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Global economic policy uncertainty, oil shocks and volatility in some Southern African Development Community stock markets: A GARCH-MIDAS approach

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This study investigates the effects of global economic policy uncertainty and oil shocks on stock market volatility in Botswana, Mauritius, and South Africa. Datasets from periods preceding and during the COVID-19 pandemic are utilized to provide evidence on the impact of global economic policy uncertainty (GEPU) and oil shocks on stock returns volatility in these countries. The examination employs a mixed data sampling model based on generalized autoregressive conditional heteroskedasticity (GARCH-MIDAS). The GARCH-MIDAS approach allows for combining high-frequency stock data with low-frequency GEPU and oil shock data to forecast the long-term component of volatility. Additionally, this method demonstrates a better fit for that relationship when compared to traditional GARCH. The results indicate that both GEPU and oil consumption demand shocks have positive and significant impacts on stock volatility for the three countries in our in-sample case (which corresponds to the period before the COVID-19 pandemic). The volatility coefficient estimates for Botswana, Mauritius, and South Africa are 0.076, 0.001 and 0.119, respectively, all significant at the 1% level. This suggests that stock returns in these countries react positively to changes in oil demand shocks. Forecasting data during the COVID-19 period also shows that incorporating global economic policy uncertainty and oil shocks using a GARCH-MIDAS approach improves forecasting accuracy. The application of the GARCH-MIDAS approach in this study facilitates the separation of short-term and long-term volatility components effectively, thus enabling us to address a significant shortfall of previous research that has explored the impact of economic policy uncertainty on stock market returns.

Key words: Global economic policy uncertainty, oil consumption demand shock, generalized autoregressive conditional heteroskedasticity (GARCH-MIDAS), Southern African Development Community (SADC) countries, stock market volatility.

INTRODUCTION

The COVID-19 pandemic has raised questions about its impact on the correlation between global economic policy uncertainty (GEPU) and the volatility of stock market returns within specific Southern African Development Community (SADC) markets. The seminal paper by Baker et al. (2016) defines economic policy uncertainty (EPU) as uncertainty arising from fiscal, monetary, or regulatory policy, with their EPU index calculated by

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assessing the relative frequency of terms pertaining to economics (E), politics (P), and uncertainty (U). Subsequently, numerous studies have investigated the correlation between EPU and the stock market (Sharif et al., 2020; Yu et al., 2021). Consequently, numerous studies have explored the correlation between these two variables from various perspectives and employing a range of methodologies. Practitioners such as Ko and Lee (2015), Wu et al. (2015), Christou et al. (2017a), Cheng (2017), Phan et al. (2018), Mei et al. (2018), Xiong et al. (2018), and Yu et al. (2018) showcase pertinent research in this regard. The initial segment of the literature concentrates on the impacts of Economic Policy Uncertainty on stock markets. More specifically, Wu et al. (2016) employ a panel Granger causality method to evaluate the influence of EPU on stock markets across eight OECD nations, comprising India, Italy, Spain, the UK, Canada, France, Germany, the United States, and China. Christou et al. (2017b) employ a Bayesian panel vector autoregression model to investigate the impact of US EPU shock on the stock market returns of Pacific Basin countries, such as Australia, Canada, China, Japan, Korea, and the US. Additionally, their research explores the effects of EPU on other financial markets. For instance, Fang et al. (2018) conducted research on the futures market, while Demir and Ersan (2017) focused on the currency market, and Reboredo and Naifar (2017) examined the bond market.

Krol (2014) and Beckmann and Czudaj (2017) centered their study on foreign exchange markets. The second part of the empirical literature explores the correlation between these two variables. Bekiros et al. (2016) and Caggiano et al. (2017) investigate the correlation between the United States' EPU and the American stock market. Xiong and Yu (2018) employ a dynamic conditional correlation multivariate generalized autoregressive conditionally heteroskedastic model to examine the correlation between China's EPU and its stock market. Previous literature has also explored the correlation between EPU and various markets, including the stock-bond correlation (Fang et al., 2017) and gold-stock correlation (Gao and Zhang, 2016).

However, previous studies have some limitations. Firstly, the short-term volatility component in stock returns is linked to its own past information, while the long-term component of volatility is associated with macroeconomic fundamentals (Asgharian et al., 2013; Engle et al., 2013). Given this observation, it is fitting to deploy a model that distinguishes between the overall volatility of stocks into its long-term and short-term components by incorporating the GEPU variable in the former. This model is known as the generalized autoregressive conditional heteroskedasticity extended mixed data sampling (GARCH-MIDAS) model. These studies examine the relationship between the variables, factoring in global financial crises. Further research shows that COVID-19 significantly affects the correlation between GEPU and stock market returns' volatility. Notably, Sharif et al. (2020), Yang and Yang (2021), Ahmed and Sarkodie (2021), Youssef et al. (2021), and Apostolakis et al. (2021) have reported such findings. Previous research has given greater attention to developed countries and less to emerging ones. Therefore, our study focuses on the SADC, a market that has received limited examination and integration.

Thus, a major query arises from our reflections: Has the COVID-19 outbreak changed the dynamics of the link between GEPU and the instability of stock market returns in particular SADC markets? The aim of this study is to investigate the effects of global economic policy uncertainty and oil shocks on stock market volatility in Botswana, Mauritius, and South Africa both before and during the COVID-19 pandemic. The study has two specific objectives as follows: To investigate the effects of GEPU and shocks in oil consumption demand on stock volatility in the SADC nations prior to and following the COVID-19 outbreak, and to demonstrate the dynamic connection between the pandemic, GEPU, and stock market return volatility in these same regions. To achieve our objective, we examine the following hypotheses in our study: i) The impact of GEPU and oil consumption demand shocks on stock volatility in SADC countries is positive and significant; ii) The relationship between the COVID-19 pandemic, GEPU, and stock market volatility is ever-changing.

