Yearly Standard Deviations (N=9) 5.722	6.449	14.180

Figure 1 Moving 3-month standard deviations of Ghana sovereign bond (GDB and GFB) and stock markets monthly rate of returns from May 2009 - July 2018



Note: For Panel A and B, data is computed from the S&P Ghana Sovereign Bond Index daily returns. Whiles Panel C is computed from the Ghana Stock Exchange Composite (GSEC) Index daily returns.

5.3 Analysis of monthly Ghana Foreign Bond (GFB) market volatility

Similarly, the 3-month moving standard deviation of the monthly rate of return plot for GFB is shown in Figure 1(B). We show that the foreign bond seems to be a bit more volatile than domestic bonds. The most substantial volatility spike is in November 2014 (10.6%) followed by August/September 2015 and September 2009 when about 9.6% and 8.0% volatility were reached respectively. July 2012, November 2012 and December 2014 also recorded peaks of about 7.1%. There is also noticeable significant volatility at about 6.9%, 6.7% and 6.1% in September 2014, October 2009, and April 2014 respectively. However, January 2011 saw the lowest volatility of foreign bond return of about 0.3% with some slow trough between 0.4% -1%. The test for 9-year trend in the GFB volatility is insignificant ($t = -0.47$). As captured again in Panel C of Table 2, the average monthly standard deviation for the GFB is about 1.3%. However, the annual standard deviation of monthly return of about 6.5%. Indicating that GFB return is more volatile compared to the GDB return series. In all, the annual volatility pattern in the Ghana sovereign bond markets is higher compared to 1.3% in Switzerland (reported by Young and Johnson, 2004), 2.8% in the UK (reported by Johnson and Young, 2002) and 1.2% in the US (reported Reilly, Wright and Chan, 2000).

5.4 Analysis of monthly stock market volatility

Figure 1(C), graphs the 3-month moving standard deviation for the stock series for the May 2009 - July 2018 periods. Starting from August 2009, there is a high peak of about 22.1%, which then declined to about 8.4% in September 2009 and increased again to about 11.0% in October 2009. The most substantial volatility peak in stock return occurred in February and March 2011 where at 111.8% and 111.9% spikes were reached. Other spikes are also documented at about 19.2% (November 2011), 24.4% (December 2011) and 27.9% (January 2012).

However, minor volatility peaks are seen around September 2012, November 2014 and September 2011. The test for 9-year trend in the Ghana stock volatility is negatively significant at a 1% confidence level ($t = -2.50$).

