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Volatility Spillovers between the Global Economy Policy Uncertainty Index and Equity Markets: Evidence from Developed and Emerging Economies

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Abstract

This study analyses whether the Global Political Uncertainty Index has an impact on volatility in some developed and emerging markets. This study, which analyses the period between January 2003 and October 2022, uses the GARCH MIDAS approach, which allows low-frequency and high-frequency data to be analyzed together. The results show that the Global Political Uncertainty Index has a significant impact on the volatility of all markets included in the analysis. According to the results of the analysis, while an increase in global political uncertainty increases volatility in all markets, emerging markets are more affected by such uncertainty than developed markets. The markets most affected by global political uncertainty are Greece, India and China, while the least affected markets are Turkey and Canada.

Keywords: Global Policy Uncertainty, Stock Market, Volatility

Jel: C58, G10, G19

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1. Introduction

The pace of change in global markets and increasing digitalization is accelerating by the day. Many countries trying to keep up with this pace are also entering an environment of uncertainty. Developing countries are more vulnerable to uncertainty because of their fragile structure. In an environment of uncertainty, the reluctance of investors and consumers to make investment and spending decisions has a negative impact on the economy. In such cases, economic contraction is observed. The decrease in confidence in the markets in an uncertain economy may reduce the appetite of actors who will invest in the stock market.

The inability to predict the probability of outcomes in an economy is associated with economic uncertainty. The overall management of the economy to eliminate uncertainty is shaped by the policy choices made by decision makers. Economic policy uncertainty (EPU) occurs when the outcomes and alternative outcomes of the policy process cannot be predicted (Makin, 2012). Although there is no consensus on economic uncertainty and policy uncertainty in the past, policy uncertainty can be explained as economic risks associated with imperfect policies and regulators and supervisors (Al-Thaqeb and Algharabali, 2019).

The uncertainty indices used so far in the literature are VIX (Volatility Index), ESI (Economic Sentiment Index), UCRY (Cryptocurrency Uncertainty Index), BSI (Bloomberg Political Risk Index). The Economic Political Uncertainty Index (EPU) developed by Baker, Bloom and Davis (2016) and the Global Economic Policy Uncertainty Index (GEPU) developed by Davis (2016) are among the most preferred indices. Baker et al. (2013) constructed an index consisting of three subcomponents related to economic policy uncertainty to measure the policy uncertainty of the US economy. The first component is constructed based on data mining of some words in economic and political news in newspapers. The second component is the index calculated based on the number and size of federal tax provisions. The third component refers to the index calculated based on the size of disagreements between forecasters on state and local government purchases and the level of the consumer production index. Then, Baker et al. (2016) constructed the Economic Policy and Uncertainty (EPU) index by including the US and 11 European countries. They tested the index using the VAR method and found that the results are effective on stock markets and different sectors. Using the same method, Davis (2016) developed the global economic policy uncertainty index (GEPU), which was constructed from the EPU index of 21 countries (Korkmaz and Güngör, 2018:212).

The attitudes of those wishing to invest in equity markets in the face of uncertainty affect their investment decisions. For this reason, tracking some measurable uncertainties is beneficial to the investor in portfolio optimisation. With the acceleration of financialisation and globalisation and the development of digital channels, it has become imperative for an investor investing anywhere in the world to follow global markets and events. Recently, the relationship between global economic policy uncertainty and volatility has been discussed.

Therefore, the aim of this study is to analyse the impact of the Global Political Uncertainty Index on stock market volatility and to provide some information that can be used to forecast for investors. At the same time, it also aims to contribute to the financial literature by examining whether the effect of the uncertainty index differs according to the market structure by examining developed markets which are Canada, USA, France, Germany, UK, Japan and emerging markets which are Brazil, Turkey, Greece, China, India together. Following the literature review section, the study consists of four general chapters: data set and methodology, results and conclusions.

2. Literature Review

A review of the literature on global economic policy uncertainty shows that there are studies using macroeconomic variables in general. In general, the literature has examined the effects of uncertainty indices on gold prices, exchange rates and oil prices. At the same time, the relationship between uncertainty and volatility has recently been discussed in the national literature. Some prominent studies are presented in this section.

Sum (2012) uses data on economic policy uncertainty and monthly closing stock market index data for the period 1993-2012 for European Union countries, Switzerland, Turkey, Norway, Russia, Croatia and Ukraine to analyse the impact of the EMU index on stock markets through regression analysis. As a result of the study, they concluded that the EMU index reduced stock market returns in countries other than Croatia, Lithuania, Latvia, Malta, Bulgaria, Estonia, Slovakia, and Slovenia.

