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The examination of the impact of global uncertainties on developed and developing markets with structural VAR model*

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Abstract

This study aims to examine the impact of global uncertainties on developed and developing markets with the help of the Structural VAR model. Due to the integration of financial markets, it is of great importance for securities market investors to be able to predict the direction of the markets. One of the variables to be used to predict the development of financial markets is the MSCI indices. In the study, the Developed Markets Index (MSCIWO) was used to represent developed markets, and the MSCIEF Emerging Markets Index was used to represent emerging markets. In the study, two separate models were established to measure the impact of global uncertainties on developed and developing markets. Using monthly data from 2014-2023, this study identifies differences between developed and emerging markets and shows how these markets react to different types of uncertainty. The results obtained from the study show that the effect of the Global Economic Policy Uncertainty Index (GEPU) variable on developed and developing capital markets is positive in the long term. Additionally, it was determined that the Geopolitical Risk Index (GPR) variable has a long-term negative impact on both markets. Analysis results indicate that the effect of the VIX variable on advanced markets is not significant, whereas it shows a negative impact on developing markets.

Keywords: *Global Uncertainties, Developed and Developing Markets, Structural VAR Model*

JEL Classification Codes: *C58, G11, G15*

1. Introduction

In recent years, both developed and emerging markets have increasingly faced global economic uncertainties. Factors such as changes in global trade policies, geopolitical tensions, fluctuations in financial markets, and volatility in energy prices have particularly heightened uncertainty and volatility in markets. This situation creates an environment where risks for investors are elevated. Understanding these effects is crucial for correctly guiding economic policies and the decision-making processes of investors. Over the past decade, there has been a significant increase in the number and diversity of financial instruments in financial markets. Additionally, technological advancements have further increased the diversity of financial instruments. This situation underscores the importance of risk management and directing funds toward secure investment vehicles. Although it is difficult to predict exactly how financial markets will evolve in the future, it is possible to make some forecasts about the potential directions of the markets. In this context, due to the financial markets becoming increasingly integrated through globalization and technological advancements, investors must monitor the uncertainties arising in global markets.

One of the variables that show the development of financial markets and are also a leading indicator is Morgan Stanley Capital International (MSCI) indices. MSCI indices contribute greatly to financial market investors' evaluation of investment opportunities in different countries, portfolio diversification, and risk distribution. MSCI indices enable stock market performance analysis based on regional and selected countries and enable foreign investors or funds to follow the performance of stock markets in the markets they are interested in. MSCI indices are diversified according to various criteria such as the

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All Country World Index, World Index, Emerging Markets Index, Sector Indices, etc. Created to measure the performance of global capital, MSCI indices today contribute significantly to evaluating investment opportunities, especially for investors and countries (https://www.msci.com/, Accessed on: 04/11/2024).

The GEPU index was created by Davis (2016). This index is a GDP-weighted national EPU index for 24 countries, which collectively account for two-thirds of global output (Korkmaz and Güngör, 2018). High GEPU values are generally stated to harm economic activity and investments. The GPR index is an indicator used to measure and monitor geopolitical risks worldwide. The index is created by combining a series of data and indicators that include various geopolitical events and factors. The GPRI is considered an important indicator for investors, companies, and policymakers to monitor and analyze the effects of geopolitical events on the global economy and financial markets (Caldara and Iacoviello, 2018: 2-8). The VIX index, often referred to as the "Fear Index," is a volatility measure based on the S&P 500 index in the United States, calculated since 1993. This index attempts to show future volatility levels based on market expectations. The VIX index is generally used to reflect the concern or fear that investors feel about future uncertainty or risk in the market. A high VIX index means that investors are anxious or fearful about future market conditions (Fountain, Herman & Rustvold 2008:469; Whaley, 2000:12). The OVX index is an important tool for monitoring and evaluating uncertainties in the energy markets. The volatility of crude oil prices is often closely related to economic indicators such as economic growth, inflation, and consumer prices, as well as financial markets.

