JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

Examining the Effects of the COVID-19 Crisis, Financial Stress, and Oil Price Volatility on Stock Return Volatility of Pharmaceutical Companies During Recession and Expansion Periods

1. Negar. Ehtemami : Department of Economics and Management, SR.C., Islamic Azad University, Tehran, Iran
2. Lotf Ali. Agheli*: Department of Economics, Tarbiat Modares University, Tehran, Iran
3. Kambiz. Peykarjou: Department of Economics and Management, SR.C., Islamic Azad University, Tehran, Iran

*corresponding author's email: aghelik@modares.ac.ir

ABSTRACT

The development of a financial stress index has been one of the most important policy priorities for developing countries prior to the occurrence of economic shocks. Uncertainty arising from financial stress, which has received increased attention in recent decades and is often considered one of its most significant costs, essentially refers to uncertainty regarding future levels of financial stress. The present study investigates the effects of the COVID-19 crisis, financial stress, and oil price volatility on stock return volatility of the entire group of pharmaceutical companies operating during recession and expansion periods over the time span from 1991 to 2024, using a time series approach. The Markov-switching method was employed to estimate the model across recessionary and expansionary regimes. From the perspective of purpose, the research is applied, and in terms of nature, it is descriptive-analytical and classified as an ex post facto study. Based on the estimation results of the Markov model, the coefficients are statistically significant at the 95% confidence level, and their signs are consistent with theoretical foundations. The intercept value in the first regime is 0.21, while in the second regime it is −0.39. The regime with a negative intercept represents a recession period, whereas the regime with a positive intercept indicates an expansion period. The variance of the disturbance terms in the first regime is 0.33 and in the second regime is 0.49. These findings indicate that the second regime (recession period) exhibits greater volatility compared to the first regime (expansion period). The estimated relationships reveal a positive impact of financial stress, the COVID-19 crisis, oil price shocks, and inflation rate on stock return volatility of pharmaceutical companies during recession periods. Additionally, a negative relationship between financial stress and stock return volatility during expansion periods is confirmed.

Keywords: COVID-19 crisis, financial stress, oil price volatility, stock return volatility, pharmaceutical companies

Introduction

The pharmaceutical industry occupies a distinctive position in modern economies because it lies at the intersection of public health, industrial policy, financial markets, and macroeconomic stability. Unlike many other sectors, pharmaceutical firms are simultaneously exposed to input-side cost pressures, demand shocks, regulatory interventions, exchange-rate dynamics, and shifts in investor sentiment. This multidimensional exposure makes the stock performance of pharmaceutical companies highly sensitive to broad economic disturbances, especially in

Article history:
Received 15 January 2026
Revised 17 April 2026
Accepted 25 April 2026
First Published 20 May 2026
Final Publication 01 March 2027

How to cite this article:
Ehtemami, N., Agheli, L. A., & Peykarjou, K. (2027). Examining the Effects of the COVID-19 Crisis, Financial Stress, and Oil Price Volatility on Stock Return Volatility of Pharmaceutical Companies During Recession and Expansion Periods. *Journal of Management and Business Solutions, 5*(2), 1-19. https://doi.org/10.61838/jmbs.279

countries where macroeconomic instability, oil dependency, inflation, and financial fragility interact in persistent ways. In such settings, stock return volatility in the pharmaceutical sector cannot be understood only through firm-level fundamentals; rather, it must be analyzed within a broader framework that incorporates oil price fluctuations, financial stress, crisis conditions, and regime-dependent macroeconomic behavior (1-3).

In emerging and oil-dependent economies, the role of energy-market disturbances in shaping financial outcomes has long attracted scholarly attention. Oil price fluctuations affect production costs, transportation expenses, inflation expectations, exchange-rate pressures, and investor risk perceptions. These channels are particularly relevant for pharmaceutical firms because this sector relies heavily on imported raw materials, active pharmaceutical ingredients, packaging inputs, specialized machinery, and global supply networks. Consequently, oil market volatility is not merely an external macroeconomic event; it is a determinant of sectoral profitability, expected cash flows, and market valuation. Empirical evidence has shown that fluctuations in global oil prices are capable of altering stock returns across industries, and in the case of pharmaceutical companies, these effects may be amplified during periods of crisis or uncertainty (4-6).

The Iranian context provides a particularly compelling case for investigating these relationships. The structure of the Iranian economy has historically been shaped by oil revenues, macroeconomic imbalances, inflationary episodes, exchange-rate instability, sanctions-related constraints, and recurring financial tensions. In such an environment, the capital market does not operate independently from the broader macro-financial system. Instead, sectoral stock performance reflects continuous interactions among real shocks, financial conditions, and policy uncertainty. Pharmaceutical firms in Iran are especially vulnerable because they operate in a strategically important but highly regulated sector, with demand that is socially essential yet economically affected by inflation, cost shocks, and supply-chain disruptions. Prior Iranian studies have documented that oil price fluctuations, the COVID-19 crisis, and financial stress significantly influence the profitability, stock returns, and market performance of pharmaceutical companies, highlighting the need for more integrated and dynamic analysis of stock return volatility in this sector (1, 2, 7).

The COVID-19 crisis further reinforced the importance of analyzing pharmaceutical-sector behavior under stress conditions. Although the pharmaceutical industry might initially appear resilient because of increased healthcare demand during a pandemic, the actual economic effects of COVID-19 were far more complex. The pandemic disrupted international supply chains, intensified uncertainty in raw material procurement, altered consumption patterns, strained public budgets, and produced abrupt changes in financial market expectations. At the same time, the crisis affected transportation systems, energy demand, and commodity prices, thereby strengthening the links between oil shocks and stock market volatility. In Iran, evidence suggests that the COVID-19 shock significantly interacted with oil price fluctuations and financial conditions to influence the returns and performance of pharmaceutical firms, especially during turbulent periods (2, 7, 8).

Beyond oil and pandemic-related disruptions, financial stress itself has become an essential concept for explaining stock market instability. Financial stress reflects the degree of tension, fragility, and uncertainty within the financial system and may emerge through credit constraints, liquidity shortages, interest-rate pressures, exchange-market instability, and deteriorating expectations. For listed firms, rising financial stress affects access to funding, increases perceived risk, changes portfolio reallocation behavior, and often magnifies volatility in equity markets. In sectors like pharmaceuticals, where production continuity and inventory financing are crucial, the transmission of financial stress can be especially consequential. The literature on Iran has increasingly recognized that financial tensions are not peripheral variables but central drivers of firm performance and stock return behavior in the pharmaceutical industry (1-3).

At the same time, recent global scholarship has emphasized that macroeconomic and financial relationships should not be analyzed through purely linear frameworks. Economic systems are shaped by asymmetries, nonlinear adjustments, threshold effects, and regime-dependent responses. Shocks that appear moderate in normal periods may become highly disruptive during recessionary episodes, while variables that destabilize returns in one regime may exert weaker or even opposite effects in another. This insight is particularly relevant for stock return volatility, which tends to cluster, persist, and respond differently to positive and negative news. In oil-linked and crisis-prone economies, a nonlinear regime-switching perspective may offer a more realistic representation of sectoral financial dynamics than conventional linear models. Therefore, examining pharmaceutical stock volatility through recession and expansion regimes can uncover structures that remain hidden in average-effect models (9-11).