This study's choice of the SADC is underlined by its status as one of the major players in the exploration and export of crude oil, and that its main trading and investment partner (Europe) is suffering from the devastating COVID-19 pandemic (McKibbin and Fernando, 2021). Subsequently, this development constrains them to certain policies in favor of intra-regional trade and investment, which should have an impact on its stock market. Furthermore, we find the impact of health responses taken by some of the SADC countries, on the stock market to be worth studying. Indeed, the Tanzanian government officially declared the virus to be over and stopped recording cases towards the end of April 2020. Similarly, Madagascar has also become a center of attention with its claim to have discovered a cure for the deadly COVID-19 pandemic (Mthembu, 2020). There is agreement that these events may have an impact on the link between oil and stock prices in the region, which necessitates the present study.

Two important contributions can be drawn from this study. First, we take into account the COVID-19 health crisis in the analysis of the relationship between GEPU and the returns of certain Southern African Development Community (SADC) countries' stock exchanges. The analysis of this study is relevant insofar as this pandemic has had very costly repercussions on the stock market returns of these places. Second, in this article, we employ a model that is underutilized in the literature, namely the

GARCH-MIDAS model of Engle et al. (2013).

REVIEW OF LITERATURE

EPU may impact stock prices. Although many studies have investigated the impact of EPU on numerous macroeconomic variables, research into the link between EPU and stock prices or returns only emerged after the 2008 global financial crisis (Li et al., 2016). Baker et al. (2016) made a significant contribution by developing EPU or GEPU indexes, which have been utilized in various recent empirical studies. The EPU index calculates the average of three main indicators of uncertainty: major news on the EPU, the expiry of tax provisions, and forecasters' disagreements about government purchases and inflation. Recently, investors, policymakers, and academics have shown a great deal of interest in the effects of EPU on the stock market (Jin et al., 2019). It is conceivable that the uncertainty of a country may affect the stock prices in another country. Mensi et al. (2014) conducted a thorough analysis of quantile regressions for the BRICS nations, encompassing Brazil, Russia, India, China, and South Africa, using data spanning from September 1997 to September 2013. The study concluded that US EPU did not have any impact on the BRICS stock markets. Momin and Masih (2015) carried out a study on the impact of US EPU on the stock returns of BRICS countries, employing an autoregressive distributed lag model for the period between January 2000 and March 2015. They ascertained that solely the Indian stock market was affected by the US EPU. Dakhlaoui and Aloui (2016) investigated the impact of the US EPU on stock returns of BRICS countries, using daily data from July 4, 1997 to July 27, 2011.

The study discovered a negative correlation between BRICS stock indices and EPU in the US, with volatility distribution varying between negative and positive values. Moreover, the link between uncertainty and stock returns was inconsistent during periods of global economic crisis. Aydin et al. (2022) posited that political volatility within a nation could affect its stock prices and yields. Ozoguz (2009) utilized Markov switching and intertemporal capital asset pricing models to examine the relationships between the aforementioned variables in the US during the period of January 1961 to December 2001. It was observed that there existed a negative correlation between insecurity and stock prices. Sum (2012) conducted an analysis using ordinary least squares (OLS) methodology to examine data from February 1993 to April 2012. The results showed that EPU has an adverse impact on stock market returns in various countries, including the European Union, Turkey, Ukraine, Switzerland, Russia, and Norway. The findings indicate a negative association between the two variables. Antonakakis et al. (2013) applied a dynamic conditional correlation model to investigate the relationship between S&P500 returns and EPU in the United States from January 1985 to January 2013. Bijsterbosch and Guérin (2013) employed a Markov regime-switching model on US variables ranging from January 1986 to January 2012, and ascertained that high episodes of EPU cause a reduction in stock prices and bond yields. As per Kang and Ratti's (2013) analysis, which was conducted through a vector autoregression (VAR) model, a favorable oil demand shock against the US oil demand led to an increase in apprehension regarding future oil supply and concomitantly, induced EPU that ultimately impacted stock proceeds in a negative manner. Brogaard and Detzel's (2015) research indicated that EPU had a significant impact on stock returns in Europe and Canada. The authors employed the generalized method of moments to investigate the relationship between share market returns and EPU in the USA, using monthly data ranging from May 1985 to December 2012. They observed a negative association between the fluctuations of EPU and stock market returns that was contemporaneous. Chang et al. (2015) conducted a panel causality test using bootstrap methods on seven nations of the Organization for Economic Co-operation and Development from January 2001 to April 2013. Their findings indicate that government policy uncertainty was provoked by stock price volatility in the USA and the UK, while stock price indices influenced government policy uncertainty in Italy and Spain. However, no causal relationship was detected between the factors in Canada, Germany, and France. Ko and Lee (2015) utilized wavelet analysis to examine eleven countries in Asia, Europe, and North America, from January 1998 to December 2012. Their findings indicate that stock prices decrease after an upsurge in EPU. The study follows a conventional academic structure, employing clear, concise language, and technical terms where necessary. There is no biased or ornamental language within the text, and any abbreviations are adequately explained at first use. Adequate spelling, grammar, and punctuation are observed, adhering to the standards for British English.

