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RESEARCH ARTICLE

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Twitter policy uncertainty and stock returns in South Africa: Evidence from time-varying Granger causality

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Abstract

The study uses time-varying Granger causality models that incorporate two proxies for Twitter policy uncertainty and South African returns stock returns to investigate the causal relationship between Twitter uncertainty and South African stock returns for the period between 2017 and 2023. The findings demonstrate that Twitter Market Uncertainty and Twitter Economic Uncertainty mostly lead JSE returns around the start of the COVID-19 pandemic and the Russia-Ukranainan war respectively. The findings also show significant out-of-sample forecasts using uncertainty indexes from Twitter.

KEYWORDS

behavioral finance, social media, South Africa, time-varying causality

1 | INTRODUCTION

Uncertainty indices (UIs) are comparatively new techniques for quantitatively evaluating uncertainty developments. Several proxies of uncertainty have been used in empirical studies and these have mostly relied on news. However, given the significance of social media in the contemporary world, Baker et al. (2021) construct Twitter uncertainty indexes (TUI) reflecting the impressions of economic uncertainty based on the opinions of social media users by utilizing *tweets* posted on Twitter (now called X). Two of these TUIs reflect uncertainty in the economy in general (Twitter Economic Uncertainty—TEU) and uncertainty specifically in equity markets (Twitter Market Uncertainty—TMU). According to El Khoury and Alshater (2022), TEU and TMU are specifically built using user *tweets* and are more accurate than news at representing uncertainty. The aim of this study is therefore to use these two variants of Twitter uncertainty to examine their in-sample and out-of-sample predictive power of stock returns.

From a theoretical view, Song et al. (2022) suggest that the interconnectedness of Economic Policy Uncertainty (EPU) and macroeconomic as well as financial variables can be explained by two mechanisms. The first is the supply–demand channel in which increasing uncertainty is associated with dwindling production motivation leading to volatility in financial markets and instability in macroeconomic variables. The second theoretical channel in which EPU affects the real economy is through market sentiment (Albulescu, 2021; Bernanke, 1983). Due to the imperfect rationality of market players, information asymmetry increases the likelihood of the convergence and the herd effect. Thus, theoretically, EPU will have an impact on market players' choices, and higher levels of uncertainty will slow down choices about production, investment, and consumption.

Empirically, several studies have been conducted to establish the relationship between TUI and stock market features like returns, volatility, and volume. Yeşiltaş et al. (2022) create high-frequency TUI between 2013 and 2021 using Turkish data to examine how TUI is related to a suite of macroeconomic variables. They report that in the Turkish market, TUI can predict stock market volatility. El Khoury and Alshater (2022) investigate the connectedness of TUI and sectoral returns in the USA. The results show that the direction of TUI's effect on net connectedness changes from one sector to another, implying that TUI can signal either good or bad news depending on the sector. Behera and Rath (2022) investigate the connectedness of TUI and stock returns in G7 countries, and they report that TUI and G7 average returns are net receivers of shocks. Becerra and Sagner (2023) create a daily-frequency measure of economic uncertainty for Chile using data scraped from Twitter accounts, closely adhering to the methodology suggested by Baker et al. (2016). In an empirical exercise, they report that these indexes have a medium-to-low correlation with the volatility of local stock returns.

Bales et al. (2022) investigate if the source of uncertainty (newspaper, Twitter, or financial market) affects bank stock returns in the United States. For various time horizons, they describe directional spillovers and Granger causality between uncertainty and bank returns using discrete wavelet transformation. They report findings that show how important it is to make this distinction across different investing horizons. Also, the study found that despite the moderate correlation between news and Twitter-based indicators, they reflect different sources of investor perception. Bank stocks are negatively impacted by Twitter-based uncertainty in the short term, while newspaper-based policy uncertainty affects bank stocks mostly in the medium term.

Given China's rigorous censorship of news and social media, an important question to answer would be whether *tweets* regarding the uncertainty of Chinese economic policy by international Twitter users offer valuable information above and beyond existing indexes. Based on a total of 76,765 *tweets* that contain phrases related to Chinese economic policy uncertainty, Lee et al. (2023) create novel daily and monthly frequency "censorship-free" indices of Twitter-based Chinese economic policy uncertainty from March 2010 to April 2022. They report that shocks to their index are highly correlated with future returns on the Chinese stock market as well as with investment, consumption, unemployment and production. This is contrary to results that use conventional Chinese EPU as they report that current Chinese economic policy UIs are not significantly related to economic variables.

