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Research article

Industry-specific effects of economic policy uncertainty on stock market volatility: A GARCH-MIDAS approach

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Abstract: In recent years, monetary authorities have used unconventional monetary policy practices to stabilize economies. As a result, economic policy uncertainties have increased; subsequently, this has created fragilities in financial markets and exposed investors to greater levels of investment risk. However, recent literature suggests that volatility dynamics differ across industries, with some industries having hedging capabilities. On this basis, this study's objective is to explore the impact of economic policy uncertainty (EPU) on the volatility of different industries in South Africa. The GARCH-MIDAS approach was employed to achieve this objective, and nine industry-specific indices were evaluated from 3 January 2000 to 29 December 2023. The industry-specific analysis revealed that EPU has a negative relationship with the volatility in the following four industries: consumer discretionary, financials, health care, and technology. However, a positive relationship was found for the basic materials industry, while no significant effect was reported for consumer staples, energy, industrials, and telecommunications. Overall, these findings indicate that the EPU effects are asymmetric across industries and, therefore, it follows that the impact of EPU should be accounted for when making asset allocation choices.

Keywords: economic policy uncertainty; GARCH-MIDAS; Johannesburg Stock Exchange; stock market volatility

JEL Codes: E60, G10, G11

1. The background and introduction of the study

The literature extensively discusses the influence of macroeconomic policy on the economy and the financial market. Thus, economic policy uncertainty (EPU) is an important component that can be associated with the effectiveness of macroeconomic policy. Hence, EPU strongly influences economic activity (Msomi & Ngalawa, 2023). Many studies conducted after the global financial meltdown show that increased EPU resulted in volatility within the stock market (Liu and Zhang, 2015; Chiang, 2019; Su et al., 2024).

Stock market volatility increases the financial market risks (Su et al., 2019). More recently, a large body of literature focused on risk management in financial markets when there is EPU (Li, 2022; Mashilal et al., 2024; Naik & Sethy, 2022; Zhang, et al., 2024). Qian et al. (2020) showed that many factors correlated with stock market volatility during high EPU. Along this point, Su et al. (2024) argued that the literature showed that EPU is linked with increased stock market volatility. The central bank's actions determine the stock market's volatility (Lyu & Hu, 2024).

The connection between economic policy and the stock market is well-established in the literature (Tzika & Pantelidis, 2024). Therefore, the central bank can provide a clear policy direction, such as expanding the quantity of money in circulation (by reducing interest rates). Furthermore, the microstructure theory predicts that an increase in liquidity reduces the inventory risk in the stock market (Shi et al., 2022). Hence, when there is an increase in liquidity through the action of the monetary policy authorities, the cost of obtaining funding declines, thereby giving the agent the perception that holding the stock of assets is less risky. Therefore, monetary policy uncertainty affects the cost of financing and the decision to hold assets (Ye et al., 2023). In this sense, examining the relationship between the economic policy uncertainty and the stock market volatility is essential. For instance, if policymakers and market participants can understand how EPU influences stock market volatility, then they can ascertain how different macroeconomic events relate to the behavior of the stock market. Although there is extensive literature on EPU and stock market volatility, it's still a grey area for policymaking and practice. This creates uncertainty about the impact of a policy or the course of action to be taken by market participants.

Since stock market volatility relates to the extent of financial asset price fluctuation, it is concerned with the size of the price variations in a given period. Comprehending the dynamics of prices in the stock market benefits market participants in determining the opportunities and risks in the stock market (Bollerslev et al., 2018). A large body of literature indicates that forecasting stock market volatility assists stock market participants in making informed investment decisions (Ratnawati & Anggraeni, 2022; Singh, 2022; Ye et al., 2023). Some of the literature adds that anticipating fluctuations in the stock market indicates the future macroeconomic policy direction (Li, 2024; Sarwar, 2014; Su et al., 2019b; Zeng, et al., 2024).

