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Volatility Spillovers Between Financial Asset and Commodity Prices: Evidence from Türkiye[12]

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Abstract

This study examines volatility spillover effects among key commodities, the USD/TRY exchange rate, and the Borsa Istanbul (XU100) using CCC-GARCH and DCC-GARCH models to overcome ARCH model limitations. Analyzing daily data from 2010 to 2023, the results reveal significant short-term volatility clustering, especially influenced by recent price shocks. Long-term spillovers are notable, with persistent volatility connections indicated by high GARCH terms. Correlation analysis shows moderate positive correlations between Gold and Silver with XU100, while Crude Oil and Natural Gas exhibit weak correlations, suggesting limited short-term spillovers. A significant negative correlation exists between USD/TRY and XU100, highlighting the complex relationship between currency and stock market volatility. Overall, short-term spillovers are weak, but long-term relationships show strong persistence, especially regarding USD/TRY and Natural Gas. These findings stress the importance of nuanced volatility-based trading strategies during market turbulence and suggest that fund managers should consider investor behavior and biases when building portfolios.

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Özet

Bu çalışma, ARCH modeli sınırlamalarını aşmak için CCC-GARCH ve DCC-GARCH modellerini kullanarak, temel emtialar, USD/TRY döviz kuru ve Borsa İstanbul (XU100) arasındaki oynaklık yayılma etkilerini incelemektedir. 2010-2023 yılları arasındaki günlük verileri analiz eden sonuçlar, özellikle son fiyat şoklarından etkilenen önemli kısa vadeli oynaklık kümelenmesini ortaya koymaktadır. Uzun vadeli yayılmalar dikkat çekicidir ve yüksek GARCH terimleri ile gösterilen kalıcı oynaklık bağlantıları vardır. Korelasyon analizi, Altın ve Gümüş ile XU100 arasında orta düzeyde pozitif korelasyonlar gösterirken, Ham Petrol ve Doğal Gaz zayıf korelasyonlar sergilemektedir ve bu da sınırlı kısa vadeli yayılmaları düşündürmektedir. USD/TRY ile XU100 arasında önemli bir negatif korelasyon bulunmaktadır ve bu, döviz kuru ile borsa oynaklığı arasındaki karmaşık ilişkiyi vurgulamaktadır. Genel olarak, kısa vadeli yayılmalar zayıf görünse de uzun vadeli ilişkiler, özellikle USD/TRY ve Doğal Gaz ile ilgili olarak güçlü bir kalıcılık göstermektedir. Bu bulgular, piyasa dalgalanmaları sırasında oynaklık temelli işlem stratejilerinin önemini vurgulamakta ve fon yöneticilerinin portföy oluştururken yatırımcı davranışlarını ve önyargılarını dikkate almaları gerektiğini ortaya koymaktadır.

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INTRODUCTION

Volatility is essential for academics, policymakers, and financial market participants for various reasons. Firstly, economic analysts rely on accurately predicting financial asset volatility to effectively manage portfolio risk. For investors, volatility acts as a critical measure of the risk associated with their investments. Theoretically, it is fundamental in determining financial asset prices; for example, evaluating a stock's price requires consideration of the underlying asset's volatility as a risk factor. Additionally, understanding asset volatility is crucial for calculating Value-at-Risk in portfolio management.

From an economic standpoint, volatility plays a significant role; policymakers utilize market volatility estimates to assess the economy's vulnerability. Since Engle's seminal paper in 1982, interest in quantifying volatility spillovers in financial markets has grown considerably. These factors collectively emphasize the importance of understanding and measuring the impact of volatility across various financial sectors.

In recent decades, the rise of international equity investment has increased the demand and supply for foreign currencies and stocks, significantly influencing stock, commodity, and foreign exchange markets. This heightened interconnectedness has amplified volatility transmission among these markets, raising risks for international portfolios. As a result, investors have increasingly adopted portfolio diversification strategies to mitigate volatility risk.

The integration of global financial markets, driven by capital flows and liberalization, has allowed investors to diversify and reduce idiosyncratic risk while optimizing returns. However, this interdependence has also led to potential drawbacks, including spillover effects where disturbances in one market impact others, particularly during crises. Ebrahim (2000) emphasized the need to understand these transmission mechanisms for effective policy formulation.

Theoretical models explaining the linkages between stock prices, commodity prices, and exchange rates include the flow-oriented model, which suggests a positive relationship between exchange rates and stock prices based on trade balances, and the stock-oriented model, which posits a negative relationship with causality running from stock prices to exchange rates.

Most research has focused on volatility transmission between foreign exchange and stock markets in developed countries, with some studies examining developing and emerging markets. The portfolio balance model suggests that rising domestic asset prices can lead to currency appreciation due to increased demand for those assets, while the monetary model indicates a weaker or negligible relationship between stock prices and exchange rates. This study specifically investigates the volatility spillover from commodity prices and exchange rates to the Borsa Istanbul.

LITERATURE REVIEW

The volatility of financial markets has been rigorously investigated utilizing the ARCH-GARCH methodology, first introduced by Engle (1982) and later refined by Bollerslev (1986), Nelson (1991), among other researchers. Early studies predominantly focused on univariate ARCH-GARCH models to quantify volatility; however, there was a swift transition toward multivariate approaches, notably multivariate-GARCH models, to analyze conditional variances and covariances across various financial markets (Ghosh, 2014). Prominent models in this field include the vector error correction-generalized autoregressive conditional heteroscedasticity (VEC-GARCH) model (Bollerslev *et al*., 1988) and the Baba-Engle-Kraft-Kroner (BEKK) model developed by Engle and Kroner (1995). A substantial amount of literature has explored volatility spillovers across markets, especially during critical events such as the global financial crisis and the Hong Kong protests. Ross (1989) underscored that volatility, beyond being a price measure, serves as a crucial source of market information. Factors affecting multiple financial variables often initiate volatility spillovers, as interconnected markets experience spillovers driven by common risks (Bollerslev *et al*., 1992). Cross-market hedging also contributes to these spillovers (Ederington & Lee, 1993).