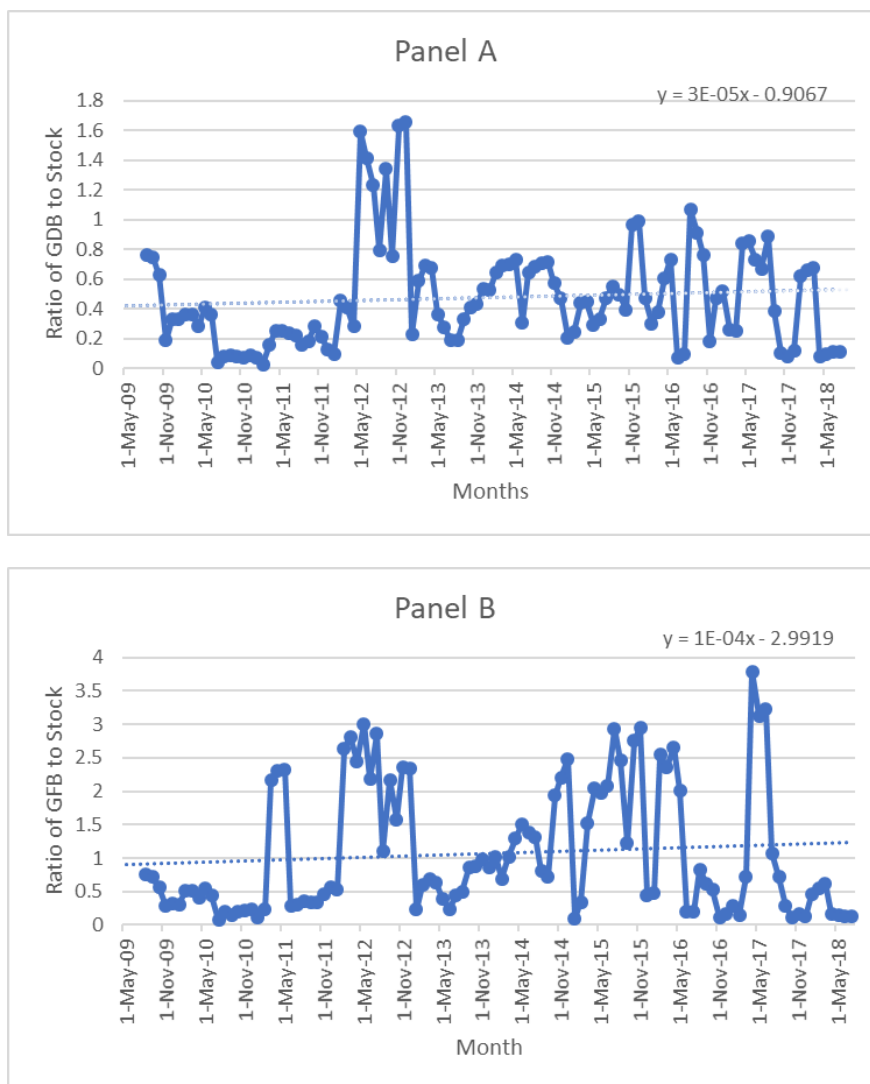
Comparing Ghana stock to the bond market, it is obvious that the stock patterns are more volatile than the bond. Again, volatility concentration in the stock also differs from both GDB and GFB asset classes. The lowest (ascending) and highest (descending) discrete average monthly standard deviation of stock returns relative to the GDB and GFB are presented in Panel A and B of Table 2. We see that the highest and lowest top 10 monthly volatility in the stock occurs at different months to the GFB volatility. The same is also seen for the GDB volatility to the stock volatility except for June 2009 and October 2009 which appear within the first ten highest (even that the spike level is higher in the stock). The average monthly standard deviation for stock return (Panel C of Table 1) is about three times the GFB (4.0854 versus 1.310) and about five and a half times the GDB (4.0854 versus 0.7158). However, the average annual standard deviation for stock (14.180) is about two and a half times the average annual standard deviation for GDB (5.722%) and GFB (6.449%).

Young and Johnson (2004:12) reported thrice (4.484 versus 1.249) for Swiss stock versus bond markets, Johnson and Young (2002: 105) reported twice (5.377% versus 2.755%) in the UK, while Reilly, Wright and Chan (2000:85) reported 3.7835 versus 1.770 for the US stock versus bond markets. In terms of annual standard deviation percentile levels, volatility percentage in the Ghana stock and bond market appears to be higher. Suggesting that volatility patterns observed from the Ghanaian stock and bond market are higher compared to those in the developed market.

5.5 Ratio of Bond volatility to Stock volatility

The ratio of moving 3-month standard deviation of GDB to the stock is graphed in Figure 2(A). It shows clearly that the volatility relationship between the GDB and stock is not stable and ranges from 0.029 to 1.66 in the ratio. Whereas volatility in the stock is generally higher, there were several months within the 9 years when the stock volatility was lower than GDB (signified by a ratio over 1.0). The trend in the ratio of volatility over time has a slope coefficient of about 0.0000332 ($p=0.356$), implying that GDB returns are insignificantly volatile compared to the stock market. This supports findings by Johnson and Young (2002) and Young and Johnson (2004) who establish no relationship among the bond and stock volatility ratio for the UK and Swiss markets respectively.

Figure 2 Ratio of Moving 3-Month Standard Deviation of Returns for Ghana Sovereign Bond (GDB and GFB) to Stock from May 2009 - July 2018



This is also confirmed by the summary statistics of the discrete ratio of monthly standard deviation for GDB to stock as presented in Table 3 (list 10 highest and lowest volatility ratio). The ratio of volatility is significantly substantial and ranges from a low of about 1/663rd (0.002) in October 2011, to a high of about 3 and half times (3.455) in September 2012. In terms of concentration, the highest monthly ratio of volatility started in April 2012, with about 5 out of the top 10 highest ratio volatility captured within 2012. Also, in the case of low volatility concentrations, 5 out of the 10 low months were all below 2012 while the rest were above 2011. Averagely, the monthly GDB volatility pattern is about 0.749 to the stock volatility. The mean of the annual ratio of GDB volatility to stock volatility is also about 0.7550. Implying that the Ghana domestic bond market volatility on the average exhibit about 3/4th of the annual stock market volatility over the period measured.

