Ekonomi, Politika & Finans Araştırmaları Dergisi, 2025, 10(2): 484-501
Journal of Research in Economics, Politics & Finance, 2025, 10(2): 484-501
Araştırma Makalesi / Research Article, https://doi.org/10.30784/epfad.1666589

THE INTERACTION BETWEEN ECONOMIC UNCERTAINTIES AND FINANCIAL CYCLES IN TÜRKIYE: FREQUENCY DOMAIN SYMMETRIC AND ASYMMETRIC CAUSALITY ANALYSIS

Türkiye'de Ekonomik Belirsizlikler ve Finansal Çevrimler Arasındaki Etkileşim: Frekans Alanında Simetrik ve Asimetrik Nedensellik Analizi

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Keywords:
Economic Policy Uncertainty, Financial Cycles, Symmetric and Asymmetric Causality

JEL Codes:
E30, E44, D80

Abstract

This study analyzes the impact of the Turkish Economic Uncertainty Index on financial cycles with monthly data for the period 2010:01–2024:12. Financial cycles are represented by a composite index formed by indicators such as banking spread, real housing prices, and the BIST100 index. In order to examine the relationship at the short-, medium-, and long-term levels, Breitung and Candelon (2006) applied a frequency domain symmetric and asymmetric causality test. The findings show that decreases in economic uncertainty significantly affect the positive component of financial cycles in both the short and long term. On the other hand, it was found that the economic uncertainty index tended to decrease in the short term during financial contraction periods. The results indicate that reducing uncertainties not only provides market confidence but also supports persistent financial expansion processes. The study makes an original contribution to the literature by revealing for the first time the impact of policy uncertainty on financial cycles on a frequency-based basis through the asymmetric effect channel.

Anahtar Kelimeler:
Ekonomik Politika Belirsizliği, Finansal Çevrimler, Simetrik ve Asimetrik Nedensellik

JEL Kodları:
E30, E44, D80

Öz

Bu çalışma, Türkiye ekonomik belirsizlik endeksinin finansal çevrimler üzerindeki etkisini 2010:01–2024:12 dönemi için aylık verilerle analiz etmektedir. Finansal çevrimler, bankacılık spreadi, reel konut fiyatları ve BIST100 endeksi gibi göstergeler üzerinden oluşturulan bileşik bir endeks ile temsil edilmiştir. İlişkiyi kısa, orta ve uzun dönem düzeyinde inceleyebilmek amacıyla Breitung ve Candelon (2006) frekans alanı simetrik ve asimetrik nedensellik testi uygulanmıştır. Bulgular, ekonomik belirsizlikteki azalışların finansal çevrimlerin pozitif bileşenini hem kısa hem de uzun vadede anlamlı şekilde etkilediğini göstermektedir. Buna karşılık, finansal daralma dönemlerinde ekonomik belirsizlik endeksinin kısa vadede azalma eğilimi gösterdiği tespit edilmiştir. Elde edilen sonuçlar, belirsizliklerin azaltılmasının sadece piyasa güveni sağlamakla kalmayıp, aynı zamanda kalıcı finansal genişleme süreçlerini desteklediğine işaret etmektedir. Çalışma, asimetrik etki kanalıyla politika belirsizliğinin finansal döngüler üzerindeki etkisini frekans-temelli olarak ilk kez ortaya koyarak literatüre özgün bir katkı sağlamaktadır.

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Received Date (Makale Geliş Tarihi): 27.03.2025 Accepted Date (Makale Kabul Tarihi): 20.05.2025

1. Introduction

Economic policy uncertainty (EPU) affects many aspects of countries, from their level of development to their business activities and even their real and financial markets. The most prominent example of global uncertainty is the 2008 Global Financial Crisis, which started with the bursting of the housing bubble in the US and later resulted in the negative impact of many macroeconomic indicators and financial markets. Then, with the COVID-19 pandemic in 2020, essential activities such as production and foreign trade came to a standstill, creating a widespread environment of uncertainty. Financial markets, especially stock markets, were also affected by this uncertainty, with the S&P500 and NASDAQ losing approximately 5% of their value (Dai et al., 2021). In the same period, BIST100 also fell by approximately 15%. The COVID-19 pandemic has imposed a similar or even more significant uncertainty on financial markets than the Global Financial Crisis (Narayan et al., 2021; Vidya et al., 2022).

This study investigates a critical issue regarding EPU, which is an important risk factor on financial markets and negatively affects returns. Policy-related uncertainties have significant effects on consumers and investors. In an economic environment where uncertainty is high, new investors may hesitate to enter the market, which may cause consumers to reduce their current spending (Fasanya et al., 2020). In addition, policy uncertainty slows down economic activity by delaying investment, production, and consumption decisions; at the same time, it can affect credit expansion and asset prices by increasing uncertainty premiums on financial markets (Pastor and Veronesi, 2012; Baker et al., 2016). For this reason, it would not be wrong to say that EPU directly affects financial markets. Although it has different effects on stock markets from different industries, economic uncertainties can increase long-term volatility in stock markets (Yu et al., 2018). Uncertainty shocks negatively affect financial markets, especially by causing increases in credit spreads and significant decreases in stock returns (Popp and Zhang, 2016). In addition, uncertainty is generally accepted as an important factor that harms investment decisions; if it increases, it will create an economic expectation that threatens future earnings and negatively affects stock prices (Chen and Chiang, 2020).

It is also thought that the causal relationship between EPU and financial markets may be bidirectional. On the one hand, policy uncertainty can affect the decision-making processes of businesses and households, leading to significant consequences on both the real economy and financial markets. On the other hand, when economic activity weakens, credit conditions tighten, and volatility increases in financial markets, the likelihood of government intervention increases, which may lead to increased policy uncertainty (Ludvigson et al., 2021). This interaction between EPU and financial cycles is critical for financial stability and macroeconomic management. Financial cycles carry a dynamism that can create severe crises and long-term economic expansion processes. Especially during periods of financial expansion, the increase in risk appetite can make the responses to uncertainty shocks asymmetric (Pastor and Veronesi, 2012; Ludvigson et al., 2021).