A substantial body of literature has examined volatility spillovers within stock markets, investigating interrelations between various countries, across different indices, and between spot and futures markets. For instance, Tse and Booth (1995) explored the relationship between U.S. Treasury bills and Eurodollar futures, while Tse (1999) analyzed the interactions between the spot and futures markets of the Dow Jones Industrial Average (DJIA). Ebrahim (2000) utilized a trivariate GARCH model to assess the flow of information between foreign exchange and money markets in Canada. Moreover, Ågren (2006) identified spillover effects from oil prices to stock prices in Japan, Norway, the UK, and the USA. In a similar vein, Fedorova and Saleem (2009) discovered direct connections between equity and currency markets in Russia, Hungary, Poland, and the Czech Republic. Moon and Yu (2014) examined short-run volatility spillovers between the S&P 500 and the Shanghai Stock Exchange, revealing symmetric volatility between these markets. Additionally, Wang et al. (2017) demonstrated that volatility originating from U.S. stock markets significantly influences other global markets, particularly during economic downturns. Their findings suggest that incorporating U.S. market data can enhance the accuracy of international stock price forecasts.

Bissoondoyal-Bheenick *et al*. (2018) explored volatility spillovers among the stock markets of the U.S., China, and Australia, highlighting a bilateral relationship between these markets. Similarly, Caloia *et al*. (2018) assessed the strength of volatility transmission across five European Economic and Monetary Union (EMU) markets. Alqahtani (2020) focused on the spillover effects between returns and oil prices, while Zhang et al. (2020) developed a volatility network among G20 countries, concluding that economic and trade links significantly contribute to spillovers into the U.S. market.

Recent research has also focused on commodity market volatility (Cui *et al*., 2021; Cevik *et al*., 2021; Maitra *et al*., 2021; Aziz & Hussain, 2021). Yasir and Onder (2022) investigated time-varying herding behavior in the BRIC countries and Turkey, discovering evidence of herding phenomena in China under different market conditions. Ahmed *et al*. (2022) utilized a bivariate EGARCH (1) model to analyze return linkages and volatility spillovers among Asian emerging markets, revealing significant asymmetric spillovers in all markets except China.

Several studies specifically addressed volatility spillovers between stock indices and commodity prices in Turkey. Aksu and Topcu (2014) found bidirectional spillovers between the Istanbul Stock Exchange (ISE) 100 and energy commodities like crude oil and natural gas using a multivariate GARCH framework. Gurdgiev and Sekmen (2016) highlighted short-term spillovers from oil prices to stock returns, emphasizing the influence of energy prices on stock market dynamics. Ozdemir and Gokce (2017) confirmed the substantial impact of crude oil price volatility on stock returns. Akcay and Kutan (2018) identified bidirectional spillovers between the stock and foreign exchange markets, indicating a high degree of interconnectedness. Caglayan and Yuksel (2019) noted macroeconomic factors such as inflation and GDP growth as significant drivers of volatility spillovers.

Aydogan and Balcilar (2020) observed increased spillovers during the global financial crisis, while Berument and Inan (2021) reported similar bidirectional spillovers between stock and foreign exchange markets. Cetin and Duzce (2022) reinforced the importance of energy prices in driving these spillovers. Demirer and Kutan (2015) explored financial contagion effects during crises and identified heightened spillovers. Dizaji and Gokbulut (2016) demonstrated how exchange rate volatility affects stock returns, while Erdogan and Gungor (2017) identified oil price volatility, interest rates, and global conditions as key determinants of spillovers. Kocak and Akdeniz (2018) used a DCC model to illustrate time-varying spillover dynamics, and Ocal and Yildirim (2019) emphasized the role of macroeconomic factors. Ozdemir and Tansel (2020) found significant spillovers during crises, suggesting contagion effects, while Yilmaz and Simsek (2021) reported increased spillovers amid global economic uncertainty, highlighting the influence of external factors on Turkey's market dynamics.

DATA

Data used for this study were gathered from yahoofinance.com, Investing.com and www.macrotrends.net were extracted as daily prices of the six assets spanning the period from January 1, 2010 to December 31, 2023 (727 observations). The data were then transformed to weekly data for Borsa Istanbul 100 index (XU100), USD/TRY and gold, crude oil, silver and natural gas spot prices quoted in United States dollars. XU100 Index, which acts as the main market indicator for Borsa Istanbul, is a market capitalization-weighted index that covers at least 75% of the total market capitalization, number of shares traded, traded value, and number of executed trades in the market (Bildik, 2001).

The return series of Borsa Istanbul 100 (XU100), Crude Oil (WTI), Silver, NATGAS, Gold, Copper and USD/TRY are computed as log differences of the two successive prices i.e. $r_t = \log(P_t/P_{t-1})$. The time series of return data has been plotted, clearly illustrating how volatility has fluctuated over time. See figure 1. The key observation is that XU100, Silver, Gold and NATGAS experienced pronounced volatility clustering around the same time.

