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Volatility spillovers from COVID-19 to stocks, exchange rates and oil prices: evidence from Türkiye

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Abstract

Global crises destabilize stocks, exchange rates, and oil prices. Most recently, the COVID-19 pandemic, which started in Wuhan, China, in December 2019, has been another factor leading to volatility in global financial markets. This makes it important to investigate how volatility spreads among financial assets during the relevant period. This study's main contribution to the existing literature is the simultaneous analysis of the volatility spread from COVID-19 to exchange rates, stock, and oil prices in Türkiye during the period January 1, 2020, to July 15, 2022. Understanding such interactions throughout the pandemic period is essential for policymakers and investors.

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1. Introduction

Global financial crises have significantly changed economic and financial systems, leading to more comovement in financial markets. The COVID-19 pandemic has exacerbated these dynamics, particularly in the areas of exchange rates, stocks, and oil prices. Despite extensive discussions on these topics in the literature, there is no consensus on how the pandemic has impacted these variables. Such crises can decrease oil and stock returns; they can also have potential effects on exchange rate stability. Volatility spillovers between these markets have increased during the COVID-19 pandemic (Sadorsky 2012; Wen *et al.* 2019; Liu *et al.* 2020; Zhu *et al.* 2024). In other words, global crises destabilize stocks, exchange rates, and oil prices. Most recently, the COVID-19 pandemic, which started in Wuhan, China, in December 2019, has been another factor leading to volatility in global financial markets. This makes it important to investigate how volatility spreads among financial assets during relevant periods (Liu *et al.* 2020; Abuzayed *et al.* 2021).

Some empirical studies in the literature have found a negative relationship between COVID-19 and stock markets (Al-Awadhi *et al.* 2020; Ashraf 2020; He *et al.* 2020; Ozkan 2021; Rahman *et al.* 2021; Xu 2021), while others such as Harjoto *et al.* (2021) found that the pandemic had positive effects on stock markets. Several studies have investigated the volatility spillover between COVID-19 and stock markets. Okorie and Lin (2021) and Chundakkadan and Nedumparambil (2022) observed that the pandemic had high contagion and volatility effects on stock markets. Studies by Gil-Alana and Monge (2020), Liu *et al.* (2020), and Zhu *et al.* (2024) investigated the effects of the COVID-19 pandemic on oil prices. Although these studies also include stock markets, they suggest that the pandemic positively affected crude oil returns and that market volatilities are extremely vulnerable to the pandemic. Empirical studies on the relationship between COVID-19 and exchange rates include Narayan (2020a,b, 2022) and Narayan *et al.* (2020). They suggest that exchange rates in the face of the pandemic exhibit a bubble-like behavior, with the possibility of deviations from the usual efficiency of the foreign exchange market. Studies by Topcu and Gulal (2020), Rai and Garg (2022), Antonakakis *et al.* (2023), Chang *et al.* (2024), Hussain *et al.* (2024), and Prananta and Alexiou (2024), which collectively analyze these markets, concluded that that the pandemic negatively impacted exchange rates, stock markets, and oil prices, while also increasing the volatility spillovers between markets.

Up to authors' knowledge, there is not any study analyzing the volatility transmission from COVID-19 to exchange rates, stock, and oil prices in Türkiye during the period January 1, 2020, to July 15, 2022. However, such an analysis may provide additional information to policymakers and investors while making their decisions which may affect the overall economy. The following part of the study includes methodology, data, empirical findings, policy implications and conclusions.

2. Methodology

This study uses stochastic volatility modeling to understand the volatility transmission between the number of COVID-19 cases ($covid$), stock ($bist100$), exchange rate (usd), and oil markets (oil). Taylor (1986) introduced the stochastic volatility modeling approach. Unlike GARCH, which models volatility as a deterministic process, the conditional variance equation includes a stochastic component where volatility modeling is based on an unobserved and latent process. Harvey *et al.* (1994) developed multivariate stochastic volatility models. This study uses the Dynamic Conditional Correlation-Stochastic Volatility Model to allow for a time-varying correlation between returns and volatility spillover. This model introduced by Yu and Meyer