Besides the stock market, other studies have examined the linkages between TUI and other asset classes. Aharon et al. (2022) investigate the relationship between the performance of four cryptocurrencies and two Twitter-based metrics of economic and market uncertainty. The authors specifically investigate the behavior of Bitcoin, Ethereum, Bitcoin Cash, and Ripple in the presence of TUI using a variety of techniques, including quantile regressions, Granger causality in distributions using copula functions, and directional prediction tests. The findings from the study show a significant causal relationship between TUI and cryptocurrency returns. The effect is particularly more pronounced for Bitcoin and in the tails of return distributions.

Gök et al. (2022) look at Granger causality between three safe-haven assets—Bitcoin, gold, and US 10-year Treasury notes—and TEU. The results show differences in the causal relationship when considering the mean and the variance using daily data (June 1, 2011 to August 30, 2021). For the raw series, TEU Granger causes volatility but not the returns of Treasury notes, volatility but not the returns of Bitcoin, and neither the volatility nor the returns of gold. The causality is primarily significant at the low and medium quantiles of Bitcoin and Treasury notes. Yang and Tao (2022) collect the daily data of BTC and TEU between 2020 and 2022 to examine the guided-lag interactions between the variables in a time-frequency domain. The authors conclude that BTC and TEU exhibit bidirectional causality in the frequency range from 0 to 64 days but do not depend on one another in the high-frequency range (64–256 days). Additionally, they report that the volatility of the price of bitcoin is influenced by geopolitical conflicts like the war between Russia and Ukraine in 2022.

French (2021) examines the bidirectional causal relationship between TMU and Bitcoin before and after the COVID-19 epidemic. The results demonstrate that the TMU is just a leading indicator of Bitcoin returns during the COVID-19 pandemic and that the pandemic has a substantially bigger impact on the TMU's effect on Bitcoin's conditional volatility. Additionally, the salient Bitcoin market has an impact on the uncertainty level of people's *tweets* during the pandemic. When viewed as a whole, the findings imply that the information found through online communities like Twitter has a far greater influence on bitcoin markets after COVID-19.

In South Africa, Snyman (2019) constructed TEU using *tweets* localized to South Africa. They report that their TUI peaks around politically significant events. They also report a significant correlation between the TUI and various macroeconomic variables, including stock market returns. However, their TUI is localized and in a global economy, as we have now, it might be of paramount importance to understand how world economic uncertainty affects macroeconomic variables. Also, they used simple correlation analysis to examine how TUI is associated with macroeconomic variables. Other studies in the African context have rather used proxies for economic policy uncertainty extracted from news articles (e.g., Asafo-Adjei et al., 2020). As shown by empirical literature, the majority of the studies on the association between TUI and stock returns are rather concentrated on developed markets and emerging markets in the Asia Pacific region.

South Africa is chosen because it is the most liquid and influential stock market in Africa and is more appropriate for a study of this nature because of the ease with which changes in policy uncertainty shocks are absorbed by the market (Nyakurukwa & Seetharam, 2022). An understanding of how TUI and stock returns are connected therefore provides insights for the international investor who would like to diversify investments using African markets. We use time-varying Granger causality tests to establish the stability of the causal relationship between stock returns and two TUI proxies in a three-variable (TEU, TMU, JSE stock returns) VAR framework using a sample period between 2017 and 2022.

We proceed as follows: Section 2 looks at the data and methods used; Section 3 presents the results and Section 5 concludes this study.

2 | DATA AND METHODS

2.1 | Data

Our data are sampled at the daily granularity and starts from 20 April 2017 to 20 April 2023 . The sample period is motivated by the availability of data. We use the JSE All Share Index as a proxy for the South African stock market, and the data for this are sourced from EquityRT. Baker et al. (2021) developed TEU and TMU indices that are used as proxies for TUIs.[1] TMU focuses on uncertainty in equity markets, while TEU reflects economic uncertainty in general. We use log-transformed versions of the TUI proxies as well as JSE stock returns.

