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RESEARCH ARTICLE **Open Access**

The Mechanism of Volatility Spillover and Noise Trading Among Financial Markets and the Oil Market: Evidence from Iran

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Abstract
This study aimed to investigate the mechanisms behind the volatility spillovers using the daily and monthly data from the oil, foreign exchange, gold, and capital markets from 2010 to 2019 with the ARCH and GARCH models. The results of this study showed that the abnormal volatility of the foreign exchange and gold on the previous day positively affects the abnormal volatility of the oil market today. It was also found that the abnormal volatility of the capital market on the previous day negatively affects the abnormal volatility of the oil market today. Overall, the findings of this study confirmed the positive impact of the foreign exchange and gold markets on the abnormal volatility in the oil market in both the short term (daily) and long term (monthly) but did not confirm the positive impact of the capital market on the abnormal volatility in the oil market.
Keywords: Volatility spillover, Volatility, Noise Trading, Financial Markets, GARCH Model

Introduction

Noise trading research is an important research trend in behavioral finance (Chang & Fang, 2020). The increased ties between markets have caused a significant interconnection in price volatility, stock returns, or returns on other assets in different markets, leading to the rise of a wave of price increase or decrease from one or more sectors and spilling inflations over other sectors due to the ties among industries (Yin et al., 2020).

In recent decades, with the development of the financial market, investors face more noise trading. Thus, many studies have addressed financial market volatility. For instance, DeLong et al. (1990) found that share price volatility could not be explained most of the time through fundamental changes. They also found that asset prices responded to not only the information but also to irrational "noise trading"(Feng et al, 2014). According to the studies, a large group of traders in the financial markets of developing countries involve in impulse trading (Abdolbaghi et al., 2020). Hence, their collective movements will not only affect the stock price trend but also the market as a whole. In such a situation,

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identifying noise trading and volatility created in the financial markets becomes particularly important. Some researchers treated noise trading as a form of operational risk in financial markets (Feng et al, 2014). Su (2021) believes that the adoption of different approaches to measuring and modeling volatility may lead to conflicting results. Increased integration between major financial markets has captured the attention of academics, researchers, and policymakers. Thus, they have tried to model volatility and analyze the mechanism of volatility spillovers among major international financial markets. The economic development of countries is strongly dependent on their level of energy consumption (Zenga et al., 2021). Crude oil is a strategic commodity in the world and many factors affect its price (Dehghani, 2015). Instability in financial markets has created an uncertain environment for investors, and the possibility of unfavorable changes in markets is always a concern for financial actors. To encourage investors and help policymakers, we need to pay more attention to turbulent cycles and disruptive transactions in financial markets. Thus, understanding the impact of parallel financial markets on the oil market and the relationships of these markets is of particular importance for investors. Meanwhile, turbulence prediction is one of the most important topics studied in the financial markets around the world (Khodayari et al., 2019). Compared to other studies, an innovative aspect of this study is that after conditional modeling of the turbulence of each of the gold, currency, capital, and oil markets, the abnormal volatility of the markets is used as an indicator of the disturbance in the final modeling. To this end, the present study presents a short-term and long-term analysis of capital, gold, and foreign exchange market volatility and its impact on oil market return using autoregressive conditional heteroskedasticity (ARCH) models to offer better insights to investors and policymakers in this field. The following section first provides a review of the literature and describes the methodology taken in this study. After that, the findings of the data test will be reviewed and then the conclusions and discussion will be discussed.