Table 3 Summary Statistics of Bond Volatility Versus Stock Volatility for May 2009 – July 2018

A. High Volatility Ratio			
Months	Ratio of Std. Dev. GDB/Stock	Months	Ratio of Std. Dev. GFB/Stock
Sep-12	3.4555	Mar-17	7.633
Aug-12	3.4479	Aug-15	6.838
Apr-12	3.2221	Apr-12	6.156
Jul-16	2.3776	Jan-16	5.987
May-12	2.1427	Jun-15	5.784
Jul-12	2.1416	Sep-14	5.314
Oct-15	2.1014	Jan-12	5.119
Mar-17	1.8616	Aug-12	4.755
May-17	1.8471	Sep-12	4.576
Feb-14	1.7377	Jul-15	4.402
B. Low Volatility Ratio			
Months	Ratio of Std. Dev. GDB/Stock	Months	Ratio of Std. Dev. GFB/Stock
Oct-11	0.0015	Mar-11	0.003
Mar-11	0.0023	Oct-11	0.008
May-18	0.0646	May-10	0.049
Jul-17	0.0795	Feb-13	0.073
Feb-13	0.0923	Jul-17	0.089
Feb-18	0.0926	Jun-10	0.114
Jun-10	0.0940	Dec-12	0.123
Dec-11	0.1189	Jun-09	0.133
Jun-18	0.1340	Nov-10	0.164
May-10	0.1466	May-09	0.172
Mean of Monthly Ratio of GDB Std. Dev. to Stock Std. Dev. = 0.7488			
Mean of Monthly Ratio of GFB Std. Dev. to Stock Std. Dev. = 1.4547			
Mean of Yearly Ratio of GDB Std. Dev. to Stock Std. Dev. = 0.7550			
Mean of Yearly Ratio of GFB Std. Dev. to Stock Std. Dev. = 0.9514			

Similarly, the relationship between the ratio of the GFB volatility to the stock is also not stable. As graphed in Figure 2B, there are several periods when the 3-month moving deviation of the GFB was again more volatile than the stock (signified by a ratio over 1.0), fluctuating between 0.0684 (July 2010) and 3.793 (April 2017). However, the least-squares trending slope coefficient is insignificant (0.0000975, $p=0.324$), indicating that the increase in the GFB volatility was also less to the stock volatility.

Table 3 presents a summary of the discrete calendar month ratio with the highest and lowest volatility relationship between these two asset markets. The average month GFB standard deviation to stock standard deviation is 1.4547. However, the mean annual ratio of GFB volatility to stock is about 0.9514. Implying that, passably, the annual GFB market volatility has been increasing about the same times as the annual volatility of the stock market within the period measured. Studies by Young and Johnson (2004, p. 14) found that “bond market in Switzerland exhibits less than one-third the volatility of the stock market” (Reilly, Wright and Chan (2000) found similar results) whiles Johnson and Young (2002, p. 106) found “bond market exhibits roughly half the volatility of the stock market”.

To ascertain the variations in the ratio of volatility over time, we examine the monthly variances of stock and bond returns during a yearly period. The results in Table 4 show the ratio of stock variance to the GDB and GFB for each year. In the case of stock variance to GDB variance, the differences in variance follow an up and down pattern, increasing significantly to about 110906 in 2011 and declining sharply to 0.6 (2014) before rising again to about 18 (2018). The F-test of the stock variance to GDB variance shows that two (2012 and 2014) out the 9-years are not significant. However, stocks remain more volatile compared to GDB. Similarly, in the case stock variance to the GFB variance, there is a steep rise to about 13403 in 2011 and sharply declined between 2012 and 2017 (i.e., from 0.06 to 1.8) before increasing again to about 11 (2018).