Xiong et al. (2018) conducted a study on the impact of EPU on the stock returns of companies in the tourism industry. The study utilized multiple regression approaches to analyze data from January 2002 to December 2013. Xiong et al. (2018) conducted a study on the impact of economic policy uncertainty (EPU) on the stock returns of companies in the tourism industry. Xiong et al. (2018) conducted a study on the impact of EPU on the stock returns of companies in the tourism industry. Findings revealed that changes in EPU negatively affected the stock returns of Turkish tourism firms. The researchers implemented the dynamic conditional correlation-bivariate generalized autoregressive conditional heteroskedasticity model spanning January 1995 to December 2016. The findings revealed that the EPU's absolute variations held greater impact on Shanghai stock market returns as opposed to Shenzhen's. Moreover, the study unveiled increased volatility of stock returns in periods of financial crises. Guo et al. (2018) conducted a quantitative regression analysis to investigate the correlation between EPU and stock yields in G7 and BRICS countries from February 1985 to August 2015. The study yielded important findings highlighting asymmetrical association between EPU and stock markets of the USA and Italy. In contrast, EPU had a detrimental impact on stock markets of Germany, Japan, India, and China. Furthermore, there was moderate impact of uncertainty on the Canadian and Russian stock exchanges, whereas no association between EPU and stock prices was observed in the UK and France. Chiang (2019) examined the correlation between EPU, risk and additional stock returns in G7 countries from January 1997 to June 2016, using a generalized mistake distribution GARCH model. The outcomes revealed that an increase in EPU contributes to a reduction in excess stock returns. Gao et al. (2019) investigated the associations among stock prices, economic policy uncertainty, and global oil prices in China from January 2005 to December 2017. They used a rolling window Toda-Yamamoto causality test to determine that the bidirectional causality between the variables was mainly associated with the 1997 Asian crisis, the 2008 financial crisis, and China's economic structural reforms.

In the present global economic landscape, the rise of globalization has bolstered the connections among nations and heightened their reciprocal impact. This is especially evident in the instance of developing countries, which possess vast populations and offer significant prospects for economic expansion. It is crucial to investigate the impact of global economic policy uncertainty on the stock markets of these countries. This becomes particularly relevant considering the limited research conducted on these markets in comparison to those of developed countries.

Several recent studies have highlighted the volatility of oil prices. Two sets of research studies use different methods to examine the reasons for instability in the oil market. The first set applies GARCH-class models and cites examples including Chan and Grant (2016), Nomikos and Pouliasis (2011), Wang and Wu (2012), Wang et al. (2016), and Sadorsky (2006). The second set of papers relies on recognized volatility models, including Haugom et al. (2014) and Sevi (2014). Both sets of models gather insightful data from recorded unpredictability or costs. The efficient market hypothesis of Fama (1970) justifies the predictive power of fundamental variables, while commodity markets are not as efficient as more developed financial markets (Chen et al., 2010). Furthermore, several studies have suggested inefficient weak-form markets for crude oil (Tabak and Cajueiro, 2007; Wang and Liu, 2010), meaning that the current oil price does not encompass all of the fundamental information available. It may be inferred that the current unpredictability in oil prices does not encompass all previous information pertaining to macroeconomic instability. There have been many attempts to understand and forecast fluctuations in oil prices based on supply and demand fundamentals (Baumeister and Kilian, 2012; Boffelli et al., 2016). However, to our knowledge, the financial origins of price volatility have not been fully considered in scholarly literature, except for significant contributions from Conrad et al. (2014) and Pan et al. (2017). Conrad et al. (2014) analyzed the effect of macroeconomic factors on oil price volatility from a sample-based approach. Other scholars have re-evaluated this issue through an out-of-sample outlook by testing whether the incorporation of macroeconomic elements into volatility models can produce more precise forecasts. Concentrating on daily volatility which is of significant interest to option market traders, the study observed that objective evaluations of the data are imperative for accurate predictions. Including macroeconomic data in a GARCH or realized volatility model is challenging due to the incompatible data frequencies of the oil price and its fundamental factors.

To clarify, while oil price data is available daily, data on oil output and demand is obtained monthly or even less frequently. Fortunately, the GARCH-MIDAS class specifications recommended by Engle et al. (2013) effectively resolve the mixed-frequency problem in volatility modelling. This model divides daily conditional volatility into two parts: a short-term volatility element that adheres to the standard daily GARCH process (Bollerslev, 1986) and a long-term component that considers mixed-frequency data sampling (MIDAS) regression with monthly, quarterly, or even lower frequency variables (Ghysels et al., 2004). In recent times, GARCH-MIDAS models have gained popularity for identifying links between high-frequency volatility and low-frequency macroeconomic variables (Conrad et al., 2014; Conrad and Loch, 2015a, b). Yu et al. (2018) and Yu and Huang (2021) deployed the GARCH-MIDAS approach to demonstrate that GEPU increases Chinese stock market volatility and has predictive capabilities. Li et al. (2020) examined the impact of GEPU on the volatility of China's stock market by analyzing the directional effects (up and down) and found that both up and down GEPU positively affect Chinese stock market volatility. Moreover, Li et al. (2020) established that the GEPU index can anticipate shifts in Chinese stock market volatility.

Wang et al. (2021) used a GARCH-MIDAS model with a skew student's t-distribution to examine the impact of domestic and foreign EPU on China's financial stocks. In a recent study, Li et al. (2019) analyzed the effects of EPU on Chinese stock market volatility through a predictive regression method. The results indicated that the EPU index had a significantly negative influence on the future volatility of the Chinese stock market.

EMPIRICAL METHODOLOGIES

The study adopts two major empirical methodologies. Firstly, it employs the generalized autoregressive conditional heteroscedasticity model with mixed data sampling. Secondly, it employs loss functions.

Specifically, the study uses a novel component, the generalized autoregressive conditional heteroskedasticity (GARCH) model based on mixed data sampling (MIDAS) regression. The new component GARCH model is known as MIDAS-GARCH, wherein macroeconomic variables are directly incorporated into the long-term component's specifications. The MIDAS regression models, introduced by Ghysels et al. (2006), provide a framework for integrating macroeconomic variables sampled at varying frequencies with the financial series. Additionally, Forsberg and Ghysels (2006) demonstrate that MIDAS has a relative advantage over Anderson et al. (2007) proposed Heterogeneous Autoregressive Realized Volatility (HAR-RV) model, as shown through simulation.

To explore the correlation between GEPU/oil consumption shock and stock markets in SADC nations, the GARCH-MIDAS model proposed by Engle et al. (2013) is utilized. Monthly frequency data for GEPU and oil consumption shocks, along with daily frequency data for stock returns, are utilized in this model (Appendix Figures 1, 2 and 3). The model assumes that stock returns on specific days, i within a given month, t follow a specific equation process.

