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The connectedness between gold, oil, and BIST sector stock markets: evidence from the asymmetric TVP-VAR method and portfolio strategies

Zekai Şenol [1], Bahri Fatih Tekin [2] & Eda Başak Yıldırım [3]

[1] Sivas Cumhuriyet University, Faculty of Economics and Administrative Sciences, Department of Finance and Banking, Sivas, Türkiye
[2] Sivas Cumhuriyet University, Cumhuriyet Vocational School of Social Sciences, Securities and Capital Markets Program, Sivas, Türkiye
[3] Sivas Cumhuriyet University, Institute of Social Sciences, Sivas, Türkiye

Abstract This study investigates the connectedness and portfolio strategies between gold, oil, and Borsa Istanbul (BIST) sector indices of banking, trade, services, and industrials. The study period is from January 3, 2018 to May 21, 2024, a period of high volatility in the Turkish economy and financial markets. An asymmetric TVP-VAR (Time-Varying Parameter Vector Autoregression) analysis is employed alongside multiple portfolio strategy approaches. The findings reveal that gold and oil are net volatility receivers for BIST indices, exhibiting an asymmetric pattern in their connectedness. In addition, COVID-19 and Russia's invasion of Ukraine significantly influenced both symmetric and asymmetric connectedness. Among BIST sectors, services (XUHIZ) is a net volatility transmitter, while banking (XBANK) and trade (XTCRT) are net volatility receivers. It is determined that gold and oil, especially gold, can be used as hedging instruments for BIST basic sectors. In portfolio strategies, gold and oil should be included in the portfolios formed from BIST sectors in terms of risk management and diversification. These results offer valuable insights for investors, portfolio managers, and risk managers.

Keywords Borsa Istanbul · Gold · Oil · Volatility · Connectedness · Asymmetric TVP-VAR

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Corresponding author: Zekai Şenol zsenol@cumhuriyet.edu.tr

1. Introduction

The rising uncertainties in today's world and the financialization of international commodities spark increased interest among equity hedgers, investors, and academics in the price volatility of key global commodities, such as gold and oil (Mensi et al., 2021b; Cheng et al., 2023;Wu and Mai, 2024). These strategic commodities play essential roles in economic development and monetary policy, serving as valuable alternative assets for effective risk management strategies (Mensi et al. (2021b); Nekhili et al., 2023).

Gold, which is known as a safe haven among these commodities, acts as a robust hedge during periods of stock market volatility and provides portfolio diversification opportunities for investors (Echaust et al., 2024). Although no longer a part of the international monetary system, gold remains a fundamental asset in investment strategies (Cheng et al., 2023; Kang et al., 2023), functioning as both a hedge and a safe-haven asset, offering protection against downturns in various asset classes, including equities, and supporting financial risk management (Cheng et al., 2023; Mensi et al., 2022a; Nekhili et al., 2023). This role becomes particularly critical during crises, linking its importance to broader market dynamics.

Fluctuations in crude oil prices significantly influence financial markets and the economy. As both a strategic commodity and an investment asset, crude oil diversifies portfolios and affects stock prices through multiple channels (Hanif et al., 2024). For instance, when oil prices rise, production costs increase for companies dependent on oil, reducing potential dividends or cash flows and negatively impacting stock returns (Zhu et al., 2024). The response of sectoral stock returns to oil price shocks varies based on the sector's dependence on crude oil (Al-Fayoumi et al., 2023). As prominent global commodities, gold and crude oil have interconnected price movements that influence other financial assets. With the advancement of financial liberalization and globalization, economic signals now travel swiftly between markets, strengthening intermarket connections and amplifying risk transmission. Changes in gold and oil prices can directly or indirectly affect stock market performance (Cheng et al., 2023; Kang et al., 2023).

In recent decades, global markets have been disrupted by multiple crises, including the 1997 Asian financial crisis, 2008 global financial crisis, European sovereign debt crisis, and COVID-19 pandemic. Ongoing geopolitical challenges, such as the Russia-Ukraine war, further intensify risks (Wu and Mai, 2024). These crises have heightened uncertainty in economic policies and oil prices, attracting significant interest from investors, policymakers, and researchers who seek to understand the effects of fluctuations in oil prices on financial markets (Hasan et al., 2023). During periods of instability, investors tend to hedge their portfolios to mitigate risks or pivot to safer investments. These crises have underscored the importance of hedging strategies (Echaust et al., 2024).

The concepts of market connectedness and spillovers have gained prominence following the foundational work by Diebold and Yilmaz (2009, 2012, 2014). Spillovers between assets are critical for fund allocation, risk management, and diversification, particularly during times of elevated uncertainty (Mensi et al., 2024b). Volatility spillovers have become a focal point in hedging strategies since the global financial crisis, with investors increasingly viewing volatility funds as both hedging tools and investment opportunities (Kang et al., 2023). While most studies focus on spillovers between broader stock indices, less attention has been given to interactions between commodities and sectoral indices. However, understanding sectoral vulnerabilities is essential for constructing diversified portfolios because neglecting these nuances can expose investors to disproportionate losses (Mensi et al., 2022b). Accurate measurement of commodity-equity market connectedness is crucial for hedging, risk management, asset pricing, business cycle analysis, and portfolio allocation. Identifying volatility spillovers across markets helps investors manage risks by reallocating funds and adjusting their positions. It is also essential to quantify the frequency of volatility linkages (sources of systemic risk) and determine whether market reactions to shocks are symmetric or asymmetric. Such insights support better forecasting, reduce uncertainty, and enhance investment decisions (Mensi et al. 2021a).

This research provides many additions to the existing literature. First, it focuses on the connectedness between gold, a key precious metal, and oil, a critical energy commodity, both of which hold prominent positions in investment portfolios. This study explores their connectedness with BIST sector indices, providing actionable insights for portfolio management. Second, although prior research has examined the relationships between gold, oil, and stock markets (e.g., Raza et al., 2016; Bouri et al. 2021; Nekhili et al., 2023; Zhu et al., 2024), studies focusing on sectoral indices remain limited. By analyzing sector indices instead of the BIST 100 index, this research enhances portfolio management through more detailed sector-level insights. Third, unlike previous studies that rely on standard TVP-VAR models, this research utilizes the asymmetric TVP-VAR approach developed by Adekoya et al. (2022) to capture market responses to both positive and negative news. Finally, this study calculates portfolio weights and hedge ratios while developing strategies such as minimum correlation portfolios (MCP), minimum variance portfolios (MVP), risk-parity portfolios (RPP), and minimum connectedness portfolios (MCoP). This study is the first to investigate the connectedness between gold, oil, and BIST sector indices using Adekoya et al.'s (2022) asymmetric TVP-VAR model.

2. Literature

Oil and gold are closely monitored in financial markets, with extensive research examining their relationship with stock markets. Key studies include Bouri et al. (2021), Mensi et al. (2021a, 2021b, 2022a, 2022b), Dai et al. (2022), Kang et al. (2023), Cheng et al. (2023), and Bhattacherjee et al. (2024). These studies analyze different markets, focusing on U.S. stock markets (Bouri et al. 2021; Mensi et al. 2022b; Kang et al. 2023; Bhattacherjee et al. 2024), Chinese stock markets (Mensi et al., 2021b; Dai et al. 2022; Cheng et al. 2023; Wu and Mai 2024), and developed markets (Mensi et al. 2021a; 2022a).

Bouri et al. (2021) identify significant volatility spillovers between crude oil, gold, and U.S. equities, whereas Mensi et al. (2022b) find that oil and gold act as net recipients of volatility from the S&P 500, with oil receiving more than gold. Bhattacherjee et al. (2024) examine extreme time-frequency linkages between U.S. sectors and commodities, showing that sectors act as net transmitters and commodities as net receivers across different frequencies. Kang et al. (2023) explore the spillover and hedging roles of U.S. Islamic stocks, oil, and gold against risks from VIX and OVX, revealing that Islamic stocks receive greater spillovers than these commodities.