Table 4 Monthly Return Variances of Sovereign Bonds and Stocks for May 2009 –July 2018

Year	1 Year Return Variance			Ratio of Stock Variance to GDB Variance	Ratio of Stock Variance to GFB Variance
	GDB Returns	GFB Returns	Stock Returns		
2009	0.520	0.463	12.230	23.520 (0.0006)	26.439 (0.0001)
2010	0.178	0.265	0.729	40.100 (0.0138)	2.756 (0.0536)
2011	0.027	0.224	3010.544	110906.029 (4.31E-26)	13430.080 (4.75E-21)
2012	0.361	0.749	0.411	1.139 (0.4164)	0.549 (0.1675)
2013	0.573	0.574	2.441	4.263 (0.0119)	4.252 (0.0120)
2014	0.406	3.850	0.233	0.573 (0.1847)	0.060 (0.0000)
2015	0.034	5.148	0.420	12.379 (0.0001)	0.082 (0.0001)
2016	0.034	0.390	0.881	25.629 (3.01E-06)	2.262 (0.0958)
2017	0.115	1.082	2.037	17.704 (1.98E-05)	1.882 (0.0012)
2018	0.158	0.257	2.985	18.916 (0.0012)	11.623 (0.0044)

Authors' Computation, using STATA 14.2. Note: P-value in parenthesis. Due to the data structure, yearly values for 2009 and 2018 were computed between May 2009-Dec 2009 and Jan 2018-Jul 2018 respectively.

In conclusion, it appears that the Ghana stock, GDB and GFB market volatility are marching to different rhythms. Even though stock seems to be slightly more volatile than the bond, there is a tendency that the bond market can increase significantly over time particularly for the GFB.

5.6 Correlation between bond and Stock return

Figure 3 graphs the moving 3-month correlation coefficient of returns for Ghana Sovereign Bond (GDB and GFB) with GSE stock which also confirms a high level of volatility and instability over the period measured. In the case of the correlation between GDB to the stock return, the observations from the graph suggest that there were several periods when GDB rates of return were moving in the same direction to the stock rates of return. The trend slope coefficient is 0.00005 ($p=0.512$) but insignificant.

On the other hand, several periods of the rates of return of GFB were moving counter to the stock rates of return. The slope coefficient for the correlation between GFB and stock is -0.000035 ($p=0.661$) but insignificant. Implying that the Ghanaian bond market remains an effective market for diversification.

Findings in the UK reported by Johnson and Young (2002) found a negative and insignificant correlation between the bond and stock return. Report from Switzerland (Young and Johnson, 2004) found a negative and significant correlation, while Reilly, Wright and Chan (2000) found a positive and significant correlation between the US bond and stock return.

5.7 Daily market volatilities

Because most financial returns exhibit random walk, we first explore stationary issues in the GDB, GFB and stock series. Table 5 presents the results from the stationarity test for the daily return series. In the case of the log GFB and log GDB, the null hypothesis of a unit root is rejected by the data regardless of whether the DF, ADF or PP was used for testing purposes. On the other hand, in the case of the log of stock daily return series, the null hypothesis of a unit root is not rejected by DF and ADF but is rather reject by PP. In the case of the 1st difference variables, the null hypothesis of a unit root in the data is rejected unambiguously with the use of either the DF, ADF and PP procedures. Implying stationarity at the first difference in log of all three daily series (i.e., mean-reverting). This is confirmed by further examination of their correlograms (plots not shown).

Table 5 Unit Root Tests for log of daily return Individual Series

Test	GDB	GFB	Stocks	Δ_1 GDB	Δ_1 GFB	Δ_1 Stocks
DF (Test Statistics)	-1.548	-2.115	-5.316**	-37.312**	-39.168**	-17.151**
ADF (Test Statistics)	-1.573	-2.553	-5.316**	-22.788**	-20.446**	-28.824**
Phillips-Perron (PP)	-0.783	-1.867	-2.795	-37.337**	-39.180**	-3.440**

Authors' Computation, using STATA 14.2. **Critical Value @ 0.05 level for DF and ADF = -3.41 in all cases. **Critical Value @ 0.05 level for PP = -2.860 in all cases.