The presence of a unit root in each of the series were tested using the Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1981) test and Phillip Perron (PP)Test.

Table 1: Unit Root Tests

	ADF		PP	
Assets	**Constant**	**Constant and Trend**	**Constant**	**Constant and Trend**
XU100	-42.82	-44.99	-44.546	-46.634
USD/TRY	-33.786	-34.03	-33.314	-33.756
Gold	-26.169	-26.153	-26.182	-26.149
Silver	-26.376	-26.358	-26.385	-26.355
Crude Oil (WTI)	-32.803	-32.782	-33.772	-33.906
NATGAS	-31.270	-31.251	-32.260	-31.828
Copper	-28.294	-28.286	-28.385	-28.331

The ADF test statistics are reported for each asset under both constant and trend specifications. The ADF statistics are compared against critical values to determine whether the null hypothesis of a unit root (non-stationarity) can be rejected. If the ADF statistics are less negative than the critical value, then we fail to reject the null hypothesis, indicating that the series is non-stationary. In the table, the ADF statistics for all assets are quite negative, suggesting stationarity, particularly under both constant and trend specifications. Like the ADF test, the Phillips-Perron test statistics are reported for each asset under both constant and trend specifications. The PP statistics are compared against critical values to determine stationarity. Like the ADF test, a more negative PP statistic indicates stronger evidence against the presence of a unit root. In the table above, the PP statistics are also very negative for all assets, indicating strong evidence against the presence of a unit root and suggesting stationarity.

Table 2: Descriptive Summary Statistics

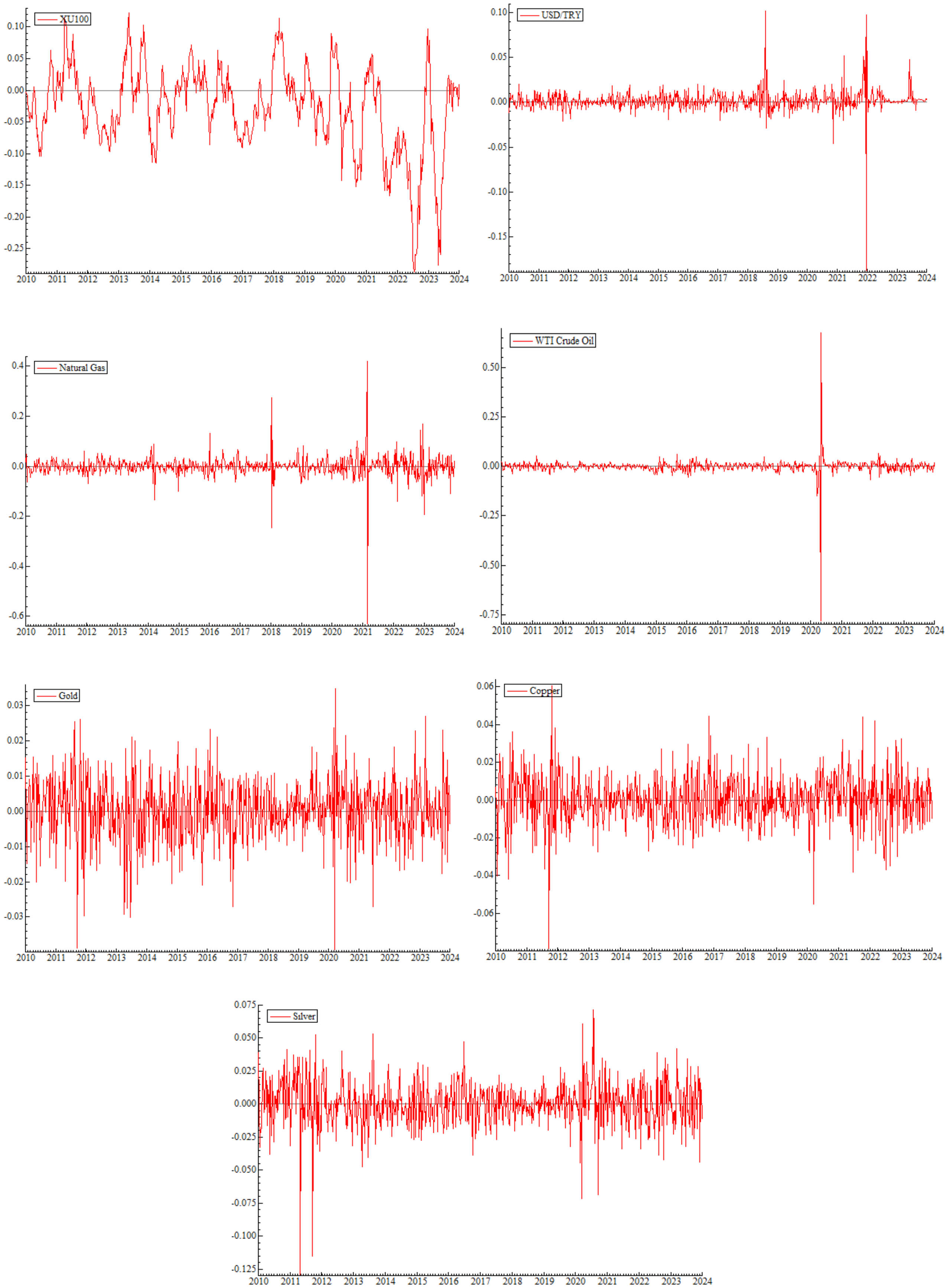
	XU100	USD/TRY	Gold	Silver	Crude Oil (WTI)	NATGAS	Cooper
# of Obs	727	727	727	727	727	727	727
Minimum	-0.2871	-0.1879	-0.0392	-0.1291	-0.7824	-0.6292	-0.0786
Maximum	0.1222	0.1020	0.0348	0.0710	0.6750	0.4200	0.0606
Median	-0.0198	0.00115	0.0006	0.00012	0.00148	-0.0010	0.00006
Mean	-0.0287	0.0017	0.0003	0.00018	-0.1396	-0.0004	-0.00006
Std Dev	0.0680	0.0125	0.0090	0.01775	0.0433	0.0449	0.0134
Skewness	0.2628	-2.9413	-0.3180	-0.8289	-1.3932	-2.5038	-0.1386
Kurtosis	-0.7007	87.2239	4.5457	10.0169	12.387	68.6764	5.4772
Median	-0.3321	0.0414	0.00065	0.00012	-0.073	-0.0349	0.00006
Variance	0.00462	0.00015	0.00008	0.0003	0.0018	0.0020	0.00018
Jarque-Bera	38.047	4.20	47.534	40.87	7.45	7.40	37.725