Ko and Lee (2015) used the period 1998-2014 in their study of 11 developed countries and examined the relationship between economic policy uncertainty and stocks using the wavelet approach. As a result of the study, they found that economic policy uncertainty reduces stock market returns.

Guo et al. (2017) examined the asymmetric dependence between EMU index and stock returns with panel quantile regression analysis using monthly closing data of EMU index and stock market index including G7 countries, China, Russia and India. As a result of the study, they concluded that economic policy uncertainty has a negative impact on stock market returns in countries other than the UK and France.

Wei et al. (2017) used the GARCH-MIDAS model to estimate the relationship between crude oil market volatility and the EPU index and found that the EPU index is effective on oil market volatility.

Yu et al. (2018) used the GARCH-MIDAS model and DCC-MIDAS model to investigate the relationship between global economic policy uncertainty and US stock markets and crude oil.

Demir and Ersan (2018) investigated the relationship between EPU index and stock returns of tourism companies traded in Borsa Istanbul for the period 2002-2013, using the panel regression model with monthly data and monthly closing prices of companies traded in tourism sector. As a result of the study, they found that the EPU index has a negative impact on stock market returns. Fang et al. (2018) examined the effect of the GEPU index on returns in the global gold futures market with the GARCH-MIDAS model, using monthly GEPU index data and daily stock returns. As a result of the study, they concluded that the GEPU index has a significant and positive effect on the volatility of stock returns.

Korkmaz and Güngör (2018) investigated the relationship between the GEPU index and the returns of companies operating in Borsa Istanbul during the period 1997-2018 and concluded that the GEPU index has an increasing effect on the volatility of companies' stock returns.

Gürsoy (2021) examined the relationship between the GEPU index and dollar/TL, euro/TL, inflation and BIST100 index variables in Turkey using the Hatemi-J asymmetric causality test with monthly data for the period 2013-2020. As a result of the study, it was found that the global economic and political uncertainty index had a positive effect on the dollar and euro exchange rates, while there was no relationship between other variables.

Gürsoy and Kılıç (2021) examined the impact of economic and political uncertainty in global markets on financial markets using monthly data for the period 2010-2020 and examined the GEPU index, Turkish 5-year CDS premiums and BIST banking index using the DCC-GARCH model. As a result of the study, they found that there is a strong bidirectional relationship between GEPU index, CDS premium and BIST banking index.

Tokatlıoğlu (2023) examined the GEPU index in different indices of Borsa Istanbul with the GARCH-MIDAS method to predict stock prices and exchange rate volatility in Turkey. As a result of the study, he found that the global economic political uncertainty index has an effect on stock prices and the long-term volatility of the US dollar and euro exchange rates.

Chau et al. (2014) investigate the volatility spillovers between the political uncertainty index and stock markets in the MENA region using the multi-GARCH methodology. Analysing the period between 2009 and 2012, the hypothesis that political uncertainty contributes to financial volatility is confirmed.

Looking at the use of the GARCH-MIDAS method in the literature, we find that many studies prefer this method for multiple analyses. For example, Xie et al. (2012) applied the GARCH MIDAS method to examine the effect of investor sentiment on stock volatility in the Shanghai-A stock market (Xie et al., 2021). According to Xie et al. (2012), the volatility of the Chinese stock market is positively influenced by the B-W investor sentiment index. Sreenu et al. (2021) used the GARCH MIDAS model to investigate the volatility interaction between Indian macroeconomic variables and future commodity markets. The study identified the effect of the long-term volatility factor in the commodity market and found that the majority of the validated data showed that low-frequency variables have a positive effect on the long-term variance of the commodity futures market.

3. Data Set and Methodolgy

3.1. Data Set and Preliminary Analysis

The study uses data for the period between January 2003 and October 2022. Global policy uncertainty index data are monthly, and stock data are daily closing data. MSCI classification is taken into account in the classification of developed and emerging markets. Accordingly, **as developed markets** are Canada, the USA, France, Germany, the UK, Japan and **as emerging markets** are Brazil, Turkey, Greece, China, India are included in the study. In addition, as a prerequisite for financial time series research, the return series of stock indices are obtained with the formula ln(pt)-ln(pt-1). The formula ln(yt)-ln(yt-1) was also used to express GPU at the same level with other variables.

Descriptive statistics of the data are given in Table 1.

