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ECONOMIC POLICY UNCERTAINTY, FINANCIAL FACTORS, AND BIST 100 VOLATILITY IN TÜRKİYE: EVIDENCE FROM A TVP-VAR MODEL

Ekonomik Politik Belirsizlik, Finansal Faktörler ve Türkiye'de BIST 100 Oynaklığı: TVP-VAR Modelinden Kanıtlar

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Keywords:
BIST 100 Volatility, Economic Policy Uncertainty, TVP-VAR, Interest Spread, Exchange Rate Return

JEL Codes:
C32, E44, G12, E52, F31.

Abstract

This study examines how macroeconomic and financial factors affect Turkish stock market volatility over time. The dependent variable is a GARCH(1,1) based conditional volatility series that captures the volatility clustering common in financial markets. The independent variables are the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016), the sovereign yield spread between Türkiye and the United States on 10-year government bonds, and the USD/TRY exchange rate return. The analysis uses monthly data from February 2010 to December 2024. A TVP-VAR model is estimated, and the resulting impulse response functions, computed separately for each period, are presented as three-dimensional surface plots. The findings indicate that EPU shocks have a strongly positive effect on BIST 100 volatility during the 2014-2015 global monetary policy normalization process, but turn negative during the 2018 currency crisis. Interest rate spread shocks discipline volatility through credible monetary policy in the 2010-2013 period, yet this stabilizing effect nearly vanishes during the unconventional monetary policy episode of 2021-2022. Exchange rate return shocks reach their strongest negative effect in the 2016-2018 period before exhibiting a partial recovery following the return to orthodox monetary policy.

Anahtar Kelimeler:
BIST 100 Oynaklığı, Ekonomik Politik Belirsizlik, TVP-VAR, Faiz Koridoru, Kur Getirisi

JEL Kodları:
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Öz

Bu çalışma, makroekonomik ve finansal faktörlerin zaman içinde Türkiye borsa volatilitesini nasıl etkilediğini incelemektedir. Bağımlı değişken, finansal piyasalarda yaygın olarak görülen volatilite kümelenmesini yansıtan, GARCH(1,1) modeline dayalı koşullu volatilite serisidir. Bağımsız değişkenler ise Baker, Bloom ve Davis (2016) tarafından geliştirilen Ekonomik Politika Belirsizliği (EPU) endeksi, Türkiye ile ABD arasında 10 yıllık devlet tahvillerine ilişkin getiri farkı ve USD/TRY döviz kuru getirisidir. Analizde Şubat 2010 ile Aralık 2024 arasındaki aylık veriler kullanılmıştır. TVP-VAR modeli tahmin edilmiş ve her dönem için ayrı ayrı hesaplanan sonuçtaki etki tepki fonksiyonları, üç boyutlu yüzey grafikleri olarak sunulmuştur. Bulgular, EPU şoklarının 2014 - 2015 küresel para politikası normalleşme süreci boyunca BIST 100 volatilitesi üzerinde güçlü bir pozitif etkiye sahip olduğunu, ancak 2018 döviz krizi sırasında bu etkinin negatife döndüğünü göstermektedir. Faiz oranı farkı şokları, 2010 - 2013 döneminde inandırıcı para politikası yoluyla volatiliteyi dizginlemiştir. Ancak bu istikrar sağlayıcı etki, 2021 - 2022 dönemindeki geleneksel olmayan para politikası sürecinde neredeyse ortadan kalkmıştır. Döviz kuru getiri şokları, 2016 - 2018 döneminde en derin olumsuz etkisine ulaşmış, ardından geleneksel para politikasına geri dönülmesiyle kısmi bir toparlanma göstermiştir.

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1. Introduction

While economic indicators are crucial for understanding current financial trends, political uncertainties in fragile economies also significantly influence these developments. Notably, much research explores the connection between low returns and high volatility (Beaulieu et al., 2005; Fitzsimons and Sun, 2012; Salisu et al., 2023; Parihar and Gupta, 2024).

The 2008 Global Financial Crisis began with issues in the U.S. housing market and deepened in the subprime mortgage market, eventually taking on a systemic dimension with the bankruptcy of Lehman Brothers on September 15, 2008, and evolving into a global crisis (Swedberg, 2010). The global crisis, by affecting the U.S.'s economic partners, triggered a financial spillover effect and brought about Economic Policy Uncertainty (EPU). This situation also led to increased volatility in stock markets (Rastogi, 2014). In his study, Schwert (2011) noted that the most prominent indicator of the crisis was the extreme volatility in stock returns.

In 2013, political developments in Türkiye, together with the U.S. Federal Reserve's announcements about reducing asset purchases, heightened both domestic and external uncertainty, putting significant pressure on exchange rates and stock prices in financial markets (Eichengreen and Gupta, 2015). During the 2018 currency crisis, the Central Bank of Türkiye's decision to keep interest rates low under political pressure, along with management changes, eroded confidence in monetary policy and paved the way for rising long-term market interest rates (Gürkaynak et al., 2023). In 2020, the COVID-19 pandemic tightened financial conditions by pressuring exchange rates, credit spreads, and stock prices in emerging markets (Ahmed et al., 2020). In 2021, despite rising inflation, the reduction in the policy rate led to a sharp depreciation of the Turkish lira, an acceleration in inflation, and higher long-term borrowing costs (Gürkaynak et al., 2023). Taken together, these periods show that uncertainty-driven shocks have had divergent effects in financial markets and laid the groundwork for regime shifts.

According to Haddow et al. (2013), "While the most likely outcome of a distribution is defined by the mean or first moment, the width of the distribution or, in other words, the second moment represents the uncertainty regarding that outcome. This is because this width reflects the range of outcomes or the variability in those outcomes." In this context, uncertainty is not merely about knowing what the outcome will be but also about the degree of fluctuation it contains. Based on this definition of uncertainty, macroeconomic uncertainty can be defined as heightened uncertainty surrounding forecasts of future values of key macroeconomic variables such as growth, inflation, interest rates, and exchange rates.

An environment of uncertainty increases volatility in financial markets and complicates economic decision-making. However, because uncertainty is not directly observable, various measurement methods have been developed in the literature (Bloom, 2014). Among these methods, the JLN index developed by Jurado et al. (2015), the VIX index calculated by the Chicago Board Options Exchange, and the EPU index created by Baker et al. (2016) stand out.

This study examines the relationship between EPU and the BIST through the lens of Minsky's Financial Instability Hypothesis. Financial stability is a state in which asset prices do not fluctuate excessively and the capacity of financial intermediaries to meet their obligations remains intact (Crockett, 1996). Minsky (1992) argues that prolonged periods of economic stability gradually make financial structures more fragile. During these periods, speculative and Ponzi-style borrowing patterns gradually replace the hedge financing structures that initially prevailed, this transformation fuels systemic risk. When monetary authorities tighten policy to curb inflation, they push speculative entities toward Ponzi schemes, forcing firms with insufficient cash flow to sell assets. The resulting selling pressure drives down asset prices, leading to widespread losses across the market. In this context, EPU disrupts investor behavior, deepening volatility in the BIST and potentially triggering the destabilization dynamics predicted by Minsky.

The impact of interest rate and exchange rate channels on the BIST can be analyzed using the Arbitrage Pricing Theory (APT). The Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), explains an asset’s expected return solely in terms of market risk. Ross (1976) expanded this approach, demonstrating that asset returns are determined by multiple systematic factors, including interest rates, inflation, and exchange rates. From this perspective, macroeconomic uncertainty is a decisive systematic risk factor in asset pricing, and the effects of fluctuations in spreads and exchange rates on the BIST are also examined within this framework.