2.2 | Econometric model

2.2.1 | In-sample relationships

Several studies have used Granger causality to understand the causal relationship between variables in a VAR framework. Granger causality can be illustrated by a bivariate $VAR(m)$ model given by:

$$y1_t = \phi_0^{(1)} + \sum_{k=1}^{m} \phi_{1k}^{(1)} y1_{t-k} + \sum_{k=1}^{m} \phi_{2k}^{(1)} y2_{t-k} + \varepsilon 1_t \tag{1}$$

$$y2_t = \phi_0^{(2)} + \sum_{k=1}^{m} \phi_{1k}^{(2)} y1_{t-k} + \sum_{k=1}^{m} \phi_{2k}^{(2)} y2_{t-k} + \varepsilon 2_t \tag{2}$$

where $y1_t$ and $y2_t$, respectively, represent the time series of interest. Variable $y1_t$ is said to Granger cause variable $y2_t$ if the past values of $y1_t$ have predictive power for the current values of $y2_t$, conditional on the past values of $y2_t$. The null hypothesis of no causality from $y1$ to $y2$ involves testing the joint significance of $\phi_{1k}^{(2)}\ (k=1,...,m)$ by means of a Wald test. Granger causality may be supported across a single time frame but may however be unstable when different periods are taken into account, just like with other characteristics of structural stability (Swanson, 1998). Shi et al. (2018) and Shi et al. (2020) prove that it is possible to assess the stability of causal relationships over time through stationary VAR and lag-augmented VAR (allowing for non-stationary variables) respectively. To examine the time-varying stability of the causal relationship between TUI and stock returns on the Johannesburg Stock Exchange, we, therefore, depend on the time-varying Granger causality framework of Shi et al. (2020). This method allows for the variation in Granger causal orderings and date-stamping the timing of the changes using recursive methods. The method uses the following algorithms that generate a sequence of test statistics:

- Forward expanding (FE) window
- The rolling (RO) window
- The recursive evolving (RE) window

Considering a sample of $T+1$ observations $\{y0, y1, ..., yT\}$, a number r such that $0 < r < 1$ and considering $[Tr]$ to denote the integer part of the product, then $\mathcal{T}_{r1,r}$ will be taken to denote a Wald test statistic computed over a subsample starting at $y[T_{r1}]$ and at $y[T_r]$. The FE algorithm is a standard forward recursion that is based on Thoma (1994). The Wald test statistic is computed first for a minimum window length $(\tau_0 = [Tr_0] > 0$, and the sample size then expands sequentially by one observation until the final test statistic is computed using the entire sample. At the conclusion of the FE algorithm, a sequence of Wald statistics, $\mathcal{T}_{r1,r}$ with $r1 \in [0, r - r0]$ and $r \epsilon [r0, 1]$ are generated, which are the sup norms of the Wald statistics at each observation. In the RO algorithm (Arora & Shi, 2016; Swanson, 1998), a window of size $[T_w]$ is rolled through the sample advancing one observation at a time, and a Wald statistic is computed for each window.

The FE and RO recursions are specific cases of the RE algorithm. A set of test statistics that may be placed in an upper triangular square matrix with column and row dimensions equal to the maximum number of acceptable observations is defined for each observation in turn. The leading entry in each column is the FE Wald statistic, the main diagonal is the RO Wald statistic, and the largest elements in each column are the RE statistics. The information obtained from these test statistics can be applied to the entire sample or used to focus on the timing of these time-varying events through time-varying analysis. With regard to the RE algorithm, for a given observation of interest, the algorithm estimates a test statistic for every possible subsample of size $r0$ or larger with the observation of interest providing the common endpoint of all the subsamples. The procedure is repeated taking the observation of interest to be every point in the sample, subject only to the minimum window size. Thus, every observation in the sample beyond the first is associated with a set of Wald statistics. Philliphi and Yu (2015) suggest that inference be based on a sequence of supremum norms of these statistics. We depend on the recursive evolving window approach as it provides higher power than the other algorithms (Shi et al., 2020) and is more favorable when performed in conjunction with a bootstrap engine for maintaining family-wise size control.

We use a three-variable VAR framework for daily data of the following variables[2]:

- TMU.ENG—The logarithm of the daily Twitter Market Uncertainty from English-language *tweets*;
- TEU.ENG—The logarithm of the daily Twitter Economic Uncertainty from English-language *tweets*;
- JSE—The logarithm of the daily closing prices on the South African All Share Index (JALSH).