Studies focusing on Chinese markets emphasize asymmetric spillovers. Mensi et al. (2021b) demonstrate dynamic spillovers between Chinese sector indices, oil, and gold, intensified during major crises, with negative spillovers outweighing positive ones. Similarly, Cheng et al. (2023) find asymmetric volatility spillovers, showing that gold's positive spillovers increased during the COVID-19 pandemic. Wu and Mai (2024) report higher spillovers from oil than gold in Chinese sectors, with oil exerting a stronger asymmetric impact. Dai et al. (2022) highlight that during crises, Chinese markets act as net transmitters of volatility, with gold and oil as net receivers.

Mensi et al. (2021a) investigate volatility spillovers across developed and BRICS markets, finding stronger short-term spillovers than long-term spillovers. Gold and oil are net receivers from both short- and intermediate-horizon stock markets. Mensi et al. (2022a) similarly show that European sectors transmit volatility to gold and oil, with increased spillovers during major crises, such as the 2011-12 European debt crisis and the COVID-19 pandemic. Mensi et al. (2024b) report stronger return spillovers between gold, oil, and MSCI stock markets during bull and bear phases, confirming that gold and oil are consistent net recipients of spillovers.

Additional research emphasizes oil's central role in market dynamics. Qi et al. (2022) find that oil acts as a net receiver from clean energy markets, while Costola and Lorusso (2022) highlight that geopolitical uncertainties increase spillovers from Russian energy markets to crude oil. Al-Fayoumi et al. (2023) explore disaggregated oil shocks in GCC countries, showing that demand shocks consistently transmit volatility across sectors, with more pronounced effects during high-volatility periods. Meanwhile, Feng et al. (2023) and Zhu et al. (2024) note that oil has evolved from a risk receiver to a transmitter in recent years, with stock markets highly exposed to oil shocks under extreme conditions. Hanif et al. (2024) examine oil shocks in major economies, finding that demand-related shocks drive spillovers to the U.S., India, and Russia, while risk shocks transmit volatility to China and India.

Hedging and diversification strategies also feature prominently in the literature. Hung and Vo (2021) show that gold provides effective hedging, with Mensi et al. (2021a) confirming its superior hedging efficiency over oil for developed and BRICS markets. Mensi et al. (2022b) further highlight gold's effectiveness in U.S. sectors, although its hedging properties declined during the COVID-19 pandemic. Kang et al. (2023) observe that Islamic stocks, oil, and gold offer effective protection against VIX and OVX risks. Dai et al. (2022) find that oil and gold futures provide cost-efficient hedging for Chinese stock markets, while Qi et al. (2022) note improved oil hedging efficiency in the post-COVID-19 period. In contrast, Echaust et al. (2024) argue that index futures outperform both gold and oil as hedging instruments against stock market risks.

Several other studies are relevant to this context. Hung and Vo (2021) find weak spillovers between gold and the S&P 500, with increased return spillovers during COVID-19. Chen and Qi (2024) report that Chinese energy stocks act as net transmitters in the short terms and as net receivers in the long run. Bahloul and Khemakhem (2021) demonstrate strong spillovers between commodities and Islamic equity markets, with commodities serving as net transmitters of both returns and volatility. Kang et al. (2017) explore cross-market spillovers, showing that these effects intensify during crises.

In the Turkish context, Akkoc and Civcir (2019) identify time-varying spillovers from gold and oil to Turkish equities, with gold having a stronger impact. Coskun and Taspinar (2022) highlight the high interconnectedness between Turkish energy equities and fossil fuel markets, noting that volatility spillovers peaked during COVID-19, surpassing levels seen during the 2008 financial crisis. They emphasize that the spillover effects within the Turkish market are long-lasting.

As seen above, while the literature is based on spillovers between gold and oil and stock markets, this study focuses on stock market sector indices. Asymmetric spillovers are used to identify the effects of positive and negative news on shock spillover. In this study, hedge and portfolio strategies are obtained, and balanced portfolios are created in terms of risk and return from gold and oil and BIST sectors.

3. Data

In this study, daily data on ounce gold (XAU), Brent oil (BRENT), banking (XBANK), trade (XTCRT), services (XUHIZ), and industrials (XUSIN) indices from January 3, 2018, to May 21, 2024 were converted into return series and used. Daily return rates are calculated using the following formula:

$$r_t = \left(\frac{x_t - x_{t-1}}{x_{t-1}}\right) \times 100 \tag{1}$$

In Equation 1, r_t is the daily rate of return, x_t is the value of the variable at time t, and x_{t-1} is the value of the variable at time t-1.

The calculated daily rates of return are categorized as positive and negative returns for each series.

$$S_t = \begin{cases} 0, & eğer\; r_t < 0 \\ 1, & eğer\; r_t \geq 0 \end{cases} \tag{2}$$

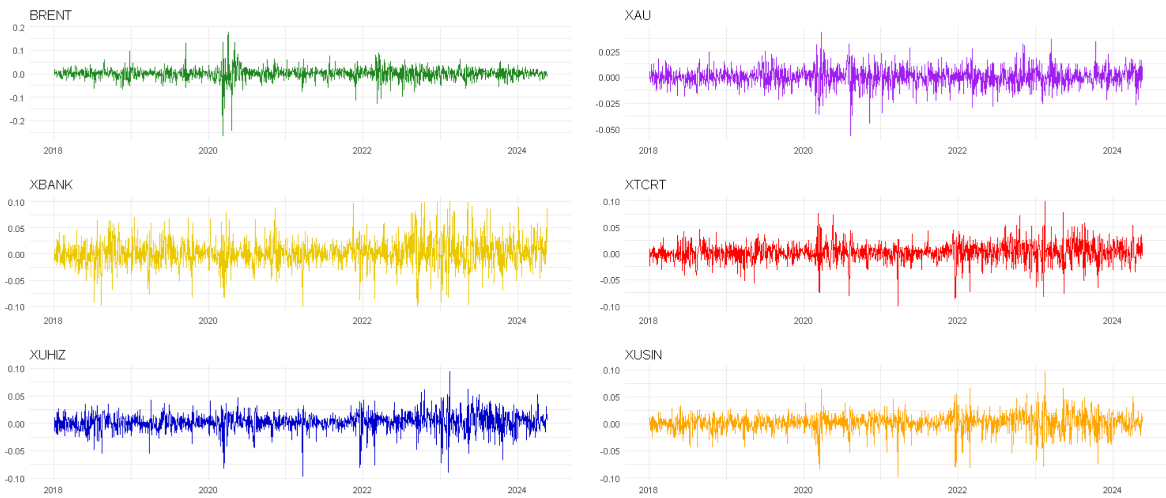
$$r_t^+ = S_t.r_t \tag{3}$$

$$r_t^- = (1 - S_t).r_t \tag{4}$$

In the above equations, $r_t^+$and r_t^- represents positive daily rates of return and negative daily rates of return, respectively. By distinguishing positive and negative returns, this approach reveals whether markets react more strongly to bad news than good news, offering practical insights for risk management strategies.

Figure 1

Daily Rates of Return Series



4. Method

4.1. Asymmetric connectedness approach based on TVP-VAR

This study applies the asymmetric dynamic TVP-VAR (Time-Varying Parameter Vector Autoregression) method introduced by Adekoya et al. (2022), which builds on the TVP-VAR framework of Antonakakis et al. (2020a). Adekoya et al. (2022) incorporate asymmetry by distinguishing between positive and negative daily return rates, calculated following the methodology outlined by Antonakakis et al. (2020a). The lag length of the TVP-VAR model is determined to be one according to the Bayesian Information Criterion (BIC). This asymmetric TVP-VAR method is employed to capture spillovers between gold, oil, and BIST indices over time- a critical feature during volatile periods such as the COVID-19 pandemic or geopolitical crises. This flexibility helps investors understand shifting risk dynamics.

