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The Role of Macroeconomic Variables in Forecasting Equity Market Volatility in the East African Community Using Garch-Midas Model

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Abstract

This study delves into the dynamic relationship between macroeconomic variables and equity market volatility in the East African Community. The research employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model coupled with the Mixed Data Sampling (MIDAS) approach. Through a comparative process, it is found that the different macroeconomic variables exhibit heterogeneous effects on the different countries in the East African community that is macroeconomic factors significantly explain the variation in stock market volatility in Uganda and including these factors in the GARCH-MIDAS model improved its forecasting ability, however, in Kenya it was found that majority of the macroeconomic variables had insignificant effects on stock market volatility and didn't improve the forecasting ability of the GARCH-MIDAS model.

Keywords: GARCH, MIDAS, stock market, forecast volatility, East African Community

1. Introduction

The East African Community (EAC) is a regional intergovernmental organization in East Africa formed in 1967 and revived in 1999. It includes six member countries: Kenya, Uganda, Tanzania, Rwanda, Burundi, and South Sudan. Originally established to promote economic development and

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regional trade, the EAC collapsed in 1977 due to political and economic differences but was revived with a broader vision of cooperation in various fields. With a combined population of over 180 million people, the EAC represents a significant regional market with economic growth potential. The community's economic significance lies in its efforts to achieve deeper economic integration through a common market, customs union, and plans for a monetary union and political federation. The region's strategic location, natural resources, and growing consumer base have attracted international interest, leading to increased investment and trade opportunities. Through ongoing initiatives to harmonize policies and eliminate trade barriers, the EAC aims to enhance regional trade, collaboration, and the overall development of its member countries.

Equity markets hold immense significance in the East African Community (EAC) due to their pivotal roles in capital allocation, economic growth, financial stability, and overall development. As a regional bloc, the EAC benefits greatly from the establishment and growth of these markets. Firstly, equity markets facilitate capital formation by allowing businesses to raise funds through the issuance of stocks, thereby stimulating economic growth and job creation. Additionally, they efficiently allocate resources by directing capital towards promising ventures, promoting innovation, and encouraging entrepreneurship. Furthermore, equity markets attract foreign investment, injecting much-needed capital into the region and bolstering economic growth. On the other hand, they also contribute to financial stability by providing risk diversification opportunities for investors, encouraging long-term investment horizons, and improving corporate governance standards. As a result, equity markets instill investor confidence, safeguard the financial system, and mobilize domestic savings to support economic development. To unlock the full economic potential of the EAC and achieve sustainable growth, nurturing and developing robust equity markets remain crucial in attracting investments and ensuring the region's prosperity in the years to come.

Market volatility in equity markets refers to the fluctuation of financial asset prices over a specific time frame, reflecting the market's uncertainty and potential for rapid changes. It is measured using statistical metrics like standard deviation or the VIX. For investors, understanding volatility is vital for risk assessment, portfolio diversification, and timing investment decisions. High volatility signals greater risk, prompting investors to diversify their portfolios across various assets and sectors. They can also time their market entry during low volatility periods. Policymakers, on the other hand, analyze market volatility as an indicator of economic stability and financial system resilience. They use this data to make informed decisions about monetary policies and regulatory interventions. Financial institutions also rely on

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volatility forecasts to manage risk, allocate capital, and adjust trading strategies. For them, understanding market fluctuations is essential to maintain stability and ensure financial system resilience. Overall, accurate volatility forecasting is crucial for investors, financial institutions, regulators, and central banks to make informed decisions, manage risks, and maintain economic and financial stability. By anticipating and responding to volatility effectively, stakeholders can navigate uncertain market conditions more adeptly and optimize their investment strategies accordingly.

While existing literature has delved into the study of equity market volatility within individual East African countries (Maqsood et al., 2017; Marselline, 2019; Namugaya et al., 2014, 2019), a significant research gap lies in the absence of a comparative analysis across these nations. Moreover, none of the current studies have harnessed the potential of the GARCH-MIDAS model, which uniquely allows the incorporation of crucial macroeconomic variables into equity market volatility forecasting. By employing the GARCH-MIDAS model, this research explores how various macroeconomic factors influence market volatility across the East African region, providing deeper insights into the interconnectedness and interdependencies of these economies and enhancing the accuracy and robustness of volatility predictions.

The GARCH-MIDAS model is an extension of the traditional GARCH model designed to forecast equity market volatility by incorporating macroeconomic variables observed at different frequencies. It enables researchers to combine high-frequency financial market data with lower-frequency macroeconomic data, allowing for a more comprehensive analysis. The model's advantages including improved forecasting accuracy, and the inclusion of macroeconomic information, aid in conducting a comparative analysis across the East African Community (EAC) region. By utilizing the GARCH-MIDAS approach to investigate the impact of macroeconomic factors on fluctuations in the EAC stock markets. The primary emphasis of this research is on forecasting variance, aiming to assess whether the inclusion of economic variables can enhance the predictive capabilities of conventional volatility models.

