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Can the Global Economic Uncertainty Index and Twitter Uncertainty Index Be Decision Variables in Portfolio Management Strategies?

Küresel Ekonomi Belirsizlik Endeksi ve Twitter-Belirsizlik Endeksi Portföy Yönetimi Stratejilerinde Karar Değişkeni Olabilir mi?

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ÖZ

Bu çalışma, Twitter Tabanlı Belirsizlik Endeksi, Küresel Ekonomi Politikası Belirsizlik Endeksi ve Türkiye BIST Banka Endeksi arasındaki ilişkileri Vektör Otoregresif Model (VAR) ve Granger nedensellik analizi yöntemini kullanılarak incelemektedir. Varyans ayrıştırma sonuçlarına göre BIST banka endeksi standart sapmasında meydana gelen değişimin %11,11 Küresel Ekonomi Belirsizlik Endeksi, %1,29'u Twitter Tabanlı Belirsizlik Endeksi tarafından açıklamaktadır. Ekonomik belirsizliklerin BIST banka endeksi üzerindeki etkileri orta şiddettedir. Twitter belirsizlik endeksinin etkisi ise düşük şiddette ve dalgalıdır. Küresel Ekonomi Belirsilik Endeksinin Türkiye bankacılık sektörü endeksi üzerindeki etkisi Twitter Tabanlı Belirsizlik Endeksine göre daha baskındır. BIST banka endeksinin kendi şoklarına karşı piyasa hafızası kısa süreli, ekonomik belirsizliklere ve sosyal medya kaynaklı belirsizliklere karşı piyasa hafızası daha uzun sürelidir. Bankacılık sektörü endeksi ile Küresel Ekonomi Politikası Belirsizlik Endeksi arasında çift yönlü, Twitter Tabanlı Belirsizlik endeksinden bankacılık sektör endeksine doğru tek yönlü nedensellik mevcuttur. Çalışma sonuçları portföy yöneticileri tarafından belirsizlik şoklarına karşı piyasa hafızasının tahmin edilmesinde, etki tepki sonuçlarına göre kısa vadeli portföy yönetim stretijilerinde portföy seçimi, portföy risk yönetimi kararlarına destek amaçlı ve şoklar karşısında dönemsel zamanlama stretejisinin planlanıp uygulanmasında kullanılabilir.

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A B S T R A C T

The paper examines the relationships between the Twitter-Based Uncertainty Index, the Global Economic Policy Uncertainty Index, and the Turkey BIST Banking Index using the Vector Autoregressive Model (VAR) and Granger causality analysis methods. According to variance decomposition results, 11.11% of the variation in the standard deviation of the BIST bank index is explained by the Global Economic Uncertainty Index, and 1.29% is explained by the Twitter-Based Uncertainty Index. The effects of economic uncertainties on the BIST bank index are moderate. The effect of the Twitter uncertainty index is low and volatile. The effect of the Global Economic Uncertainty Index on the Turkish banking sector index is more dominant than that of the Twitter-Based Uncertainty Index. The market memory of the BIST banking index is short-term against its own shocks, while its market memory is longer-term against economic uncertainties and social media-driven uncertainties. A two-way causality has been identified between the banking sector index and the Global Economic Policy Uncertainty Index, and a one-way causality has been identified from the Twitter-Based Uncertainty Index to the banking sector index. The results of the study can be used by portfolio managers to predict market memory against uncertainty shocks, to support portfolio selection and portfolio risk management decisions in short-term portfolio management strategies based on impact-response results, and to plan and implement periodic timing strategies in response to shocks.

1. Introduction

In an environment of uncertainty, investors' cognitive processes become more complex. Uncertainties weaken investors' forecasts. The literature on behavioural finance indicates that uncertainties, investor emotions, and social

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sharing have a detrimental effect on asset pricing, which, in turn, negatively impacts financial stability and functioning. This effect has been observed to be more pronounced in the markets of Developing Countries (Akkuş, 2017:28; Anwer et al., 2024; Sikhwal, 2024). In periods of heightened uncertainty, monetary authorities, including central banks (CBs) and regulatory supervisory institutions, intervene in financial markets to mitigate the shock effect of uncertainty, thereby making it central to policy decisions. In other words, uncertainties play a pivotal role in shaping countries' economic and financial policies and in determining market prices (Ilgin, 2022:458). The Türkiye BIST stock market is also among the most sensitive markets to global-scale uncertainties. Nevertheless, the extant literature provides no compelling evidence regarding which uncertainty index the Turkish stock market is most sensitive to. Consequently, the exploration of the correlation between uncertainty indices and the BIST stock market and indices emerges as a compelling subject for both investors and academics. The extant literature lacks studies examining the relationships between social media-driven and economic uncertainties and the banking sector index, a key factor in Turkey's financial system.

The banking sector in Turkey requires meticulous oversight. The banking sector is one of the intermediary institutions that plays a significant role in the emergence of financial crises or in mitigating the shocks of crises. The most severe financial crisis in Turkey's history was precipitated by the crisis that emerged in this sector in 2001 (Özatay, 2014). Furthermore, the banking sector exerts considerable influence on liquidity flows within the financial system (TBB, June 2024 report). It is imperative to undertake a thorough analysis of the factors that exert influence on the banking sector index (XBANK). This index is a crucial metric for evaluating the performance of banking sector stocks within the BIST in Türkiye. As demonstrated by Mohammed et al. (2023) and Günay et al. (2023), the presence of macroeconomic uncertainties, in combination with the dissemination of negative news via social media platforms such as Twitter and Facebook, increases investors' perceptions of uncertainty. This, in turn, has been found to lead to reduced investment decisions. The decline in investment has been shown to weaken businesses' ability to grow and sustain their assets, leading to a loss of stock market value (Anwer et al., 2024).