Table 1. Descriptive Analysis

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ARCH-LM F-Stat
BRAZIL	0.000661	0.020186	-0.491159	11.94317	11888.84	305.20
CANADA	0.000306	0.012661	-1.488431	28.5326	97051.38	334.52
CHINA	0.000215	0.017987	-0.347449	7.859676	3539.59	145.01
FRANCE	0.00021	0.015992	-0.315777	11.88688	11658.27	232.96
GERMANY	0.000432	0.016065	-0.281612	11.19076	9900.23	177.78
GREECE	-0.000251	0.019794	0.086584	10.30143	7834.433	103.68
JAPAN	0.000331	0.016513	-0.456755	10.43208	8235.319	360.56
INDIA	0.000799	0.016781	-0.295909	14.91002	20885.46	141.98
TURKEY	0.000747	0.016755	-0.441456	7.623347	3253.997	119.14

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ARCH-LM F-Stat
UK	0.00017	0.013323	-0.444395	14.03463	17999.97	327.47
USA	0.000421	0.013784	-0.566982	14.87402	20897.1	306.33
GPU	0.020718	0.195394	1.379607	6.673279	209.3035	35.90

When the descriptive statistics data in Table 1 are analysed, it is seen that the series examined do not fit the normal distribution. The presence of excess kurtosis indicates that the distribution has heavier tails than a normal distribution, implying a higher probability of extreme events in the data (Dhesi, Shakeel & Ausloos, 2019). Studies have shown that financial time series tend to exhibit leptokurtic behaviour, meaning that they have thicker tails compared to a normal distribution (Hafner & Herwartz, 2022). This excessive kurtosis can have important implications for risk management and financial modelling as it affects the probability of extreme events in the market. Moreover, the presence of excess kurtosis, along with other characteristics such as volatility and skewness, highlights the challenges of accurately modelling financial time series (Dhesi et al., 2019; Lanne and Saikkonen, 2007).

When the kurtosis values of the series are analysed, it is understood that the data show thick tail characteristics and have characteristics specific to financial time series. However, the alternative hypothesis stating that the series do not follow a normal distribution is accepted in the J-B test results.

Another test, the ARCH-LM test, is a statistical test used to detect autoregressive conditional varying variance (ARCH) in time series data, particularly in the financial context. This test assesses whether past information can predict future variance by indicating the presence of varying variance in the data (Sjölander, 2010; Kumar, 2015; Bollerslev, 1986). The ARCH-LM test, which is widely accepted as the standard test for identifying ARCH effects, is a valuable tool for analysing volatility clustering and detecting changing variances in financial time series (Bollerslev, 1986; Kumar et al., 2022). In financial modelling, the ARCH-LM test plays a crucial role in assessing volatility patterns and capturing the dynamics of market volatility (Lim and Hooy, 2012). Using the ARCH-LM test, researchers can determine whether the data exhibit characteristics such as volatility clustering, which has important implications for risk management and forecasting (Baillie et al., 1996). By identifying changing variance through the ARCH-LM test, researchers can determine the appropriateness of using ARCH group models to accurately model the data (Quaicoe et al., 2015). In other words, this test can be used to make a preliminary determination of whether the data are suitable for modelling with ARCH group models. According to the results of the ARCH-LM test, the series included in the analysis are suitable for working with ARCH group models. In addition, a stationarity analysis was carried out as a preliminary check. Stationarity means that the statistical properties of the time series do not change over time. The stationarity condition is crucial in the modelling and forecasting process, because for non-stationary series, information from past data can be misleading in predicting future values (James, 2019). The stationarity condition is particularly necessary for the applicability of classical time series models such as ARIMA and ARCH. Such models improve the ability of past values to predict future values based on the assumption that the series is stationary (Butler & Kazakov, 2011). For non-stationary series, the predictive power of the model can be reduced, which can lead to inaccurate results. In addition, the stationarity test is an important step in understanding the properties of the time series. In this study, the stationarity results of the stock index return series are presented in Table 2.