The study has significant implications for the financial industry, academic research, and policymakers in the region. By enhancing volatility forecasting through the incorporation of macroeconomic variables into the GARCH-MIDAS model, the research provides valuable insights for investors, risk analysts, and policymakers in managing investment decisions, risk exposures, and implementing effective policy measures. Moreover, it contributes to the financial literature, promotes regional economic integration, and fosters the development of East African financial markets, ultimately benefiting market participants and the overall stability of the region's financial sector.

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It also makes significant contributions to the existing literature by providing a region-specific analysis for the East African Community, introducing the innovative GARCH-MIDAS framework for volatility forecasting, identifying relevant macroeconomic variables impacting stock market volatility, offering practical implications for risk management and policy recommendations, shedding light on financial market integration, contributing to research on emerging markets, inspiring methodological insights, and advancing academic knowledge in the field of financial econometrics and the relationship between macroeconomic variables and stock market volatility.

The structure of the paper is as follows: Section 2 delves into the existing literature, while section 3 explains the data and data sources. The methodology and the basic structure of the GARCH-MIDAS model are discussed in sections 4 and 5. The empirical estimation results are presented in Section 6, along with out-of-sample predictions to test the model's accuracy. The paper concludes in Section 7.

2. Literature review

The Mixed Data Sampling (MIDAS) model is a statistical and econometric framework designed for analyzing time series data that exhibit different frequencies of observations. It was developed to address the challenges of combining and analyzing data sampled at different frequencies, such as daily, monthly, or quarterly data, in a coherent and meaningful way. (Z. Chen et al., 2022) used the model to show the role of jumps and leverage in predicting the volatility of China's crude oil futures, and it was found that, these effects were useful in predicting volatility.

The GARCH-MIDAS model, combining the GARCH and MIDAS models, has emerged as a powerful tool for modelling volatility in financial markets by incorporating high-frequency and low-frequency data. Studies have used it to study volatility dynamics in a variety of financial markets.

In the commodities space, (Zhao, 2022) explores different factors that influence crude oil price volatility, categorized into four perspectives: commodity attributes, macroeconomic factors, geopolitical events, and alternative energy. The researcher uses the GARCH-MIDAS model which considers both level effect and volatility effect, and single and multi-factor models. To address multicollinearity issues, the Lasso-adaptive method is used for variable selection in the multi-factor models. The study finds that multi-factor models outperform single-factor models in predicting crude oil price volatility. In the long run, the most influential factors on oil price volatility are supply and demand. (Y. Fang et al., 2023) studied the relationship between global economic policy and the volatility of crude futures, the research's primary objective was to pinpoint the factors

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responsible for oil price volatility and investigate how both long-term trends and short-term volatility elements reacted to these variables. Additionally, the study explored whether the impact of influencing factors differed among various oil types, including WTI and Brent crude oil. Also (Liang et al., 2022; Raza et al., 2023; Salisu, Gupta, et al., 2022) used the GARCH-MIDAS model to forecast volatility in the commodities space.

From the foreign exchange market, (Zhou et al., 2020) used the GARCH-MIDAS model to study the impact of the relative economic policy uncertainty between China and the United States (the Sino-US EPU ratio) on the Chinese exchange rate volatility and examined whether the Sino-US EPU ratio can predict Chinese exchange rate volatility. Their study found that the Sino-US EPU ratio had a positive impact on the long-term volatility of the Chinese exchange rate, and the GARCH-MIDAS model with Sino-US EPU ratio performed better than the traditional GARCH-type models.

Further looking at the studies related to the stock market, (Tumala et al., 2023) studied how stock market volatility responds differently to the variants of oil shocks in Nigeria and South Africa. It was found that stock market volatility in these two countries responded in a similar way to oil supply shock and oil consumption demand but there was a different response to economic activity shock and oil inventory demand shock. Utilizing Markov switching to enhance the GARCH-MIDAS model, (Wang, Wu, et al., 2022) found that incorporating Markov switching in short- and long-term forecasting improved the volatility forecasting accuracy in the renewable energy stock market. In addition (T. Fang et al., 2020; Salisu, Ogbonna, et al., 2022; Segnon et al., 2023; Wang, Zhao, et al., 2022) also used the GARCH-MIDAS model to forecast volatility in the stock market