Social media platforms such as Twitter, Instagram, and Facebook can influence financial markets and stock exchanges, just as they do in other areas. Financial market actors closely monitor social media statements and make trading decisions based on their market impact. Consequently, the TEU index, which gauges uncertainty on Twitter, is regarded as a pivotal indicator for understanding the trajectory of financial markets. In this context, the primary problem and motivation of the study are to investigate the dynamic relationships among the TEU and GEPU indices and the BIST XBNK index.

The study's findings may enhance the existing body of knowledge by offering novel evidence on the impact of shocks in the GEPU and TEU uncertainty indices on the XBANK index, and on the extent to which changes in the XBANK index's standard deviation are attributable to the TEU and GEPU indices. This information may assist investors who wish to include BIST banking sector index stocks in their portfolios in their decision-making process regarding the extent to which they should consider the TEU and GEPU uncertainty indices. The use of this instrument in index option trading decisions in the context of VİOP markets, along with its capacity to facilitate short-term speculative gains, merits further examination. From this standpoint, the study can contribute to the management of uncertainty and to more effective market functioning in uncertain conditions by examining the relationships among the Twitter uncertainty index (TEU), the economy-based uncertainty index (GEPU), and the banking sector index (XBANK). The study is significant as it is one of the pioneering empirical studies to examine the effects of TEU and GEPU on the Turkish banking sector (XBANK).

The dynamic relationships among variables are examined using vector autoregression (VAR) and Granger causality analysis. The VAR approach is a highly suitable method for examining dynamic relationships among multiple variables, as it effectively addresses endogeneity and captures mutual dependencies over time (Sikhwal, 2024). The accuracy and robustness of the analyses were ensured by fulfilling the prerequisites of the VAR approach, the ADF stationarity test, the LM autocorrelation test, and the investigation of characteristic roots. The study is structured in five sections. The initial section serves as an introduction, while the subsequent section presents the conceptual framework, a review of the extant literature, and empirical studies testing the relationship between uncertainty indices and financial assets. The third section of the text provides a detailed exposition of the data set, and the econometric methodology employed. The fourth section of this study presents the results of the VAR analysis, the VAR analysis precondition tests, and the Granger causality analysis. The fifth section of the text is intended to facilitate discussion and to provide a conclusion.

2. Conceptual Framework and Literature

2.1. The Effects of Uncertainty on Financial Markets

The prevailing consensus in the economics and finance literature characterises uncertainty as situations that are unclear or unknown, thereby accelerating market downturns and contractions and hindering their recovery (Sikhwal, 2024; Coşkun and Kadaz, 2024). Globally, open economies are integrated, and waves of uncertainty in one market can spread rapidly through social media and affect other markets. In addition, market participants are seeking to understand the impact of uncertainty on asset pricing in capital markets. The efficient market hypothesis posits that market actors do not possess the same level of information, leading to differing investment behaviours in the face of uncertainty. In summary, information asymmetry has been shown to impact investor behaviour in conditions of uncertainty significantly. As demonstrated in the extant literature, economic units tend to defer investment and consumption decisions until macroeconomic and financial uncertainties are either eliminated or mitigated by accurate information (Sikhwal, 2024).

About the investment behaviour of economic units, for example, Valle-Cruz et al. (2022) tested the effect of Twitter data from accounts belonging to organisations such as Bloomberg, CNN News, Investing.com, and The New York Times on stock market behaviour during the pandemic. The study's findings demonstrate a statistically significant correlation between Twitter data and stock market behaviour. Vu et al. (2012) emphasises that fluctuations in stock prices and social media activity, specifically tweets about specific stocks and the companies that issue them, are highly effective at predicting the price movements of prominent stocks such as Apple, Amazon, Google, and Microsoft, which trade on the NASDAQ index.

As demonstrated in the extant literature, the uncertainty engendered by social media posts leads investors to adopt a "wait and see" approach in their investment decision-making (Bloom, 2007). This state of affairs gives rise to a deferral of consumer behaviour regarding goods other than necessities across the economy, the suspension of new investment decisions by companies with the potential to increase production, sudden exits from financial markets, and increased volatility (Parker and Preston, 2005). In circumstances characterised by high uncertainty, economic units transitioning to a "static" position may impede the dynamism of economic activity and delay stock market trading decisions. In environments characterised by elevated uncertainty, economic entities prefer the banking system's deposit pool, which is perceived as offering greater security.

In particular, the banking system is struggling to convert the deposits it collects into loans due to the narrowing of credit channels under “high uncertainty.” This situation has a high potential to affect banks' profitability ratios, dividend payout ratios, and stock prices. Therefore, it is important to thoroughly analyse and clarify the relationship between the financial system and liquidity flows, particularly between the banking system and the stock market, and to examine the uncertainty indices of both to ensure their continued stability.

The pricing of stocks and shares in the market is determined by the consideration of prospective economic, political and financial uncertainties and risk factors. However, recent literature does not fully explain the dynamic relationships among the stock market, indices, and the Twitter Uncertainty Index (TEU), a social media tool that frequently affects all areas. Consequently, investors lack sufficient information about the relationships between TEU and GEPU uncertainty indices and stock prices or indices. The relationship between GEPU and TEU uncertainty indices and stock price formation can be explained to facilitate investors' price-movement predictions.