The growing importance of complexity in economic analysis also supports this broader perspective. Recent studies on economic governance, economic complexity, sustainability transitions, and structural transformation show that sectoral outcomes emerge from interconnected systems rather than isolated variables. Economic governance institutions can moderate how structural complexity affects growth, trade, and investment, while green innovation and technological development reshape the resilience and efficiency of economic systems. Although these studies are often situated in different domains, they collectively reinforce a central methodological point: modern economic behavior is nonlinear, interdependent, and highly sensitive to contextual conditions. For stock markets in emerging economies, this means that volatility should be interpreted within a network of institutional, macroeconomic, and sector-specific influences rather than as a standalone financial phenomenon (12-14).

The relevance of technological and structural transformation to economic resilience further enriches the conceptual backdrop of the present study. Research on the digital economy, green technology, renewable energy systems, and decarbonization has shown that systemic adaptation capacity can reshape how economies absorb shocks and allocate resources. While these studies are not directly focused on pharmaceutical equities, they indicate that modern economies respond to crises through interconnected channels involving innovation, investment, institutions, and infrastructure. In this sense, the investigation of stock return volatility in pharmaceutical companies is part of a broader inquiry into how strategic sectors behave under structural stress and uncertainty. The value of such analysis increases when it is situated in a macro-financial environment characterized by multiple, overlapping shocks (11, 15, 16).

In the Iranian pharmaceutical sector, the sensitivity of stock returns to oil shocks has already been documented in multiple studies, but the evidence also suggests that the magnitude and direction of these effects depend on surrounding economic conditions. Some studies have shown that oil price fluctuations exert direct effects on pharmaceutical stock prices and returns, while others have highlighted the interactive role of crisis episodes such as COVID-19 or broader financial disturbances. These findings imply that oil price changes should not be treated as isolated exogenous variables; rather, their impact may be mediated by recessionary conditions, market expectations, inflationary pressures, and financial stress. Thus, a more refined empirical design is needed to capture how these determinants jointly shape stock return volatility across distinct macroeconomic regimes (5, 6, 8).

Inflation also plays a major role in this analytical framework. In economies experiencing recurrent inflationary pressures, the volatility of sectoral stock returns is influenced by shifts in production costs, consumer purchasing power, discount rates, monetary conditions, and speculative behavior. For pharmaceutical firms, inflation affects both the cost structure and pricing environment, especially in contexts where government intervention, subsidy policy, or import dependence complicate market adjustment. Oil shocks often transmit into inflation, and financial stress may intensify inflationary expectations, making it difficult to disentangle these forces in a simple linear setting. Therefore, a comprehensive model of pharmaceutical stock volatility must consider inflation not as a background variable but as an active channel through which macroeconomic shocks are transmitted to sectoral financial outcomes (1-3).

The need for such an integrated approach is further justified by the theoretical and empirical literature on volatility asymmetry. Financial and commodity markets typically react differently to positive and negative shocks of similar magnitude. This asymmetry is especially evident in oil markets, where supply concerns, geopolitical tensions, and demand collapses produce different volatility responses. Since pharmaceutical firms are linked to oil both directly through cost channels and indirectly through broader macroeconomic transmission mechanisms, oil shock asymmetry can translate into nonlinear equity-market responses. Moreover, crisis conditions amplify these asymmetries by heightening uncertainty and increasing sensitivity to adverse information. A framework that combines oil shock measurement, volatility modeling, and regime switching is therefore well suited to the realities of the sector under investigation (4, 9, 10).

Another important motivation for this study lies in the limited scope of much of the existing empirical work. Prior research has often concentrated on stock returns, profitability, or stock prices rather than explicitly modeling stock return volatility across different macroeconomic regimes. Yet volatility itself is a critical variable because it reflects the degree of uncertainty perceived by investors and has implications for portfolio allocation, risk management, pricing efficiency, and sectoral capital formation. In sectors considered strategically essential, such as pharmaceuticals, persistent volatility may affect investment planning, financing conditions, and even production continuity. The issue is therefore not only whether oil prices, COVID-19, or financial stress influence stock performance, but how they alter the instability and risk structure of returns across recession and expansion periods (2, 7, 8).

From a policy perspective, this topic is equally important. If stock return volatility in pharmaceutical companies rises sharply during recessionary periods in response to oil shocks, inflation, or financial stress, policymakers may need to design stabilizing mechanisms that go beyond conventional industrial support. Such mechanisms could include financial market monitoring, targeted liquidity support, macroprudential coordination, exchange-rate management, and crisis-specific interventions for strategically important sectors. Furthermore, the broader literature on governance and structural adjustment suggests that resilience depends not only on sector-specific policies but also on institutional quality and the broader architecture of economic management. This reinforces the importance of analyzing volatility in a way that is sensitive to cyclical regimes and systemic tensions (12-14).

For investors and financial analysts, the issue is no less consequential. Sectoral portfolio decisions in emerging markets require an understanding of how macroeconomic shocks are transmitted to specific industries over time. If the response of pharmaceutical stock volatility differs between recession and expansion regimes, then static risk assumptions become inadequate. Investors need models that account for the probability of regime changes, the persistence of volatility, and the asymmetric effects of oil and crisis shocks. The capital market relevance of this problem becomes especially acute in the Iranian context, where abrupt macroeconomic changes can quickly alter the risk-return profile of listed firms (3, 5, 6).

In methodological terms, the use of regime-switching models is particularly justified in such a context. Markov-switching frameworks allow researchers to distinguish between latent states of the economy and to estimate whether the effects of explanatory variables differ across those states. This is highly appropriate when expansion and recession periods exhibit different volatility patterns and when the transmission of financial stress and oil shocks is not constant over time. By combining such an approach with volatility measures and macro-financial variables, the study can contribute not only to the empirical literature on pharmaceutical stocks in Iran but also to the broader literature on sectoral vulnerability under overlapping macroeconomic shocks (1, 2, 9).

The present research also responds to a broader scholarly shift toward multidimensional interpretation of economic fragility. Whether the focus is on green technology, digital transformation, renewable energy systems, ecological efficiency, or economic complexity, recent studies increasingly show that resilience and volatility are embedded in structural relationships rather than isolated indicators. This insight is valuable for the present article because it supports the view that the stock return volatility of pharmaceutical firms should be analyzed as a product of interacting macroeconomic, sectoral, and crisis-related forces. In this sense, the study is not merely about stock market behavior; it is about the capacity of a strategically essential industry to withstand instability in a volatile economic environment (11, 14-16).

Given the strategic importance of the pharmaceutical industry, the volatility-enhancing role of oil price shocks, the disruptive consequences of the COVID-19 crisis, the amplifying effect of financial stress, and the likelihood that these relationships vary across recession and expansion regimes, a regime-sensitive time-series analysis is both theoretically and empirically warranted (1-16).

Accordingly, the aim of this study is to investigate the effects of the COVID-19 crisis, financial stress, oil price shocks, and inflation on the stock return volatility of pharmaceutical companies in Iran during recession and expansion periods.