This study aims to investigate the long-term effects of global uncertainties on the capital markets of developed and emerging countries using a Structural VAR model. There are numerous studies in the literature examining the impact of global uncertainties on capital markets. The most important difference of this study from those in the literature is the recognition that the long-term characteristics of time series can be lost when differences are taken. Therefore, to address this issue, the study utilizes techniques such as short- and long-term Structural VAR (SVAR) models and the HP filter. By employing these approaches, the aim is to ensure that the obtained results are more reliable and that the analysis is based on more robust foundations. This allows for a healthier understanding and interpretation of the effects of global uncertainties on developed and emerging markets. Additionally, by disentangling uncertainties from different variables, the study reveals the differences and similarities in responses between developed and emerging markets. Finally, the interaction between capital markets and global uncertainties cannot be fully understood through linear models and analyses alone. Therefore, all data were subjected to F-matrix SVAR dynamic interaction analysis. In the first part of the study, research conducted in the literature is introduced by the purpose of the study. Following the third section, which introduces the methodology and data set, the findings and results obtained from the analyses are presented.

2. Conceptual Framework

There are numerous studies in the literature that investigate the impact of uncertainty shocks on economic and financial indicators using the SVAR method (Bloom, 2009; Bachmann, Elstner & Sıms, 2013; Bekaert, Hoerova & Duca, 2013; Caggiano, Castelnuovo &And, 2014; Fernandez-Villaverde et al., 2015; Jurado, Ludvıgson & And, 2015; Leduc and Liu, 2016; Baker, Bloom & And, 2016; Basu and Bundick, 2017; Altıg et al., 2020; Caldara and Iacoviello, 2022).

Miescu (2019) examined the response of macroeconomic indicators in emerging markets to uncertainty shocks using the SVAR method, utilizing both global and country-specific uncertainty indicators. The results show that uncertainty shocks in emerging economies lead to significant declines in GDP and stock price indices, trigger inflation, and cause currency depreciation. Trung (2019) investigated the impact of US uncertainty shocks on emerging economies, finding that US uncertainty shocks reduce capital inflows, investment, consumption, and export output in emerging economies. Kang et.al. (2020) found that global financial uncertainty shocks are more significant than non-financial shocks. Llosa, Forero &Tueste (2022) determined that uncertainty shocks cause recessions in emerging economies, particularly during periods of financial distress, promote low interest rates, and weaken local currencies against the US dollar. An et.al. (2022) investigated the impact of GEPU on international capital flows, using annual data from 31 developed and emerging countries for the period 2000-2020. The results indicated that GEPU has a significantly negative effect on booms in developed economies.

The literature contains many studies examining the impact of uncertainty indices on stock returns and the returns of various financial assets. Kara et.al. (2020), found that economic policy uncertainty negatively affects stock markets, flattens the yield curve, and leads to currency depreciation. Fossung (2021) determined that the effect of geopolitical risk on the Technology sector within the S&P 500 index is negative across all event windows from 10 days before to 10 days after a geopolitical event, while it has a positive effect on the Communication Services sector. The study also revealed that the Consumer Staples sector shows a negative impact from geopolitical risk across all event windows. Kyriazis (2021) found that the GPR index has a negative impact on the returns and volatility of oil prices. Chang et al. (2018) determined that the VIX index has significant short-term negative effects on European ETF returns. Assaf, Charif & Mokni, K (2021), discovered that the EPU contributes the most to energy markets, followed by the World Trade Uncertainty Index. Vuong, Nguyen & Keung (2022), stated in their study that the VIX index is a good measure for assessing investors' fears regarding securities investments and provides a solid basis for firms listed on the U.S. stock market to make decisions regarding their capital structures. Apaitan, Luangaram & Manopimoke (2022), investigated the effects of local and global uncertainty on the Thai economy using the SVAR method. The results indicated that uncertainty shocks primarily lead to sudden and significant declines in stock prices and foreign portfolio investments, subsequently affecting the real economy through investment and trade channels. Salisu, Gupta & Demirer (2022), explored the impact of oil price uncertainty shocks on the stock markets of 26 developed and emerging countries using the GVAR model. The findings revealed that uncertainty shocks originating from oil prices have statistically significant and negative effects on the majority of global stock markets. Zhou et.al. (2022), noted the significant international spillover of EPU and highlighted that the policy uncertainty diffusion network varies over time. Miescu (2022) found that uncertainty shocks have significantly contractionary effects on GDP, stock prices, and local currencies in emerging countries.