Table 2. Unit Root Test Results

Değişkenler	ADF		PP	
BRAZIL	t-stat %1 p-value	-61.3442*** -3.43202 0.0001	t-stat %1 p-value	-61.3759*** -3.43202 0.0001
CANADA	t-stat %1 p-value	-61.1039*** -3.43202 0.0001	t-stat %1 p-value	-61.1699*** -3.43202 0.0001
CHINA	t-stat %1 p-value	-58.8534*** -3.43202 0.0001	t-stat %1 p-value	-58.8725*** -3.43202 0.0001
FRANCE	t-stat %1 p-value	-45.092*** -3.43202 0.0001	t-stat %1 p-value	-61.0011*** -3.43202 0.0001
GERMANY	t-stat %1 p-value	-59.1051*** -3.43202 0.0001	t-stat %1 p-value	-59.16*** -3.43202 0.0001
GREECE	t-stat %1 p-value	-40.6522*** -3.43202 0.0000	t-stat %1 p-value	-50.4164*** -3.43202 0.0001
JAPAN	t-stat %1 p-value	-59.8494*** -3.43202 0.0001	t-stat %1 p-value	-59.9208*** -3.43202 0.0001
INDIA	t-stat %1 p-value	-58.6481*** -3.43202 0.0001	t-stat %1 p-value	-58.6674*** -3.43202 0.0001
TURKEY	t-stat %1 p-value	-40.857*** -3.43202 0.0001	t-stat %1 p-value	-50.1369*** -3.43202 0.0001
UK	t-stat %1 p-value	-46.0307*** -3.43202 0.0001	t-stat %1 p-value	-62.1113*** -3.43202 0.0001
USA	t-stat %1 p-value	-65.7062*** -3.43202 0.0001	t-stat %1 p-value	-65.9334*** -3.43202 0.0001
GPU	t-stat %1 p-value	-18.436*** -3.45787 0.0000	t-stat %1 p-value	-20.41*** -3.45787 0.0000

The stationarity of the stock market return series and the change series of the global political index variable were analysed using ADF and PP unit root tests. As can be seen from the results in Table 2, all variables included in the analysis are stationary. The t-statistics of both tests are negative and significant at the 1% level. This indicates that the series are stationary. In addition, the fact that the results of the ADF and PP tests are very close to each other shows the consistency of the results. More specifically, the fact that the t-statistics are much lower (negative) than the critical value confirms that the series do not contain a unit root and are stationary. Therefore, the null hypothesis H0 that the series are not stationary is rejected. Therefore, it can be interpreted that the series are suitable for modelling with the ARCH group. This is because stationarity results mean that the mean and variance of the series are constant over time and the correlation decreases over time. In the next step of the study, the relationship between the Global Political Uncertainty Index and stock market volatility is analysed using the GARCH MIDAS method.

3.2. Method: GARCH MIDAS

The GARCH model has been widely used to model financial time series, particularly to capture volatility dynamics (Mantegna et al., 2000). This model is known for its ability to account for asymmetric responses in volatility, which is very important in the analysis of financial data (Xu and Zhu, 2021). The GARCH process, a subclass of multiplicative random walks, is essential for modelling financial time series (Mori et al., 2021). The GARCH-MIDAS method in financial time series analysis combines the Generalised Autoregressive Conditional Variance (GARCH) model with the Mixed Data Sampling (MIDAS) regression approach. Using the GARCH-MIDAS model, it is possible to examine the relationship between low-frequency macroeconomic variables and daily price volatility (Sreenu et al., 2021). In other words, the GARCH-MIDAS approach allows for the joint examination of economic and financial variables with different frequencies in the estimation of market volatility (Nguyen and Walther, 2019).

In this study, since the global policy uncertainty index is monthly and the stock market return series are daily, the GARCH MIDAS method, which allows the analysis of data at different frequencies, is preferred.

The MIDAS component includes low frequency data. In the model, the effect of low frequency data on the volatility of high frequency data is analysed. The first stage of this two-component model is the GARCH component. For returns with a constant conditional mean and conditional volatility, the model is expressed as in Equation 1. GARCH MIDAS is defined as follows under the assumption of returns on day i of month t (Asgharian, Hou & Javed; 2013: 601-602):

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t},$$
$$\forall i = 1, \dots \dots, N$$
$$\varepsilon_{i,t}\big|\Phi_{i-1,t} \sim N(0,1) \quad (1)$$

N is the number of trading days in month t, Φ_{i-1} is the information setup until the (i-1) th day of period t. Equation (1) expresses the variance as a short-term component defined by $g_{i,t}$ and a long-term component defined by τ_t. The conditional variance dynamics of the component $g_{i,t}$ is a GARCH (1,1) process, as follows:

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

τ_t defined as smoothed realized volatility in the spirit of MIDAS regression:

$$\tau_t = m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)RV_{t-k}$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \qquad (3)$$

Where K is the number of periods over which we smooth the volatility. Asgharian, Hou & Javed (2013) have modified this equation by involving the economic variables along with the RV in order to study the impact of these variables on the long-run return variance:

$$\tau_t = m + \theta_1\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)RV_{t-k} \\ + \theta_2\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)X_{t-k}^{l} \\ + \theta_3\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)X_{t-k}^{v} \qquad (4)$$

Where X_{t-k}^{l} represents the level of a macroeconomic variable and X_{t-k}^{v} represents the variance of that macroeconomic variable. Finally, the total conditional variance can be defined as follows:

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

The weighting scheme used in Equations 4 and 5 is described by the beta lag polynomial:

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

In the empirical implementation of this study, the constraint w=1, which implies that the weights are monotonically decreasing, is used. In addition, with reference to Engle et al. (2013), the GARCH MIDAS model is estimated with maximum likelihood and heteroskedasticity and autocorrelation consistent (HAC) standard errors are constructed.