As discussed above, there are multiple channels through which EPU can affect financial cycles. First, increased uncertainty can increase risk perception in credit markets, limiting credit supply and negatively affecting credit expansion (Bernanke, 1983; Bloom, 2009). Banks and financial institutions follow a more cautious credit policy by tightening credit conditions during periods of uncertainty. This can trigger a contraction in financial cycles. Second, increased uncertainty can also affect international capital flows and disrupt liquidity conditions in financial markets. In heightened uncertainty, investors turn to safe-haven assets; capital outflows may occur from emerging economies. This process can deepen financial contraction (Pastor and Veronesi, 2012). Third, uncertainty shocks can have a direct effect on asset prices. Increased uncertainty can lead to higher risk premiums and lower asset prices, such as stocks and housing markets. Downturns in these asset markets, which are important components of financial cycles, can trigger the contraction phase of the cycle (Borio, 2014).

This study examines the impact of EPU on financial cycles in both the short and long-term using a frequency-based approach and evaluates whether this relationship is asymmetric. The impact of EPU on financial cycles can be asymmetric depending on the direction of the shock. While increasing uncertainty (positive EPU shock) accelerates the contraction trend of the financial cycle, decreasing uncertainty (negative EPU shock) supports financial expansion; this effect is often more limited and delayed. The fundamental theoretical framework of the study is based on the literature explaining the effects of uncertainty shocks on financial market variables. It emphasizes the effects of financial cycles on macroeconomic stability. Thus, the study addresses the role of uncertainty in economic activities and its interaction with financial vulnerabilities from a holistic perspective.

The research proceeds as follows: The next section reviews the relevant literature. Section 3 explains the dataset and methodology. Section 4 presents the analysis results, and Section 5 presents the general evaluation of the results and policy recommendations.

2. Literature Review

Financial cycles represent not only short-term financial volatility movements but also longer-term and structural change processes. Financial cycles, which are formed by factors such as borrowing trends, credit size, asset prices, and risk appetite, are fundamental dynamics that determine the expansion and contraction phases of the economic system (Borio, 2014). The literature defines financial cycles as dynamic processes that can create longer and more profound effects than economic cycles. While risk appetite increases in periods of financial expansion, financial stability may weaken in periods of contraction (Claessens et al., 2012). In this context, financial cycles affect not only the formation of financial crises but also the speed and strength of the recovery process after the crisis. Therefore, understanding the impact of EMU on financial cycles is of critical importance in terms of both financial stability policies and macroeconomic governance.

Financial cycles can be affected by uncertainties at different frequencies and timings. Aizenman and Pinto (2005) emphasized that there is a positive relationship between policy uncertainty and financial fragility. Increases in uncertainty can affect lending behaviour by changing the risk perception of investors and banks. This can determine the direction and severity of financial cycles. Liu et al. (2023) examined the relationship between EPU and financial cycle variables (total credit, housing, and stock prices) in the Chinese economy using wavelet analysis in the time-frequency domain. The study revealed that this relationship varies in frequency and time and is significantly strengthened, especially in crisis periods (e.g., the 2008 crisis, COVID-19, trade wars). In addition, it was determined that EPU acts as a leading indicator that drives financial cycles in some periods and as a responsive variable in others.

The effects of macroeconomic uncertainty shocks on financial cycles may vary in level and depending on the current cycle. In this context, Popp and Zhang (2016) analyzed the effects of uncertainty shocks depending on the regime. They showed that these shocks have more substantial and permanent effects, especially during recession periods. Alessandri and Mumtaz (2019) analyzed the macroeconomic effects of economic uncertainty shocks, mainly how they differ depending on financial regimes. The regime-dependent nonlinear Threshold VAR model they estimated using monthly data for the US economy shows that the effect of uncertainty shocks on outputs is approximately six times larger during financial crisis periods compared to standard times. The study also emphasizes that the uncertainty-financial cycle interaction is not linear and constant over time but varies significantly depending on regimes. The findings support the key role played by the financial channel in transmitting uncertainty shocks.

Fasanya et al. (2021) analyzed the impact of global economic policy uncertainty (GEPU) on volatility spillovers in financial markets for the Asia-Pacific manufacturing sector. The findings reveal a strong volatility interaction across markets, and GEPU significantly affects this interaction, especially at medium quantile levels. This suggests that the impact of uncertainty shocks on the financial system has a nonlinear structure.

In summary, studies in the literature focus on the structure of financial cycles and the impact of EPU on these cycles. Previous studies show that financial cycles contribute to economic fluctuations through credit expansion, risk appetite, and asset prices, while increases in uncertainty weaken these cycles by creating credit crunches and market volatility (Bloom, 2009; Claessens et al., 2012; Borio, 2014). The literature also revealed that the uncertainty-financial cycle relationship becomes more pronounced during crises and differentiates over time (Popp and Zhang, 2016; Alessandri and Mumtaz, 2019; Liu et al., 2023).

In studies explicitly conducted for Türkiye, the effects of EPU on the stock market (Korkmaz and Güngör, 2018; Koncak and Nazlıoğlu, 2024), inflation (Tümtürk and Kırca, 2024), exchange rates, and CDS (Aydın et al., 2024) have been analyzed. However, there is no study that directly addresses the relationship between EPU and financial cycles at both time and frequency levels and in an asymmetric structure.

