Investigating Volatility Transmissions among Sovereign Bonds in African and Emerging Markets Using Multivariate GARCH Models

Debalke, Negash Mulatu

Addis Ababa University

22 August 2023

Investigating Volatility Transmissions among Sovereign Bonds in African and Emerging Markets Using Multivariate GARCH Models

Negash Mulatu DEBALKE
ORCHID: https://orcid.org/0009-0003-5136-9596
Department of Economics[1], College of Business and Economics, Addis Ababa University, Ethiopia
negash.mulatu@aau.edu.et; negash2016@yahoo.com

Abstract

The study examined volatility transmissions between Ethiopia and Ghana's sovereign bonds and emerging markets. Five Multivariate GARCH models were estimated using time series price indices. AIC and BIC criteria identified the VCC-MGARCH model as the best. The result shows own-volatility spillovers are higher than cross-volatility spillovers. In addition, it confirms cross-spillovers were unidirectional, from emerging markets to Ethiopia, with no significant spillover to Ghana. There is no bidirectional volatility spillover. Both Ethiopia and Ghana exhibit significant ARCH and GARCH effects, emphasizing the importance of addressing past variations and squared returns in volatility management. Significant adjustment parameters suggest that deviations from long-term equilibrium are corrected, indicating the markets' stability mechanisms. Thus, policymakers should monitor these mechanisms for market stability. Finally, policy implications emphasize monitoring and managing external influences, addressing market dynamics persistence, and implementing policies to reduce excessive volatility.

Keywords: Sovereign Bond; Ethiopia; Ghana; Africa; Emerging Markets; Return; Volatility; Spillover; M-GARCH.

[1] P.O. Box 5563, Department of Economics, Addis Ababa University, 6-Kilo, Entoto Street, Addis Ababa, Ethiopia

1. Introduction

In today's interconnected financial landscape, where capital and financial information traverse borders with unprecedented ease, the global markets have complicatedly interlinked, and displayed both collaborative success and susceptibility to shocks. This phenomenon creates the significance of comprehending the issue volatility among markets, as well as the potential trajectories of future bond prices and returns. Understanding the transmission of return volatility between sovereign bonds has become a topic of paramount importance, especially in regions marked by a mix of emerging economies and developing markets, such as the African continent.

After the global financial crisis in 2008, African countries turned to sovereign bonds for funds. Bond issuance soared from $1 billion in 2011 to $6.2 billion in 2014. Africa became the fastest-growing region for sovereign ratings over 15 years (Vellos, 2015; World Bank, 2015). The global ratings of S&P rated seventeen sub-Saharan African sovereigns in 2016, up from twelve in 2008. Stable global markets and promising returns drew investors that makes international markets more accessible. On average, these bonds yielded 6.6% returns over 10 years. By 2017, twenty-one nations in Africa had $115 billion foreign currency-denominated sovereign debt (Gross, 2020). Moreover, Fitch Ratings (2020) projected a rise in median government debt/GDP ratio for nineteen Fitch-rated Sub-Saharan African sovereigns, from 57% in 2019 to 71% in 2020, in which this rate was 26% in 2012. These stats, combined with pandemic turmoil, raised concerns about currency stability, debt refinance, and economic volatility tied to sovereign bonds (Velde, 2014).

Since the subject has high practical relevance as financial integration gains momentum, abundant researches have delved into the dynamics of return volatility transmission. However, a substantial proportion of these explorations have been channeled towards well-established stock markets in developed economies or have revolved around the complex relationship between commodity prices and stock markets (Chevallier, 2015; Bala and Takimoto, 2017; Morema and Bonga-Bonga, 2020). Majority of them concentrated on volatility spillover between international equity markets (e.g. Boako and Alagidede, 2017; Panda et al., 2019). Meanwhile, there remains a noticeable gap in the literature concerning volatility spillovers within the context of African asset markets, while its understanding is more crucial within the realm of the continent’s financial sector. Furthermore, the African financial landscape, particularly in relation to sovereign bond markets, has remained relatively underexplored in terms of volatility spillover analysis with respect to emerging markets on a global scale. This research endeavors to address this gap by embarking on an investigation that delves into analyzing the transmission of return volatility between sovereign bonds in African economies and global emerging markets.

The main aim of this study is to ascertain whether there exists a discernible presence of return volatility spillover between the sovereign bonds of Ethiopia and Ghana, and the bonds of emerging markets globally. Furthermore, this inquiry extends to the comparison of various iterations of the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model. Through this comparative analysis, the study seeks to identify the most effective model that can provide superior estimations of return volatility spillovers. In essence, this research endeavors to shed light on a pivotal facet of the financial world, magnifying the complex connections that cross borders and influence the trajectories of economies. By focusing on the unique landscape of the SSA countries sovereign bond markets and their connections to emerging markets, this study strives to contribute to a more comprehensive understanding of global financial dynamics. The study would also contribute to the existing literature on modelling of financial market interdependence and volatility transmission. Moreover, the findings of this study could have implications for investors, policymakers, and market participants who seek to understand the complexities of bond markets in their economies.

2. A Review of the Empirical Literature

The literature review goes in into the extensive body of scholarly work that investigates the dynamics of volatility transmission and interdependence within financial markets, and other important markets. This section briefly presents methodological approaches and empirical findings that have contributed to the understanding of volatility spillovers, contagion risks, and the factors driving transmission across diverse markets. The review has created a good foundation for the present research through identification of gaps and opportunities for further exploration in the context of applying Multivariate GARCH models to analyze the transmission of return volatility among sovereign bonds.

Employing MGARCH models, Bala and Takimoto (2017) studied stock returns volatility spillovers between emerging and developed markets. The study has examined the impacts of global financial crisis on stock market volatility interactions and modified the BEKK-MGARCH model by including financial crisis dummies. In addition, the study conducted unit root tests using ADF, and applied Inclan and Tiao's (IT) break test to identify the number and position of break points in variance of the returns. Moreover, it applied the DCC-with-skewed-t density model to improve diagnostics by considering fat tails and skewed features of the series.

Beirne et al. (2010) studied the dynamics of forty-one emerging market economies comprising from Asia, Europe, Latin America, and the Middle East. The study found that the way different markets influence each other varies significantly depending on the specific country and region. In places like emerging Asia and Latin America, the focus is on how returns spill over from one market to another, whereas, in emerging Europe, it is the variance that takes the spotlight. Moreover, the balance between local and global influences shifts as well. In Asia, global spillovers are the dominant force, while in Latin America and the Middle East, it's the regional interactions that hold sway.

In their work, Yiu et al. (2020) applied a VAR-MGARCH to understand how US bond market movements affect Indonesia, Malaysia, the Philippines, and Thailand. They found that changes in the US market impact these countries, and there's a mutual effect on market volatility. They also used an analysis method to study volatility changes. The research highlights that when emerging market risks rise, bond yields go up in these ASEAN-4 countries. Exchange rates can help lessen these effects. Given the significant issuance of government bonds by these countries to combat Covid-19, it's crucial to consider how US market trends might affect them as the US adjusts its monetary policy and interest rates.

A study by Li and Giles (2015) probed into the connections between stock markets in the United States, Japan, and six emerging Asian countries during the period from 1993 to 2012. Their analysis involved the use of VAR and MGARCH techniques. To ensure the reliability of their data, they employed tests such as the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to assess the stationarity of the returns series. Additionally, they utilized the Ljung and Box tests to detect any serial correlations within the data. Similarly, in a separate study by Yavas and Dedi (2016), GARCH models were developed to explore the interconnectedness of stock returns and volatility in the United Kingdom, Germany, China, Russia, and Turkey. The outcomes of their research provided confirmation of significant co-movements in returns across these countries.

MGARCH models find widespread use in examining how the relationships between different types of prices and economic factors evolve over time. For example, Chevallier (2015) conducted a study to understand the connections between energy and emissions markets. To do this, it has employed a combination of Vector Autoregressive (VAR) and MGARCH frameworks, examining daily data from April 2005 to December 2008. This analysis utilized various models, including Baba, Engle, Kraft, and Kroner (BEKK), Constant Conditional Correlation (CCC), and Dynamic Conditional Correlation (DCC) models. To estimate model parameters and ensure their statistical robustness, it utilized the Berndt–Hall–Hall–Hausman (BHHH) algorithm, which yields quasi-maximum likelihood parameter estimates and its associated asymptotic robust standard errors. Furthermore, the study conducted tests such as the Augmented Dickey-Fuller (ADF) test for assessing stationarity, the Ljung–Box–Pierce Portmanteau test to determine the optimal lag, and the Jarque–Bera test for checking normality.