4. Findings

Table 3 shows the parameter results of the GARCH MIDAS model for all variables. The parameter represents the average return, the parameter α represents short-term shocks and the parameter b represents long-term shocks. However, the GARCH model condition is α+b<1. MIDAS parameters are , q, w and m. Secondly, in the estimation of the GARCH-MIDAS model, m: the initial value of the log-likelihood function, ω, which is included in the equation τ_t, which is the long-run component of total volatility: the weight required for MIDAS regression and θ is the total effect of the low frequency variable on the volatility of the high frequency variable. A positive and statistically significant θ parameter means that the independent variable will cause high volatility on the dependent variable in the long run.

Table 3. GARCH MIDAS Parameter estimation results

Variables	m	α	β	q	w	M	LLF	AIC	BIC
Canada-S&P TSXR	0.000498 (3.1365) 0.00171	0.12253 (15.558) 0.0000	0.85057 (90.544) 0.0000	0.08871 (6.8063) 0.0000	1.1284 (1.7679) 0.077422	0.01059 (16.086) 0.0000	9613.28	-19214.6	-19177.5
United States-S&P 500R	0.000892 (4.872) 0.0000	0.14161 (12.558) 0.0000	0.81743 (62.889) 0.0000	0.12626 (10.313) 0.0000	4.0652 (3.2397) 0.0011968	0.010392 (14.704) 0.0000	9228.81	-18445.6	-18408.6
Germany-DAXR	0.000985 (4.6146) 0.0000	0.1287 (9.8253) 0.0000	0.82148 (39.989) 0.0000	0.13137 (7.6659) 0.0000	10.681 (1.8557) 0.063495	0.01231 (13.219) 0.0000	8597.2	-17182.4	-17145.4
Japan-Nikkei 225R	0.000821 (3.441) 0.0000	0.13438 (11.813) 0.0000	0.79819 (49.269) 0.0000	0.13508 (10.276) 0.0000	8.2883 (2.7278) 0.0063767	0.012983 (16.793) 0.0000	8340.42	-16668.8	-16631.8
India-Nifty 50R	0.001102 (4.824) 0.0000	0.097838 (10.454) 0.0000	0.8643 (44.602) 0.0000	0.19783 (29.293) 0.0000	2.5392 (7.5997) 0.0000	0.0060856 (7.5704) 0.0000	8494.64	-16977.3	-16940.3
United Kingdom-FTSE 100R	0.000414 (2.2493) 0.02449	0.15068 (11.008) 0.0000	0.76121 (36.925) 0.0000	0.15254 (14.805) 0.0000	10.596 (4.4439) 0.0000	0.0086602 (17.362) 0.0000	9176.38	-18340.8	-18303.8
France-CAC 40R	0.000763 (3.3733) 0.0000	0.14528 (10.766) 0.0000	0.79992 (39.845) 0.0000	0.14036 (9.4124) 0.0000	9.6665 (2.3257) 0.020038	0.012047 (13.782) 0.0000	8588.06	-17164.1	-17127.1
Brazil-BOVESPAR	0.000851 (2.8086) 0.0000	0.10137 (10.475) 0.0000	0.84054 (48.054) 0.0000	0.081655 (4.1725) 0.0000	3.9274 (1.488) 0.13676	0.017258 (18.394) 0.0000	7840.28	-15668.6	-15631.6
China-Shanghai CompositeR	0.000457 (1.7984) 0.07212	0.075972 (11.274) 0.0000	0.86147 (36.588) 0.0000	0.19339 (26.121) 0.0000	17.189 (3.2365) 0.001210	0.0078899 (10.236) 0.0000	8180.71	-16349.4	-16312.4
Turkey BIST100R	0.00111 (4.3725) 0.0000	0.11047 (12.36) 0.0000	0.83789 (67.232) 0.0000	0.0024657 (3.0414) 0.0000	1.0473 (11.693) 0.0000	0.00020253 (7.9147) 0.0000	7829.4	-15646.8	-15609.8
Greece ATHEX	0.000612 (2.3441) 0.01907	0.10099 (13.723) 0.0000	0.87379 (90.863) 0.0000	0.21621 (15.678) 0.0000	2.9484 (2.9839) 0.0028	0.0083328 (5.6219) 0.0000	7797.17	-15582.3	-15545.3