Although the relationship between EPU and macroeconomic indicators has been extensively examined in the existing literature, its impact on financial cycles has been addressed to a limited extent, especially with frequency-based and asymmetric approaches. In particular, empirical analyses that reveal the relationship between EPU and financial cycles changes at different time scales and according to shock directions are not found in the literature, especially in the Turkish economy. The aim of this study is to contribute to the literature by analyzing the impact of EPU on financial cycles in the frequency domain and from a symmetric/asymmetric perspective in the case of Türkiye. This method was chosen based on the assumption that the relationship between EPU and financial cycles may vary depending on the frequency and direction of the shock. Considering the dynamic structure of the Turkish economy, this method provides more explanatory results by allowing the separation of relationships according to time and shock type. Thus, short-term market reactions and long-term structural effects will be separated, and a more comprehensive analysis will be presented for decision makers. In this respect, the study aims to contribute significantly to the existing literature methodologically and empirically. In addition, while previous studies used GEPU, this study used the Türkiye economic uncertainty index, which has just begun to be calculated by Kilic and Balli (2024). In this sense, the study is quite different from the existing studies in the literature.

3. Data and Methodology

3.1. Data Set and Index Estimation

This study aims to investigate the impact of EPU on financial cycles in Türkiye using monthly data for the period 2010:01-2024:12. For this purpose, the Türkiye economic uncertainty index (TEUI) calculated by Kilic and Balli (2024) was used as the EPU indicator. This index was calculated depending on the frequency of occurrence of the words “economy” and “uncertainty” in 6 leading newspapers published in Türkiye, utilizing the methodology of Baker et al. (2016). Unlike other uncertainty indices, TEUI focuses on the Turkish economy. The monthly time series of the index is obtained from Policy Uncertainty (2024). EPU measures the level of uncertainty arising from decisions and practices regarding economic policies. An increase is observed in the index, especially in periods when uncertainty increases regarding the decision-making processes of policymakers, legal regulations, and the direction of future economic policies. This index is an important indicator for investors and businesses because an increase in EPU may lead to the postponement or reconsideration of investment and consumption decisions (Baker et al., 2016).

The second indicator, financial cycles, is a dynamic process in which the interactions between asset valuations, risk perceptions, risk taking, and financial constraints reinforce each other (Borio, 2014). Many indicators have been used in the literature in terms of financial variables. Many variables, from real exchange rates to housing prices, from stock prices to banking spreads, can be used to represent financial cycles (Goodhart and Hofmann, 2005; Hatzius et al., 2010; Liu, 2016; Ma and Zhang, 2016; Karagöl, 2021). Based on this, banking spread (BS), which shows the difference between loan interest and deposit interest, was used as a credit market indicator, the realized housing price index (RHPI) was used to represent housing markets, and the realized BIST100 Return Index (RBIST) was used to represent stock markets. RBIST and housing price index data were converted to real series by eliminating the effect of inflation. CPI (Consumer Price Index, 2005=100) was used for real values. All variables were obtained from the CBRT Electronic Data Distribution System. In addition, seasonal adjustment was made in the series using the TRAMO/SEATS method. Time series graphs of the variables are shown in Figure 1.

The upper panel of the Figure 1 shows the Türkiye economic uncertainty index (TEUI). As can be seen in the figure, fluctuations are directly caused by uncertainties. The most significant increases in uncertainty are due to inflation, interest rates, exchange rates, and general elections in 2011 (Kilic and Balli, 2024). The sudden increase in the dollar exchange rate and the crises with the US in 2018, the COVID-19 pandemic and global lockdowns in 2020, the sudden jumps in the exchange rate, rising inflation, and foreign trade deficit in 2022, and the new economic management after the general elections in 2023 have caused an increase in uncertainty. Slight upward movements begin in 2024; this may reflect the uncertainty of expectations regarding the effects of tight monetary policies on the economy. The lower panel of the figure shows the time series graphs of the components of the FC. The BS has been relatively flat and has had limited fluctuations until 2018. This indicates that the intermediation cost of the banking sector is relatively stable. Significant increases have occurred in 2018 and beyond, especially in the 2018 currency crisis, the 2020 pandemic, and the tightening process after 2023. The sharp increase in the spread in 2022–2023 may be due to the increase in loan interest rates rising faster than deposit interest rates. This indicates that financial conditions are tightening and the banking sector demands a higher risk premium. A slightly upward and fluctuating structure exists in the real BIST100 index (RBIST) between 2010 and 2017. During this period, inflation-adjusted returns are relatively stable. A rapid recovery in real terms is striking as of mid-2022. This increase is associated with nominal BIST increases and stock returns that do not remain below high inflation. The RHPI is relatively stable until 2021. A rapid and striking increase in real housing prices is observed as of 2021. The main reasons for this increase are the motivation to protect against inflation and the negative real interest rate environment.