Methods and Materials

The present study is applied in terms of purpose and descriptive-analytical in nature, and it is classified as an ex post facto study. Following prior studies, this research examines the effects of the COVID-19 crisis, financial stress, and oil price volatility on the stock return volatility of the entire group of pharmaceutical companies operating during recession and expansion periods over the time span from 1991 to 2024 using a time series approach. The Markov-switching method is employed to estimate the model across recessionary and expansionary regimes. The Markov-switching model was first introduced by Quandt (1972) and Quandt and Goldfeld (1973), and was later extended by James Hamilton (1989) to extract business cycles. Unlike other nonlinear methods such as STAR and ANN, where transitions between regimes occur gradually, in the Markov-switching model transitions occur abruptly. In this framework, it is assumed that the regime occurring at time $t$is unobservable and depends on a latent process s_t. In a two-regime model, $s_t$can take values of 1 and 2. A two-regime $AR(1)$model can be expressed as:

$$y_t = \begin{cases} \phi_{0,1} + \phi_{1,1} y_{t-1} + \varepsilon_t & \text{if } s_t = 1 \\ \phi_{0,2} + \phi_{1,2} y_{t-1} + \varepsilon_t & \text{if } s_t = 2 \end{cases}$$

Or more compactly:

$$y_t = \phi_{0,s_t} + \phi_{1,s_t} y_{t-1} + \varepsilon_t$$

To complete the model, the characteristics of the process $s_t$must be specified. In the Markov-switching framework, $s_t$is assumed to follow a first-order Markov process, implying that it depends only on the previous regime s_{t-1}. Transition probabilities are defined as follows:

$$P(s_t = 1 \mid s_{t-1} = 1) = p_{11}$$
$$P(s_t = 2 \mid s_{t-1} = 1) = p_{12}$$
$$P(s_t = 1 \mid s_{t-1} = 2) = p_{21}$$
$$P(s_t = 2 \mid s_{t-1} = 2) = p_{22}$$

Where p_{ij}represents the probability of transitioning from state $i$at time $t-1$to state $j$at time t, subject to the constraints:

$$p_{11} + p_{12} = 1$$
$$p_{21} + p_{22} = 1$$

In the final model, $s_t = 1$represents the first regime (expansion), and $s_t = 2$represents the second regime (recession). The variable Rdenotes return changes resulting from fluctuations in the stock market index for pharmaceutical companies. The standard deviation of the average stock return during the fiscal year is calculated after computing stock returns, and stock return volatility is ultimately estimated using ARCH and GARCH models.

Financial Stress Index (FSI) Calculation: The financial stress index is computed using Principal Component Analysis (PCA). This method reduces the dimensionality of observations based on a composite index and groups similar observations. In PCA, correlated variables in a multidimensional space are transformed into a set of uncorrelated components, each representing a linear combination of the original variables. These uncorrelated components, known as principal components (PCs), are derived from the eigenvectors of the covariance or correlation matrix. The primary applications of PCA include dimensionality reduction and identification of structural relationships among variables. A key advantage of PCA in econometrics is the elimination of multicollinearity caused by a large number of explanatory variables.

A composite index based on the volatility of the selected variables is estimated and introduced as the financial stress index. The index incorporates three sectors: government, monetary, and foreign exchange. After measuring financial stress in each sector, an aggregate financial stress index for the Iranian economy is computed by combining sectoral indices. A critical issue in aggregation is the selection of appropriate weights. Given the economic conditions of Iran, it is assumed that these sectors do not contribute equally to financial stress; therefore, a weighting method is required.

The cyclical components of variables are regressed on the cyclical component of a reference variable (e.g., output growth). The resulting correlation coefficients are used to determine weights according to:

$$W_k = \frac{r_k^2}{\sum_{k=1}^{n} r_k^2}$$

Accordingly, in this study, after calculating sector-specific stress indices, the cyclical components of variables in each sector are regressed on the cyclical component of output growth, and the resulting correlation coefficients are used to compute weights for the aggregate financial stress index.

Table 1. Financial Stress Index Components

Variable Category	Variable	Definition	Operational Definition
Government Stress	GEXP	Government size	Ratio of total government expenditure to GDP
	TAXINC	Total tax revenue	Ratio of total tax revenue to GDP
	CU/M1	Currency to money ratio	Ratio of currency in circulation to M1
Monetary Stress	SHD/LOD	Short-term to long-term deposits	Ratio of short-term deposits to long-term deposits
	M1/M2	Money to liquidity ratio	Ratio of money supply to liquidity
	Depo	Deposit balance ratio	Ratio of deposit balance to GDP
	Pdebt	Non-government debt ratio	Ratio of non-government debt to banks relative to GDP
	RInt	Real interest rate	Nominal interest rate minus inflation rate
Exchange Rate Stress	RER	Real exchange rate	$RER = ER \times \frac{P_{out}}{P_{in}}$

Finally, the financial stress index is computed using PCA and incorporated into the model.

The variable COVID represents the global COVID-19 crisis, taking the value of 1 during crisis months and 0 otherwise. The outbreak of COVID-19 in Iran was officially confirmed on February 19, 2020.

The variable OIL represents crude oil price shocks in Iran, calculated using the EGARCH model.

The inflation rate (INF) is defined as the change in a price index, typically measured by the Consumer Price Index (CPI).

Findings and Results

Initially, the financial stress index is measured and extracted using PCA. This method is widely applied across disciplines, particularly in economics for index construction. Many economic phenomena are influenced by multiple factors across different dimensions. Including all such factors in econometric models leads to issues such as multicollinearity, increased model complexity, and higher statistical error. Therefore, techniques such as PCA are used to reduce dimensionality and improve estimation accuracy.

Multivariate data analysis plays a crucial role in information analysis. Datasets often include numerous variables, each potentially with multiple dimensions, making interpretation difficult. PCA reduces these dimensions by transforming data into a smaller set of principal components, facilitating interpretation. It is a non-parametric method widely used in applications ranging from neural networks to computer graphics due to its ability to extract meaningful information from complex datasets. In this method, correlated variables are transformed into uncorrelated principal components, each representing a linear combination of original variables. These components are derived from eigenvectors of the covariance or correlation matrix. The primary function of PCA is dimensionality reduction and identification of relationships among variables, effectively grouping them. Its key advantage in econometrics is the elimination of multicollinearity caused by a large number of explanatory variables. In this study, the following variables are used to construct the composite financial stress index:

Table 2. Study Variables and Their Definition

Variable	Definition
GEXP	Government size
TAXINC	Total tax revenue
CU/M1	Currency to money ratio
SHD/LOD	Short-term to long-term deposits ratio
M1/M2	Money to liquidity ratio
Depo	Deposit balance ratio
Pdebt	Non-government debt ratio
RInt	Real interest rate
RER	Real exchange rate

To determine the general orientation of data points, an ellipse is drawn to illustrate the correlation structure among variables.