The TVP-VAR model is represented as follows:

$$r_t = B_t r_{t-1} + u_t \qquad u_t \sim N(0, \Sigma_t) \tag{5}$$

$$vec(B_t) = vec(B_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \tag{6}$$

Where r_t and r_{t-1} are the $k\,x\,1$ dimensional vectors representing the rate of return at time t and $t-1$, respectively. u_t denotes the $k\,x\,1$ dimensional error term vector. B_t and Σ_t are $k\,x\,k$ dimensional matrices, representing the coefficient matrix and the variance-covariance matrix, respectively. Additionally, $vec(B_t)$ and v_t are $k^2\,x\,1$ dimensional vectors, while R_t is a k^2xk^2 dimensional matrix. Koop et al. (1996) and Pesaran and Shin (1998) proposed Wold's theorem-based Generalized Forecast Error Variance Decomposition (GFEVD). As a result, the TVP-VAR(p) (autoregressive) model must be converted into a TVP-VMA(∞) (moving average) representation.

$$r_t = \sum_{i=1}^{p} B_{it} r_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \tag{7}$$

The GFEVD simplifies complex volatility interactions into a clear measure of how much one asset's shocks drive another's fluctuations, thereby aiding portfolio diversification decisions. While effective for time-varying and asymmetric spillovers, this model does not account for frequency domains (e.g., short-vs.long-term horizons), which could influence investor behavior across different time scales. The generalized forecast error is normalized by calculating the variance decomposition as follows:

$$\psi^g_{ij,t}(H) = \frac{\Sigma^{-1}_{ii,t} \Sigma^{H-1}_{t=1} \left(\iota_{i'} A_t \Sigma_t \iota_j\right)^2}{\Sigma^k_{j=1} \Sigma^{H-1}_{t=1} \left(\iota_i A_t \Sigma_t A'_t \iota_i\right)} \tag{8}$$

$$\tilde{\psi}^g_{ij,t}(H) = \frac{\psi^g_{ij,t}(H)}{\Sigma^k_{j=1} \psi^g_{ij,t}(H)} \tag{9}$$

$\tilde{\psi}^g_{ij,t}(H)$, indicates the effect of variable j on variable i in terms of variance shares of forecast errors. H denotes the prediction interval. Σ_t, represents $k\,x\,k$ dimensional variance-covariance matrix and ι_i represents a vector with 1 in rank i and 0 in other ranks. With the normalization process, it is seen that $\Sigma^k_{j=1} \tilde{\psi}^g_{ij,t}(H) = 1$ or $\Sigma^k_{i,j=1} \tilde{\psi}^g_{ij,t}(H) = k$.

$$CTO^g_{i\to j,t}(H) = \sum_{j=1,\, i\neq j}^{k} \tilde{\psi}^g_{ji,t}(H) \tag{10}$$

In Equation 10, the effect of variable i on variable j is computed. This calculation measures the total effect of i on all other variables j, which is referred to as the effect "TO others." In the subsequent stage, the effect of i received from all other variables j, termed the effect "FROM others," is calculated. This effect can be expressed as follows:

$$CFROM^g_{i\leftarrow j,t}(H) = \sum_{j=1,\, i\neq j}^{k} \tilde{\psi}^g_{ij,t}(H) \tag{11}$$

The difference between the total effect of variable i transmitted to other variables (CTO) and the total effect of variable i received from other variables (CFROM) indicates the net total directional connectedness. This calculation can be expressed as follows:

$$CNET^{g}_{i,t}(H) = CTO^{g}_{i\rightarrow j,t}(H) - CFROM^{g}_{i\leftarrow j,t}(H) \tag{12}$$

The net total directional connectedness can be used to determine which variables are receivers and transmitters. The total connectedness index (TCI) is calculated as follows:

$$TCI^{g}_{t}(H) = \frac{\Sigma^{k}_{i,j=1,\, i\neq j}\tilde{\psi}^{g}_{ij,t}(H)}{\Sigma^{k}_{i,j=1}\tilde{\psi}^{g}_{ij,t}(H)} = \frac{\Sigma^{k}_{i,j=1,\, i\neq j}\tilde{\psi}^{g}_{ij,t}(H)}{k} \tag{13}$$

In studies such as Chatziantoniou and Gabauer (2021) and Adekoya et al. (2022), it is stated that while the total connectedness index should take values between 0 and 1, with this calculation, it takes values in the range of $0\,,\ \frac{k-1}{k}$. Therefore, in order for the interpretation to be more accurate, a few adjustments should be made in the calculation of the total connectedness index. These adjustments are described as follows:

$$TCI^{g}_{t}(H) = \left(\frac{k}{k-1}\right)\frac{\Sigma^{k}_{i,j=1,\, i\neq j}\tilde{\psi}^{g}_{ij,t}(H)}{k} = \frac{\Sigma^{k}_{i,j=1,\, i\neq j}\tilde{\psi}^{g}_{ij,t}(H)}{k-1} \qquad 0 \leq TCI^{g}_{t}(H) \leq 1 \tag{14}$$

In addition, Gabauer (2021) states that the connectedness between variables can be calculated by decomposing the total connectedness index into a pairwise connectedness index. Accordingly, the pairwise connectedness index can be calculated as follows:

$$PCI^{g}_{ijt}(H) = 2\left(\frac{\tilde{\psi}^{g}_{ij,t}(H) + \tilde{\psi}^{g}_{ji,t}(H)}{\tilde{\psi}^{g}_{ii,t}(H) + \tilde{\psi}^{g}_{ij,t}(H) + \tilde{\psi}^{g}_{ji,t}(H) + \tilde{\psi}^{g}_{jj,t}(H)}\right) \quad 0 \leq TCI^{g}_{t}(H) \leq 1 \tag{15}$$

4.2. Multiple portfolio strategies

4.2.1. Minimum variance portfolio (MVP)

The minimum variance method, used in the construction of multiple portfolios, focuses on identifying asset weights that minimize the portfolio's overall variance, effectively reducing its risk (Markowitz, 1959). According to this approach, portfolio weights are calculated as follows:

$$W_{\Sigma_t} = \frac{\Sigma_t^{-1}T}{\mathrm{T}\Sigma_t^{-1}T} \tag{16}$$

In Equation 16, W_{Σ_t} represents the $k\,x\,1$ dimensional portfolio weight vector, T represents the k-dimensional unit vector, and Σ_t is the $k\,x\,k$ dimensional variance-covariance matrix at time t as mentioned before.

4.2.2. Minimum correlation portfolio (MCP)

Christoffersen et al. (2014) proposed an alternative portfolio construction method known as the minimum correlation portfolio approach. In the minimum correlation portfolio approach, portfolio weights are determined by minimizing the conditional correlations. The calculation of portfolio weights is expressed in the following formula:

$$\mathrm{P}_t = diag(\Sigma_t)^{-0.5}\Sigma_t diag(\Sigma_t)^{-0.5} \tag{17}$$

$$W_{P_t} = \frac{P_t^{-1}T}{TP_t^{-1}T} \tag{18}$$

P_t represents a $k\,x\,k$ dimensional conditional correlation matrix.

4.2.3. Minimum connectedness portfolio (MCoP)

The minimum connectedness portfolio technique, as outlined by Broadstock et al. (2022), is an alternative method that minimizes connectedness using a pairwise connectedness index. In this approach, while the weights of the variables with minimum spillover effects are increased in the portfolio, the weights of the variables with high spillover effects are decreased in the portfolio. Thus, a weight combination that achieves minimum connectedness is created. The weights of the variables in the minimum connectedness portfolio can be calculated as follows:

$$W_{C_t} = \frac{PCI_t^{-1}T}{TPCI_t^{-1}T} \tag{19}$$

In Equation 19, PCI_t represents the pairwise connectedness index matrix.