When the parameter results in Table 3 are analyzed, it is seen that all parameters are statistically significant. Therefore, the GARCH MIDAS model is accepted to be explanatory. It is observed that the average return parameter of all indices is positive. When the values of a which is the short-term shock parameter, are analyzed, it is seen that short-term shocks are effective on the current volatility in all indices included in the study. In addition, β indicates the long-term memory of volatility. A high β indicates that volatility has long-term effects, and the market will continue to be affected by previous volatility levels. In Table 3, in general, β values are quite high in all countries. Especially in countries such as Greece (ATHEX) and Turkey (BIST 100R), β values are above 0.80, suggesting that long-term volatility dependence is strong in these indices. When the ω parameter is analyzed, it is seen that the MIDAS parameter is not statistically significant in Brazil BOVESPA index, the variable with the highest MIDAS weight is China-Shanghai Composite and the variable with the lowest MIDAS weight is Turkey BIST100. The parameter θ, which shows the total effect of the low-frequency variable on the volatility of the high-frequency variable, is statistically significant in all variables. In other words, the global policy uncertainty index is effective on the volatility of all stock markets included in the analysis. When the coefficient value of θ parameter is analyzed, it is observed that the coefficient is positive. Therefore, it is possible to say that an increase in the global policy index will cause an increase in the volatility of all stock markets included in the analysis. This result is also correct in terms of investment theories. As a matter of fact, as uncertainty increases in a market, volatility in that market is an expected result. When the impact level is analyzed, it is seen that the index most affected by the global policy uncertainty index is the Greek ATHEX, followed by the Indian and Chinese markets. The indices least affected by global policy uncertainty are Turkey BIST100 and Canada S&P TSX. These results are surprising in terms of the size of the markets. For example, while the volatility of a theoretically developed market is expected to be less affected by an exogenous factor such as global policy uncertainty, this result obtained for Borsa Istanbul is not consistent with the theory.

Another finding obtained from the GARCH MIDAS model is related to the US markets. As a developed market, the SP500 is affected by the global policy uncertainty index and the volatility dependence of the market is strong. However, it should be noted that the average return of the US markets is positive and high compared to other markets. When the model findings of the UK, another developed market, are analysed, it is understood that this market is also affected by the global policy uncertainty index. In addition, just like the SP500, the FTSE100 is also affected by short and long term shocks and volatility persistence is found. It is observed that the average return of the FTSE is relatively lower than the SP500. In addition, the impact of GEPU on the FTSE 100 is found to be greater than that of the US.

5. Conclusion

In this study, whether the global policy uncertainty index has an effect on the stock market volatility of some developed and emerging countries included in the MSCI classification is analysed by means of the GARCH MIDAS method. The data for the period between January 2003 and October 2022 are used in the study, and it is found that global policy uncertainty has a statistically significant effect on the volatility of all indices included in the analysis. The results are consistent with the studies of Wei et al. (2017), Yu et al. (2017) and Fang et al. (2018).

In the study, the effect of the global policy uncertainty index on market volatilities differs. The impact level of the global policy uncertainty index is higher in the Indian, Chinese and Greek markets compared to other markets. This finding can be interpreted as the economies of these countries are likely to be more dependent on foreign trade, political stability and global economic developments, and therefore, global policy uncertainty may create greater concerns for investors in these countries and affect the markets more. In the case of Greece, the results obtained can be explained by the fact that Greece is a country that has experienced economic difficulties such as debt crises within the European Union and has a fragile structure against global economic developments and policy uncertainties for a long time. Another result of the study is that Turkish and Canadian stock markets are the least affected by the global policy uncertainty index. In particular, the results obtained for Turkey show that contrary to the theoretical expectations, global uncertainties have a more limited impact on the stock market. The fact that Turkey and Canada are less affected by global policy uncertainty could stem from different factors. For example, Turkey's domestic market appears to be more determined by local factors than global events. From the Canadian perspective, it can be argued that economies rich in natural resources, such as Canada, act based on global demand and supply balances and are less affected by policy uncertainty. In particular, markets based on natural resources such as the energy and mining sectors tend to be more isolated from global policy uncertainties.

The findings show that the UK and the USA markets are affected by the GEPU, but the degree of impact is different. Although the USA markets are less affected by the GEPU index, the persistence of the effect is higher than the UK, whereas the UK markets are more affected by short-term shocks. Based on the findings, it can be argued that although the US markets react to uncertainty shocks, they will have a higher recovery capacity due to their larger and more liquid size. In addition, the fact that the US markets are less responsive to global uncertainties may be related to the weight of technology companies in this market. The fact that the UK market is more dependent on foreign trade and the fluctuations experienced after the Brexit process may have caused this market to become more sensitive to an exogenous variable such as GEPU. While the US market is more stable, highly dependent on long-term volatility and resilient, the UK market is more sensitive to short-term shocks, more dependent on global trade and more vulnerable to uncertainties. Therefore, it is important for investors and policymakers to determine their strategies by taking these differences into account.