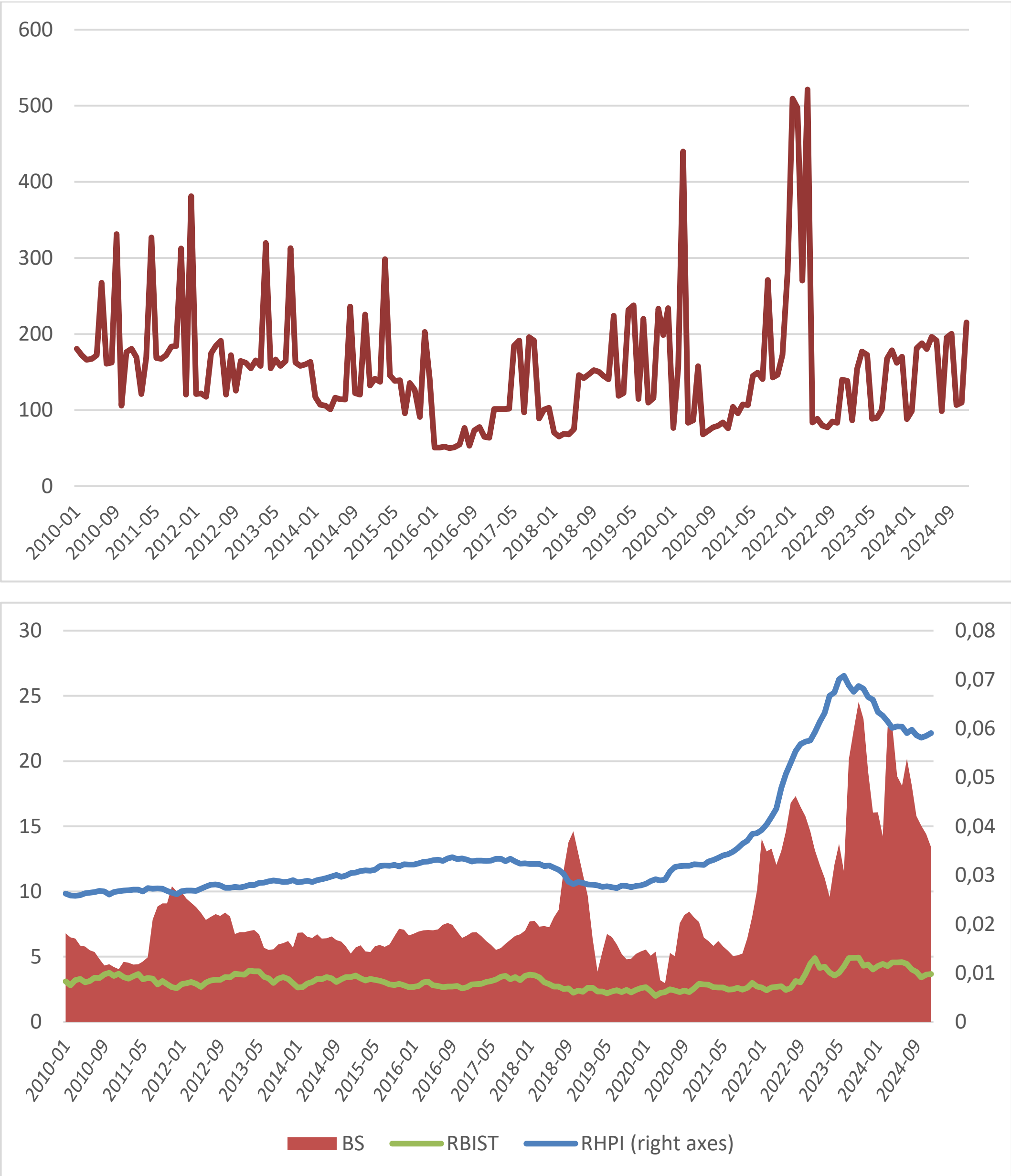

Figure 1. The Trend of the Series

Instead of separately considering the indicators selected from the credit market, housing market, and stock market to represent the characteristics of financial cycles, the study aimed to calculate an FC, as in the study of Ma and Zhang (2016). It is thought that calculating the index with variables selected from different financial markets will better represent financial cycles. Since the data used in creating financial cycle indices are expressed in different units, bringing them together in the index calculation is only possible by expressing them on the same scale. This method allows each series to be compared on the same scale, prevents negative values in the dataset, and provides easy interpretation in the index's composition. An alternative method, z-score standardization, can normalize the series around the mean. However, it is found to be incompatible because it can change the structure of the FC due to its potential to produce negative values. This preference is also a common practice in studies on the creation of financial cycles and is supported in the literature (Schüler et al., 2015). Based on this, the empirical normalization method, which allows the series to be scaled between 0-1, was used (Karagöl and Doğan, 2021). In the empirical normalization method, the values of the series are calculated with the following equation:

$$A_i^n = \frac{A_i - A_{min}}{A_{max} - A_{min}} \tag{1}$$

In Equation 2, A^n represents the normalized observation, A_i represents the relevant observation, A_{min} represents the minimum observation of the relevant variable, and A_{max} represents the maximum observation. After the series are normalized, the variables must be weighted to create the index. In the literature, methods include equal weighting (1/3), correlation coefficient with output gap, or weighting with inverse variance. However, the inverse variance weighting method proposed in the study of Ma and Zhang (2016) was used in this study. Here, each variable is weighted inversely proportional to its volatility. This means that the weight assigned to each variable reflects its relative stability throughout the sample period, i.e., a higher weight is assigned to a relatively more stable variable and is calculated with the following formula:

$$w_i = \frac{1}{\sigma_i^2} \Big/ \sum_i \frac{1}{\sigma_i^2} \tag{2}$$

where w_i is the weight of the variable, σ_i is the variable's standard deviation. Based on this, the calculated weights of each indicator are given in Table 1.

Table 1. Calculated Weights for Financial Cycle

Variable	Normalized Value	Weight
VNBS	23.88491	0,40
VNHPI	12.99895	0,22
VNBIST	22.45751	0,38
Total	59.34137	1,00

When the model is estimated with OLS, it is seen that the housing price index coefficient has a negative sign, and when calculating the cycle index, it will be assumed that the variable affects the cycle negatively. Similarly, the literature shows that real declines in housing prices lead to credit contraction in the banking sector, deterioration in balance sheets, and financial tightening, thus deepening the contraction phases of financial cycles (Claessens et al., 2012; Borio, 2014). Based on this, the weight vector calculated will be as follows:

$$w_i = [0.40, -0.22, 0.38] \tag{3}$$

After the FC was created, the HP filter was used to analyze better the periods of contraction and expansion in the series. The HP filter identifies excessive variability in margins (Bloechl, 2014). Hodrick and Prescott (1997) stated that the optimization problem should also be solved when separating the trend and cycle components in a time series:

$$min_{(g_t)_{t=-1}} \left\{ \sum_{t=1}^{T} c_t^2 + \beta \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\} \tag{4}$$

where g_t represents the trend component, c_t represents the cycle component, and β represents the smoothing parameter. The graph of the financial cycle series, which is detrended with the help of the HP filter, is given in Figure 2.