Lanzilotta et al. (2023) analyzed how economic uncertainty affects domestic variables in a small and open economy like Uruguay over a 15-year period using the VAR method. The results indicated that economic uncertainty has a significant impact on the real economy, while not affecting nominal variables. Aslan and Açıkgöz (2023) found in their study that global EPU has a persistent and negative impact on exports. Lai et al. (2023) identified an asymmetric relationship between geopolitical risk and global stock markets. Shaik et al. (2023) investigated the effects of the geopolitical risk index on stocks, oil, and gold, considering periods of the global financial crisis, COVID-19, and the Russia-Ukraine war. The study's results showed that geopolitical risk exhibited high volatility during the Russia-Ukraine war period compared to the COVID-19 period, and the least volatility was observed during the global financial crisis period. Bossman & Gubareva (2023), examined the asymmetric financial effects of geopolitical risk from the Russia-Ukraine conflict on the stock markets of the seven major emerging (E7) and developed (G7) countries. The study's findings indicate that, except for Russia and China, all E7 and G7 stocks responded positively to GPR under normal conditions. Nam et al. (2023) investigated the relationship between the geopolitical risk index and stock market returns in Vietnam using the TVP-VAR method, considering the period from 2012 to 2022. The findings from the analysis show that geopolitical risk has a heterogeneous impact on the returns of financial assets, and the market does not respond uniformly to geopolitical tensions. Plakandaras et.al. (2023) found that geopolitical events in emerging countries are not very significant for the global economy because their effects on the examined assets are usually temporary and only of regional importance. In contrast, they found that gold prices are affected by fluctuations in geopolitical risk. Ghani and Ghani (2024) examined the impact of economic policy uncertainty (EPU) indices on the volatility of Pakistan's stock market, determining that the US economic policy uncertainty index is a stronger predictor of volatility in Pakistan's stock market.

3. Model Specifications and Data

The Structural VAR (SVAR) model was developed by Sims (1986) and Bernanke (1986) as an alternative to the VAR model introduced by Sims (1980). In the SVAR model, the ordering of variables is crucial; unlike the VAR model, the SVAR model allows for the classification of variables as either endogenous or exogenous during the model construction phase. In the SVAR framework, the dynamics of certain variables are defined with specific constraints, while others are treated as external shocks (Pedroni, 2013: 184).

As noted by Rubio-Ramirez, Waggoner & Zha (2010), the Structural VAR (SVAR) model typically analyzes three different types of matrices over two time periods: short-term and long-term. These matrices are referred to as A-B Restrictions (Short-Term), S Restrictions (Short-Term), and F Restrictions (Long-Term). This study conducts an analysis of the long-term effects of global uncertainties on developed and emerging capital markets. Therefore, the SVAR short-term matrices (A-B matrices) are not aligned with the objectives of this research.

A simple SVAR model can be written as follows (Pfaff, 2008:4):

$$X_t = A_0 + A_1 X_{t-1} + \cdots + A_p X_{t-1} + e_t \tag{1}$$

$X_t = n \times 1\ vector\ of\ endogenous\ variables.$

X_{t-1} = The lagged vector of these variables

e_t = Error term and uncorrelated structural shocks

To separately examine the long-term effects of global uncertainties on developed and emerging markets, two separate models have been established in this study. The first and second SVAR models can be written as shown in Equations 2 and 3.

$$f(\log((MSCIWO), log(GEPU), log(\ GPR), log(OVX), log\ (VIX)\ ) \tag{2}$$

$$f(\log((MSCIEF), \log(GEPU), \log(\ GPR), \log(OVX), \log(VIX)\ ) \tag{3}$$

The aim of this study is to examine the impact of global uncertainties on developed and emerging markets using the structural VAR model. The study utilizes the GEPU, GPR, OVX and VIX indexes to measure investors' concerns about future uncertainty or risk. Using monthly data from 2014 to 2023, this research identifies the differences between developed and emerging markets and demonstrates how these markets respond to different types of uncertainty. Table 1 provides descriptive information about the variables.