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

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

where $r_{i,t}$ is the logarithmic return on a specific day i within a given month t. The total volatility of daily returns can be defined as $(\sigma_{i,t}^2 = \tau_i \times g_{i,t})$ which is the sum of two components: τ_t is the long-term component that is believed to reveal the source of stock market volatility, and the short-term component that accounts for short-lived daily fluctuations (Engle et al., 2013; Yu et al., 2021). The value of N_t represents the number of trading days in the month t, and $\Phi_{i-1,t}$ represents the information set available up $(\mathrm{i}-1)^{th}$ to the given day of the period t. The conditional variance $g_{i,t}$ of the short-term component follows a daily GARCH (1, 1) process (Bollerslev, 1986):

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

Low-frequency variables, such as realized volatility or macro variables, can describe the long-term component τ_t. Two different specifications for the long-term component without changes in the short-term equation exist. The first specification examines the effect of realized volatility on the long-term component of the total volatility. Smoothed realized volatility is defined as the variable in the spirit of MIDAS regression. The following τ_t is the specification for the MIDAS filtering.

$$\tau_t = m + \theta_{rv} \sum_{k-1}^{K} \varphi_k(w_1) RV_{t-k} \tag{3}$$

Monthly smoothed realized volatility is denoted by $(RV_t = \sum_{i=1}^{N_t} r_{i,t}^2)$ with a fixed span of time representing the number of periods K used to smooth the realized volatility. The second specification involves directly inserting macroeconomic variables into the long-term component.

$$\tau_t = m + \theta_{rv} \sum_{k=1} \varphi_k(w_1) RV_{t-k} + \theta_{gepu} \sum_{k=1}^{K} \varphi_k(w_1) GEPU_{t-k} \tag{4}$$

The log difference of $GEPU_{t-k}$ denotes the level of change rate of monthly global economic policy uncertainty. Equation 4, as used by Yu et al. (2021), captures information explained by both the realized volatility and economic policy uncertainty and is compared to a basic model in which the long-term component does not involve GEPU information. The weightage method utilized in both Equations 3 and 4 is explained using a beta lag polynomial as:

$$\varphi_k(w_1) = \frac{(K/k)^{w_1-1}}{\sum_{j=1}^{K} (j/K)^{w_1-1}} \tag{5}$$

where the coefficients in Equation 5 equate to 1, we examine how GEPU affects stock volatility. We utilize the estimated daily total variance $\sigma_{i,t}^2$ as a measure of the total variance's accuracy. The realized total volatility is denoted $r_{i,t}^2$ as the variable. The GARCH-MIDAS-RV+GEPU model, developed using Equations 1, 2, 4, and 5, is assessed against the conventional GARCH-MIDAS-RV model that is constructed by Equations 1, 2, 3, and 5, to determine its predictive capability. Comparison is also made with a simplistic GARCH (1, 1) model (Bollerslev, 1986), shown.

$$r_t = \mu + \varepsilon_t \tag{6}$$

where $\varepsilon_t = \sigma_t z_t$, $z_t \sim N(0,1)$, and the conditional variance process, σ_t^2, has the form:

$$\sigma_t^2 = k + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{7}$$

Secondly, in order to assess the predictability of volatility in a particular model, we utilize various loss functions that compare the estimated predicted variance to the realized volatility. The six loss functions employed in this study are presented in the following equations.

$$MSE = \frac{1}{T} \sum_{i=1}^{T} (\hat{\sigma}_t^2 - \sigma_t^2)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (\hat{\sigma}_t^2 - \sigma_t^2)^2} \tag{9}$$

The data

Three stock markets in SADC countries, namely, Botswana, Mauritius and South Africa were considered. The countries were selected based on data availability. The authors use daily data from the http://www.investing.com/ database for the period from 01/05/2008 to 24/04/2022. Their data are divided into two periods. The first period (before COVID-19 pandemic) goes from 01/05/2008 to 04/03/2020, the second period (during COVID-19) goes from 05/03/2020 to 24/04/2022. They opt for the monthly GEPU index computed by Baker et al. (2016), which is deemed a reputable proxy for real-world economic policy uncertainty. It can be obtained from their website (http://www.policyuncertainty.com/). Additionally, we incorporate the monthly oil consumption shock, available on Baumeister and Hamilton's (2019) website. The analysis encompasses GEPU and oil consumption shocks that occurred from May 2008 to April 2022, including the financial crisis around June 2009, the European Sovereign debt crises, US-China trade tensions, Brexit, and the new context of COVID-19 as a global pandemic. The study utilized a total of 3,258 observations.

RESULTS AND DISCUSSION

Table 1 displays the descriptive statistics for three data series of stock indices and the GEPU index. The sample size for each selected SADC stock market's stock index series is 3258, while the GEPU index and oil consumption each have 168 observations. The stock index has a daily data frequency, whereas the GEPU index has a monthly frequency. Table 2 presents the descriptive statistics for the stock returns of the SADC markets examined, along with the logarithms of the GEPU change rate and oil consumption. The table includes 3257 stock return observations for each country, 167 GEPU observations and 93 oil consumption observations. Tables 1 and 2 indicate that the kurtosis values of both the stock index and return series are positive. However, the South Africa stock index series and logarithm of oil consumption exhibit negative skewness, while the remaining stock index and return series for all SADC stock markets have positive skewness. Statistical properties of the variables in our study are presented in Table 3. Based on the results from the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Vratio (VR) tests, all statistics significantly reject the null hypothesis of a unit root at the 1% level. This confirms that all of our series are stationary. Additionally, the Jarque-Bera (JB) test of all stock returns, GEPU, and oil consumption indicates that all of their distributions deviate significantly from normality at the 1% level.

Furthermore, the Autoregressive Conditional Heteroscedasticity (ARCH) test statistics for each individual stock return exceeded 100 according to Engle's (1982) analysis, with critical values of the ARCH test at the 1% level of 6.6635. This implies noteworthy heteroskedastic effects. Notably, the descriptive statistics obtained over the study period take precedence for both in-sample (before COVID-19) and out-of-sample (during COVID-19) data.