Source: Author's calculation.

The minimum and maximum values give the range within which each variable fluctuates over the observed period. For instance, the XU100 ranges from -0.2871 to 0.1222, indicating its fluctuations from a minimum decrease to a maximum increase. The mean represents the average value of each variable over the observed period. A mean close to zero for most variables suggests relatively stable behavior around the mean. Higher standard deviations indicate greater volatility or variability in the data. For example, Crude Oil (WTI) has a relatively high standard deviation of 0.0433, indicating significant price fluctuations over the observed period. Skewness measures the asymmetry of the distribution negative skewness (0.2628 for XU100) suggests a longer right tail, indicating more frequent occurrences of positive returns than negative ones. Kurtosis measures the thickness of the tails of the distribution. Higher kurtosis (87.2239 for USD/TRY) indicates heavier tails, implying more frequent extreme values or outliers. Extreme skewness and kurtosis values, such as those for USD/TRY and Crude Oil (WTI), indicate non-normal distributions and potential for extreme events. The statistics suggest that while some variables like Gold and Silver have relatively low volatility and are close to normally distributed, others like Crude Oil (WTI) and USD/TRY exhibit significant volatility and non-normal behavior. Investors and analysts should consider these characteristics when making decisions or modeling future behavior. Extreme skewness and kurtosis values highlight the need for risk management strategies to mitigate the impact of potential outliers or extreme events. Additionally, understanding the distribution and behavior of each variable can inform portfolio construction, hedging strategies, and risk assessment in financial markets. The descriptive statistics above indicate that we can reject the hypothesis that all of the variables are normally distributed.

Figure 1 below presents log return series for each of the variables. XU100 displayed huge volatility over the past years. The graph reveals significant negative returns, particularly in 2010, with this trend continuing into 2011, despite minor recoveries. A recovery begins in 2011, leading to consistent positive returns until the index peaks in 2013. After this peak, a downturn occurs from after 2013 to 2016, marked by high volatility and sharp declines in 2014 and 2016. Recovery seems to start after 2016 with gradual positive returns, although fluctuations persist, especially in 2018. Notable performance in XU100 suggests seasonal trends, while high volatility correlates with geopolitical and economic events, particularly significant declines in 2014 and 2016. Overall, sharp recoveries follow prolonged downturns, indicating returning investor confidence.

Figure 1: Return Series of XU100, USD/TRY and Key Commodities



Source: Author's compilation

For the USD/TRY, the graph reveals significant fluctuations in exchange rates for the Lira, marked by both increases (e.g., +0.102) and decreases (e.g., -0.028), indicating high volatility. This variability is especially pronounced in 2018 and 2019, likely due to political and economic events in Turkey. Challenges like high inflation, trade deficits, and shifting monetary policies contribute to these rapid changes, often influenced by external factors such as geopolitical tensions and the strength of the USD. Currency markets are also affected by speculation and differences in interest rates, particularly between Turkey and the US, impacting investor confidence and demand for the Lira.

Commodity prices have been volitile as seen in the graphs. These volitilities are reflects the complex interplay of market forces, including supply and demand dynamics, weather patterns, and market sentiment. Volatility in these commodities prices have presented both risks and opportunities for traders, investors, and businesses. Table 3 below contains correlation results for all of the assets.

Table 3: Correlation Matrix

	XU100	USD/TRY	Natural Gas	WTI Crude Oil	Gold	Copper	Silver
XU100	1						
USD/TRY	-0.0793*	1					
Natural Gas	-0.0318	-0.017	1				
WTI Crude Oil	0.0303	-0.0143	0.0056*	1			
Gold	0.0469*	-0.1396*	0.0153	0.0149	1		
Copper	0.042*	-0.1449*	-0.0033	0.0853*	0.2826*	1	
Silver	0.0496*	-0.173*	0.0465	0.0654	0.7966*	0.4479*	1

*, **, *** is 1%, 5%, 10% respectively.

