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TVP-VAR FREQUENCY CONNECTEDNESS ANALYSIS ON CPI-BASED MONTHLY REAL RETURN VOLATILITY OF FINANCIAL INVESTMENT INSTRUMENTS

Abstract

Purpose: This study explores volatility transmission among the real returns of financial investment instruments, using the Diebold-Yilmaz approach and data from the Turkish Statistical Institute. The dataset includes monthly real return rates of instruments like Gross Interest Rate (GIR) for deposits, ingot Gold (GOLD), Istanbul Stock Exchange 100 Index (BIST-100), United States Dollar (USD), Euro (EUR), and Government Domestic Debt Instruments (GDDI) from January 2005 to April 2023.

Methodology: Real return rates were adjusted using the Consumer Price Index (CPI). Absolute values of real returns served as volatility proxies. To evaluate volatility spillover among these instruments, the Time-Varying Parameter Vector Autoregressive (TVP-VAR) frequency connectedness approach was utilized.

Results: The average of the Total Connectedness Index (TCI) suggests 40.37% of error variance in investment instruments is due to network connectedness, with short-term and long-term values at 33.95% and 6.41%, respectively. Dynamic TCI values spiked during events like the 2008 crisis, 2018 and 2021 exchange rate shocks, and COVID-19. USD and EUR consistently caused net volatility spillovers, GOLD in the long run, GDDI in the short run and aggregate. GIR was most impacted by network shocks. The study also examined the Net Pairwise Connectedness Index (NPCI) to identify dominant instruments in the network.

Conclusion: The findings show the interdependencies and significant roles of particular investment instruments in the transmission of volatility, offering insights for portfolio diversification and risk management.

Keywords: Real return, CPI, TVP-VAR frequency connectedness, volatility

1. Introduction

The concept of volatility is defined as the change in the price of a product in financial markets within a certain period of time. This concept can also be used in terms of volatility, mobility, fluctuation and similar meanings. Especially with the increasing integration among financial markets, the volatility in one market can also affect the other. This situation is referred to as "volatility spillover". Since these volatilities on financial investment instruments lead to uncertainty, they emerge as a risk factor for investors. As a matter of fact, when making investment decisions, investors look at whether a shock in one market affects the other market. Therefore, estimating volatility spreads among financial investment instruments is of great importance for risk management and effective portfolio diversification for both investors and financial institutions (Poon & Granger, 2003; Verma & Jackson, 2012; Topaloğlu, 2020; Cao & Wen, 2019).

With the developing technology, today's investors are able to invest in global stock exchanges as well as in their own countries. Due to the increasing risks with these investments, investors prefer to invest in a wide range in order to minimize risks while forming their investment portfolios, and therefore they apply to different investment instruments. At this point, traditional investment instruments such as foreign currency and gold have been among the most preferred investment instruments by investors. Due to the high volatility of foreign exchange markets, risk-seeking investors who aim to earn higher returns often invest their money in these markets. Gold, on the other hand, is an investment instrument that is seen as a safe harbor by investors, especially during periods of increased uncertainty (Baur & Lucey, 2010). Moreover, investment instruments such as the Gross Interest Rate (GIR) for deposits, the Istanbul Stock Exchange 100 (BIST-100) Index, and Government Domestic Debt Instruments (GDDI) are among the alternative investment areas where savings are evaluated in Turkey. Such investment instruments are affected by many factors such as economic developments, market conditions, political factors and even developments in international markets, and may show high volatility over time. Therefore, it is important to understand the interaction of investment instruments with each other and the volatility spread mechanism among them for an effective portfolio diversification.

In the literature, there are many studies on the relationship between various financial investment instruments. However, in addition to the financial assets used in these studies, methods used and the time period (daily, weekly, monthly, etc.) vary. While some of the empirical studies focused on the effect between investment instruments, others investigated the causal relationship between these instruments (Wang & Chueh, 2013; Bhunia, 2013; Başarır, 2019; Cingöz & Kendirli, 2019; Güney & Ilgın, 2019; Jain & Biswal, 2019). On the other hand, as financial markets become increasingly integrated, strong correlations emerge among financial assets, leading to the transmission of volatility from one market to another. These volatility spillovers also lead to the transmission of market risks. In line with these developments, the number of studies on volatility spillovers among financial investment instruments is increasing day by day.

For example, Sumner et al. (2010), used weekly data for the period from 1 October 1970 to 25 April 2009 to reveal the interrelationship between gold, stock and bond returns and volatilities with the spillover index approach of Diebold and Yilmaz (2012). According to the results, there was no evidence of return spillovers for the whole sample, but evidence of volatility spillovers was recorded. Return spreads were high in the early 1980s, mid-1990s, and the 2008 crisis, while volatility spreads were high in the late 1970s, early 1990s, and the 2008 crisis.

Badshah et al. (2013) revealed the spillover between stock, gold, and exchange rate volatility indices and the causality relationship between them, using daily data for the period from 3 June 2008 to 30 December 2011, defined by Rigobon's (2003) heteroscedasticity approach. The findings of the study showed that increased stock market volatility was associated with increased gold and exchange rate volatility. They also found a significant unidirectional spillover from the stock market to gold and exchange rates.

Shahrazi et al. (2014) used daily data from 2007 to 2013 to investigate the volatility and contagion between Iranian gold and foreign exchange markets using the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model. The findings showed that when a shock is transmitted from the gold market to the foreign exchange market, there is a two-way volatility spillover between the gold and foreign exchange markets. Similarly, Hein (2015) examined the connection and volatilities between the S&P 500 stock index, gold, crude oil and exchange rate (CHF/USD) returns between January 1999 and December 2013 using the GARCH model. The analysis showed that there is a significant contagion between the return volatilities of the variables. Moreover, a positive relationship was also found between gold and oil, while a negative relationship was found between gold and the exchange rate. The study also revealed that gold was a safe investment instrument during the 2008 crisis.

By using weekly data from 6 January 1987 to 22 July 2014, Antonakakis and Kizys (2015) investigated the dynamic connectedness between the returns and volatility of commodities (gold, silver, platinum, palladium) price, crude oil price and exchange rate (EUR/USD, JPY/USD, GBP/USD, CHF) /USD) markets with the generalized VAR method of Diebold and Yilmaz (2012). They found that gold, silver, platinum, CHF/USD and GBP/USD exchange rates were net transmitters of return and volatility spillovers during the sampled period, while palladium, crude oil, EUR/USD and JPY/USD exchange rates were net receivers. It was also revealed that gold is the largest volatility transmitter, exhibiting a strong bidirectional correlation between gold and silver, platinum and palladium in terms of bilateral return spreads.

Roy and Roy (2017) investigated the extent of financial contagion in Indian asset markets using daily data from 3 April 2006 to 31 March 2016. They used the commodity future price index, bond price, exchange rate, gold price and stocks as variables and daily returns of assets was estimated by the DCC-MGARCH method, while volatility spillover estimation was performed by a generalized VAR approach. The stock market was found to have the highest financial contagion, while the gold market was observed to have the lowest financial contagion. Furthermore, it was found that whilst gold, bonds, and foreign exchange were net volatility receivers, commodities and equities were net volatility transmitters.