Letting $x \overset{GC}{\Rightarrow} y$ to represent that the direction of the Granger causality being tested runs from x to y, we test the following relationships:

$$\text{TMU.ENG} \overset{\text{GC}}{\Rightarrow} \text{JSE}$$

$$\text{TEU.ENG} \overset{\text{GC}}{\Rightarrow} \text{JSE}$$

using the Recursive Evolving Window algorithm (see Shi et al., 2020). We include four lags in the VAR model (based on the Schwartz and Akaike statistics), an initial estimation window of 20% of the observations (software default), and the size of the tests over one year (used in Shi et al., 2020). The tests are robust to heteroskedasticity. The sequence of RE statistics is graphed and compared with the bootstrap percentiles extracted from methods outlined in Shi et al. (2020) and Shi et al. (2018). These estimates are used to identify periods in which the potential Granger causal relationships vary significantly. The estimated origination date of a change is determined as the first instance at which the test statistic exceeds its critical value. Subsequent changes are then identified similarly.

2.2.2 | Out-of-sample relationships

To establish the out-of-sample ability of our UIs in forecasting the closing prices of JALSH, we depend on the direct multistep VAR-LP model of Rossi and Wang (2019). Assume a VAR model with time-varying parameters as follows:

$$y_t = \Phi_{1,t} y_{t-1} + \Phi_{p,t} y_{t-p} + \varepsilon_t \tag{3}$$

where $y_t = \left[y_{1,t} + y_{2,t}, \ldots, y_{n,t}\right]'$ is an $n \times 1$, vector $\Phi_{jt}, j = 1, \ldots p$ are functions of time-varying coefficient matrices, and ε_t represents idiosyncratic shocks that are assumed to be heteroscedastic and serially correlated. The endogenous variables vector (y_t) in the VAR model include the closing prices of the JALSH as well as the two proxies of uncertainty used in the study.

In implementing the direct multistep VAR-LP forecasting model with time-varying parameters, we specifically want to establish whether the TEU.ENG and TMU.ENG can forecast the closing prices of JALSH out of sample. To do that, we iterate the above Equation (3) and thereby projecting y_{t+h} onto the linear space generated by $\left(y_{t-1}, y_{t-2}, \ldots, y_{t-p}\right)'$ utilizing the following:

$$y_{t+h} = \Phi_{1,t} y_{t-1} + \Phi_{2,t} y_{t-2} + \Phi_{p,t} y_{t-p} + \varepsilon_{t+h}$$

Assuming that θ_t is a subset of $\left(\Phi_{1,t} + \Phi_{2,t}, \ldots, \Phi_{p,t}\right)$, our null hypothesis hypothesizes that the lags of the UIs do not Granger cause JALSH closing prices out of sample using different forecasting horizons:

$$\mathrm{H_0} : \theta_\mathrm{t} = 0, \forall_\mathrm{t} = 1, 2, \ldots, \mathrm{T}$$

Following Cepni et al. (2023), we select the length of the VAR based on the Schwarz Information Criterion and a standard trimming parameter of 0.1. The test statistics used in the model include the robust versions of the mean and exponential Wald test (Andrews &

Ploberger, 1994), the Nyblom (1989) test, and the Quandt (1960) and Andrews (1993) quasi-likelihood-ratio tests.

3 | RESULTS

3.1 | Descriptive statistics

We start by visualizing the variables used in the study as shown in Figure 1. Notably, it can be observed that across all three panels of Figure 1, the effect of COVID-19 on the variables is evident. Around the time COVID-19 was announced as a global pandemic in 2020, there is a sharp increase in the log-transformed scores for uncertainty using both proxies. Around the same time, we also observe that the log-transformed prices of JALSH have a sharp drop. Beyond the early COVID-19 period of 2020, policy uncertainty measured by both proxies starts decreasing, and this period is also associated with an increase in the prices of JALSH. There is therefore rudimental evidence that shows that these two proxies of policy uncertainty are negatively associated with JALSH prices. Robust econometric methods should therefore be used to establish if this relationship is statistically significant.

In Table 1, we present the descriptive statistics of the variables which show that all the variables are not normally distributed (the Jarque Bera test rejects normality at the 1% level of significance) which justifies the utilization of the non-parametric and data-driven methods used for the econometric model. The specification of the models we use in this study needs prior knowledge of the stationarity of the variables so that nonstationarity can be correctly specified in the models. We, therefore, test the null hypothesis that the variables have a unit root against the alternative hypothesis that the variables are stationary using the Augmented Dickey–Fuller test. The results in Table 1 show that we cannot reject the null hypothesis and conclude that the variables have unit roots and are therefore not stationary. This means these

TABLE 1 Descriptive statistics.