2. Literature Review

2.1. Economic Policy Uncertainty

The theoretical architecture of EPU traces to Knight's (1921) foundational distinction between immeasurable uncertainty and quantifiable risk. Building on this foundation, Bernanke (1986) operationalized the insight by demonstrating that irreversibility renders investment highly sensitive to policy opacity: firms rationally delay capital commitments when future policy conditions cannot be reliably anticipated. Arouri et al. (2016) subsequently established a long-run relationship between EPU and US stock markets, cautioning that conventional causality tests fail to adequately capture its dynamics.

The empirical literature expanded rapidly during the 2000s and 2010s. Bloom (2009) provided the first rigorous VAR-based empirical confirmation that uncertainty shocks generate sharp but transient contractions in output and employment by inducing a generalized wait-and-see response among firms. Jurado et al. (2015), employing a latent-factor approach, showed that genuine uncertainty spikes are substantially more persistent and contractionary than conventional proxies suggest, since realized volatility conflates uncertainty with predictable variation. Baker et al. (2016) then enabled systematic cross-country quantification by constructing a newspaper-based EPU index across 12 economies and documenting the negative effects of uncertainty on investment and employment through panel-VAR analysis. Pástor and Veronesi (2013) complemented this strand by theoretically establishing that political uncertainty raises the risk premium demanded by investors, thereby linking uncertainty directly to asset pricing.

Subsequent methodological advances shifted attention toward time-varying and regime-dependent frameworks. Chuliá et al. (2017) demonstrated that uncertainty's impact on financial markets intensifies during crisis regimes, directly motivating the use of time-varying estimation frameworks. Gabauer and Gupta (2018) decomposed time-varying monetary policy uncertainty spillovers between Japan and the United States via TVP-VAR, finding that monetary uncertainty dominates internal and external transmission. Mumtaz and Surico (2018) then demonstrated within a TVP-VAR framework that the macroeconomic impact of policy uncertainty varies considerably over time. The multi-country connectedness analysis of Nyakurukwa and Seetharam

(2023), employing a conditional TVP-VAR approach, further reveals that spillovers across fiscal, monetary, and aggregate uncertainty categories are themselves time-varying and structurally heterogeneous.

The importance of country-specific measurement is underscored by Kilic and Balli (2024), who constructed an economic uncertainty index for Türkiye derived from Turkish-language newspaper sources and showed that it substantially outperforms English-language alternatives in explaining industrial production, inflation, and the exchange rate; an unexpected rise in uncertainty translates into declines in both output and stock prices. This finding reinforces the methodological position of the present study.

2.2. Exchange Rates and Stock Markets under Uncertainty

International evidence on the EPU-exchange rate nexus consistently documents uncertainty-induced volatility amplification, though the precise channels and magnitudes vary across methodological and institutional contexts. Krol (2014) found that both home-country and US EPU directly increase exchange rate volatility across ten industrial and emerging economies, with this effect reinforced during downturns and among more financially integrated economies. Balcilar et al. (2016) extended this finding to tail dynamics by demonstrating, through nonparametric causality-in-quantiles testing, that EPU generates significant causal effects not only at the conditional mean but also across the distributional tails of exchange rate returns. Beckmann and Czudaj (2017) documented asymmetric effects of EPU on exchange rate expectations, while Mueller et al. (2017) provided a high-frequency dimension by showing that monetary policy uncertainty significantly amplifies currency excess returns around FOMC announcement days, particularly for currencies with pronounced interest-rate differentials relative to the United States, a result directly relevant to Türkiye's high-rate environment.

The EPU-stock market relationship has been documented with equal consistency. Christou et al. (2017) showed, using a Bayesian panel VAR, that EPU shocks significantly depress stock returns across Pacific Rim economies. Abid (2020) confirmed a long-run EPU-exchange rate relationship in emerging markets using ARDL bounds testing. Antonakakis et al. (2020) documented heterogeneous dynamic correlations among stock returns, implied volatility, and policy uncertainty across US business cycle phases, finding that rising uncertainty dampens returns and elevates market risk. Liu (2020), using an LT-TVP-VAR model, found that macroeconomic and financial uncertainty jointly destabilize foreign exchange markets by increasing exchange market pressure and jump risk.

More recent contributions have refined both the measurement of uncertainty and the modeling of its market effects. Pei (2022) demonstrated that the Chinese EPU is the primary driver of the stock price-exchange rate correlation and that this correlation strengthens markedly during high-uncertainty episodes, prefiguring the joint modeling approach adopted in the present study. Wang et al. (2022) documented time- and state-dependent effects of EPU on exchange rate pass-through in China. Salisu et al. (2023) identified a signal quality mechanism through which EPU's predictive power for stock market volatility is substantially enhanced when uncertainty signals are precise and persistent. A growing strand additionally incorporates geopolitical risk as a complementary uncertainty dimension: Chen et al. (2024), combining TVP-VAR with wavelet coherence analysis, characterized the time-frequency dependence between EPU, VIX, and geopolitical risk and their dynamic effects on commodity and financial markets; Hu and Borjigin (2024) showed that energy-equity volatility spillovers are systematically amplified by EPU, geopolitical risk, and climate risk in a manner that varies across economic cycle phases. Kumar and Rao (2026) reached analogous conclusions for India using combined ARDL and TVP-VAR frameworks.

2.3. Macroeconomic Determinants of BIST-100

The Turkish-language literature has examined the macroeconomic determinants of the BIST-100 using a variety of conventional methods, yielding results that are broadly consistent in direction but heterogeneous in magnitude. The earliest contributions within this sample period established the baseline relationships. Aktaş and Akdağ (2013) found that the deposit rate, CPI, the dollar exchange rate, capacity utilization, and consumer confidence jointly affect BIST-100 returns over 2008-2012. Altınbaş et al. (2015) identified the exchange rate as the single statistically significant determinant in a multi-factor cointegration framework, with unidirectional causality running from industrial production and oil prices to the exchange rate. Poyraz and Tepeli (2015) established treasury bill rates and the currency basket as the dominant influences over a longer horizon. Boyacıoğlu and Çürük (2016) refined the exchange rate dimension by showing that changes in the real effective exchange rate index positively and significantly affect manufacturing firms' stock returns, pointing to a competitiveness channel absent from aggregate analyses.

Subsequent work extended both the empirical coverage and the methodological toolkit. Sancar et al. (2017) corroborated directional findings using structural-break-aware unit root and Maki cointegration tests, documenting positive effects of monetary aggregates, inflation, and industrial production, alongside a negative exchange rate effect. Yalçınkaya (2019) applied SVAR analysis to data spanning 1992-2018 and found that global economic, political, and geopolitical uncertainty shocks generate adverse effects on Turkish interest rates, inflation, the exchange rate, and stock prices, confirming the empirical relevance of uncertainty modeling for the Turkish context. Karaca et al. (2021), using ARDL bounds testing and VECM causality analysis, found that interest rate increases and higher industrial production have positive short- and long-run effects on the BIST Financial Index, whereas exchange rate appreciation exerts a negative effect.

Two structural studies are particularly pertinent to the present work. Rodriguez et al. (2024) demonstrated the empirical payoff of relaxing parameter-stability constraints: TVP-VAR-SV models for Peru over 1992-2017 reveal that impulse responses to external shocks differ markedly across episodes of high inflation, economic crisis, and monetary policy change, with uncertainty regimes playing a decisive role in modulating transmission. Ünlü (2024), using structural VAR for January 2014 to June 2023, demonstrated that exchange rate and interest rate policy constitute the dominant drivers of Turkish stock returns, while global EPU and oil price shocks exert comparatively limited effects.