GARCH models are designed to capture the time-varying nature of volatility in financial markets, acknowledging that volatility tends to cluster in certain periods. There exists a vast amount of literature applying GARCH models to forecasting stock market volatility in developed economies and advanced economic blocs, but few studies exist that attempt to understand the volatility dynamics in developing economies and less advanced economic blocs. The East African Community is one of those less advanced economic blocs, nonetheless, the few studies that have attempted to study volatility in this region include (Namugaya et al., 2014) who strived to model stock returns volatility on the Uganda Securities Exchange (USE) using different specifications of the univariate GARCH models that is symmetric and asymmetric, their study found that the GARCH (1,1) outperformed other competing models in modelling returns volatility. Utilizing various univariate specifications of GARCH type models, (Maqsood et al., 2017) aimed to model stock returns volatility for Kenya's Nairobi Securities Exchange (NSE), the study found that the TGARCH (1,1) model was more appropriate in terms of

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capturing the presence of volatility clustering and the leverage effect on the NSE. While using the Vector Autoregressive (VAR) and Granger causality, (Marselline, 2019) studied the interdependencies among East African markets in relation to Johannesburg Stock Exchange (JSE), the study found that JSE has a low contributory impact on the returns on the East African markets.

This study makes several notable contributions to existing literature. Firstly, it conducts a region-specific analysis of the East African Community, filling a gap in the literature that often focuses on more developed or global markets. Secondly, it introduces the innovative GARCH-MIDAS framework, enabling the incorporation of macroeconomic variables with different sampling frequencies for more accurate volatility forecasting. Thirdly, by identifying and analyzing relevant macroeconomic variables impacting stock market volatility in the EAC, the study offers valuable insights for policymakers and investors. Moreover, it provides risk management implications, aids in formulating appropriate macroeconomic policies, and sheds light on financial market integration and cross-market linkages.

3. Data

For this study, the two largest stock markets in the East African community were considered that is Kenya and Uganda. The price index of the Nairobi All Share Index and the Uganda All Share Index were used to calculate the stock market returns of the respective countries. The data spans from August 2011 to June 2023 and was collected from investing.com The conditional variance model incorporates several financial and macroeconomic factors that previous studies have identified as significant contributors to stock market volatility, therefore in this study we will also use these variables.

The variables utilized in this analysis for both countries include:

1. Short-term interest rate: This refers to the yield on the three-month Treasury bill.
2. Crude Oil: This refers to the Brent Crude Oil benchmark.
3. Exchange rate: Represented by the exchange rate of the respective countries to the U.S. dollar.
4. Inflation: Assessed as the percentage change in the monthly consumer price index (CPI).

The CPI for Uganda was obtained from the official website of the Uganda Bureau of Statistics, while the CPI for Kenya was retrieved from the official website of the Central Bank of Kenya. Excluding these variables, the rest of the variables were retrieved from investing.com.

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4. Methodology

By employing MIDAS regression, a methodology introduced by (Ghysels, Sinko, et al., n.d.) that enables the inclusion of macroeconomic variables sampled at distinct intervals together with financial series, we can deploy the new class of component GARCH model, called GARCH-MIDAS, which incorporates these macroeconomic variables directly into the long-term component of the model. Recent years have seen much attention devoted to this new class of the GARCH model, thanks in large part to the research of (Ghysels, Santa-Clara, et al., n.d.), (Ghysels, Sinko, et al., n.d.) , and (Andreou et al., 2010). (X. Chen & Ghysels, 2011) have extended the MIDAS setting to cover a multi-horizon semi-parametric framework, and (Ghysels & Valkanov, n.d.) have provided a comprehensive study of the impact of news on forecasting volatility, including a novel method. (Ghysels & Valkanov, n.d.) have examined Granger causality with mixed-frequency data, and (Kotze, 2007) has used MIDAS regression to study high-frequency data on asset prices and low-frequency inflation forecasts. The inclusion of macroeconomic variables in the GARCH-MIDAS model is significant for several reasons. First, it enhances forecasting accuracy by capturing the impact of economic fundamentals on volatility, providing more precise predictions compared to models relying solely on past financial data. Second, it enables dynamic modelling of volatility, allowing the model to adapt to changing economic conditions and potential structural shifts. Third, for risk management purposes, the incorporation of macroeconomic variables is crucial in accurately assessing the overall risk environment.

The formal description of the GARCH-MIDAS model can be presented as follows

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t} \quad \forall i = 1, \dots, N_t \tag{1}$$

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1)$$

where $r_{i,t}$ is the return on day i in the month t , the number of trading days in month t is N_t and the information set up to day (i-1)th is $\Phi_{i-1,t}$. τ_t represents the long-term component of volatility, while $g_{i,t}$ represents the short-term component of volatility.

The short-term $g_{i,t}$ component follows a GARCH (1,1) process and is presented as

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{2}$$

The smoothed realized volatility known as τ_t is defined using the principles of MIDAS regression.