4.2.4. Risk parity portfolio (RPP)

Following the approach of Maillard et al. (2010), we use the risk-parity portfolio. The strategy assigns weights to portfolios based on an equal distribution of risk contributions. In theory, it is believed that with the same level of risk, a portfolio can produce superior results and be more resilient to market declines and economic crises. In mathematical terms, this issue can be defined as the following minimization challenge:

$$\min \sum_{i,j=1}^{N} \left(w_{it}(H_t w_t)_i - w_{jt}(H_t w_t)_j\right)^2 \tag{20}$$

4.3. Portfolio performance

Hedge efficiency is a portfolio performance measurement method introduced by Ederington (1979) that provides information about the reduction in portfolio risk. Whether a reduction in risk is significant for hedge efficiency can be calculated based on Antonakakis et al. (2020b):

$$HE_i = 1 - \frac{var_p}{var_i} \tag{21}$$

In Equation 21, HE_i indicates the percentage by which the variance of this variable can be reduced in the absence of hedging for variable i. Therefore, a high hedge efficiency means that the risk can be reduced more, whereas a low hedge efficiency means that the risk can be reduced less. var_p and var_i represent the portfolio variance and variance of variable i, respectively.

5. Findings

5.1. Results of the asymmetric TVP-VAR method

This study aims to investigate the return connectedness between ounce gold (XAU), Brent oil (BRENT), and BIST main sectors, including banking (XBANK), trade (XTCRT), services (XUHIZ), industrials (XUSIN), and portfolio strategies that can be formed within the framework of these financial assets. This study covers the period from January 3, 2018 to May 21, 2024. The study period represents the volatile period in the Turkish economy and financial markets. Data were taken from the Foreks FxPlus data platform of ForInvest.

Table 1

Descriptive statistics

	BRENT	XAU	XBANK	XTCRT	XUHIZ	XUSIN
Mean	0.048	0.042*	0.173***	0.172***	0.168***	0.168***
Variance	6.668	0.787	6.685	3.23	2.646	2.797
Skewness	−0.982***	−0.228***	0.122**	−0.246***	−0.603***	−0.638***
Kurtosis	16.753***	3.203***	2.391***	3.674***	4.390***	4.345***

	BRENT	XAU	XBANK	XTCRT	XUHIZ	XUSIN
JB	18848.670***	693.356***	382.655***	910.513***	1373.224***	1358.479***
ERS	-8.71***	-14.518***	-9.623***	-4.934***	-6.31***	-13.706***
Q(20)	26.034***	11.487	18.575**	11.85	14.637	16.415*
$Q^2(20)$	323.696***	150.942***	211.220***	166.490***	186.268***	239.613***

***, ** ve * represents %1, %5, and %10 significance levels, respectively.

It is observed that all variables are left-skewed except for XBANK. ERS (Elliott et al. 1992) unit root test results indicate that the series are stationary.

Table 2

Correlations

	BRENT	XAU	XBANK	XTCRT	XUHIZ	XUSIN
BRENT	1					
XAU	0,068***	1				
XBANK	0,023	0,024	1			
XTCRT	0,03	0,02	0,267***	1		
XUHIZ	0,02	-0,001	0,414***	0,574***	1	
XUSIN	0,055***	0,024	0,404***	0,378***	0,564***	1

Among the BIST sectors, only industrials (XUSIN) is significantly correlated with oil (BRENT), while gold (XAU) is not significantly correlated with the BIST indices (Table 2). The BIST sectors have significant correlation relationships among themselves.

Table 3

Connectedness test results

Symmetric	**BRENT**	**XAU**	**XBANK**	**XTCRT**	**XUHIZ**	**XUSIN**	**FROM**
BRENT	90,16	3,27	1,69	1,15	1,63	2,11	9,84
XAU	3,65	90,99	1,51	0,89	1,66	1,3	9,01
XBANK	1,06	0,78	50,7	9,46	19,64	18,36	49,3
XTCRT	0,78	0,64	8,52	46,2	28,69	15,18	53,8
XUHIZ	0,9	0,75	14,53	23,22	37,01	23,59	62,99
XUSIN	1,25	0,62	15,44	14,23	26,74	41,73	58,27
TO	7,63	6,05	41,69	48,95	78,36	60,54	243,21
Inc. Own	97,79	97,04	92,39	95,15	115,37	102,27	cTCI/TCI
Net	-2,21	-2,96	-7,61	-4,85	15,37	2,27	48,64/40,53
Positive	**BRENT**	**XAU**	**XBANK**	**XTCRT**	**XUHIZ**	**XUSIN**	**FROM**
BRENT	92,72	3,35	0,67	1,01	0,93	1,32	7,28
XAU	3,79	90,83	1,19	0,91	1,72	1,55	9,17
XBANK	0,56	0,88	61,17	6,49	16,45	14,44	38,83
XTCRT	1,13	0,81	5,46	54,41	27,04	11,15	45,59
XUHIZ	0,59	1,08	11,85	21,6	43,53	21,35	56,47
XUSIN	0,84	1,1	12,42	10,67	24,82	50,15	49,85
TO	6,9	7,23	31,6	40,69	70,96	49,82	207,19

Inc. Own	99,62	98,06	92,77	95,1	114,49	99,96	cTCI/TCI
Net	−0,38	−1,94	−7,23	−4,9	14,49	−0,04	41,44/34,53
Negative	**BRENT**	**XAU**	**XBANK**	**XTCRT**	**XUHIZ**	**XUSIN**	**FROM**
BRENT	86,93	3,61	2,67	1,56	2,63	2,6	13,07
XAU	4,4	87,75	2,36	1,62	2,05	1,82	12,25
XBANK	1,64	0,75	47,47	11,03	20,16	18,95	52,53
XTCRT	1,39	0,58	10,48	44,56	26,7	16,28	55,44
XUHIZ	1,46	0,55	15,44	21,93	36,36	24,26	63,64
XUSIN	1,76	0,37	16,05	14,92	26,99	39,91	60,09
TO	10,64	5,86	46,99	51,06	78,53	63,92	257,01
Inc. Own	97,58	93,61	94,46	95,62	114,9	103,83	cTCI/TCI
Net	−2,42	−6,39	−5,54	−4,38	14,9	3,83	51,40/42,84

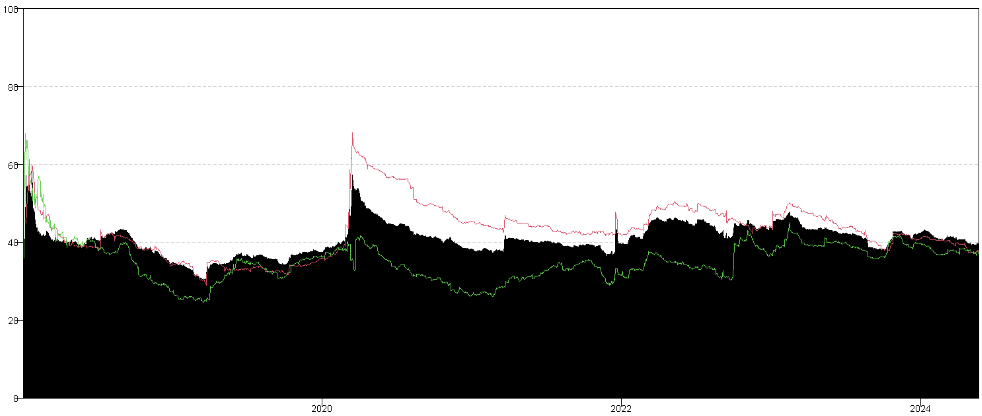
Table 3 presents the symmetric and asymmetric connectedness. The first part of the table shows symmetric connectedness. The total connectedness index is 40.53. This result indicates a moderate level of connectedness between the oil, gold, and BIST basic indices. Among the BIST basic indices, services (XUHIZ) and industrials (XUSIN) are net shock transmitters, whereas banking (XBANK) and trade (XTCRT) indices are net shock receivers. Gold (XAU) and oil (BRENT) are net shock recipients.

Table 3 displays positive returns at the center and negative returns at the bottom. There is a difference between the total connectedness indices differ. The total negative connectedness index (42.84) is higher than the positive total connectedness index (34.53). This indicates an asymmetric effect, meaning that negative returns have a higher effect than positive returns in terms of connectedness among BIST indices, gold, and oil. The obtained asymmetric effect result is similar to those of Mensi et al. (2021b), Mensi et al. (2022a), Cheng et al. (2023), and Wu and Mai (2024).