Literature Review

Most recently, the noisy rational expectations equilibrium (NREE) paradigm has led to the development of myriad models of trading under asymmetric information.1 “Noise” or “liquidity” trading is an essential ingredient of these models. Without it, asset prices would perfectly reveal traders' private information (Peress & Schmidt, 2018). According to Delong et al. (1990), noise traders are investors who are irrational, do not have access to internal information, and use incorrect messages or even information as correct information in their trading activities. Therefore, the noise in the financial market reflects the vital role of investors in making decisions on trading activities (Chang & Fang. 2020). Financial markets have experienced a lot of turmoil in recent years (Taheri et al, 2019). Volatility is one of the most important financial market phenomena and plays a fundamental role in financial and economic market transactions. Volatility spillovers in markets mean that there may be a relationship between volatility in different markets so that volatility can be transferred from one market to another (Tsay, 2010). Spillovers occur when volatility in one market cause volatility in other markets, especially in turbulent periods (Su, 2021). Volatility creates uncertainty, reduces investment, and undermines public confidence. Misunderstanding market interconnections can lead to adopting ineffective and counterproductive economic policies (Beirne et al., 2008). Volatility spillovers can be considered a reciprocal effect of price volatility in different markets (Pandi & Wipul, 2018). Oil price volatility has a significant impact on the economies of many countries (Jiang et al., 2020). Stock market volatility a proxy of the general economy contains valuable information about the crude oil market (Chen et al., 2022). The economic development of a country strongly depends on the performance of the capital market and its financial system (Ahmadvand & Mirzaei, 2022). Monitoring stock market changes and accurately tracking its positive and negative volatility are effective in the proper use of emotional factors in investor decisions (Salmani Denglani & et al, 2019). In general, risk and return are two important factors that are considered by small investors when making decisions (Keshavarz et al., 2022). Therefore, forecasting future returns and volatility in oil markets is essential for investors in determining asset prices, risk coverage, derivative pricing, and risk control (Oyuna & Yaobin, 2021). The foreign exchange market is another important financial market in the world. Overall, the size, complexity, global landscape, and relative continuity of transactions in the foreign exchange market have made it an ideal candidate for studying the effects of volatility spillovers and information dissemination (Su, 2021). Exchange rate volatility can cause instability and significantly affect capital movements, economic growth, and international trade (Naderi, 2019). The gold market is one of the most liquid and largest markets due to its characteristics and its attractiveness to investors (Jena & et al, 2018). Gold is used to manage risk and protect the value of total assets against inflation and the risk of exchange rate volatility (Wu & chiu, 2017). Awareness of the characteristics of turbulence and the mechanisms of transmission of turbulence among markets is of great importance for policymakers and capital market participants. Many investors use turbulence spillovers to reduce risk and diversify their portfolios (Zhu & et al., 2017). In recent decades, financial market volatility has been addressed by many researchers around the world. For instance, Engel et al. (1990) used GARCH models to investigate the effects of short-term and long-term volatility. Su (2021) suggested that the adoption of different approaches to measuring or modeling volatility can lead to different results. Increased integration between major financial markets has focused the attention of academics, researchers, and policymakers on modeling volatility and analyzing the mechanism of volatility spillovers among major international financial markets (Jamil & Mobin, 2021). Since Engel and Bollerslev's study, a large body of literature has contributed to developing generalized autoregressive conditional heteroskedasticity (GARCH) models to illustrate the statistical properties of volatility (Baklachi et al., 2020).

