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Nonlinear Contagion and Causality Nexus between Oil, Gold, VIX Investor Sentiment, Exchange Rate and Stock Market Returns: The MS-GARCH Copula Causality Method

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Abstract: The fluctuations in oil have strong implications on many financial assets not to mention its relationship with gold prices, exchange rates, stock markets, and investor sentiment. Recent evidence suggests nonlinear contagion among the factors stated above with bivariate or trivariate settings and a throughout investigation of contagion and causality links by taking especially nonlinearity into consideration deserves special importance for the relevant literature. For this purpose, the paper explores the Markov switching generalized autoregressive conditional heteroskedasticity copula (MS-GARCH—copula) and MS-GARCH-copula-causality method and its statistical properties. The methods incorporate regime switching and causality analyses in addition to modeling nonlinearity in conditional volatility. For a sample covering daily observations for 4 January 2000–13 March 2020, the empirical findings revealed that: i. the incorporation of MS type nonlinearity to copula analysis provides important information, ii. the new method helps in the determination of regime-dependent tail dependence among oil, VIX, gold, exchange rates, and BIST stock market returns, in addition to determining the direction of causality in those regimes, iii. important policy implications are derived with the proposed methods given the distinction between high and low volatility regimes leads to different solutions on the direction of causality.

Keywords: copulas; Markov processes; GARCH; tail inference; financial markets

MSC: 62H05; 60J05; 62M10; 62G32; 91G15

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1. Introduction

Oil, which is used in a wide range from electricity production to transportation, from industrial production to agriculture, is a strategic and vital commodity for many economies. Nowadays, oil price movements behaving out of expectations have been affecting the whole economy including the real sector and financial markets. As an example, the financial market and oil price movements in the first quarter of 2020 are among the unusual behavior due to the massive downward pressure of the COVID-19 outbreak on the price of crude oil. Amid the COVID-19 pandemic in late 2019 and early 2020, oil consumption has reduced in China and the rest of the world because of decreasing industrial production and transatlantic transportation. On the other hand, the oil conflict between Saudi Arabia and Russia in March 2020 also led to increased supply while decreasing prices. With the impact of unprecedentedly falling demand and rising supply, the WTI entered the negative zone for the first time in its history. In the oil market, both supply and demand shocks have an

effect on the prices of macroeconomic and financial variables. Oil price variations have a major impact on the dynamics of global energy markets, as well as global financial markets, owing to the financialization of commodities.

As the above-mentioned example suggests, oil price shocks might be among the most common sources of volatility in the stock markets around the world. Strong oscillations in the price of oil have impacts on financial asset returns in addition to their impacts on expectations and the economy. The growing convergence of stock and oil markets has reduced the benefits of diversity, forcing investors to seek out an alternative asset that lowers portfolio risk [1]. Based on this quest for alternative assets, gold is extensively presented as an asset to obtain improvement in the diversification of a portfolio [2] in addition to providing a hedge [3] against excessive movement of stock indices and returns which particularly occurs in times of high volatility [4]. Further, gold is seen as a safe-haven asset class for many nations, predominantly in the MENA area, in addition to being highly demanded during political turmoil and economic crises throughout the world. Therefore, gold demand is strong in emerging countries in addition to strong financial uncertainties. As shown by [5], there is a clear relationship between the drop in oil prices and the demand for gold in the MENA countries (see for MENA countries [5]. According to Connolly et al. [6] and Chiang et al. [7], stock and bond market volatility rises when stock market uncertainty rises. Hence, a decline in global stock markets can increase current gold demand in these countries. These relations can exhibit different structures in the longer periods compared to the very short term.

Oil prices can also have an impact on stock returns, either indirectly through the discount rate or directly through predicted cash flows. Oil price shocks affect stock returns, according to several empirical studies that use flexible graphical models that allow for extensions to higher dimensions. The increase in oil prices, on the other hand, is anticipated to improve the total trade imbalances in the petrol-importing economies. Expectations of exchange rate depreciation and increased inflation will rise as the trade gap rises.

According to the literature, oil prices have a variety of effects on stock markets and the direction, and the size of these effects depends on the structure of the economy in addition to the type of oil shock [8]. Basher et al. [9] further emphasize that the stock price formulation necessitates the anticipated present value of discounted future cash flows which is drastically lowered after sharp oil price shocks resulting in lower stock prices. Moreover, policymakers respond to rising oil prices by increasing the interest rates to control inflation expectations which affect the discount rate in the stock pricing formula leading to lower stock market prices [9]. As discussed by Bayer and Filion [10], Hammoudeh et al. [11], the hikes in oil prices raise operating costs leading to negative effects since increases in oil prices lead to lower earnings and for non-oil-related industries, the substitution of oil in the short and medium run is not possible for businesses. Huang et al. [12] show that the impact of crude oil movements on stock markets can be completely explained by their effect on current and future real cash flows. According to Faff and Brailsford [13], there is a markup effect of oil prices that causes businesses to raise the prices of their goods which has a negative influence on stock markets as long as the increasing production costs due to oil price hikes are passed on to customers. Le and Luong [14] emphasize that the oil price hike's effect depends on the structure of the economy, for importers of oil, losses occur for businesses resulting in a decline in realized stock returns, whilst countries that export oil might experience the opposite consequences. Rahman [15] evaluates the asymmetric responses of stock markets to oil price shocks and according to the findings, responses to positive and negative oil price shocks differentiate, and this asymmetric response is driven by the oil price volatility which has negative effects on stock returns. Wen et al. [16] confirm that the type of shock matters for stock markets' response and while oil demand shocks lead to a positive stock-risk association, oil risk shocks affect the stock-risk relation negatively. Maghyereh and Abdoh's [17] findings emphasize the extreme level of dependence among these variables in GCC countries.