Table 1. Descriptive Information about the Variables

Variables	Kode	Source
Developed Markets Index	MSCIWO	investing.com
Emerging Markets Index	MSCIEF	investing.com
Global Economic Policy Uncertainty Index	GEPU	https://www.policyuncertainty.com
Crude Oil ETF Volatility Index	OVX	investing.com
Geopolitical Risk Index	GPR	https://www.matteoiacoviello.com/gpr.htm
Chicago Board Options Exchange Volatility Index	VIX	investing.com

4. Econometric Findings

Non-stationary series provide reliable results in level VAR impulse-response models (Ashley and Verbrugge, 2009). In this study, ADF unit root tests were applied to determine the stationarity levels of the variables. The most commonly used method for stationarity testing is the Augmented Dickey-Fuller (ADF) unit root test developed by Dickey and Fuller. The stationarity analysis of the variables included in the study has been investigated using the ADF unit root test. In this analysis, the following regression equation is used. The ADF test is calculated by adding a constant term and trend, as well as a constant term only, to the following regression equation (Gujarati and Porter, 2014: 757).

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \, \Delta Y_{t-i} + \varepsilon_t \qquad (4)$$

The lag length denoted by "m" in the equation is determined using the Akaike, Schwarz, and Hannan-Quinn information criteria. In this study, the Schwarz information criterion was preferred when determining the lag length. According to the ADF test applied to the variables, the probability value of the statistical result should be less than 0.05. The test establishes the following hypotheses: H0: Contains a unit root, H_1: Does not contain a unit root. If the H_0 hypothesis is accepted, it is concluded that the variables are not stationary, and it becomes necessary to take the natural logarithm and/or difference of the variables until stationarity is achieved. The logarithms of all included variables were taken and adjusted for seasonality. The results in Table 2 show that the data are stationary at I(0) and I(1). According to Table 1, GPR, OVX, and GEPU are stationary at level values, while the other series are stationary at I(1).

Table 2. ADF Unit Root $Testi^{1,2}$

	I(0)				I(I)			
	Constant		Constant and Trend		Constant		Constant and Trend	
Variables	**t-Statistic**	**Prob.**	**t-Statistic**	**Prob.**	**t-Statistic**	**Prob.**	**t-Statistic**	**Prob.**
LGEPU	-2.535094	0.1100	-3.687828	0.0272	-11.59703	0.0000	-11.57225	0.0000
LGPR	-4.666173	0.0002	4.649529	0.0014	-13.59818	0.0000	-13.54353	0.0000
LVIX	-3.001607	0.0378	-3.414174	0.0546	-15.83187	0.0000	-15.77191	0.0000
LOVX	-3.522566	0.0091	-3.607209	0.0336	-8.672365	0.0000	-8.681592	0.0000
LMSCIEF	-1.952446	0.3075	-1.926466	0.6341	-10.44434	0.0000	-10.40548	0.0000
LMSCIWO	-3.489117	0.8853	-2.741939	0.2222	-12.02522	0.0000	-11.97598	0.0000

[1]All variables are taken in natural logarithms.
[2]All variables are seasonally adjusted.

4.1. MSCIWO First Long-Term SVAR Model

To interpret the results obtained from the SVAR method, one of the most important steps is to set the model according to the appropriate lag length. Since the study consists of monthly data from 2014 to 2023, the number of observations exceeds 100. For datasets with more than 100 observations, the AIC (Akaike) information criterion holds more significance compared to other information criteria. In this context, the appropriate lag length for the model has been determined as two (2), based on the AIC information criterion (Table 3).

Table 3. Optimum Lag Length[3]

Lag	FPE	AIC	SC	HQ
0	6.92	0.005	0.131	0.056
1	6.94	-6.90	-6.146*	-6.594*
2	6.20*	-7.015*	-5.63	-6.45
3	7.13	-6.88	-4.87	-6.06
4	9.04	-6.66	-4.02	-5.59
5	1.16	-6.43	-3.17	-5.11
6	1.29	-6.36	-2.47	-4.78
7	1.42	-6.32	-1.79	-4.48
8	1.35	-6.44	-1.292	-4.35

[3]Determined According to the AIC Information Criterion.