To inform on the issue of ARCH effects in all three series, we regress each stationary series on a constant only and no other variables using OLS. The OLS residuals are retrieved and Lagrange Multiplier (LM) ARCH test conducted using 1st, 2nd, 3rd, 4th, and 5th order lags. Table 6 illustrates the results of the ARCH-LM test for the log of daily return series

with their respective test and p-values. The estimated effects for the moving average terms in the ARCH are well determined at the first, second, and third lag orders for the GFB, while that of the stock is only determined in the second and third lag orders. This confirms that GFB and stock are characterised by volatility clustering. To help inform market participants of the great value in the Ghanaian sovereign bond and stock assets, we apply the ARCH and GARCH models to the daily return series.

Table 6 Lagrange Multiplier (LM) test for autoregressive conditional heteroscedasticity (ARCH) for the log of daily returns series

Lags	Δ_1 GDB	Δ_1 GFB	Δ_1 Stock
ARCH ~ χ^2_1	0.019 (0.8903)	36.436 (0.0000)	0.318 (0.5725)
ARCH ~ χ^2_2	0.072 (0.9646)	38.933 (0.0000)	202.167 (0.0000)
ARCH ~ χ^2_3	0.368 (0.9468)	31.535 (0.0000)	91.769 (0.0000)
ARCH ~ χ^2_4	-	-	2.000 (0.7358)
ARCH ~ χ^2_5	-	-	-
Sample Size	2406	2406	2277

Authors' Computation, using STATA 14.2. P-value in parenthesis.

Even though the LM test for the ARCH effect is not well determined at the first, second, and third lag orders for the GDB, the estimates for the ARCH(1) series did converge. Table 7 presents the result for the GDB ARCH (1) model. We show that volatility patterns in the GDB are very different from that of the GFB and stocks. The coefficient for the lagged-1 daily return period for the OLS and the ARCH(1) is positively significant. Suggesting that if the daily GDB volatility continues to display regular patterns over time, then future values could be forecast for the series using the ARCH(1) model. Again, the ARCH parameters (α_0, α_1) are statistically significant at the one percent confident levels which suggests that the autoregressive conditional heteroscedasticity model fits the GDB daily volatility series well. This is an indication of volatility clustering. This finding also implies that the current period volatility in daily domestic bond return series in the Ghanaian market is related to the prior period. The GARCH(1, 1) model for GDB series did not converge. Reilly, Wright and Chan, (2000) found similar results using the discrete annual standard deviation of the US bond market over 1950–1999 period.

Table 7 Autoregressive models for log of daily Ghana Domestic bond return series from May 2009 - July 2018

Variables	Model 1	Model 2	Model 3
	OLS	ARCH(1)	ARCH(1) AR(1)
Lag 1 period	0.0524** (0.0254)		0.126*** (0.0478)
L0.arch (α_0)		0.000553*** (8.13e-05)	0.000560*** (9.08e-05)
L1.arch (α_1)		0.112*** (0.00865)	0.108*** (0.00969)
Constant	0.000455*** (8.89e-05)	9.64e-06*** (5.59e-08)	9.61e-06*** (5.58e-08)
Log likelihood		8302.815	8306.543
AIC		-16599.63	-16605.09
Observations	1,438	1,921	1,921
R-squared	0.003		

Authors' Computation, using STATA 14.2. Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

The results of the daily return volatility series for the GFB is presented in Table 8. Again, they are markedly different from that of the GDB and stock volatility series. We note that the first lagged period for the OLS and GARCH(1,1) models are not statistically significant. Telling that daily return volatility of the Ghana Eurobond series does not depend on the previous day's volatility because it does not exhibit regular patterns over time.

Table 8 Autoregressive models for log of daily Ghana foreign bond return series from May 2009 - July 2018

Variables	Model 1 OLS(GFB)	Model 2 ARCH(3)	Model 3 GARCH(1,1) AR(1)
Lag 1 period	-0.0143 (0.0259)		-0.0483 (0.0313)
L0.arch(α_0)		0.000239* (0.000134)	-3.75e-06* (2.23e-06)
L1.arch(α_1)		0.356*** (0.0243)	0.312*** (0.0211)
L2.arch(α_2)		0.137*** (0.0162)	
L3.arch(α_3)		0.274*** (0.0184)	
L1.garch(β_1)			0.775*** (0.0460)
Constant	0.000186 (0.000205)	1.79e-05*** (9.00e-07)	-3.75e-06* (2.23e-06)
Log likelihood		6772.1341	6769.752
AIC		-13534.27	-13529.5
Observations	1,438	1,921	1,921
R-squared	0.000		