VIX is a barometer for worldwide investors and its level influences decision-making [18]. The prices of gold, stock, oil, exchange rates, and VIX are all under the influence of macro and microeconomic factors, as well as non-economic factors such as geopolitical tensions, wars, as well as speculative activities. More volatility and uncertainty in oil and gold prices, stock returns, VIX, and exchange rates result from increased speculative activity. Moreover, uncertainty and volatility in gold and oil prices may affect the decisions of manufacturers for industrial production and investors for portfolio allocation. Gold price, stocks, exchange rate, VIX, and oil may exhibit evidence of dependence, persistency, and nonlinear behavior. As put forth by Hamilton [19], nonlinear and/or asymmetric behavior occurs when, for example, an economic crisis is on stage or high volatility regime is less persistent than the boom stage, or when the periods of economic expansion take longer than the crisis stage. Under such conditions, investigation of regime dependency has strong implications for the effectiveness of policy decisions.

The movements of oil, gold, VIX, exchange rate and stock return cannot be analyzed by traditional methods such as VAR, GARCH, and cointegration, since they are sensitive to many economic and non-economic factors such as COVID-19, geopolitical events, wars, internal conflicts, etc. This study attempts to contribute to the literature in the areas of theory, methodology, and application. Following the discussion above, it is critical to assess whether there exists contagion and causality relations between oil prices, stock markets, investor sentiment, exchange rates, and gold prices, however, the traditional methods become biased under the sensitivities stated above. Further, the series analyzed are subject to heteroskedastic behavior in addition to nonlinearity. Therefore, it is important to construct models to capture nonlinear tail dependence contagion relations in addition to regime-dependent causal links. For this purpose, the paper contributes to the utilization of Markov switching generalized autoregressive conditional heteroskedasticity copula and causality (MS-GARCH-copula causality) methodologies. The models to be utilized allow the assessment of nonlinear dependence and persistency structures, in addition to regime-dependent contagion and causality behavior among oil and gold prices, VIX investor fear index, exchange rates, and stock markets in an emerging market, Turkey.

The use of the copula method is not new. However, the extension of the copula analysis to nonlinear Markov switching causality is a hybrid approach proposed. In the paper, the MS-GARCH copula method will be advanced to the MS-GARCH copula causality to contribute to various aspects. The existing literature on contagion in terms of both tail dependence coefficients and copula parameters were discussed in [20–23]. Bildirici [24] by TAR-TR-GARCH and TAR-TR-TGARCH copula methods found evidence of nonlinear tail dependence and Bildirici's [25] results indicated chaotic behavior in oil price, VIX, and stock returns in addition to contagion [26,27] did not conduct but could be thought of favoring the necessity of simultaneous analysis of the direction of causality. On the other hand, a few numbers of papers used copula-causality tests such as Lee and Yang [28] and Hu and Liang [29]. However, these papers did not analyze the different structures and the direction of causality among the regimes. Since each regime has a different characteristic, every economic regime needs regime-specific policies instead of common ones. If it is not taken into regimes, the direction of causality and policy recommendations determined by the causality results will be incorrect. In the application aspect, the MS-GARCH copula causality method provides tests for the presence of causality, asymmetric behavior, persistence, and contagion impact simultaneously for managers and policymakers.

The study has five parts. The second part contains the literature review. The data and methodology are given in the third section. The analysis and results are reported in Section 4. Discussion, implications, and policy suggestions are in the fifth section. The last section concludes.

2. Literature Review

In this section, the literature review will be given in three sub-headings.

2.1. Oil and Stock Return

Some early empirical results go back to Pindyck and Rotemberg [30], who test and confirm the existence of the comovement phenomenon in commodity prices. Leybourne et al. [31] use a novel framework to re-examine the comovement in commodity prices. However, they show their concerns because they find an excess comovement only in monthly time series.

The relationship between oil prices and stock prices has been studied by a large number of papers. Refs. [32–35] analyzed this relationship and revealed a positive (or insignificant) relation that is not easily clarified by standard economic theory. Studies in China have become more widespread in the literature at both the country and sectoral levels, most recent studies include [36,37]. Chiou and Lee [38], Miller and Ratti [39], Nandha and Faff [40], and Park and Ratti [41] have found that an increase in oil prices means a decrease in stock returns. Currently, this idea has become widely accepted in the literature and seems almost axiomatic. More recent studies such as Arouri and Nguyen [42] and Fayyad and Daly [43] show that the impact of oil on stock markets is sensibly different across economic sectors (e.g., oil versus non-oil industries) and across countries (e.g., net oil-exporting versus net oil-importing ones). Bjornland [44] and Jimenez-Rodriguez and Sanchez [45] argue that a positive relationship between oil price movements and stock market returns is expected in the case of an oil exporting country.