Şenol (2021) used the GARCH model to study the volatility correlations and spillovers among the BIST-100 index, currency rate, interest rate, and CDS premiums from 2 January 2010 to 10 April 2020. The findings show that there is a unidirectional volatility spillover from CDS premiums to the exchange rate and that there is a mutual volatility spillover between the exchange rate and the BIST 100 index and interest rate, and between CDS premiums and the interest rate. Additionally, it has been determined that there is a positive volatility relationship between CDS premiums and exchange rates and interest rates, and a negative volatility relationship between the BIST 100 index and these two factors.

Cihangir et al. (2020) investigated the interaction between returns by examining the dynamic effect between four investment instruments (gold, foreign exchange, stock market and interest return) using the Vector Autoregressive (VAR) method from January 2002 to November 2019. They found that due to a shock in one financial instrument, other financial instruments reacted in the same way in the first period and vice versa in subsequent periods. In the same way, Şeker (2021) analyzed the interaction between interest rates, USD, EUR, gold, the BIST 100 index and government domestic debt instrument returns for the period 2005 to 2021 using the VAR approach. The results of the impulse-response analysis revealed that all return variables responded positively to the shocks that occurred in them in the first period. In addition, it was also determined that there were both complementarity and substitution relationships between the return variables, and at the same time, government domestic debt instruments, interest and USD returns were more in interaction with each other.

Using daily data from February 2017 to February 2021, Önem (2021) revealed volatility interaction among gold and silver price returns and BIST Mining Index returns with the diagonal VECH GARCH approach. According to the results, intense volatility clusters were determined in gold and silver price returns and BIST Mining Index returns, and these volatilities were found to have permanent effects. Wen et al. (2021) examined the dynamic volatility spillovers between the Chinese stock market and commodity markets from May 2009 to June 2020, using the TVP-VAR approach. They revealed that there was a very high correlation between the stock market and commodity prices and that the stock market acts as a net shock receiver. On the other hand, it was found that the volatility between the stock market and the commodity market increases during crisis periods. Correspondingly, Ahmed and Huo (2021), investigated a dynamic relationship between the Chinese stock market, commodity markets and global oil prices with daily data for the period between July 2012 and June 2017, by using a three-variable VAR-BEKK-GARCH model. They found that there were a unidirectional return and volatility spillover effect from the Chinese stock market and the global oil market to the commodity market, as well as a unidirectional return spillover effect from the oil market to the Chinese stock market.

Yilmaz and Kılıç (2022) investigated the return and volatility interaction among interest rate, gold, USD and EUR investment instruments with weekly data from January 2010 to July 2021, using the VAR Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) method. They revealed that there was a bidirectional return interaction between interest rate-USD and USD-EUR, and a one-way return interaction between interest rate to EUR and gold to USD. They also determined that volatility interaction is bidirectional between USD-EUR, gold-USD, EUR-gold, and unidirectional from USD to gold.

Şak and Öcal Özkaya (2022) investigated the volatility spillovers between USD, EUR, gold and the BIST 100 index with daily data from January 2000 to August 2022, using the Diebold and Yilmaz (2012) approach. They found that EUR and USD were volatility transmitters, while gold and the BIST 100 index were volatility receivers. According to the bilateral connectedness, gold and the BIST 100 index were dominated by the USD, and in recent years, there has been a spillover from gold to the BIST 100 index.

In the post-COVID-19 period, a trend of rising inflation has emerged in the world economy. Developing markets, including Turkey, have been significantly affected by this situation. In Turkey, alongside dramatic increases in inflation, currency-related risks have escalated, leading to uncertainties in investors' portfolio formation efforts. The country's unique political risks, along with fluctuations in the currency, have increased these uncertainties. This situation in Turkey did not start only in the post-COVID-19 period; its roots go back further. For instance, the currency fluctuation experienced in August 2018 negatively impacted all markets and caused structural ruptures. Naturally, in such situations, the risk transmission and spread in portfolios formed among traditional investment instruments have become significant issues. When we examined the literature, we noticed a gap in the comprehensive examination of risk transmission among traditional investment instruments based in Turkey and, more importantly, in studies on inflation-based real returns. Additionally, the lack of application of the Diebold-Yılmaz connectedness approach emerged as a notable shortcoming.

Therefore, we examine the volatility pass-through between inflation-adjusted real returns announced monthly by the Turkish Statistical Institute (TSI). Our research applies the TVP-VAR frequency method based on the Diebold-Yılmaz connectedness approach. In this way, short- and long-term volatility transmissions between traditional investment instruments in Turkish financial markets are revealed. For this purpose, real return rates on gross deposit interest, gold bullion, the Borsa Istanbul 100 Index, the US dollar, EURO and Government Domestic Debt Securities, which are the most popular instruments by investors in Turkish financial markets, are defined as variables in connectivity analysis. Volatilities of real return rates were obtained from the absolute values of returns based on Poon's (2005) study. In other words, the absolute values of CPI-based monthly real returns were used as proxy values for volatility values. Summary statistics show that the volatilities of the financial instruments mentioned are flat and skewed to the right, and also stationary and have an ARCH effect. In addition, the Elliott, Rothenberg, and Stock (ERS) unit root test result shows that the volatility series are stationary at level. Thus, we demonstrate that the volatility connectedness in the network formed by these financial investment instruments can be analyzed with a Time-Varying Parameter Vector Autoregressive (TVP-VAR) based approach. In our study, we use the novel TVP-VAR frequency connectedness approach proposed by Chatziantoniou et al. (2021), which effectively benefits from the essence of the works of Baruník and Krehlík (2018) and Antonakakis et al. (2020). The paper is organized as follows: an overview of the TVP-VAR Connectedness Approach in the time and frequency domains comes first, then a discussion of the dataset. The findings are explained in the parts that follow. The study concludes with a summary of the findings and their consequences.

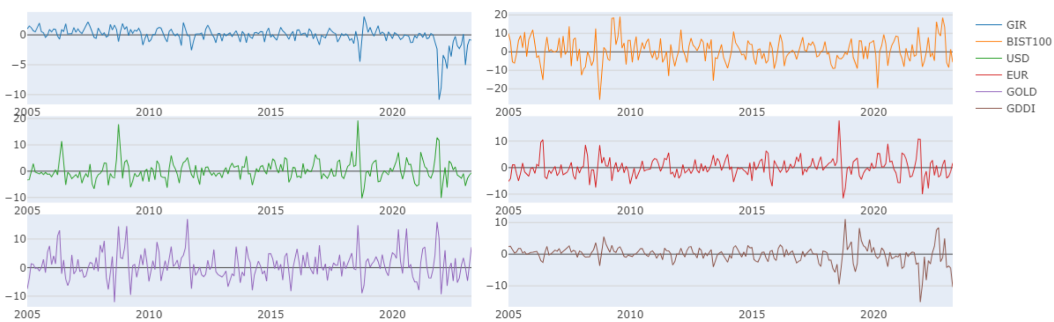
2. Data set

In this study, the volatility pass-through among the real returns of the investment instruments most preferred by the investors in the Turkish financial markets will be examined by means of the Diebold-Yilmaz (2012; 2014) approach. For this purpose, data from the Turkish Statistical Institute (TSI) database on monthly real return rates of investment instruments like the Gross Interest Rate (GIR) for deposits, ingot Gold (GOLD), the Istanbul Stock Exchange 100 Index (BIST-100), United States Dollar (USD), Euro (EUR) and Government Domestic Debt Instruments (GDDI) between January 2005 and April 2023 were calculated by reducing the

Consumer Price Index (CPI). Figure 1 illustrates the real return series of financial investment instruments. The data set can be downloaded from TSI's website[1]. TSI calculates the returns of assets included in the real return rates of financial investment instruments as follows.