Furthermore, the estimated parameters of the impact that GEPU and oil consumption demand shock (OCDS) have on stock market volatility in three SADC countries are presented. Tables 4 and 5 display the findings from the GARCH and GARCH-MIDAS models, which include the entire sample (01/05/2008 to 24/04/2022) divided into subsamples. The study consists of two datasets: in-sample data (01/05/2008 to 04/03/2020), representing the pre-COVID-19 period, and out-of-sample data (05/03/2020 to 24/04/2022), representing the during-COVID-19 period.

The GARCH (1, 1) model parameters are significant at the 1% level in all cases, except for μ in South Africa, where they are significant at the 5% level, and for k, which is non-significant in Botswana. These findings suggest that the GARCH (1, 1) model is a good fit for the daily data. The GARCH-MIDAS model, α, β, θ_{RV}, and m shows positive and significant coefficients, confirming its suitability for the mixed data sampling model. The importance lies in examining the statistical significance of the coefficient θ_{RV} to understand if OCDS or GEPU impact the long-term volatility of SADC countries.

Additionally, the sum of ARCH and GARCH terms α and β is less than one $(\alpha + \beta < 1)$, inferring that OCDS does not have a permanent effect on stock market returns. The empirical results from Table 5 for the GARCH-MIDAS-RV+OCDS model demonstrate significant coefficients θ_{RV} for Botswana, Mauritius, and South Africa at 1%, indicating a positive response in stock returns to changes in oil consumption demand shocks. The estimated coefficients for Botswana, Mauritius, and South Africa were 0.076, 0.001, and 0.119, respectively. This contradicts the findings of Salisu and Gupta (2021), who reported a negative response for South Africa.

The impact of GEPU on stock market returns is not permanent. In the GARCH-MIDAS-RV+GEPU model, the estimated coefficients for Botswana, Mauritius, and South Africa are 0.056, 4.052e-04, and 0.033, respectively. These outcomes indicate that GEPU has a significant and positive effect on SADC stock markets for the in-sample data. This conclusion aligns with the findings of Yu et al. (2021).

The same positive impact of OCDS and GEPU on stock markets is obtained for all three countries in the full sample (Table 6). The estimated coefficient θ_{RV}, which is realized volatilities, is 0.117 for Botswana, 0.170 for Mauritius, and 0.119 for South Africa in for OCDS. For GEPU case, θ_{RV} is 0.016, 0.099, and 0.014 for Botswana, Mauritius, and South Africa respectively. In all cases (full sample and in-sample), the coefficient of the unconditional mean for stock returns μ is not significant, except for South Africa.

To assess the efficacy of the models GARCH and

Table 1. Descriptive statistics of the GEPU index, stock index series and oil consumption.

Variable	Obs.	Freq.	Mean	Median	Min	Max	Std.	Skew.	Kurt.
Botswana	3258	Daily	8.074	7.599	6.074	11.097	1.205	0.610	2.292
Mauritius	3258	Daily	617.048	1.916	1.001	9986.00	7641.027	12.347	153.547
South Af.	3258	Daily	2.766	3.085	1.086	4.226	0.784	-0.407	1.820
GEPUindex	168	Month	171.899	151.220	79.848	437.144	70.618	1.179	4.003
Oilcons	168	Month	0.139	0.629	-2.420	8.732	4.210	-0.929	6.354

Source: Author calculations using the data of the regression (www.investing.com and www.policyuncertainty.com). GEPU = Global economic policy uncertainty; oilcons = oil consumption.

Table 2. Descriptive statistics of the GEPU change rate, stock return series and oil consumption.

Variable	Obs.	Freq.	Mean	Median	Min	Max	Std.	Skew.	Kurt.
Botswana	3257	Daily	-6.46E-05	0.000	-1.897	2.074	0.151	0.852	63.024
Mauritius	3257	Daily	-0.003	-0.002	-499.51	499.934	17.496	0.003	814.215
South Af	3257	Daily	-0.011	-0.018	-3.970	4.115	0.565	0.405	9.209
URGEPU	167	Monthly	5.073	5.019	4.380	6.080	0.376	0.462	2.376
Oilcons	93	Monthly	0.751	0.913	-2.859	2.167	0.928	-0.869	4.260

Source: Author calculations using the data of the regression (www.investing.com and www.policyuncertainty.com). GEPU=Global economic policy uncertainty; oilcons=oil consumption; URGEPU=GEPU change rate.

Table 3. Statistical properties of GEPU, stock return series and oil consumption.

Variable	ADF	PP	VR	JB	ARCH
Botswana	-15.302***	-63.621***	4.819***	489629.5***	188.165***
Mauritius	-12.903***	-57.140***	11.977***	89360408***	365.836***
South Af	-42.784***	-57.647***	13.072***	5324.812***	687.59***
URGEPU	-4.711***	-4.563***	3.019**	8.705**	0.308
Oilcons	0.360**	-9.015***	3.188***	17.853***	0.110

*** and ** denote significance at 1 and 5% levels, respectively. ADF=Augmented Dickey-Fuller; PP=Phillips-Perron; VR=Vratio; JB=Jarque-Bera; GEPU=global economic policy uncertainty; oilcons=oil consumption; URGEPU=GEPU change rate.

Table 4. In-sample estimates of the GARCH model for three stock returns.

Variable	k	α	β	μ
Botswana	-0.005(0.006)	0.011***(3.780e-04)	0.264***(0.012)	0.272***(0.021)
Mauritius	0.004***(5.400e-04)	0.243***0.339)	0.006***(0.001)	8.960e-04***(2.080e-04)
South Africa	0.004*** (0.001)	0.082***(0.008)	0.901***(0.009)	-0.019**(0.008)

***, ** and * represent 1, 5, and 10% level of significance, respectively. GARCH = Generalized autoregressive conditional heteroscedasticity

GARCH-MIDAS-RV+OCDS/GARCH-MIDAS-RV+GEPU, we employed the optimal log-likelihood function (Log-L), the Akaike information criterion (AIC), and the Bayesian information criterion (BIC). Table 7 presents the in-sample results. Upon comparison of the traditional GARCH (1, 1) model with GARCH-MIDAS-RV+OCDS based on criterion information and log-likelihood function selection, the GARCH-MIDAS-RV+OCDS model outperformed GARCH (1, 1).