Bouri and Demirer [46] investigated the dependence characteristics between oil and stock markets in the importing and exporting emerging countries. They found that there is a significant volatility spillover from oil prices to emerging importers during the post-global financial crisis. Ji et al. [47] tested the connections between stock return and oil price changes in BRICS countries using the structural VAR model and GARCH-based CoVaR methods. They concluded that the relationship between oil shocks and stock returns is time-varying, and there is an important risk spread in the BRICS countries. Zhou et al. [48] studied the dependence between oil price volatility and stock return in BRICS countries. They found that oil price shocks have an impact on stock return and oil volatility is in a high quantile. That is, there is a high probability of big gains and losses in the stock markets of BRICS countries. Nasir et al. [49] investigated the effects of oil price shocks on BRICS economies. The study concludes that volatility in oil prices affects these economies differently, as the economies have different characteristics. The findings showed that comparing the two major oil exporters (Russia and Brazil), shocks in oil prices affected the Russian economy more than the Brazilian economy. When the two major oil importers (India and China) are compared, changes in oil prices have a relatively greater impact on India.

Ferreira et al. [50] analyzed the stock market comovements by cointegration and causality tests. Pereira et al. [51] tested the stock exchanges before and after the subprime crisis by using the DCCA. Monti et al. [52] tested the US financial and the Eurozone debt crises by DCCA and DMCA. Tursoy and Faisal [53] used the ARDL model and the Granger causality test to examine the short-run and long-run relationship between gold prices, stock prices, and crude oil prices in their study for the period 1986–2016. According to the results of this study, there is a negative relationship between gold prices and stock prices in both the short and long term. On the other side, there is a positive relationship between oil prices and stock prices. Additionally, the direction of causality is from stock prices to gold prices in the short-run and long-run.

2.2. VIX and Oil Price

Brown and Cliff [54] researched the relationship between investor sentiment and asset valuations using the direct survey method with monthly data between 1963 and 2000. They concluded that there is a strong relationship between investor sentiment, asset pricing models, and market bubbles. Moreover, their paper identifies investors' irrational sentiment affects asset prices. Using consumer confidence as a tool to measure investor

behavior, Lemmon and Portniaguina [55] analyzed the relationship between consumer confidence and stock prices for the period 1956–2002. In the study, the confidence index is considered a potential indicator of optimism. Using time series analysis, they stated that investors value small stocks more than their bigger counterparts when the confidence index is high. Beckmann et al. [56] examined the impact of economic confidence on financial markets for central and Eastern European countries using monthly data between 1997 and 2008. While they found a strong link between economic confidence and stock prices in the short term, a long-term relationship was observed for the Czech Republic. According to another result of the study, global trends (economic confidence for this study) have the power to influence the stock market more than domestic factors. Moreover, it was noted that global sentiments and stock prices affected domestic variables to a higher degree when the domestic economies have undergone an important degree of integration with global markets. Using panel data of 15 European countries and the US over the period of 1995–2009, Zouaoui [57] investigated the impact of investor sentiment on the international stock market. According to the results of the study, investor sentiment is an important tool to predict crises, and the impact of investor sentiment on the stock market is related to cultural and institutional factors.

Creating an index of investors with six parameters to measure the trend, Ding et al. [58] analyzed how crude oil price fluctuations between 2005 and 2015 affected the trends of investors investing in the Chinese financial market. In their study, the Granger causality and SVAR methods were used. The researchers concluded that there is causality from the fluctuations of the international crude oil price to the tendency of the investors, and also there is a negative relation between the variables. Qadan and Nama [59], using the SVAR method and causality test, explored the relationship between oil prices and investor sentiment for the period 1986–2016. They measured investor tendencies using different indices impacted by the oil prices. Furthermore, they determined that investor trends can predict the stock prices of oil companies, and unexpected oil price shocks significantly affect investor sentiment. Within this respect, Bildirici and Badur [60,61] emphasized the importance of confidence and oil prices on the stock market.

2.3. VIX and Stock Return

The first focus of the VIX stock returns relationship is that VIX is an important indicator of future stock performances. The second strand focuses on modeling VIX with volatility models to overcome predictability challenges. In addition to being an effective investment tool, VIX could also be evaluated as an economic predictor, since it could hinder not only financial turmoil but also economy-wide deep recessions. In the paper of Copeland and Copeland [62], it is emphasized that VIX is a days-ahead predictor of stock performance. They differentiated the effects of VIX on large and small-capitalization stocks. They showed that in the days following the increase in daily VIX, portfolios of large-capitalization stocks outperformed their counterparts, hence VIX could enhance the returns to the investor if used effectively in portfolios. Giot [63] discussed the relationship between return and volatility in the implied volatility indices and showed that sharp inclines in VIX points at oversold markets and future returns are positive (negative) after the periods with very high (low) levels of VIX. Arak and Mijid [64] demonstrated that VIX is effectively used to estimate future stock market volatility or fear of market participants. Whaley [65] pointed to VIX as a marker at the prices of portfolio insurance due to the fact that S&P 500 index options market is affected by hedgers that buy index put options if they are concerned about a potential drop in the market. Chang et al. [66], following the linear VAR approach, showed that the negative effects of a positive shock in VIX on stock returns are statistically evident in the selected markets of Europe and the USA.

In addition to the correlation between the markets and VIX indicated in studies above, linkages between high and rising levels of VIX with a future rebound in the stock market are evaluated. The overlook suggests that the lead–lag relationship between stock markets and VIX varies considerably. As one of the early signs of this finding, Guo and

Wohar [67] utilized econometric techniques to investigate selected implied volatility indices and showed that the mean volatility and the standard deviation of the VXO and VIX are subject to structural breaks which result in the division of the VIX into the subsamples of pre-1992, 1992–1997 and post 1997 periods. The relationship between market risk and VIX has also been investigated by various studies. Durand et al. [68], using their three-factor model, showed that changes in VIX effects not only the value premium in the Fama and French markets but also the market risk premium. Shaikh and Padhi [69] revealed that VIX is an indicator of investor fear when the market drops and expected stock market volatility rises, moreover, expected volatility is influenced by the actual return volatility within 30 calendar days. They concluded that the direct link between the market turmoil and VIX should not be disregarded.