Statistic	JSE	TEU.ENG	TMU.ENG
Mean	11.01217	4.91223	4.86874
Min	10.54437	3.17881	3.15455
Max	11.29963	6.50815	7.06799
SD	0.128591	0.58540	0.52084
JB	21.865***	20.621***	14.189***
ADF test	−2.7049	−3.0509	−5.6566

Note: Min, Max, and SD represent the minimum, maximum, and standard deviation of the log-transformed variables.
***Represents statistical significance at the 1% level of significance.

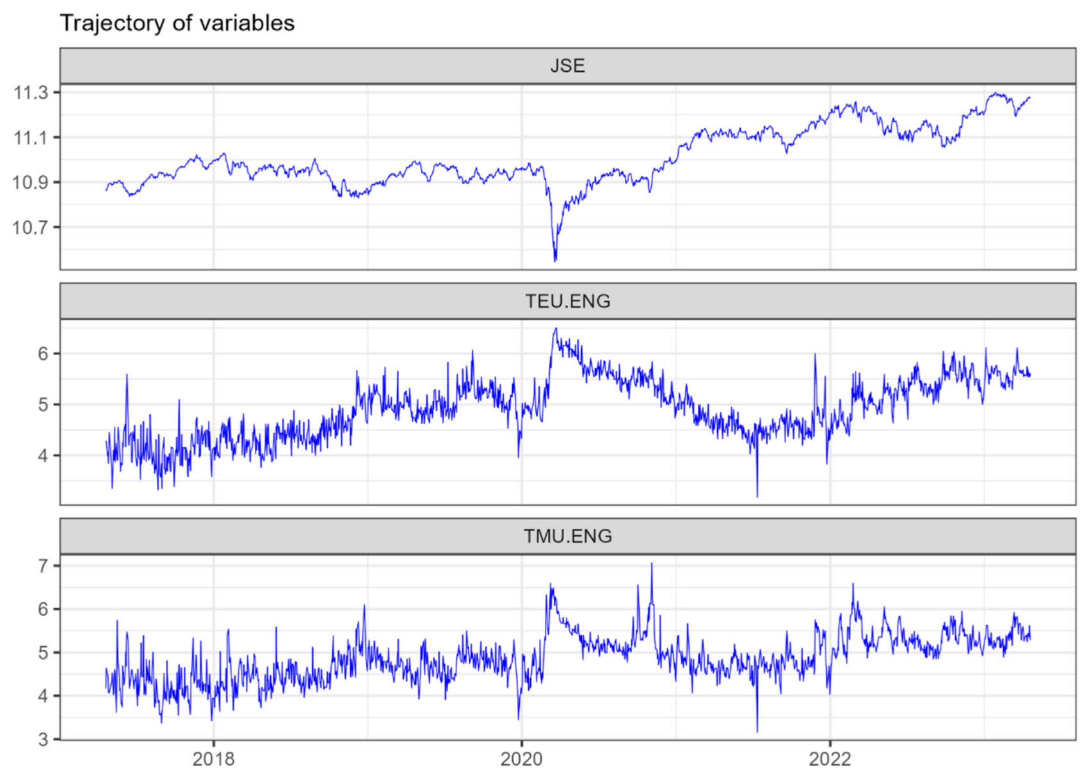

FIGURE 1 Visualization of study variables.

characteristics of our variables need to be correctly modeled to reduce biased estimates caused by misspecification.

3.2 | In-sample time-varying Granger causality

In this section, we report the results on the causal relationship between the two proxies of TUI and JSE returns using a time-varying Granger causality framework. The results explained in this section are visualized in Figures A1 and A2 in the Appendix. These plots display the 90th (black dashed line) and 95th (red dotted line) percentiles of the empirical distribution of the bootstrap statistics, to be compared with the sequence of the Recursive Evolving Window test statistics (blue solid line). There is significant causality if the blue line is above the red dotted line. The Schwartz and Akaike lag-order selection statistics recommend four lags, and these were used in the VAR model. Since there are I(1) variables as reported previously, our analysis proceeds following the lag-augmented VAR which is robust in the presence of integrated variables. We use a lag of 1 for the augmented version of the VAR. The model specified is also robust to heteroscedasticity. We also include a linear trend which enters the model as an exogenous variable.