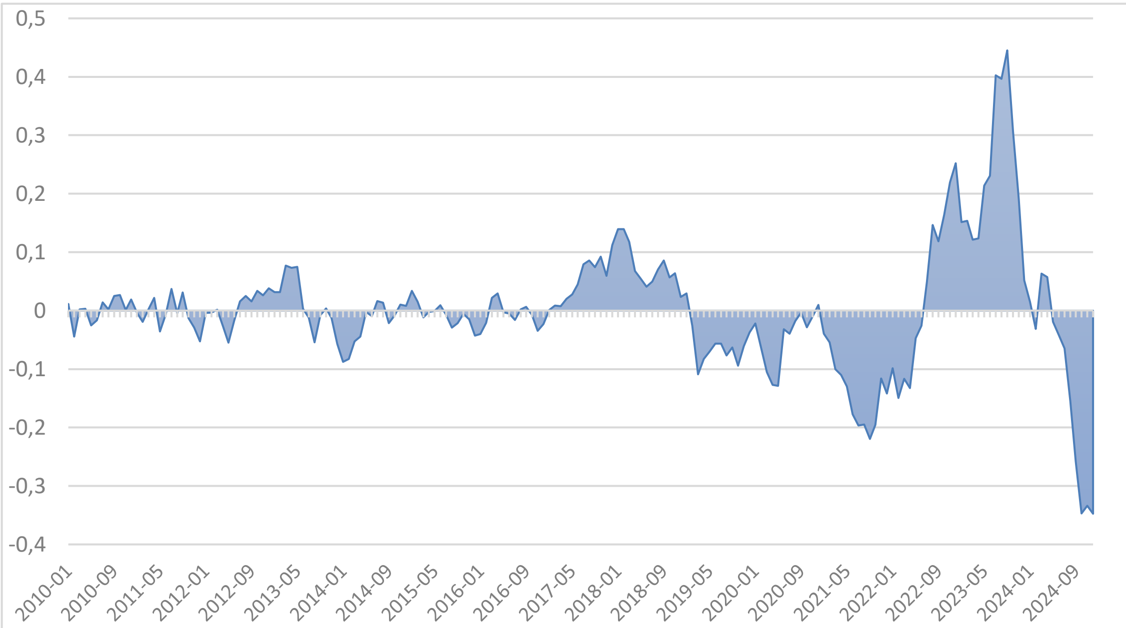

Figure 2. Financial Cycle Index

The financial cycle index (FC), shown in Figure 2, provides important information about the course of credit volume, asset prices, and general financial conditions in the Turkish economy. The time series graph of the index reveals remarkable dynamics regarding the direction and strength of the financial cycle from the beginning of 2010 to the end of 2024. A value above zero in the index represents periods of financial expansion, while a value below zero represents periods of financial contraction. Financial cycles experienced more limited fluctuations until 2016 due to the recovery effects after the global financial crisis. In 2017, the financial cycle entered the positive zone and gave expansion signals. This period is consistent with the credit growth supported by the Credit Guarantee Fund implemented in 2017. However, this expansion was short-lived, and by the middle of 2018, the FC had rapidly turned negative. The exchange rate shock experienced in the summer of 2018 (especially the sharp increase in

USD/TRY) and the subsequent financial fragilities, interest rate hikes, and credit crunch caused the financial cycle to sharply contract. The economic uncertainty created by the COVID-19 pandemic in 2020 and the foreign exchange reserve losses and exchange rate pass-through in 2021 contributed to the continuation of this contraction. The index has moved into strong positive territory since mid-2022. This expansion, which peaked in early 2023, was shaped by the impact of various fiscal and monetary expansion tools, primarily subsidized loans provided through public banks. At the same time, keeping the policy rate low, facilitating access to credit, and pre-election fiscal expansion supported this process. Tight monetary policy practices that began in the second half of 2023, successive increases in policy rates, and the slowdown in credit expansion caused the index to contract again. At the same time, increasing borrowing costs reduced the credit demand of households and firms and increased the perception of risk in the financial system. This period is an important indicator that financial cycles in Türkiye have become quite sensitive and fragile.

3.2. Methodology

The main reason for choosing the frequency domain asymmetric causality method in this study is the assumption that the effect of EPU on financial cycles may vary depending on the time scale (short, medium, long term) and the shock direction (positive/negative shocks). Traditional time series methods can only measure the average effects of such relationships (Geweke, 1982; Hosoya, 1991). Although the Toda–Yamamoto (1995) causality test can detect a general causality relationship without being sensitive to the integration degrees of the variables, it cannot distinguish which dynamics the effects occur over in the short, medium, or long term. Unlike traditional Granger causality tests, this method provides diverse information about the timing and severity of the effects for policymakers. The primary method used in this study, which investigates the relationship between the financial cycle and the Turkish economic uncertainty index, is the frequency domain causality test of Breitung and Candelon (2006). This causality test, unlike standard time series causality tests, can separate short-, medium- and long-term causality between variables, and has been used recently both when examining the relationship between cycles and in many other macroeconomic models (Bozoklu and Yilanci, 2013; Gomez-Gonzalez et al., 2015; Strohsal et al., 2019; Kırca and Canbay, 2021). The frequency domain causality test of Breitung and Candelon (2006) allows us to determine whether the relationship between two variables is permanent or temporary.