The nonlinearity of VIX and the direction of the effect of VIX on stock markets is further questioned in recent studies. With this respect, ref. [70] showed TAR-TR-TGARCH type threshold effects of VIX even which also exist even within two distinct regimes of low and high volatility [71] showed the threshold effect of VIX on stock volatility forecastability, especially in expansionary periods. Ref. [72] noted time-varying jumps in VIX which have positive impacts on S&P stock market. Ref. [73] confirm time-varying hedging effectiveness of VIX in stock markets of BRICS. Ref. [74] investigate Markov switching copula effects and show that estimated copula parameters are regime-dependent, their signs not only depend on the regime; but also on the stock market analyzed.

3. Data and Methodology

The dataset and the descriptive statistics in addition to unit root and stationarity results are given in the first section followed by the methodology in the second section below.

3.1. Data

This paper uses a dataset consisting of 4902 daily samples of Volatility Index (VIX), gold price (GOLD), oil price (OIL), the exchange rate (EX), the stock price (BIST), and Istanbul BIST 100 stock index and the sample covers 04.01.2000–13.03.2020. OIL is Brent future oil price per barrel and GOLD is an ounce gold price, both in USA dollars and both obtained from Yahoo Finance. EX is the daily average Turkish lira per USA dollar exchange rate and BIST is the Istanbul Stock Exchange BIST100 Index both series are obtained from the Central Bank of Turkey EVDS database. VIX is the CBOE investor sentiment index and is obtained from investing.com. Data definitions and selected descriptive statistics for the dataset are given in Table 1.

Table 1. Descriptive statistics and data sources.

	GOLD	OIL	BIST	VIX	EX
Definition, Source:	Gold price, per ounce, Yahoo Finance	Brent future oil price, Yahoo Finance	Istanbul BIST100 index, EVDS	CBOE Vix index, Investing.com	TL/Dollar exchange rate, EVDS
Mean	0.041	−0.023	0.039	−0.031	0.029
Std.Dev.	2.451	2.549	3.964	6.098	2.617
Kurtosis:	18.140	21.357	31.201	5.469	4.937
Jarque-Bera	789.125	956.805	2460.910	488.648	397.065

According to the results of the first three stages, if the existence of excess kurtosis and high Jarque-Bera (JB) are determined, and also if the BDS test emphasizes the nonlinear structure of variables in addition to the non-rejection of ARCH effects and if the series is integrated I(0) series so that they are found to be stationary by the unit root test, the MS-GARCH copula causality stage will proceed. Table 1 displays the results for the return series. For all return series, the returns have a non-normal distribution. In Table 2, the BDS test favors evidence of non-linearity in the variables for the returns series.

Table 2. BDS test results.

Dimension	GOLD	OIL	BIST	VIX	EX
2	247.616	271.614	244.359	187.712	165.193
3	267.239	292.337	245.535	202.078	177.109
4	291.584	317.792	248.054	218.271	191.882
5	326.309	354.030	255.789	240.818	213.144
6	373.546	403.192	267.294	271.197	242.118

The results of the ARCH-LM and ADF unit root tests are given in Table 3. ARCH-LM test indicates the ARCH effect in data, which is one of the required assumptions before the application of ARCH-type models. ADF test is employed to assess whether the time series has a unit root. ADF test confirmed that the variables are I(0), so all series are stationary.

Table 3. ARCH-LM and ADF test results.

	GOLD	OIL	BIST	VIX	EX
ARCH-LM:	42.283	36.971	29.440	38.262	20.534
Decision:	ARCH effects cannot be rejected for all variables				
ADF:	−10.262	−8.261	−67.294	−5.673	−14.780
Decision:	All variables are I(0) stationary processes [1]				

[1] In the ADF test, the optimum lag length is selected with SIC information criteria. The ARCH-LM test is conducted for orders 1–2. Higher order tests confirm the same finding which is available upon request.

3.2. Methodology

The MS-GARCH copula causality method consists in two stages. At the first stage, the MS-GARCH copula model should be derived. The second stage is based on the extension of the MS-GARCH copula to causality modeling to obtain the MS-GARCH copula causality analysis. Following Bildirici and Ersin [75], the MS-GARCH model is given as,

$$x_{t,(st)} = k_{0,(st)} + \sum_{i=1}^{f} k_{i,(st)} X_{t-i,(st)} + \sum_{n=1}^{m} \alpha_{n,(st)} \varepsilon_{t-n,(st)} + \xi_{t,(st)} \quad (1)$$

$$\sigma^2_{t,(st)} = \alpha_{0,(st)} + \sum_{n=1}^{q} \sigma_{i,(st)} \sigma_{t-n,(st)} + \sum_{n=1}^{p} \beta_{i,(st)} \xi^2_{t-n,(st)} \quad (2)$$

where

$$\sigma_{t-i-1,(st-i)} = E\left(\xi_{t-i-1,\,(s_{t-i-1})} \middle| s_{t-i}, X_{t-i-1}\right) \quad (3)$$

and non-negativity constraints for parameters are assumed for ϕ, α, κ, $\beta > 0$, and the states and/or regimes are denoted by s_t which follows a Markov-switching process,

$$L = \prod_{t=1}^{T} f(X_t | s_{t=i},\ X_{t-1}) P_r[s_{t=i} | X_{t-1}] \quad (4)$$

and

$$\pi_{nt} = \Pr[s_t = n | X_{t-1}] = \sum_{i=0}^{1} \Pr[s_t = n | s_{t-1} = i] \Pr[s_t = n | X_{t-1}] \sum_{i=0}^{1} \psi_{ni} \pi^*_{it-1} \quad (5)$$

In the literature, refs. [76,77] point at two possibilities to define σ_{t-1} and ξ^2_{t-1} and we assume the appoach of [76].