Researchers argue that increasing convergence in financial markets in recent decades has intensified the volatility spillovers between them. Estimating volatility is an important issue in certain parts of the financial community (Yazdani et al., 2022). Economists have addressed spillovers in the capital market. Lee and Min Kim (2022) analyzed the state-dependent volatility transmission mechanism between oil, stock, dollar, and bond prices to further examine the role of oil price uncertainty in financial markets by incorporating a Markov-switching model and a Bayesian MCMC algorithm. They found that oil prices spill with the highest degree of volatility over other markets during crises. The interdependence between the stock and oil markets was solid and stable, regardless of the regime shift. In contrast, the effect of oil price uncertainty on the foreign exchange or bond market during crises was double that during non-critical periods. Xiao and Wang (2022) examined the predictability of good and bad oil price volatility for stock returns. Their results showed that bad oil volatility negatively predicts stock returns because it leads to reduced economic activity. They also found that predicting bad oil volatility for stock returns could capture the attention of small investors. Jamil and Mobin (2021) examined the mechanism of volatility spillovers between Pakistani stock, currency, and commodity markets with daily data from 1997 to 2016. The results of their EGARCH model confirmed two-way volatility spillovers between the two variables in the three markets except for the volatility spillovers from the foreign exchange market to the commodity market. Su (2021) examined the values and determinants of volatility in the foreign exchange market (FX) using the realized volatility criteria and heterogeneous autoregression (HAR) models. The results confirmed the meteor shower effects and heat wave effects on the FX market. Trabelsi et al. (2021) studied the relationship between the returns of gold and seven sectoral indices in the Bombay Stock Exchange (BSE) using daily data from 2000 to 2018. They found that gold returns could help predict future returns on gold, consumer goods, and oil and gas stock indices. Zeinoldini et al. (2020) investigated the effect of oil price shocks on the performance of the Iranian stock market with multiple regression using annual data from 1989 to 2017. Their results indicated that interest rate changes adversely affect stock index returns and oil prices. Besides, the industrial production index and the exchange rate positively affect the return of this index. They also found that inflation did not significantly affect the performance of this index Baguero and Matthew (2019) examined the relationship between oil prices, the stock market, and the financial performance of European oil and gas companies using the VAR-GARCH model for the data from 2005 to 2014. The results showed that in most cases, the reaction of stock markets to changes in crude oil prices varies in different sectors. Balcilar et al. (2019) examined dynamic returns and volatility spillovers between the S&P 500, crude oil, and gold and showed a bidirectional return and volatility spillover in these assets. The data also revealed that oil plays a central role in the information transmission mechanism. The role of oil and gold as a safe haven has changed over time in financial and nonfinancial economic turbulence time-span. Botshekan and Mohseni (2018) investigated the spillovers of oil price volatility on stock market returns using multivariate GARCH models for 12 years until March 2017. The results confirmed the existence of conditional correlations in short-term volatility and the effects of oil price spillovers on the stock market index. Tehrani and Khosroshahi (2017) examined the volatility spillovers and the interaction of stock, currency, and gold markets, and showed that the residual variables were significantly dependent on the shocks of a previous period. Besides, the long-run effect of shocks on the overall index was due to their volatility. They also showed the overall index and the dollar and coin markets had the largest share of dollar volatility, respectively. Abdolbaghi et al. (2017) examined exponential general autoregressive conditional heteroskedastic (E-GARCH) in modeling volatility based on noise trading and found a significant positive relationship between the noise factor and efficiency. Their findings also indicated a relative increase in trading volume, transaction value, and the number of trades as noise trading increases. Fotros and Hoshidari (2016) addressed the impact of the volatility of oil price returns on the volatility of stock index returns using the multivariate GARCH model. The variables used in this study were monthly data, world crude oil price, Tehran Stock Exchange price index, and exchange rate from 2001 to 2016. Their results confirmed a negative and significant relationship between volatility of crude oil price returns and volatility in the returns of the Tehran Stock Exchange index and also between exchange rate volatility and the volatility of the returns of the Tehran Stock Exchange index. . Hakimian and Ahmadi (2016) examined the long-run relationship between the total return index of the Tehran Stock Exchange, crude oil, the dollar, and the gold coin over six years using the VAR-GARCH model. Changes in the overall index depended on changes in the previous trading day, crude oil, gold, and dollar returns, respectively. Filis et al. (2011) applied the DCC-GARCH-GJR model to study the correlation between the stock market and oil prices in Canada, Mexico, and Brazil (exporters) and the USA, Germany, and Netherlands (importers). They concluded that demand-side shocks could not affect the relationship between markets.

Given the importance of the oil market as a powerful variable and its relationship with other financial markets, this study aimed to model and investigate the effect of noise trading and parallel market turbulence spillovers on oil market returns volatility. Besides, it employed the autoregressive conditional heteroscedasticity (ARCH) model to explain the trend of conditional variance based on past information and analyze the behavior of turbulence and the impact of abnormal short-term and long-term disturbances in the gold, currency, and capital markets on oil market returns.