On the other hand, the results are more striking for Greece and Turkey, which are among the emerging markets. Greece stands out as one of the markets most affected by the GEPU. The high volatility dependence of the ATHEX index can be explained by the country's prolonged economic crises and its uncertain relations with the European Union. Surprisingly, global policy uncertainty has a more limited impact on Turkey. The low uncertainty sensitivity of the BIST 100 index can be interpreted as the market is mostly driven by domestic dynamics and is relatively resilient to global developments. However, this suggests the need for more detailed research on investor behaviour and market structure in Turkey.

These results suggest that the volatility dynamics of markets can be affected by both short-term shocks and long-term uncertainties. The fact that Turkey is unexpectedly less affected by this uncertainty can be explained by different factors such as investor behaviour or local dynamics. In addition to all these, it would be beneficial to conduct specific research on why the impact of global policy uncertainty in Turkey is low.

References

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. *The Journal of Economic Asymmetries*, 20. doi:10.1016/j.jeca.2019.e00133

Asgharian, H., Hou, A. J., & Javed, F. (2013). The importance of the macroeconomic variables in forecasting stock return variance: A GARCH-MIDAS approach. *Journal of Forecasting*, 32(7), 600-612.

Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 74(1), 3-30. https://doi.org/10.1016/s0304-4076(95)01749-6

Baker, S. & Bloom, N. (2013). Does Uncertainty Reduce Growth? Using Disasters As Natural Experiments Using Disasters As Natural Experiments, 1-35. doi:10.3386/w19475

Baker, S., Bloom, N. & Davis , S. (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, 131(4). doi:https://doi.org/10.1093/qje/qjw024

Baker, S., Bloom, N., & Davis, S. J. (2013). Measuring Economic Policy Uncertainty. (Erişim: 22.06.2018), http://www.policyuncertainty.com/media/EPU_BBD_2 013.pdf.

Baker, S.R., Bloom, N., & Davis, S.J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593-1636.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Butler, M. & Kazakov, D. (2011). The effects of variable stationarity in a financial time-series on artificial neural networks. 2011 IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr). https://doi.org/10.1109/cifer.2011.5953557

Chau, F., Deesomsak, R., & Wang, J. (2014). Political uncertainty and stock market volatility in the Middle East and North African (MENA) countries. *Journal of International Financial Markets, Institutions and Money*, 28, 1-19.

Davis, S. J. (2016). An Index of Global Economic Policy Uncertainty. *NBER Working Paper* No. 22740. (Erişim: 22.06.2018), http://faculty.chicagobooth.edu/steven.davis/pdf/Global%20Economic%20Policy%20Uncertainty%209%20Oct ober%202016.pdf

Davis, S. J. (2016). Global Economic Policy Uncertainty Index Data. (Erişim: 02.12.2020),

Demir, E., & Ersan, O. (2018). The impact of economic policy uncertainty on stock returns of Turkish tourism companies. *Current Issues in Tourism*, 21(8), 847–855.

Dhesi, G., Shakeel, B., & Ausloos, M. (2019). Modelling and forecasting the kurtosis and returns distributions of financial markets: irrational fractional brownian motion model approach. *Annals of Operations Research*, 299(1-2), 1397-1410. https://doi.org/10.1007/s10479-019-03305-z

Fang, L., Chen, B., Yu, H., & Qian, Y. (2018). The importance of global economic policy uncertainty in predicting gold futures market volatility: A GARCH- MIDAS approach. Wiley Future Markets, 38, 413-422.

Guo, P., Zhu, H., & You, W. (2017). Asymmetric dependence between economic policy uncertainty and stock market returns in G7 and BRIC: A quantile regression approach. *Finance Research Letters*, 25, 251- 258. http://dx.doi.org/10.1016/j.frl.2017.11.001.