This study examines the long-term effects of global uncertainties on developed and emerging markets. For this purpose, the SVAR long-term matrix aligns with our objective. As seen in Table 4, the first long-term SVAR (F matrix) model shows no issues with autocorrelation and changing variance.

Table 4. Autocorrelation and Changing Variance Test [4]

Lag	Prob.
1	0.12
2	0.16
3	0.62
4	0.95
5	0.09
6	0.38
7	0.19
VAR Residual Heteroskedasticity Testi:	
Prob: 0.0705	

[4]Indicates the Probability Values. ($p > 0.05$)

As shown in Figure 1 (Equation 1), the effect of the GEPU variable on the MSCIWO index is positive in the long term. However, the effect of the GPR variable on the MSCIWO index is negative in the long term. The OVX variable negatively affects the MSCIWO index up to the fourth period, after which it shows a positive impact. These results indicate that changes in the GEPU, GPR, and OVX indices significantly influence the MSCIWO index, which represents developed countries. In contrast, the effect of the VIX index is found to be insignificant.

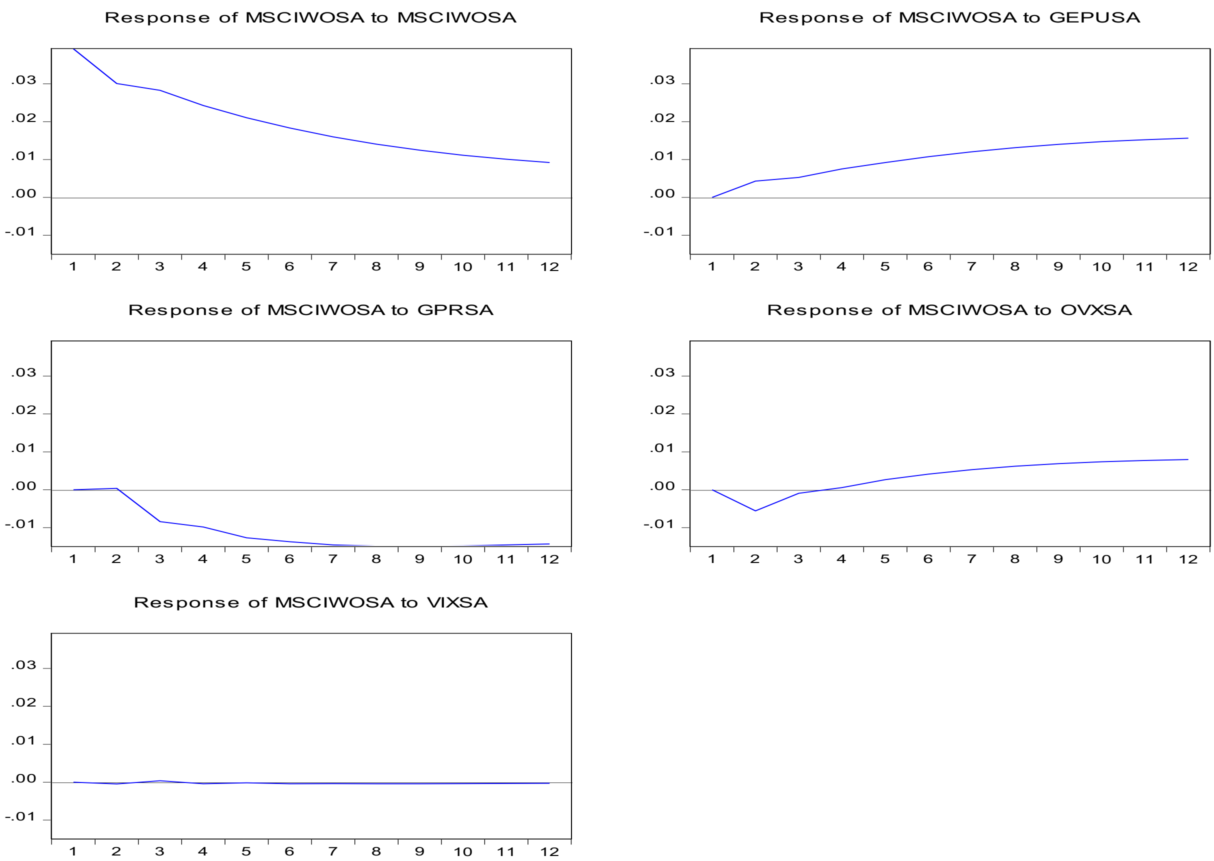

Figure 1. Structural VAR Results for the MSCIWO Index

Variance decomposition analyses were conducted within the framework of the SVAR model to determine the dynamic relationships between the series. When examining the findings presented in

Table 5, it can be stated that the largest portion of the forecast error variance for MSCIWOSA is explained by the variable itself. Additionally, it is observed that the GEPU and GPR variables contribute approximately 11% and 15%, respectively, to the explanation of MSCIWOSA's forecast error variance. Moreover, it can be noted that the contribution of the VIX variable to MSCIWOSA's forecast error variance is relatively low. These results are consistent with the findings obtained from the impulse-response analysis conducted for MSCIWOSA.

Table 5. Variance Decomposition Results

Variance Decomposition of MSCIWOSA:					
Period	MSCIWOSA	GEPUSA	GPRSA	OVXSA	VIXSA
1	100.0000	0.000000	0.000000	0.000000	0.000000