(2006) demonstrated better adaptation to the data. Main advantage of this method is that compared to multivariate GARCH models with complicated structure, it requires a smaller number of parameters to be estimated and has better fit to the data. The mean (return) equation in equation (1) and stochastic volatility in equation (2) show a bivariate Dynamic Conditional Correlation-Stochastic Volatility Model (Yu and Meyer 2006, 365-366) where r_{ij} is return and H_{ij} is conditional variance-covariance matrix of error process for each $i,j = bist100, usd, oil$, and $covid$;

$$r_{ijt} = H_{ijt}^{\frac{1}{2}} e_{ijt}$$

$$where, e_{ijt} \sim N_2\left(0, \Sigma_{eiej,t}\right), H_{ijt}^{1/2} = \begin{bmatrix} exp\left(h_{i,t}/2\right) & 0 \\ 0 & exp\left(h_{j,t}/2\right) \end{bmatrix}, \Sigma_{eiej,t} = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}, \rho_t = \frac{exp(q_t)-1}{exp(q_t)+1},$$
$$q_{t+1} = \alpha_0 + \alpha_1(q_t - \alpha_0) + \sigma_\rho \omega_t \text{ and } \omega_t \sim iidN(0,1) \quad (1)$$

$$\begin{bmatrix} h_{i,t+1} \\ h_{j,t+1} \end{bmatrix} = \begin{bmatrix} \gamma_i \\ \gamma_j \end{bmatrix} + \begin{bmatrix} \beta_{ii} & \beta_{ij} \\ \beta_{ji} & \beta_{jj} \end{bmatrix} \begin{bmatrix} h_{i,t} - \gamma_i \\ h_{j,t} - \gamma_j \end{bmatrix} + u_t \; where, \mathrm{u} \sim N_2\left(0, diag(\sigma_1^2, \sigma_2^2)\right) \quad (2)$$

Here, ρ_t, γ_i and γ_j show the time-varying dynamic correlation coefficient and constant parameters. Volatility is persistent if β_{ii} and β_{jj} estimates are statistically significant and approach unity. Statistically significant β_{ij} and β_{ji} indicate the volatility spillover from j to i and vice versa, respectively. The predictability of volatility is high if variances of the volatility process (σ_1^2 and σ_2^2) are close to zero. The Markov Chain Monte Carlo (MCMC) Bayesian estimation method was used to estimate the model in WinBUGS 1.4. MCMC approach directly consider uncertainty in parameters and smoothing problem. Prior distributions given in equation (3) and estimations are based on the program written by Yasuhiro Omori.

$$\begin{aligned}
&\gamma_i \sim N(0, 0.04) \\
&\beta_{ii} = 2\beta_{ii}^* - 1; \;\; \beta_{ii}^* \sim \mathrm{beta}(20, 1.5) \\
&\beta_{ij} \sim N(0, 0.1) \\
&\sigma_1^2 \sim Inverse - gamma(2.5, \quad 0.025) \\
&\gamma_j \sim N(0, 0.04) \\
&\beta_{jj} = 2\beta_{jj}^* - 1; \;\; \beta_{jj}^* \sim \mathrm{beta}(20, 1.5) \\
&\beta_{ji} \sim N(0, 0.1) \\
&\sigma_2^2 \sim Inverse - gamma(2.5, \quad 0.025) \\
&\alpha_0 \sim N(0.7, 0.1) \\
&\alpha_1 = 2\alpha_1^* - 1; \;\; 2\alpha_1^* \sim \mathrm{beta}(20, 1.5) \\
&\sigma_q^2 \sim Inverse - gamma(2.5, \; 0.025) \qquad (3)
\end{aligned}$$

Five thousand iterations were performed to determine initial values. The coefficient estimations were performed by excluding the first 4000 observations.

3. Data

The data set includes daily BIST National 100 - Price Index, Turkish Lira to US $ (TRY) - Exchange Rate, Daily Europe Brent Spot Fob U$/BBL, and COVID-19 Cases World 'Dead' - Economic Series from January 1, 2020 to July 15, 2022. All the data were obtained from DataStream. The daily percentage changes and return series were employed in the analysis for

BIST National 100, Turkish Lira to US dollar Exchange Rates, Europe Brent Spot oil prices and COVID-19 Cases shown by $r_{bist100}$, r_{usd}, r_{oil}, and r_{covid}, respectively. Table I shows the descriptive statistics. Average daily returns are calculated as 0.11%, 0.16%, and 0.07% for BIST100 Index, US dollar/TRY, and Spot oil, respectively. On average, COVID-19 cases increased by 2.54% daily. The highest standard deviation was recorded by COVID-19 cases, implying higher volatility. Spot oil return has the second highest standard deviation, making it the riskiest asset in this portfolio. The Jarque-Bera statistics indicate that the series is not distributed normally.