Comparing the fitness of GARCH (1,1) and GARCH-

Table 5. In-sample estimates of the GARCH-MIDAS model for three stock returns.

Variable	μ	α	β	θ_{RV}	w	m
				Oil consumption demand shock		
Botswana	-1.586e-06 (3.466e-05)	0.179*** (0.007)	0.317*** (0.014)	0.076*** (0.002)	6.744*** (1.169)	0.001*** (1.078e-05)
Mauritius	3.449e-06 (2.903e-05)	0.251*** (0.019)	0.444*** (0.039)	0.001*** (4.147e-04)	2.096*** (0.501)	0.001*** (2.958e-05)
South Africa	-1.991e-04** (8.980e-05)	0.083*** (0.010)	0.881*** (0.018)	0.119*** (0.037)	8.639 (10.173)	0.004*** (5.735e-04)
				GEPU		
Botswana	-1.020e-05 (3.861e-05)	0.050*** (0.003)	0.900*** (0.004)	0.056** (0.025)	6.22 (1.620e+16)	0.044** (0.0192)
Mauritius	8.396e-06 (2.943e-05)	0.265*** (0.020)	0.362*** (0.045)	0.001*** (4.052e-04)	2.105*** (0.483)	0.001*** (2.690e-05)
South Africa	-2.087e-04** (8.923e-05)	0.087*** (0.013)	0.872*** (0.023)	0.126*** (0.033)	8.385 (8.906)	0.003*** (5.465e-04)

***, ** and * represent 1, 5, and 10% level of significance, respectively. GARCH = generalized autoregressive conditional heteroskedasticity.

Table 6. Full sample estimates of GARCH-MIDAS for three stock returns.

2008-2022		Botswana	Mauritius	South Africa
GARCH-MIDAS+Oil consumption	μ	1.510e-05 (2.680)	-1.731e-05 (2.807e-05)	-2.064e-04** (8.224e-05)
	α	0.157*** (5.975e-03)	0.316*** (0.015)	0.100*** (0.011)
	β	0.341*** (0.014)	0.441*** (0.020)	0.843 *** (0.019)
	θ_{oil}	0.117*** (1.971e-3)	0.170*** (5.266e-03)	0.119 *** (0.019)-
	w	6.030*** (0.388)	26.616*** (1.893)	8.168** (4.130)
	m	1.09e-03*** (8.866e-06)	1.271e-03*** (4.473e-05)	4.083e-03*** (3.156e-4)
GARCH-MIDAS+GEPU	μ	1.653e-05 (0.532)	-3.119e-05 (3.227e-05)	2.008e-04** (8.206e-05)
	α	0.151*** (5.688e-03)	0.050*** (1.720e-03)	0.106*** (0.011)
	β	0.342*** (0.0142)	0.900*** (0.010)	0.833*** (0.020)
	θ_{gepu}	0.016*** (5.085e-04)	0.099*** (6.770e-03)	0.014*** (4.737e-03)
	w	5.681*** (0.290)	5*** (0.133)	8.118** (4.026)
	m	1.113e-06*** (1.894e-08)	-1.028e-6*** (1.754e-07)	1.711e-05*** (2.613e-06)

The levels of significance are represented by ***, **, and *, respectively, indicating 1, 5, and 10%. GARCH-MIDAS refers to generalized autoregressive conditional heteroskedasticity extended mixed data sampling, while GEPU refers to global economic policy uncertainty.

MIDAS-RV+GEPU models shows that the latter has superior fitness for the given countries. This is owing to the smaller AIC and BIC, and larger Log-

Table 7. In-sample evaluation results for the GARCH and GARCH-MIDAS models.

Variable	GARCH			GARCH-MIDAS		
	AIC	BIC	Log-L	AIC	BIC	Log-L
			Oil consumption demand shock			
Botswana	-1.057	-1.044	1461.079	-23207.7	-23172.2	11609.9
Mauritius	2.594	2.607	-3563.671	-23024	-22988.5	11518
South Africa	1.358	1.371	-1862.799	-17745.3	-17709.8	8878.67
			GEPU			
Botswana	-	-	-	-21337.2	-21301.7	10674.6
Mauritius	-	-	-	-22525.4	-22490	11268.7
South Africa	-	-	-	-17364.1	-17328.7	8688.06

AIC, BIC, and Log-L values are used to compare fitness of the two models. AIC is the Akaike Information Criteria, BIC is the Bayesian Information Criteria, and Log-L is the optimal log-likelihood function. GARCH-MIDAS =generalized autoregressive conditional heteroskedasticity extended mixed data sampling.

Table 8. Results of out-of-sample volatility forecast validation.

Model	MSE	RMSE
	Botswana	
GARCH	4.248e-05	6.517e-03
GARCH-MIDAS	306.600e-12#	1.751e-05#
	Mauritius	
GARCH	0.018"	1.341e-01
GARCH-MIDAS	0.761	8.726e-01#
	South Africa	
GARCH	8.843e-02	2.973e-01
GARCH-MIDAS	7.322e-09#	8.557e-05#

# denotes that the GARCH-MIDAS model outperforms the GARCH model and "denotes that the GARCH model outperforms the GARCH-MIDAS model. GARCH-MIDAS=generalized autoregressive conditional heteroskedasticity extended mixed data sampling.