2	98.00639	0.741667	0.005956	1.237827	0.008161
3	95.61382	1.360625	2.080349	0.935282	0.009928
4	92.68222	2.486855	4.043383	0.775400	0.012145
5	88.51238	3.881337	6.784873	0.810381	0.011029
6	84.04193	5.519732	9.403144	1.022222	0.012972
7	79.42534	7.316979	11.87039	1.373198	0.014095
8	74.95483	9.191292	14.02295	1.815347	0.015583
9	70.74334	11.08280	15.85231	2.305002	0.016543
10	66.86237	12.94030	17.36905	2.811151	0.017122

4.2. MSCIEF Second Long-Term SVAR Model

n the second long-term SVAR model, where the MSCIEF variable is included, the appropriate lag length has been determined to be two (2) based on the AIC information criterion (Table 6).

Table 6. Optimum Lag Length[5]

Lag	FPE	AIC	SC	HQ
0	3.73	-0.61	-0.487	-0.56
1	1.41	-6.18	-5.434*	-5.88*
2	1.40*	-6.20*	-4.82	-5.64
3	1.53	-6.12	-4.11	-5.30
4	1.94	-5.89	-3.26	-4.82
5	2.38	-5.71	-2.4	-4.39
6	3.01	-5.52	-1.62	-3.94
7	3.27	-5.481	-0.96	-3.65
8	3.51	-5.48	-0.33	-3.40

[5]Determined According to the AIC Information Criterion.

As shown in Table 7, the constructed second long-term SVAR (F matrix) model does not exhibit issues of autocorrelation and changing variance.

Table 7. Autocorrelation and Changing Variance Test[6]

Lag	Prob.
1	0.14
2	0.08
3	0.39
4	0.95
5	0.40
6	0.72
7	0.21
VAR Residual Heteroskedasticity Testi: **Prob:** 0.3712	

[6]Indicates the Probability Values ($p > 0.05$)

As shown in Figure 2 (Equation 2), the results obtained from the model that includes the MSCIEF index are similar to those of the first SVAR model. The effect of the GEPU variable on MSCIEF is positive in the long term, while the effect of the GPR variable is negative. The OVX variable negatively affects the MSCIEF index until the sixth period, after which it has a weak positive effect. It was determined that the effect of the VIX index on developed markets is not significant. According to Figure 2, the VIX index shows a weak positive impact on the MSCIEF index representing emerging markets until the third period, and a negative impact thereafter.