This correlation matrix provides insight into the relationships between different financial and commodity assets. Turkish Lira exchange rate (USD/TRY) exhibits a weak negative correlation with the XU100, implying a slight tendency for the Turkish Lira to strengthen when the XU100 decreases. This correlation is statistically significant at a 10% level. Natural Gas demonstrates weak correlations with other assets, without statistical significance WTI Crude Oil shows a weak positive correlation with Gold, indicating a slight tendency for its price to increase alongside Gold. This correlation is significant at a 10% level. Gold has weak positive correlations with XU100, Copper, and Silver, suggesting slight tendencies for their prices to move in the same direction. It also has a weak negative correlation with USD/TRY, indicating a tendency for the Turkish Lira to strengthen with Gold price increases. The correlations with USD/TRY, Copper, and Silver are statistically significant at different levels. Copper displays weak positive correlations with XU100, WTI Crude Oil, and Silver, along with a weak negative correlation with USD/TRY. These correlations are significant at a 1% level Silver exhibits weak positive correlations with XU100, WTI Crude Oil, Gold, and Copper, and a weak negative correlation with USD/TRY. These correlations are statistically significant at a 1% level. In summary, while some weak correlations exist among the assets, they aren't robust enough for predictive purposes. Additionally, the significance levels vary, indicating differing degrees of reliability in the observed relationships.

METHODOLOGY

The study employs both the Dynamic Conditional Correlation (DCC) estimator and the Conditional Correlation Covariance (CCC) estimator. Introduced by Engel (2002), the DCC estimator offers several advantages over multivariate GARCH models, particularly in identifying correlation and volatility spillovers among assets. The DCC-GARCH model is designed to capture dynamic, time-varying covariance. A key benefit of this model is its ability to handle large correlation matrices, which multivariate GARCH models struggle with due to their numerous parameters. In contrast, the DCC model's number of parameters remains independent of the number of correlated series. These attributes render the DCC estimators both flexible and straightforward, akin to a univariate GARCH model. The DCC-GARCH model is dynamic, accommodating time-varying means, variances, and covariances of the return series r_t where:

$$r_t = u_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t | \Omega_{t-1} \rightarrow (N 0_1 H_t)$$

The conditional variance of each return is derived from the residuals of the mean equation as:

$$h^2{}_{i,t} = \alpha_0 + \sum_{j=1}^{pi} \alpha_j x^2{}_{i,t-j} + \sum_{j=1}^{qi} \beta_j \sigma^2{}_{i,t-j} \tag{2}$$

where $\sum_{j=1}^{pi} \alpha_j + \sum_{j=1}^{qi} \beta_j < 1$

Then, the multivariate conditional variance H_t can be estimated as:

$$H_t = D_t R_t D_t \tag{3}$$

In this context, H_t denotes the conditional covariance matrix of r_t. The matrix D_t is a diagonal matrix of dimensions (k×k) containing time-varying standard deviations, which are derived from the univariate GARCH specifications outlined in Equation (3).

Additionally, r_t is a (k×k) time-varying matrix that is obtained by standardizing the residuals from the mean equation (1) of the univariate GARCH model, utilizing their conditional standard deviations from Equation (2), resulting in $\eta_k = \varepsilon_k / \sqrt{h_{it}{}^2}$

The standardized residuals are subsequently utilized to estimate the parameters of conditional correlation in accordance with Equations (1) and (3):

$$R_t = (diag(Q_t))^{-\frac{1}{2}} \; Q_t (diag(Q_t)^{-\frac{1}{2}}) \tag{4}$$

$$Q_t = (1 - \theta_1 - \theta_2) Q + \theta_1 \eta_{t-1} \acute{\eta}_{t-1} + \theta_2 Q_{t-1} \tag{5}$$

Here, Q (bar) represents the unconditional covariance of the standardized residuals. Generally, Q_t does not have ones on its diagonal; therefore, it is scaled as indicated in Equation (4) to derive R_t, which is a positive definite matrix. In this model, the conditional correlations are dynamic, meaning that vary over time. As stated in Equation (5), θ_1 and θ_2 are assumed to be positive scalars, with the constraint that $\theta_1 + \theta_2 < 1$. Finally, the conditional correlation coefficient, p_j, between any two foreign exchange rates (or any two stock indices or commodity prices), i and j, is represented by the following equation:

$$p_j = \frac{q_{jt}}{\sqrt{q_{j,t} q_{j,t}}}, i, j = 1,2 \dots \dots, n, and\ i \neq j \tag{6}$$

$$p_j = \frac{(1-\theta_1-\theta_2)q -_{12} + \theta_1 \eta_{1,t-1}\eta_{2,t-1} + \theta_2 q_{12,t-1}}{\sqrt{\left[(1-\theta_1-\theta_2)q -_{11} + \theta_1 \eta^2{}_{1,t-1} + \theta_2 q_{11,t-1}\right]}\sqrt{\lfloor(1-\theta_1-\theta_2)q -_{22} + \theta_1 \eta^2{}_{2,t-1}\theta_2 q_{22,t-1}\rfloor}}$$

The parameters of the DCC model are estimated using the likelihood of this estimator and can be written as follows:

$$L = -\frac{1}{2}\sum_{t-1}^{T}(n\ log(2\pi) + 2log|D_t| + log|R_t| + \acute{\eta}_t R^{-1}{}_t \eta_t) \tag{7}$$

Where $D_t = dlog\{\sqrt{h_{i,t}}\}$ and R_t is the time varying correlation matrix.

Another multivariate GARCH model, the Conditional Correlation Covariance (CCC) GARCH model was used to measure volatility spillovers. The Multivariate GARCH (1,1) model generalizes the univariate GARCH (1,1) framework to multiple time series, capturing not only the conditional variances but that conditional covariances between the series. One common form is Constant Conditional Correlation (CCC) model proposed by Bollerslev (1990). The return equation for a N – dimensional time series is:

$$r_t = \mu + \in_t \tag{8}$$

Here r_t is a N x 1 vector of returns, and μ is a N x 1 vector of mean returns. $\in_t$ is the N x 1 vector of shock terms.