Understanding the factors behind the stock market volatility movement is essential. There are many reasons which lead to stock market fluctuations, such as EPU and the political landscape. As mentioned earlier, EPU guides investor decisions, sentiments, and behavior, thus leading to stock market volatility (Zeng et al., 2024). Furthermore, there is a consensus in the literature that economic policy has different effects on the stock market (Ehrmann & Fratzscher, 2004; Thorbecke, 1997). This strengthens the reason to study the effect of economic policy in relation to the stock market volatility. As noted, stock market volatility can be associated with EPU (Zeng et al., 2024).

Taking into consideration all that is discussed above, we extend the analysis of the study in relation to EPU and the stock market volatility's effect on industry-specific responses. The purpose is to understand the relationship between these variables, which is a grey area in the literature. Eventually, the economic decisions influence the environment that industries function in. Therefore, while the literature discusses the impact of EPU on the stock market volatility, it remains unclear how each industry is affected.

Understanding the relationship will allow market participants to understand the patterns with which the EPU and the stock market volatility relate. Therefore, the stock market participants can take preventative measures against risk. Consequently, macroeconomic policymakers can also design policies that promote favorable stock market conditions. However, recent literature suggests that the characteristics of volatility differ across industries, with some industries possessing hedging capabilities. Therefore, it is important to examine how the effect of EPU varies across different industries. Therefore, the main contribution of this study is to provide insight into how EPU influences the volatility of different industries, which remains unstudied, to the knowledge of the authors. Such an insight will assist investors with asset allocation and hedging decisions, as well as assist policymakers with devising policies to maintain stability in financial markets. Furthermore, the findings of the study can be used to implement policy and for decision making by investors. This is because this study can be used in other markets with similar characteristics to that which is covered in this work.

The findings of this study indicate that EPU has a negative relationship with the volatility of the following four industries: consumer discretionary, financials, health care, and technology. Alternatively, there is a positive relationship in the basic material industry, while no significant effect is found for the consumer staples, energy, industrials, and telecommunications industries. Overall, these findings confirm that the effect of EPU is not uniform across the various industries and, therefore, has important implications for different stakeholders.

The rest of the paper is organized in the following order: literature review, methodology, results, discussion, and conclusions.

2. Literature review

Wang et al. (2024) stated that the stock market is prone to macroeconomic shocks that result in volatility. Further, they confirmed that EPU leads to stock market volatility. This is because EPU affects the investor's sentiments and expectations (Campbell & Shiller, 1986). Ghani & Ghani (2024) linked the stock market volatility to the EPU of the United States of America (USA). Furthermore, they showed that the uncertainty of the United States of America's economic policy was a good predictor of the emerging economies' stock market volatility.

Furthermore, a string of expanding literature connected ECU to a decline in the stock market returns (Li et al., 2019; Xiong et al., 2018). Wen et al. (2019) stated that the literature showed that when there was EPU, consumption and investment declined, which impacted stock market activities. Macchiarelli et al. (2021) added that these factors impacted the economy by increasing the cost of living via the channel of inflationary pressure. Therefore, they led to the emergence of uncertainty about the economic policy in use or to be implemented (Msomi & Ngalawa, 2024). According to Mashilal et al. (2024), the financial market is integrated into the global economy. Therefore, EPU in one country may affect the stock market in other countries.

The link between EPU and the financial market may also be viewed as the spillover effect of the government's actions when it tries to influence the economy through economic policy (Beckmann & Czudaj, 2017). As noted by Mbanyele (2023), the impact of EPU on the stock market is disproportional in the stock market. Furthermore, the impact of various economic policy transmissions varies depending on the perceived risky nature of the companies in the stock market. In the literature, a key aspect of stock market volatility and EPU is their correlation (Arouri et al., 2016; Zhang et al., 2023).