Taken together, the existing literature has examined EPU-stock market and EPU-exchange rate linkages largely in isolation, and domestic studies of BIST-100 determinants have generally employed parameter-stable specifications unable to accommodate the structural discontinuities that characterize the Turkish economy, including the 2018 currency crisis, the unorthodox monetary policy experiment of 2021-2022, and the subsequent return to conventional tightening from mid-2023 onward. A comprehensive, simultaneous, and time-varying analysis of EPU, the interest rate spread, and exchange rate returns as joint determinants of BIST-100 volatility within a TVP-VAR framework remains absent from the literature. The present study addresses that gap.

3. Data and Methodology

The dataset used in this study covers the period from February 2010 to December 2024. The difference between bond yields, referred to as the "spread" in the literature, is an important indicator reflecting the country's risk premium and sensitivity to global financial conditions. In this study, the spread variable was constructed by taking the difference between the 10-year bond yield of the Republic of Türkiye and the 10-year bond yield of the United States. This indicator reflects how investors price Türkiye-specific macroeconomic risks and provides the opportunity to analyze sensitivity to external shocks. Bond rates for Türkiye were obtained from the Central Bank of the Republic of Türkiye's electronic data distribution system (EVDS), while those for the U.S. were sourced from the Investing.com website. The EPU variable, representing political uncertainty, was calculated by Baker, Bloom, and Davis and obtained from the website accessible at https://www.policyuncertainty.com.

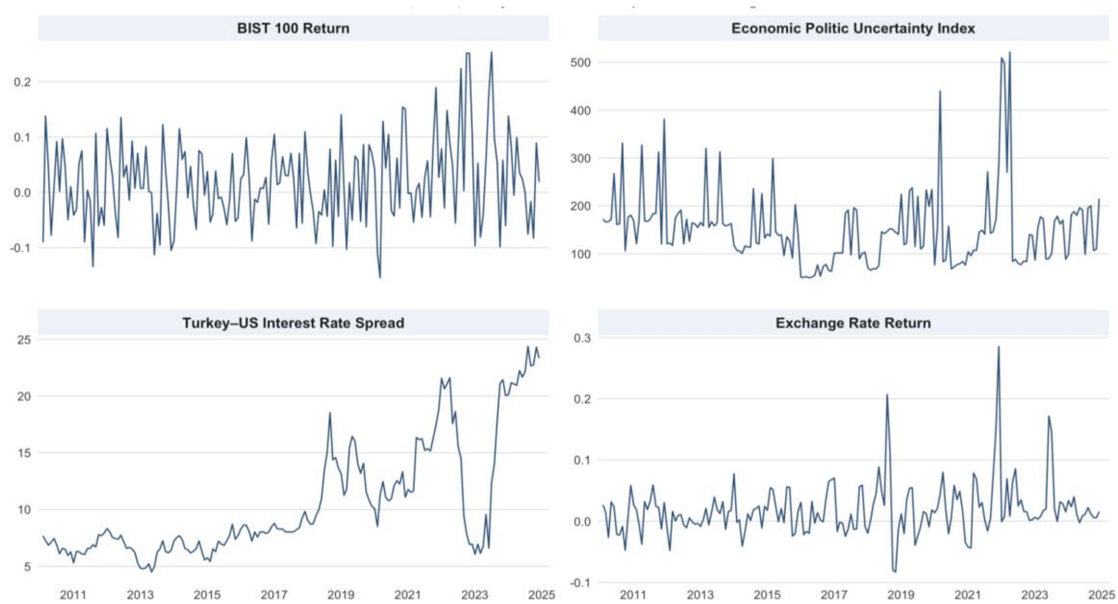
Methodologically, the study first presents descriptive statistics and graphs related to the variables. In the second stage, the Welch test was applied to determine the presence of seasonal effects that could cause co-movement, followed by stationarity tests. To perform a TVP-VAR analysis - an autoregressive-based analysis method - it is first necessary to determine the appropriate AR structure. Accordingly, the lag length was determined, and the process moved on to identifying time-varying effects.

3.1. Descriptive Statistics

The time-series behavior of all four variables over the sample period is illustrated in Graph 1, which reveals co-movement patterns and simultaneous spikes, particularly during the 2018 currency crisis, the 2020 pandemic shock, and the 2021–2022 unconventional monetary policy episode.

An examination of the descriptive statistics for the return series used to calculate volatility reveals a total of 179 observations. The mean of the series was 0.0191, and the standard deviation was 0.0762. During the period under review, the lowest value of -0.1543 was observed on March 1, 2020, and the highest value of 0.2531 was observed on July 1, 2023. When considering a band of three standard deviations centered around the mean, the lower bound was -0.2095, and the upper bound was 0.2477. It is observed that 176 observations (98.32%) fell within this band, while 3 observations fell outside the band. Observations falling outside the band indicate the presence of unusual fluctuations or exceptional shocks during the relevant period.

Descriptive statistics for the EPU series show 179 observations. The series' mean is 152.5233, and its standard deviation is 80.186. During the analyzed period, the lowest value of 49.9036 was recorded on April 1, 2016, and the highest value of 521.2946 was recorded on April 1, 2022. A band of three standard deviations centered on the mean has a lower bound of -88.0348 and an upper bound of 393.0814. Of the 179 observations, 175 (97.77%) fall within this band, while 4 lie outside. Observations outside the band indicate unusual fluctuations or exceptional shocks during the relevant period.



Graph 1. Time Series of BIST 100 Return, EPU, Interest Rate Spread, and Exchange Rate Return

Upon examining the descriptive statistics for the interest rate spread series, a total of 179 observations were identified. The series' mean was 10.5655, and its standard deviation was 5.1136. During the analyzed period, the lowest value of 4.492 was observed on May 1, 2013, and the highest value of 24.374 was observed on August 1, 2024. Considering the three-standard-deviation band centered around the mean, the lower bound was calculated as -4.7754 and the upper bound as 25.9063. It was observed that 179 observations (100%) fell within this band, while 0 observations fell outside it. This result indicates that outliers in the series are quite limited and that the observations largely remained within the expected range of variability.

Analysis of the descriptive statistics for the exchange rate returns reveals 179 data points. The mean of the series is 0.0187, with a standard deviation of 0.0432. The lowest recorded value was -0.0829 on November 1, 2018, and the highest was 0.2856 on December 1, 2021. Using a three-standard-deviation band centered on the mean, the lower limit is -0.1109, and the upper limit is 0.1483. Most observations, 175 or 97.77%, lie within this range, with only 4 falling outside, which suggests the occurrence of unusual fluctuations or shocks during this period.

3.2 Seasonality Tests

In time series analysis, seasonal effects are patterns that manifest as systematic increases or decreases in the series during specific periods and can create spurious correlations among observations. The presence of such patterns may indicate that relationships between variables stem not from actual economic dynamics but solely from shared seasonal movements. This situation carries the risk of spurious relationships. Therefore, testing whether the series contains seasonal components before proceeding with the analysis is one of the prerequisites for obtaining reliable results.

Table 1. Results of the Welch Seasonality Test for the Variables

Variable	Test Statistics	p value
BIST 100 Return	1.3398	0.2235
Economic Politic Uncertainty Index	1.0879	0.3848
Türkiye-US Interest Rate Spread	0.6759	0.7560
Exchange Rate Return	1.7820	0.0754

According to the results of the Welch seasonality test presented in Table 1, none of the variables exhibit a statistically significant seasonal pattern at the 5% level. For the BIST 100 return, the test statistic is 1.3398, and the p-value is 0.2235; for the EPU index, the test statistic is 1.0879, and the p-value is 0.3848; and for the Türkiye-U.S. interest rate spread, the test statistic is 0.6759, and the p-value is 0.7560. These findings indicate that the seasonal means of the series do not differ significantly from one another. Therefore, the analysis could proceed without performing any seasonal adjustment.