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$$\tau_t = m + \theta \sum_{k=1}^{k} \varphi_k(w_1, w_2) RV_{t-k} \quad (3)$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,j}^2$$

K indicates the length of time we use to attenuate the volatility. The equation is altered to incorporate economic variables, allowing us to examine the influence of these variables on long-term return variance.

$$\tau_t = m + \theta_2 \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{t-k}^{l/v} \quad (4)$$

The level of a macroeconomic variable is denoted by X_{t-k}^{l} and X_{t-k}^{v} denotes the variance of the same macroeconomic variable in this analysis, the component τ_t remains unchanged during a set time period (such as a month).

The conditional variance is expressed as follows:

$$\sigma_{it}^2 = \tau_t g_{i,t} \quad (5)$$

The beta lag polynomial provides a description of the weighting scheme applied in equation (3) and equation (4).

$$\varphi_k(w) = \frac{(\frac{k}{K})^{w_1-1}(1-\frac{k}{K})^{w_2-1}}{\sum_{j=1}^{k}(\frac{j}{K})^{w_1-1}(1-\frac{j}{K})^{w_2-1}} \quad (6)$$

5. Estimation method

5.1 Model Specifications

Three different model specifications are employed, which vary in how they define the long-term variance component, τ_t , while keeping the equation for the short-term variance, g_{it} , constant across all three cases. The specifications are as follows:

- Model 1: The RV model employs only the monthly realized volatility (RV) for the long-term variance component as defined by the MIDAS equation. This model does not include any economic variables.
- Model 2: In the X^l model, our focus is solely on examining how the long-term variance component is impacted by macroeconomic variables' level
- Model 3: In the X^v model, our focus is solely on examining how the long-term variance component is impacted by macroeconomic variables' variance

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Through an examination of these three options, we can explore how much of the long-term variation can be clarified by considering the previous realized volatility of returns and the macroeconomic factors.

5.2 Estimation Strategy

We make our estimates by observing returns on a daily basis, but we use a monthly frequency in the MIDAS equation to account for long-term factors. The preferred way to measure monthly variance is by using realized volatility. However, since daily data is not available for most macroeconomic variables, we cannot use this measure. Instead, we use the squared first differences as a measure of the variance of the economic variables. The models described above were estimated using an estimation window, and the estimated parameters were then used to predict variance outside of the sample. A ten-year estimation window was used, and the parameters were kept for the subsequent year.

The first estimation window began in October 2012 and ended in December 2021. However, 14 months of lagged data before each time period were needed to calculate the historical realized volatility. This means that the realized volatility for October 2012 was estimated using data from August 2011 to September 2012. The out-of-sample forecast covered the period from January 2022 to June 2023.

The prediction for long-term variance is based on the estimated value of τ_t obtained from the MIDAS equation. As τ_t values are calculated on a daily basis, they are multiplied by the number of trading days in each month. For short-term variance, the estimated daily total variance σ_t^2 is used as the prediction.

To assess how well a particular model predicts variance, there exist several methods. One of these methods involves comparing the variance predicted by the model to the actual monthly volatility, which we estimate by adding up the squared daily log returns for each month. We apply the Root Mean Square Error. The root-mean-square error (RMSE), is a statistical measure of the differences between predicted values and observed values. It is specified as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\sigma_{t+1}^2 - E_t(\sigma_{t+1}^2))^2}{T}} \tag{8}$$

5.3 Weights and number of lags in the MIDAS equation

Throughout the estimation process, we have implemented various approaches aimed at streamlining the process and enhancing the efficacy of the model. One of the initial steps involved selecting appropriate weights (w_1 and w_2) for the beta functions outlined in equation (6). There are three options available to us:

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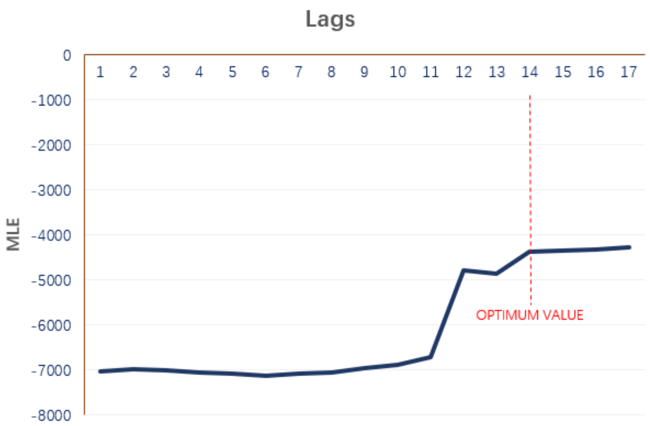
1. We can consider both w_1 and w_2 as variables and calculate their values within the model.
2. We can decide a value for w_1 beforehand and let the model calculate the value for w_2.
3. We can set fixed values for both w_1 and w_2 before running the model.