The impact of various policies designed to ease the pressure on the stock market volatility contributes to its course of action (Li et al., 2023). According to To et al. (2023), stock market volatility is an important signal for an impact on the government economic policy. The extent of volatility in the stock market indicates the confidence of the market participants regarding the government's economic policy's effectiveness in managing investor concerns (Engelhardt et al., 2021). Additionally, this is highlighted by Zhang et al. (2023), who argued that stock market volatility is also affected by geopolitical risks that affect the supply of production inputs. Therefore, uncertain economic conditions or circumstances linked to economic activities are at the heart of stock market volatility (Zeng et al., 2024). Bollerslev et al. (2018) stated that stock market volatility could also be perceived as a risk management measure.

The industry-specific interaction between EPU and the stock market is not extensive in the literature. However, the industries' responses to economic uncertainty differ. For example, EPU in the banking sector is associated with a positive strong response (Younis et al., 2024). Antonopoulou et al. (2022) added that the link between EPU in the banking sector is direct, and that it impacts the stock market returns. As such, this is evidence that EPU has positive implications for some industries. Furthermore, Shahzad et al. (2017) argued that EPU influences the decision to invest in the commodity market. While these findings are interesting, it is important to note that these results may not be true for commodities not included in the data. Moreover, these findings are based on the data collected; therefore, new data might reveal different trends and insights regarding the responses of different industries.

On the contrary, Zhu et al. (2022) argued that EPU does not lead to positive stock market returns. Furthermore, they provided evidence that the effect of EPU results in an asymmetric impact for different countries. This implies that the relationship between EPU and stock market volatility differs across countries. There are many factors that could influence the relationship, such as the development of the financial industry and the structure of the economy (Allen et al., 2018; Wu et al., 2016).

3. Methodology

In the finance literature, volatility is commonly modelled using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Recently, the GARCH-Mixed Data Sampling (GARCH-MIDAS) model, which was introduced by Engle et al. (2013), has gained popularity among researchers for its ability to distinguish between short-term (high frequency) and long-term (low frequency) volatility and, subsequently, modeled the determinants of long-term volatility using low-frequency variables. Accordingly, several studies have employed the model to investigate the effect of EPU on volatility (Ghani & Ghani, 2024; Li et al., 2020; Yu & Huang, 2021). However, these studies do not cover the South African market or examine industry-specific effects.

The model assumes that the log return ($r_{i,t}$) on day i of month t can be specified as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t \cdot h_{i,t}} \times \varepsilon_{i,t}, \tag{1}$$

where $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$ when $\Phi_{i-1,t}$ is the information set available on day $i-1$ of month t.

In Equation (1), μ is the unconditional mean while the volatility component ($\sqrt{\tau_t \cdot h_{i,t}}$) is comprised of two parts: a short-term volatility component ($h_{i,t}$) and a long-term volatility component (τ_t).

The short-term volatility component ($h_{i,t}$) assumes a daily GARCH (1,1) process as follows:

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

In Equation (2), α is the ARCH term, while β is the GARCH term, and both coefficients should be greater than zero. The long-term volatility component (τ_t) follows a smoothed realized variance process with an exogeneous variable based on a varying weighted function, and can be defined as follows:

$$(\tau_t) = m + \theta \sum_{k=1}^{K} \emptyset_k(\omega_1, \omega_2) X_{t-k} \quad (3)$$

In Equation (3), m is a constant term and θ is the parameter estimate of the weighted effects of the exogenous variable (X_{t-k}). To capture the effects of EPU on long-term volatility, the exogenous variable is the log difference of the quarterly World Uncertainty Index (WUI), which is employed as a proxy for EPU. The optimal lag length (K) of the EPU proxy represents the number of periods over which the volatility is smoothed and is selected based on the lag length, which maximizes the log-likelihood function (LLF) and minimises the Bayesian information criteria (BIC). A selection is made between 4, 8, and 12 lags that represent the volatility being smoothed over 1, 2, and 3 years, respectively.