L than those of the traditional GARCH (1,1) model. Involving OCDS and/or GEPU in the GARCH-MIDAS-RV model leads to improved fitness compared to the GARCH (1,1) model. In conclusion, GARCH-MIDAS-RV+GEPU are recommended for better model fitness. The out-of-sample projection pertains to the period from 05/03/2020 to 24/04/2022, which coincides with the COVID-19 era. To assess the out-of-sample forecast capability of a volatility model, the loss function is utilised. It pertains to the anticipation of OCDS as well as GEPU variables concerning stock volatility in Botswana, Mauritius, and South Africa.

Table 8 displays the mean square error (MSE) and root mean square error (RMSE), providing insight into the effectiveness of two models in predicting the daily total volatility of stock in particular countries. The GARCH-MIDAS-RV+OCDS model outperforms the GARCH model for SADC countries when considering both MSE and RMSE.

CONCLUSION AND POLICY IMPLICATIONS

The response of stock market volatility in Botswana, Mauritius, and South Africa to GEPU and oil consumption demand shocks (OCDS) was examined by using the GARCH-MIDAS approach. Our dataset comprises subsamples from 01/05/2008 to 24/04/2022, with the first being the in-sample data (01/05/2008 to 04/03/2020) corresponding to the pre-COVID-19 period and the second being the out-of-sample data (05/03/2020 to 24/04/2022) corresponding to the during-COVID-19 period. Our study presents evidence of the effects of GEPU and oil shocks on stock market volatility in three SADC nations, utilizing empirical analysis within the sample and prediction outside it.

During the in-sample analysis, the findings indicate that the GARCH (1, 1) model is a good fit for daily data, displaying significant parameters for all targeted SADC countries with the exception of one. The GARCH-MIDAS model also demonstrates a good data fit, with a positive and significant coefficient for either OCDS or GEPU on the countries' long-term volatility. These results suggest that both OCDS and GEPU have a noteworthy and positive influence on the SADC stock market in the in-sample data. The models' fitness performance is evaluated using optimum log-likelihood function, AIC, and BIC. The models GARCH-MIDAS-RV+OCDS and GARCH-MIDAS-RV+GEPU outperform the traditional GARCH (1, 1) model. The results of out-of-sample prediction indicate the GARCH-MIDAS-RV+OCDS model showing better performance than the GARCH model for SADC countries when MSE and RMSE are used. Furthermore, the influence of OCDS and GEPU on stock market returns appears to be transient rather than enduring, indicating that these factors do not have a lasting effect.

Given these results, it is advisable that policymakers in the chosen SADC nations focus on the effects of oil consumption and global economic policy uncertainty and their possible influence on stock market instability. As the SADC countries are net importers of oil and have a fragile economic context post COVID-19, global economic policy uncertainty shocks have significant effects: i) an increase in risk premium leads to more volatility and correlation in stock markets, especially in weaker economic conditions; ii) generally, lesser developed countries' stock returns experience negative effects; iii) crude oil price volatility is also impacted negatively, and is directly linked to major events, with varying impacts depending on the type of event.

This suggests that measures to stabilize oil prices and promote economic stability and transparency could help in reducing stock market volatility. Moreover, policymaker could consider implementing policies to encourage investment diversification to reduce the impact of global shocks on the domestic stock market. Policies that promote the development of financial markets, including stock markets, could also increase resilience to external shocks and contribute to overall economic growth. Furthermore, given the better fitness performance of the GARCH-MIDAS-RV+OCDS and GARCH-MIDAS-RV+GEPU models compared to the traditional GARCH (1, 1) model, policymakers could consider using these models in their forecasting and risk management processes. Finally, the study highlights the importance of considering the impact of external factors on domestic stock market volatility and the need for policymakers to implement policies that promote economic stability and financial market development.

CONFLICT OF INTERESTS

The author has not declared any conflict of interests.

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Appendix Figures

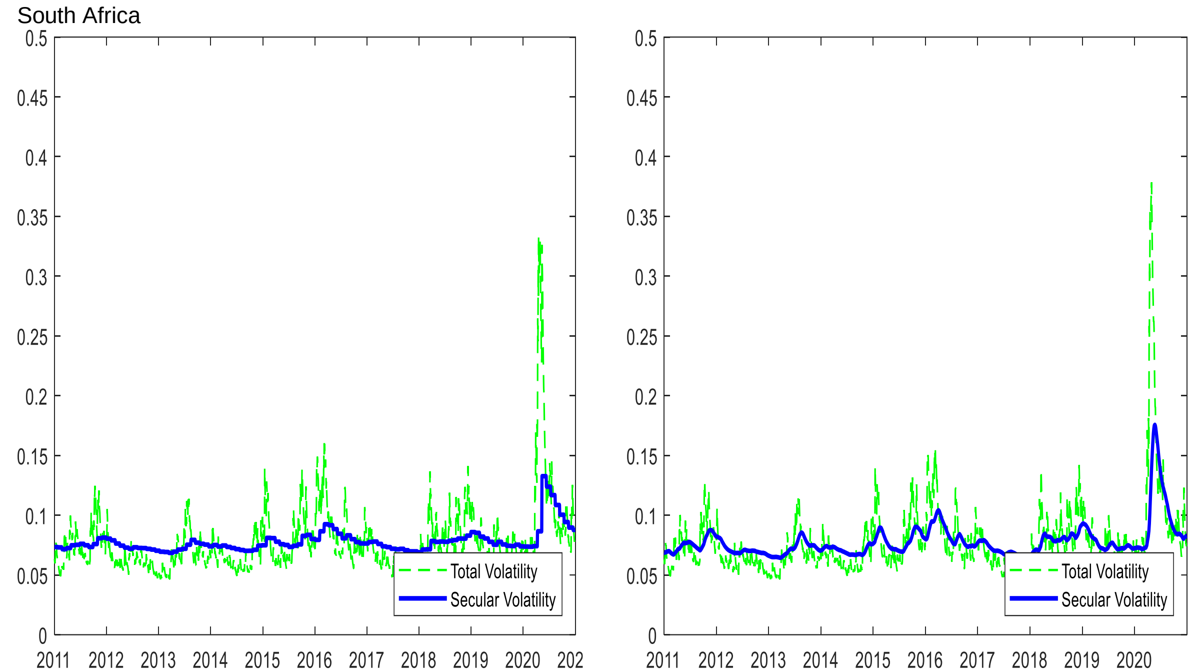

Figure 1. GARCH-MIDAS-RV+GEPU GARCH-MIDAS-RV + oil consumption shock.