Gold (XAU) and oil (BRENT) exhibit a significant asymmetric effect. Gold (XAU) is a net shock receiver at −1.94 for positive returns, while it is a net shock receiver at −6.39 for negative returns. Similarly, oil (BRENT) is a net shock receiver of −0.38 in positive returns and a net shock receiver of −2.42 in negative returns.

Figure 2

Asymmetric total dynamic connectedness



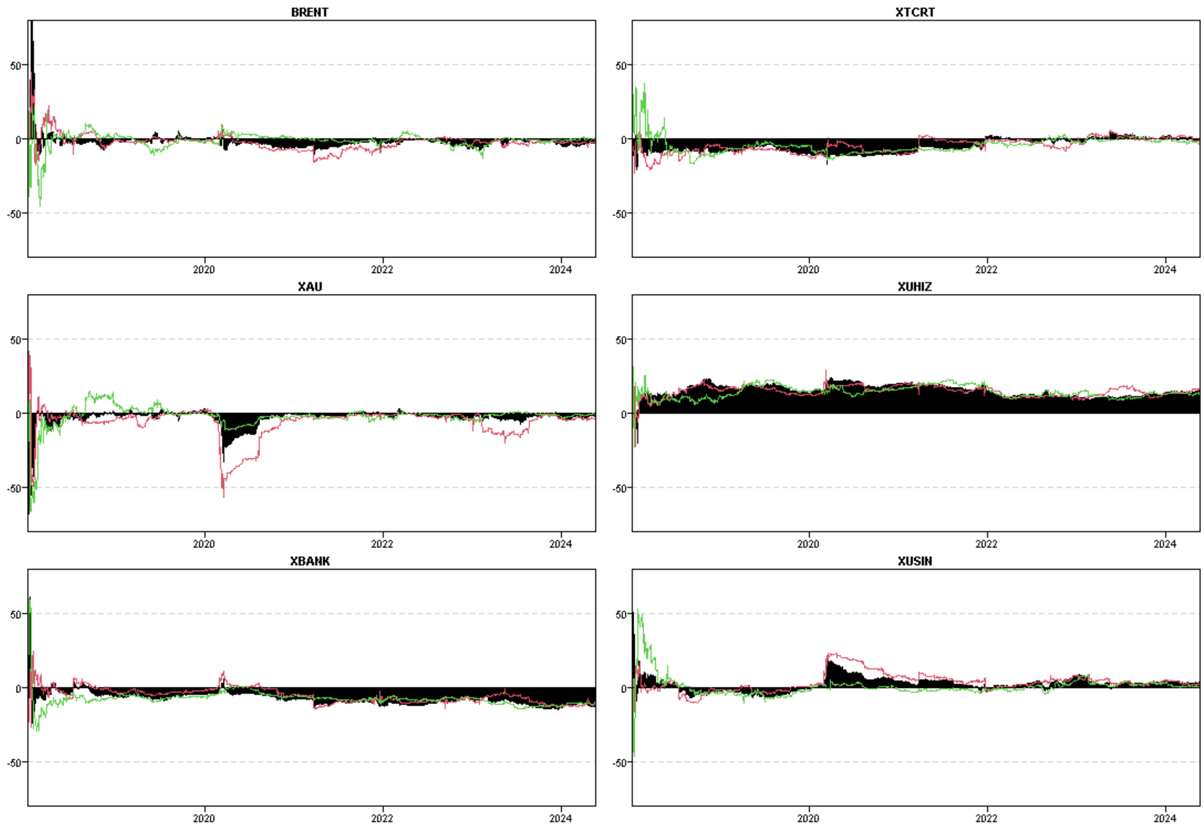
Note: The black area represents the average total dynamic connectedness, the green line graph shows the positive return total dynamic connectedness, and the red line graph shows the negative return total dynamic connectedness.

Connectedness was slightly higher during the COVID-19 period, the Russian invasion of Ukraine, and the Israeli-Hamas conflict. Negative return interconnectedness is higher than positive return interconnectedness, especially after the COVID-19 period. This situation indicates that negative news effects are greater than positive news effects. Asymmetric spillovers are affected by COVID-19 and policy changes in the Turkish economy and financial markets in recent years. In addition, the result may be indicative of the BIST performance, which started with COVID-19 and rose in a significant trend until 2023 and then continued on its way, although it partially lost its momentum.

Figure 3 shows the dynamic total net connectedness. The black area indicates net total direct symmetric aggregate connectedness, green color indicates the net total direct positive connectedness, and red color indicates net total direct negative connectedness. Positive and negative values indicate net shock transmission and reception, respectively. Dynamic connectedness refers to the change in the positive and negative shock transmission or reception over time. In the distribution of financial assets in the sample, oil (BRENT) generally receives volatility from other markets. The asymmetric effect on oil prices increased during the COVID-19 period. Gold received more negative shocks than positive shocks from BIST sector indices during the COVID-19 and the Israeli-Hamas conflict.

Figure 3

Dynamic total net connectedness (NET)

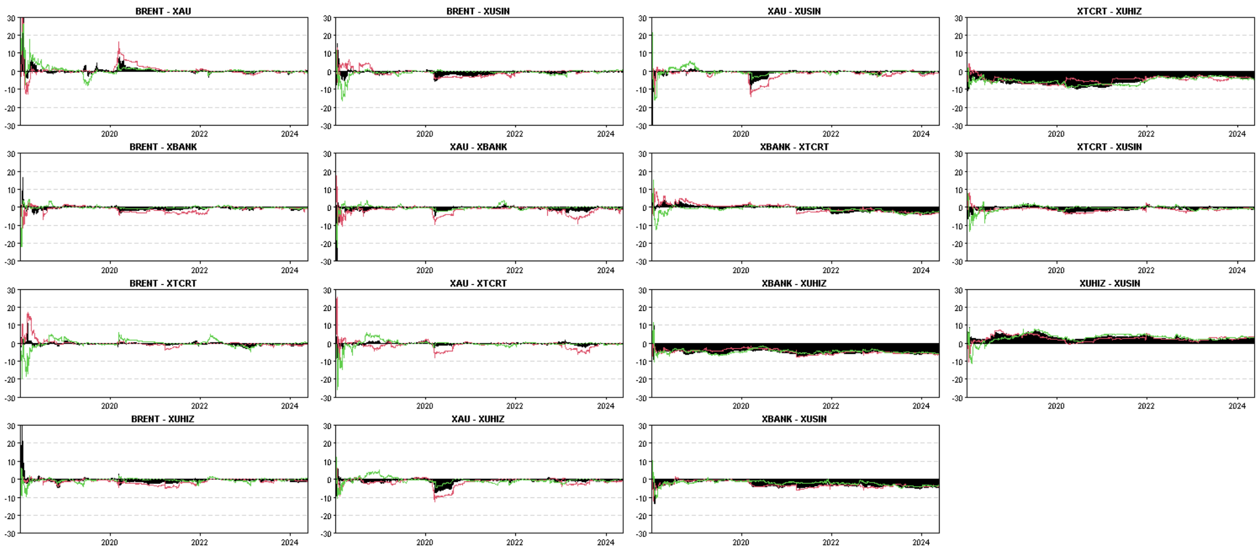


Gold acts as a net shock receiver within the mix of financial assets, with its asymmetric effects intensifying during specific periods. Both gold and oil are identified as net shock receivers in relation to the BIST indices. This aligns with previous studies, such as Mensi et al. (2022b), Bhattacherjee et al. (2024), Dai et al. (2022), Mensi et al. (2021a), Mensi et al. (2022a), and Mensi et al. (2024 a), which also highlight gold and oil as net receivers in stock markets. Our findings are consistent with these results. Similar to Cheng et al. (2023), this study finds that gold absorbs slightly more spillovers than oil, whereas in other studies, such as Mensi et al. (2021b), Mensi et al. (2022b), Mensi et al. (2022a), and Kang et al. (2023), oil is shown to receive more spillovers than gold.