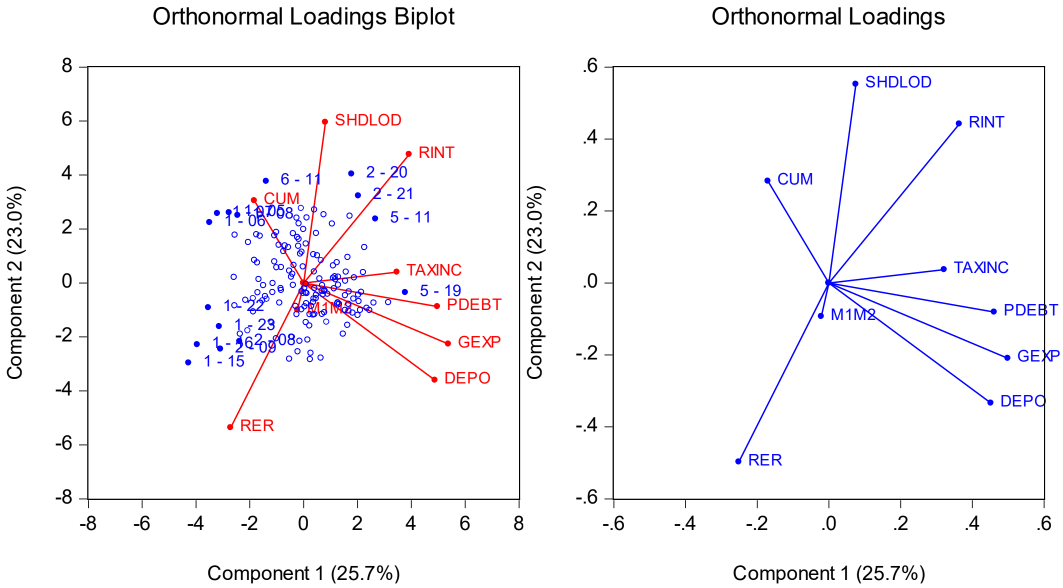

Figure 1: Data transformation into principal components

The principal direction of the dispersion of points is neither along X_1, nor along X_2, nor along the other variables; rather, it lies between them and is more aligned with the major axis of the ellipse. This axis is called PC_1, which represents the first principal component of the variability in X_1, X_2, and the other variables. The second component (PC_2) lies along the minor axis of the ellipse, is exactly perpendicular to PC_1, and explains the remaining variation in X_1, X_2, and the other variables. PC_1, PC_2, and the other components constitute new axes for explaining X_1, X_2, and the remaining variables. Therefore, it can be stated that X_1, X_2, and the other variables up to $X_9$are linear combinations of PC_1, PC_2, ..., PC_9. That is:

$$X_i = a_{i1}PC_1 + a_{i2}PC_2 + a_{i3}PC_3 + a_{i4}PC_4 + a_{i5}PC_5 + a_{i6}PC_6 + a_{i7}PC_7 + a_{i8}PC_8 + a_{i9}PC_9$$

Likewise, the values of the principal components can be obtained using the following equations:

$$PC_1 = W_1X_1 + W_2X_2 + W_3X_3 + W_4X_4 + W_5X_5 + W_6X_6 + W_7X_7 + W_8X_8 + W_9X_9$$

$$PC_2 = W_{10}X_{10} + W_{11}X_{11} + W_{12}X_{12} + W_{13}X_{13} + W_{14}X_{14} + W_{15}X_{15} + W_{16}X_{16} + W_{17}X_{17} + W_{18}X_{18}$$

...

$$PC_9 = W_{73}X_{73} + W_{74}X_{74} + W_{75}X_{75} + W_{76}X_{76} + W_{77}X_{77} + W_{78}X_{78} + W_{79}X_{79} + W_{80}X_{80} + W_{81}X_{81}$$

Where $W_i$is the regression coefficient of the principal components on the variables.

The principal components can be calculated using the original dataset and, in the absence of access to the original data, by using the covariance matrix or the correlation matrix. Usually, when the variables in the dataset are measured in different units or have different variances, the correlation matrix is used. When the correlation matrix is employed, standardized variables with a mean of zero and a standard deviation of one are effectively used.

The first extracted principal component captures the largest amount of data dispersion in the entire dataset. This means that the first component is correlated with at least some of the variables. The second extracted component has two important properties. First, it captures the largest proportion of the dataset variance not explained by the first component. In other words, the second component is correlated with some observed variables that do not have a high correlation with the first component. Second, the second component is uncorrelated with the first component; that is, the correlation between the two components is zero. The remaining extracted components in this method also possess these two properties.

The number of extracted components in each model is equal to the number of variables under examination. However, it is possible to select only a certain number of these components. Usually, the first two or three components account for a substantial proportion of the data dispersion. Therefore, selecting the first two or three components is generally sufficient for further analysis. In some cases, however, it is necessary to consider additional criteria for determining the required number of components. These criteria are as follows:

The first criterion (Scree Test): plotting the eigenvalues against the related principal components yields the scree plot. This plot shows the change in the degree of importance of the eigenvalues for each principal component. Figure 2 presents a hypothetical scree plot. As can be seen, the eigenvalue of the first vector (the variance explained by the first vector) is approximately 2.3, the eigenvalue of the second vector is approximately 2.1, and so on, while the eigenvalue of the ninth vector is less than 0.4. This indicates that the decline in importance is initially rapid and then levels off. The breakpoint indicates the maximum number of principal components that should be taken into account. One fewer principal component than the number indicated by the breakpoint may also be appropriate. Accordingly, in Figure 2, the first component or the first three components may be selected.

The second criterion (Eigenvalue): components with eigenvalues greater than one are retained, and the remaining components are disregarded.

The third criterion (Variance): components that explain a larger percentage of dispersion are sufficient for continuation of the analysis; usually, the first component accounts for the largest variance.

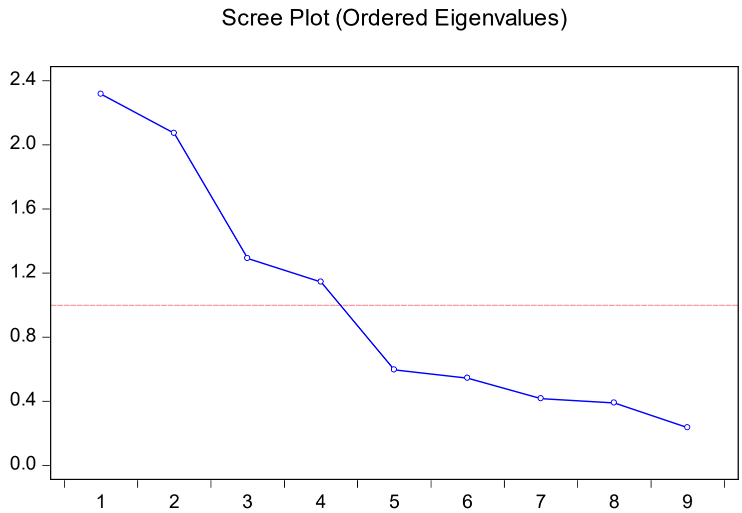

Figure 2. Eigenvalues of the Principal Components

To extract the financial stress index, nine variables were used: government size, total government tax revenues, the ratio of currency in circulation to money supply, the ratio of short-term deposits to total long-term deposits, the ratio of money to liquidity, the deposit balance ratio, the non-government debt balance ratio, the real interest rate, and the real exchange rate.