Table I. Descriptive Statistics

	$r_{bist100}$	r_{usd}	r_{oil}	r_{covid}
Mean	0.110782	0.162855	0.076238	2.544015
Median	0.185501	0.0614	0.305827	0.672685
Maximum	5.810361	8.445248	41.20225	128.4016
Minimum	-10.3068	-29.3969	-64.3699	-24.3622
Std. Dev.	1.64161	1.644479	4.899065	8.859652
Skewness	-1.56873	-8.33088	-2.80616	9.507
Kurtosis	10.90186	163.2294	60.40272	120.1209
Jarque-Bera	1993.807	715817.4	91757.91	388341.2
(Probability)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sum	73.33758	107.8102	50.4698	1684.138
Sum Sq. Dev.	1781.318	1787.55	15864.56	51884.16
Observations	662	662	662	662

Table II. Correlations

	$r_{bist100}$	r_{usd}	r_{oil}	r_{covid}
$r_{bist100}$	1			
r_{usd}	0.012971	1		
	(0.333268)			
r_{oil}	0.112396***	-0.05508	1	
	(2.905911)	(-1.4172)		
r_{covid}	-0.07314*	0.014507	-0.06797*	1
	(-1.88401)	(0.372724)	(-1.75011)	

Notes: t-Statistic are in parentheses. *, **, *** indicate a statistical significance of 10%, 5%, 1%, respectively.

Table II shows that the BIST 100 index and spot oil returns are positively and statistically significantly correlated. Moreover, there is evidence of a negative and statistically significant cross-correlation between COVID-19 cases and the BIST 100 index and between COVID-19 cases and spot oil prices. The unit root test results in Table III indicate that all series are stationary.

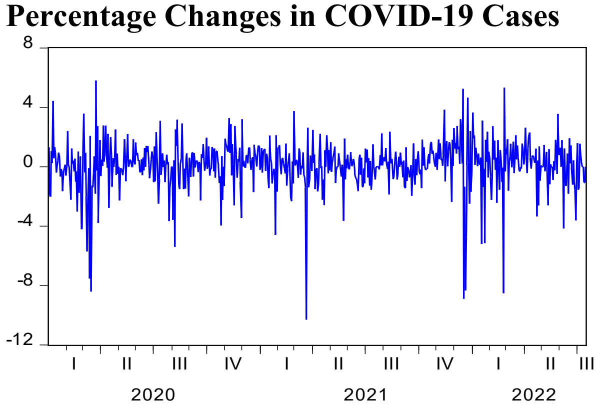
Table III. Results of Unit Root Tests

	Phillips-Perron			Augmented Dickey-Fuller		
	Constant	**Constant & Trend**	**Without Constant & Trend**	**Constant**	**Constant & Trend**	**Without Constant & Trend**
$r_{bist100}$	-26.5108***	-26.5215***	-26.4798***	-15.6277***	-15.6459***	-15.5383***
r_{usd}	-23.4032***	-23.4356***	-23.1803***	-15.7996***	-15.8344***	-15.5438***
r_{oil}	-26.6117***	-26.6421***	-26.6233***	-20.7223***	-20.7589***	-20.7301***
r_{covid}	-18.5619***	-19.3242***	-17.8387***	-7.7098***	-8.7467***	-7.0495***

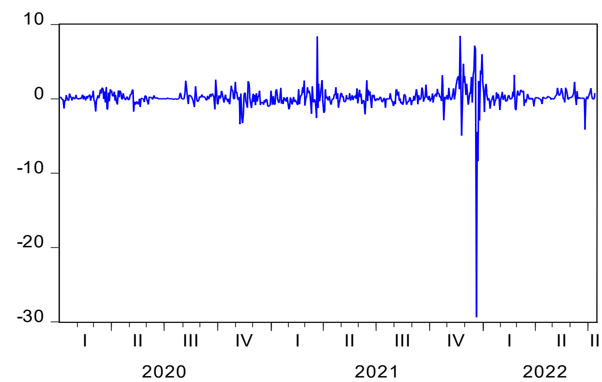
Notes: *, **, *** indicate a statistical significance of 10%, 5%, 1%, respectively. Lag lengths were determined using Bayesian Information Criteria.