3.3 Stationarity and Unit Root Tests

Granger and Newbold (1974) demonstrated empirically that regression analysis involving two non-stationary independent time series can yield high R^2 values and significant t-statistics. They defined this relationship as spurious regression when no true relationship existed between the series. Because the mean, variance, and covariance of a non-stationary series change over time, the fundamental assumptions of classical regression analysis are violated, resulting in inconsistent estimated coefficients and biased standard errors. Under these conditions, inferences based on test statistics lose their econometric validity, and the findings derived from the model reflect not a genuine relationship but the misleading similarity of series that share a common stochastic trend. The fundamental approach to eliminating the spurious regression problem begins with testing the stationarity properties of the series included in the analysis.

For a series to be considered stationary, its mean must be constant, its variance must be finite, and the covariance between two periods must depend solely on the time lag between them. When working with series containing a unit root, the presence of a cointegration relationship between the series should be investigated; if cointegration cannot be detected, a first-difference transformation should be applied to achieve stationarity, and the analysis should proceed accordingly.

According to the results presented in Table 2, four unit root tests were applied to the variables in this study. These are, in order, the Augmented Dickey- Fuller (ADF, 1981), Kwiatkowski- Phillips- Schmidt- Shin (KPSS, 1992), Phillips- Perron (PP, 1988), and Zivot-Andrews (ZA, 1992) tests. While the null hypothesis in the ADF, PP, and ZA tests assumes a unit root, the null hypothesis in the KPSS test is formulated in favor of stationarity. Therefore, the KPSS findings are interpreted in the opposite direction to those of the other tests. For the BIST 100 Return, all four tests indicated level stationarity. The ADF test statistic in the constant model was -8.574, well below the critical value (-2.880). The KPSS tau model yielded a low statistic of

0.106, indicating that the null hypothesis was confidently supported. Although the ADF trend model was selected for the Political Uncertainty series, the series was still found to be level-stationary; the KPSS selection of the "Mu" model indicates that the series does not contain a deterministic trend. The fact that the PP and ZA results also align in the same direction confirms that this finding remains consistent across different test frameworks.

Table 2. Unit Root Test Results

Test	Statistic	Bist100 Return	Political Uncertainty	Spread	Exchange Rate Return
ADF	t-statistic	-8.574	-6.023	-0.943	-9.702
	%5 CV	-2.880	-3.430	-2.880	-3.430
	Model	Drift	Trend	Drift	Trend
	Result	I(0)*	I(0)*	I(1)	I(0)*
KPSS	t-statistic	0.106	0.212	0.162	0.031
	%5 CV	0.146	0.463	0.146	0.146
	Model	Tau	Mu	Tau	Tau
	Result	I(0)	I(0)	I(1)*	I(0)
PP	t-statistic	-156.239	-129.324	-19.059	-99.501
	p-value	0.0100	0.0100	0.0800	0.0100
	Result	I(0)*	I(0)*	I(1)	I(0)*
ZA	t-statistic	-13.174	-9.856	-4.962	-9.720
	%5 CV	-5.080	-5.080	-5.080	-5.080
	Result	I(0)*	I(0)*	I(1)	I(0)*

The interest rate spread was found to be I(1) based on all four unit root tests. Accordingly, its first difference was taken prior to inclusion in the TVP-VAR system. This transformation was applied to ensure stationarity. The degree of integration of the Interest Rate Spread was found to be I(1) in all four tests. In the ADF constant model, the value of -0.943 failed to exceed the critical value of (-2.880); in the PP model, the p-value of 0.08 failed to exceed the significance threshold; in the ZA model, even when accounting for structural breaks, the statistic of -4.962 did not reach the required critical value of -5.080; and in the KPSS tau model, the test statistic of 0.162 barely exceeded the critical value of 0.146. This consistent pattern indicates that the breaks in the series are insufficient to explain its unit- root behavior and that first differencing is required. The ADF trend model was selected for the Exchange Rate Return, and the statistic of -9.702 was significantly smaller than the critical value (-3.430). In the KPSS tau model, an extremely low statistic of 0.031 was obtained, and the PP and ZA tests also confirmed stationarity.

3.4. Derivation of Volatility

The primary objective of this study is not to model the direct relationship between variables, but rather to explain the volatility behavior over time in the return series derived from the BIST 100 index. Accordingly, the volatility series used as the dependent variable is not derived directly from the raw return data. In the financial econometrics literature, the assumption of constant variance is the most fundamental basis for ordinary least squares estimation. Since this assumption is violated in the present context, modeling conditional variance becomes necessary.

The Autoregressive Conditional Heteroskedasticity (ARCH) model, developed by Engle (1982), posits that the variance of the error terms is not constant but depends on past shocks. The ARCH(q) model with q lags is presented in Equation 1.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \quad (1)$$

Bollerslev (1986) extended this framework to propose the Generalized ARCH (GARCH) model, in which the conditional variance depends not only on past squared errors but also on past conditional variance. The p- and q-lagged GARCH (p, q) model is given in Equation 2.

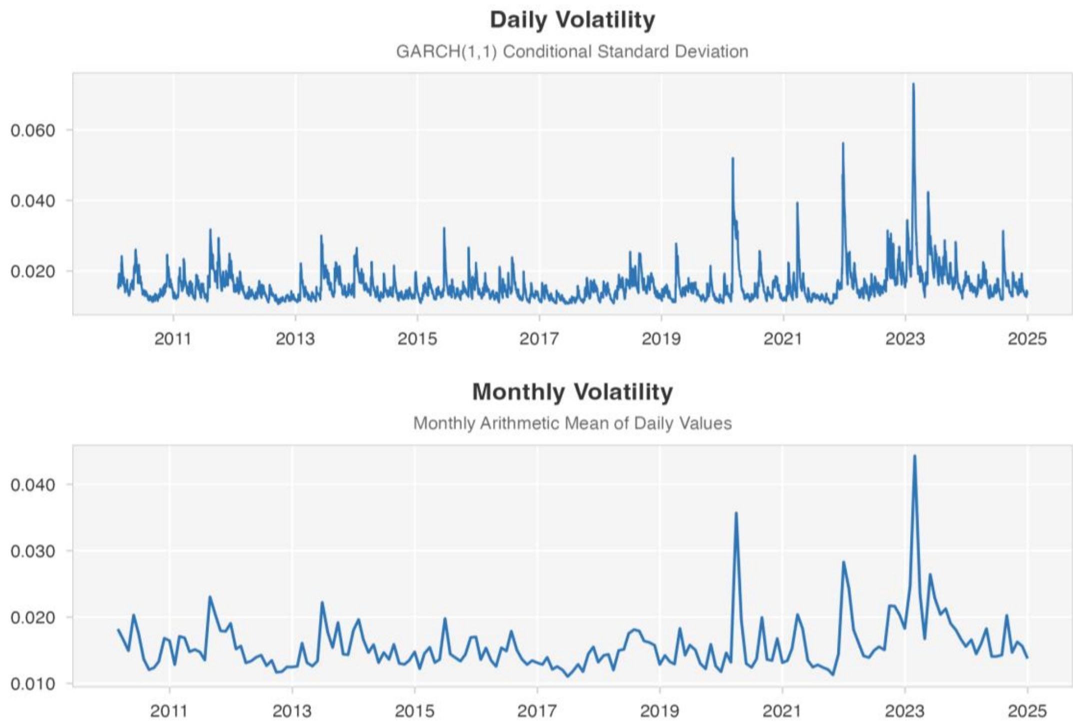
$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (2)$$

In this equation, the α coefficient captures the immediate effect of past shocks on conditional variance, while the β coefficient captures the persistence of volatility. A sum of α and β approaching one indicates strong volatility clustering and that shocks maintain their effects over a long period.