When w_2 is increased with w_1 equal to 1, the latest observations receive greater weight. If w_1 is greater than 1, it results in counterintuitive weightings, such as assigning lower weight to recent observations. Therefore, following (Engle et al., 2013), we fix w_1 to 1 to ensure monotonically decreasing weights. We let the model decide the value of w_2.

Figure 1



The second decision concerns determining the number of lags to use in the MIDAS equation (K in equations 3, 4 and 6). The number of lags is determined by the number of years, known as MIDAS years, and the time-span t used to compute τ_t in equations (3) and (4), which can be a month, quarter, or half year. We choose a monthly time-span to ensure adequate out-of-sample predictions. The graph in Figure 1 plots the maximum likelihood function values for different lags in the MIDAS equation, indicating that the optimum value increases with the number of lags. The number of lags is selected by considering the value beyond which there is a minimal increment in the MLE value. Therefore, we limit the number of lags in the MIDAS equation to 14

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Table 1. Statistical Summary and statistical tests

	Mean	Standard Deviation	Kurtosis	Skewness
use_returns	0	1.922	174.274	0.515
nse_returns	0.007	1.312	285.064	-0.904
Brent	76.474	25.836	-1.2	0.152
kenya_3m_yield	8.857	2.657	7.508	2.549
kes_usd	101.41	12.444	1.052	0.766
kenya_cpi	7.089	3.246	5.097	2.204
uganda_cpi	5.965	5.081	5.163	2.327
uganda_3m_yield	10.232	3.103	2.146	0.709
ugx_usd	3307.216	495.142	-1.206	-0.732

Variable	Q-test	p-value	Q^2 test	p-value	ADF	p-value	Unit root
use_returns	310.49	0.000	695.313	0.000	-74.587	0.001	No
nse_returns	-60.36	0.000	726.021	0.000	-61.773	0.001	No

6. Results and analyses

6.1 Descriptive analysis

Table 1 displays the statistical properties of the primary variables and the statistical tests on the timeseries. It can be seen that the Kenya equity market has a higher return and lower risk compared to the Uganda equity market. This is due to the mean value of Kenya daily stock market return (nse_returns) being higher than Uganda's daily returns (use_returns). Similarly, the Kenya daily returns standard deviation is lower than that of Uganda. The unit root test, autocorrelation and ARCH effect tests are also shown in table 1. The logarithmic returns of both Kenya and Uganda passed the ADF stationarity test. The Ljung-Box Q-test for residual autocorrelation was carried out and it was found that both series showed weak autocorrelation. These return series exhibit a fluctuation clustering effect, according to the Q^2 test for ARCH effects. When the autocorrelation coefficient of the return shows weak persistence and no significant smooth decay, the standard GARCH model may not be able to effectively fit. This is because volatility has obvious term characteristics and is affected by different components in the long and short term. Therefore, decomposing the volatility into components is helpful for measuring and predicting stock market volatility.

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Figure 2

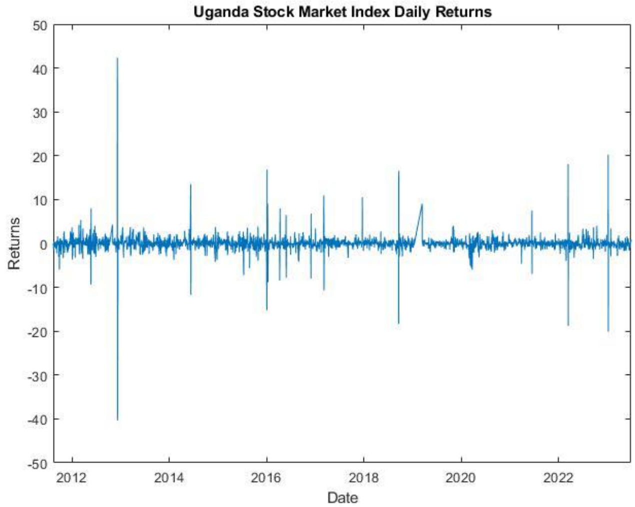
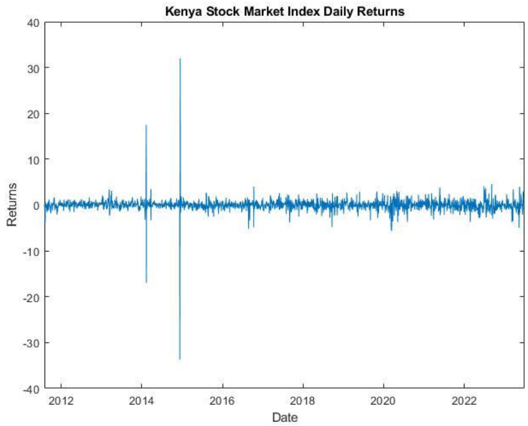


Figure 3



6.2 In-sample estimations

In the models, the main parameter that we focus on is the long-term composition of stock market volatility, which is characterized by the MIDAS polynomial. The coefficients θ reflect the impact of various factors on the long-term composition of stock market volatility, while the parameter ω is the optimal estimation coefficient of weight attenuation of low-frequency variables in the Beta function.