The weighting scheme is computed based on an unrestricted Beta function as follows:

$$\emptyset_k(\omega_1, \omega_2) = \frac{(k/(K+1))^{\omega_1 - 1} \times (1 - k/(K+1))^{\omega_2 - 1}}{\sum_{j=1}^{K} (j/(K+1))^{\omega_1 - 1} \times (1 - j/(K+1))^{\omega_2 - 1}} \quad (4)$$

In Equation (4), the weights, $\emptyset_k$, are dependent on two parameters (ω_1 and ω_2), and the weights should sum to one. According to Yu and Huang (2021), this Beta weighting scheme is superior because it is flexible enough to accommodate different lag structures, including hump-shaped weighting schemes. Additionally, the GARCH-MIDAS model is estimated using the quasi-maximum likelihood estimation consistent with Engle et al. (2013).

4. Data and variables

This study surveys 9 industry indices as classified by the JSE's Industry Classification Benchmark (ICB) for categorizing companies. These industries include Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Technology, and Telecommunications. The real estate and utilities industries are omitted due to data unavailability for the full sample period. In addition, the overall South African stock market is proxied by the JSE's All Share Index (J203). The daily closing prices for the indices are obtained from Bloomberg for the sample period ranging from 3 January 2000 to 29 December 2023.

EPU is proxied by the WUI, which is freely available for South Africa on a quarterly frequency via the following website: https://worlduncertaintyindex.com/. The index was created by Ahir et al. (2022), and has been widely used as a proxy for EPU in recent studies by Hong et al. (2024), Javed et al. (2023), Olalere & Mukuddem-Petersen (2024), and Zaria & Tuyon (2023). The WUI is constructed based on the frequency of the word "uncertainty" (and its variants) in the Economist Intelligence Unit's (EIU) quarterly reports for each country. Accordingly, an increase in the value of the WUI is associated with an increase in EPU. To ensure comparability across countries, the index is rescaled and normalized, and an increase in the value of the index is associated with an increase in EPU (Ahir et al., 2022). The index distinguishes itself from alternative measures of EPU by concentrating on a single data source (that is, the EIU reports), which specifically focuses on economic and political developments, and by employing a standardized structure and process (Ahir et al., 2022).

5. Results

A summary of the descriptive statistics is provided in Table 1. The change in WUI exhibits a mean value of −0.031, which indicates that uncertainties surrounding South Africa's economic policy have decreased on average. Nevertheless, EPUs in South Africa over the last few years has resulted from inefficient service delivery, rising corruption levels, economic recessions, and credit rating downgrades, amongst other factors (Fasanya & Makanda, 2024). As a result, the country has experienced increasing inflation and interest rates coupled with frequent fluctuations in the Rand, which subsequently intensified EPU. Regarding the industry returns, the mean values indicate that the market and its respective industries generate positive returns on average, except for the healthcare and technology industries. The industry with the highest average return is the consumer staples industry, which is non-cyclical in nature. A further analysis reveals that the industry with the largest possible losses is the energy sector, which may be attributed to South Africa's current energy crisis and volatility in commodity prices due to recent geopolitical tensions.

Table 1. Summary of descriptive statistics.

Variable	Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis
WUI	−0.031	−1.574	1.871	0.699	0.121	3.146
Basic Materials	0.033	−15.665	12.091	1.794	−0.147	7.674
Consumer Discretionary	0.057	−10.470	9.146	1.377	−0.163	6.263
Consumer Staples	0.045	−10.041	14.212	1.468	0.205	8.190
Energy	0.054	−81.586	32.702	3.759	−32.541	191.831
Financials	0.026	−13.096	7.489	1.309	−0.446	10.179
Health Care	−0.0003	−81.459	6.281	3.238	−58.588	413.062
Industrials	0.031	−11.438	7.643	1.224	−0.288	8.029
Technology	−0.004	−20.799	18.896	2.051	−0.456	14.440
Telecommunications	0.025	−15.915	19.650	2.030	−0.055	8.972
All Share Index	0.0004	−0.097	0.075	0.012	−0.182	7.463

Table 2 presents the results of the tests conducted to examine the stationarity of the variables used in the study. The null hypothesis of a unit root is rejected for all the series in the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests, while the null hypothesis of stationarity is accepted with the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Therefore, all three tests conclude that the variables are stationary at levels and can be used in the analysis.