In this study, the GARCH (1,1) model was applied to the monthly return series derived from the daily closing prices of the BIST 100, and the conditional standard deviations for each month were computed to form a volatility series. As shown in Figure 1, this series rises sharply during critical periods, including the 2018 currency crisis, the 2020 pandemic, and the 2021-2022 monetary policy shifts. During calm periods, however, it remains low and relatively stable. This volatility series was specified as the dependent variable in the TVP-VAR model, while the EPU Index, the Türkiye-U.S. interest rate differential, and the exchange rate return were included in the system as independent variables to explain it. This framework allows for the capture of both average-level relationships among variables and the time-varying dynamic effects of the financial uncertainty environment on volatility behavior.

The study is based on a logarithmic return series calculated from the daily closing prices of the BIST 100 index. To test the applicability of the GARCH model, the ARCH-LM test was first applied; in this test, where the null hypothesis asserts the absence of an ARCH effect, $\chi 2 = 583.15$ and $p < 0.0000$ were obtained. This finding statistically confirms the presence of a strong ARCH effect in the return series and highlights the necessity of conditional variance modeling. Accordingly, the GARCH (1,1) model was applied to the series, yielding estimated conditional standard deviations as a daily volatility series. However, because the other variables in the study were monthly, the daily volatility series was converted to monthly for time-matching. This conversion was performed by taking the arithmetic mean of the daily conditional standard deviations for each month, thereby obtaining a monthly volatility measure.

An examination of the GARCH(1,1) conditional standard deviation series in Graph 2 shows that the BIST 100 volatility followed a relatively low and stable trend during 2010-2018, then settled at a structurally high level in the subsequent period. In the daily series, volatility rises sharply at the beginning of 2020 due to the global financial shock caused by COVID-19, and again from late 2021 through 2022-2023 due to Türkiye-specific monetary policy changes and exchange rate pressures. In the monthly series, these sudden price reactions are smoothed out, yet the seasonal pattern of volatility clusters remains intact. This finding demonstrates that the GARCH model adequately captures volatility dynamics and that the monthly transformation ensures frequency consistency while preserving the series' fundamental behavioral characteristics.



Graph 2. BIST100 Daily and Monthly Volatility Series

3.5. Time-Varying Parameter Vector Autoregressive (TVP-VAR) Model

Vector autoregressive (VAR) models were introduced into the economic literature by Sims (1980) and have enabled the examination of dynamic relationships among variables without imposing structural constraints. In the simple two-variable case, a structural VAR system can be written as shown in Equation 3, where the y_t series is influenced by current and past z_t values, and the z_t series is influenced by current and past y_t values (Enders, 2015).

$$\begin{aligned} y_t &= b_{10} - b_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \varepsilon_{yt} \\ z_t &= b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \varepsilon_{zt} \end{aligned} \tag{3}$$

In this system, both variables are assumed to be stationary, and the error terms εyt and εzt are independent white-noise processes (Enders, 2015). The equations can be expressed in matrix form as shown in Equation 4.

$$By_t = \Gamma_0 + \Gamma_l y_{t-1} + \varepsilon_t \tag{4}$$

Here, B denotes the structural parameter matrix that captures instantaneous relationships, Γ_0 the constant vector, and Γ_1 the lag coefficient matrix. The reduced form is obtained by pre-multiplying by B^{-1}, and in each equation, only the previous period's values appear as independent variables. This relationship is given in Equation 5.

$$y_t = A_0 + A_1 y_{t-1} + e_t, e_t \sim N(0, \Sigma) \quad (5)$$

The general p-lagged, n-variable VAR(p) model is given in Equation 6.

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t, u_t \sim N(0, \Sigma) \quad (6)$$

Here, y_t denotes an (n × 1) vector of variables, A_i denotes (n × n) coefficient matrices, u_t denotes the error vector, and Σ denotes an (n × n) covariance matrix. This fixed-parameter structure assumes that the coefficients are constant across the sample; it can lead to serious model specification problems during periods of structural breaks, such as financial crises and changes in monetary policy regimes.

To address this limitation, in the time-varying parameter VAR (TVP-VAR) framework of Cogley and Sargent (2001, 2005) and Primiceri (2005), the coefficient matrices are treated as state variables that follow a random walk, as illustrated in Equation 7.

$$\begin{aligned} y_t &= A_{lt} y_{t-1} + \cdots + A_{pt} y_{t-p} + u_t, u_t \sim N(0, \Sigma_t) \\ \text{vec}(A_t) &= \text{vec}(A_{t-1}) + v_t, v_t \sim N(0, Q) \end{aligned} \quad (7)$$

Here, both the coefficient matrices At and the error covariance matrix Σ_t vary over time. Q is the covariance matrix that governs the rate of coefficient evolution. Parameter updates are performed within the Kalman filter framework using the forgetting factor (λ) approach proposed by Koop and Korobilis (2010). When λ = 1, the model reduces to a standard VAR with fixed parameters, whereas λ < 1 increases the model's ability to adapt to structural changes. In this study, λ = 0.99 was used.

Using the estimated Pt and Σt matrices for each time step t, the Cholesky decomposition $\Sigma_t = P_t P_t'$ is applied, and the h-step-ahead impulse-response function is obtained as follows.

$$\text{IRF}(h, t) = \Phi_{\text{h}}^{(\text{t})} P_t \quad (8)$$

In this equation, $\Phi_{\text{h}}^{(\text{t})}$ is the h-step impulse response matrix of the VAR system at period t, computed from the covariance matrix. These functions, computed separately for each period, show how the impact of a shock on a specific variable evolves over the horizon and over time, and clearly visualize regime shifts that are not observable in models with fixed parameters.

Before estimating the VAR model, the lag length must be determined. Information criteria for the lag length of the VAR models are presented in Table 3. An examination of Table 3 shows that, according to both the Schwarz (SC) criterion and the Final Prediction Error (FPE) criterion, the appropriate lag length that yields the lowest information criterion value is 1. Furthermore, the parsimony principle, widely used in model selection, supports this choice, as it offers a simpler, more interpretable structure with fewer parameters. Accordingly, the analyses determine the optimal lag length to be 1.

Table 3. Lag Length Selection Criteria for the VAR Model

Lag	AIC	HQ (Hannan-Quinn)	SC (Schwarz)	FPE
1	-8.3759	-8.2585	-8.0866*	0.0002*
2	-8.4672	-8.2324	-7.8885	0.0002
3	-8.6963*	-8.3442*	-7.8282	0.0002
4	-8.6918	-8.2223	-7.5344	0.0002

The economic interpretation of coefficient estimates from VAR models is challenging because these parameters cannot be linked to 'deep' structural parameters such as technology, preferences, and optimization behavior. Cooley and LeRoy (1985) also emphasized that, whilst reduced-form VAR models summarize dynamic characteristics, they lack structural economic meaning. To overcome these difficulties, the structural vector autoregression (SVAR) approach, developed by Sims (1981), Bernanke (1986), and Shapiro and Watson (1988), shifts the focus from coefficients to error terms. Within the SVAR framework, the impact of shocks on the system is examined via impulse response functions (IRFs); thus, the dynamic relationships between variables are interpreted through shock transmission mechanisms rather than coefficients (Breitung, Brüggemann and Lütkepohl, 2004). However, because the impulse response functions obtained from SVAR and structural VECM (SVECM) models are highly nonlinear functions of the model parameters, the statistical inference process is significantly complicated. It is known that, particularly with small samples, standard asymptotic inference methods can yield misleading results for IRF estimates (ibid.).