- Deposit interest return rate calculations are made using the weighted average deposit interest rates applied to savings deposits actually opened in banks.
- The monthly average of the combined index of the 1st and 2nd session closing prices obtained from Borsa Istanbul (BIST 100) is used in the stock market index. The BIST 100 index is calculated from the stocks of the 100 companies with the largest market value and daily average trading volume among stocks that have been traded on the stock exchange for at least 60 days.
- US Dollar and Euro are the 1-month average of the foreign exchange buying rate of the Central Bank of the Republic of Turkey for 1 US Dollar and 1 Euro.
- Istanbul Stock Exchange monthly average gold bullion prices (TL/gr) are used in gold prices.
- Real return rates of government domestic debt securities are calculated using the "BIST-KYD GDS All Index" within the scope of BIST-KYD GDS Indices published by Borsa Istanbul. This index reflects the yields of discounted and fixed-interest coupon government domestic debt securities traded in the debt securities market covering all maturities (TSI, 2024).

Figure 1 Real return series of financial investment instruments



Source: Authors' own calculations

3. *Volatility series*

When working with a monthly frequency data set, choosing the appropriate volatility model becomes a bit complicated. Simply selecting the most appropriate model among historical or conditional models based on predictive power using error metrics is an insufficient approach because this approach neglects whether the model is reliable and valid. The assumptions of the applied model should be checked with diagnostic tests. Generally, meeting these assumptions is related to the number of observations. Generalized Autoregressive Conditional Heteroskedastic (GARCH) family models, which are widely used, have difficulties in their application to low-frequency data sets due to both the number of observations and diagnostic tests.

Hwang and Pereira (2006) recommend using a minimum of 250 observations for ARCH(1) models and at least 500 observations for GARCH(1,1) models to reduce biases and convergence problems. GARCH estimates derived from low-frequency data also face the problem of temporal aggregation, as highlighted by Drost and Nijman (1993). In small samples, maximum likelihood estimates for the GARCH(1,1) model exhibit significant negative bias, and frequently the estimates do not comply with Bollerslev's non-negativity conditions, causing the estimated model to fail diagnos-

1 https://data.tuik.gov.tr/Kategori/GetKategori?p=Enflation-ve-Fiyat-106

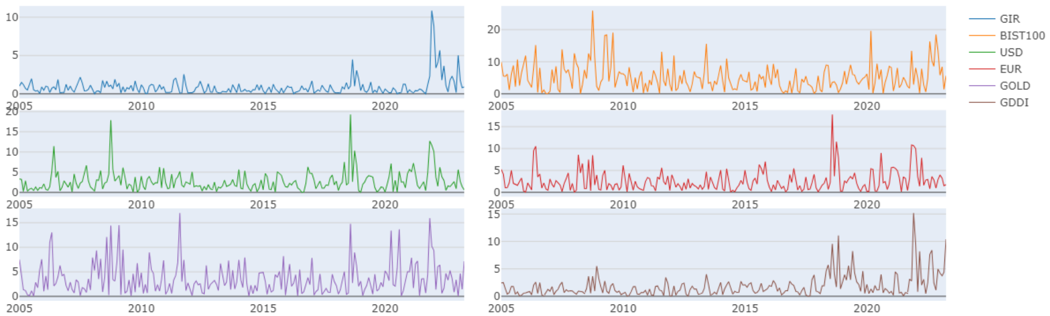
tic tests. Heteroskedastic Autoregressive (HAR) models, also from the GARCH family, are not a suitable approach for our study since they obtain monthly volatilities using daily data. Additionally, a commonly used approach to forecasting future volatility based on the average change in historical volatility is the exponentially weighted moving average (EWMA). According to Arı (2022), EWMA models showed better prediction results than both the GARCH family and Conditional Autoregressive Range (CARR) type models. Since CARR models are range-based and our data set does not contain the lowest and the highest values, they are not suitable for use in this study. In addition, the change of the lambda coefficient used in the EWMA model does not produce good results because it is sensitive to capturing volatility clouds.

For this reason, Open-High-Low-Close (OHLC) based volatility approaches, which do not have complex assumptions, are preferred, especially in volatility connectivity studies. Since the data we have does not include OHLC data, the most appropriate approach seems to be to accept the absolute values of the return data as volatility data.

It has been revealed in the literature that using monthly frequency data in volatility calculations has various advantages. For example, Figlewski (1997) found that the size of the forecast error doubled when daily data over a 24-month period was used to forecast volatility rather than monthly data. Because volatility mean reversion can be difficult to manipulate using high-frequency data, weekly or monthly volatility forecasts are sometimes preferable when applications extend beyond a 10-year time horizon. Current practice is to use the monthly absolute value as an indicator of macro volatility because many macroeconomic variables are only accessible in the monthly range (Poon, 2005).

The volatilities of real return rates of the series were obtained based on the study of Poon (2005) over the absolute values of returns. In other words, the absolute values of CPI-based monthly real returns were used as proxy values for volatility values. Figure 2 showcases the real return volatility series of these financial investment instruments. It is evident from the figure, the 2008 Global Financial Crisis, the currency shock in August 2018, the announcement of the COVID-19 pandemic in March 2020, the currency shock in December 2021, and the Russia-Ukraine war that started in late February 2022 caused an increase in volatility in almost all series.

Figure 2 Real return volatility series of financial investment instruments



Source: Authors' own calculations

Summary statistics for the volatility series, as detailed in Table 1, reveal that the volatilities of the financial investment instruments exhibit skewness and excess kurtosis, and lack an ARCH effect. The Jarque-Bera (JB) test statistic further corroborates the non-normal distribution of these series at a 1% significance level. To assess stationarity, the Elliott-Rothenberg-Stock (ERS) unit root test, particularly suited for distributions with skewness and kurtosis, was employed. The results from the ERS test indicate that all series are stationary at their level. This confirms the appropriateness of the dataset for analysis using the TVP-VAR model.

Table 1 Summary statistics of volatility series

Statistics	GIR	BIST-100	USD	EUR	GOLD	GDDI
Mean	0.89	**5.159**	2,742	2,609	3,598	1,853
Variance	1.445	18,128	6,989	6,277	10,703	4,343
Skewness	4.742***	1.540***	2.823***	2.184***	1.653***	2.925***
Ex.Kurtosis	30.382***	3.362***	11.996***	7.120***	3.050***	11.245***
JB	9285.995***	190.556***	1611.339***	639.696***	185.509***	1472.901***
ERS	-4.594***	-2.839***	-5.928***	-3.211***	-2.788***	-3.259***
Q(20)	126.134***	17.411**	26.421***	19.954**	13.353	117.170***
Q^2(20)	74.775***	22.470***	10.534	21.484***	11.410	55.156***
Spearman	GIR	BIST-100	USD	EUR	GOLD	GDDI
GIR	1.000					
BIST-100	0,097	1.000				
USD	0.162	0.258	1.000			
EUR	0.079	0.195	**0.546**	1.000		
GOLD	0.073	**0.049**	0.249	0.300	1.000	
GDDI	0.417	0.265	0.295	0.277	0.187	1.000

Note: ***, **, * denote significance levels at 1%, 5% and 10%.
Source: Authors' own calculations

Additionally, Table 1 elaborates the unconditional correlation matrix among the real return volatilities of financial investment instruments. The most substantial correlation is observed between USD and EUR with 0.546, followed by GDDI and GIR having a value of 0.417. With a value of 0.049, the correlation between the BIST-100 index and GOLD is the weakest.