Table 3. Correlation Matrix of Financial Stress Indicators

	GEXP	TAXINC	CUM	SHDLOD	M1M2	DEPO	PDEBT	RINT	RER
GEXP	1.000000								
TAXINC	0.165995	1.000000							
CUM	-0.103783	-0.358379	1.000000						
SHDLOD	-0.128613	-0.008877	0.187941	1.000000					
M1M2	0.032978	0.100707	0.131337	-0.228512	1.000000				
DEPO	0.609053	0.161638	-0.323739	-0.170545	-0.061763	1.000000			
PDEBT	0.525666	0.109060	0.025898	-0.031410	0.009685	0.414297	1.000000		
RINT	0.131295	0.223358	0.124128	0.476611	0.000612	0.114349	0.313530	1.000000	
RER	-0.122007	-0.310014	-0.085014	-0.443305	0.055429	0.146620	-0.060383	-0.518628	1.000000

Table 3 shows that there is a relatively high correlation among the above-mentioned indicators. Therefore, by reducing the dimensionality of the variables, the financial stress index is extracted using principal component analysis.

Table 4 shows that the eigenvalue of the first component is larger than the others, and approximately 25% of the total dataset dispersion is explained by this component. Therefore, this component is the best choice for constructing this index.

Table 4. Estimation Results of the Composite Financial Stress Index Using PCA

Eigenvalues: (Sum = 9, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.316320	0.244827	0.2574	2.316320	0.2574
2	2.071493	0.781555	0.2302	4.387813	0.4875
3	1.289938	0.146412	0.1433	5.677751	0.6309
4	1.143526	0.547791	0.1271	6.821277	0.7579
5	0.595735	0.052060	0.0662	7.417012	0.8241
6	0.543675	0.127906	0.0604	7.960688	0.8845
7	0.415769	0.027118	0.0462	8.376457	0.9307
8	0.388651	0.153759	0.0432	8.765108	0.9739
9	0.234892	---	0.0261	9.000000	1.0000

Eigenvectors (Loadings)

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
GEXP	0.498997	-0.209736	0.225361	-0.013214	-0.400467	-0.400655	-0.003541	0.177866	0.550911
TAXINC	0.321701	0.036918	-0.570283	0.345787	-0.134822	0.300890	0.564911	0.144004	0.042207
CUM	-0.169882	0.283044	0.647471	0.162744	-0.275140	0.050451	0.580694	-0.126092	-0.118197
SHDLOD	0.075269	0.552262	0.002317	-0.266789	0.329713	-0.259983	0.140067	0.649376	-0.023430
M1M2	-0.021142	-0.093035	0.152450	0.848350	0.316871	-0.270020	-0.170742	0.194220	-0.088122
DEPO	0.452132	-0.334017	0.055934	-0.201237	0.294130	-0.355547	0.301367	-0.227171	-0.533882
PDEBT	0.461104	-0.081160	0.379751	-0.013977	0.021906	0.649800	-0.268456	0.307592	-0.216769
RINT	0.363735	0.441806	0.072586	0.069640	0.444137	0.110177	-0.047849	-0.546552	0.389847
RER	-0.251386	-0.497532	0.170049	-0.131740	0.502373	0.212369	0.360148	0.165463	0.434087

The relationship between the observed variables and the principal components can be expressed using factor loadings, and an estimate of the principal components using factor scores can be written as follows:

$$PC_1 = 0.49\,GEXP + 0.32\,TAXINC - 0.16\,CUM + 0.07\,SHDLOD - 0.02\,M1M2 + 0.45\,DEPO + 0.46\,PDEBT + 0.36\,RINT - 0.25\,RER$$

Thus, it can be stated that the linear combination of the first component, PC_1, for the financial stress index is as presented above.

Finally, the weights of each sub-index in the composite financial stress index are presented in the following table.

Table 5. Relative Importance of Variables in the Composite Financial Stress Index

Variable Name	Relative Importance of Variables
Government size	25.74
Total government tax revenues	23.02
Ratio of currency in circulation to money supply	14.33
Ratio of short-term deposits to total long-term deposits	12.71
Ratio of money to liquidity	6.62
Deposit balance ratio	6.04
Non-government debt balance ratio	4.62
Real interest rate	4.32
Real exchange rate	2.61
Total	100

Table 5 shows the relative importance of the components of the aggregate index, disaggregated by the variables selected under the cyclical components regression method. Based on the obtained weights, government size has the greatest contribution to the composite financial stress index. Finally, using the make command in Principal Component Analysis, the composite index related to financial stress is extracted and employed in the final research model.

In this article, in order to obtain the oil price shocks used in the study, the EGARCH model proposed by Nelson (1991) is employed. One of the major limitations of the ARCH and GARCH approaches is their assumption of symmetry; that is, negative and positive shocks of equal magnitude are assumed to have the same effect on volatility, whereas the volatility of the series does not respond identically to the nature of the news (negative versus positive shocks). Accordingly, to address this issue and to analyze the behavior of series volatility, it is necessary to use an asymmetric model (Verbeek, 2005).

$$\ln\,\sigma_t^2=\alpha_0+\alpha_1\frac{|\,u_{t-1}\,|}{\sqrt{\sigma_{t-1}^2}}+\beta\ln\,\sigma_{t-1}^2+\gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}},\alpha_0=\omega-\alpha\sqrt{\frac{2}{\pi}},\alpha_1=\alpha$$

This model has several advantages. First, in this model, the dependent variable, σ_t^2, is specified in logarithmic form; therefore, the coefficients of the right-hand-side variables may be either positive or negative, while σ_t^2remains positive in all cases. Consequently, there is no longer any need to impose non-negativity restrictions on the coefficients. Second, this model also accounts for the effects of asymmetric shocks, because $\gamma$is the coefficient of u_{t-1}, and u_{t-1}can be either positive or negative. The parameter γcaptures the effects of positive and negative shocks, whereas $\alpha$is the coefficient that considers only the absolute value $|\,u_{t-1}\,|$. If $\gamma=0$, the model is symmetric; otherwise, it is asymmetric. The effect of positive shocks is equal to $\alpha+\gamma$, and the effect of negative shocks is equal to $\alpha-\gamma$. If $\gamma$is negative, this indicates that the effect of negative shocks is greater than that of positive shocks, and vice versa.

Table 6. Results of EGARCH Model Estimation

Conditional Mean Equation	Oil Shock	Conditional Variance Equation ($\ln\sigma_t^2$)	Oil Shock
$\boldsymbol{a_0}$	1.1819**(0.4208)	α_0	5.0827***(0.3473)
$\boldsymbol{\rho_{t-1}}$	0.6435***(0.0499)	$\ln\sigma_{t-1}^2$	0.1645***(0.3473)
$\boldsymbol{\rho_{t-2}}$	0.3944***(0.0336)	$\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}$	2.1276***(0.4938)
$\boldsymbol{\rho_{t-3}}$	—	$\frac{\lvert u_{t-1}\rvert}{\sqrt{\sigma_{t-1}^2}}$	1.4403***(0.8498)

The positive value of the parameter γ in the estimated EGARCH model indicates that positive oil price shocks in global oil markets generate greater price uncertainty (volatility). Since the absolute effects of negative and positive shocks of equal magnitude on oil price volatility are not the same, initial price shocks in global oil markets have an asymmetric effect on the formation of oil price volatility. This result is consistent with the realities of global oil markets, because positive oil shocks usually occur when the continuous flow of oil trade (oil supply security) in world markets is disrupted or, at a minimum, when concern exists about such disruption. This, in turn, creates uncertainty among oil demanders and ultimately leads to price volatility in global oil markets. By contrast, negative shocks occur when agents in global oil markets are confident about the continuous flow of oil (oil supply security). Under these conditions, the concerns of oil demanders are reduced, and as a consequence, oil price volatility declines. For this same reason, a form of downward price stickiness also prevails in oil markets. Accordingly, if a negative price shock equal in magnitude to a preceding positive shock occurs in global oil markets, that negative shock cannot fully offset the equally sized positive shock and return oil prices to their initial level. Largely for this reason, negative price shocks play a weaker role in reducing price volatility in global oil markets.