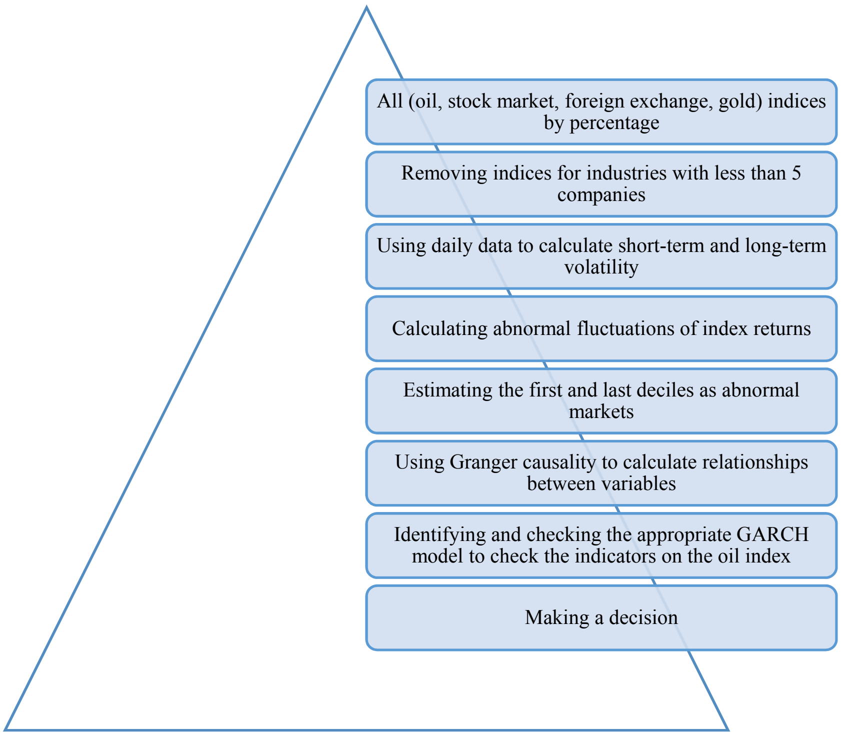

Figure 1. *The procedure used to conduct the study*

Research Methodology

This descriptive study was conducted using the analysis of variance (ANOVA) with daily and monthly data from the foreign exchange, gold, and capital markets from 2010 to 2019. The data required to measure the research variables were collected from the RahavardNovin database, the Statistical Center of Iran (SCI), and the official website of the Tehran Stock Exchange using the library method. The collected data were then classified and codified to measure the variables in question. In the traditional econometric models, the constant variance of error terms is always considered one of the main and classic assumptions of econometrics. To get rid of this restricting assumption, Robert Engel proposed a new model called ARCH. One reason for using ARCH models is the existence of small and large prediction errors in different clusters of a series. This problem can be observed when analyzing the trend of an economic variable (such as inflation rate or exchange rate). Thus, the series in question may exhibit different behaviors over different years. In other words, the volatility is high in some years and low in other years. Thus, the variance is expected not to be constant during the heteroscedastic process of the series and is a function of the behavior of error terms. The main advantage of the ARCH model is its ability to explain the trend of conditional heteroscedasticity according to its past information (Fallah Shams & Panahi, 2014).

Table 1

Indicators and evaluation methods

Evaluation method	Equation	Index	symbol
The ratio of the exchange rate logarithm at time t to the exchange rate at time (t-1)	$\mathrm{RUSD}_t = \ln\left(\frac{\mathrm{USD}_t}{\mathrm{USD}_{t-1}}\right) * 100$	Returns foreign exchange	RUSD
Foreign exchange returns have regressed over their previous break, residuals have been fixed, and the first and last deciles are estimated as abnormal foreign exchange fluctuations.	$\mathrm{RUSD}_{i,t+1} = \beta_0 + \beta_1 \mathrm{RUSD}_{i,t} + \varepsilon_{i,t}$	Abnormal Returns in foreign exchange	ARUSD
The ratio of the stock index rate logarithm at time t to the total stock index at time (t-1)	$R\mathrm{Index}_t = \ln\left(\frac{\mathrm{Index}_t}{\mathrm{Index}_{t-1}}\right) * 100$	Returns Index	R Index
Capital market returns have regressed over their previous break, residuals have been fixed, and the first and last deciles are estimated as abnormal capital market returns.	$\mathrm{RIndex}_{i,t+1} = \beta_0 + \beta_1 \mathrm{RIndex}_{i,t} + \varepsilon_{i,t}$	Abnormal Returns Index	AR Index
The ratio of the logarithm of the oil price at time t to the oil price at time (t-1)	$Roil_t = \ln\left(\frac{\mathrm{oil}_t}{\mathrm{oil}_{t-1}}\right) * 100$	Returns Oil	Roil
Oil returns have regressed over their previous break, residuals have been fixed, and the first and last deciles are estimated as abnormal oil fluctuations.	$\mathrm{Roil}_{i,t+1} = \beta_0 + \beta_1 \mathrm{Roil}_{i,t} + \varepsilon_{i,t}$	Abnormal Returns oil	AR oil
The ratio of the logarithm of the price of gold at time t to the price of gold at time (t-1)	$RGold_t = \ln\left(\frac{Gold_t}{Gold_{t-1}}\right)$	Returns gold price	R Gold
Gold returns have regressed over their previous break, residuals have been fixed, and the first and last deciles are estimated as abnormal Gold fluctuations.	$\mathrm{RGold}_{i,t+1} = \beta_0 + \beta_1 \mathrm{RGold}_{i,t} + \varepsilon_{i,t}$	Abnormal Returns Gold	AR Gold

There was a significant difference between unconditional variance and conditional variance in the data collected in this study. Besides, modeling and analysis were performed in this study assuming that conditional variance is a function of past errors and varies over time. Finally, Model 9 was used to analyze the data and test the research hypotheses.