3.1 Volatility connectedness via the TVP-VAR approach in the time domain

In their groundbreaking work, Diebold and Yilmaz (2012; 2014) introduced the connectedness approach, which uses both static and dynamic time-series network analysis to identify linkage and spillover within a given network. The dynamic method uses the rolling window VAR approach, while the static method uses a Vector Autoregression (VAR) model for the entire dataset. Thus, it reveals the return or volatility spreads within the network. This method has grown in popularity because it allows researchers to draw meaningful conclusions about networks. By using the TVP-VAR technique, Antonakakis et al. (2020) improved the connectedness approach that Diebold and Yilmaz (2014) had initially constructed. The TVP-VAR-based connectedness approach has several advantages, including insensitivity to outliers, no data loss, no requirement to specify arbitrary window size, and application to low-frequency datasets. This enhancement increases the variance-covariance matrix's adaptability by incorporating forgetting components and applying a Kalman filter. These developments make this method especially appropriate for researching the dynamic relationships between the volatilities of financial assets. The basic work of Koop and Korobilis (2013; 2014) on VAR models and the use of EWMA forgetting factors is incorporated into this methodology. The structure and features of the TVP-VAR(2) model, selected based on Bayesian Information Criteria (BIC), can be expressed as follows:

$$y_t = A_t z_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{2}$$

$$vec(A_t) = vec(A_{t-1}) + \upsilon_t \qquad \upsilon_t \sim N(0, S_t) \tag{3}$$

In the above model, expressed in matrix form, the properties of vectors and related matrices are listed as follows. The vector z_{t-1} is a $2k \times 1$ vector, and the vector y_t has a dimension of $k \times 1$. A_t is a $k \times 2k$ matrix. Vectors ϵ_t and υ_t are $k \times 1$ and $2k^2 \times 1$ dimensional vectors, respectively. Additionally, matrices Σ_t and S_t are time-varying variance-covariance matrices, with dimensions $k \times k$ and $2k^2 \times 2k^2$, respectively. The last vector is $vec(A_t)$ with a $2k^2 \times 1$ dimension. This structure of matrices and dimensions provides a thorough framework for dissecting the time-varying relations in the model.

Generalized Forecast Error Variance Decomposition (GFEVD) values obtained from the vector model are the most basic element of the Diebold and Yılmaz methodology. This approach is very important to investigate the effects of shocks to the variables in a network on the dynamic relationships of the variables in a time series framework. Using the equation $y_t = \sum_{h=0}^{\infty} A_{ht}\epsilon_{t-h}$, the Time-Varying Parameter Vector Moving Average (TVP-VMA) model is obtained from the TVP-VAR model, where $A_0 = I_k$ and I_k is an identity matrix. As a result of this transformation, it becomes easier to evaluate the effect of the shock in variable j on the other variable i. The TVP-VMA transformation allows the impact of shocks on variable i to be measured by variable j in terms of both magnitude and direction at various time intervals. This assessment is made possible by a comprehensive calculation process described in the equation below, which gives a clear picture of the impact over time.

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\sum_{h=0}^{H-1}\left(\epsilon_i^T A_{ht}\Sigma_t\epsilon_j\right)^2}{\left(\epsilon_i^T\Sigma_t\epsilon_j\right)\sum_{h=0}^{H-1}\left(\epsilon_i^T A_h\Sigma_t A_{ht}^T\epsilon_i\right)} \tag{4}$$

One can obtain $\sum_{j=1}^{m}\tilde{\phi}_{ij,t}^{g}(H) = 1$ and $\sum_{i,j=1}^{m}\tilde{\phi}_{ij,t}^{g}(H) = k$ using the above equation. As mentioned before, Diebold and Yılmaz (2012; 2014) proposed connectedness indices based on the GFEVD technique. These indices are determined by computing the proportion of the forecast error change of a particular variable that can be attributed to shocks to other variables in the system. These calculations are made as follows.

Directional connectedness to others - TO

$$TO_{jt}(H) = \sum_{i=1, i\neq j}^{k}\tilde{\phi}_{ij,t}^{g}(H) \tag{5}$$

Directional connectedness from others - FROM

$$FROM_{jt}(H) = \sum_{i=1, i\neq j}^{k}\tilde{\phi}_{ji,t}^{g}(H) \tag{6}$$

Net total directional connectedness - NET

$$NET_{jt}(H) = \sum_{i=1, i\neq j}^{k}\tilde{\phi}_{ij,t}^{g}(H) - \sum_{i=1, i\neq j}^{k}\tilde{\phi}_{ji,t}^{g}(H) = TO_{jt} - FROM_{jt} \tag{7}$$

Total connectedness index – TCI

$$TCI_t(H) = k^{-1}\sum_{j=1}^{k} TO_{jt} \equiv k^{-1}\sum_{j=1}^{k} FROM_{jt} \tag{8}$$

Net pairwise directional connectedness – NPDC

$$NPDC_{ij,t}(H) = \tilde{\phi}_{ij,t}^{g}(H) - \tilde{\phi}_{ji,t}^{g}(H) \tag{9}$$

3.2 *Volatility connectedness via the TVP-VAR approach in the frequency domain*

We use the novel TVP-VAR frequency connectivity methodology introduced by Chatziantoniou et al. (2021). In fact, the novel approach skillfully combines the basic concepts proposed by Baruník and Krehlík (2018) and expanded by Antonakakis et al. (2020). Additionally, the methodology applied in this study is consistent with studies presented by Huang et al. (2023) and Akbulut et al. (2023), and it includes a comprehensive appendix that serves as a guide to put this methodology into practice. The TVP-VAR frequency connectivity model makes it possible to analyze volatility dependence over various periods by decomposing volatility dependence into short- and long-term components and accounting for changes in coefficients and the variance-covariance matrix over time. Interestingly, it does this without suffering the negative effects of adopting an arbitrary sliding window, including variable parameters, data loss, or outliers.