The banking sector (XBANK) is a significant shock receiver, whereas the services sector (XHIZM) is a shock transmitter for the entire sample period. Trade (XTCRT) is a volatility receiver until 2022 and a low-level volatility transmitter after that. Industrials (XUSIN) is a spillover receiver in 2019 and a spillover transmitter in other periods. In particular, in the banking sector, volatility is receiving, and in the services sector, there is volatility transmitting persistence. The sample period is a period of high volatility experienced by the Turkish economy and financial markets. Risks have increased during this period, especially in the banking sector. The results of the analysis are an indicator of these risks. We believe that the fact that the services sector is a net shock transmitter during both the COVID-19 and other periods is due to the shares in the sector. In the services industry, the transportation sector saw a notable decline during the COVID-19 pandemic, whereas sub-sectors like healthcare, retail, and energy services experienced growth during the same period. Regarding the asymmetric effects in the sectors, the negative shock transmission in the industrials (XUSIN) sector is significantly higher than the positive shock transmission during the COVID-19 period.

Figure 4

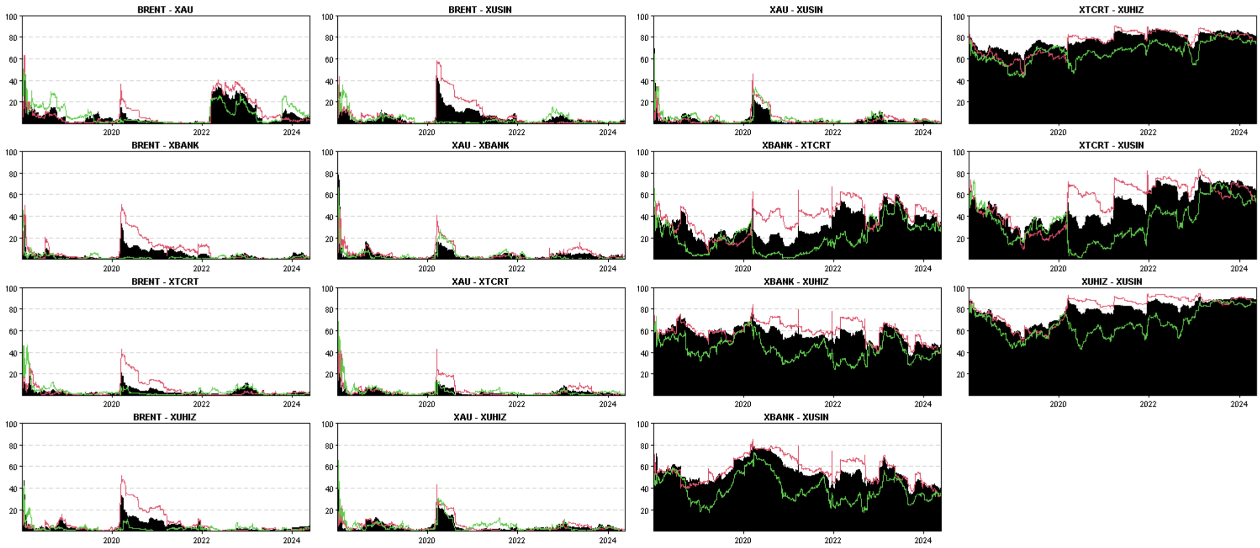
Dynamic net pairwise directional connectedness (NPDC)



Examining the net pairwise connectedness (Figure 4), it is understood that oil received shock spillovers from the banking, services, and industrials sectors during the COVID-19 period, and this spillover is asymmetric. Compared with gold, the persistence of shock receivers from BIST indices is higher in oil (Figure 5). This result is consistent with those of Mensi et al. (2021), Mensi et al. (2022a), and Kang et al. (2023). Persistence is observed in the net shock receiver of the services sector to other BIST sectors (Figure 5). Asymmetric spillovers among BIST sector indices increased, especially after COVID-19.

Figure 5

Pairwise connectedness index (PCI)



5.2. Results of portfolio strategies

Figure 6 shows cumulative return performances of different portfolio approaches. Although the returns of the minimum variance portfolio perform better during the COVID-19 period, the three different approaches exhibit similar performances in other periods. In 2018 and the beginning of 2019 and in the spring of 2020, when COVID-19 was declared a pandemic, portfolio returns were negative, while returns increased in trend from mid-2020 to 2024. During this period, the price of a barrel of Brent oil, which was \$30-\$40 at the time of the COVID-19 pandemic, rose to \$120 during Russia's invasion of Ukraine and then reached \$70-\$80. An ounce of gold, on the other hand, was between \$1,650 and \$2,050 from the beginning of COVID-19 until the beginning of 2024, while it rose above \$2,300 in 2024. From the start of COVID-19 until mid-May 2024, the BIST 100 index surged from 1,000 to above 10,000 levels as of research data collection. The BIST sector indices have the most significant impact on cumulative portfolio return performance. The return of the minimum variance portfolio (MVP) was higher than the other portfolios until spring 2022, after which it lagged behind the other portfolios.

Figure 6

Cumulative portfolio returns

Figure 7 shows the dynamic portfolio weights of the financial assets considered in each portfolio approach. In the minimum variance portfolio (MVP), gold has an important place, and partial changes in the portfolio weight have occurred over time. Dynamic portfolio weighting suggests that investors can adjust allocations in real time based on market conditions. For instance, increasing gold's weight in MVP during crises like COVID-19 enhances risk reduction, while reducing banking sector exposure mitigates volatility reception. After gold, services and the industrials sector occur in the MVP. The services sector showed significant changes within the portfolio, but industrials played a role in the portfolio until 2022. The share of the banking sector in the MVP is very low. In the minimum correlation portfolio (MCP), the weights of oil, gold, banking, and trade sectors were close to each other and followed a stable course. Although the industrials sector was present in this portfolio at a certain level until 2022, the services sector gained a place in this portfolio distribution after 2022. In 2022, industrials are replaced by services in the MCP. In the minimum connectedness portfolio (MCoP), the services sector is absent, whereas other financial assets are close to each other and have maintained their ratios over time. In the risk parity portfolio (RPP), the proportion of gold is slightly higher than that of other assets, and the proportion of other assets is close to each other at a low level. The distribution of assets in the RPP has not changed substantially over time.