The shock term is modelled as:

$$\in_t = H_t^{1/2} \boldsymbol{z_t} \tag{9}$$

Here, H_t is a N x N conditional covariance matrix, $H_t^{1/2}$ is a N x N positive definite matrix, and z_t is a N x 1 vector of standard normal innovations.

In the CCC-GARCH (1,1) model, the conditional covariance matrix H_t is constructed as:

$$H_t = D_t R D_t \tag{10}$$

Where $D_t = \frac{diag(h_t)1}{2}, and\ h_t$ is a N x 1 vector whose element are univariate GARCH (1,1) variances for each time series. R is a positive definite constant conditional correlation matrix.

RESULTS

A common characteristic observed in financial time series data is its deviation from the standard white noise produced by a Gaussian stochastic process in two main ways. First, the unconditional distribution is highly leptokurtic, meaning it is more peaked at the center and features fat tails, resulting in a higher frequency of extreme observations than would be expected under the Gaussian distribution. Second, financial time series exhibit volatility clustering, characterized by phases of relative calm followed by episodes of heightened volatility, which can make variance seem somewhat predictable (Chinzara & Aziapono, 2009). As a result, the Gaussian assumptions in the DCC-GARCH methodology may not hold. To address this issue, this study employs the t-DCC-GARCH approach, which assumes that market yields adhere to a multivariate t-distribution, as proposed by Pesaran and Pesaran (2007). Calculation results and explanations for the DCC-GARCH and CCC-GARCH models can be found in Table 4 and Table 5, respectively.

Table 4: DCC-GARCH Model Results

Panel A: DCC-GARCH Model for USD/TRY and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
USD/TRY Mean Equation				*XU100 Mean Equation*			
L USD/TRY	0.0063	0.0469	0.894	L USD/TRY	0.0048	0.0579	0.934
L XU100	-0.0009	0.0035	0.806	L XU100	0.954	0.0122	0.000
ARCH (USD_TRY)				*ARCH (XU100)*			
ARCH L1	0.5253	0.0851	0.000	ARCH L1	0.0628	0.0177	0.000
GARCH L1	0.4704	0.0837	0.000	GARCH L1	0.8971	0.0291	0.000
Constant	0.0000117	0.0000037	0.002	Constant	0.0000179	0.0000082	0.028
				Correlation (USD/TRY, XU100)	-0.2519	0.0679	0.000
				DCC Adjustment Parameters			
				Lambda1	0.0343	0.0156	0.027
				Lambda2	0.9233	0.0254	0.000

Panel B: DCC-GARCH Model for Natural Gas and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
Natural Gas Mean Equation				*XU100 Mean Equation*			
L Natural Gas	0.0815	0.0428	0.057	L Natural Gas	-0.028	0.0175	0.111
L XU100	-0.0293	0.0138	0.033	L XU100	0.9527	0.0115	0.000
ARCH (Natural Gas)				*ARCH (XU100)*			
ARCH L1	0.5644	0.0681	0.000	ARCH L1	0.0583	0.0162	0.000
GARCH L1	0.4516	0.0467	0.000	GARCH L1	0.9086	0.0251	0.000
Constant	0.000135	0.0000303	0.000	Constant	0.000015	0.000007	0.031
				Correlation (Natural Gas, XU100)	0.0000158	*0.0374*	*1*
				DCC Adjustment Parameters			
				Lambda1	0.0343	0.0156	0.027
				Lambda2	0.9233	0.0254	0.000

Panel C: DCC-GARCH Model for Gold and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
Gold Mean Equation				*XU100 Mean Equation*			
L Gold	0.026	0.0391	0.507	L Gold	-0.0818	0.0828	0.324
L XU100	0.0001	0.0042	0.978	L XU100	0.955	0.0115	0.000
ARCH (Gold)				*ARCH (XU100)*			
ARCH L1	0.069	0.0206	0.001	ARCH L1	0.0558	0.0161	0.001
GARCH L1	0.8849	0.0405	0.000	GARCH L1	0.9094	0.0255	0.000
Constant	0.000004	0.00000215	0.081	Constant	0.000016	0.00000721	0.029
				Correlation (Gold, XU100)	0.0982	0.0395	0.013
				DCC Adjustment Parameters			
				Lambda1	0.0465	0.0361	0.198
				Lambda2	0.2632	0.4216	0.532

Table 4: DCC-GARCH Model Results (*continue…*)

Panel D: DCC-GARCH Model for Silver and XU100							
Variable	**Coefficient**	**S.E.**	**p-Value**	**Variable**	**Coefficient**	**S.E.**	**p-Value**
Silver Mean Equation				*XU100 Mean Equation*			
L Silver	0.0135	0.0393	0.730	L Silver	-0.0233	0.0431	0.588
L XU100	-0.004	0.0079	0.613	L XU100	0.9531	0.0115	0.000
ARCH (Silver)				*ARCH (XU100)*			
ARCH L1	0.0788	0.0153	0.000	ARCH L1	0.0536	0.016	0.001
GARCH L1	0.9134	0.0151	0.000	GARCH L1	0.9082	0.0266	0.000
Constant	0.000004	0.00000208	0.059	Constant	0.000017	0.00000762	0.027
				Correlation (Silver, XU100)	0.1576	0.0409	0.000
				DCC Adjustment Parameters			
				Lambda1	0.0734	0.0401	0.067
				Lambda2	0.4012	0.2997	0.181

Source: Author's estimation.