One can evaluate the spectral density of y_t at frequency ω by using the frequency response function given as $\Psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where i is the imaginary unit of a complex number (the square root of -1) and ω is the frequency. A Fourier transform of the TVP-VMA(∞) effectively describes the spectral density of y_t across ω. Thus,

$$S_y(\omega) = \sum_{h=-\infty}^{\infty} E(y_t y_{t-h}')e^{-i\omega h} = \Psi\left(e^{-i\omega}\right)\Sigma_t\Psi'\left(e^{i\omega h}\right). \tag{10}$$

As a result, we may calculate the GFEVD, which is frequency domain integration of the spectral density and the GFEVD. This calculation is performed as follows:

$$\phi_{ij,t}^{g}(\omega) = \frac{(\Sigma_t)_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Psi\left(e^{-i\omega h}\right)\Sigma_t\right)_{ij,t}\right|^2}{\sum_{h=0}^{\infty}\left[\Psi\left(e^{-i\omega h}\right)\Sigma_t\Psi'\left(e^{i\omega h}\right)\right]_{ii}} \tag{11}$$

$$\tilde{\phi}^{g}_{ij,t}(\omega) = \frac{\phi^{g}_{ij,t}(\omega)}{\sum_{i=1}^{k} \phi^{g}_{ij,t}(\omega)} \tag{12}$$

The equation for aggregating all frequencies within a specified range of interest is given by $\tilde{\phi}^{g}_{ij,t}(d) = \int_a^b \tilde{\phi}^{g}_{ij,t}(\omega)d\omega$, where d is defined as the interval (a, b), with both a and b falling within the spectrum (- π, π), ensuring that $a < b$. Thus, the frequency connectedness metrics can be outlined as follows:

$$\mathrm{TO}_{jt}(d) = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^{g}_{ij,t}(d) \tag{13}$$

$$\mathrm{FROM}_{jt}(d) = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^{g}_{ji,t}(d) \tag{14}$$

$$\mathrm{NET}_{jt}(d) = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^{g}_{ij,t}(d) - \sum_{i=1, i\neq j}^{k} \tilde{\phi}^{g}_{ji,t}(d) = \mathrm{TO}_{jt} - \mathrm{FROM}_{jt} \tag{15}$$

$$\mathrm{TCI}_{t}(d) = k^{-1} \sum_{j=1}^{k} \mathrm{TO}_{jt} \equiv k^{-1} \sum_{j=1}^{k} \mathrm{FROM}_{jt} \tag{16}$$

$$\mathrm{NPDC}_{ij,t}(d) = \tilde{\phi}^{g}_{ij,t}(H) - \tilde{\phi}^{g}_{ji,t}(H) \tag{17}$$

Then all the frequency connectedness metrics may be computed, which gives information on spillovers in the particular frequency range denoted by d. This is stated in the following way:

$$\phi(H) = \sum_{d} \phi(d). \tag{18}$$

Within this context, a group of connectedness metrics [NPDC, TO, FROM, NET, TCI], each of which has been previously discussed, is represented by the symbol φ(·). This suggests that the totality of frequencies associated with the frequency connectedness measure is in agreement with the corresponding connectedness seen in the time domain.

4. *Empirical findings*

Total Connectedness Index (TCI): The average TCI results among financial investment instruments are presented in Table 2. The TCI shows that 40.37% of the variance in these financial investment instruments - specifically, the generalized estimated error variance - is due to the connectedness relationship in these networks. TCI values are 33.95% in the short term (1-12 months) and 6.41% in the long term (12-inf).

The diagonal entries of the 6x6 matrix depicted in Table 2 represent the variance in prediction errors attributed to the variables themselves. In contrast, the off-diagonal elements detail how the error variances are broken down among the variables. In accordance with the data, the BIST-100 index is the investment instrument with the highest self-induced volatility in total data with 72.91%. In the short run, the BIST-100 index accounts for 64.77%, whereas in the long run, it is realized as GDDI with 12.3%. As a result, it is possible to say that the BIST-100 index and GDDI are investment instruments least affected by the network. In contrast, investment instruments with the lowest self-induced volatility spillovers and thus most affected by network spillovers are USD (47.32% and 40.24%, respectively) in the total and short run, and EUR (6.43%) in the long run. USD is the investment instrument that is most affected by the network, with 52.68% (FROM), and with 63.13% (TO), it also has the most volatility spreads in the network. In the short and long run, USD is the investment instrument most affected by the network with 43.77% (FROM) and 8.9% (FROM), respectively, while USD (in the short run) and EUR (in the long run) exhibited the highest volatility spreads in the network with 53.96% (TO) and 9.52% (TO), respectively.

Net total directional connectedness: NET values are obtained from the difference between the volatility emitted by a variable in the network and the volatility affecting it. A positive NET value indicates that the variable is a net volatility transmitter in the network, while a negative NET value indicates that the variable is a net volatility receiver. According to the data given in Table 2, USD is the highest volatility transmitter in the network with 10.45%, followed by EUR (8.46%) and GDDI (1.12%), respectively.

The highest net volatility transmitter in the short term is USD with 10.19%, while in the long run, it is EUR with 2.85%. GIR acts as the highest net volatility receiver for all periods.

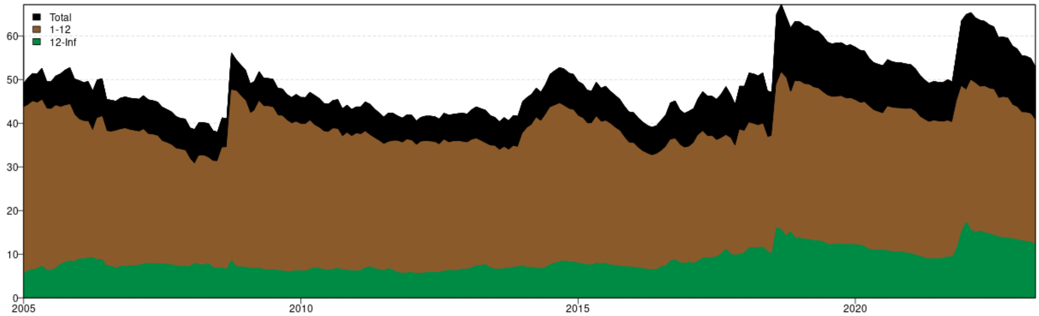
Table 2 Total, short-run, and long-run average TCI

Total	GIR.Total	BIST-100.Total	USD.Total	EUR. Total	GOLD. Total	GDDI. Total	FROM. Total
GIR	65.16	1.13	6.27	5.02	3.13	19.27	34.84
BIST-100	0.80	72.91	12.16	5.48	3.88	4.77	27.09
USD	2.23	8.54	47.32	22.57	11.61	7.72	52.68
EUR	1.72	4.21	22.04	50.57	13.66	7.8	49.43
GOLD	1.46	2.85	12.89	15.55	63.77	3.48	36.23
GDDI	15.09	4.11	9.76	9.27	3.7	58.08	41.92
TO	21.3	20.84	63.13	57.89	35.98	43.04	242,19
Inc.Own	86.47	93.75	110.45	108.46	99.76	101.12	**TCI**
Net	-13.53	-6.25	10.45	8.46	-0.24	1.12	**40.37**
Short-run	**GIR.1-12**	**BIST-100.1-12**	**USD.1-12**	**EUR.1-12**	**GOLD.1-12**	**GDDI.1-12**	**FROM.1-12**
GIR	55.34	1.04	4.92	3.83	2.52	15.17	27.48
BIST-100	0.69	64.77	11.2	4.95	3.29	4.25	24.38
USD	1.8	7.83	40.24	18.5	9.41	6.23	43.77
EUR	1.46	4.0	19.01	44.14	11.4	6.88	42.76
GOLD	1.23	2.71	11.37	13.91	57.27	3.05	32.26
GDDI	11.76	3.71	7.45	7.18	2.97	45.78	33.07
TO	16.94	19.29	53.96	48.37	29.59	35.57	203.72
Inc.Own	72.28	84.06	94.19	92.51	86.86	81.35	**TCI**
Net	-10.54	-5.08	10.19	5.62	-2.67	2.5	**33.95**
Long-run	**GIR.12-Inf**	**BIST-100.12-Inf**	**USD.12-Inf**	**EUR.12-Inf**	**GOLD.12-Inf**	**GDDI.12-Inf**	**FROM.12-Inf**
GIR	9.82	0.1	1.35	1.19	0.62	4.1	7.36
BIST-100	0.11	8.14	0.96	0.53	0.6	0.52	2.72
USD	0.43	0.71	7.09	4.08	2.2	1.49	8.9
EUR	0.26	0.21	3.02	6.43	2.26	0.93	6.67
GOLD	0.23	0.14	1.52	1.64	6.5	0.43	3.97
GDDI	3.32	0.4	2.31	2.09	0.73	12.3	8.85
TO	4.37	1.55	9.17	9.52	6.4	7.47	38.47
Inc.Own	14.19	9.69	16.26	15.95	12.9	19.77	**TCI**
Net	-2.99	-1.17	0.26	2.85	2.43	-1.38	**6.41**