Breitung and Candelon (2006) extended the Wald test procedure of Geweke (1982), which imposes correct restrictions on the coefficients to test Granger causality in a specific frequency range, to a two-variable VAR model. Since this test is based on VAR models, it is used when the variables are stationary. If the variables are I(0), the VAR(p) model determines the appropriate lag. However, if the variables are not stationary, the maximum degree of cointegration of the variables (d_{max}) is determined here, and the appropriate lag is VAR(p+d_{max}). A restricted VAR model for the frequency domain causality test can be defined as follows:

$$\begin{aligned} Y_t &= \phi_{21,1}Y_{t-1} + \phi_{21,2}Y_{t-2}, \dots, +\phi_{21,p}Y_{t-p} + \phi_{22,1}X_{t-1} + \phi_{22,2}X_{t-2}, \dots, +\phi_{22,p}X_{t-p} \\ X_t &= \phi_{11,1}Y_{t-1} + \phi_{11,2}Y_{t-2}, \dots, +\phi_{11,p}Y_{t-p} + \phi_{12,1}X_{t-1} + \phi_{12,2}X_{t-2}, \dots, +\phi_{12,p}X_{t-p} \end{aligned} \tag{5}$$

If we want to express this model in matrix form with the lag operator (L):

$$\phi(L) = \begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{pmatrix} \begin{pmatrix} X_t \\ Y_t \end{pmatrix} = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{6}$$

where, $\phi(L) = I - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$is the 2x2 delay polynomial and ε_{1t} and ε_{2t} are the error terms including white noise.

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \Psi(L)\eta_t = \begin{pmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} \tag{7}$$

In Equation 7, $\Psi(L) = \phi(L)^{-1}G^{-1}$is expressed as $\eta_t = G\varepsilon_t$). G represents the lower triangular matrix. Y_t is the sum of two components: real and prediction. The predictive power of X_t is calculated by comparing the spectrum of the real component with the prediction component at each frequency (Bozoklu and Yılancı, 2013). The measurement of causality proposed by Geweke (1982) is defined as follows:

$$M_{X\to Y}(\omega) = log\left[1 + \frac{\left|\Psi_{12}(e^{-i\omega})\right|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{8}$$

Under the condition $\Psi_{12}\left(e^{-i\omega}\right) = 0$, Equation 8 equals zero. It is stated that Y_t does not Granger cause X_t at frequency ω. Breitung and Candelon (2006) are based on the following linear constraints:

$$\sum_{j=1}^{p} \phi_{12j} \cos(j\omega) = 0 \tag{9}$$

$$\sum_{j=1}^{p} \phi_{12j} \sin(j\omega) = 0 \tag{10}$$

As a result of the test, test statistics are calculated using the Wald-F test at each ω frequency value. The hypotheses for each frequency are as follows:

$$H_0\!: R(\omega)\beta = 0 \; and \; R(\omega) = \begin{pmatrix} \cos(\omega) \; \cos(2\omega) \ldots \cos(p\omega) \\ \sin(\omega) \sin(2\omega) \ldots \sin(p\omega) \end{pmatrix} \tag{11}$$

When testing the H_0 hypothesis, if the probability values of the test statistics are less than 10%, 5%, and 1%, the null hypothesis is rejected. Three different test statistics are used to determine whether the causal relationships between variables are significant in the long, medium, and short term. A significant probability value of ω at a frequency of 0.5 indicates long-term causality, a significant probability value of 1.5 indicates medium-term causality, and a significant probability value at a frequency of 2.5 indicates short-term causality (Ciner, 2011). Long-term causality generally indicates a permanent relationship, whereas short-term causality reflects a temporary association. Furthermore, based on the statistically significant frequency values, the duration over which the relationship between the variables persists can be calculated using the formula 2π/ω (Tastan, 2015).

The methodology described above represents a symmetric frequency domain causality relationship. However, the relationship between variables may not always be symmetric. Traditional causality tests grounded in the assumption of symmetry do not differentiate between the impacts of positive and negative shocks (Bahmani-Oskooee et al., 2019). However, as Hatemi-J (2019) highlights, participants in financial markets tend to respond more strongly to negative news than to positive developments. Ranjbar et al. (2017) developed the asymmetric frequency domain causality test, which considers the relationships at different frequencies of positive and negative shocks of variables. Based on this, the study has also tested whether variables have an asymmetric causality relationship. A causality test used the variables' positive and negative components (cumulative shocks).

Positive and negative shocks in the variables are defined as in Equation 12 (Hatemi-J, 2012):

$$\begin{aligned} \epsilon_{1t}^{+} &= \max(\epsilon_{1t}, 0), \epsilon_{2t}^{+} = \max(\epsilon_{2t}, 0) \rightarrow \textit{positive shocks of both variables} \\ \epsilon_{1t}^{-} &= \min(\epsilon_{1t}, 0), \epsilon_{2t}^{-} = \min(\epsilon_{2t}, 0) \rightarrow \textit{negative shocks of both variables} \end{aligned} \quad (12)$$

Hatemi-J (2012) assumes the causal relationship between positive and negative shocks operates similarly at all frequencies. However, Granger (1969) pointed out that the causality between two variables may exhibit different characteristics at different frequency components of the time series. Based on this approach, Bahmani-Oskooee et al. (2019) adapted Hatemi-J's asymmetric causality test in the time domain to the frequency domain. Based on this, if we rearrange Equation 6 to include positive and negative components:

$$\phi(L) = \begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{pmatrix} \begin{pmatrix} X_t{}^{+,-} \\ Y_t{}^{+,-} \end{pmatrix} = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \quad (13)$$

There are four different combinations of positive and negative shocks, and all of them will be discussed in the study ($X_t{}^{+}, Y_t{}^{+}; X_t{}^{+}, Y_t{}^{-}; X_t{}^{-}, Y_t{}^{+}; X_t{}^{-}, Y_t{}^{-}$).