Three different time-varying copulas utilized are the Gumble, Student's t, and Clayton. According to [78], the time-varying copula could also be stated to allow time-variation

in the dependence. In the context of Sklar's extended theorem version, the time-varying copulas will be obtained. Student's t copula is stated as,

$$C_\tau(u_1,\ u_2|\theta,\ v) = \int_{-\infty}^{\tau_u^{-1}(u_1)} \int_{-\infty}^{\tau_u^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\theta^2)}} \exp\left(1 + \frac{s^2 - 2\theta st + t^2}{v(1-\theta^2)}\right)^{-\frac{-v+2}{2}} dsdt \quad (6)$$

which has symmetric tail dependence as,

$$\lambda_{LT} = \lambda_{UT} = -2\tau_{v+1}(\sqrt{v+1}\ \frac{\sqrt{1-\theta}}{\sqrt{1+\theta}}) > 0 \quad (7)$$

Clayton and Gumble copulas (hereafter CC and GC, respectively), are asymmetric copulas [78]. GC can be expressed as:

$$C(\hat{u}_{1t,}\hat{u}_{2t}|\ \theta) = \exp\left(-\left[(-\ln(u_1))^\theta + (-\ln(u_2))^\theta\right]^{\frac{1}{\theta}}\right) \quad (8)$$

and $\theta\ \in\ ]1,\ +\infty[$. GC is expressed as $\lambda_L = 0\ \ and\ \lambda_U =\ 2 - 2^{-\frac{1}{\theta}}$. CC is expressed as:

$$C(u_1,\ u_2|\theta) =\ (u_1{}^{-\theta} +\ \ u_2{}^{-\theta} - 1)^{-\frac{1}{\theta}}\ \ \ and\ \ \ \theta\ \in\ ]0,\ +\infty[\ \ \lambda_U = 0\,.$$

Note that $\lambda_U = 0\ \ and\ \lambda_L =\ 2^{-\theta^{-1}}$. Following [78], LL of copula is achieved after taking the non-observable variables as,

$$LL = \sum_{t=1}^{T} ln\left[\sum_{j=1}^{n} \left(\hat{u}_{1t,}\hat{u}_{2t}|S_{t=j},\ \Omega_{t-1},\ \Theta\right) Pr\left(S_{t=j}|\Omega_{t-1}\right)\right] \quad (9)$$

To obtain $\Pr(s_t = j|\Omega_{t-1}\,)$ and $\Pr(s_t = j|\Omega_t\,)$, Kim's filter [79] was used,

$$\Pr(s_t = j|\Omega_{t-1}\,) =\ \sum_{i=1}^{n} P_{ij}^{t-1} \Pr(s_t = i|\Omega_{t-1}\,) \quad (10)$$

where

$$\Pr\left(s_{t=j}|\Omega_t\right) = \frac{c\left(\hat{u}_{1t,}\hat{u}_{2t}|S_{t=j},\ \Omega_{t-1}\right) Pr\left(S_{t=j}|\Omega_{t-1}\right)}{\sum_{j=1}^{n} c\left(\hat{u}_{1t,}\hat{u}_{2t}|S_{t=j},\Omega_{t-1}\right) Pr\left(S_{t=j}|\Omega_{t-1}\right)} \quad (11)$$

Further, $P_{ij} = \Pr\left(S_{t=j}|S_{t-1=i}\ ,\ \Omega_{t-1}\right); \Pr\left(S_{t=j}|\Omega_t\right) = \Pr\left(S_{t=j}|\Omega_t\right) \sum_{i=1}^{n} \frac{\text{Pij}\ Pr(S_{t+1=i}|\Omega_t)}{Pr(S_{t+1=i}|\Omega_t)}$ define the transition and smoothed probabilities. The time-varying dependence parameter is given as,

$$\hat{\Theta} = \arg\max_{\Theta} \sum_{t=1}^{T} \ln(c(\hat{u}_{1t},\ \hat{u}_{2t}; \Theta)) \quad (12)$$

Therefore, a copula-based Granger causality is developed [80–83] as an extention of the traditional Granger causality [84,85]. The method allows detecting nonlinear, high-order causality. If we denote $\{A = a_t,\ B = b_t\}$, a null hypothesis of causality $A \to B$ can be defined as:

$$f(b_{t+1}|b_t^n a_t^m) = f(b_{t+1}|b_t^n). \quad (13)$$

In Equation (13), f denotes to conditional probability density function, $a_t^m = (a_t,\ \ldots,\ a_{t-m+1})$ and $b_t^n\ =\ (b_t,\ \ldots,\ b_{t-n+1})$ characterize the past information of A and B, with m and n orders, respectively.