Note: The findings of the study are derived from employing a TVP-VAR model with a two-lag order, selected on the basis of the Bayesian Information Criterion (BIC), and involve a forecast error variance decomposition looking 10 steps ahead. This analysis utilized the R programming language and the “ConnectednessApproach” package developed by Gabauer (2022). Important terminology used in the study includes “Inc.Own” to denote one’s own contributions, “TCI” for the Total Connectedness Index, “NET” indicating Net Total Connectedness, and “NPT” representing Net Pairwise Total Connectedness. The analysis categorizes the short run as a period of 1-12 months and the long run as any period extending beyond 12 months.
Source: Authors’ own calculations

Dynamic Total Connectedness Index: Dynamic TCI illustrates how the interconnections among the variables fluctuate over time. Figure 3 not only showcases the dynamic progression of the average total connectedness index but also its decomposition into short-term (1-12 months) and long-term (beyond 12 months) components. As depicted in Figure 3, dynamic TCIs undergo notable variations as time progresses. Accordingly, the highest connectedness between the series occurred in September 2018, with a value of 55.95%, which this points to the exchange rate shock experienced at that time. Connectedness, which started to decline after 2018, rose again (47.08%) in March 2020, the date when the COVID-19 pandemic was declared. Similarly, with the impact of the Russia-Ukraine war that started at the end of February 2022, the interconnectedness between the series increased to a serious level of 54.42%. In addition, the dynamic connectedness between the series increased significantly during the 2008 global financial crisis and the exchange rate shock in December 2021.

Figure 3 Dynamic TCI plots



Source: Authors' own calculations

Robustness analysis: We followed two ways to examine the sensitivity of our results: First, we examined return connectivity of the variables because in spillover analysis, return transmission and connectedness are used as an indicator of robustness. The second is to test the approach using different forecasting horizons. We make an alternative h-step forward estimation for the forecasting error variance decomposition obtained from the TVP-VAR model. We apply a 20-steps ahead forecasting horizon instead of 10. According to the average TCI tables given in Appendix A, the spillover index appears to have a comparable structure and pattern. This shows that connectivity analysis is not always sensitive to returns and forecast horizons. Similar approaches have also been commonly used as robustness checks in numerous previous studies (Diebold & Yilmaz, 2012; 2014; Billah et al., 2022).

Net Pairwise Directional Connectedness (NPDC): NPDC indicates bilateral volatility transfer between two variables, with positive NPDC values signifying dominance of one investment instrument over another, and negative values indicating the opposite. The Pairwise Connectedness Index (PCI) quantifies the intensity of the relationship between variables, with values spanning from zero (indicating a weak connection) to one (signifying a strong connection). Examining the pairwise volatility connectedness is essential for grasping how volatility shocks propagate across different investment instruments, particularly in times of crises or epidemics, and observing how these interactions change over time.

Table 3 displays NPDCI and PCI values, illustrating the connectedness between various investment instruments. The highest level of the pairwise connectedness is found between USD and EUR across all timeframes, with PCI values reaching 62.99% overall, 52.95% for the short run, and 10.06% for the long run. With an NPDCI of 0.53% overall and 1.05% in the long term, USD acts as a net transmitter, showing its influence over EUR. Conversely, in the short term, EUR becomes the net transmitter with an NPDCI of -0.51%, indicating its dominance over USD. In other words, in the total and long run, USD is the net volatility transmitter, EUR is the net volatility receiver, while in the short term, EUR is the net volatility transmitter and USD is the net volatility receiver. According to PCI values, the lowest pairwise connectedness for all periods (2.73% (total), 2.44% (short term), 0.29% (long term)) is found between GIR and the BIST-100 index. Based on an NPDCI value, as GIR is a net volatility transmitter in total (0.33%) and short term (0.34%), it acts as a net volatility receiver in the long term (-0.01%). The minimal NPDCI and PCI values between the two investment instruments indicate that these two investment instruments can be used effectively for portfolio diversification. As a matter of fact, according to the data in Table 3, it is observed that the lowest bilateral relationship emerged between GOLD and GDDI with an NPDCI value of 0.08%. Therefore, we have demonstrated that these two investment instruments are preferable for portfolio diversification.

Table 3 NPDCI and PCI

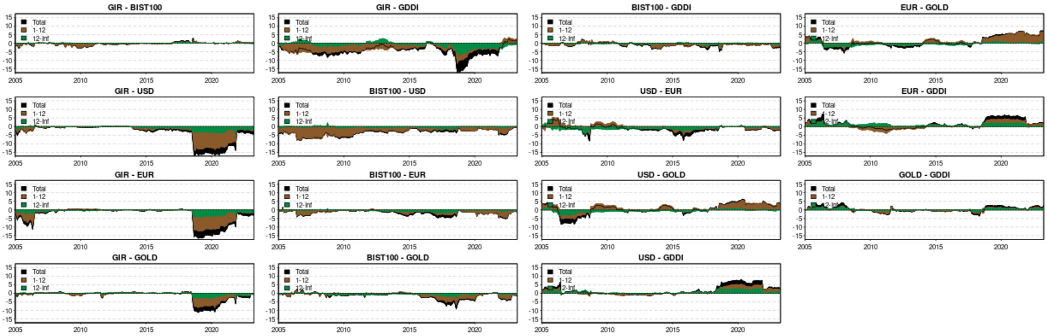
Time Domain	BIST-100	USD	EUR	GOLD	GDDI
GIR	0.33 (2.73)	4.04 (14.98)	3.30 (12.18)	1.67 (7.73)	4.18 (42.75)
BIST-100		3.62 (28.82)	1.26 (14.54)	1.03 (9.60)	0.66 (12.77)
USD			0.53 (62.99)	-1.28 (37.10)	-2.04 (28.57)
EUR				-1.88 (41.81)	-1.46 (27.52)
GOLD					-0.21 (11.61)
Frequency Domain Short-run (1 - 12 months)					
GIR	0.34 (2.44)	3.11 (11.81)	2.37 (9.49)	1.29 (6.20)	3.40 (33.42)
BIST-100		3.36 (26.48)	0.94 (13.44)	0.58 (8.53)	0.53 (11.47)
USD			-0.51 (52.93)	-1.95 (31.47)	-1.22 (22.36)
EUR				-2.50 (36.20)	-0.30 (22.58)
GOLD					0.08 (9.68)
Frequency Domain Long-run (12 – inf months)					
GIR	-0.01 (0.29)	0.92 (3.16)	0.92 (2.69)	0.38 (1.52)	0.77 (9.33)
BIST-100		0.25 (2.33)	0.32 (1.10)	0.45 (1.06)	0.12 (1.30)
USD			1.05 (10.06)	0.67 (5.63)	-0.81 (6.21)
EUR				-0.61 (5.61)	-1.16 (4.94)
GOLD					-0.92 (1.92)