Table 2. Results of the tests for stationarity.

Variable	Model	ADF test stat.	KPSS test stat.	PP test stat.	Order of Integration
WUI	Constant	−10.765*	0.078	−15.526*	I(0)
Basic Materials	Constant	−74.168*	0.127	−74.229*	I(0)
Consumer Discretionary	Constant	−74.372*	0.156	−74.313*	I(0)
Consumer Staples	Constant	−76.459*	0.127	−76.526*	I(0)
Energy	Constant	−84.529*	0.085	−84.828*	I(0)
Financials	Constant	−74.377*	0.075	−74.445*	I(0)
Health Care	Constant	−76.662*	0.197	−76.659*	I(0)
Industrials	Constant	−75.502*	0.371	−75.484*	I(0)
Technology	Constant	−72.452*	0.375	−72.430*	I(0)
Telecommunications	Constant	−56.911*	0.297	−76.549*	I(0)
All Share Index	Constant	−75.359*	0.099	−75.562*	I(0)

Note: * represents statistical significance at a 1% level of significance.

In order to confirm the appropriateness of the GARCH models, tests for autoregressive conditional heteroscedasticity in the returns are conducted. The results of the tests for ARCH effects are presented in Table 3. For all the return series, the F-statistics and Obs*R-squared are statistically significant, thereby indicating the presence of significant heteroscedasticity in the return series. This finding implies that the GARCH models are appropriate for modeling the respective return series.

Table 3. Results of the ARCH tests.

Industry	F-statistics	Obs*R-squared
Basic Materials	179.709*	1160.361*
Consumer Discretionary	52.925*	395.995*
Consumer Staples	77.211*	560.695*
Energy	206.730*	1297.447*
Financials	276.599*	1616.769*
Health Care	276.340*	1615.519*
Industrials	54.756*	593.222*
Technology	56.223*	418.945*
Telecommunications	71.579*	523.370*
All Share Index	169.828*	1108.729*

Note: * represents statistical significance at a 1% level of significance.

Given the relevance of GARCH models for modeling the returns, the next step is to estimate the GARCH-MIDAS models. However, prior to estimating the GARCH-MIDAS models, the appropriate lag lengths (K) for the smoothing volatility must be determined. This study selects the appropriate lag lengths for the smoothing volatility based on the model, which maximizes the log-likelihood function and minimizes the information criteria. The model is selected for each industry and the market appears in bold in Table 4. Notably, the log-likelihood function and the Bayesian information criteria are consistent in terms of their lag length selection. These results are consistent with the unreported Akaike information criteria (AIC).

Table 4. Lag length selection for smoothing volatility

Industry	4 Lags	8 Lags	12 Lags
Basic Materials	−10757.0	−10274.4	−9796.6
	(21574.9)	(20609.7)	(19654.0)
Consumer Discretionary	−10754.3	−10278.7	−9801.4
	(21569.6)	(20618.4)	(19663.8)
Consumer Staples	−9528.6	−8971.7	−8408.9
	(19118.1)	(18004.3)	(16878.8)
Energy	−10163.5	−9640.7	−9137.3
	(20387.8)	(19342.3)	(18335.6)
Financials	−8845.6	−8467.3	−8047.1
	(17752.1)	(16995.4)	(16155.0)
Health Care	−10976.9	−12067.6	−11600.7
	(22014.7)	(24196.0)	(23262.3)
Industrials	−8604.6	−8204.6	−7826.5
	(17270.2)	(16470.1)	(15713.9)
Technology	−11090.7	−10402.9	−9815.8
	(22242.2)	(20866.8)	(19692.5)
Telecommunications	−11528.7	−11044.8	−10515.0
	(23118.2)	(22150.5)	(21090.8)
All Share Index	26617.9	25372.0	17344.8
	(−53174.9)	(−50683.2)	(−34628.8)

Notes:

1. The table presents the value of the log-likelihood function (LLF) alongside the Bayesian information criteria (BIC) in parentheses.
2. The optimal model selected by the LLF and BIC appears in bold.