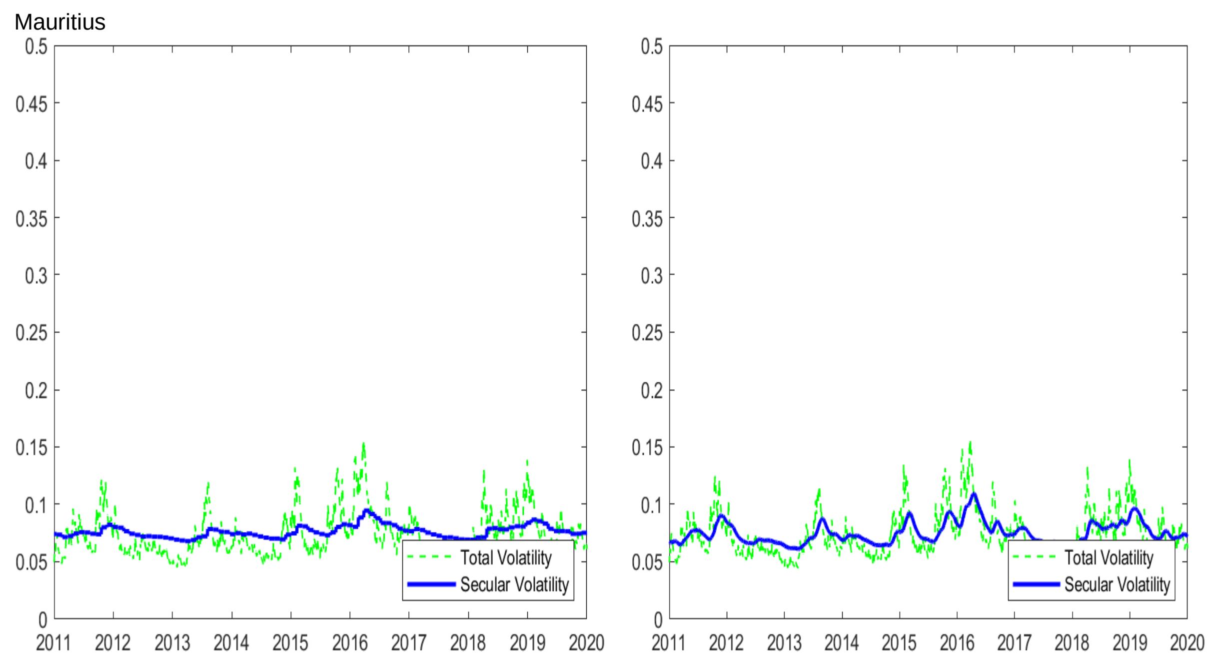

Figure 2. GARCH-MIDAS-RV+GEPU GARCH-MIDAS-RV + oil consumption shock.

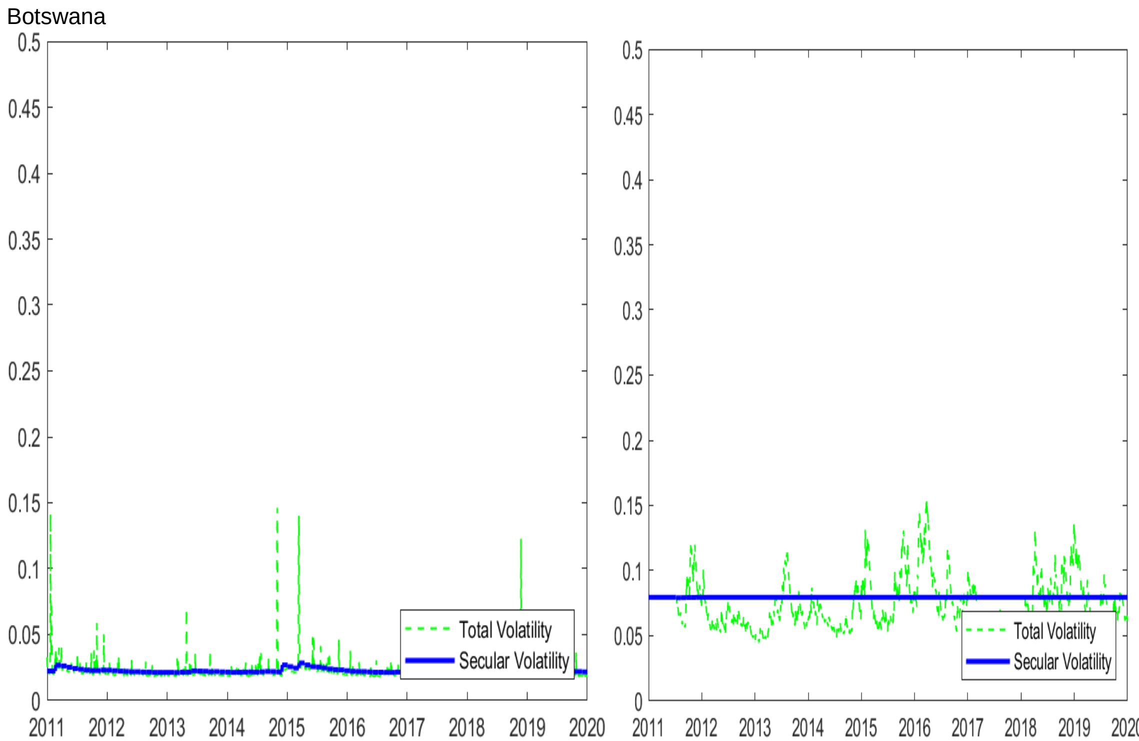

Figure 3. GARCH-MIDAS-RV+GEPU GARCH-MIDAS-RV + oil consumption shock.