Note: PCIs are presented in parentheses.
Source: Authors' own calculations

The net pairwise directional dynamic connectedness between the two variables is presented visually in Figure 4. GIR was a net receiver of volatility against other investment instruments throughout the whole period, and the impact of shocks received from USD, EUR, GOLD and GDDI has increased significantly after 2018. Similarly, the BIST-100 index acted a net receiver of volatility against other investment instruments. On the other hand, USD and EUR were net receivers of volatility against GOLD until 2008, while GOLD acted as a net receiver of volatility against these two investment instruments after 2008. Being a net volatility receiver against USD and EUR, the shocks received by the GDDI investment instrument increased after 2018. In addition, while EUR was a net volatility receiver against GDDI in the short term between 2008 and 2015, it became a net volatility transmitter investment instrument after 2015. Finally, while GOLD was a net volatility receiver against GDDI in the 2008-2018 period, it became a net volatility transmitter in other periods.

Considering the studies using the connectivity approach, the findings overlap with the study of Şak and Öcal Özkaya (2022). Similar to that study, USD and EURO financial instruments were found to be transmitters, and GOLD and BIST were found to be receivers. Although Şak and Öcal Özkaya (2022) used the rolling window VAR approach in their study and the period of the data set was longer, obtaining similar results shows that the approach is robust and that the relationship between financial assets in Turkey has a characteristic structure.

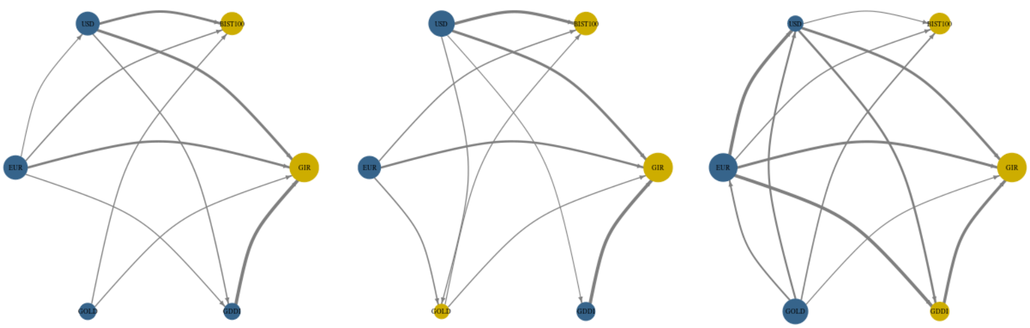
Figure 4 Net pairwise directional connectedness



Source: Authors' own calculations

Network plots: Figure 5 visually presents the bilateral relationships between investment instruments. This visual representation allows us to see the dynamic interaction between variables in a TVP-VAR based frequency connectedness analysis. Blue and yellow nodes indicate that the variable is a net volatility transmitter and a net volatility receiver, respectively. The direction and thickness of the arrows determine the direction and strength of the volatility spread between the variables. In both the overall and short-run network plots, the investment instruments represented by USD, EUR, and GDDI emerge as having dominant volatility within the network. They are the primary drivers of network dynamics, influencing the flow and transmission of volatility among the various investment instruments included in the analysis. Moreover, for both periods, the strongest volatility spillover is from GDDI to GIR. In the long term, USD, EUR and GOLD are the most dominant investment instruments in the network. Although Yılmaz and Kılıç (2022) examined the interaction between variables with a different methodology, they obtained results parallel to our findings. For example, the fact that USD and EURO are more dominant, in other words, a transmitter, as opposed to the GIR variable, can be seen as similar results. Another similarity in their studies is that the interaction between USD and EURO is an indication of a strong bilateral connectedness.

Figure 5 Network plots



Note: A time-domain network (left), a short-run network (middle), a long-run network (right).
Source: Authors' own calculations

5. *Conclusion*

In this study, the volatility pass-through between the real returns of selected financial investment instruments is analyzed using the innovative TVP-VAR connectedness approach in the frequency domain. For this purpose, firstly, the real return volatilities of financial investment instruments are obtained based on the study of Poon (2005), and then the time and frequency (short and long terms) connectedness between these investment instruments is revealed by using the method based on the approach of Diebold and Yilmaz (2012; 2014). According to the findings, while the total connectedness index (TCI) was 40.37%, it was 33.95% in the short run and 6.41% in the long run. The BIST-100 index is the investment instrument with the highest self-induced volatility in total and in the short term, which means that the BIST-100 index is the investment instrument that is least affected by the network. In the long run, the investment instrument with the highest self-driven volatility is GDDI. The investment instrument with the lowest self-induced volatility and thus most affected by the network is USD both in total and in the short term, while EUR is observed in the long term. This is an expected situation. As a matter of fact, since USD and EUR have become global investment instruments, shocks in other investment instruments can spread to these investment instruments in a short time. On the other hand, USD is an investment instrument that both transmits the highest volatility in the network and receives the highest volatility from the network. When we look at the dynamic total connectedness, we observe that the connectedness between these investment instruments increased significantly during periods of turbulence at both global and local levels, such as the 2008 global financial crisis, the currency shock experienced in our country in 2018 and 2021, the COVID-19 outbreak announced in March 2020, and the Russia-Ukraine war that started in February 2022. According to the NET values of the variables, USD (in total and in the short term) and EUR (in the long term) is the highest net volatility transmitter, while GIR is the highest net volatility receiver for all periods. When it comes to results of the net bilateral connectedness between variables, the highest net bilateral connectedness for all periods is between USD and EUR, while the lowest net bilateral connectedness is between GIR and BIST-100 index. A low degree of connectedness among investment instruments indicates that they can be used effectively in portfolio diversification. Therefore, this study reveals important results for investors, portfolio managers, risk managers and foreign exchange trading companies.

Another interesting result is that the spread through the network is higher in the short term, i.e. 84% of the total risk spread occurs in the short term. This is because USD and EUR are the most effective investment instruments in the network and have high volatility. This is an expected result. In an emerging market like Turkey, inflation is mostly caused by the effect of USD and EUR, the reserve currencies in the world, on raw material prices. Furthermore, this situation is affecting all financial markets, especially the low deposit interest rate and high inflation that emerged with the economic policies implemented in the last five years led to a high depreciation of the Turkish Lira. As a result, negative real deposit interest drove investors away from the local currency and increased demand in foreign exchange markets. Moreover, it led investors to stay away from local financial instruments such as BIST-100, GDDI, and GIR, and it impacted the connectedness index.

In addition, interest in the cryptocurrency market in Turkey is increasing dramatically. Considering the number of wallets in the country, it ranks among the top five countries in the world with the highest number of investors in the cryptocurrency market. This situation makes it necessary to reveal the relationship between cryptocurrency markets and traditional investment instruments. For example, the inflation-discounted real Bitcoin return, or the risk spread between a crypto stock market index and Turkish investment instruments can be revealed with the connectivity approach.