Al Nasser and Hajilee (2016) explored into the integration of stock markets in five emerging economies (Brazil, China, Mexico, Russia, and Turkey) and three developed markets (the U.S., U.K., and Germany). They used a bounds testing approach for cointegration and identified evidence of integration between these two sets of markets. In 2012, Gupta and Guidi examined how the Indian stock market was interconnected with markets in Hong Kong, Japan, and Singapore. They discovered no cointegration but noted that correlations between these markets increased during financial crises. Besides, Huang et al. (2000) explored the relationships between the stock markets in the United States, Japan, and the South China Growth Triangle (SCGT) region. Their research revealed that, except for Shanghai and Shenzhen, these markets weren't cointegrated. They also found that fluctuations in returns and volatility in the U.S. had a significant impact on the SCGT markets.

Focusing on the MENA region, a limited number of studies have delved into the connection between global equity markets and those in the MENA region, using various analytical tools such as VAR analysis, GARCH models, or a combination of both. For instance, in a study by Neaime in 2016, it was observed that equity markets in oil-producing nations like Bahrain, Kuwait, Saudi Arabia, Oman, and the UAE displayed a lower vulnerability to international financial crises. Consequently, these markets presented opportunities for diversifying investment portfolios. In contrast, markets in non-oil producing countries, especially Morocco, Egypt, and Tunisia, were found to have stronger ties with Western markets, rendering them more susceptible to global financial crises. In terms of regional influence, Saudi Arabia emerged as the most influential among the GCC markets, while Egypt played a pivotal role among non-oil producing countries. Consequently, financial crises in these two nations could potentially have a ripple effect, affecting the remaining countries in the MENA region.

Using the VAR method, and a weekly data on returns and range-based volatility over 2005–2017, Habibi and Mohammadi (2022) examined the interconnectedness in financial markets of eleven MENA and four Western economies. It has constructed a number of spillover indexes for stock returns and their volatilities. In a study by Neaime (2012), volatility spillovers in the MENA region were investigated using GARCH models. The findings highlighted two key points. Firstly, oil-producing MENA markets, particularly Saudi Arabia, significantly influenced the UAE and Kuwait markets in both mean and variance. Secondly, non-GCC markets like Egypt, Jordan, Morocco, and Tunisia had strong causal links with mature equity markets in the US, UK, and France. This vulnerability to global financial crises makes them less appealing for international portfolio diversification compared to other MENA markets.

Additionally, in 2011, Abou-Zaid conducted a study that explored the impact of the U.S. and U.K. stock markets on selected emerging markets in the MENA region, specifically Egypt, Israel, and Turkey. The research focused on daily volatility movements and employed a multivariate GARCH in mean approach. The results revealed that Egypt and Israel were notably influenced by the U.S. stock market, whereas Turkey did not exhibit the same level of sensitivity. Similarly, Maghyereh et al. (2015) utilized a DCC-GARCH model to analyze five MENA countries and their relationship with the U.S. stock market. The study discovered significant contagious effects, with the strength of pairwise correlations with the U.S. depending significantly on the conditional volatility of U.S. equities.

In the context of African countries, there have been relatively few studies conducted. In one such study by Emenike (2021), a bivariate BEKK-GARCH model was employed to explore the connections in sovereign bond volatility among African nations. Examining eight countries, the research revealed that there was a one-way influence of volatility from Morocco to Egypt's sovereign bonds. However, there was no interaction observed between the bonds of Ghana and Nigeria. On the other hand, Uganda-Kenya and Botswana-South Africa exhibited two-way interactions. To sum it up, full interaction was found between Uganda-Kenya and Botswana-South Africa, partial interaction between Egypt and Morocco, and no interaction between Ghana and Nigeria sovereign bonds.

Debalke (2023) examined the existence of volatility and spillover effects between sovereign bond returns of South Africa and Ethiopia and the world's long term interest rate using weekly data in the period of 2014–2022. An MGARCH-DCC model is estimated to analyze the direction and strength of sovereign bonds' volatility interaction. The result indicated that volatility from the long-term world interest rate and South Africa's sovereign bond return affected the Ethiopian sovereign bond return negatively and positively, respectively. Both Ethiopia and South Africa's markets display high persistence in their volatilities. The findings suggest that African financial policy makers should consider their own economies realities and specific reactions to volatility and spillover effects from the world's long-term interest rate.

In a broader context, Giovannetti and Velucchi (2013) conducted a study that examined the connections between established financial markets such as the US and UK, China, emerging markets in South Saharan Africa, and North African countries. They focused on how market volatility influenced these connections. Using a Multiplicative Error Fully Interdependent Model, they investigated how volatility moved across markets and impacted their interactions. The results showed that South Africa and the US had significant influences on African financial markets, with China's influence on the rise. The research also pointed out that while the US, Kenya, and Tunisia tended to generate volatility effects, South Africa and China absorbed them.

Additionally, Ncube et al. (2012) examined into the effects of unexpected changes in United States bond yields, the tightening of the federal funds rate, and monetary stimulus shocks on South Africa's economy using structural VAR models. Their research unveiled that US monetary stimulus shocks had several impacts on South Africa, including weak consumer price inflation, an appreciation of the rand against the dollar, revaluation of real stock prices, lower bond yields, decreased monetary aggregates, and a drop in real interest rates. In another financial realm, Morema and Bonga-Bonga (2020) explored the influence of fluctuations in gold and oil prices on the volatility of the South African stock market. They employed the Vector Autoregressive Asymmetric Dynamic Conditional Correlation (VAR-ADCC) GARCH model, which specifically utilizes Vector Autoregressive Moving Average (VARMA) to model conditional variances and covariance. Additionally, they applied the Ljung-Box Portmanteau test to examine serial correlation in the standardized errors (SEs) and squared standardized errors (SSEs).

In summary, this literature review provides an extensive exploration of scholarly work examining the dynamics of volatility transmission and interdependence across various financial markets, which covers studies that encompass a wide range of methodologies and geographic regions. It evaluates their methodological approaches, and empirical findings contributing to the comprehension of volatility spillovers, contagion risks, and the factors driving transmission across diverse markets.

In conclusion, this literature review offers a comprehensive overview of research efforts into volatility transmission and interdependence across various financial markets and regions. The studies discussed employ diverse methodologies, from Multivariate GARCH models to cointegration analysis and VAR frameworks, and provide good insights into the nature of market interactions. Key findings include the vulnerability of non-oil producing countries in the MENA region to global financial crises, the varying influences of the US, UK, and China on African markets, and the impact of global economic shocks on South Africa's economy. Additionally, studies highlight the importance of considering regional and global factors when analyzing market dynamics.

Finally, the majority of studies in the review appear to focus on regions outside of Africa, such as MENA, developed markets, and emerging markets in Asia and Europe. There does appear to be a gap in the analysis of the transmission of return volatility between sovereign bonds in SSA countries and emerging markets. Further research in this area could provide valuable insights for investors, policymakers, and financial institutions operating in these markets. This knowledge would contribute to a deeper understanding of the interconnectedness of financial markets and support to making informed decisions in an increasingly globalized and interdependent economic landscape.