In Figure A1, the analysis reveals an interesting temporal dynamic pattern in the causal relationship between TEU.ENG and JSE, showing its nonconstant nature over time. The presence of alternating periods of statistical significance and insignificance indicates a fluctuating pattern. However, a notable observation emerges as the strength of the causal connection experiences spikes, particularly during the onset of news related to COVID-19 in late 2019. The temporal evolution of this relationship gains further clarity in Figure A2, where the focus shifts to TMU.ENG. Here, two distinct spikes in significant causality are evident, aligning with key global events. The first spike coincides with the commencement of the COVID-19 pandemic, mirroring the pattern observed in TEU.ENG. The second spike, however, corresponds to the initiation of the Russian-Ukrainian war in 2022. This dual manifestation of significant causality suggests an interplay between TUI proxies and stock returns (JSE) during significant global events.

The results from the study mostly show that TEU affects the JSE during the COVID-19 period. This is in line with literature that generally shows that economic uncertainty measured from various proxies affects macroeconomic and financial variables mostly in the presence of locally and globally significant events like the global financial crisis of 2008 (Asafo-Adjei et al., 2020) and COVID-19 (Lang et al., 2022). This shows that even diversifying portfolios in an African market like South Africa is not enough to protect investors in times of globally significant negative events.

TABLE 2 Out-of-sample forecasting results.

Direction of causality	Max Wald
TEU.ENG → JSE	15.871 (7.898) [10.453] {17.268}
TMU.ENG → JSE	19.104 (7.934) [9.888] {14.671}

Note: The 90th, 95th, and 99th percentiles of the empirical distribution of the bootstrap statistics are in parentheses, brackets, and curly brackets, respectively.

3.3 | Out-of-sample forecasting

In out-of-sample forecasting tests, we first report the results for the whole sample in Table 2 using the VAR-LP model and a 1-day forecasting horizon. The results show that both proxies of TUI can significantly forecast stock returns in a 1-day forecasting horizon.

We also date-stamp the out-of-sample forecasts using the method explained in the methodology section. We use forecasting horizons of 1 day and 1 week in our models respectively. The results are shown in Figures A3 and A4, respectively. In all the models, there is empirical evidence that shows that TEU.ENG and TMU.ENG can significantly forecast stock prices across time in a multistep fashion. This is consistent using different forecasting horizons.

4 | CONCLUSION

The study sought to examine the causal relationship between Twitter uncertainty and JSE stock returns using a time-varying causality model that included two proxies of Twitter policy uncertainty and JSE stock returns. The results show that TMU.ENG and TEU.ENG lead JSE returns around the period characterized by heightened uncertainty caused by the COVID-19 pandemic and the war in Ukraine. The results show that Twitter policy uncertainty can be used to predict JSE stock returns. Future studies can expand the analysis at a sectoral level to understand the specific sectors on the JSE that can be impacted by Twitter uncertainty.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Available online (https://www.policyuncertainty.com/twitter_uncert.html).

[2] Data are publicly available online (https://www.policyuncertainty.com/twitter_uncert.html/).