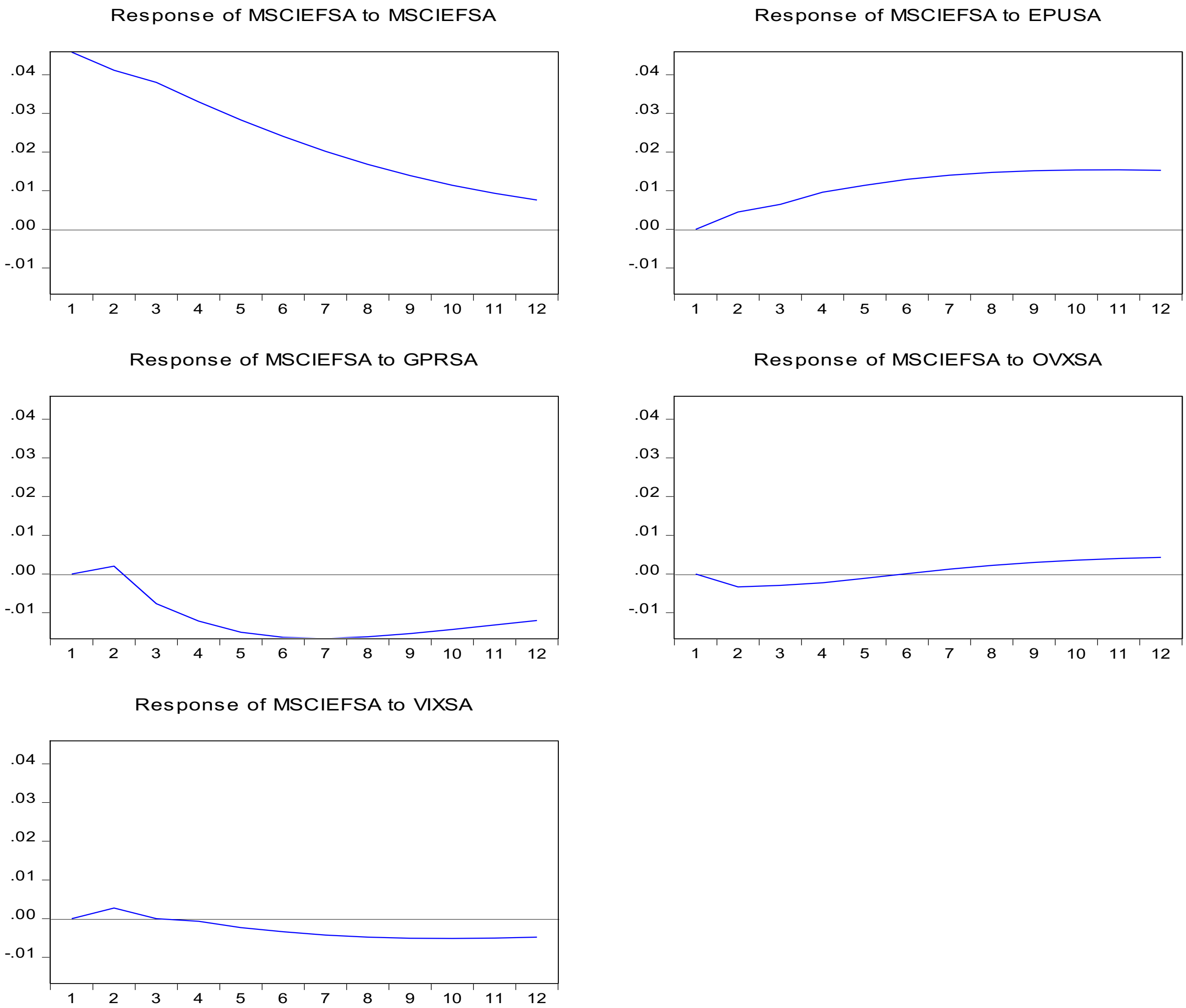

Figure 2. Structural VAR Results for the MSCIEF Index

Variance decomposition analyses were conducted within the framework of the SVAR model to determine the dynamic relationships between the series. When examining the findings presented in Table 8, it can be stated that the largest portion of the forecast error variance for MSCIEFSA is explained by the variable itself. Additionally, it is observed that the GEPU and GPR variables contribute approximately 10% and 13%, respectively, to the explanation of MSCIEFSA's forecast error variance. Moreover, it can be noted that the contributions of the OVX and VIX variables to MSCIEFSA's forecast error variance are relatively low. These results are consistent with the findings obtained from the impulse-response analysis conducted for MSCIEFSA.