Twitter is a microblogging platform that serves as a barometer for the expectations and perceptions of the future among large audiences. It also serves as a conduit through which governments, central banks, and corporate entities can disseminate their views to the public. This reciprocal exchange of information enables policymakers to accomplish their objectives by assuaging public anxieties through communications channels. Consequently, data on policymakers' social media use, specifically their Twitter posts, are regarded by the general public and investors as a pertinent factor in decision-making (Agarwal et al., 2011, p. 30). The extant literature provides substantial evidence in support of this hypothesis. For instance, Zhang et al. (2011) emphasised in their study that Twitter posts can be utilised to predict stock index price movements. The study tested the predictive power of Twitter posts for price movements in the S&P 500 and NASDAQ stock indices. In a study by Mao et al. (2012), the relationship between stock prices and news and tweets was investigated. The investigation used stocks listed on the S&P 500 index, as well as social media posts and tweets related to these companies. A substantial body of evidence was presented indicating that the number of tweets can predict stock prices with a 68% success rate.

The pricing of stocks and shares in the market is determined by the consideration of prospective economic, political and financial uncertainties and risk factors. However, recent literature has been unable to provide a comprehensive explanation for the dynamic relationship between the Twitter Uncertainty Index (TEU), a social media tool that frequently impacts all areas, and stock markets and indices. Investors are also unaware of the relationship and effects of the TEU and GEPU uncertainty indices on stock pricing. Elucidating the impact of the GEPU and TEU uncertainty indices on stock price formation could facilitate the prediction of price movements.

Recent years have seen a proliferation of studies on uncertainty, which have significantly advanced our understanding of the relationship between uncertainty and financial instruments and markets (Maquieira et al., 2023; Yıldırım et al., 2023). A body of research has yielded encouraging results, indicating a dynamic interplay between the Twitter uncertainty index and the stock market. These findings suggest that the Twitter uncertainty index may serve as a significant predictor of stock market indices (Nisar and Yeung, 2018). A study testing the predictive power of China's EPU and TEU indices for volatility in the Chinese securities market finds that both indices successfully predict stock market volatility (Lu & Lang, 2023). Tafti et al. (2016) conducted a study to examine the effect of Twitter posts on NASDAQ index stock prices. The study's findings demonstrated a direct correlation between increased Twitter posts and increased stock volume.

The extant literature suggests that stock markets are sensitive to global uncertainties. As Korkmaz and Güngör

(2018) demonstrate, there is a statistically significant relationship between the Borsa Istanbul (BIST) sub-indices and the GEPU index. A study conducted in Malaysia supports the hypothesis that the GEPU Index has a statistically significant effect on the stock returns of 10 sector indices on the Malaysian stock exchange. However, the effect on technology stocks alone is statistically insignificant (Hoque and Zaidi, 2019). Other studies have demonstrated that the GEPU index exerts a statistically significant adverse effect on the stock returns of companies operating in the copper sector (Maquieira et al., 2023) and is a determining variable in stock market index volatility (Dong and Yoon, 2019). However, other studies have revealed that the GEPU index does not demonstrate a statistically significant relationship with the BIST100 index (Gürsoy, 2021). In this context, investors must comprehend the impact of uncertainties in VİOP transactions on sector indices, particularly when implementing a diversified portfolio strategy. The present study is significant in that it unveils this information. The subsequent section of the study will review the extant literature on this topic.

2.2. Literature Review

This section of the study examines the relationship between stock market indices and the stock market, using the EPU and GEPU uncertainty indices, which measure economic uncertainty, and the Twitter-based uncertainty index (TEU), which measures social media uncertainty.

A review of the extant literature reveals that numerous indices have been developed to measure global uncertainty. The following indices have been identified as playing an important role in shaping investor decisions: the Economic Policy Uncertainty Index (EPU), the Global Economic Policy Uncertainty Index (GEPU), the World Uncertainty Index (WUI), the Trade Policy Uncertainty Index (TPU), the Climate Policy Uncertainty Index (CPU), and the US Monetary Policy Uncertainty Index (MPU). The advent of a discerning understanding of the repercussions of uncertainty indices on financial markets has engendered a marked increase in interest in this subject in the financial literature. Consequently, a plethora of studies have emerged to elucidate the effects of uncertainty. For instance, studies by Korkmaz and Güngör (2018), Hoque and Zaidi (2019), Dong and Yoon (2019), and Gürsoy (2021) examined the relationship between the Global Economic Policy (GEPU) index and stock price movements. A significant proportion of the extant literature focuses on the relationship between Twitter posts and the Twitter-based uncertainty index (TEU), as well as on the correlation between crypto asset prices and volatility. (Günay, 2019; Park, Lee, 2019; Kraaijeveld & Smedt, 2020; Gazel, 2021; Wu et al., 2021; Aharon et al., 2022). Several studies have been conducted that examine the impact of economic policy uncertainty (EPU), geopolitical risk (GPR), and market sensitivity (VIX) indices on stock returns (Pala, 2024). The extant literature focuses on the relationships between the GEPU and TEU indices and the volatility of various financial assets. However, no studies examine the relationships with the banking sector index.

The TEU index is a significant indicator of uncertainty arising from social media and a means to comprehend the outlook in financial markets. The index was developed by Baker, Bloom, Davis, and Renault (2021) and has been in existence since June 2011. It is a tool that scans the Twitter platform for keywords related to uncertainty and economics, such as "uncertainty, ambiguity, economy, economists, etc." The TEU-USA index has been shown to reach approximately 500 million messages per day on Twitter shared by Twitter users in the US. The index facilitates access to the opinions and expectations of Twitter users, who constitute the vast majority of social media users, rather than journalists and experts. The index is calculated using geographic area restrictions and limits the proportion of US Twitter users to 50%. The TEU-WGT index is derived by assigning a weight to each tweet in the TEU-USA index based on the number of retweets.