DCC-GARCH estimations were conducted for XU100, Turkish Lira, Natural Gas, Gold and Silver. In all panels, the dynamic correlation between asset pairs in the short run is generally weak, except for USD/TRY and XU100, where there is a significant negative short-run correlation. The short-run volatility spillovers are more pronounced for the XU100 and commodities like Silver and Gold, as indicated by positive correlations in some cases.

Across all panels, the GARCH terms for both assets (especially XU100) are large and significant, indicating long-term volatility persistence. The high and significant Lambda2 values across several panels (especially USD/TRY and Natural Gas) suggest that correlation dynamics between these assets are highly persistent over time, meaning volatility linkages between the markets adjust slowly and persist in the long run. This model shows that while short-term volatility spillovers are less pronounced in most cases, the long-run relationships between these financial markets demonstrate strong volatility persistence and adjustment over time. The estimation results for the CCC-GARCH model are displayed in Table 5 below.

Table 5: CCC-GARCH Model Results

Panel A: CCC GARCH Model for USD/TRY and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
USD/TRY Mean Equation				*XU100 Mean Equation*			
USD/TRY L1	0.0161	0.0475	0.734	USD/TRY L1	-0.0011	0.0586	0.985
XU100 L1	0.0012	0.0035	0.731	XU100 L1	0.944	0.0116	0.000
ARCH (USD/TRY)				*ARCH (XU100)*			
Turkish Lira L1	0.5586	0.0896	0.000	ARCH L1	0.0608	0.0167	0.000
Turkish Lira L I	0.4453	0.0846	0.000	GARCH L1	0.9045	0.026	0.000
Constant	0.0000124	3.79E-06	0.001	Constant	0.0000159	7.18E-06	0.027
				Correlation (USD/TRY, XU100)	*-0.2904*	*0.0345*	*0.000*

Table 5: CCC-GARCH Model Results (*continue…*)

Panel B: CCC-GARCH Model for Natural Gas and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
Natural Gas Mean Equation				*XU100 Mean Equation*			
Natural Gas L1	0.0781	0.0429	0.069	Natural Gas L1	-0.0268	0.0178	0.132
XU100 L1	-0.0308	0.0138	0.026	XU100 L1	0.9538	0.0116	0.000
ARCH (Natural Gas)				*ARCH (XU100)*			
ARCH L1	0.5632	0.0679	0.000	ARCH L1	0.0583	0.0164	0.000
GARCH L1	0.4495	0.0466	0.000	GARCH L1	0.9083	0.0254	0.000
Constant	0.000137	0.0000306	0.000	Constant	0.0000151	0.00000704	0.032
				Correlation (Natural Gas, XU100)	0.0000158	*0.0374*	*1*

Panel C: CCC-GARCH Model for WTI Crude Oil and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
WTI Crude Oil Mean Equation				*XU100 Mean Equation*			
Crude Oil WTI L1	0.2964	0.0469	0.069	WTI Crude Oil L1	0.0161	0.0203	0.428
XU100 L1	-0.0024	0.0082	0.026	XU100 L1	0.9532	0.0116	0.000
ARCH (WTI Crude Oil)				*ARCH (XU100)*			
ARCH L1	0.6167	0.0855	0.000	ARCH L1	0.0578	0.0164	0.000
GARCH L1	0.3512	0.0827	0.000	GARCH L1	0.9076	0.0258	0.000
Constant	0.0000893	0.0000215	0.000	Constant	0.0000157	0.0000073	0.031
				Correlation (WTI Crude Oil, XU100)	*0.035*	*0.0373*	*0.348*

Panel D: CCC-GARCH Model for Gold and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
Gold Mean Equation				*XU100 Mean Equation*			
Gold L1	0.0324	0.039	0.405	Gold L1	-0.0885	0.0832	0.287
XU100 L1	-0.0001	0.0042	0.990	XU100 L1	0.9545	0.0115	0.000
ARCH (Gold)				*ARCH (XU100)*			
ARCH L1	0.0702	0.0211	0.001	ARCH L1	0.0543	0.0157	0.001
GARCH L1	0.8823	0.0415	0.000	GARCH L1	0.9115	0.0249	0.000
Constant	0.0000039	0.0000022	0.080	Constant	0.0000154	0.0000071	0.029
				Correlation (Gold, XU100)	*0.1034*	*0.037*	*0.005*

Panel E: CCC-GARCH Model for Copper and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
Copper Mean Equation				*XU100 Mean Equation*			
Copper L1	-0.023	0.0394	0.560	Copper L1	0.0426	0.0558	0.445
XU100 L1	-0.002	0.0068	0.764	XU100 L1	0.9548	0.0115	0.000
ARCH (Copper)				*ARCH (XU100)*			
ARCH L1	0.0451	0.0136	0.001	ARCH L1	0.0564	0.0163	0.001
GARCH L1	0.9278	0.0216	0.000	GARCH L1	0.9065	0.0267	0.000
Constant	0.0000048	0.0000025	0.054	Constant	0.0000167	0.0000076	0.028
				Correlation (Copper, XU100)	*0.1896*	*0.0358*	*0.000*

Table 5: CCC-GARCH Model Results (*continue…*)

Panel F: CCC-GARCH Model for Silver and XU100							
Variable	**Coefficient**	**S.E.**	**Prob.**	**Variable**	**Coefficient**	**S.E.**	**Prob.**
Silver Mean Equation				*XU100 Mean Equation*			
Silver L1	0.0263	0.0392	0.502	Silver L1	-0.0232	0.0434	0.592
XU100 L1	-0.0042	0.0079	0.595	XU100 L1	0.9534	0.0116	0.000
ARCH (Silver)				*ARCH (XU100)*			
ARCH L1	0.0812	0.0159	0.000	ARCH L1	0.0543	0.0158	0.001
GARCH L1	0.9126	0.0154	0.000	GARCH L1	0.9115	0.0252	0.000
Constant	3.64E-06	2.04E-06	0.074	Constant	0.0000154	0.0000071	0.029
				Correlation (Silver, XU100)	*0.1633*	*0.0363*	*0.000*

Source: Author's estimation.