Figure 7

Dynamic multivariate portfolio weights

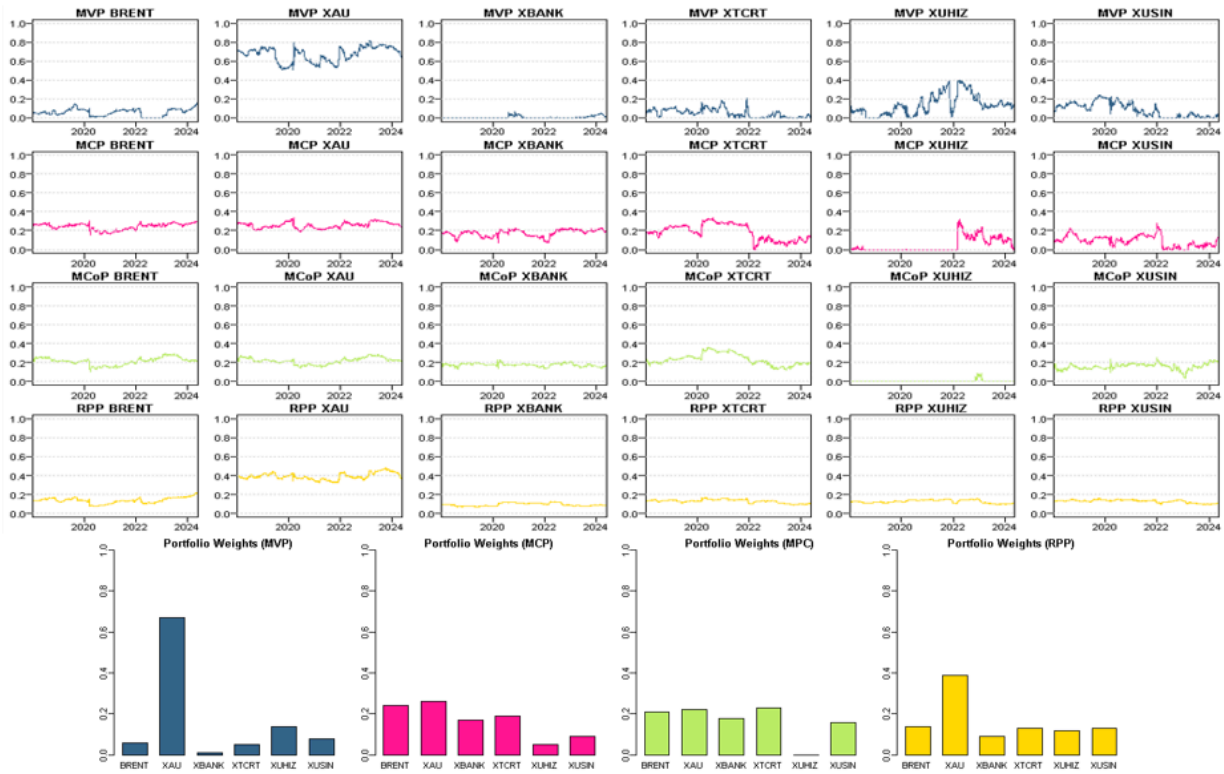


Table 4 shows the portfolio allocations of financial assets. In the MVP, with an average portfolio allocation that if we invested on average 5% in oil, 67% in gold, 1% in banking index, 5% in trade index, 14% in services index, and 8% in industrials index, then each asset volatility in the portfolio would be statistically reduced by 92% for oil, 34% for gold, 92% for banking index, 84% for trade index, 80% for services index, and 82% for industrial index. In MCP, on average, investing 24% in oil, 26% in gold, 17% in banking index, 19% in trade index, 5% in services index, and 9% in industrial index would statistically reduce the volatility of each asset in the portfolio by 81% for oil, 80% for banking index, 59% for trade index, 50% for services index, and 53% for industrial index. In MCoP, if the portfolio weighting is 21% for oil, 22% for gold, 18% for banking, and 23% for trade, the volatility of each financial asset would be decreased by 81% for oil, 80% for banking, 59% for trade, and 53% for industrials. In RPP, if the portfolio weights are composed of oil 14%, gold 39%, banking 59%, trade 13%, services 12% and industrials 13%, the volatility of each financial asset would be statistically decreased by 88% for brent oil, 88% for banking, 75% for trade, 69% for services and 71% for industrials.

Table 4

Multivariate portfolio weights

	Mean	Std. Dev.	%5	%95	HE	Prob.
Minimum variance portfolio (MVP)						
BRENT	0,05	0,04	0	0,12	0,92	0,000
XAU	0,67	0,08	0,53	0,77	0,34	0,000
XBANK	0,01	0,01	0	0,04	0,92	0,000
XTCRT	0,05	0,05	0	0,13	0,84	0,000
XUHIZ	0,14	0,1	0	0,35	0,8	0,000
XUSIN	0,08	0,07	0	0,21	0,82	0,000
Minimum correlation portfolio (MCP)						
BRENT	0,24	0,03	0,18	0,29	0,81	0,000
XAU	0,26	0,03	0,21	0,31	−0,68	0,000
XBANK	0,17	0,04	0,11	0,22	0,8	0,000
XTCRT	0,19	0,08	0,06	0,31	0,59	0,000
XUHIZ	0,05	0,07	0	0,19	0,5	0,000
XUSIN	0,09	0,06	0	0,19	0,53	0,000
Minimum connectedness portfolio (MCoP)						
BRENT	0,21	0,04	0,15	0,28	0,81	0,000
XAU	0,22	0,03	0,16	0,27	−0,67	0,000
XBANK	0,18	0,02	0,15	0,2	0,8	0,000
XTCRT	0,23	0,06	0,14	0,33	0,59	0,000
XUHIZ	0	0,01	0	0	0,51	0,000
XUSIN	0,16	0,03	0,11	0,21	0,53	0,000
Risk parity portfolio (RPP)						
BRENT	0,14	0,03	0,08	0,18	0,88	0,000
XAU	0,39	0,04	0,33	0,46	−0,04	0,040
XBANK	0,09	0,02	0,07	0,12	0,88	0,000
XTCRT	0,13	0,02	0,1	0,16	0,75	0,000
XUHIZ	0,12	0,02	0,1	0,15	0,69	0,000
XUSIN	0,13	0,02	0,01	0,15	0,71	0,000

Notes: Markowitz (1959) introduced the Minimum Variance Portfolio (MVP), whereas Christoffersen et al. (2014) developed the Minimum Correlation Portfolio (MCP). Broadstock et al. (2022) later proposed the Minimum Correlation Portfolio (MCoP). Additionally, Maillard et al. (2010) introduced the Risk-Parity Portfolio (RPP). HE denotes hedging efficiency.

These portfolios provide portfolio diversification benefits in a dynamic framework. When MVP, MCP, MCoP, and RPP are compared, the proportion of gold is higher for MVP and RPP. Gold accounted for 67% of MVP, 26%

of MCP, 22% of MCoP, and 39% of RPP. In MVP and RPP, the hedging efficiency of assets other than gold, i.e. the volatility reduction ratios) is quite high. In MCP, MCoP, and RPP, the hedging efficiency of gold is negative, and the volatilities of oil and BIST sectors decrease statistically significantly in these portfolio allocations. These results show that gold is an important risk-hedging instrument for BIST sectors. On the other hand, oil was allocated 5% in MVP, 24% in MCP, 21% in MCoP, and 14% in RPP. In this respect, gold and oil, especially gold, have an important place in portfolios formed from BIST markets. These results reveal the role of gold and oil in BIST markets' portfolio allocation and hedging efficiency. Portfolio risk is reduced in portfolio allocations based on BIST sectors and gold and oil.

Table 5

Optimal hedge ratio

	Mean	Std. Dev.	Min	Max
XBANK/BRENT	0,06	0,10	−0,18	0,18
XTCRT/BRENT	0,04	0,06	−0,09	0,12
XUHIZ/BRENT	0,03	0,06	−0,11	0,10
XUSIN/BRENT	0,06	0,05	−0,05	0,13
XBANK/XAU	0,13	0,29	−0,34	0,59
XTCRT/XAU	0,07	0,15	−0,17	0,32
XUHIZ/XAU	0,05	0,21	−0,31	0,41
XUSIN/XAU	0,07	0,16	−0,24	0,35
BRENT/XBANK	0,10	0,15	−0,08	0,53
BRENT/XTCRT	0,10	0,12	−0,09	0,35
BRENT/XUHIZ	0,14	0,22	−0,11	0,75
BRENT/XUSIN	0,21	0,23	−0,05	0,9
XAU/XBANK	0,02	0,03	−0,04	0,08
XAU/XTCRT	0,02	0,04	−0,03	0,08
XAU/XUHIZ	0,02	0,06	−0,06	0,13
XAU/XUSIN	0,02	0,05	−0,05	0,13

Note: The optimal hedge ratio was developed by Kroner and Sultan (1993).

Optimal hedge ratios determine the amount of asset B to buy (long) or sell (short) to hedge the risk of holding a ₺100 long position in asset A. As shown in Table 5, all optimal hedge ratios are positive. This implies that a long position in one asset should be offset by a short position in another asset to effectively manage risk. For instance, a ₺100 long position in the banking sector (XBNK) should be hedged with a ₺6 short position in Brent oil. Similarly, a ₺100 long position in the banking index (XAU) requires a ₺13 short position in gold (XAU) for effective risk management. The hedge ratios between the BIST basic sectors and gold and oil are relatively low, indicating high hedging effectiveness and low hedging costs. Among the BIST sectors, the banking sector exhibits the highest hedging costs. When investing in Brent oil, the industrials sector (XUSIN) has the highest hedging cost. Conversely, hedging with gold (XAU) across BIST sectors is notably inexpensive. These findings suggest that to hedge long positions in BIST sectors, short positions in gold or oil should be used. This aligns with the results of Hung and Vo (2021), Mensi et al. (2021a), Mensi et al. (2022b), and Dai et al. (2022). Furthermore, the conclusion that gold offers superior hedging properties compared to oil is consistent with the findings of Mensi et al. (2022a) and Mensi et al. (2022b).