Table 3 represents the estimated parameters when we consider the realized volatility and the levels of the macroeconomic variables. As can be seen from the results, for Uganda, the parameters for short-term variance (α and β) are all significant at the 1% level of significance excluding the β for the 3-month yield. On the contrary, the values are relatively small and their sum is close to 0.5 on average. This implies that there is low volatility persistence. For all the various influencing factors, we can see that the average value of α is 0.2, this means that past shocks have a low impact on current volatility, the average value of β is 0.38, which implies that past volatility has a weak impact on current volatility. Further looking at Kenya, we can see different outcomes, Kenya has relatively more volatility persistence as can be seen from the sum of the parameters for short-term variance (α and β), their sums are close to 1 for the various influencing factors. The different specifications give various results for the parameter estimations, well as realized volatility parameters show that past shocks have a weaker impact on current volatility and past volatility has a greater impact on current volatility, this relationship is reversed for CPI, 3-month yield and the exchange rate (KESUSD).

When the coefficient θ is positive and statistically significant, it implies that an increase in the level of the factor will lead to increased stock market volatility. Conversely, when the coefficient θ is negative and statistically significant, it implies that an increase in the level of the factor will reduce stock market volatility. From the results in Table 3, we see that excluding realized volatility, the coefficients for Uganda's macroeconomic variables are significant at the 1% level of significance. A positive coefficient for CPI indicates that an increase in the CPI leads to an increase in stock market volatility. A positive coefficient for the 3-month treasury yield indicates that an increase in the 3-month treasury yield leads to an increase in stock market volatility. A positive coefficient for the UGX/USD exchange rate indicates that an increase in the UGX/USD exchange rate leads to an increase in stock market volatility. On the other hand, the coefficient of Brent crude oil is negative indicating a reduction in stock market volatility for increases in the Brent crude oil price level. However, for Kenya, we can see that the realized volatility's coefficient is positive and statistically significant at the 1% level showing that increases in realized volatility lead to increases in stock market volatility. The macroeconomic variables give mixed results, moreover the coefficients of the CPI and 3-month yield aren't statistically significant. Brent's positive coefficient of 0.052 is significant at the 1% level implying increases in Brent crude oil prices lead to increases in stock market volatility. However, the coefficient of the exchange rate (KES/USD) is negative and only significant at the 5% level. This implies that increases in the exchange rate lead to decreases in stock market volatility.

From the perspective of AIC and BIC, it can be seen that for Uganda and Kenya, the values from the macroeconomic model specifications were lower than the model specifications using realized volatility. Well as these aren't absolute measures of model quality, they represent on a relative basis how well the different models fit the data.

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Table 3. Estimation results for the level effect

	Uganda				
	RV	Brent	CPI	3M yield	UGX/USD
mu	0.028	0.037	0.040	0.073***	0.032
	(0.292)	(0.202)	(0.152)	(0.009)	(0.222)
alpha	0.234***	0.260***	0.257***	0.308***	0.261***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
beta	0.383***	0.391***	0.364***	0.000	0.389***
	(0.000)	(0.000)	(0.000)	(1.000)	(0.000)
theta	0.000	-0.011***	0.419***	0.314***	0.001***
	(1.000)	(0.000)	(0.000)	(0.000)	(0.000)
w	29.114	38.788	21.742***	5.819***	6.218
	(1.000)	(0.496)	(0.000)	(0.000)	(0.197)
m	1.401***	2.805***	0.312***	-1.333***	-0.116
	(0.000)	(0.000)	(0.000)	(0.000)	(0.625)
LL	-3596.8	-3591.95	-3553.18	-3547.46	-3590.79
AIC	7205.61	7195.9	7118.36	7106.92	7193.58
BIC	7240.51	7230.8	7153.26	7141.82	7228.48

Note: p values are in brackets (); ***, **, and * indicate statistically significant at the significance level of 1 percent, 5 percent, and 10 percent, respectively.