Authors' Computation, using STATA 14.2. Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

When we consider the GARCH(1,1) for the GFB series, the coefficient of the estimated variance parameters (α_1 and β_1) are significant. However, the coefficient of the estimated α_0 is negative and statistically significant which violate the non-negative assumption ($\alpha_0 \geq 0$) of the model. This indicates that the GARCH(1,1) model does not present a weak model for the Ghana Eurobond series and does not closely track the daily volatility return. We note that the ARCH(3) provides a better fit for the GFB daily volatility series. The ARCH(3) model shows that all the coefficients of the variance parameters ($\alpha_0, \alpha_1, \alpha_2$, and α_3) for the GFB daily series are positive and statistically significant. Signifying volatility clustering in the series by the conditional heteroscedastic model. Thus, the GFB market is inefficient. The analysis of the daily stock return volatility series is presented in Table 9. The first lagged value of the OLS is not significant.

However, the introduction of the GARCH(1,1) made the first lagged period significant. Additionally, the α_0, α_1 coefficients of the GARCH(1,1) model are all positively significant while the β_1 coefficient is negatively significant. This is also a violation of the non-negative assumption of the conditional heteroscedasticity model. Signifying that the GARCH(1,1) does not seem to closely mimic the Ghana stock market return volatility well. On the other hand, the ARCH(2) model seems to be a better fit for the stock series with only the α_2 coefficient significant. This implies that the stock market is also inefficient. Again, similar to the GFB, we see that the stock return series does depend on previous volatility. Our findings agree with Gbeda and Peprah (2018) who assert that the GSE return information cannot be predicted.

Table 9 Autoregressive models for log of daily stock return series from May 2009 - July 2018

Variables	Model 1 OLS(Stock)	Model 2 ARCH(2)	Model 3 GARCH(1,1) AR(1)
Lag 1 period	-0.0220 (0.0596)		1.340*** (0.00455)
L0.arch(α_0)		0.00668 (0.0264)	0.000816** (0.000321)
L1.arch(α_1)		0.00310 (0.00317)	0.0552*** (0.00140)
L2.arch(α_2)		0.0443*** (0.00266)	
L1.garch(β_1)			-0.999*** (5.36e-05)
Constant	0.00581 (0.00747)	0.0361*** (0.000314)	0.0678*** (0.000174)
Log likelihood		393.02926	2912.959
AIC		-778.0585	-5815.917
Observations	1,268	1,761	1,761
R-squared	0.000		

Authors' Computation, using STATA 14.2. Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

In this study, we analyze and document across 9-years from May 2009 - July 2018 changes in the Ghana sovereign domestic bond, Ghana sovereign foreign bond and stock market as epitomized by the S&P Ghana Sovereign Bond Index return series and the Ghana Stock Exchange Composite total equity return series.

The results suggest that there are significant volatility swings across all asset classes over the period measured. In particular, the most substantial volatility was noticed in January 2013 and November 2014 for GDB and GFB respectively while that of the stock was observed in February and March 2011. Unlike the insignificant trend in volatility in the GFB, the trend in volatility for GDB and stock are negatively significant. The average monthly standard deviation for stocks return is about three times to the GFB and about five and a half times to the GDB. However, the average annual standard deviation for the stock is about two and a half times the average annual standard deviation for GDB and GFB. Potential investors who are interested in investing in these markets should, therefore, choose their asset base on how much risk they can take.

Further analysis confirms the instability between the GDB, GFB and Stock markets. The trend ratios in both GDB volatility and GFB volatility to stock market volatility has been relatively increasing with several periods well over the stock volatility. Nevertheless, there was no significant trend in bond to stock standard deviations. The average correlation between GDB and the stocks is about 0.220, while that of the GFB to the stocks is about 0.046.

We finally investigate the volatility clustering predictability of the bond/stock market daily series. The evidence suggests that the ARCH model can be used to explore volatility clustering and predict future values in GDB return series. However, it cannot be used to predict future values in the GFB and stock daily series. We document that all three asset classes are inefficient as they exhibit some form of volatility clustering. This research highlight some very important implications for asset allocation for the bond and stock markets in an emerging market. An investigation of the volatility of stocks and bonds in the light of inflation in developing markets would be an exciting research subject and we leave it for future studies.

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