3. Methodology of the Study

3.1. Data and Context

In addition to data availability, Ethiopia and Ghana have been selected as case studies for this research for several convincing reasons. Firstly, Ethiopia and Ghana represent two distinct African markets, each with unique economic, political, and financial characteristics. Secondly, both countries are considered emerging economies within the African context. This choice enables us to gain insights into how African developing economies engage with the global emerging market. Thirdly, they have both issued noteworthy sovereign bonds in recent years, which is a vital factor for studying their relationships with international bonds. These bond issuances have series implications for their fiscal policies, economic stability, and interactions with global investors. Fourthly, their economic and financial developments can have ripple effects on neighboring countries and regional markets. Fifthly, the financial policies and strategies of Ethiopia and Ghana can serve as indicators of broader trends in African financial markets. By analyzing their sovereign bond behavior, we can uncover insights with policy implications for other African nations. In summary, selecting Ethiopia and Ghana as case studies for this research allows us to shed light on the dynamics of the African sovereign bond market and its potential connections with the global emerging market. Since the emerging markets are progressing and rapidly industrializing, investors across the world closely watch to sovereigns issued by the government of these nations so as to take advantage of the rapid growth occurring in their financial markets.

The study utilizes a weekly time series data spanning the period 49^{th} week of 2014 to 6^{th} week of 2022 containing sovereign bond prices indices of Ethiopia and Ghana, representing the SSA countries. Then, it utilizes JPM's emerging market bond index, for the same period, which is a benchmark index for measuring the performance of sovereign issued by emerging market countries globally. Utilizing these bond price indices, the study calculates the weekly returns by measuring the difference in the logarithms of consecutive bond price indexes, as illustrated below:

$$r_{i,t} = \ln(P_{i,t}/P_{i,t} - 1) \times 100$$

Where, $r_{i,t}$ denotes the continuously compounded percentage weekly returns for index i at time t and $P_{i,t}$ denotes the price level of index i at time t.

Because the data is non-stationary at level, it uses the first difference of natural logarithms of the bond price indices to make the series stationary. This conversion also helps to get the weekly bond yields/returns. Then, it applied the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to test stationarity of the data. Moreover, it has employed histograms, autocorrelation and partial autocorrelation functions along with the Portmanteau (Q) test in order check the data for normality and autocorrelation.

3.2. Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) Models

Research has identified a recurring pattern in financial asset returns, characterized by clustered volatility, where changes in volatility vary over time. To study this phenomenon in financial data, studies have been employing the generalized autoregressive conditional heteroscedasticity (GARCH) models (Fama, 1965). Within the realm of financial markets, scholars have extensively turned to multivariate GARCH models and their variations to grapple with these complexities (Li and Giles, 2015).

The use MGARCH models presents a robust analytical framework to discover the dynamics of volatility transmission across these diverse markets. The models allow for the exploration of both the contemporaneous and lagged relationships between sovereign bond return volatilities, offering valuable insights into the degree of interconnectedness, spillover effects, and potential contagion risks (Chevallier, 2015; Demirel and Unal, 2020). Overall, a significant body of the literature underscores the prevalence of Multivariate GARCH modeling as a key analytical method for exploring the transmission or spillover of volatilities in financial returns. In line with this, the current study fits three variants of MGARCH models: the Constant Conditional Correlation (CCC) Model, the Dynamic Conditional Correlation (DCC) Model, and the Varying Conditional Correlation (VCC) Model. It estimated each of these models, performed adequacy tests, and compared their performance. Ultimately, its selects one of the variants based on its better relative ability to capture the data.

I. Constant Conditional Correlation (CCC) Model

The CCC-MGARCH model allows for time-varying conditional variances and covariance. Its conditional variance matrix is given by:

$$H_t = D_t R D_t = \rho_{ij}\sqrt{h_{ii,t}h_{jj,t}}$$

where Dt is the (n×n) diagonal matrix that the diagonal elements are the conditional standard deviations, and R is a (n×n) time-invariant correlation matrix.

Then, conditional variance of the GARCH (1,1) specification is given by:

$$h_{ii,t} = c_i + a_i\varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$$

$$h_{ij,t} = \rho_{ij}\sqrt{h_{ii,t}h_{jj,t}} \quad , i, j = 1 \ldots\ldots n$$

where c is a n×1 vector, α_i and bi are diagonal (n×n) matrices.

II. Dynamic Conditional Correlation (CCC) Model

The DCC is used to capture the dynamic time-varying behavior of conditional covariance. The respective conditional covariance matrix Ht is now defined as:

$$H_t = D_t R_t D_t$$

where $D_t = \text{diag}\sqrt{\{H_t\}}$ is the diagonal matrix with conditional variances along the diagonal, and Rt is the time-varying conditional correlation matrix.

III. Varying Conditional Correlation (VCC) Model

It applies VCC approach of Tse and Tsui (2002). The conditional correlation matrix D_t is given by

$$D_t = (1 - \theta_1 - \theta_2)D + \theta_1 D_{t-1} + \theta_2 \Psi_{t-1}$$

where θ_1 and θ_2 are scalar parameters ($0 \leq \theta 1 + \theta 2 < 1$), D is k× k positive definite matrix with unit diagonal elements, and $\Psi t{-}1$ is the k× k sample correlation matrix.

Finally, models are estimated using the Maximum Likelihood (ML) approach. Then after, stationarity is tested using Augmented Dickey Fuller (ADF) and PP Phillips-Perron (PP) tests. Serial correlation and normality tests on the SEs and SSEs residuals are performed to check for model adequacy. In addition, Wald test is used to check model fitness. Finally, Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC) are employed to select the best model.

4. Results and Discussions

4.1. Testing for Stationarity, Normality and Autocorrelation

After visualizing time-series plots of the returns (Figure 1), unit root tests are made using the ADF and PP methods. Test results for unit root shows that the returns' series is stationary (see table 1 below).

Figure 1: stationarity of bonds' return series

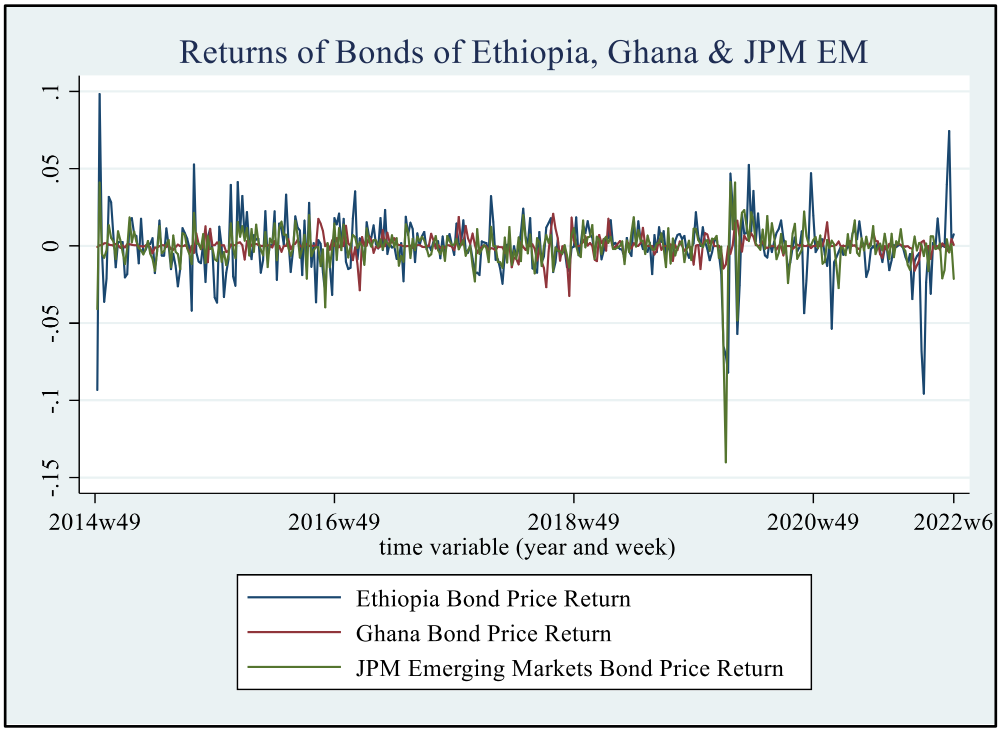


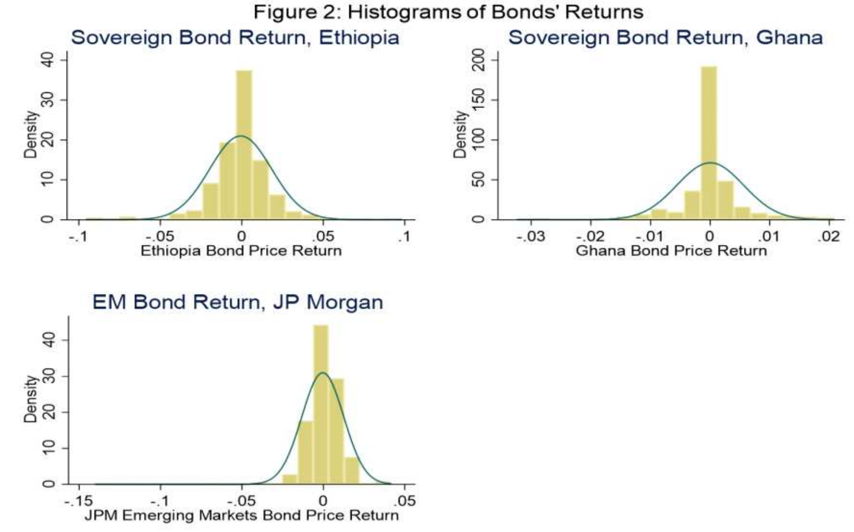
Table 1: ADF and PP test results for unit root test; Number of obs = 372