For this reason, in this study as well, after estimating the Time-Varying Parameter VAR Model, and due to the difficulty of interpreting the estimated coefficients from an economic perspective, graphs based on the median values of the impulse response functions calculated from the estimated VAR model have been included. The primary reason these graphs are three-dimensional is that the individual graphs, calculated for each period, are combined to form a three-dimensional surface.

Accordingly, because interpreting the coefficients from the estimated TVP-VAR model is difficult from an economic perspective, graphs based on the median values of the model's impulse response functions have been presented. The primary reason these graphs are three-dimensional is that the impulse-response functions are calculated separately for each period, and the period-specific graphs are combined to form a three-dimensional surface. This allows the dynamic relationships between variables to be observed through a single visual representation, encompassing both cross-sectional and temporal dimensions (Antonakakis et al., 2020).

Table 4. Average Connectivity Table (TVP-VAR, H = 10)

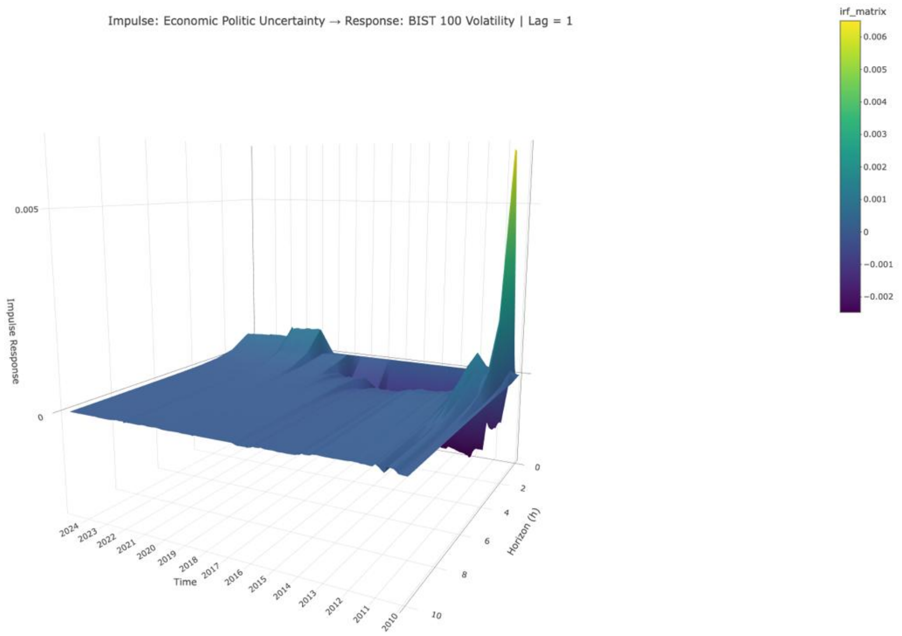
	BIST 100 Volatility	EPU	Spread	Exchange Rate Return	FROM
BIST 100 Volatility	55.34	11.87	23.61	9.18	44.66
EPU	11.43	78.22	6.14	4.21	21.78
Spread	27.83	2.31	57.94	11.92	42.06
Exchange Rate Return	5.12	2.89	7.63	84.36	15.64
TO	44.38	17.07	37.38	25.31	-
NET	-0.28	-4.71	-4.68	9.67	-

As reported in Table 4, the Total Connectedness Index (TCI) is at 31.04%, meaning about one-third of the forecast error variance among the four system variables results from cross-variable shock transmission. The remaining 68.96% is due to each variable's individual dynamics.

The FROM value of BIST 100 volatility (44.66) is very close to its TO value (44.38), resulting in a NET of −0.28 and indicating the variable is nearly balanced within the system. However, the high FROM value indicates that external shocks primarily drive volatility in the BIST 100. Breaking down the external sources, the interest rate spread is the largest factor at

27.83, followed by EPU at 11.43, with the exchange rate return contributing the least at 5.12.EPU registers a NET value of −4.71, positioning it as a net receiver. Explaining 78.22% of its own forecast error variance internally, EPU exhibits a relatively autonomous trajectory within the system. Nonetheless, with a contribution of 11.43 to BIST 100 volatility, it remains the second largest source of external shocks transmitted to the equity market.

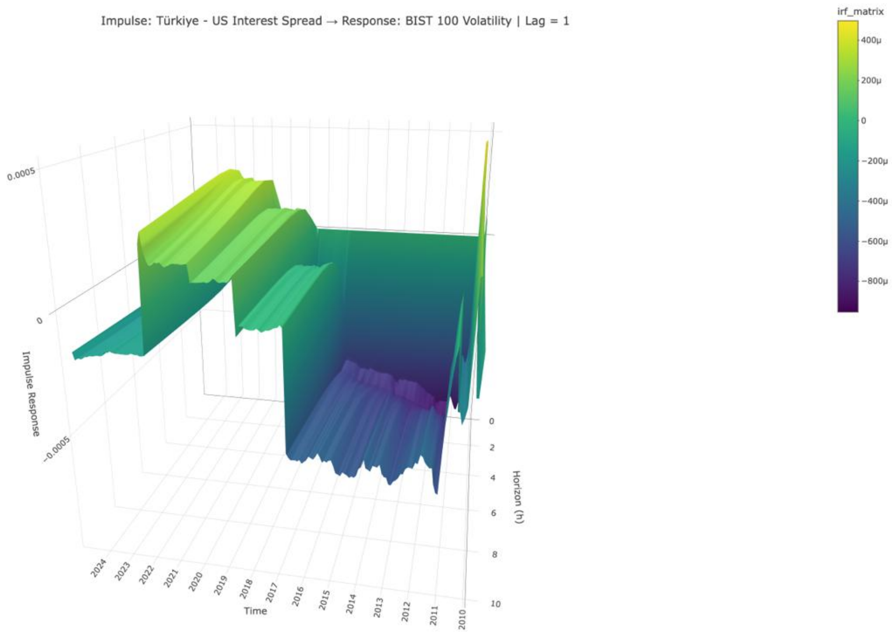
The interest rate spread, which varies from 42.06 to 37.38, functions as a two-way transmission channel, both generating and absorbing significant shocks. While it mainly drives BIST 100 volatility, it is also strongly influenced by the exchange rate return (11.92) and BIST 100 volatility (23.61). This highlights the spread's role as a key intermediary variable within the system. The exchange rate return, with NET = 9.67, acts as the only net transmitter, explaining 84.36% of its own variance internally and showing the most autonomous behavior among all variables. Although its direct impact on BIST 100 volatility is relatively small (5.12), its influence on the interest rate spread is much larger (11.92). This pattern indicates that exchange rate shocks may affect BIST 100 volatility partly through an indirect pathway involving the interest rate spread.



Graph 3. Response of BIST 100 Volatility to EPU

As illustrated in Graph 3, when examining the response of BIST 100 volatility to a one-standard-deviation shock to the EPU variable, the impulse-response functions exhibit significant heterogeneity over time. When examining the response of BIST100 volatility to a one-standard-deviation shock to the EPU variable, the impulse-response functions exhibit significant heterogeneity over time. The strong positive response observed during the 2014-2015 period indicates that, during this period, the global monetary policy normalization process (the FED's termination of its asset purchase program) and domestic political uncertainties simultaneously exerted a volatility-increasing effect on the BIST100. In contrast, in 2018, the impact of the EPU shock on BIST100 volatility turned sharply negative, partly due to the foreign exchange crisis experienced by Türkiye. This finding suggests that the market circuit breaker mechanisms and regulatory interventions implemented during that period served to suppress volatility. By the end of 2021, however, with the introduction of the exchange rate-protected deposit (KKM) scheme developed in response to the sharp depreciation of the Turkish lira, the impact-response functions were observed to fluctuate once again; this reflects the uncertain impact of the aforementioned policy intervention on market volatility.