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APPENDIX A

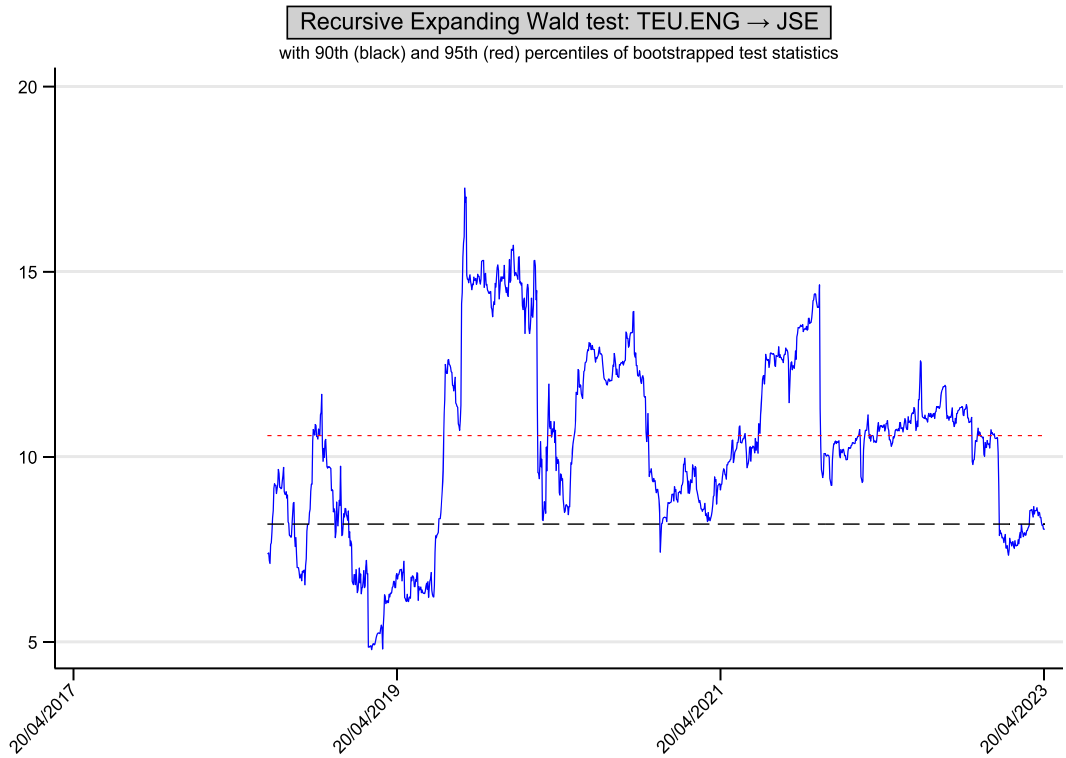

FIGURE A1 TEU.ENG to JSE.

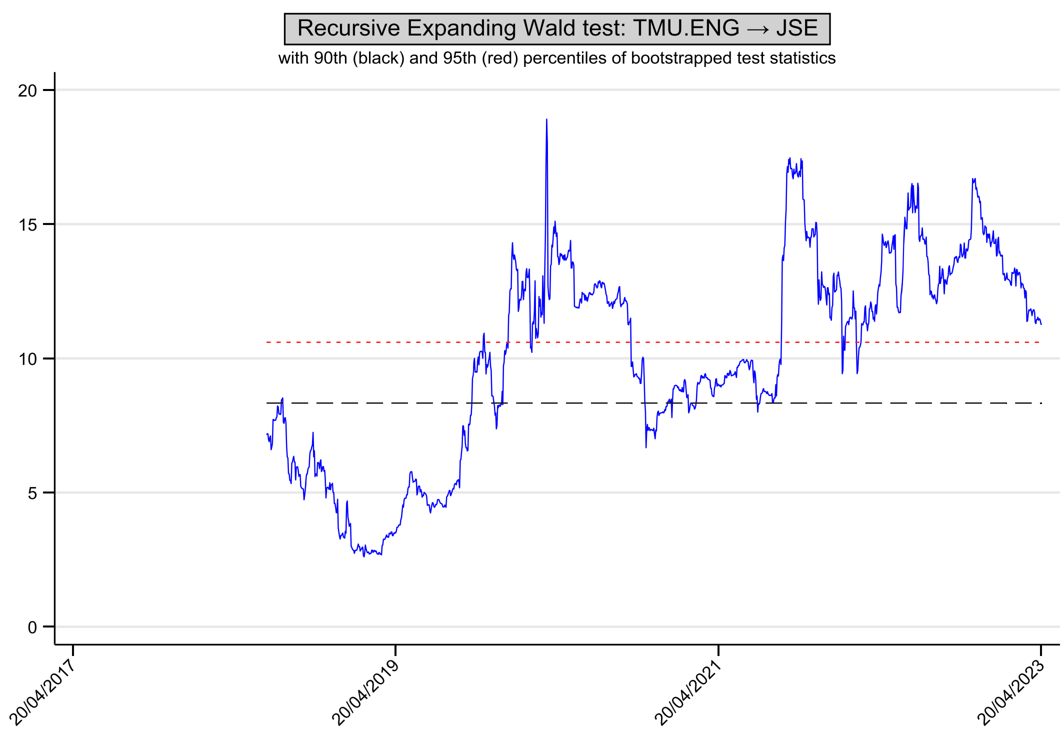

FIGURE A2 TMU.ENG to JSE.