Research Findings

Table 2 presents descriptive statistics for the currency, gold, oil, and capital market indices under short-term (daily) and long-term (monthly) volatility conditions. The short-term volatility data showed that the foreign exchange return has a relatively small mean (0.145) and dispersion/standard deviation (2.4). Besides, the oil price return has a relatively small mean (0.069) and a relatively high dispersion (11.27). The stock index returns also showed a relatively small mean (0.831) and a relatively high dispersion (7.847) with a relatively high variance and elongation. Moreover, the mean and dispersion values for the gold returns are 0.089 and 1.876, respectively. By comparison, the oil returns and the stock index have the smallest and highest mean values. In addition, under long-term volatile conditions, the mean and dispersion (standard deviation) values for the foreign exchange returns are 2.5023 and 7.9006, respectively. The corresponding values for the oil price returns are -1.2522 and 12.1845, showing a relatively considerable dispersion. Moreover, the mean and dispersion values for the stock returns are 2.7437 and 20.2216, respectively, confirming a relatively high variance and elongation. The corresponding values for the gold returns are 1.4901 and 6.3635, respectively. By comparison, the oil returns and the stock index have the smallest and highest mean values.

Table 2
Descriptive statistics of indicators

Kurtosis	Skewness	Standard deviation	Mini	Max	Average	Indicators
Panel 1. Descriptive statistics of daily information						
6.475	-0.198	2.400	-29.922	26.127	0.145	RUSD
7.163	-0.150	0.023	-0.302	0.259	0.00004	ARUSD
12.945	1.470	7.874	-75.310	74.573	0.831	R Index
11.885	1.974	0.077	-0.746	0.763	0.00009	AR Index
27.864	0.960	1.876	-16.967	21.572	0.089	R Gold
25.836	1.104	0.0186	-0.156	0.212	0.00002	AR Gold
21.430	-0.154	11.279	-33.075	19.401	-0.069	Roil
36.789	-10.959	0.099	-0.304	0.198	-0.00003	AR oil
Panel 2. Descriptive statistics of monthly information						
9.5449	1.1442	1.9006	-27.562	39.975	2.5023	RUSD
0.4186	1.3534	0.0788	-0.2754	0.3816	0.0001	ARUSD
-10.6299	-0.1619	20.2216	-84.224	7.7045	2.7437	R Index
10.5830	-0.3614	0.2007	-0.8875	0.7531	0.0007	AR Index
5.5147	0.7912	6.3636	-11.829	2.7504	1.4901	R Gold
5.1424	0.5721	0.0632	-0.1570	0.2573	-0.000001	AR Gold
8.3660	-1.2769	12.1845	-62.425	2.9852	-0.2522	Roil
8.3359	-1.3056	0.1217	-0.6117	0.2827	-0.0006	AR oil

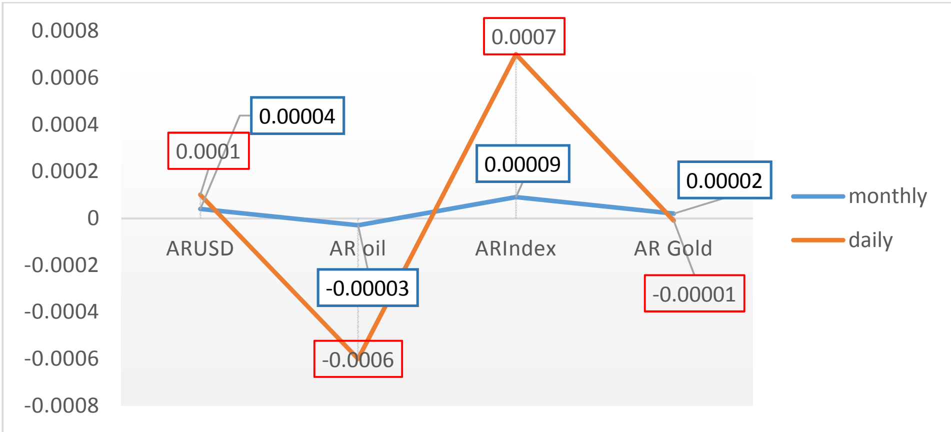

Figure 2. *The abnormal volatility means for the indicators in the short and long terms*

Table 3 shows the field data from the Dickey-Fuller unit root test for all markets in question and specifically for each series. The null hypothesis testing the non-stationary of the time series indicates that all time-series data are stationary.