The left side of Equation (13) can be regarded as the predictability of B with information from the past of both time series, while the right side expresses the predictability of B based on its own past. Therefore, Granger causality in the context of LL ratio is,

$$GC_{A\to B} = E[log\frac{f(b_{t+1}|b_t^n, a_t^m)}{f(b_{t+1}|b_t^n)}] \tag{14}$$

A high-dimensional copula can be recursively represented into a set in low dimensions, hence leading to an easy-to-implement and efficient estimation of GC by using conditional copula. Thus, GC equation is rewritten as follows:

$$GC_{A\to B} = E[log\frac{f(b_{t+1}|b_t^n, a_t^m)}{f(b_{t+1}|b_t^n)}] = E[log\frac{h(b_{t+1},\ a_t^m|b_t^n)}{f(b_{t+1}|b_t^n) \times\ \mathrm{g}(\mathrm{a_t^m}|\mathrm{b_t^n})}] \tag{15}$$

where the marginal densities of B and A are f and g and the conditional joint density of (A, B) is h. The h of (A, B) could also be stated based on a copula density function (c) as,

$$h(b_{t+1},\ a_t^m|b_t^n) = f(b_{t+1}|b_t^n) \times g(a_t^m|b_t^n) \times c(u,\ v|b_t^n) \tag{16}$$

where $u = F(b_{t+1}|b_t^n)$ and $v = G(a_t^m|b_t^n)$. F and G stand for the conditional marginal distributions of B and A. If Equation (16) is substituted in Equation (15), the copula-based Granger causality is obtained by the following formula,

$$CGC_{A\to B} = E[logc(F(b_{t+1}|b_t^n),\ G(a_t^m|b_t^n)|b_t^n)] \tag{17}$$

4. Analysis and Results

The analysis procedure consists of three stages:

1. Getting the coefficients of the variables and the number of regimes, in each one of the regimes, determining the regime durations and transition probabilities, and then finding the contagion by the MS-GARCH copula causality method.
2. Determining the evidence of copula and the direction of causality by MS-GARCH copula causality method.
3. Comparing the results obtained by the MS-GARCH copula causality method for return variables with the ones of GARCH copula causality method.

4.1. MS-GARCH Copula Results

The three time-varying copula functions given in the methodology section, the Gumble, Student's t, and Clayton copulas are compared by using the deviance information criterion (DIC) following Zhu et al. [80]. The results are reported in Table 4. Among the compared copula, the lowest DIC is obtained for the Gumble copula. Further, the lowest acceptance rate is 39% and is calculated for the Gumble copula, satisfying the 20–40% condition which suggests strong mixing. As a result, the MS-GARCH copula model is estimated by assuming Gumble as the copula function in each distinct regime.

Table 4. Model selection results for MS-GARCH copula.

	Student-t	**Gumble**	**Clayton**
Acceptance:	0.471	0.392	0.440
DIC:	−1926.331	−2584.214	−2105.104

The model estimation results are given in Table 5, where the model coefficient estimation results and the transition probabilities are reported.

Table 5. MS-GARCH copula model results for return series.

Coefficient:	ARCH	GARCH	Cons.	$p(s_t \mid s_{t-1})$	Diagnostics:	
			Dependent Variable: BIST			
Regime 1:	0.198 *[1]	0.721 **	0.018 ***	$p(1 \mid 1)$:	LogL: 2546.12	
	(1.82)	(2.49)	(2.88)	0.64 ***		
Regime 2:	0.19 **	0.614 **	0.011 *	$p(2 \mid 2)$:	RMSE:	ARCHLM: 0.33
	(2.44)	(1.97)	(1.92)	0.76 ***	0.11	[0.51]
			Dependent Variable: GOLD			
Regime 1:	0.104 **	0.808 **	0.01 **	$p(1 \mid 1)$:	LogL: 1965.23	
	(2.38)	(2.02)	(2.12)	0.63 ***		
Regime 2:	0.0224 ***	0.9467 ***	0.015 ***	$p(2 \mid 2)$:	RMSE:	ARCHLM: 0.28
	(2.93)	(2.87)	(3.40)	0.72 ***	0.27	[0.30]
			Dependent Variable: VIX			
Regime 1:	0.142 **	0.761 **	0.027 *	$p(1 \mid 1)$:	LogL: 9768.42	
	(2.33)	(2.19)	(1.82)	0.61 ***		
Regime 2:	0.0166 **	0.83 **	0.01 **	$p(2 \mid 2)$:	RMSE:	ARCHLM: 0.36
	(2.33)	(2.60)	(2.46)	0.74 ***	0.233	[0.45]
			Dependent Variable: OIL			
Regime 1:	0.116 ***	0.712 ***	0.11 **	$p(1 \mid 1)$:	LogL: 46587.4	
	(3.87)	(2.58)	(2.48)	0.66 ***		
Regime 2:	0.067 **	0.728 ***	0.03 ***	$p(2 \mid 2)$:	RMSE:	ARCHLM: 0.32
	(2.26)	(3.24)	(3.55)	0.77 ***	0.31	[0.46]
			Dependent Variable: EX			
Regime 1:	0.39 ***	0.505 **	0.137 *	$p(1 \mid 1)$:	LogL: 37,659.7	
	(3.24)	(1.99)	(1.84)	0.64 ***		
Regime 2:	0.105 ***	0.76 **	0.07 *	$p(2 \mid 2)$:	RMSE:	ARCHLM: 0.26
	(3.16)	(2.31)	(1.81)	0.78 ***	0.38	[0.30]
			Regime-dependent copula results, regime 1			
	OIL-GOLD	OIL-VIX	OIL-BIST	OIL-EX	GOLD-VIX	
	0.484 ***	0.533 ***	0.0972 ***	0.253 ***	0.760 ***	
	GOLD-BIST	GOLD-EX	VIX-EX	VIX-BIST	EX-BIST	
	0.694 ***	0.712 ***	0.323 ***	0.723 ***	0.471 ***	
			Regime-dependent copula results, regime 2			
	OIL-GOLD	OIL-VIX	OIL-BIST	OIL-EX	GOLD-VIX	
	0.475 ***	0.51 ***	0.025 ***	0.007 **	0.692 ***	
	GOLD-BIST	GOLD-EX	VIX-EX	VIX-BIST	EX-BIST	
	0.145 ***	0.301 **	0.593 ***	0.681 ***	0.029 ***	

[1] For the parameters, the t values are reported in parentheses. *, **, *** denote significance at 10%, 5% and 1% significance levels, respectively. The *p* values of ARCH-LM tests are given in brackets.