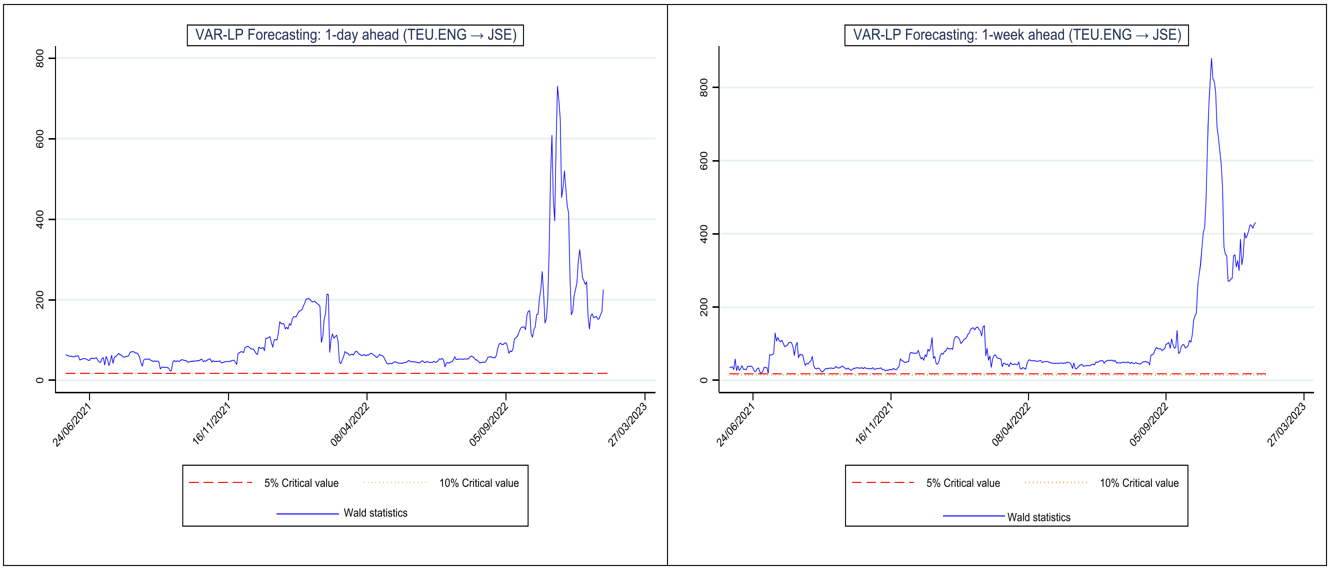

FIGURE A3 Out-of-sample forecasts (TEU.ENG).

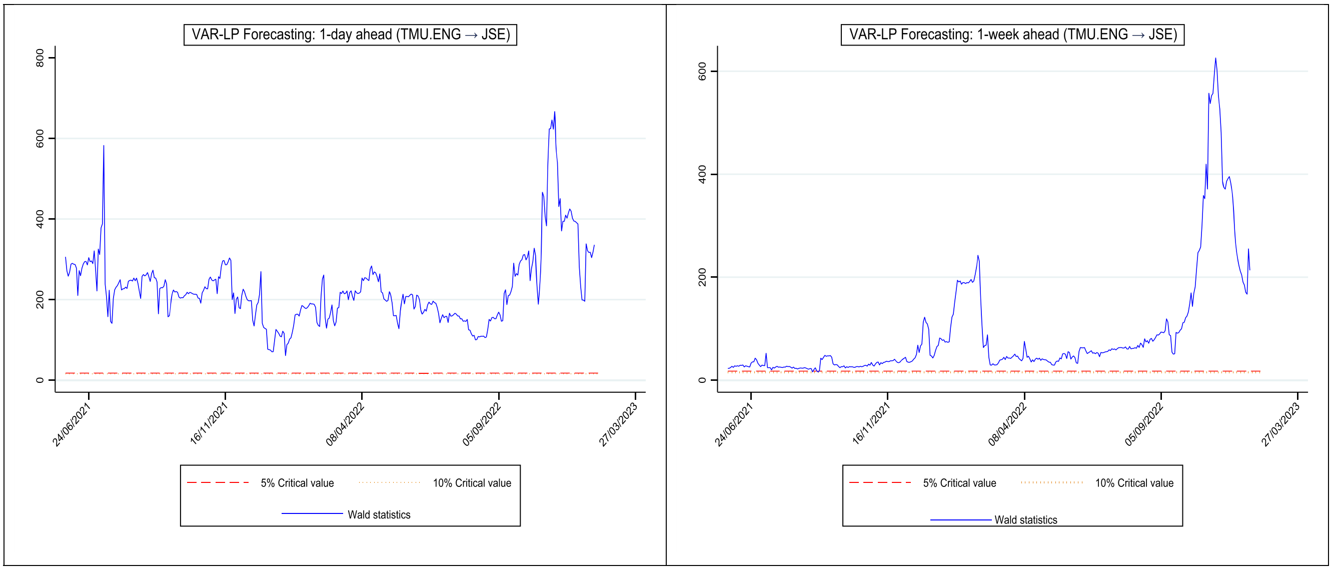

FIGURE A4 Out-of-sample forecasts (TMU.ENG).