Table 3
Stationary results of indicators

Sig.	Statistical value –t	Variables
		1. Daily information means test
0.00	-28.302	ARUSD
0.00	42.615 -	AR Gold
0.00	-22.525	AR oil
0.00	18.823-	AR Index
		Panel 2. Monthly data means test
0.00	28.892-	ARUSD
0.00	48.471-	AR Gold
0.00	47.735-	AR oil
0.00	19.390-	AR Index

We tested the effects of heterogeneity of variance in the models to assess the ARCH or GARCH effects in the models. The null hypothesis of this test confirmed the existence of homogeneous variance. Table 4 shows the outputs of the White test to check the heterogeneity of variance:

$$\begin{aligned}\mathrm{ARoil}_{i,t} = \gamma_0 + \gamma_1\mathrm{ARoil}_{i,t-1} + \gamma_2\mathrm{ARUSD}_{i,t} \\ + \gamma_3\mathrm{ARUSD}_{i,t-1} \\ + \gamma_4\mathrm{ARGold}_{i,t} \\ + \gamma_5\mathrm{ARGold}_{i,t-1} \\ + \gamma_6\mathrm{ARIndex}_{i,t} \\ + \gamma_7\mathrm{ARIndex}_{i,t-1} + \varepsilon_{i,t}\end{aligned}$$

Table 4
Results of Schwartz and Akaike statistics to examine Model 9

Phrases	Akaike	Schwarz	Statistics
q=1, p=1	4.556	4.5100	Short term volatility
q=1, p=2	4.566	4.515	
q=2, p=1	4.561	4.520	
q=2, p=2	4.568	4.512	

			Statistics
q=1, p=1	1.587	1.306	long term volatility
q=1, p=2	1.889	1.345	
q=2, p=1	1.992	1.365	
q=2, p=2	1.998	1.666	

As can be seen, the null hypothesis confirmed the existence of homogeneous variance in the selected time series, as indicated by the White test. Following the White test output shown in the table above, the null hypothesis is rejected, confirming the existence of heterogeneity of variance in the models. Thus, the models can be implemented as ARCH or GARCH models.The conditional correlation model: To specify a GARCH (p, q) model, the number of optimal lags for p and q terms must first be determined using Schwarz and Akaike statistics, which examine the model for different p and q values. The terms with the lowest Schwarz and Akaike values were then selected as suitable terms in the model as shown in Table 5:

Table 5
Heterogeneity test results

Sig.	Statistics	Model result
0.00	45.0785	Panel 1. Daily information means test
0.048	4.004	Panel 2. Monthly data means test

As can be seen, in the short and long-term volatility model, the minimum Akaike value and the minimum Schwarz value are obtained for q = 1 and p = 1. Thus, the heterogeneity of variance in the model in both short-term and long-term volatility should be addressed using the GARCH (1, 1) model.

Table 6
The estimation results

$$\mathrm{ARoil}_{i,t} = \gamma_0 + \gamma_1 \mathrm{ARoil}_{i,t-1} + \gamma_2 \mathrm{ARUSD}_{i,t} + \gamma_3 \mathrm{ARUSD}_{i,t-1} + \gamma_4 \mathrm{ARGold}_{i,t} + \gamma_5 \mathrm{ARGold}_{i,t-1} + \gamma_6 \mathrm{ARIndex}_{i,t} + \gamma_7 \mathrm{ARIndex}_{i,t-1} + \varepsilon_{i,t}$$

Long time			**Short time**			
Sig.	**Z**	**Coefficients**	**Sig.**	**Z**	**Coefficients**	**Variables**
0.012	2.486	0.015	0.0001	-3.880	-0.0017	C
0.874	0.162	0.032	0.0011	3.263	0.0715	ARoil (-1)
0.521	-0.639	-0.040	0.00	17.122	0.0064	ARIndex
0.603	-0.519	-0.024	0.121	-1.550	-0.0160	ARIndex (-1)
0.462	0.735	0.107	0.0013	3.205	0.082	ARUSD
0.719	0.358	0.055	0.226	1.210	0.0358	ARUSD (-1)
0.007	2.167	0.235	0.011	2.519	0.0798	ARGold
0.170	-1.370	-0.237	0.001	3.065	0.0114	ARGold (-1)
Estimation of variances			**Estimation of variances**			
0.00	19.587	0.016	0.00	11.423	3.88E-05	C
0.00	4.279	1.182	0.00	16.778	0.907	RESID(-1)^2
0.025	2.240	0.231	0.00	24.249	0.528	GARCH(-1)
	0.107			0.416		R^2
	0.106			0.410		R^2 adjusted
	1.741			1.801		Durbin-Watson
	1.473			4.539		statistic HQ