Table 6

Optimal portfolio weights

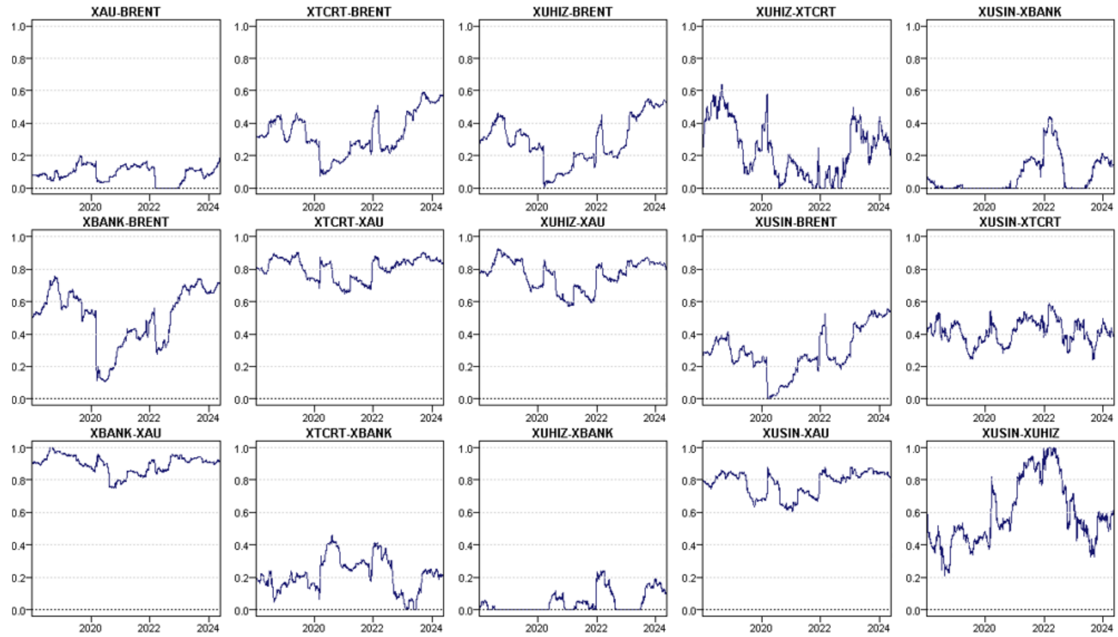
	Mean	Std. Dev.	Min	Max	HE	Prob
XBANK/BRENT	0,49	0,17	0,28	0,84	0,56	0,000
XTCRT/BRENT	0,67	0,13	0,44	0,89	0,37	0,000
XUHIZ/BRENT	0,71	0,14	0,48	0,96	0,36	0,000
XUSIN/BRENT	0,71	0,14	0,48	0,98	0,33	0,000
XBANK/XAU	0,10	0,06	0,03	0,22	0,90	0,000
XTCRT/XAU	0,20	0,07	0,12	0,32	0,81	0,000
XUHIZ/XAU	0,23	0,09	0,12	0,40	0,78	0,000
XUSIN/XAU	0,22	0,07	0,14	0,36	0,78	0,000

Note: Optimal portfolio weights were developed by Kroner and Ng (1998).

The optimal portfolio weights in Table 6 show the proportions of assets A and B that should be invested to minimize risk without any change in the expected return of both assets. In the pairwise optimal portfolio weights of the gold and BIST sectors, the gold weight varies between 10% and 23% (Table 6). For the optimal portfolio weight in the pairing of gold and banking, ₺90 of ₺100 should be invested in the banking index and ₺10 in gold. Accordingly, investors can hold less gold in their portfolios in order to minimize risk without any change in expected return, in addition to BIST sector indices. Hedging efficiency is high for the optimal portfolio weights of gold and the BIST sector. In the bivariate portfolio weights of oil and BIST sectors, the oil ratio is between 49% and 71%. According to the optimal portfolio weights for oil and banking, ₺51 of the ₺100 should be invested in the banking index and ₺49 in oil. In order to minimize risk without any change in return, investors should invest more than half in oil, together with the BIST indices, except for the banking sector. In the bivariate portfolio weighting of oil and BIST sectors, the hedge ratio is medium for banking and slightly low for other sectors.

Figure 8

Optimal dynamic portfolio weights



There are no notable differences in the optimal portfolio weights between the gold and BIST sectors over time (Figure 8). However, we observed significant differences in optimal portfolio weighting between the oil and BIST indices. The COVID-19 pandemic and Russia's invasion of Ukraine significantly influenced these differences.

6. Conclusion

This study examines return connectedness and portfolio strategies involving gold (ounce), Brent oil, and BIST sector indices. Banking, trade, services, and industrials are used as BIST basic sectors. Asymmetric TVP-VAR analysis and different portfolio approach strategies are used in this study. The study period is from 2018 to 2024 when Turkish financial markets are volatile. The findings obtained in this study are as follows: Gold and oil are net shock receivers for BIST indices. There are asymmetric effects in return connectedness among gold, oil, and BIST basic indices. In other words, negative news effects are more significant than positive news effects. The effects of COVID-19 and Russia's invasion of Ukraine were observed in dynamic connectedness. In the post-COVID-19 period, negative return connectedness was found to be higher than positive return connectedness. Among the BIST sectors, services are net shock transmitters, while banking and trade sectors are net shock receivers. In optimal portfolio strategies that involve risk hedging and diversification, there has been a noticeable increase in portfolio returns following the COVID-19 pandemic. It is determined that gold and oil, especially gold, are necessary for managing portfolio risk in which portfolios are to be formed from BIST sectors. Gold was found to be a risk-hedge instrument for BIST sectors. Hedge efficiency is high and hedge cost is low in portfolios composed of the BIST basic sectors of gold and BIST basic sectors–oil. The results obtained are useful for investors, portfolio managers, and risk managers. For investors, these findings suggest practical adjustments: increasing gold allocations during high-volatility periods (e.g., post-COVID-19) can hedge BIST sector risks, while oil's role as a diversifier strengthens during geopolitical tensions like Russia's invasion of Ukraine. Policymakers should encourage gold-backed instruments to stabilize financial markets during crises. However, while this study effectively analyzes connectedness using the asymmetric TVP-VAR model, it excludes frequency domains, limiting insights into short-, medium-, and long-term spillovers. Alternative methods, such as wavelet coherence, can address this issue by examining time-frequency dynamics, and Markov switching models can test robustness across market regimes. The focus on the BIST indices, though novel, omits comparisons with other markets (e.g., the U.S. or China), and the 2018-2024 period may not capture longer-term trends. Future research could expand to international markets, test additional portfolio strategies, or extend the time frame to enhance applicability.

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Author Details
Zekai Şenol (Assoc. Prof. Dr.)
[1] Sivas Cumhuriyet University, Faculty of Economics and Administrative Sciences, Department of Finance and Banking, Sivas, Türkiye
0000-0001-8818-0752 zsenol@cumhuriyet.edu.tr

Bahri Fatih Tekin (Lecturer)
[2] Sivas Cumhuriyet University, Cumhuriyet Vocational School of Social Sciences, Securities and Capital Markets Program, Sivas, Türkiye
0000-0002-0541-4371 ftekin@cumhuriyet.edu.tr

Eda Başak Yıldırım (Phd. Student)
[3] Sivas Cumhuriyet University, Institute of Social Sciences, Sivas, Türkiye
0009-0008-9383-9097 edaabasak@gmail.com

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