The initial testing of the economic uncertainty measurement was conducted in studies by Baker et al. (2011) and Baker et al. (2013) across countries, including Germany, Spain, Italy, France, and the United Kingdom. This research specifically focused on developing a methodology for the five largest European economies. In the study by Baker et al. (2016), the methodology was applied to several countries, including China, South Korea, India, Japan, Canada and Russia. In reference to the aforementioned studies, Davis (2016) developed the Global Economic Policy Uncertainty (GEPU) Index. This index was based on the GDP-weighted average of the national economic policy (EPU) indices of 21 countries. When evaluated, this index accounts for 71% of global production adjusted for purchasing power parity and approximately 80% of market exchange rates (Davis, 2016). In this context, investors must understand the impact of economic uncertainties on the Turkish banking sector index and the relationship between them to facilitate effective portfolio creation and management. The present study aims to contribute to the extant literature by empirically demonstrating the aforementioned relationship.

Table 1 presents a literature review of studies examining the relationship between uncertainty indices such as EPU and GEPU, which measure economic uncertainty, and the Twitter-based uncertainty index (TEU) and stock markets.

As illustrated in Table 1, extant literature focuses on the relationship between economic uncertainties, such as EPU and GEPU, and the returns, volatility, and prices of indices and stocks. There are no studies examining the relationship between social media-based uncertainty indices and the banking sector index. The present study aims to address this lacuna in the extant literature by conducting an analysis of the dynamic relationship between the banking sector index, a pivotal component of Turkey's financial system, and the TEU and GEPU uncertainty indices.

Table 1: Literature Review

Authors	Variables and the purpose of the study	Findings-Results
Brogaard and Detzel (2014)	The relationship between the EPU index and the stock market indices of 21 countries has been tested.	There is a statistically significant and negative relationship between the EPU index and country stock market indices.
Arouri et al. (2014)	It has tested the effect of the EPU Index on stock market returns in Gulf Cooperation Council countries.	Increases in the EPU index have a statistically significant and negative effect on the stock market returns of selected countries.
Liu and Zhang (2015)	They tested the effect of the EPU index on the volatility of the S&P 500 index.	Increases in the EPU index are increasing volatility in the S&P 500 index.
Li et al. (2016)	It tested the relationship between the EPU index and stock returns for China and India.	There is a two-way causality between EPU and stock returns in India.
Tafti et al. (2016)	The effect of Twitter posts on the price movements of NASDAQ-listed stocks has been investigated.	The sharp increase in Twitter posts is driving up stock trading volume.
Chen et al. (2017)	The impact of the China EPU index on stock prices on the Chinese stock market has been tested.	During periods when the China EPU index rises, stock prices decline more sharply.
Christou et al. (2017)	The impact of the EPU index on the stock market returns of selected countries has been tested.	The EPU index has a statistically significant and negative effect on stock market returns in the United States, Austria, China, Japan, Canada, and Korea.
Korkmaz and Güngör (2018)	The relationship between Borsa Istanbul (BIST) sub-indices and the GEPU index has been tested.	There is a statistically significant relationship between BIST and GEPU.
Guo et al. (2018)	They tested the impact of the EPU index on the stock markets of G7 and BRIC countries.	In all countries except the UK and France, increases in the EPU index have a statistically significant and negative effect on stock market returns.
Nisar and Yeung (2018)	They tested the predictive power of Twitter data on the performance of the FTSE 100 index.	The results show that Twitter data has strong predictive power for future FTSE 100 performance.
Hoque and Zaidi (2019)	The impact of the GEPU Index on 10 sector indices comprising the Malaysian stock exchange has been investigated.	The GEPU index has a statistically significant effect on stock returns across all sector indices. However, it has no significant effect on technology stocks.
Dong and Yoon (2019)	The impact of the GEPU index on MSCI Asia country stock indices has been tested.	The GEPU index plays a decisive role in the volatility of stock market indices in Asian countries. The results indicate that global indicators have a statistically significant effect on Asian stock markets.
Chiang (2020)	The effect of the EPU index on stock returns in Japan and the United States has been tested.	The uncertainty index is statistically significant and negatively affects the stock returns of both countries.
Xu et al. (2021)	The relationship between the China EPU index and Chinese stock returns has been examined.	The Chinese EPU index has a statistically significant and negative impact on stock returns with a one-month lag.
Gürsoy (2021)	The causal relationships among GEPU, Euro/TL, Dollar/TL, inflation, and the BIST100 index have been investigated.	No statistically significant relationship was found between the GEPU index and inflation data or the BIST100 index. There is a statistically significant causality between the GEPU index and both exchange rates.
Valle-Cruz et al. (2022)	The impact of Twitter data on stock market behaviour was tested during the COVID-19 pandemic.	The correlation between Twitter data and stock market behaviour is statistically significant and high.
Maquieira et al. (2023)	The impact of EPU and GEPU uncertainty indices on the returns of companies operating in the copper sector has been tested.	The uncertainty indices used have a statistically significant and negative effect on selected stocks.
Lu and Lang (2023)	The ability of the China EPU index and TEU index to predict volatility in the Chinese securities market has been tested.	The EPU index and TEU indices have been shown to predict stock market volatility successfully.

3. Data Sources and Research Model

3.1. Data

The time dimension of the variables covers monthly data from June 2011 to April 2023. It is important to note that data for the (GEPU) index and (TEU) index have not been published prior to June 2011. In view of the non-publication of data on uncertainty indices after April 2023, the upper time limit of the study has been set at April 2023. The set of variables comprises 143 observations. The data source and definitions are presented in Table 2 below.