4. Results

First, Breitung and Candelon (2006) applied symmetric and asymmetric causality tests to the Türkiye economic uncertainty index and financial cycle series. However, to perform the causality test in the frequency domain, firstly, the stationarity levels of the variables should be examined and the maximum lag length (d_{max}) should be determined. For this purpose, traditional unit root tests such as the Augmented Dickey-Fuller (ADF) developed by Said and Dickey (1984) and the structural break unit root test developed by Perron (1989) and Perron and Vogelsang (1992) are used in the study. Although classical unit root tests were developed under the assumption of linearity, they are generally robust to minor nonlinear deviations, especially in macroeconomic time series (Enders, 2015; Hamilton, 2020). In addition, studies such as Caner and Kilian (2001) and Glynn et al. (2007) indicate that unit root tests can produce meaningful results in practical applications even when the linearity assumption is violated. For this reason, unit root tests were performed directly on the series without performing a linearity analysis (Table 2).

Table 2. Unit Root Test Results

Variable	ADF Test	Breakpoint Test
TEUI	-6.0480*** (0.0000)	-10.0602*** (<0.01)- Break Date: 2022M04
FC	-3.2597** (0.0183)	-4.3043* (0.0739)- Break Date: 2024M01
$TEUI^{+}$	-0.2638 (0.9264)	-2.3840 (0.9289)- Break Date: 2019M03
$\Delta TEUI^{+}$	-14.7264*** (0.0000)	-16.1705*** (<0.01) Break Date: 2020M03
$TEUI^{-}$	-0.5054 (0.8861)	-2.6666 (0.8434)- Break Date: 2019M05
$\Delta TEUI^{-}$	-15.5530*** (0.0000)	-17.5639*** (<0.01)- Break Date: 2022M05
FC^{+}	1.8730 (0.9998)	-2.0325 (0.9808)- Break Date: 2021M10
ΔFC^{+}	-7.2418*** (0.0000)	-15.2750*** (<0.01)- Break Date: 2023M07
FC^{-}	3.1536 (1.0000)	-0.1468 (>0.99)- Break Date: 2023M08
ΔFC^{-}	-9.6097*** (0.0000)	-11.7335*** (<0.01)- Break Date: 2023M07

Note: ***, **, and * indicates stationarity with a 1%, 5%, and 10% level of statistical significance, respectively. The values in parentheses indicate probability values. *Δ* is the difference operator.

The financial cycle series becomes stationary because it is detrended with the HP filter (Gomez-Gonzalez et al., 2015). In addition, the Türkiye economic uncertainty index, which is not separated into its components, is also stationary at the level value. In order to perform asymmetric tests, the series were separated into positive and negative components. As a result of the unit root tests, it was seen that all variables separated into their components became stationary at the first difference. Then, the appropriate VAR(p) model with the variables was determined using the Akaike Information Criterion (AIC), as indicated by Breitung and Candelon (2006). The symmetric and asymmetric causality test results in the frequency domain obtained based on the stationarity and VAR(p) values determined for each model are given in Table 3 and Table 4.

Table 3. Symmetric Causality Test Findings in the Frequency Domain

H_0 Hypothesis	Long Term (ω=0.5)	Mid- Term (ω=1.5)	Short Term (ω=2.5)	Var ($p+d_{max}$)
	T-stat. (Prob.)	T-stat. (Prob.)	T-stat. (Prob.)	
TEUI ↛ FC	2.9422 (0.2296)	4.4898 (0.1059)	5.0135 (0.0815)	4
FC↛ TEUI	0.5111 (0.7744)	2.7394 (0.2541)	5.4068 (0.0669)	4

Table 3 summarizes the findings of the symmetric causality test in the frequency domain. According to the findings of this test, there is a significant causality at the 10% level, both from EPU to the financial cycle and from the financial cycle to EPU in the short term. Although there seems to be a two-way causality relationship in the short term, this causality is relatively weak at the 10% level. This shows that the relationship between uncertainty and the financial cycle is limited to short-term market reactions. For example, policy uncertainty increases during election periods or sudden political developments in Türkiye, leading to temporary fluctuations in stock and credit markets. However, such effects do not create a permanent financial cycle change, and market conditions can quickly normalize when the shocks are overcome. Similarly, short-term fluctuations in financial markets (such as sudden exchange rate shocks or stock market volatility) can also lead to temporary increases in uncertainty in policymakers' decision-making processes. However, such effects are generally weak and short-lived because they do not permanently change macroeconomic fundamentals. In this context, the weak causality found to be significant at the 10% level reflects the short-term, fragile, and temporary interactions between financial cycles and EPU.

Table 4. Asymmetric Causality Test Findings in the Frequency Domain

H_0 Hypothesis	Long Term (ω=0.5)	Mid- Term (ω=1.5)	Short Term (ω=2.5)	Var ($p+d_{max}$)
	T-stat. (Prob.)	T-stat. (Prob.)	T-stat. (Prob.)	
$TEUI^+ \nrightarrow FC^+$	2.2378 (0.3266)	0.7359 (0.6921)	1.1841 (0.5531)	3
$TEUI^+ \nrightarrow FC^-$	0.4655 (0.7923)	1.6680 (0.4343)	0.9570 (0.6196)	5
$TEUI^- \nrightarrow FC^-$	2.1967 (0.3334)	2.1669 (0.3384)	2.1965 (0.3334)	3
$TEUI^- \nrightarrow FC^+$	17.3254 (0.0001)***	24.9998 (0.0000)***	9.9019 (0.0007)***	4
$FC^+ \nrightarrow TEUI^+$	0.2500 (0.8824)	0.3137 (0.8548)	0.3146 (0.8544)	3
$FC^+ \nrightarrow TEUI^-$	2.2106 (0.3310)	1.9647 (0.3744)	3.4531 (0.1778)	5
$FC^- \nrightarrow TEUI^-$	0.3748 (0.8290)	0.6053 (0.7388)	0.7856 (0.6751)	3
$FC^- \nrightarrow TEUI^+$	0.3095 (0.8566)	2.9193 (0.2323)	6.0354 (0.0488)**	4

Notes: ***, **, and * indicates significance level at 1%, 5%, and 10%, respectively.