The GARCH-MIDAS models are estimated with the optimal lag lengths selected in Table 4, and the results are presented in Table 5. The mean return (μ) for the market and various industries are positive and statistically significant, except for the Telecommunications industry, where the positive mean return is non-significant. These findings indicate that, on average, South African industries and the overall market generate positive returns after accounting for a conditional volatility. With regards to the short-run volatility component, the ARCH (α) and GARCH (β) terms are positive and statistically significant, which confirms that the current short-term volatility is dependent on historical residual shocks and a past conditional volatility, respectively. Furthermore, the ARCH and GARCH parameters sum to less than one, which suggests that the short-term conditional variance is stationary.

Table 5. Results of the GARCH-MIDAS estimations.

Industry	μ	α	β	m	θ	ω_1	ω_2
Basic Materials	0.041**	0.054*	0.939*	1.121*	0.558**	49.966***	26.957
	(2.117)	(14.003)	(207.1)	(7.937)	(2.284)	(1.657)	(1.603)
Consumer Discretionary	0.042**	0.059*	0.932*	1.247*	−2.470**	4.223	2.964
	(2.202)	(14.312)	(184.4)	(9.204)	(−2.148)	(1.388)	(1.382)
Consumer Staples	0.065*	0.067*	0.919*	0.604*	−0.367	49.734	42.188
	(4.289)	(14.566)	(161.2)	(6.220)	(−1.621)	(0.638)	(0.642)
Energy	0.1221*	0.068*	0.932*	−0.009	0.101	5.000	4.999
	(47.650)	(36.073)	(458.5)	(−0.033)	(0.116)	(0.133)	(0.155)
Financials	0.058*	0.102*	0.879*	0.491*	−0.423**	46.598	48.463
	(4.219)	(15.686)	(109.8)	(4.137)	(−1.997)	(1.377)	(1.334)
Health Care	0.101*	0.251*	0.749*	7.066*	−6.288*	6.200*	2.733*
	(10.607)	(35.504)	(106.2)	(11.797)	(−47.780)	(5.219)	(3.982)
Industrials	0.061*	0.090*	0.887*	0.312*	0.203	32.190	49.755
	(4.515)	(13.115)	(103.7)	(3.471)	(0.968)	(0.536)	(0.515)
Technology	0.082*	0.054*	0.943*	1.603*	−0.940*	40.293*	40.532*
	(4.460)	(29.024)	(539.3)	(6.782)	(−5.830)	(5.021)	(5.037)
Telecommunications	0.012	0.074*	0.926*	−0.127	0.105	5.000	5.000
	(0.758)	(21.839)	(333.3)	(−0.556)	(0.153)	(0.192)	(0.189)
All Share Index	0.0038*	0.134*	0.866*	−0.308	−0.690*	6.902	3.235
	(68.676)	(15.883)	(102.8)	(−0.663)	(−2.910)	(0.336)	(0.274)

Notes:

1. *, **, *** represent statistical significance at a 1%, 5%, and 10% level of significance, respectively.
2. T-statistics are provided in parentheses.

In terms of the long-run volatility component, the constant term (m) is positive and significant for all industries except for the Telecommunications and Energy industries, as well as the overall stock market, where it is negative but non-significant. The beta weighting scheme estimates a ω_1 that is greater than one for the market and all the industries. This suggests that a lower weight is given to the most recent observations of the explanatory variable, which is the change in EPU (Asgharian et al., 2013). The coefficient of interest is θ, which captures the effect of changes in the EPU on long-term volatility, and these results are discussed in the next section.