To calculate stock return volatility in accordance with the existing literature on volatility models, stock returns must first be modeled using ARMA models, and the relevant lags in stock returns must be identified. For this purpose, the Box–Jenkins methodology was applied, and the result of stock return modeling is presented in the following table.

Table 7. Estimation of the Stock Return Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.003883	0.000469	2142.666	0.0000
MA(1)	-0.113128	0.031363	-3.607082	0.0003

According to the above model, stock returns are related to their own one-period lag, $AR(1)$, and to the one-period lag of their disturbance term, $MA(1)$. To examine the existence of conditional heteroskedasticity in stock returns, the ARCH test must be used. The result of this test is presented in Table 8.

Table 8. ARCH Test

Heteroskedasticity Test: ARCH	Value	Statistic	Probability
F-statistic	3.198927	Prob. F(1,80)	0.0277
Obs*R-squared	3.210755	Prob. Chi-Square(1)	0.0271

Given the obtained probability values, the null hypothesis of no conditional heteroskedasticity in stock returns is rejected. Therefore, stock returns exhibit conditional heteroskedasticity.

Finally, in order to obtain stock return volatility, the EGARCH model proposed by Nelson (1991) is employed.

Table 9. EGARCH Model for Stock Returns

$$\log(\text{GARCH}) = C(3) + C(4) \times \left| \frac{\text{RESID}(-1)}{\sqrt{\text{GARCH}(-1)}} \right| + C(5) \times \frac{\text{RESID}(-1)}{\sqrt{\text{GARCH}(-1)}} + C(6) \times \log(\text{GARCH}(-1))$$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.003883	0.000469	2142.666	0.0000
MA(1)	-0.113128	0.031363	-3.607082	0.0003
Variance Equation				
C(3)	0.347601	4.2×10^{-104}	8.4×10^{102}	0.0000
C(4)	-0.863386	0.048117	-17.94366	0.0000
C(5)	-0.452962	0.010840	-41.78519	0.0000
C(6)	0.740037	0.040186	18.41519	0.0000

At this stage, the magnitude of the volatility derived from stock returns has been calculated. For use in the main model, this measure is transformed into a variable. For this purpose, the Make variance garch command must be used to generate this volatility series as a variable.

Initially, in order to ensure the absence of spurious regression, unit root and cointegration tests are employed. In this study, the conventional Phillips–Perron test is used.

Table 10. Results of the PP Test for the Model Variables

Variable	Test Statistic	Probability	Variable Status
COVID	-1.174659	0.6735	---
D(COVID)	-6.467001	0.0000	I(1)
FSI	-0.211710	0.9273	---
D(FSI)	-3.490523	0.0149	I(1)
INF	-0.478836	0.8831	---
D(INF)	-5.313643	0.0001	I(1)
OIL	-0.926999	0.7668	---
D(OIL)	-5.976299	0.0000	I(1)
R	-2.557488	0.3007	---
D(R)	-8.303689	0.0000	I(1)

Considering the theoretical foundations of stationarity tests, the null hypothesis H_0in these tests is defined as non-stationarity of the variable. Based on the test results, it can be stated that all model variables are stationary at first difference, that is, $I(1)$.

Since the variables in the model are integrated of the same order, $I(1)$, a cointegration test was used to identify the existence of a long-run equilibrium relationship among the model variables, and the Johansen–Juselius approach was employed for this purpose. To implement this test, it is necessary to determine the number of cointegrating vectors. In examining the results of the cointegration test, an appropriate specification must be selected regarding the presence or absence of a deterministic trend and an intercept in the cointegrating vector. In this regard, five specifications are presented: the first specification, with no intercept and no trend; the second specification, with a restricted intercept and no trend; the third specification, with an unrestricted intercept and no trend; the fourth specification, with an unrestricted intercept and a restricted trend; and the fifth specification, with an unrestricted intercept and an unrestricted trend. These five specifications are estimated for the variables, ranging from the most restricted (the first specification) to the least restricted (the fifth specification). Then, the null hypothesis of no cointegrating vector is tested against the alternative of one cointegrating vector, followed by the null hypothesis of at most one cointegrating vector against the alternative of two vectors. This procedure continues up to the existence of $n-1$cointegrating vectors, where $n$denotes the number of variables. A summary of the results of the trace test (λ_{Trace})and the maximum eigenvalue test (λ_{Max})regarding the number of cointegrating vectors based on the five above-mentioned specifications is presented in Table 11. As can be observed, the null hypothesis of no cointegrating vector against the existence of one cointegrating vector among the variables is rejected in the model; therefore, there is at least one cointegrating vector among the variables under study.

Table 11. Summary of the Results for the Number of Cointegrating Vectors

Specification	First Specification	Second Specification	Third Specification	Fourth Specification	Fifth Specification
Trace test	2	3	1	3	3
Maximum eigenvalue test	2	3	1	1	2

The estimation results of the model and the related cointegration tests are reported in Table 12. According to the results, the trace test confirms the existence of four cointegrating vectors, while the maximum eigenvalue test confirms the existence of two cointegrating vectors at the 5% significance level. As Johansen states, in the case of inconsistency between the results, the maximum eigenvalue test has priority over the trace test because it has a stronger alternative hypothesis. Therefore, the existence of four cointegrating vectors among the model variables can be accepted.

Table 12. Results of the Cointegration Test

H_0	H_1	Trace Statistic	95% Critical Value	Probability	Maximum Eigenvalue Statistic	95% Critical Value	Probability
$r = 0$	$r = 1$	76.45552	69.81889	0.0134	35.99871	33.87687	0.0275
$r \leq 1$	$r = 2$	40.45682	47.85613	0.2066	22.10929	27.58434	0.2148
$r \leq 2$	$r = 3$	18.34752	29.79707	0.5405	9.462063	21.13162	0.7935
$r \leq 3$	$r = 4$	8.885459	15.49471	0.3761	8.019574	14.26460	0.3767
$r \leq 4$	$r = 5$	0.865885	3.841466	0.3521	0.865885	3.841466	0.3521

The Markov-switching model is an appropriate estimation model when the pattern of the data under investigation is nonlinear. To ensure the nonlinearity of the data pattern, the LR test is used. The value of this statistic is calculated from the maximum likelihood values of two competing models: one model with a single regime (linear model) and another with two regimes (nonlinear model), and it follows a chi-square distribution. If the value of the statistic exceeds the critical value at the desired confidence level, it can be concluded that the linear model is not appropriate at that confidence level and that a nonlinear model should be used instead.