	Kenya				
	RV	Brent	CPI	3M yield	KES/USD
mu	-0.733***	0.058**	0.203***	0.226***	0.132***
	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)
alpha	0.076***	0.277***	0.879***	0.880***	0.715***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
beta	0.924***	0.474***	0.110***	0.111***	0.219***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
theta	0.154***	0.052***	17.573	17.439	-0.606**
	(0.000)	(0.000)	(0.583)	(0.554)	(0.047)
w	4.876***	1.001***	5.556***	49.98	2.974***
	(0.000)	(0.000)	(0.000)	(0.262)	(0.006)
m	0.010	-1.731***	-50.863	-71.765	68.801**
	(0.992)	(0.000)	(0.582)	(0.559)	(0.047)
LL	-4519.5	-3372.83	-3434.34	-3456.78	-3393.4
AIC	9050.99	6757.65	6880.68	6925.56	6798.81
BIC	9086.14	6792.8	6915.83	6960.71	6833.96

Note: p values are in brackets (); ***, **, and * indicate statistically significant at the significance level of 1 percent, 5 percent, and 10 percent, respectively

To further diversify the research, we consider the variance of the macroeconomic variables. Table 4 represents the estimated parameters when we consider the variance of the macroeconomic variables. As can be seen from the results, for Uganda, the parameters for short-term variance (α and β) are

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all significant at the 1% level of significance. Similar to the levels' values, the values are relatively small and their sum is close to 0.5 on average. This implies that there is low volatility persistence. For all the various influencing factors, we can see that the average value of α is 0.26, this means that past shocks have a low impact on current volatility, the average value of β is 0.37, which implies that past volatility has a weak impact on current volatility. Further looking at Kenya, we can see different outcomes, Kenya has relatively more volatility persistence as can be seen from the sum of the parameters for short-term variance (α and β), their sums are close to 1 for the various influencing factors. The different specifications give various results for the parameter estimations, well as realized volatility parameters show that past shocks have a weaker impact on current volatility and past volatility has a greater impact on current volatility, this relationship is reversed for CPI, 3-month yield and the exchange rate (KESUSD).

Similarly to what was stated before, when the coefficient θ is positive and statistically significant for the variance of a macroeconomic factor, it implies that an increase in the variance of the factor will instigate stock market volatility. Conversely, when the coefficient θ is negative and statistically significant, it implies that an increase in the variance of the factor will reduce stock market volatility. From the results in Table 4, we see that excluding the 3-month yield, the coefficients for Uganda's macroeconomic variables are significant at the 1% level of significance. A positive coefficient for CPI indicates that an increase in the CPI variance leads to an increase in stock market volatility. A positive coefficient for Brent crude oil variance indicates that an increase in Brent crude oil variance leads to an increase in stock market volatility. A positive coefficient for the UGX/USD exchange rate variance indicates that an increase in the UGX/USD exchange rate variance leads to an increase in stock market volatility. However, for Kenya, the macroeconomic variables exhibit quite different results, moreover the coefficients of the CPI, the exchange rate (KESUSD) and 3-month yield aren't statistically significant. Brent's positive coefficient of 0.053 is significant at the 1% level implying increases in Brent crude oil prices variance lead to increases in stock market volatility.

Similarly from the perspective of AIC and BIC, it can be seen that for Uganda and Kenya, the values from the macroeconomic variance model specifications were lower than the model specifications using realized volatility. Well as these aren't absolute measures of model quality, they represent on a relative basis how well the different models fit the data.

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Table 4. Estimation results for the variance effect

	Uganda			
	Brent	CPI	3M yield	UGX/USD
mu	0.021	0.0002	0.047	0.049*
	(0.482)	(0.995)	(0.103)	(0.063)
alpha	0.228***	0.263***	0.265***	0.272***
	(0.000)	(0.000)	(0.000)	(0.000)
beta	0.383***	0.375***	0.326***	0.385***
	(0.000)	(0.000)	(0.000)	(0.000)
theta	-0.009***	404.6***	79.475	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
w	2.497***	12.714***	7.683	3.900***
	(0.000)	(0.000)	(0.000)	(0.000)
m	2.288***	0.529***	1.266***	0.980***
	(0.000)	(0.000)	(0.000)	(0.000)
LL	-3589.71	-3561.61	-3536.74	-3483.32
AIC	7191.42	7135.22	7085.48	6978.64
BIC	7226.33	7170.12	7120.39	7013.54

Note: p values are in brackets (); ***, **, and * indicate statistically significant at the significance level of 1 percent, 5 percent, and 10 percent, respectively.