Table 8. Variance Decomposition Results

Variance Decomposition of MSCIEFSA:					
Period	MSCIEFSA	GEPUSA	GPRSA	OVXSA	VIXSA
1	100.0000	0.000000	0.000000	0.000000	0.000000
2	98.88096	0.528379	0.103617	0.291924	0.195117
3	97.17731	1.148498	1.167334	0.367966	0.138894
4	94.09007	2.288833	3.130861	0.371834	0.118401
5	90.36091	3.591167	5.545028	0.332402	0.170495
6	86.44613	5.060145	7.919836	0.294298	0.279587
7	82.66914	6.595373	10.01381	0.282629	0.439047
8	79.16580	8.151653	11.75227	0.306761	0.623518
9	76.00237	9.687692	13.13053	0.365811	0.813600
10	73.18993	11.17552	14.18736	0.453607	0.993581

5. Conclusion and limitations of study

In this study, the long-term effects of global uncertainties on the capital markets of developed and developing countries are analyzed using the Structural VAR model. In this context, the long-term relationship between the GEPU, GPR, OVX, and VIX indices and developed and developing capital markets is examined through impulse response functions. There are many studies in the literature that investigate the impact of global uncertainties on capital markets. The difference of this study from other studies in the literature is the testing of the interaction between dynamic long-term series using HP filters. Additionally, by distinguishing uncertainties from different variables, the differences and/or similarities in responses between developed and developing markets are revealed. The impact of uncertainties on the capital markets of countries has been investigated in the literature. However, this study uses MSCI indices, which were created to measure the performance of global capital.

According to the results of the first SVAR model, which includes the MSCIWO variable representing developed markets, it was found that the effect of the GEPU variable on the MSCIWO index is positive in the long term. Similar results were obtained in the second model, which included the MSCIEF variable representing emerging markets. These results indicate that investors may turn to developed markets due to increased risks arising from economic policy uncertainties. Increases in the GEPU index may enhance investors' confidence in the markets of developed countries and positively reflect the performance of both developed and emerging capital markets.

The study found that the long-term impact of the GPR variable on the MSCIWO and MSCIEF indices is negative. Particularly during geopolitical crises, wars, or international tensions, investors and markets may turn to less risky assets or traditional financial instruments such as gold. This can negatively affect both developed and emerging capital markets. These results are consistent with the findings of Fossung (2021), Bossman et al. (2023), and Plakandaras et al. (2023) in the literature. It was found that the OVX variable negatively affected the MSCIWO index until the fourth period and the MSCIEF index until the sixth period, after which it had a positive impact. The results indicate that the negative impact of oil price volatility lasts longer in emerging markets. These findings are similar to those of Salisu et al. (2022), who found that uncertainty shocks caused by oil prices have a statistically significant and negative impact on the majority of global stock markets. It was determined that the effect of the VIX index on developed markets is not significant. The VIX index had a weak positive impact on the MSCIEF index, representing emerging markets, until the third period, after which it had a negative effect. These results are consistent with the findings of Chang et al. (2018), who found that the VIX index has significant short-term negative effects on European ETF returns.

Although the study has significant contributions, it is not possible to continue research without limitations. In this study, the dataset used for the analysis covers a specific time frame, and the limited number of uncertainty indices used constitutes the constraints of the study. These limitations are thought to create opportunities for future research. When evaluating the results obtained from the study, it is evident that changing global economic conditions in the face of global uncertainties can continuously alter market dynamics. Therefore, it is recommended that investors and portfolio managers develop more resilient and flexible portfolios in response to uncertainties and market fluctuations.

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ETİK VE BİLİMSEL İLKELER SORUMLULUK BEYANI

Bu çalışmanın tüm hazırlanma süreçlerinde etik kurallara ve bilimsel atıf gösterme ilkelerine riayet edildiğini yazar beyan eder. Bu çalışma etik kurul izni gerektiren çalışma grubunda yer almamaktadır.

ARAŞTIRMACILARIN MAKALEYE KATKI ORANI BEYANI

1. yazar katkı oranı: %100