Table 13. Results of the LR Test for the Model

Test Statistic	Probability Value
15.236	0.0000

As the results in the above table indicate, the value of the LR test statistic is greater than its critical value at the 5% significance level. Therefore, it can be concluded that, instead of linear models, the nonlinear Markov-switching approach is more appropriate for estimating the model. The following table presents the results of estimating the Markov-switching model for the study model.

Table 14. Results of Estimating the Parameters of the Markov-Switching Model $MS(2)$-$AR(1)$ During Recession and Expansion Periods

Variable	Coefficient	Standard Error	t-Statistic	Probability
c_1	0.212527	0.090308	2.353357	0.0356
c_2	-0.393667	0.142781	-2.757139	0.0201
σ_1	0.332052	0.090912	3.652455	0.0003
σ_2	0.496421	0.175702	2.825358	0.0069
$R(-1)$	0.897400	0.289110	3.104009	0.0041
$FSI(1)$	0.237776	0.086521	2.748188	0.0054
$FSI(2)$	0.016839	0.006021	2.796881	0.0049
$COVID(1)$	0.110132	0.055542	1.982849	0.0491
$COVID(2)$	0.016559	0.007091	2.335214	0.0355
$OIL(1)$	0.483512	0.071280	6.783245	0.0000
$OIL(2)$	0.288743	0.100192	2.881899	0.0040
$INF(1)$	0.235516	0.085117	2.762255	0.0053
$INF(2)$	0.276170	0.096685	2.856400	0.0042

Based on the results of the Markov model estimation, the coefficients are significant at the 95% confidence level, and their signs are consistent with theoretical expectations. The intercept in the first regime is 0.21, and in the second regime it is -0.39. According to Hamilton's view (1988), as cited in Kazerouni et al. (2012, p. 19), the regime with a negative intercept indicates a recession regime, whereas the regime with a positive intercept indicates an expansion regime. Therefore, in this study, the first regime represents the expansion period, and the second regime represents the recession period. The variance of the disturbance terms corresponding to the first regime is 0.33, and in the second regime it is 0.49. These figures indicate that the second regime (the recession period) exhibits greater volatility than the first regime (the expansion period) in the present study. The estimated relationships indicate the positive effects of financial stress, the COVID-19 crisis, oil price shocks, and the inflation rate on stock return volatility of listed pharmaceutical companies during recession periods. In addition, the existence of a negative relationship between financial stress and stock return volatility during expansion periods is confirmed.

Table 15 presents the years assigned to each regime, or in other words, the cycles of stock return volatility in Iran during recession and expansion periods. As the results in the table below show, in 1991, 1996–2006, 2014–2017, and 2019–2020, financial stress led to a reduction in stock return volatility in Iran during expansion periods. In contrast, during recession years, namely 1992–1995, 2007–2013, 2018, and 2021–2024, financial stress increased the stock return volatility of pharmaceutical companies listed on the Tehran Stock Exchange.

Table 15. Years Classified Under Each Regime

Regime	Years
Regime 1	1991; 1996–2006; 2014–2017; 2019–2020
Regime 2	1992–1995; 2007–2013; 2018; 2021–2024

Table 16 presents the transition probabilities from one regime to another and the duration of each regime. As can be seen from the transition probability functions of the estimated model for the Iranian economy in the following table, if the Iranian economy is in the expansion period at time t, it will remain in the same state with a probability of 0.85530, while there is also a probability of 0.13946that the Iranian economy, under other factors, will switch to the recession state. If the economy is in a recession state at time t, it will remain in the same state at time $t+1$with a probability of 0.14470, while there is a probability of 0.86054that the Iranian economy, under other factors, will move to the expansion state. Moreover, in the present study, the economy experienced 18 periods of expansion compared with 16 periods of recession.

Table 16. Transition Probabilities From One Regime to Another for the Model

	Regime 1	Regime 2
Regime 1	0.85530	0.13946
Regime 2	0.86054	0.14470

As noted in the model introduction section, the error terms of the Markov-switching model must be normally distributed and free from autocorrelation and heteroskedasticity. The results of the tests related to these properties are presented below.

Table 17. Results of the Relevant Diagnostic Tests for the Model

Test Type	Test Statistic	Test Statistic Value	Probability Value
Autocorrelation test	$\chi^2(3)$	5.5381	0.3538
Normality test	$\chi^2(2)$	0.46371	0.7931
Homoskedasticity test	$F(1,1)$	0.51551	0.2277

According to the results obtained from the classical assumption tests, all classical assumptions are confirmed at the 95% confidence level.

Discussion and Conclusion

The findings of the present study provide strong empirical evidence that the behavior of stock return volatility in pharmaceutical companies is fundamentally shaped by macroeconomic shocks, financial conditions, and regime-dependent dynamics. The estimation results of the Markov-switching model indicate that the coefficients of the explanatory variables are statistically significant at the 95% confidence level and their signs are consistent with theoretical expectations. More specifically, the results reveal that financial stress, the COVID-19 crisis, oil price shocks, and inflation exert a positive and significant effect on stock return volatility during recession periods, while the effect of financial stress becomes negative during expansion periods. In addition, the estimated variance parameters confirm that volatility is substantially higher during recession regimes compared to expansion regimes, suggesting that the pharmaceutical sector is more vulnerable to instability under adverse macroeconomic conditions. These findings highlight the importance of accounting for nonlinear dynamics and regime shifts when analyzing stock market behavior in emerging economies.

The positive relationship between financial stress and stock return volatility in recession periods suggests that increased instability in the financial system amplifies uncertainty in equity markets. During periods of recession, financial constraints, liquidity shortages, and deteriorating expectations intensify risk perceptions, leading to heightened fluctuations in stock returns. This result is consistent with prior evidence emphasizing the critical role of financial tensions in shaping firm performance and market volatility, particularly in sectors with high dependence on external financing and supply chains such as pharmaceuticals (1, 2). The observed negative relationship between financial stress and stock return volatility during expansion periods can be interpreted as a stabilization effect, where moderate levels of financial discipline and controlled credit conditions may reduce speculative behavior and dampen excessive volatility. This dual effect underscores the nonlinear nature of financial stress and its regime-specific impact, reinforcing the argument that its influence cannot be adequately captured through linear models.

The results related to the COVID-19 crisis further demonstrate that this global shock significantly increased stock return volatility in the pharmaceutical sector during recession regimes. Although pharmaceutical firms experienced increased demand during the pandemic, the overall uncertainty associated with supply disruptions, input shortages, regulatory interventions, and global economic slowdown appears to have dominated the market response. These findings align with previous studies showing that the COVID-19 crisis, when combined with financial stress and oil price fluctuations, significantly affected stock returns and profitability in pharmaceutical companies (2, 8). The results suggest that crisis-induced uncertainty plays a more important role than demand-side advantages in determining stock market behavior, particularly in unstable macroeconomic environments.

Oil price shocks also exhibit a positive and significant effect on stock return volatility during recession periods. This finding is theoretically consistent with the role of oil as a key driver of production costs, inflation, and macroeconomic expectations. In oil-dependent economies such as Iran, fluctuations in oil prices transmit rapidly through multiple channels, including exchange rates, fiscal revenues, and inflation, thereby affecting firm-level performance and investor sentiment. The empirical literature supports this mechanism, indicating that oil price volatility has a pronounced impact on stock returns across sectors and is particularly relevant for industries with import dependence and cost sensitivity (4-6). The present study extends this literature by demonstrating that the impact of oil shocks is not uniform across economic regimes but becomes significantly stronger during recession periods, when the economy is less capable of absorbing external shocks.