	Kenya			
	Brent	CPI	3M yield	KES/USD
mu	0.055***	0.250***	0.255***	0.250***
	(0.004)	(0.000)	(0.000)	(0.000)
alpha	0.207***	0.912***	0.100***	0.100***
	(0.000)	(0.000)	(0.000)	(0.000)
beta	0.715***	0.078***	0.000	0.0008
	(0.000)	(0.000)	(1.000)	(0.901)
theta	0.053***	-1458.3	-9310.8	-118.11
	(0.000)	(0.511)	(0.991)	(0.964)
w	49.997 ***	48.479***	2.194***	1.333***
	(0.000)	(0.000)	(0.000)	(0.000)
m	0.527***	73.832	3246.5	1151
	(0.000)	(0.511)	(0.9911)	(0.964)
LL	-3159.5	-3431.62	-3443.3	-3444.19
AIC	6330.99	6875.24	6898.61	6900.39
BIC	6366.14	6910.39	6933.76	6935.54

Note: p values are in brackets (); ***, **, and * indicate statistically significant at the significance level of 1 percent, 5 percent, and 10 percent, respectively.

6.3 Out-of-Sample

In the following section, we study the capability of the different specifications of the GARCH-MIDAS model to forecast volatility. The

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parameters are estimated using a rolling window of ten years and are kept constant for the following year. The out-of-sample forecast period spans from January 2022 to June 2023. For each of the countries, nine different model specifications are used in the MIDAS: One model that incorporates realized volatility, four models that incorporate the levels of the macroeconomic variables and four models that incorporate the variance of these macroeconomic factors. A ten-year estimation window is used and the parameters are kept for the subsequent year. In table 5 we can see the results from the forecast performance of the different models using Root Mean Square Error (RMSE). RMSE is one of the most commonly used measures to evaluate the forecasting accuracy of GARCH models. It is calculated by taking the square root of the average of the squared differences between the predicted and actual values. Looking at the results from Table 5, we can evidently see that for Uganda, macroeconomic variable level model specifications, either had an RMSE value less than or equal to that of the model which included realized volatility. On the variance side, its evident that excluding the model that incorporated Brent crude oil variance, all other models have a lower RMSE value than the realized volatility model. Further looking at Kenya, the results are mixed, for the level model specifications, only Brent crude oil and the exchange rate have RMSE values less than the realized volatility value. Similarly, for variance models, only two macroeconomic models that is Brent crude oil and the exchange rate exhibit RMSE values less than the realized volatility value.

Table 5. RSME values for the various models

		Uganda (levels)				Uganda (variance)			
	RV	Brent	CPI	3M yield	UGXUSD	Brent	CPI	3M yield	UGXUSD
RMSE	36.0	36.0	35.9	34.7	36.0	36.1	35.9	35.8	35.9

		Kenya (levels)				Kenya (variance)			
	RV	Brent	CPI	3M yield	KESUSD	Brent	CPI	3M yield	KESUSD
RMSE	3.5	2.9	3.6	3.5	3.0	3.0	3.6	3.7	3.4

Conclusion

This research has utilized the GARCH-MIDAS approach to forecast stock market volatility in the East African Community. Estimation of the short-term, long-term and total variance components involved the usage of information from macroeconomic variables with a consideration of both the variance and levels of these variables. These macroeconomic variables for the respective countries included Brent crude oil, CPI, 3-month treasury yield and the exchange rate. A rolling window approach was adopted to estimate the model parameters and to carry out out-of-sample forecasts. The various

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specifications of the GARCH-MIDAS model with macroeconomic variables were considered against the GARCH-MIDAS model that only included realized volatility.

Findings of the research show that the levels of all the chosen macroeconomic variables significantly affected Uganda's stock market volatility. Also, the variances of the majority of the chosen macroeconomic variables significantly showed an effect on stock market volatility. The realized volatility showed an insignificant effect on Uganda's stock market volatility. On the other hand, realized volatility significantly affects Kenya's stock market volatility while the levels and variance of macroeconomic variables show mixed results, with levels of the CPI and 3-month yield being insignificant but the exchange rate and Brent oil being significant, for the variance only Brent had a significant effect while the CPI, exchange rate and 3-month yield were insignificant. Based on the results of the RSME and the comparative results of the AIC and BIC which were lower for the model specifications that included macroeconomic variables than the realized volatility model, it was found that incorporating macroeconomic variables (both levels and variance) improved the prediction ability of the GARCH-MIDAS model for Uganda. While for Kenya, including macroeconomic variables in the GARCH-MIDAS model didn't always improve forecasting ability. Further research should look to explore other macroeconomic variables that might affect Kenya's stock market volatility, the research can also adopt a different timeframe such as incorporating weekly and quarterly data. Finance industry practitioners and regulators are advised to recognize the country-specific nature of macroeconomic variables' impact on stock market volatility in the East African region, and should develop tailored investment, risk management strategies and regulations. They should also acknowledge the significance of different macroeconomic variables such as Brent crude oil, CPI, treasury yield, and exchange rates among others on the different countries.

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