Augmented Dickey-Fuller (ADF) test statistic					
		Test Statistic	1% c. value	5% c. value	10% c. value
Ethiopia's bond price return	Z(t)	-17.126	-3.450	-2.875	-2.570
Ghana's bond price return	Z(t)	-14.842	-3.450	-2.875	-2.570
JP Morgan Emerging Markets bond price return	Z(t)	-17.142	-3.450	-2.875	-2.570
Phillips-Perron (PP) test statistic					
Ethiopia's bond price return	Z(rho)	-338.580	-13.649	-8.000	-5.700
	Z(t)	-17.256	-2.580	-1.950	-1.620
Ghana's bond price return	Z(rho)	-274.822	-13.649	-8.000	-5.700
	Z(t)	-14.831	-2.580	-1.950	-1.620
JP Morgan Emerging Markets bond price return	Z(rho)	-309.365	-13.649	-8.000	-5.700
	Z(t)	-17.096	-2.580	-1.950	-1.620

Distribution of the sovereign bond price returns is leptokurtic (figure 2), which is expected in such time series financial data and still can be used to make the intended time-series analysis.

Figure 2: Histograms of time series of bonds' returns

Figure 2: Histograms of Bonds' Returns



The AC and PAC functions together with the Portmanteau test (table 2) show that no series autocorrelation problem exists in the returns series.

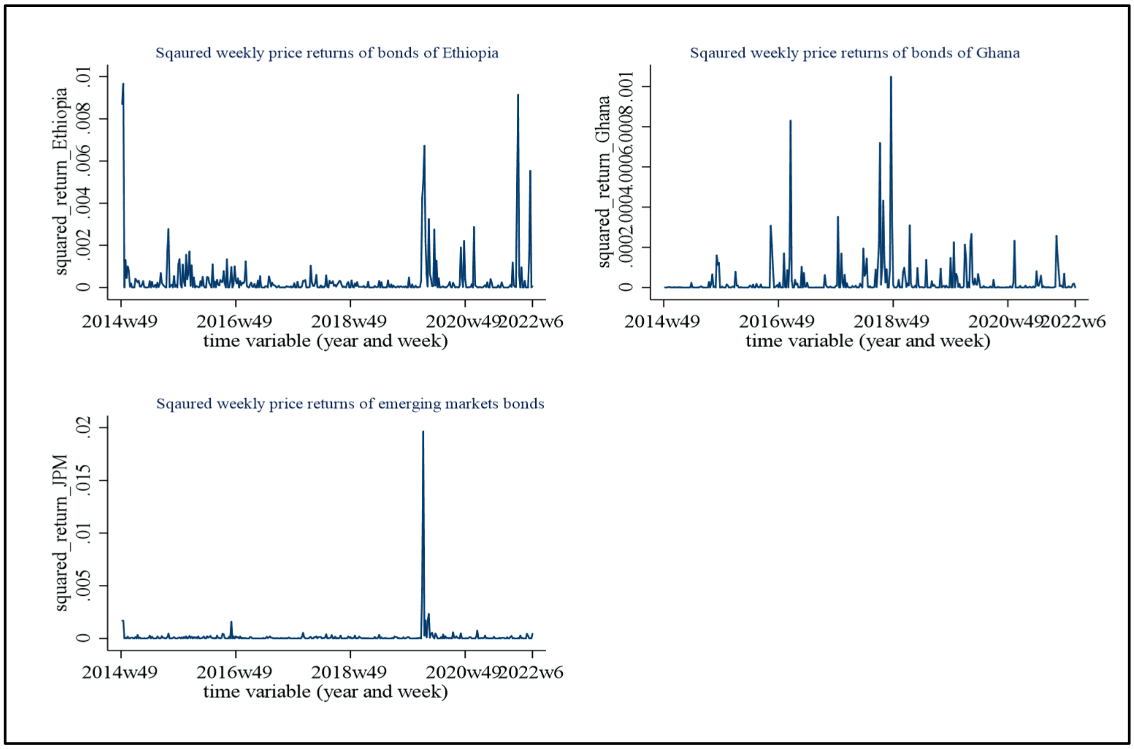
Table 2: Portmanteau (Q) test of white noise

Variable	Q statistics	Prob > chi2(1)
Ethiopia's sovereign bond return	23.0380	0.0106
Ghana's sovereign bond return	42.7182	0.0000
JPM's sovereign bond return (emerging markets)	20.2633	0.0269

4.2. Visual Inspection of Volatility in the Returns

Time-series plots of the squared weekly returns show the existence of volatility in the price returns of all the three bonds. In some cases, there is volatility clustering as periods of high volatility followed by another period of high volatility, particularly for the African bonds (figure 3). These features of the financial returns data substantiate our choice of the generalized autoregressive conditional heteroscedasticity models.

Figure 3: Time series plot of squared weekly returns



4.3.Empirical Results of MGARCH Models and Diagnostic Tests

4.3.1. Model Estimation and Adequacy

Using Maximum Likelihood (ML), parameters of five variants of the MGARCH model are estimated, assuming that the errors come from a multivariate normal distribution or student's t-distribution. Suitability of each model for examining the return spillover effects is examined using serial correlation and normality tests on Standard Errors (SEs) and Squared Standard Errors (SSEs).

Test for serial correlation: The autocorrelation function (ACF, figure 4 in the appendix) and partial autocorrelation function (PACF, figure 5 in the appendix) for all models reveal that almost all lags of returns fall within 95% confidence bands, with a very few outliers on the series of SSE. In addition, the Portmanteau test (table 3) shows that we fail to reject the null hypothesis of no serial correlation among the SEs and SSEs. Overall, the tests reveal absence of serial correlation in the SEs and only a very weak form of autocorrelation in the SSE.

Table 3: Portmanteau (Q) test statistic for serial correlation

Model	Variable	Standard Residual		Squared Standard Residual	
		Q statistic	Prob >	Q	Prob >

			chi2(40)	statistic	chi2(40)
Model 1 (CCC with Normal or Gaussian Errors)	dlnETH	31.9807	0.8129	36.7613	0.6169
	dlnGHA	49.7049	0.1398	33.6035	0.7523
	dlnJPM	48.9214	0.1575	24.4210	0.9751
Model 2 (CCC with Student-t (7) Errors)	dlnETH	30.0369	0.8742	29.2801	0.8943
	dlnGHA	47.9314	0.1821	22.3430	0.9892
	dlnJPM	48.3385	0.1716	48.4016	0.1700
Model 3 (DCC with Normal or Gaussian Errors)	dlnETH	31.5981	0.8260	40.5958	0.4440
	dlnGHA	50.0784	0.1320	33.9636	0.7378
	dlnJPM	48.0316	0.1794	17.0411	0.9994
Model 4 (DCC with Student-t (7) Errors)	dlnETH	30.1170	0.8719	29.9290	0.8772
	dlnGHA	48.3141	0.1722	22.3772	0.9890
	dlnJPM	49.2188	0.1506	22.6009	0.9879
Model 5 (VCC with Student-t (7) Errors)	dlnETH	30.1170	0.8719	28.7284	0.9076
	dlnGHA	48.3141	0.1722	22.6254	0.9878
	dlnJPM	49.2188	0.1506	40.2148	0.4607

Test for normality: The Q-Q plots of residuals appear that we have approximately normality distributed standardized errors, except for some lower tail deviations for the SE and upper tail deviations for SSE (figure 6 and figure 7 in the appendix). Moreover, the Kurtosis and Skewness test of normality confirms this because Prob>chi2 is 0.0000 for all models. Therefore, all models are adequate to modelling the return volatilities spillovers.