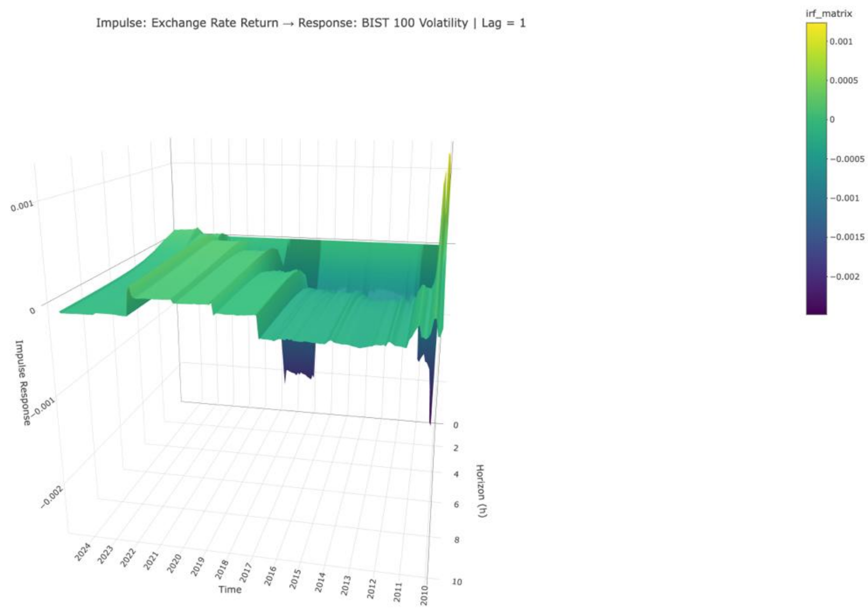
As illustrated in Graph 4, the response of BIST 100 volatility to a one-standard-deviation shock to the interest rate spread variable clearly reflects fundamental shifts in Türkiye's monetary policy regime. During 2010-2013, when the Central Bank of the Republic of Türkiye (CBRT) actively employed an asymmetric interest rate spread, a shock to the spread had a distinct negative effect on BIST100 volatility. This finding indicates that the conduct of monetary policy within a predictable and reliable framework during this period helped to discipline market volatility, consistent with the traditional monetary policy transmission mechanism.



Graph 4. Response of BIST 100 Volatility to Interest Rate Spread

From 2014 onward, however, the impact-response functions took increasingly negative values, reaching their most severe level during the 2018 currency crisis. It is assessed that, as interest rate decisions began to lose their function as a monetary policy signal during this period, the market's sensitivity to interest rate shocks paradoxically increased. During the unconventional monetary policy period of 2021-2022, which was premised on the view that raising interest rates drives inflation, the effect of the interest rate spread on BIST100 volatility appears to have declined to negligible levels. This finding can be interpreted as concrete evidence that, during this period, the monetary policy instrument largely lost its signal value in the eyes of the markets. Although a partial recovery in the interest rate spread's impact on volatility was observed following the return to orthodox monetary policy from mid-2023 onward, this effect has not yet reached the reliability level seen during the 2010-2013 period. The TVP-VAR model's capacity to statistically capture these regime shifts provides a clear methodological advantage over fixed-parameter models in economies such as Türkiye, which experience frequent structural breaks. The suitability of TVP-VAR for capturing regime-dependent monetary transmission in Turkey is further supported by Gayaker and Yalcin (2026), who document structurally changing impulse responses over a similar sample period.

As illustrated in Graph 5, the response of BIST 100 volatility to a one-standard-deviation shock to the exchange rate return variable clearly reflects the structural transformation of the Turkish economy's exchange rate regime. During the 2010-2012 period, when the CBRT pursued a low-interest-rate policy to curb capital inflows and the Turkish lira was trading at an overvalued level, the impact of the exchange rate return shock on BIST 100 volatility appears to have been quite limited. This finding suggests that intense capital inflows and a relatively stable exchange rate environment during this period suppressed market volatility, a trend consistent with Türkiye's de-dollarization process in the 2000s.



Graph 5. Response of BIST 100 Volatility to Exchange Rate Return

From mid-2012 onward, however, the picture changed fundamentally. As signals of the Fed's intention to end its asset purchase program strengthened and capital outflows began, the Turkish lira entered a sustained period of depreciation; in parallel, the impact of exchange rate shocks on BIST 100 volatility became increasingly negative. The temporary positive response observed in the 2014-2015 period corresponds to a transitional phase in which sudden increases in exchange rate volatility were directly reflected in the equity market, whilst in the 2016-2018 period, the impact-response function reached its deepest negative value (~-0.0025). The fact that this period coincided with a conjuncture in which the trend toward dollarization in Türkiye had clearly strengthened, with domestic investors moving away from TL-denominated assets toward foreign-currency-denominated assets, can be assessed as a mechanism that reinforced the suppressing effect of exchange rate shocks on stock market volatility. Following 2021, in line with the pattern observed in the previous graph, the impact of exchange rate shocks on volatility weakened significantly amid the erosion of confidence caused by unconventional monetary policy measures, whilst a partial recovery signal emerged following the return to orthodox policy after 2023.

3.6. Robustness Checks

Verifying the statistical adequacy and temporal stability of the estimated TVP-VAR model is a crucial step in the analysis. The diagnostic test results shown in Tables 5 and 6 cover this aspect from two complementary perspectives.

Table 5. Diagnostic Test Results for TVP-VAR Model Residuals

Variable	LB (10)	p	ARCH-LM	p
BIST 100 Volatility	16.754	0.0799	66.759	0.0000
EPU	17.863	0.0573	8.998	0.1091
Spread	15.656	0.1099	16.051	0.0067
Exchange Rate Return	15.082	0.1291	23.296	0.0003

The Ljung-Box test results show no significant autocorrelation in the residuals of any variable at the 5% significance level, indicating that the TVP-VAR model effectively captures the system's dynamics. The ARCH-LM test finds no conditional heteroskedasticity in the EPU residuals ($p = 0.1091$), although significant ARCH effects are present in the other three variables. This observation is consistent with the known volatility clustering in financial time series and justifies using GARCH (1,1) based conditional standard deviations as the volatility measure. Since the TVP-VAR estimator does not depend on homoskedasticity assumptions, these findings do not compromise the validity of the model's estimates.

Table 6. Model Stability (Companion Matrix Eigenvalues)

Indicator	Value
Average maximum eigenvalue	0.9547
Maximum eigenvalue (all t)	0.9810
Stability ratio (<1.00)	%100.0
Assessment	Model is stable across all periods

As presented in Table 6, eigenvalue diagnostics of the companion matrix confirm that the TVP-VAR model remains stable throughout all 179 time periods, with a stability ratio of 100% and a maximum eigenvalue of 0.9810. While the maximum eigenvalue nears but stays below the unit boundary, this aligns with the great shock persistence observed in the volatility series during episodes of structural turbulence. These findings support the robustness of the time-varying impulse response estimates provided below.