Table 4 shows the findings of the asymmetric causality test in the frequency domain. Although there are many findings between the different components of the variables, two important findings stand out. The first is the short-, medium-, and long-term causal relationship from the negative component of the Turkish economic uncertainty index to the positive component of the financial cycle. The negative component of TEUI represents the decreases in EPU, while the positive component of the financial cycle represents the expansion (revival) periods of the financial cycle. As EPU decreases, i.e., as markets become more predictable and stable, it is seen that the financial cycle accelerates in the direction of expansion. It can be said that the market responds quickly to the decrease in short-term uncertainty (e.g., the stock market rises, credit conditions loosen). In the medium term, the recovery in the financial system continues. Investments increase, and the credit market expands. In the long term, there is a more permanent financial expansion; capital markets are deepening, and asset prices may increase permanently. All these results show that the decrease in uncertainty in the Turkish economy triggers financial recovery and that this effect is temporary in the short term and may be permanent in the long term. It not only creates temporary optimism in financial markets but also initiates a cyclical expansion trend. The second important finding is the existence of short-term causality from the negative component of the financial cycle to the positive component of TEUI. Periods of financial contraction led to increased EPU in the short term. When there is a deterioration in the financial system, market pressure occurs, exchange rates fluctuate, stock markets fall, and CDS premiums increase. This leads to increased economic uncertainty.

The reduction of EPU in Türkiye not only creates positive expectations in the market but is also a determining factor in medium- and long-term financial expansion. The findings obtained in this study show that the expansionary tendency in financial cycles strengthens in periods when EPU decreases, and this effect is not limited to the short term but spreads to the medium and long term. This result is consistent with the findings of Liu et al. (2023) in their study on the Chinese economy, which indicated that the relationship between uncertainty and financial cycles becomes especially evident during crisis periods. Similarly, the findings of Popp and Zhang (2016) and Alessandri and Mumtaz (2019) in their regime-based analyses that uncertainty shocks create stronger effects, especially during financial recession periods, have also been observed in the case of Türkiye through asymmetric causality. In this context, the reduction of uncertainty not only creates a temporary market morale but also initiates a more permanent financial expansion process by activating investment and credit mechanisms. Therefore, how EPU affects financial cycles in Türkiye overlaps with the nonlinear, regime-dependent, and frequency-based approaches suggested in the literature.

When the study's findings and their comparison with the studies in the literature are evaluated, Türkiye's financial system has a more limited financial depth compared to large-scale emerging markets such as China. Türkiye has a more fragile structure in terms of the share of the banking sector in GDP, the depth of capital markets, and the diversity of alternative financing instruments. This situation causes financial cycles to respond more sensitively and immediately to policy uncertainty shocks. In addition, since the predictability level of monetary and fiscal policies in Türkiye is relatively low, market actors can give shorter-term and volatile responses to policy changes. In contrast, in economies such as China, the power of central authorities to intervene in financial markets is higher, and the effects of uncertainty shocks are felt in a more controlled and time-spread manner. These differences necessitate that the findings obtained in the study be evaluated initially in the context of Türkiye. The two-way but weak effect of EPU on financial cycles in Türkiye in the short-term points to the sensitivity of markets to shocks and the relative fragility of the financial system. On the other hand, the finding that the decrease in uncertainty supports financial expansion in the medium and long term shows that financial cycles gain stability when the uncertainty environment is permanently improved. In this respect, the findings in Türkiye support the non-linear and frequency-based relationship suggested in the literature and provide important clues about how country-specific conditions shape financial cycle dynamics.

In addition, when the significant frequencies are examined, it is seen that $\omega \epsilon (0–2.5)$. Here, using the $2\pi/\omega$ formula, it is calculated that a shock occurring in the economic uncertainty of Türkiye affects financial cycles over 2.51 months ($2\pi/2.5$).

5. Conclusion

In this study, the effect of the Turkish economic policy uncertainty index (TEUI) on financial cycles was analyzed with both symmetric and asymmetric frequency domain causality tests for the period 2010:01-2024:12. The findings revealed that there is a significant but asymmetric relationship between TEUI and financial cycles in time and frequency dimensions. It was determined that decreases in economic uncertainty positively affect financial cycles, and that this effect is not limited to the short term but spreads to the medium and long term. On the other hand, it was observed that periods of financial contraction cause economic uncertainty to increase in the short term. This bidirectional and asymmetric relationship shows a dynamic and complex interaction between policy uncertainty and financial cycles.

Based on this, it is observed that reducing economic uncertainties not only creates short-term market confidence but also brings about a permanent improvement in financial cycles. Therefore, implementing economic policies within a transparent, predictable, and consistent framework is critical for the sustainability of financial stability. The findings show policymakers' uncertainty-reducing discourses can be effective during financial contraction periods. In this context, the clear messages that the economic management gives to the market in times of crisis will prevent possible panic and speculative movements. While excessive risk appetite and asset bubbles may occur during expansion periods of financial cycles, credit tightening and liquidity problems emerge during contraction periods. Therefore, macroprudential tools such as credit growth, capital buffers, and liquidity ratios should be used proactively in order to limit fluctuations caused by uncertainty. The Central Bank should plan liquidity management simultaneously with early warning systems based on the uncertainty index. In addition, the TEUI used in the study offers a significant advantage in capturing country-specific dynamics. The more effective use of this index by economic management, financial analysts, and investors in decision-making processes will contribute to better management of uncertainty-related risks.

Although this study has important contributions, the analysis is focused only on the Turkish economy; therefore, the generalizability of the findings is limited. Conducting similar analyses in countries with different institutional structures and financial depths can contribute to the comparative evaluation of the results. Additionally, future studies would benefit from a more component-based analysis, examining the separate effects of different components of financial cycles, such as the housing market, stock market, and credit market.

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
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest
There is no potential conflicts of interest in this study.

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