The results from table 4 and 5 indicate that most markets show significant short-run volatility clustering, especially through the ARCH terms. This indicates that recent shocks (short-run volatility) in asset prices have a direct impact on their volatility in the short term. For the long-run spillovers, the GARCH terms are generally high for all panels, suggesting that volatility shocks tend to persist over time, implying long-term spillovers. The correlation terms across each of the panels vary Gold and Silver show moderate positive correlations with XU100, while other assets like Crude Oil and Natural Gas show weak or no significant correlation, suggesting limited direct spillovers between these markets and the XU100.

CONCLUSION

The results presented in Tables 4 and 5 provide a comprehensive analysis of the dynamic correlations and volatility spillovers between various assets, specifically focusing on the USD/TRY, Natural Gas, Gold, Silver, and their relationship with the XU100 index. This study utilized both CCC-GARCH and DCC-GARCH models to address the limitations of the ARCH model in analyzing the volatility spillover effects between key commodities, USD/TRY, and XU100, concentrating on daily data spanning the period from January 1, 2010 to December 31, 2023.

In the DCC-GARCH model analysis, the relationship between USD/TRY and XU100 shows a significant negative short-run correlation, suggesting that fluctuations in the Turkish Lira impact the equity index adversely. This negative correlation contrasts with the positive correlations observed between XU100 and commodities such as Silver and Gold, indicating that while currency volatility may detract from stock performance, commodities exhibit more synchronized behavior with the equity market. High GARCH coefficients further imply that past volatility influences current volatility over extended periods. The results from the volatility terms demonstrate pronounced ARCH and GARCH effects across the asset pairs, particularly highlighting the significance of volatility persistence. High GARCH coefficients imply that shocks to volatility are long-lasting, with market adjustments to these shocks occurring slowly over time. This characteristic is essential for investors and policymakers, as it suggests that past volatility influences future market behavior, necessitating a careful approach to risk management.

When comparing the DCC-GARCH and CCC-GARCH models, both models reveal significant insights into volatility dynamics. However, the DCC-GARCH model appears more adept at capturing time-varying correlations, particularly between USD/TRY and XU100, while the CCC-GARCH model shows more static relationships. Notably, while Gold and Silver show moderate positive correlations with the XU100, other commodities such as Crude Oil and Natural Gas exhibit weaker or negligible correlations. The findings underscore that while correlations can fluctuate in the short term, the long-term relationships exhibit substantial persistence, as reflected in the high $Lambda2$ values across various asset panels.

Interestingly, correlations among commodities and the XU100 index vary. For instance, Gold and Silver exhibit moderate positive correlations, whereas Natural Gas and Crude Oil demonstrate weak or negligible correlations with the XU100. This suggests that commodity prices are not uniformly correlated with the equity market, which may influence investment strategies and asset allocation decisions. Investors may consider diversifying their portfolios with commodities like Gold and Silver, which align more closely with equity movements.

The analysis emphasizes the importance of understanding market dynamics through the lens of volatility and correlation which also revealed that most markets exhibit significant short-run volatility clustering, particularly through the ARCH terms, which indicates that recent shocks in asset prices have an immediate impact on volatility. Long-term spillovers, however, are more pronounced, as evidenced by the high and significant GARCH terms across all panels, suggesting that volatility shocks persist over time, indicating strong long-term volatility linkages. As the financial landscape evolves, recognizing how these relationships change can significantly impact investment decisions. The strong volatility persistence noted across most asset pairs highlights the need for continuous monitoring of market conditions to better anticipate future movements and manage risk effectively.

The correlation analysis showed that assets like Gold and Silver exhibit moderate positive correlations with XU100, suggesting some degree of spillover from these markets. In contrast, commodities such as Crude Oil and Natural Gas show weak or no significant correlation with XU100, implying limited short-term spillovers. Notably, the USD/TRY exchange rate and XU100 displayed a significant negative short-run correlation, further underscoring the unique relationship between currency volatility and the stock market.

Overall, the findings from both the DCC-GARCH and CCC-GARCH models indicate the complex interplay between currency, commodity, and equity markets while also indicating that while short-run volatility spillovers are generally weak among most asset pairs, long-run relationships reveal strong and persistent volatility linkages. The high persistence in dynamic correlations, particularly for USD/TRYand Natural Gas, suggests that volatility adjustments in these markets occur gradually over time. This highlights the necessity of understanding both short- and long-term volatility dynamics for effective risk management and portfolio diversification within the Turkish financial market. Consequently, investors should exercise caution with volatility-based trading strategies. They need to closely monitor the behavior and investment patterns of commodity price volatility, especially during crises when outflows exceed inflows. It is also crucial for fund managers to recognize investors' behavioral tendencies and potential biases before constructing their portfolios.

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