Wald test of model's fitness: Wald test rejects the null hypothesis, which states that all the coefficients on the independent variables in the mean equations are zero. Therefore, volatility of returns from all bonds have significant effect on the mean of returns evolutions. It, therefore, tells us that all the models fitted and estimated are adequate in their overall capacity to capture the time series data for all sovereign bonds (Ethiopia, Ghana and emerging markets).

Table 4: Wald test statistics of model fitness

Model	Wald chi2(18)	Prob > chi2
Model 1 (CCC with Normal or Gaussian Errors)	72.45	0.0000
Model 2 (CCC with Student-t (7) Errors)	47.80	0.0002
Model 3 (DCC with Normal or Gaussian Errors)	76.60	0.0000
Model 4 (DCC with Student-t (7) Errors)	51.52	0.0000
Model 5 (VCC with Student-t (7) Errors)	50.77	0.0001

4.4. Choosing Model with Better Performance

All the steps we conducted above to assess the suitability of the various models consistently confirm that all of them are well-suited for modeling the spillovers of return volatilities. The results provide assurance that our data is appropriately distributed and do not exhibit any significant autocorrelation issues. Additionally, the Wald test, which is a statistical test used to evaluate the validity of coefficients in a model, further supports the notion that all the models effectively capture the underlying data dynamics.

However, even though all models appear to be suitable, we must choose one for our discussion and analysis purposes. To make this decision, we employ two widely-used criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as shown in Table 5. These criteria help us determine which model offers the best trade-off between goodness-of-fit and model complexity. Upon careful examination, it becomes evident that the VCC model with student-t (7 degrees of freedom) errors stands out as the most favorable choice. This conclusion is based on the fact that this particular model yields the most negative values for both the AIC and BIC. In statistical terms, a lower AIC and BIC value indicates a better fit to the data while penalizing for model complexity. Therefore, we can confidently assert that the VCC model with student-t (7 degrees of freedom) errors is the most suitable model for studying the transmission of return volatility in our analysis.

Table 5: Model's Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

Model type	AIC	BIC
Model 1 (CCC with Normal or Gaussian Errors)	-7388.957	-7247.974
Model 2 (CCC with Student-t (7) Errors)	-7606.028	-7465.045
Model 3 (DCC with Normal or Gaussian Errors)	-7397.000	-7248.184
Model 4 (DCC with Student-t (7) Errors)	-7612.136	-7463.321
Model 5 (VCC with Student-t (7) Errors)	-7623.403	-7474.587

4.5. Markets' Return Volatility and the Spillover Effects

The VCC-MGARCH model results, given in Table 6 (mean equation) and Table 7 (variance equation), are analyzed and discussed. The mean and variance equations in a time series or financial modeling context play important roles in understanding and modeling the behavior of a particular variable. They describe how the variable's mean (average) and variance (volatility) evolve over time, often in response to past values and other factors.

Considering results of the mean equations in Table 6, the coefficient for the lagged value of Ethiopia's sovereign bond return (dlnETH) at lag 1 is approximately 0.0319. However, the p-value ($P > |z|$) is 0.601, and suggests that it is not statistically significant in explaining the mean equation for Ethiopia's return. Similarly, the coefficient for the second lagged value is about 0.0053, with a p-value of 0.919, indicating that it is not statistically significant. Then, the coefficient for the first lagged value of Ghana's sovereign bond return (dlnGHA) is -0.1666, and statistically insignificant. Likewise, the second lagged value has a coefficient of 0.0312, which is also statistically insignificant. In the same equation, the coefficient for the lagged value of JPM's return (dlnJPM) at lag 1 is nearly 0.2389, and it is statistically significant at 1% level. This suggests that the first lagged value of JPM's return has a strong positive relationship with Ethiopia's return. Coefficient of the second lagged value is roughly 0.0545, but not statistically significant. While the lagged values of Ghana has no statistically significant influence on Ethiopia's return, the significant coefficient for the lagged value of JPM's return suggests that the past returns of JPMorgan (representing global emerging financial markets) have a strong positive impact on Ethiopia's return. This could imply that changes or movements in the global emerging financial market, as represented by JPM, have a direct influence on Ethiopia's financial returns.

Similar to Ethiopia's return mean equation, Ghana's return mean equation includes lagged values of Ethiopia's return (dlnETH), Ghana's return (dlnGHA), and emerging markets return (dlnJPM) at different lags. Notably, the coefficient for the first lagged value of Ghana's return (dlnGHA, L1) is nearly 0.2159 and statistically significant at the 1% level. This suggests that the lagged value of Ghana's return at lag 1 has a strong positive relationship with its own return, which means past returns in Ghana's financial market have a strong positive impact on its own current returns. The first lagged value of Ethiopia's return is positive and significant at 10 % and this suggests the existence of a positive short-term relationship between the two markets. There is no convincing evidence of a mean spillover in Ghana's returns due to the insignificance of the estimated coefficients of the global emerging markets.

Lastly, the mean equation for emerging markets' return includes similar lagged variables. None of the lagged variables or the constant term are statistically significant at any of the acceptable significance levels. This suggests that, for emerging markets' returns, the historical returns of Ethiopia, Ghana, and emerging markets themselves may not have a significant direct impact on the current returns of the emerging markets.

Table 6: Empirical results of the VCC MGARCH model (mean equation)

Variable	Coeff.	Std. Err	Z	P > |z|
Ethiopia's return mean equation				
dlnETH, L_1	.0318627	.0609688	0.52	0.601
dlnETH, L_2	.0052905	.0518699	0.10	0.919
dlnGHA, L_1	-.166637	.110529	-1.51	0.132
dlnGHA, L_2	.0311996	.1062621	0.29	0.769
dlnJPM, L_1	.238911*	.088785	2.69	0.007
dlnJPM, L_2	.054541	.0834607	0.65	0.513
Constant	.0006054	.0006126	0.99	0.323
Ghana's return mean equation				
dlnETH, L_1	.0172608**	.010357	1.67	0.096
dlnETH, L_2	.0041628	.0096084	0.43	0.665
dlnGHA, L_1	.2158702 *	.0672255	3.21	0.001
dlnGHA, L_2	.0273557	.0452031	0.61	0.545
dlnJPM, L_1	.0081768	.0188175	0.43	0.664
dlnJPM, L_2	.0132462	.017849	0.74	0.458
Constant	-.0000681	.0001465	-0.46	0.642
Emerging markets' return mean equation				
dlnETH, L_1	.0163357	.0302105	0.54	0.589
dlnETH, L_2	.0192168	.0301572	0.64	0.524
dlnGHA, L_1	-.0432578	.0761235	-0.57	0.570
dlnGHA, L_2	.0251359	.080135	0.31	0.754
dlnJPM, L_1	-.0440215	.058187	-0.76	0.449
dlnJPM, L_2	.0011625	.0548802	0.02	0.983

Constant	.0001275	.00043	0.30	0.767

Source: own presentation from Stata (* &*** refers to 1% & 10% significance levels, respectively)

Table 7 presents the empirical results of variance equations of the model for Ethiopia's, Ghana's, and emerging markets' returns. In Ethiopia's sovereign bond return variance equation, the coefficient for the autoregressive term (ARCH) at lag 1 is about 0.1714, with statistical significance at 1% level. The generalized autoregressive conditional heteroscedasticity (GARCH) term at lag 1 has a coefficient about 0.0439, and is statistically insignificant with a p-value of 0.622, while the second lag of the GARCH term is near to 0.6983 and it is statistically significant at 1 % level of significance. The presence of significant ARCH term in the variance of Ethiopia's return implies that past variations in Ethiopia's return have a significant impact on its own current level of volatility or risk in its financial market. Again, the significant coefficient for the GARCH term suggests that past squared volatility in Ethiopia's return have a significant impact on the current level of volatility. This suggests that volatility tends to cluster over time in Ethiopia's sovereign bond markets.