4. Conclusion

This research investigates the temporal dynamics associated with the EPU, the interest rate differential, and the return on exchange rates concerning the volatility of the BIST 100 index from February 2010 to December 2024, utilizing a comprehensive dataset comprising 179 monthly observations. The conditional volatility series, derived from a GARCH (1,1) model, was delineated as the dependent variable, and impulse response functions were computed within a Time-Varying Parameter Vector Autoregression (TVP-VAR) framework, subsequently illustrated through three-dimensional surface plots. Seasonal analysis indicated an absence of statistically significant seasonal patterns across all four series, while unit root tests ascertained level stationarity for the BIST 100 return, EPU, and exchange rate return; conversely, the interest rate spread was determined to be integrated of order one.

The results elucidate that the interrelationships among the variables manifest a time-varying structure that eludes capture by fixed-parameter models, a limitation emphasized by Nyakurukwa and Seetharam (2023), who document that the spillover effects of uncertainty across fiscal, monetary, and aggregate dimensions are intrinsically heterogeneous and temporally contingent. The time-varying influence of EPU shocks on stock market volatility aligns with the heightened uncertainty impact elucidated by Wu (2024) for the Chinese stock market within a TVP-VAR framework during periods of crisis and resonates with the findings of Mumtaz and Surico (2018), which indicate that the repercussions of policy uncertainty on macroeconomic fluctuations exhibit considerable temporal variability. In accordance with Bloom's (2009) "wait-and-see" mechanism, EPU shocks incite pronounced yet regime-dependent contractions in investor sentiment, and consistent with Pástor and Veronesi (2013), escalating policy uncertainty raises the risk premium demanded by equity market participants, thereby directly exacerbating volatility. The indirect influence exerted by EPU through the exchange rate channel corroborates Krol's (2014) assertion that economic uncertainty heightens exchange rate volatility and is consistent with empirical evidence indicating that EPU not only intensifies volatility but also disrupts market expectations and undermines forecasting accuracy (Kido, 2016; Beckmann and Czudaj, 2017; Bartsch, 2019; Olanipekun et al., 2019). These findings can further be interpreted as indicative of the Turkish context, reflecting Abid's (2020) conclusion that the integration of EPU into exchange rate models enhances forecasting efficacy in both the short and long term. The observation that the direction and magnitude of the impacts from exchange rate and interest rate variables on BIST volatility differ across temporal segments also aids in reconciling the conflicting conclusions prevalent in the Turkish literature, as evidenced by the works of Aktaş and Akdağ (2013), Altınbaş et al. (2015), and Demir (2019), which indeed mirror the realities of distinct sub-periods.

The outcomes of the study are articulated along three principal dimensions. First, while the influence of EPU shocks on BIST 100 volatility was unequivocally positive during the years 2014-2015, it exhibited a dramatic negative shift amid the currency crisis of 2018; thereafter, commencing from 2021, it began to oscillate once more as the KKM scheme exacerbated the prevailing environment of uncertainty. The amplification of the EPU effect during the crisis of 2018 is congruent with the findings of Chuliá et al. (2017), which demonstrate that the impact of uncertainty on financial markets escalates during crisis regimes.

This observation is congruent with the regime-switch findings articulated by Rodríguez et al. (2024) concerning Latin American markets, specifically regarding the pronounced external sensitivity of EPU shocks, and is also consistent with the analysis conducted by Hu et al. (2023) pertaining to Chinese commodity markets.

Furthermore, whereas the spread shock effectively mitigated volatility during the period spanning 2010 to 2013 - when the Central Bank implemented the interest rate spread as a viable monetary policy instrument - this moderating effect diminished to nearly negligible levels throughout the heterodox policy episode of 2021 to 2022. The degradation of the spread's signaling efficacy during this timeframe resonates with the findings of Gabauer and Gupta (2018), which assert that monetary policy uncertainty predominates over both internal and external transmission mechanisms, thereby compromising the stabilizing influence of interest rate tools. The significant correlation between interest rates and stock market returns is well-documented in the extant literature (Alam andUddin, 2009; Açıkalın et al., 2008; Ferrer et al., 2016; Assefa et al., 2017). Nonetheless, the intensity and orientation of this correlation are contingent upon variables such as the level of economic development, prevailing market conditions, sectoral dynamics, and economic cycles (Martínez et al., 2015; Ferrer et al., 2016; Salisu and Sikiru, 2021; Moussa and Delhoumi, 2021). Specifically, contemporary research illustrates that this relationship may exhibit asymmetry, producing divergent outcomes in both the short and long run, and could become statistically insignificant during certain sub-periods (Jansen and Zervou, 2017; McMillan, 2022; Gu et al., 2021).

In addition, the correlation between exchange rate return shocks and BIST 100 volatility has exhibited a pronounced negative trend since mid-2012, culminating in its nadir during the period from 2016 to 2018. Mueller et al. (2017) present a particularly pertinent parallel, indicating that monetary policy uncertainty considerably exacerbates currency excess returns in economies characterized by significant interest-rate differentials with respect to the United States - an assertion that is directly relevant to Turkey's elevated interest rate environment throughout the examined timeframe. Moreover, Balcilar et al. (2016) point out that EPU produces significant causal outcomes not merely at the conditional mean but also throughout the distributional extremes of exchange rate returns, illustrating the disproportionate rise of negative impacts in extreme situations. These findings align with research documenting that the volatility of the Turkish Lira against the US Dollar (TRY/USD) imposes a positive and statistically significant effect on the volatility of BIST 100 returns (Dayıoğlu and Aydın, 2019; Taştan and Güngör, 2019; Guler, 2020), and are corroborated by the evidence presented by Sancar et al. (2017) and İlhan and Akdeniz (2020), who demonstrate that increases in the exchange rate inhibit stock market returns. GARCH-based investigations further substantiate the notion that this relationship is inherently asymmetric, with depreciations of the Turkish lira yielding disproportionately heightened equity market volatility when juxtaposed with equivalent appreciations (Güler, 2020; Kök and Nazlıoğlu, 2020; Yaman and Korkmaz, 2020). Furthermore, the existence of bidirectional shock transmission mechanisms between BIST 100 and exchange rates implies that Turkish financial markets function within a highly integrated and mutually reinforcing framework (Senol, 2021; Kılıç et al., 2023). The divergence from the conclusions drawn by Boyacıoğlu and Çürük (2016), who identified a positive effect, can be attributed to the application of fixed-parameter estimation frameworks that inadequately account for the cyclical and asymmetric characteristics of the relationship.

Overall, the results indicate that volatility in the Turkish stock market is influenced not only by EPU but also by frequent interest rate policy changes and exchange rate fluctuations.

Kilic and Balli's (2024) finding that a Turkey-specific EPU index substantially outperforms English-language alternatives in explaining stock prices further reinforces the relevance of country-specific uncertainty measurement in the Turkish context. Notably, the heterodox monetary policy approach during 2021-2022 appears to have substantially eroded the market's reliance on interest rate decisions as a credible policy signal. These findings collectively align with Gürkaynak et al. (2023) and Aftab and Phylaktis (2022), who respectively document that a fragile monetary policy framework destabilizes exchange rate and inflation dynamics, and that the dampening effect of exchange rate returns on volatility acquires a more persistent character as currency fluctuations interact with global financial uncertainty.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
Ece Kepenek: Literature review, data collection and organization, contributed to writing, contributed equally to this study.

Erkan Ağaslan: Econometric model specification and estimation, interpretation of findings, writing and final revision.

Both authors contributed equally to this study.

Declaration of Researcher's Conflict of Interest
The authors declare no conflict of interest.

Declaration of Artificial Intelligence Usage
During the preparation of this study, the authors used AI-assisted tools for language editing purposes. The content was reviewed and edited as necessary, and the authors take full responsibility for the published content.

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