Table 2: Data Sources and Variable Descriptions

Variables	Definition	Data source
Twitter-based uncertainty index	(TEU)	www.policyuncertainty.com
Global economic policy uncertainty index	(GEPU)	www.policyuncertainty.com

BIST Banking Sector (XBANK) Index	www.investing.com

3.2. Research Model

The relationships among the variables in Table 2 were examined using the VAR model and the Granger causality analysis. The VAR model elucidates the interactions and relationships among variables, rather than deriving policy inferences (Sims, 1980). In multivariate models, the past values and random shocks of one variable affect the time series data of other variables. The existing literature on such relationships between multivariate time series employs Vector Autoregressive Models (VARs), which are widely deployed (see Sevüktekin and Çınar, 2014:495). The model's system of equations facilitates the elucidation of dynamic relationships among variables by incorporating both the variables themselves and the lagged values of other variables, thereby enhancing the model's flexibility and enabling forward-looking predictions. Consequently, it is favoured in time series analyses (Tari and Bozkurt, 2006; Kumar, Leona and Gasking, 1995).

In the VAR model, the relationships between variables are explained using the results of the Impulse-Response analysis and the variance decomposition. The Impulse-Response Analysis is a method used to demonstrate how a unit shock to one variable affects its own time series and other series, including timing, direction, and whether the shocks are persistent. Variance decomposition analysis is used to determine whether a change in the variance of one variable is attributable to that variable or to other variables.

This analysis enables conclusions about the model's structure and the relationships between variables (Stock and Watson, 2001, p. 106). Although variables are defined as endogenous in the VAR model equations, exogenous variables can also be included. In contrast to traditional models, there is no requirement to distinguish between endogenous and exogenous variables. (Sevüktekin and Çınar, 2014:495). The formulation of the two-variable vector autoregressive (VAR) model, as introduced into the relevant literature by Sims (1980), is as follows.

$$y_{1t} = \delta_{1t} + \sum_{i=1}^{\rho} \beta_{1i}\, y_{1t-1} + \sum_{i=1}^{\rho} \beta_{1i} y_{2t-i} + \varepsilon_{1t} \quad (1)$$

$$y_{2t} = \delta_{2t} + \sum_{i=1}^{\rho} \beta_{2i}\, y_{1t-1} + \sum_{i=1}^{\rho} \beta_{2i} y_{2t-i} + \varepsilon_{2t} \quad (2)$$

The VAR equation index explanations are provided below.

y_{1t} and y_{2t}: stationary variables

p: length of lags

ε: random error terms

t: time

i: lag for the unit of increase in the equation

In the context of the VAR model analysis, ensuring the consistency and robustness of the analysis requires preliminary investigation of the series' stationarity. Subsequently, the non-stationary series is made stationary by differencing. Subsequently, it is imperative to ascertain the most appropriate lag length for the series and to test the model's stability. The reliability and consistency of the analyses are ensured by the data passing relevant tests, as well as by variance decomposition and the interpretation of shock effects.

The Granger causality test, utilized to investigate the causal relationship between variables, assesses whether alterations in variable x exert an influence on variable y, operating under the following fundamental hypothesis:

H_0: Variable x is not a Granger cause of variable y.

H_1: Variable x is a Granger cause of variable y.

The formulation of Granger equations is expressed as follows:

$$\Delta x_t = \alpha_x + \sum_{i=1}^{k} \beta_{x,i}\, \Delta X_{t-i+} + \sum_{i=1}^{k} \gamma_{x,i}\, \Delta Y_{t-i+} + \varepsilon_{x,t} \quad (3)$$

$$\Delta Y_t = \alpha_y + \sum_{i=1}^{k} \beta_{y,i}\, \Delta Y_{t-i+} + \sum_{i=1}^{k} \gamma_{y,i}\, \Delta X_{t-i+} + \varepsilon_{y,t} \quad (4)$$

4. Data Analysis

To ensure the consistency of VAR model prediction results, series precondition tests must be performed. In the pretest phase, the stationarity of the series, the appropriate lag length, the investigation of the VAR model's characteristic roots, and the presence of autocorrelation among the series were tested.

4.1. VAR Model Prerequisite Tests

In time series analysis, non-stationarity in a series can lead to inconsistent results. The stationarity of the series was tested using the ADF unit root test, and the results are presented in Table 3.

Table 3: ADF Unit Root Test Results

		GEPU	TEU	XBANK
With Constant	t-Statistic (Prob.)	-2.3869 *(0.14)*	-2.5830 *(0.098)**	0.2632 *(0.97)*
With Constant & Trend	t-Statistic (Prob.)	-3.6773 *(0.02)***	-3.6713 *(0.02)***	-0.5011 *(0.98)*
		d(GEPU)	d(TEU)	d(XBANK)
With Constant	t-Statistic (Prob.)	-16.0573 *(0.00)****	-12.6502 *(0.00)****	-11.8997 *(0.00)****
With Constant & Trend	t-Statistic (Prob.)	-15.9988 *(0.00)****	-12.6248 *(0.00)****	-12.1053 *(0.00)****

* (10%), ** (5%), *** (1%) indicate significance at the specified significance level. The values in parentheses are p-values.

The results of the ADF unit root test, presented in Table 3, indicate that the TEU and GEPU variables are stationary at the level. The XBNK index satisfies the stationarity condition after first differencing. In the subsequent sections of the study, the level values of the GEPU and TEU variables, along with the first differences of the BIST XBANK index, are used.