6. Discussion

Overall, changes in EPU exhibit a significant, negative effect on the market return volatility, and this effect implies that the stock market volatility increases when the EPU decreases, and vice versa. This finding may be attributed to the link between uncertainty and investor sentiment. In particular, when uncertainty decreases (in this case, EPU), investors become more optimistic, thereby overweighting good news and underweighting bad news (Bird & Yeung, 2012). This optimism increases the trading activity (Liu, 2015), which leads to fluctuations in the asset prices due to the price impact of large-sized orders by informed traders (Koubaa & Slim, 2019). As a result, there is a negative relationship between EPU and the stock market volatility. Similar findings were reported by Li et al. (2019) for the Chinese stock market.

The industry analysis reveals that the negative and significant relationship between EPU and volatility holds for the following four industries: Consumer Discretionary, Financials, Health Care, and Technology. In particular, EPU exhibits the greatest negative impact on the Health Care industry and the smallest impact on the Financials industry. These results contradict the findings of Younis et al. (2024), who reported that EPU has a greater impact on banks relative to the Health Care industry. On the contrary, the volatility of the Basic Materials industry displays a positive and significant relationship with EPU. This finding is attributed to the high sensitivity of basic material prices, particularly commodity prices, to economic and government policies. Remarkably, the Consumer Staples, Energy, Industrials, and Telecommunications industries were not significantly influenced by EPU. This suggests that these industries have hedging capabilities and can assist investors to reduce their exposure to EPU shocks.

These findings have important implications for various stakeholders. Given the importance of forecasting volatility for asset pricing and portfolio management, these findings imply that EPU should be considered in forecasting volatility models. However, investors, researchers, and practitioners need to acknowledge that the effects of EPU are not uniform across industries. For investors, these varying effects suggest that certain industries provide hedging possibilities. In particular, the following South African industries exhibit hedging capabilities because they are not significantly influenced by changes in EPU: Consumer Staples, Energy, Industrials, and Telecommunications. On the contrary, the Basic Materials industry is risky during times of an increased EPU. Therefore, rational investors should reduce their exposure to this industry. Overall, these findings imply that governments and regulators should attempt to maintain the stability in economic policies rather than decrease the EPU, as it could have unintended consequences for the stock market, such as exacerbating the stock market and industry-related price volatility.

Given the recent increase in financial uncertainties, future research should explore the industry-specific effects of financial uncertainties on the market volatility. Furthermore, this study concentrates only on the return volatility; future studies could explore the industry-specific effects of EPU on other dynamics of financial markets such as returns, liquidity, and pricing efficiency. Likewise, future studies could adopt alternative measures of EPU for comparative purposes. Additionally, further studies should investigate the effect of monetary policy uncertainties and oil price uncertainties to identify any comparable effects. Moreover, future studies can investigate whether the effect of EPU on stock market volatility exhibits an asymmetrical effect.

7. Conclusions

In recent years, monetary authorities have used unconventional monetary policy practices to stabilize economies. As a result, EPUs have increased, and subsequently created fragilities in financial markets and exposed investors to greater levels of investment risks. However, recent literature suggested that volatility dynamics differed across industries, with some industries having hedging capabilities. On this basis, the objective of this study was to investigate the effect of EPU on the volatility of different industries in South Africa. To achieve this objective, the GARCH-MIDAS approach was employed, and nine industry-specific indices were evaluated for the period ranging from January 2000 till December 2023. The industry-specific analysis revealed that EPU had a negative effect on the return volatility of four industries: consumer discretionary, financials, health care, and technology. However, a positive effect was found for the basic materials industry, while no significant effect was reported for consumer staples, energy, industrials, and telecommunications. Overall, these findings indicated that the effect of EPU varied across industries and had significant implications for various stakeholders.

Author contributions

Simiso Msomi: Conceptualization, writing – original draft, writing – review and editing.
Damien Kunjal: Conceptualization, methodology, data curation, writing – original draft, writing – review and editing.
All authors have read and agreed to the published version of the manuscript.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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