The overlook to the P(st | st-1) for each model suggests a relatively higher persistence in regime 2. In all models, the regime probabilities are generally $p(1 \mid 1) < p(2 \mid 2)$ in addition to $p(2 \mid 2) > 0.7$ for all models. The findings suggest longer duration and persistence in regime 2 relative to regime 1. Further, regime 2 reflects the low volatility regime with higher returns compared to regime 1 characterized as the high volatility regime with lower returns [24,25,75]. The t statistics are reported below each parameter estimate in parentheses. Accordingly, the ARCH and GARCH parameters are statistically significant at conventional significance levels. Though the stability condition of GARCH models, i.e., the sum of ARCH + GARCH < 1, is achieved for both regimes in our estimations, the sum is very close to unity. This indicates that the shocks will persist in future periods. Moreover, ARCH-LM test results suggest no ARCH type heteroskedasticity in the residuals, i.e., the models' efficiency in controlling the ARCH type heteroskedasticity effects in the residuals.

The copula results for our models are given for regimes 1 and 2 at the bottom part of Table 5 revealing important findings regards to tail dependence and contagion.

In addition to offering vital information regarding the existence and the magnitude of tail dependence, the copula findings also contribute with important results to the examination of how OIL, GOLD, VIX, EX, and BIST returns behave following extreme rises or downfalls. The generalization of the copula-based distributional characteristics, according to our findings, is a significant tool for determining the comovements between the variables.

4.2. MS-GARCH Copula Causality Test Results

In the last stage, the results of MS-GARCH copula-based Granger causality results are evaluated. The determination of the direction of causality and the statistical significance deserves special attention to derive policy recommendations. The results are reported in Table 6.

Table 6. MS-GARCH copula causality test results.

Causality:	Regime 1:	Direction:	Regime 2:	Direction:
VIX→GOLD [1] GOLD→VIX	0.002 0.010	Bidirectional	0.025 0.011	Bidirectional
VIX→OIL OIL→VIX	0.961 0.023	Unidirectional, OIL→VIX	0.922 0.025	Unidirectional, OIL→VIX
VIX→EX EX→VIX	0.006 0.798	Unidirectional, VIX→EX	0.004 0.016	Bidirectional
VIX→BIST BIST→VIX	0.032 0.662	Unidirectional, VIX→BIST	0.029 0.774	Unidirectional, VIX→BIST
GOLD→OIL OIL→GOLD	0.745 0.009	Unidirectional, OIL→GOLD	0.026 0.003	Bidirectional
GOLD→EX EX→GOLD	0.011 0.523	Unidirectional, GOLD→EX	0.004 0.723	Unidirectional, GOLD→EX
GOLD→BIST BIST→GOLD	0.006 0.941	Unidirectional, GOLD→BIST	0.005 0.796	Unidirectional, GOLD→BIST
OIL→EX EX→OIL	0.015 0.729	Unidirectional, OIL→EX	0.002 0.861	Unidirectional, OIL→EX
OIL→BIST BIST→OIL	0.019 0.889	Unidirectional, OIL→BIST	0.014 0.856	Unidirectional, OIL→BIST
EX→BIST BIST→EX	0.008 0.016	Bidirectional	0.013 0.780	Unidirectional, EX→BIST

[1] In the causality tests, → arrows denote the direction of causality. p-value < 0.05 suggests that causality cannot be rejected at 5% significance level.

One important finding is the regime dependency in the structure of causality among the analyzed return series. As a typical, in contrast to the bidirectional causality among VIX and GOLD in both regimes 1 and 2, the direction of causality is bidirectional in regime 2 while being unidirectional in regime one between VIX and EX. Unidirectional causality cannot be rejected from OIL to VIX, OIL→VIX, in both regimes suggesting causal effects of variations in oil prices on investor sentiments. Oil also has unidirectional causal effects in both regimes, in the low and the high volatility regimes, on BIST. In addition, oil price changes have similar causal unidirectional effects on EX. This finding leads to the conclusion that changes in oil prices influence both the BIST100 stock index and the TL dollar exchange rates and such influences are accepted in both regimes. If the causality between gold and oil is investigated, a striking feature is the acceptance of bidirectional causality between the two in the highly volatile regimes (regime 2) while this finding cannot be said for regime 1. Regime 1, characterized by low volatility, is subject to unidirectional causality from oil to gold prices only. Therefore, we can also conclude that feedback effects are more likely to

exist in high volatility regimes. Additional unidirectional causality is determined from VIX to EX and from OIL to GOLD, which has strong policy implications.

5. Discussion, Implications, and Policy Suggestions

The traditional linear approaches that do not take regime-dependency and neglected nonlinearity has important effects on the linear estimators. The oil, VIX, EX and BIST series are under the influence of many factors that lead to deviations from linearity and these factors include economic crises, shocks, disputes, political events and not to mention the COVID-19. Therefore, the utilization of MS-GARCH-copula and the nonlinear Granger causality method derived from the former is a necessity. The utilization of these methods led to important regime dependent contagion and causality relations.