Turning our attention to Ghana's variance equation, we found some notable results. The autoregressive term (ARCH) at lag 1 exhibits a 1% statistically significant coefficient nearly equal to 0.4336. In simpler terms, past variations in Ghana's returns play a crucial role in shaping the current level of volatility in the country's sovereign bond market. Conversely, the first lag of the GARCH term does not reach statistical significance. However, at lag 2, the GARCH term, roughly 0.3788, is statistically significant at 1 % level of significance. Such significance of the GARCH component within Ghana's return variance equation indicates that past squared volatility in Ghana's returns has a marked impact on its own present level of volatility. Much like our observations for Ethiopia, these results suggest that volatility tends to cluster over time in Ghana's market. In other words, the presence of strong GARCH effects imply that their own past volatility affects the conditional variance of their return. Thus, periods of heightened volatility are often followed by subsequent periods of heightened volatility, a valuable insight for those monitoring and participating in the financial landscapes of the two countries.

Considering variance equation of the emerging markets' return, the coefficient for the ARCH term is approximately 0.1144, and statistically significant at 10% level. This shows the presence of a significant autoregressive component in the variance equation for emerging markets' return. The coefficient of the GARCH term at lag 1 is roughly 0.3464, but it is not statistically significant. Similarly, the coefficient for the GARCH term at lag statistically insignificant. The significant coefficient of the ARCH term tells that past variations in JPM's return have a significant impact on the current level of volatility in emerging markets. This could imply that global emerging markets financial events or shocks, as represented by JPM, have a direct influence on volatility in the emerging markets themselves. Yet, no GARCH effect is significant for emerging markets bond return.

Table 7: Empirical results of the VCC MGARCH model (variance equation)

Variable	Coeff.	Std. Err	Z	P > |z|
Ethiopia's return variance equation				

ARCH_dlnETH, arch L_1	.1714076 *	.0501413	3.42	0.001
ARCH_dlnETH, garch L_1	.0438633	.0890738	0.49	0.622
ARCH_dlnETH, garch L_2	.698265 *	.1102719	6.33	0.000
Constant	.000018 ***	9.56e-06	1.89	0.059
Ghana's return variance equation				
ARCH_dlnGHA, arch L_1	.4336316 *	.1211974	3.58	0.000
ARCH_dlnGHA, garch L_1	.0454392	.0639596	0.71	0.477
ARCH_dlnGHA, garch L_2	.3787982 *	.1214623	3.12	0.002
Constant	2.76e-06**	1.08e-06	2.57	0.010
Emerging markets' return variance equation				
ARCH_dlnJPM, arch L_1	.114396***	.0604634	1.89	0.058
ARCH_dlnJPM, garch L_1	.3463774	.2365181	1.46	0.143
ARCH_dlnJPM, garch L_2	.2524287	.2438638	1.04	0.301
Constant	.0000246 ***	.0000128	1.92	0.055
corr(dlnETH,dlnGHA)	-.1774423	.685958	-0.26	0.796
corr(dlnETH,dlnJPM)	.5748484**	.2534389	2.27	0.023
corr(dlnGHA,dlnJPM)	-.0295877	.4163518	-0.07	0.943
Adjustment lambda 1	.0203207 *	.0090726	2.24	0.025
lambda 2	.9754133 *	.0185934	52.46	0.000

Source: own presentation from Stata (*, ** &*** refers to 1%, 5% & 10% significance levels, respectively)

Besides, table 7 presents the correlations and adjustment parameters. The results shows a negative, but statistically insignificant correlation between Ethiopia's return (dlnETH) and Ghana's return (dlnGHA). Essentially, this suggests that there isn't a statistically significant linear connection between the returns of Ethiopia and Ghana. It is, however, vital to keep in mind that correlation measures only linear associations, and there might be other nonlinear relationships or interactions between these markets that are not captured by this correlation coefficient. We have observe that correlation between Ethiopia's sovereign bond return (dlnETH) and emerging markets return (dlnJPM) positive and is statistically significant with a p-value of 0.023. In simpler terms, this indicates movements in Ethiopia's return tend to be positively associated with movements in emerging markets return, which may indicate some level of dependency of Ethiopia's bond return on global emerging markets dynamics. Lastly, the correlation between Ghana's return and emerging markets return is close to zero (i.e. -0.030) and statistically insignificant. That mean, there is no statistically significant linear relationship between the returns of Ghana and emerging markets. The non-significant correlations between Ghana's return and both Ethiopia's return and JPM's return suggest that Ghana's financial market may not be as strongly influenced by these external factors or that other factors not included in the model are more relevant.

Moreover, there are statistically significant adjustment parameters (lambda 1 and lambda 2), which suggest the existence of some adjustment mechanism in the model fitted in this study. The adjustment parameter lambda 1, which represents the speed of adjustment, is significant with p-value of 0.025. This implies that there is a statistically significant adjustment mechanism in our model, which indicates that deviations from long-term equilibrium relationships between the variables are corrected through time. Secondly, the second adjustment parameter (lambda 2) is highly significant. This shows the presence of a very strong adjustment mechanism in the model, and implies that deviations from equilibrium relationships are corrected rapidly. The presence of significant adjustment parameters (lambda) indicates that the model recognizes the presence of adjustment mechanisms in that deviations from long-term relationships between variables are gradually corrected. The financial markets examined in this study have mechanisms in place to bring returns back to equilibrium over time.

4.6. Final Comments on the Modelling

It appears that VCC-MGARCH model is well-suited for capturing the characteristics of the data analyzed in this study. Firstly, the results confirm that all models, including the VCC MGARCH model, are adequate for modeling return volatility spillovers. This suggests that the model fits the data reasonably well. Secondly, the absence of a serious autocorrelation problem indicates that the model effectively captures the temporal dependencies in the data. Thirdly, the Wald test affirms that all the models, including the VCC MGARCH model, are suitable for capturing the data. This test evaluates the validity of the coefficients in the model, and the positive results suggest that the model specification is appropriate. Fourthly, the use of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for model selection supports the choice of the VCC MGARCH model as the best fit. Lower AIC and BIC values indicate a better balance between goodness-of-fit and model complexity. Finally, the VCC MGARCH model with student-t (7 degrees of freedom) errors consistently outperformed other models based on AIC and BIC. This suggests that it provides the most parsimonious representation of the data while capturing its key features. Overall, the VCC MGARCH model appears to be an appropriate choice for modeling the return volatility spillovers in our dataset. It adequately captures the data's dynamics, accounts for temporal dependencies, and provides a good trade-off between model fit and complexity.

5. Conclusions and Implications

The study analyzes the existence or otherwise of return volatility spillovers between Ethiopia' and Ghana's, and emerging markets sovereign bonds returns using VCC MGARCH models. The results revealed that correlations are varying and that both ARCH and GARCH effects play an important role in determining volatility among the bonds. The main conclusions and the corresponding policy implications from the analysis are the presented in to five categories:

Firstly, the significant positive coefficient of the lagged value of emerging markets return in Ethiopia's mean equation suggests that changes in the global emerging markets, represented by the index provided by JPMorgan, have a direct and positive impact on Ethiopia's financial returns. Therefore, policymakers in Ethiopia may need to closely monitor and assess developments in the global emerging markets, particularly those involving major institutions like JPM, as they can have a substantial influence on Ethiopia's financial stability. Appropriate policies and risk management strategies should be in place to mitigate the potential impact of external financial shocks.

Secondly, the significant positive coefficient for the lagged value of Ghana's return in Ghana's mean equation indicates that past returns in Ghana's sovereign bond market have a strong positive impact on its current returns. Ghana's financial market dynamics exhibit some degree of persistence. Policymakers in Ghana should consider the implications of this persistence for market stability and investor confidence. Monitoring and regulating the domestic financial market to prevent excessive volatility may be important.