In Figure 1, all series show volatility clustering and high volatile periods except for COVID-19 cases. Co-movements of series are also evident, such as sharp increases in COVID-19 cases associated with the declines in returns of the BIST 100 index and spot oil at the beginning of 2020 and decreases in the returns of the BIST 100 index and US dollar/TRY exchange rate at the end of 2021.

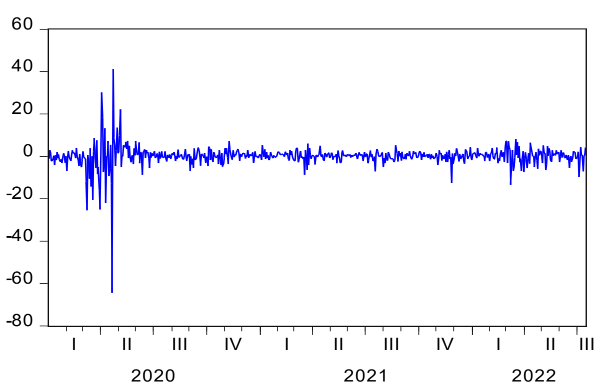
Figure 1. BIST 100 Index, USD/TRY Exchange Rate and Spot Oil Return Series and Percentage Changes in COVID-19 Cases



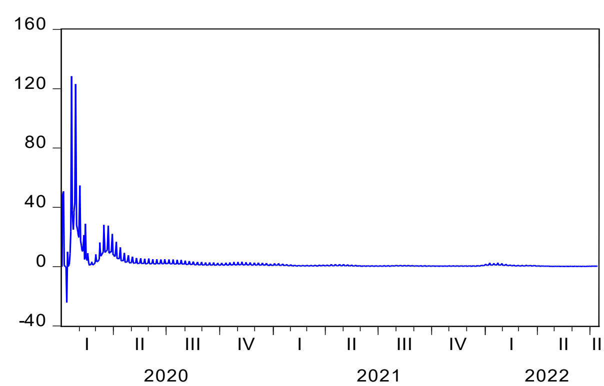
a. BIST100



b. USD



c. OIL



d. COVID

4. Empirical Findings

Table IV presents the estimation results for the posterior quantities of parameters. β_{11} and β_{22} are near to 1 and statistically significant, suggesting the existence of volatility clustering and persistency. In addition, volatility is predictable because σ_1^2 and σ_2^2 are near zero.

Table IV. Estimation Results of Dynamic Conditional Correlation-Stochastic Volatility Model

	$[r_{bist100}, r_{covid}]$	$[r_{usd}, r_{covid}]$	$[r_{oil}, r_{covid}]$	$[r_{bist100}, r_{oil}]$	$[r_{bist100}, r_{usd}]$	$[r_{usd}, r_{oil}]$
γ_1	1.608***	-0.1633	1.819**	0.3574***	0.382***	-1.244***
	(3.741)	(-0.31034)	(2.096588)	(2.624082)	(2.728898)	(-3.22447)
γ_2	7.159***	7.339***	7.145***	1.73***	-1.277***	1.674***
	(15.821)	(12.64909)	(15.21184)	(5.371003)	(-3.54329)	(4.19654)
β_{11}	0.8592***	0.9052***	0.9525***	0.771***	0.743***	0.9089***
	(16.381)	(36.23699)	(54.49085)	(15.65482)	(10.90109)	(41.1826)
β_{12}	0.01972**	0.009319	0.002231	0.009607	0.041	-0.01117
	(2.524)	(1.208847)	(0.375336)	(0.361709)	(1.542264)	(-0.37597)
β_{22}	0.9952***	0.9988***	0.999***	0.9707***	0.885***	0.9756***
	(401.939)	(1158.029)	(1344.006)	(98.2291)	(31.90768)	(103.3913)
β_{21}	0.03871***	0.01654***	-0.00318	0.05543***	0.139**	0.007844
	(4.289)	(4.78588)	(-0.30028)	(3.001083)	(2.241073)	(1.084324)
α_0	0.303	0.7633***	0.1676**	0.3086***	-0.270**	-0.1717***
	(1.585)	(3.246704)	(2.162023)	(5.480376)	(-2.50093)	(-2.83802)
α_1	0.9745***	0.9871***	0.9453***	0.8908***	0.938***	0.9524***
	(94.612)	(177.3446)	(59.49025)	(26.10785)	(53.4416)	(67.49823)
σ_1	0.4972***	0.8756***	0.3938***	0.6416***	0.636***	0.8325***
	(5.775)	(8.299526)	(9.701897)	(7.868531)	(7.727549)	(10.42319)
σ_2	0.1496***	0.1544***	0.192***	0.2528***	0.798***	0.2726***
	(12.262)	(10.28648)	(12.55723)	(9.307806)	(9.14024)	(9.841155)
σ_ρ	0.2303***	0.1475***	0.1717***	0.1825***	0.268***	0.1177***
	(6.998)	(8.194444)	(8.859649)	(5.782636)	(5.841692)	(6.509956)