Given that Turkey is a net oil importer, the findings obtained in the study with respect to oil and stock market relations coincide with the findings of Bouri and Demirer [46], which suggest volatility spillover from oil to stock markets. As pointed out by Ji et al. [47], the oil–stock relation is time-varying, and our findings confirm this nature of the relationship due to the non-rejection of regime-switching tests. Further, the regime-dependent copula results in a more than three times larger effect in terms of the contagion effect in the first regime compared to the second. The results obtained confirm Shaikh and Padhi [69] in terms of VIX-stock market relations associating investor fear with stock market drops and volatility rises. In addition, the findings obtained in our study further extend this finding into regime-dependency: copula parameter estimates are high and close in both regimes suggesting a significant degree of contagion in both regimes in addition, the direction of causality in both regimes is determined as being unidirectional from VIX to BIST stock index. In terms of oil–stock relations, our results also confirm that oil price hikes lead to declines in stock markets which are in line with the findings of Chiou and Lee [38], Miller and Ratti [39], Nandha and Faff [40] and Park and Ratti [41]. The effects of noise on Granger causality modeling is evaluated in [84]. Our findings show the necessity of modeling regime-dependent heteroskedasticity within this respect. The findings also confirm Thai Hung [86].

As shown by Bildirici and Ersin [87,88], oil price volatility necessitates importance of modeling nonlinearity and regime-dependency. The results revealed that the normality assumption is also not appropriate for modeling VIX, gold prices, and the exchange rates. Hence, neither financial nor economic decisions would be inefficiently achieved by the use of models assuming normality. MS-GARCH copula causality method does not assume normality and allows the application of optimal policies for the government's stock market investors, in addition to strategists focusing on the management of risk and optimal portfolio selection.

Our results determined that the returns of oil and gold can have an impact on price trends and expectations. The price movements of gold and oil are important for inflation targeting policy since their persistence can affect the ones of inflation and can lead to a rise in inflationary pressure and asset investments. In the presence that the magnitude and source of and return are a significant dimension of risk management in financial markets, our results across the international oil and gold markets, VIX, and Turkish stock market and exchange rate emphasize the importance of hedging instruments to reduce financial market risks.

Following the findings of the study, several recommendations are obtained. For the researchers and for practice, the regime-dependency and time-varying correlations between oil, stock, gold, VIX, and exchange rates should be kept in consideration, and generalizations to linear approaches should be avoided. For society, individuals, as well as investors, should consider that given the fact that oil, gold, and VIX are externally determined for an emerging economy, the fluctuations in these variables should be closely followed while considering the regime that the stock market is at the given period of time. Depending on the low or high volatility regime of the financial market, it should be always kept in mind that the relations between exchange rates, stock market, gold, oil,

and VIX become drastically different. For regulators, the strong fluctuations in oil and gold in addition to VIX should be closely followed since they lead to various alterations in the analyzed variables. Therefore, policies should consider eliminating (if possible) or at least lowering the negative effects due to the level of contagion to the stock markets in the economies. Further, from a macroeconomic perspective, policies focusing on price stability in economies should also be coupled with policies focusing on the limitation of pass-through mechanisms from external factors to domestic financial markets.

6. Conclusions

This paper suggested and investigated the regime-dependent causality and contagion relation between oil prices, gold prices, VIX investor sentiment, BIST100 stocks, and TL dollar exchange rates for a period of 4 January 2000–13 March 2020 by the MS-GARCH copula causality method. The MS-GARCH copula causality models for return series allow the determination of the presence of comovement, persistency, dependence, contagion, and causality in different regimes such as low and high volatility regimes and low and high return regimes.

If the results are evaluated in terms of the consequences for Turkey's financial markets, as expected, the BIST does not Granger cause the returns of oil and TL dollar exchange rates to have no effects on the oil prices determined in the world markets. However, the reverse is not true, oil prices have strong causal effects in both regimes on BIST and exchange rates in Turkey. Further, BIST does not Granger cause the gold prices and VIX. On the other hand, there is bidirectional causality between EX and BIST in both regimes, and there is significant evidence of contagion and tail dependence.

The relations between oil and gold prices and the exchange rates and the BIST100 stock markets cannot be effectively analyzed by various traditional methods assuming linearity and ignoring the regime dependency. In addition, linear models, by overly simplifying the relations by assuming an overall linear relation, are under the influence of many economic and non-economic factors such as COVID-19, geopolitical events, and disputes. Moreover, comovement, dependence, and the direction of causality cannot be determined by traditional methods in cases of inefficiencies of the parameter estimators under such factors.

The results have important implications. First, the normality assumption is not suitable for modeling the analyzed variables, and policy and economic decisions in addition to investment decisions may not be efficient if traditional approaches are utilized. The findings favor the use of the MS-GARCH copula causality method which takes nonlinearity into consideration in addition to producing improved policies for stock market investors. Second, the finding favored that oil and gold have significant impacts on the price trends and expectations, which is also an important finding in terms of the anti-inflationary policies. Further, inflationary pressures play important roles in asset investment decisions. Third, in terms of risk management in financial markets, our results regarding the relations between oil and gold markets, VIX, and Turkish stock market and exchange rates emphasize the importance of effective use of hedging instruments to reduce financial market risks in the case of a net oil importer economy.

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