Thirdly, the significant ARCH term in Ethiopia's variance equation indicates that past variations in Ethiopia's return have a significant impact on the current level of volatility. Again, the significance of GARCH term indicates that the impact of past squared returns or volatility shocks in Ethiopia's financial market, specifically with a lag of 2 periods, has a significant influence on the current volatility. This suggests that recent volatility patterns can have a lasting effect on market stability. Thus, policies aimed at reducing excessive volatility in Ethiopia's financial market could include interventions to address the factors leading to past volatility, such as regulatory changes, market oversight, or investor education to reduce panic-driven trading. Policymakers in Ethiopia should consider measures to monitor and manage volatility shocks with a lag. This may involve implementing mechanisms that help stabilize the market during periods of high volatility, such as circuit breakers, increased transparency, or risk management policies.

Fourthly, similar to Ethiopia, the ARCH term in Ghana's variance equation, is statistically significant, implies that past variations in Ghana's return have a significant impact on the current level of volatility. In addition, the significance of the GARCH term suggests that past squared returns with a lag of 2 periods in Ghana's financial market continue to impact current volatility. This indicates a need for attention to historical volatility patterns in risk management. Therefore, Ghanaian policymakers may consider measures to address factors contributing to past volatility in the financial market, which could involve regulatory adjustments, market interventions, or communication strategies to manage market expectations. Ghanaian policymakers can focus on enhancing risk management practices in the financial sector. This may involve stress-testing financial institutions to ensure they can withstand shocks, improving regulatory oversight, and fostering investor confidence through effective risk communication.

Fifthly, the significant adjustment parameters (lambda) indicate that deviations from long-term equilibrium relationships between variables are corrected over time, and the corrections happen relatively quickly. This implies that policymakers should be aware that financial markets under study have mechanisms in place to bring returns back to equilibrium over time. They can monitor these adjustment mechanisms to ensure market stability and address any issues that may hinder efficient market adjustments.

Overall, the presence of significant coefficients in the variance equations indicates that volatility in these financial markets is not purely random but exhibits some degree of persistence. Past volatility and past returns play a role in determining current levels of risk and return. The persistence of volatility shocks should be considered when formulating policies related to market stability and risk management. Policymakers should develop strategies that address the potential enduring effects of past volatility events, as these can impact market confidence and overall financial stability. It is, however, important to note that specific policy actions should be tailored to the unique characteristics and challenges of each country's financial market. Additionally, collaboration with relevant stakeholders, including financial institutions and regulatory bodies, is essential to implement effective policies that address these volatility dynamics.

In summary, the policy implications of the VCC MGARCH model results suggest the importance of monitoring and managing external influences on domestic financial markets, addressing the persistence of market dynamics, and considering policies to reduce excessive volatility. Additionally, recognizing and understanding the adjustment mechanisms in financial markets can help policymakers make informed decisions to promote market stability and efficiency. These implications provide valuable guidance for risk management and policymaking in the financial sector.

References

Abou-Zaid, A. S. (2011). Volatility Spillover Effects in Emerging MENA Stock Markets. Review of Applied Economics Vol. 7, No. 1-2, (January-December 2011).

Al Nasser, O. M., and Hajilee, M. (2016). Integration of emerging stock markets with global stock markets. Research in International Business And Finance, 36, 1–12.

Bala, D. A. and Takimoto, T. (2017). Stock markets volatility spillovers during financial crises: A DCC-MGARCH with skewed-t density approach. Borsa _Istanbul Review 17-1 (2017) 25e48. http://dx.doi.org/10.1016/j.bir.2017.02.002

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., and Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. Emerging Markets Review, 11(3), 250–260.

Boako and Alagidede, G.P. (2017), “Examining evidence of ‘shift-contagion’ in African stock markets: a CoVaR-copula approach”, Review of Development Finance, Vol. 7 No. 2, pp. 142-156, doi: 10.1016/j.rdf.2017.09.00.

Chevallier, J. (2015) Time-varying correlations in oil, gas and CO2 prices: an application using BEKK, CCC and DCC-MGARCH models, Applied Economics, 44:32, 4257-4274, DOI: 10.1080/00036846.2011.589809

Debalke, N. M. (2023). Examining volatility and spillover effects between markets for sovereign bonds of African countries and the world’s long term interest rate. MPRA Paper 117491, University Library of Munich, Germany.

Demirel, M. and Unal, G. (2020) Applying multivariate-fractionally integrated volatility analysis on emerging market bond portfolios. Financ Innov 6, 50 (2020). https://doi.org/10.1186/s40854-020-00203-3

Emenike, O. K. (2021). How does sovereign bond volatility interact between African countries? Journal of Derivatives and Quantitative Studies: Vol. 30 No. 4, 2022 pp. 246-259. https://doi.org/10.1108/JDQS-06-2021-0015

Fama, E. F. (1965). The behavior of stock-market prices. Journal of Business, 38, 34-105.

Giovannetti, G. and Velucchi, M. (2013). A spillover analysis of shocks from US, UK and China on African financial markets. Review of Development Finance 3 (2013) 169–179. http://dx.doi.org/10.1016/j.rdf.2013.10.002

Gross, A. (2020), "African countries face 'wall' of Sovereign debt repayments", available at: https://www.ft.com/content/8c232df6-4451-11ea-abea-0c7a29cd66fe.

Gupta, R., and Guidi, F. (2012). Cointegration relationship and time varying co-movements among Indian and Asian developed stock markets. International Review of Financial Analysis, 21, 10–22.

Habibi, H. and Mohammadi, H. (2022). Return and volatility spillovers across the Western and MENA Countries. North American Journal of Economics and Finance 60 (2022) 101642. http://doi.org/10.1016/j.najef.2022.101642

Huang, B.-N., Yang, C.-W., and Hu, J. W.-S. (2000). Causality and cointegration of stock markets among the United States, Japan and the south China growth triangle. International Review of Financial Analysis, 9(3), 281–297.

Li, Y. and Giles, D.E. (2015), "Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets", International Journal of Finance and Economics, Vol. 20 No. 2, pp. 155-177.

Maghyereh, A. I., Awartani, B., and Al Hilu, K. (2015). Dynamic transmissions between the US and equity markets in the MENA countries: New evidence from pre-and post-global financial crisis. The Quarterly Review of Economics and Finance, 56, 123–138.

Morema, K. and Bonga-Bonga, L. (2020). The impact of oil and gold price fluctuations on the South African equity market: Volatility spillovers and financial policy implications. Resources Policy 68 (2020) 101740. http://doi.org/10.1016/j.resourpol.2020.101740.

Ncube, M., Ndou, E., Gumata, N., 2012. How are the US Financial ShocksTransmitted into South Africa? Structural VAR evidence, Working PaperSeries. African Development Bank Group, n.157, October.

Neaime, S. (2012). The global financial crisis, financial linkages and correlations in returns and volatilities in emerging MENA stock markets. Emerging Markets Review, 13(3), 268–282.

Neaime, S. (2016). Financial crises and contagion vulnerability of MENA stock markets. Emerging Markets Review, 27, 14–35.

Panda, A.K., Nanda, S. and Paital, R.R. (2019), "An empirical analysis of stock market interdependence and volatility spillover in the stock markets of Africa and Middle East region", African Journal of Economic and Management Studies, Vol. 10 No. 3, pp. 314-335, doi: 10.1108/AJEMS-10-2018-0293.

Ratings, F. (2020), "Fitch: debt distress rising in Sub-Saharan Africa", available at: https://www.african-markets.com/en/news/africa/fitch-debt-distress-rising-in-sub-saharan-africa.

S & P Global Rating (2016), Sub-Saharan Africa Sovereign Rating Trends 2017, Standard & Poor Global.

Tse, Y. K. and Tsui , A. K. C. (2002). A multivariate generalized autoregressive conditional heteroskedasticity model with time-varying correlations. Journal of Business & Economic Statistics 20: 351-362.

Velde, D.W.T. (2014), "Sovereign bonds in sub-Saharan Africa: good for growth or ahead of time?", Briefing, Overseas Development Institute, Vol. 87, available at: https://cdn.odi.org/media/documents/8883.pdf.

Vellos, R. (2015), "Sub-Saharan Africa's sovereign bond issuance boom", available at: https://blogs.worldbank.org/opendata/sub-saharan-africa-s-sovereign-bond-issuance-boom.