Another effective factor is the impact of emerging geopolitical risks on Turkish financial markets. Türkiye is affected by the conflicts occurring around it due to its geographical location. To reveal this situation, the interaction between geopolitical risk indices and markets can be examined with the same methods. It is expected that asymmetric connectivity analyses, especially those applied to reveal asymmetric effects, will provide more detailed results. After asymmetric return and volatility modeling, the difference between positive and negative volatility spreads can be analyzed using dynamic quantile connectedness and extended joint connectedness approaches.

We can summarize our recommendations for future studies.

1. Investigate the relationship between cryptocurrency markets and traditional investment instruments in Turkey. Provide in-

sights into risk management and portfolio diversification by determining how traditional markets impact or affect cryptocurrencies. Use connectedness approaches and cointegration approaches as a method when revealing this relationship.

2. Additionally, unlike the above suggestion, examining the asymmetric effects of cryptocurrency volatility on the dynamic total connectedness index of traditional investment instruments obtained in this study with Johansen cointegration or ARDL/NARDL bounds test methods can be the subject of a future study.
3. Examine the impact of geopolitical risks specific to Türkiye on Turkish financial markets. Another study suggestion is to reveal the dynamic interconnectedness between geopolitical risk indices and traditional investment instruments. This relationship can also be investigated with methods that reveal symmetric and asymmetric effects.
4. The difference in connectivity that occurs before and after exchange rate shocks is a separate research topic that needs to be addressed. Thus, it will be revealed what investment instrument groups will provide optimum portfolio diversity in the pre- and post-crisis periods.
5. Finally, examining the risk transfer with these conventional investment instruments, especially with banking and technology sectors, will help develop sector-oriented investment and risk strategies.

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Appendix A: Findings of robustness analysis

Table A1 Total, short-run, and long-run average TCI (return connectedness)

Total	GIR.Total	BIST100.Total	USD.Total	EUR.Total	GOLD.Total	GDDI.Total	FROM.Total
GIR	55.22	1.29	6.23	6.75	4.09	26.41	44.78
BIST-100	1.08	53.79	16.17	10.87	5.38	12.72	46.21
USD	1.1	13.56	39.77	23.71	12.75	9.11	60.23
EUR	0.96	8.99	23.87	41.07	16.47	8.63	58.93
GOLD	1.29	6.67	16.19	17.24	54.57	4.04	45.43
GDDI	18.77	8.91	11.44	11.32	4.04	45.52	54.48
TO	23.2	39.43	73.9	69.89	42.73	60.91	310.05
Inc. Own	78.42	93.22	113.67	110.96	97.3	106.43	cTCI/TCI
Net	-21.58	-6.78	13.67	10.96	-2.7	6.43	62.01/51.68
Short-run	**GIR.1-12**	**BIST100.1-12**	**USD.1-12**	**EUR.1-12**	**GOLD.1-12**	**GDDI.1-12**	**FROM.1-12**
GIR	44.09	1.08	4.72	5.18	3.07	20.03	34.08
BIST-100	0.82	45.1	13.34	8.95	4.55	10.12	37.78
USD	0.91	10.79	32.78	19.67	10.56	7.74	49.66
EUR	0.79	7.45	20.27	34.98	13.58	7.41	49.49
GOLD	1.13	5.42	13.96	15.08	46.89	3.65	39.25
GDDI	14.44	7.51	8.89	8.51	3.09	35.84	42.43
TO	18.08	32.25	61.17	57.38	34.85	48.95	252.69
Inc. Own	62.17	77.35	93.95	92.36	81.74	84.8	cTCI/TCI
Net	-16	-5.52	11.51	7.89	-4.4	6.52	50.54/42.11
Long-run	**GIR.12-Inf**	**BIST100.12-Inf**	**USD.12-Inf**	**EUR.12-Inf**	**GOLD.12-Inf**	**GDDI.12-Inf**	**FROM.12-Inf**
GIR	11.14	0.22	1.51	1.57	1.02	6.38	10.69
BIST-100	0.26	8.7	2.84	1.92	0.83	2.59	8.43
USD	0.18	2.77	6.99	4.05	2.2	1.37	10.57
EUR	0.17	1.54	3.6	6.09	2.89	1.23	9.43
GOLD	0.16	1.25	2.23	2.15	7.68	0.39	6.18
GDDI	4.33	1.4	2.55	2.82	0.95	9.68	12.05
TO	5.11	7.18	12.73	12.5	7.89	11.95	57.36
Inc. Own	16.25	15.87	19.72	18.6	15.57	21.63	cTCI/TCI
Net	-5.58	-1.26	2.16	3.07	1.7	-0.09	11.47/9.56

Source: Authors' own calculations

Table A2 Total, short-run, and long-run average TCI (volatility connectedness with forecast horizon 20)

Total	GIR.Total	BIST100.Total	USD.Total	EUR. Total	GOLD. Total	GDDI. Total	FROM.Total
GIR	63.58	0.51	6.9	5.96	2.42	20.61	36.42
BIST-100	0.45	76.07	11.9	4.79	3.6	3.18	23.93
USD	2.75	7.12	46.55	24.57	11.04	7.97	53.45
EUR	2.6	2.95	23.89	49.15	13.25	8.17	50.85
GOLD	1.36	2.3	13.02	15.49	64.24	3.59	35.76
GDDI	16.72	2.19	10.49	10.09	3.34	57.18	42.82
TO	23.87	15.07	66.21	60.91	33.65	43.53	243.23
Inc.Own	87.45	91.14	112.76	110.06	97.89	100.7	cTCI/TCI
Net	-12.55	-8.86	12.76	10.06	-2.11	0.7	48.65/40.54
Short-run	GIR.1-12	BIST100.1-12	USD.1-12	EUR.1-12	GOLD.1-12	GDDI.1-12	FROM.1-12
GIR	58.03	0.5	5.97	5.12	2.1	18.25	31.94
BIST-100	0.42	71.13	11.37	4.58	3.29	3.02	22.69
USD	2.44	6.75	42.55	22.15	9.89	7.15	48.39
EUR	2.42	2.86	22.09	45.62	12.09	7.66	47.11
GOLD	1.23	2.24	12.14	14.61	60.64	3.34	33.56
GDDI	14.66	2.08	9.08	8.79	2.95	50.63	37.56
TO	21.17	14.42	60.65	55.25	30.34	39.42	221.25
Inc.Own	79.2	85.55	103.2	100.87	90.97	90.05	cTCI/TCI
Net	-10.77	-8.27	12.26	8.14	-3.23	1.87	44.25/36.87
Long-run	GIR.12-Inf	BIST100.12-Inf	USD.12-Inf	EUR.12-Inf	GOLD.12-Inf	GDDI.12-Inf	FROM.12-Inf
GIR	5.55	0.02	0.94	0.84	0.32	2.36	4.48
BIST-100	0.03	4.94	0.54	0.21	0.31	0.16	1.24
USD	0.3	0.37	4	2.42	1.14	0.82	5.06
EUR	0.18	0.09	1.8	3.53	1.16	0.52	3.74
GOLD	0.13	0.06	0.88	0.88	3.6	0.25	2.2
GDDI	2.06	0.11	1.41	1.3	0.38	6.55	5.27
TO	2.7	0.65	5.56	5.66	3.31	4.1	21.98
Inc.Own	8.26	5.59	9.56	9.18	6.91	10.65	cTCI/TCI
Net	-1.78	-0.59	0.5	1.91	1.11	-1.16	4.40/3.66

Source: Authors' own calculations