Notes: The table gives mean and t values in parentheses. *, **, *** indicate a significance level of 10%, 5%, and 1%, respectively.

Findings indicate volatility interactions. Results show bidirectional volatility transmission between the BIST 100 index and COVID-19 cases. Volatility spillovers are shown from the US dollar/TRY exchange rate to COVID-19 cases, from the BIST 100 index to spot oil prices, and from the BIST 100 index to the US dollar/TRY exchange rate. A 1% volatility shock on the BIST 100 index may raise the volatility of the US dollar/TRY exchange rate by 0.139% and the volatility of spot oil prices by 0.05543% the next day. One can relate to this finding to interaction of these markets with each other, there may be complementarity or substitutability. Due to portfolio optimization, investors may rotate their assets in different markets. A 1% shock to the volatility of the BIST 100 index and US dollar/TRY exchange rate may increase the volatility of COVID-19 cases by 0.03871% and 0.01654% the next day, respectively. This result may be related to the health consequences of macroeconomic and financial instability. As individuals have investments in stock exchanges, high volatility may affect their income and purchasing power. In addition, in Türkiye, inflation is affected highly from exchange rate fluctuations. High exchange rate volatility may cause increase in inflation uncertainty. All these may affect the well-being of individuals through their effects on uncertainty related to income and purchasing power. A 1% shock to the volatility of COVID-19 cases may increase the volatility of the BIST 100 index by 0.01972% the next day. Health related uncertainty may increase uncertainty in the whole economy which may also affect the stock exchange market by increasing its volatility. Moreover, restrictions, economic lockdowns and uncertainty related to the course of COVID-19 may also produce this result during this period. MC errors[1] are close to zero, indicating that results are reliable. As estimates of α_1 are statistically significant and positive between 0.8908 and 0.9871, correlations are positive, persistent and significant between returns on the BIST 100 index, USD/TRY exchange rate, spot oil prices, and percentage change in COVID-19 cases.

5. Policy Implications and Conclusions

The analysis of the volatility spread from COVID-19 to exchange rates, stock, and oil prices show that there are strong interactions among markets and COVID-19 also affect volatility of these markets in Türkiye during the period January 1, 2020, to July 15, 2022. Therefore, policymakers and investors should consider these interactions in their policy and investment decisions. Investigating stochastic volatility between markets is crucial for investors and policymakers. It helps to understand the interconnected structure of the financial system, particularly in contexts like the COVID-19 pandemic, which had significant effects on exchange rates, stock markets, and oil prices (Zhang *et al.* 2017). Since shocks in one market can quickly spread to others, investors must benefit from shared information and protective strategies to mitigate risks. The interconnected findings of the study highlight the importance of understanding these effects to better predict financial markets and market volatilities and develop more accurate asset pricing models. Ultimately, investors must monitor the behavior of different markets or minimize their risks and manage their portfolios in the face of uncertainty since news in one sector can affect other sectors through volatility spillovers (Malik and Ewing 2009; Sarı *et al.* 2010; Arouri *et al.* 2012; Zhu *et al.* 2024).

The study's findings are valuable for policymakers as they emphasize the importance of rapid information processing by financial markets to mitigate the risk of contagion and create effective short-term policies. In light of the COVID-19 pandemic, policymakers should allocate more resources to manage extreme market conditions, as global cooperation and strengthened regulations are essential for maintaining financial stability across borders. Investors can also benefit by improving their risk perception and management skills to proactively respond to market risks (Zhu *et al.* 2024). To further mitigate the effects of volatility spillovers, policymakers should encourage collaboration with central banks and work to enhance regulatory frameworks while promoting financial market integration. Moreover, reinforcing macroeconomic fundamentals, such as financial stability and economic growth, is crucial for reducing vulnerabilities to external shocks like pandemics (Hussain *et al.* 2024).

[1] Results are available upon request.

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