World Bank (2015), International Debt Statistics 2016, World Bank Group, doi: 10.1596/978-1-4648-0681-0.

Yavas, B. F., and Dedi, L. (2016). An investigation of return and volatility linkages among equity markets: A study of selected European and emerging countries. Research in International Business and Finance, 37, 583–596.

Appendix

Figure 4: Autocorrelation function (ACF) of standardized residuals for all models

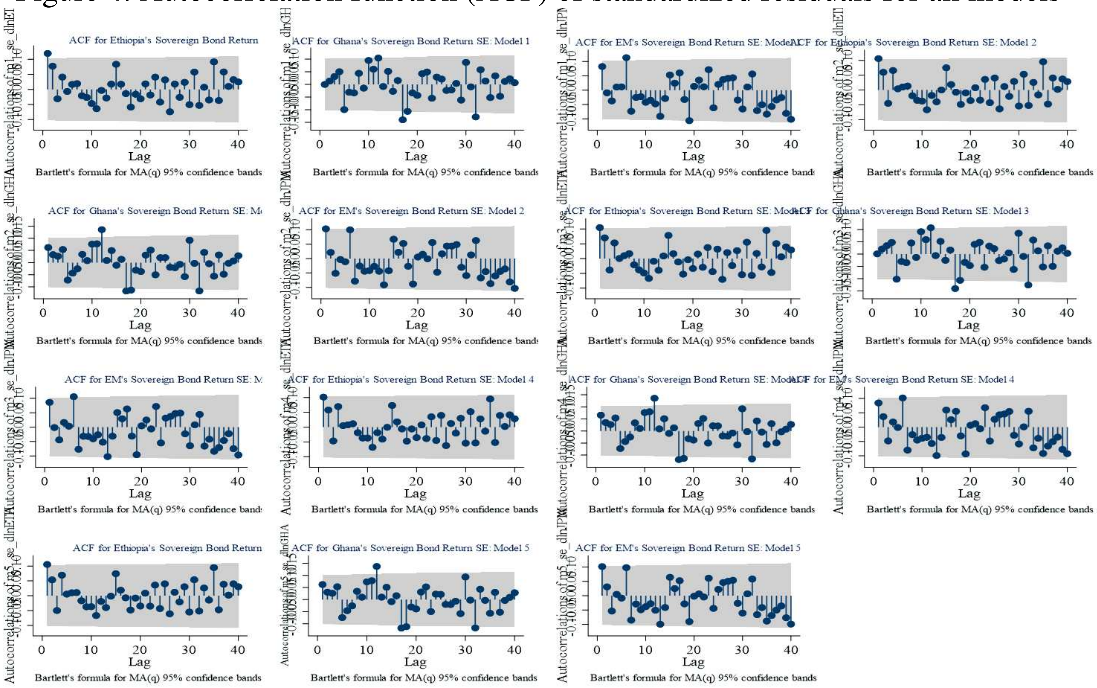


Figure 5: Autocorrelation function (ACF) of Squared Standardized Residuals

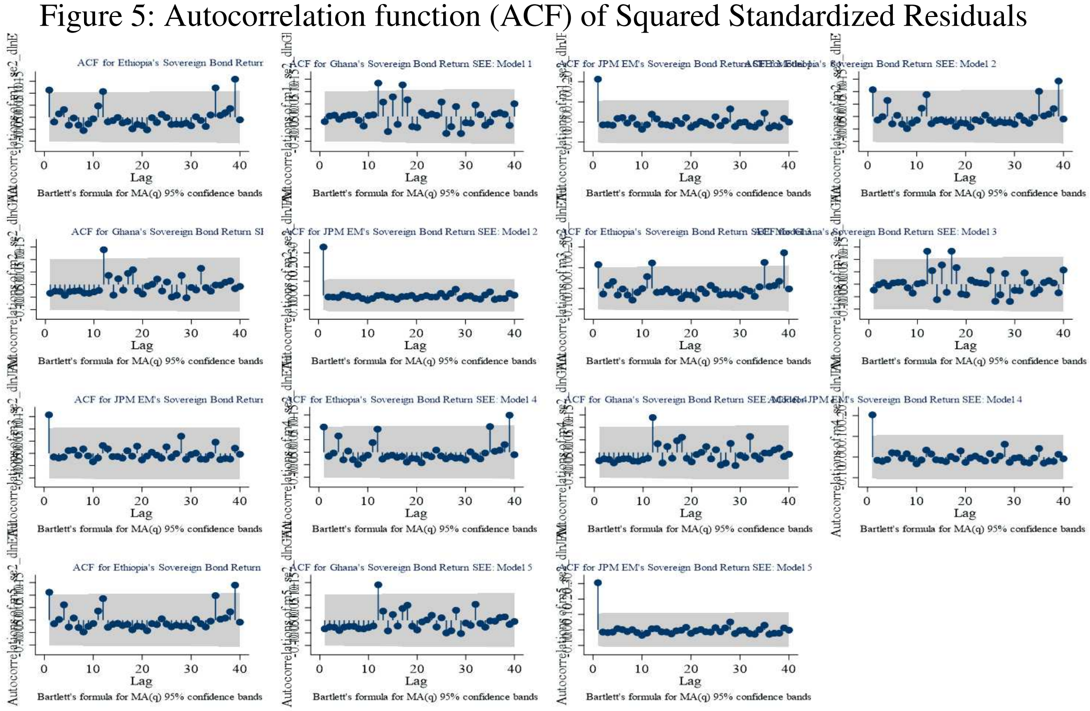


Figure 6: Q-Q plot of standardized residuals of all models

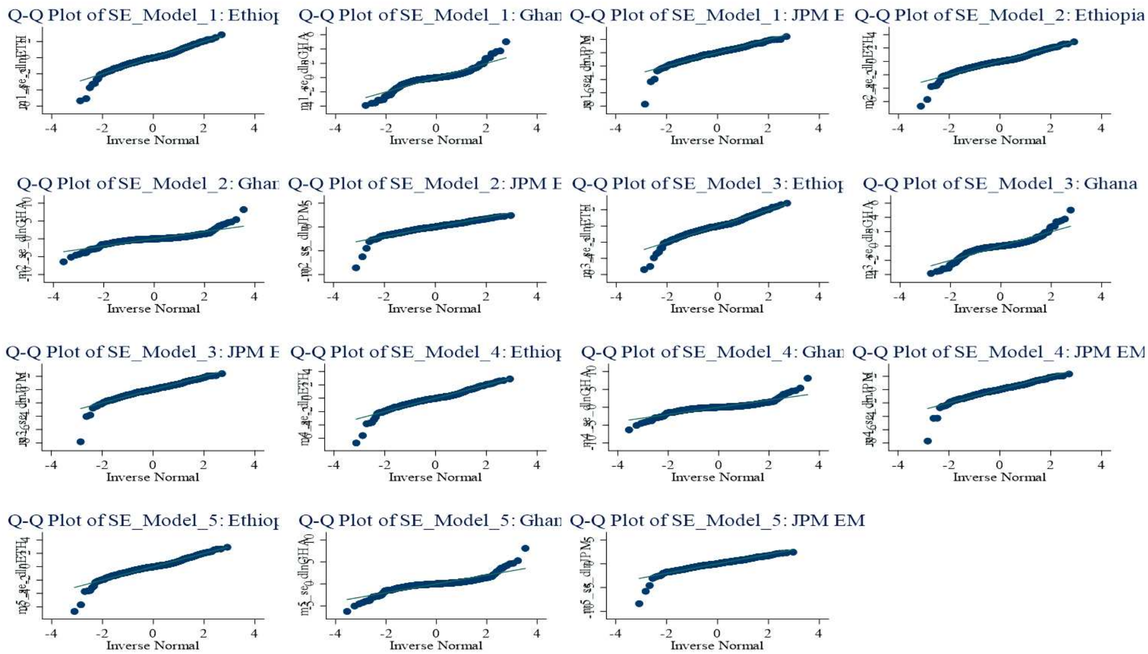


Figure 7: Q-Q plots of Squared Standardized Residuals for all models