Determining the optimal lag period is pivotal to ensuring accurate analysis and reflection of both lagged and instantaneous effects in the model. A set informs the determination of the optimal lag period of the information criteria. The AIC information criterion is used in the literature to select the model that provides the best fit among multivariate alternatives. It measures the model's goodness of fit by considering the number of terms (Sevüktekin and Çınar, 2014, p. 199). Additionally, it is widely used in cross-validation across diverse samples (Akyüz, 2018). The results of the tests conducted for this purpose are presented in the following table. 4.

Table 4: Delay Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2344.91	NA	3.32	35.04	35.10	35.06
1	-2208.94	263.82	5.00	33.14	33.40*	33.25
2	-2191.32	33.39*	4.40*	33.01*	33.47	33.20*

The AIC and HQ information criterion values in Table 4 indicate that the optimal lag length for the VAR model is 2. The values of the characteristic roots of the VAR model are shown in Table 5.

Table 5: VAR model characteristic root values

Root	Modulus
0.938646	0.938646
0.630215	0.630215
-0.549462	0.549462
0.005213 - 0.362531i	0.362569
0.005213 + 0.362531i	0.362569
0.235902	0.235902

The stability of the VAR model is tested by determining whether its characteristic roots lie within the unit circle or have magnitudes less than 1. If this condition is met, it can be concluded that the series is stationary, returns to its long-term mean, and exhibits no persistent shocks (Sikhwal, 2024). The results indicate that all variables constituting the VAR model system are stationary. The model is stable, and the results are reliable and interpretable.

To ensure consistency in VAR analysis results, there must be no autocorrelation among the model's error terms. Potential causes of this problem include incorrect model selection, failure to include explanatory variables, or measurement errors. The investigation into the autocorrelation problem in the series was conducted using the LM test, with the results presented in Table 6.

The LM test statistic is used to test for autocorrelation in the model's residuals. The results indicate the absence of an autocorrelation problem in the series up to eight lags, and the model demonstrates robustness from an econometric perspective. After completing the precondition tests, variance decomposition and impulse response analyses can now be performed on data

Table 6: LM Statistics Results

Lag	LM test statistic	LM (df)	LM Prob.	F-statistic of the LM test	F statistic (df)	F statistic Prob.
1	7.108	9	0.625	0.789	(9, 311.7)	0.6259
2	17.332	18	0.500	0.964	(18, 354.0)	0.5006
3	30.143	27	0.307	1.123	(27, 356.9)	0.3084
4	38.754	36	0.346	1.082	(36, 352.3)	0.3478
5	53.077	45	0.190	1.194	(45, 345.4)	0.1927
6	55.461	54	0.419	1.030	(54, 337.5)	0.4231
7	72.501	63	0.193	1.166	(63, 329.2)	0.1976
8	87.192	72	0.107	1.237	(72, 320.6)	0.1117

4.2. Variance Decomposition and Cause-Effect Analysis

In VAR analysis, interactions between variables are examined in two ways: through the variance decomposition table and the graph of the impulse response functions (Aktaş, 2010, p. 127). Variance decomposition analysis is used to determine whether a change in the variance of one variable is due to the variable itself or to the effects of other variables. The results of the variance decomposition analysis conducted to determine the extent to which changes in the XBANK index are explained by the GEPU and TEU uncertainty indices are presented in Table 7.

Table 7: XBANK Index Variance Decomposition Table (DXBANK GEPU TEU Ranked)

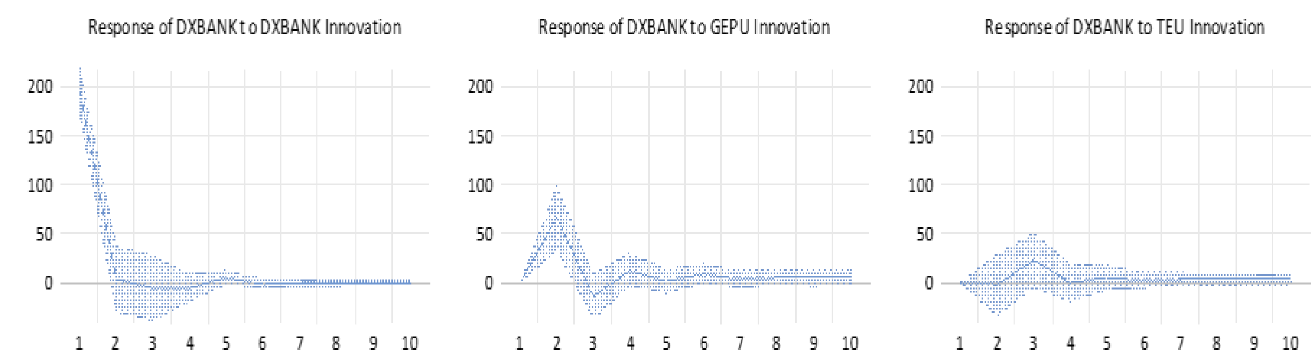
Period	S.E.	DXBANK	GEPU	TEU
1	194.5393	100.0000 (0.00000)	0.00 (0.00000)	0.00 (0.00000)
2	205.3400	89.77 (4.76693)	10.20 (4.64455)	0.01 (0.73945)
3	207.2431	88.24 (5.15004)	10.58 (4.70260)	1.17 (1.49085)
4	207.7055	87.95 (5.35188)	10.87 (4.90409)	1.17 (1.49286)
5	207.8183	87.90 (5.38510)	10.85 (4.91891)	1.23 (1.64145)
6	207.9926	87.76 (5.44650)	10.99 (4.97793)	1.23 (1.65845)
7	208.0426	87.72 (5.46087)	11.00 (4.98295)	1.26 (1.71407)
8	208.1171	87.66 (5.48303)	11.06 (5.00501)	1.27 (1.73080)
9	208.1612	87.62 (5.49509)	11.08 (5.01268)	1.28 (1.75601)
10	208.2103	87.58 (5.51161)	11.11 (5.02762)	1.29 (1.76789)