Guo, Z. (2023). Research on the augmented dickey-fuller test for predicting stock prices and returns. *Advances in Economics, Management and Political Sciences*, 44(1), 101-106. https://doi.org/10.54254/2754-1169/44/20232198

Gürsoy, S. (2021). The effect of global economic politic uncertainty to exchange rate, inflation and stock market: evidence from Turkey. *Journal of Vocational and Social Sciences of Turkey.* (5), 120-131 . DOI: 10.46236/jovosst.877608

Gürsoy, S. & Kılıç, E. (2021). The Volatility Spillovers of the Global Economic Politic Uncertainity to Turkey CDS Spread and BIST Banking Index: DCC-GARCH Model Application. *Journal of Economics and Administrative Sciences,* 35 (4). 1323-1334. DOI: 10.16951/atauniiibd.876769

Hafner, C. and Herwartz, H. (2022). Dynamic score-driven independent component analysis. *Journal of Business &Amp; Economic Statistics*, 41(2), 298-308. https://doi.org/10.1080/07350015.2021.2013244

http://www.policyuncertainty.com/global_monthly.html

James, N., Marchant, R., Gerlach, R., & Cripps, S. (2019). Bayesian nonparametric adaptive spectral density estimation for financial time series. https://doi.org/10.48550/arxiv.1902.03350

Ko, J. H., & Lee, C.M. (2015). International economic policy uncertainty and stock prices: Wavelet approach. *Economics Letters,* 134, 118–122

Korkmaz, Ö. & Güngör, S. (2018). The Impact of Global Economic Policy Uncertainty on Stock Returns of Selected Index Traded on Istanbul Stock Exchange, *Anemon Muş Alparslan University Journal of Social Science,* 6(18), 211-219. https://doi.org/10.18506/anemon.452749

Kumar, A. (2015). Impact of currency futures on volatility in exchange rate. Paradigm, 19(1), 95-108. https://doi.org/10.1177/0971890715585204

Kumar, R. R., Sarkar, K. A., Dhakre, D. S., & Bhattacharya, D. (2022). A hybrid space–time modelling approach for forecasting monthly temperature. *Environmental Modeling &Amp; Assessment*, 28(2), 317-330. https://doi.org/10.1007/s10666-022-09861-2

Lanne, M. and Saikkonen, P. (2007). Modeling conditional skewness in stock returns. *The European Journal of Finance*, 13(8), 691-704. https://doi.org/10.1080/13518470701538608

Lim, K. and Hooy, C. (2012). Non-linear predictability in g7 stock index returns. *The Manchester School*, 81(4), 620-637. https://doi.org/10.1111/j.1467-9957.2012.02303.x

Mantegna, R. & Stanley, H. and Chriss, N.A. (2000). An introduction to econophysics: correlations and complexity in finance. *Physics Today*, 53(12), 70-70. https://doi.org/10.1063/1.1341926

Mori, R., Liu, R., & Chen, Y. (2021). Measuring the topological time irreversibility of time series with the degree-vector-based visibility graph method. *Frontiers in Physics*, 9. https://doi.org/10.3389/fphy.2021.777958

Quaicoe, M. T., Twenefour, F. B. K., Baah, E. M., & Nortey, E. N. N. (2015). Modeling variations in the cedi/dollar exchange rate in ghana: an autoregressive conditional heteroscedastic (arch) models.

Springerplus, 4(1). https://doi.org/10.1186/s40064-015-1118-0

Sjölander, P. (2010). A stationary unbiased finite sample arch-lm test procedure. *Applied Economics*, 43(8), 1019-1033. https://doi.org/10.1080/00036840802600046

Sum, V. (2012) Economic policy uncertainty and stock market Returns. *International Review of Applied Financial Issues and Economics*, 1-8, https://dx.doi.org/10.2139/ssrn.2073184.

Tokatlıoğlu, Y. (2023). The Role of Global Economic Policy Uncertainty on BIST Index and Exchange Rate Volatilities: A GARCH-MIDAS Approach. *Cankırı Karatekin University Journal of the Faculty of Economics and Administrative Sciences*, 13(2), 508-534.

Wei, Y., Liu, J., Lai, X., ve Hu, Y. (2017). Which determinant is the most informative in forecasting crude oil market volatility: Fundamental, speculation, or uncertainty? Energy Economics, 68, 141–150.

Xie, D., Cui, Y., & Liu, Y. (2021). How does investor sentiment impact stock volatility? new evidence from shanghai a-shares market. *China Finance Review International*, 13(1), 102-120. https://doi.org/10.1108/cfri-01-2021-0007

Xu, Y. and Zhu, F. (2021). A new GJR-GARCH model for Z-valued time series. *Journal of Time Series Analysis*, 43(3), 490-500. https://doi.org/10.1111/jtsa.12623

Yu, H., Fang, L., ve Sun, B. (2018). The role of global economic policy uncertainty in long-run volatilities and correlations of U.S. industry-level stock returns and crude oil. *Plos One*, 13(2), 1-17.