Table 6 shows the estimation results of the GARCH (1, 1) model under the short-term and long-term volatility scenarios. Given the mean and variance values, the GARCH (1, 1) is significant. Besides, Durbin-Watson values in both short-term and long-term volatility vary from 1.5 to 2.5, indicating no sequential correlation between the residuals. In other words, the independence of the residuals is confirmed. Besides, the value of the adjusted coefficient of determination (R^2) in short-term volatility is 0.41. Thus, when estimating the dependent variable in the model, the independent variables can explain 41% of the variances in the dependent variable. Moreover, in the long-term volatility, the adjusted coefficient of determination ($R^2 = 0.10$) indicates that the independent variables can explain 10% of the variances in the dependent variable.

Conclusion

Since oil is an important resource of revenue for oil-exporting countries and plays a vital role in leading the Iranian economy, this study examined the mechanism of volatility spillovers and noise disturbances between gold, foreign exchange, capital, and Iranian oil markets. The results of model estimation showed that in the case of short-term volatility, abnormal volatility of the oil price in the previous day positively affects the abnormal volatility of the oil price today. By implication, if money flows in the oil market, the money remains in the same market the next day. Thus, the oil market currently interacts with its volatility the next day, and today's oil disturbances spill over into the next day, intensifying the disturbances in the oil market. In addition, the abnormal volatility in the currency market today positively affects the abnormal volatility in the oil market. This indicates that money flows in the currency market, spilling over the fluctuations into the oil market. The abnormal volatility in the gold prices in the previous day and today positively affects abnormal volatility in the oil market today, and as the two gold and oil markets are interacting, money flows from the gold market to the oil market. Thus, the disturbances in the gold market spill over into the oil market. The abnormal long-term volatility in the stock market last month negatively affects the abnormal volatility in the oil market in the current month, indicating that money flows into the stock market but does not spillovers into the oil market. As a result, the disturbances in the stock market do not spill over into the oil market. In contrast, under long-term (monthly) volatility conditions, the abnormal volatility in the gold market in the current month has a positive effect on the abnormal volatility in the oil market. This indicates that money flows from the gold market into the oil market, spilling over the fluctuations in the oil market.

Overall, the findings of this study confirmed the positive impact of the foreign exchange and gold markets on the abnormal volatility in the oil market in the short term (daily) and long term (monthly). In a similar vein, Tehrani and Khosrowshahi (2017) reported that the residuals of variables are significantly related to the shocks of a previous period. The effect of shocks on the total index, in the long run, was due to the volatility of the total index itself. Moreover, Xiao and Wang (2022) confirmed the impact of the capital market on the oil market. Balcilar et al. (2019) also illustrated a bidirectional return and volatility spillover in these assets. However, the data in this study did not show a two-way relationship between the oil and stock markets. The abnormal volatility of the stock market, in the long run, had no positive effect on the abnormal volatility of the oil market.

Identifying the spillover pattern can help predict market volatility and thus contribute to formulating an effective investment strategy. The insights from this study can have some implications for policymakers, investors, market players, and managers. Accordingly, policymakers can understand the behavior of the four markets and use this insight to formulate and effectively implement economic and financial stability policies. Investors and other market players can use the findings of this study to manage their portfolio risk policies. Moreover, identifying the pattern of volatility spillovers from one market to another can help the regulatory organizations to control the disturbances caused by excessive volatility. Researchers and investors are recommended to follow the changes in the capital, currency, oil, and gold markets because they have a great impact on each other. To this end, they can examine different industries and model and compare spillovers in different periods including the recession and prosperity periods or the previous period and the current COVID-19 period. Future studies can compare the performance of jump-diffusion models with stochastic volatility models to simulate the volatility behavior of crude oil prices. Furthermore, the relationship between the capital market with other parallel markets such as the housing market need to be analyzed to shed light on variables such as the inflation rate and purchase and rental prices.

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