* Standard errors: Monte Carlo (100 repetitions), standard deviations are in parentheses

As demonstrated in Table 7, the results of the variance decomposition analysis of the BIST XBANK index indicate that, in the initial period, the entirety of the variation in the standard deviation of the BIST XBANK index is attributed to its own inherent dynamics. In the second period, 10.20% of the change in the standard deviation of the BIST XBANK index is attributable to the Global Policy Uncertainty Index (GEPU), with 0.01% being ascribed to the Twitter Uncertainty Index (TEU). The findings indicate that the impact of the GEPU index on the BIST XBANK index is more significant than that of the TEU index. In the tenth period, 11.11% of the change in the standard deviation of the BIST XBANK index is attributable to the GEPU, while 1.29% is attributable to the TEU index. Following the second period, the influence of the GEPU and TEU indices on the BIST XBANK index remains negligible. It is acknowledged that economic events are prone to unforeseen shocks, with consequences that may be both short-term and long-term. In the context of impact-response analysis, it has been observed that the effects of specific variables may dissipate over time.

In contrast, the consequences of specific shocks tend to persist for extended periods. In this context, the results of the impact-response analysis of the shocks' temporal dynamics can serve as a policy tool. The following graphs illustrate the response of the BIST XBANK index to its own shock, as well as to the shocks of the other two variables, when a unit random shock is applied to any of the BIST XBANK index, TEU, and GEPU uncertainty index time series. The results of the analysis of the shocks' temporal patterns can be used as a policy tool. When a random shock is applied to any of the BIST XBANK index, TEU, and GEPU uncertainty index time series, the graphs showing the response of the XBANK index to its own shock and to the shocks of the other two variables are presented below.

Graph 1: XBANK Index's Response to Its Own Shocks and to the TEU and GEPU Indices



(a) (b) ©

The graphs above illustrate the response of the XBANK index to shocks originating from the GEPU and TEU uncertainty indices, as well as from the XBANK index itself, and the direction of its movement. Given that the data are collected monthly, each number in the periods below indicates the duration of the effect. The dashed lines delineating the shaded area represent the ±2 standard error confidence interval. The XBANK index demonstrates a robust, rapid positive response to a one-unit shock originating within the index, which gradually diminishes over approximately two periods. In summary, investors' initial positive evaluation of shocks in the XBANK index is evident (see Graph A). In the second and third periods, the effect is found to diminish and even turn negative. This finding lends support to technical analysis methodologies that propose that past price movements and market values are harbingers of future price and index movements. However, this approach contrasts with fundamental analysis methods that do not accept that past price and index movements are precursors to future price and index indicators. From the fourth period onwards, the effect weakens and disappears from the fifth period onwards. The findings indicate that the XBANK index responds rapidly and pronouncedly to internal shocks. This finding suggests that market investors have a limited memory span for shocks originating from the XBANK index.

The XBANK index has shown an initial positive response to shocks stemming from economic uncertainty (GEPU). However, this initial positive response subsequently turns negative by the conclusion of the second period. In the sixth and seventh periods, the impact of economic uncertainty diminishes and disappears. The findings indicate that economic uncertainty shocks elicit a short-term positive effect, followed by a negative impact, and that this effect dissipates in the medium term, suggesting that market memory is more protracted in response to these shocks (Graph b).

The XBANK index demonstrated a minimal and negative response to the uncertainties emanating from Twitter during the initial period. The effect is positive in the second and third periods, and negative in the fourth. The findings suggest that the impact of TEU uncertainty on the XBANK index is generally weak, transient, and volatile. Investors do not respond markedly and suddenly to uncertainty shocks originating from Twitter (Graph c). The duration of the XBANK index's responses to shocks originating from the GEPU and TEU uncertainty indices and from itself, along with a summary of market memory, is presented in Table 8.

Table 8: XBANK Index Impact Response Summary Table

The cause of the shock	Initial Response (1st Term)	Highest Positive Impact	Lowest Negative Impact	Market Memory	Result
XBANK	Very high-positive	1st term	3rd Term	4–5 periods	It reacts very strongly and briefly to its own shock, quickly regaining its balance.
GEPU	Low-positive	2nd Term	3rd Term	5–6 periods	Although the initial reaction of the XBANK index to economic uncertainties is slightly positive, it subsequently reacts with a moderately negative response.
TEU	Low-negative	3rd Term	5th term	4–5 periods	The XBANK index reacts to Twitter sentiment with low volatility, initially negative and then positive in a fluctuating manner.

*Market memory; the time it takes for the effect of a shock in variables to end on the market

When the results are evaluated on an aggregate basis, the impact of all shocks weakens after an average of 4-6 periods and approaches zero before the tenth period at the latest. In summary, the findings indicate that the GEPU and TEU uncertainty indices do not exert a long-term impact on the XBANK index. The XBANK index demonstrates a high degree of responsiveness to its own shocks, exhibiting a rapid and substantial reaction. The impact of GEPU uncertainty shocks on the XBANK index is more pronounced than on the TEU index. Furthermore, the impact-response analyses indicate a causal relationship between the variables. The results of the Granger Causality Test are presented in Table 9.

Table 9: Granger Causality Test

Variables			F-Statistic	Prob.
GEPU	→	XBANK	9.757	0.00***
XBANK	→	GEPU	2.918	0.05**
TEU	→	XBANK	3.587	0.03**
XBANK		TEU	1.212	0.30

* (10%), ** (5%), *** (1%) indicate significance at the level of significance.

Table 9. The Granger causality analysis indicates a bidirectional relationship between the GEPU uncertainty index and the XBANK index. In summary, fluctuations in the GEPU or XBANK index at any given moment directly affect the formation of the other variable's data in the subsequent period. A one-way causality has been detected from the TEU index to the XBANK index. This result indicates that any change occurring in the TEU uncertainty index at any given time affects the formation of the XBANK index in the subsequent period.

5. Discussion and Conclusion

The study's findings demonstrate, through statistical analysis, that the BIST XBANK index is sensitive to changes in the TEU and GEPU indices. The explanatory power and effect of the GEPU index on changes in the XBANK index are higher than those of the TEU uncertainty index. The findings lend support to the study by Nisar and Yeung (2018), which demonstrated the high predictive capacity of Twitter data for the future performance of the FTSE 100. This contributes to the extant literature on the use of the TEU and GEPU uncertainty indices for forecasting the XBANK index. The findings also demonstrate the utility of both variables as decision-making tools in portfolio construction within the stock market.

The findings indicate that 11.11% of the observed change in the BIST XBNK index is attributable to GEPU, while 1.29% is attributable to the TEU index. These results suggest that economic uncertainties exert a greater influence on investor sentiment compared to those stemming from social media. In making future portfolio decisions, investors are advised to monitor economic events more closely in line with these findings and to pay less attention to the impact of social media-driven uncertainties. Regarding the duration of the impact, the GEPU index exerts a more protracted influence on the XBANK index than the TEU uncertainty index. Conversely, the impact of Twitter-related shocks is characterised by their transient nature, weakness, and volatility. The impact of shocks originating from the GEPU index, which persist for an average of 6 periods, underscores the need to prioritise monitoring the uncertainty created by global economic and political developments in the context of portfolio risk management. In this context, portfolio managers should refrain from taking significant positions to reduce portfolio risk during periods of heightened GEPU uncertainty.

The findings of variance decomposition and causality analysis demonstrate that fluctuations in the GEPU and TEU uncertainty indices during any given period are conducive to the formation of the XBANK index time series. This result corroborates the findings of Korkmaz and Güngör (2018), which demonstrate a statistically significant relationship between BIST sub-indices and GEPU. However, this finding contradicts the conclusions of Gürsoy (2021), who asserted that there is no statistically significant relationship between the GEPU index and inflation, or between the BIST100 index and inflation, in Turkish markets. This phenomenon can be attributed to the BIST 100 Index's composition, which comprises a large number of stocks. The presence of more stock components in an index indicates a reduced influence of these individual stocks on the index as a whole.

The impact-response results indicate that the effect of shocks arising from GEPU and TEU volatility on the XBANK index persists for an average of 5-6 periods. This finding is consistent with Tafti et al. (2016), who found that a sharp increase in Twitter posts is associated with a rise in stock trading volume. The XBNK index's sudden, short-term response to shocks originating within itself is consistent with views supporting the technical analysis method. İnvestors can use this information to predict an increase in the XBANK index in the future, based on a positive trend in its past values, from a technical analysis perspective. This prediction can then be used to generate returns by purchasing index options.

The findings of the impact-response analysis demonstrate that the XBANK index exhibited a swift and substantial response to the shocks it generated itself, a moderate response to shocks stemming from GEPU uncertainty, and a comparatively diminished response to shocks emanating from TEU uncertainty. When portfolio managers are exposed to a shock originating from the XBANK index, they can achieve significant gains by following a short-term investment strategy of buying sector stocks. It is possible to achieve high returns in the medium term by selling, whilst accounting for the negative impact in the second period. Finally, it is recommended to follow an average return strategy. In this context, the results presented in the impact-response tables and graphs offer portfolio managers the opportunity to plan and implement an effective periodic timing strategy to mitigate sudden shocks in XBANK stocks and the index amid TEU and GEPU uncertainties.

The study's findings contribute substantially to the extant literature by predicting market memory in the face of uncertainty and revealing that it varies by type of uncertainty, thereby differing from other studies. Market memory has been shown to facilitate portfolio managers' decision-making by guiding the selection of relevant criteria and the determination of the optimal duration for information filtration. The market memory is found to be more limited in the context of XBANK index shocks (four to five periods), GEPU uncertainties (five to six periods), and TEU uncertainties (five to six periods). In light of the aforementioned findings, portfolio managers must refrain from incorporating the repercussions of TEU uncertainty after five periods or GEPU uncertainty after six periods into their portfolio selection decision processes.

The present study is distinguished from others in this field by virtue of the fact that it provides strategic decision support and contributes to the existing literature by emphasizing the priority of uncertainty indices in risk management, market timing strategies, the importance of market memory in filtering information, and the limited impact of social media-based uncertainties for those managing portfolios with a focus on the XBANK sector. The findings of this study have the potential to facilitate long-term risk management for portfolio managers and assist them in evaluating short-term trading opportunities.

The study's limitations are twofold. First, the VAR analysis is confined to a select set of variables, and second, data on post-2023 uncertainties remain unavailable. Consequently, the present study examined the relationship between a limited number of variables. As the extant literature shows, there are numerous uncertainty indices. Furthermore, these data also cover the period after 2023. For instance, the World Uncertainty Index, the Sustainability Uncertainty Index, and the Monetary Policy Uncertainty Index. It is recommended that future researchers utilize the Panel VAR model, which is based on data covering a range of uncertainty indices and other country stock market indices. This will facilitate analysis of similarities and differences among countries in their responses to uncertainty. This, in turn, will allow the development of international portfolio diversification strategies.

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