Inflation is another key variable that contributes to stock return volatility, especially during recession regimes. The positive relationship between inflation and volatility reflects the role of rising prices in increasing uncertainty about future costs, revenues, and discount rates. In inflationary environments, investors face difficulties in accurately valuing firms, which leads to increased volatility in stock prices. This effect is particularly pronounced in the pharmaceutical sector, where pricing policies, cost structures, and regulatory constraints interact with inflation dynamics. Previous research has similarly emphasized the importance of inflation as a channel through which macroeconomic shocks influence stock market behavior and firm performance (1, 3). The findings of the present study confirm that inflation acts as an amplifying factor of volatility in adverse economic conditions.

An important contribution of this study lies in its confirmation of regime-dependent asymmetry in the determinants of stock return volatility. The higher level of volatility observed in recession regimes compared to expansion regimes indicates that negative economic conditions magnify the sensitivity of stock markets to macroeconomic shocks. This result is consistent with the broader literature on nonlinear financial dynamics, which emphasizes that economic variables do not exert constant effects over time but vary depending on the state of the economy (9, 10). The application of the Markov-switching model allows for a more nuanced understanding of these dynamics by capturing the latent structure of economic regimes and their influence on volatility behavior.

The findings of this study also resonate with recent research on economic complexity, sustainability, and structural transformation. Although these studies focus on different contexts, they collectively highlight the interconnected nature of economic systems and the importance of considering multiple dimensions of analysis. For example, research on economic governance and complexity shows that institutional and structural factors can moderate the impact of macroeconomic variables on economic outcomes (12). Similarly, studies on green technology and energy systems emphasize the role of innovation and efficiency in enhancing economic resilience (13, 14). These insights support the argument that the volatility of pharmaceutical stock returns should be analyzed within a broader framework that incorporates structural and systemic factors.

Furthermore, the results related to oil price asymmetry and volatility dynamics are consistent with the theoretical literature on asymmetric shocks. Financial and commodity markets often respond differently to positive and negative shocks, and this asymmetry is particularly evident in oil markets. Positive oil price shocks, often associated with supply disruptions and geopolitical tensions, tend to generate greater uncertainty and volatility than negative shocks. This asymmetry is reflected in the findings of the present study, which show that oil shocks significantly increase stock return volatility during recession periods. These results are in line with previous empirical evidence demonstrating the asymmetric impact of oil price fluctuations on financial markets (4, 9).

Another important implication of the findings is the role of investor behavior and market expectations in shaping volatility dynamics. During recession periods, heightened uncertainty and negative expectations lead to increased risk aversion, speculative behavior, and market overreactions, all of which contribute to higher volatility. In contrast, during expansion periods, improved economic conditions and positive expectations stabilize market behavior and reduce volatility. This interpretation is consistent with behavioral finance theories and empirical studies highlighting the role of expectations and sentiment in financial markets (5, 6).

The overall results of the study contribute to the existing literature by providing a comprehensive analysis of the determinants of stock return volatility in the pharmaceutical sector within a regime-switching framework. By integrating macroeconomic variables, crisis indicators, and nonlinear modeling techniques, the study offers new insights into the complex interactions that drive volatility in emerging market contexts. The findings underscore the importance of considering both structural and cyclical factors in analyzing stock market behavior and highlight the need for more sophisticated modeling approaches in financial research.

The limitations of this study should be acknowledged. One of the main limitations is the reliance on aggregate data for the pharmaceutical sector, which may mask firm-level heterogeneity and differences in sensitivity to macroeconomic variables. Additionally, the study focuses on a specific set of macroeconomic variables, and other potentially relevant factors such as exchange rate volatility, interest rate dynamics, and political risk are not explicitly included in the model. The use of a two-regime Markov-switching model, while effective in capturing nonlinear dynamics, may also oversimplify the complexity of economic regimes, which could involve more than two distinct states.

Future research can build upon the findings of this study by incorporating additional variables and exploring alternative modeling approaches. For example, extending the analysis to include firm-level data could provide more detailed insights into the heterogeneous effects of macroeconomic shocks. Moreover, the use of higher-frequency data and more advanced nonlinear models, such as threshold models or time-varying parameter models, could enhance the understanding of volatility dynamics. Comparative studies across different sectors or countries could also shed light on the generalizability of the results and identify sector-specific or region-specific patterns.

From a practical perspective, the findings of this study have important implications for policymakers, investors, and financial analysts. Policymakers should consider the role of macroeconomic stability and financial regulation in mitigating stock market volatility, particularly during recession periods. Investors can use the insights from this study to improve portfolio management strategies by accounting for regime-dependent risk factors. Financial analysts can also benefit from incorporating nonlinear modeling techniques into their analyses to better capture the dynamics of stock return volatility.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

References

1. Karimi S, Hosseinzadeh N. The Effect of Oil Price Fluctuations, the COVID-19 Crisis, and Financial Crises on the Performance of Pharmaceutical Companies in the Iranian Stock Market. Iran Economy Journal. 2022;21(4):120-40.
2. Hosseini A, Nikou K. Investigating the Effects of the COVID-19 Crisis, Oil Price Fluctuations, and Financial Tensions on the Profitability and Stock Returns of Pharmaceutical Companies in Iran. Journal of Financial Economics and Analysis. 2024;20(3):105-25.
3. Taheri A, Zarrinkoub M. The Effect of Oil Price Fluctuations on the Stock Prices of Pharmaceutical Companies During Economic Crises. Economic Analysis Journal. 2024;13(3):130-50.
4. Asadi M, Pham SD, Nguyen TT, Do HX, Brooks R. The nexus between oil and airline stock returns: Does time frequency matter? Energy Economics. 2023;117:106444.
5. Hosseini B, Safavi A. Analysis of the Effect of Global Oil Price Fluctuations on the Stocks of Pharmaceutical Companies. Journal of Economics and Capital Market. 2023;12(2):70-85.
6. Mousavi H, Aghamohammadi A. The Effect of Oil Price Fluctuations on the Pharmaceutical Industry and the Iranian Stock Market. Capital Market Analysis Quarterly. 2024;14(1):90-110.
7. Rezaei M, Ahmadi F. The Effect of Oil Price Fluctuations on Stock Returns of Pharmaceutical Companies in the Iranian Stock Market. Economic Analysis Quarterly. 2024;20(6):160-80.
8. Rezaei M, Ahmadi F. The Effect of Oil Price Fluctuations and the COVID-19 Crisis on Stock Returns of Pharmaceutical Companies During Crisis Periods. Economic Analysis Quarterly. 2024;19(6):130-50.
9. Wang Q, Zhang C, Li R. Geopolitical risk and ecological efficiency: A combination approach based on super-efficiency-DEA and extended-STIRPAT models. Journal of Environmental Management. 2024;351:119867. doi: 10.1016/j.jenvman.2023.119867.
10. Dilanchiev A, Umair M, Haroon M. How causality impacts the renewable energy, carbon emissions, and economic growth nexus in the South Caucasus Countries? Environmental Science and Pollution Research. 2024. doi: 10.1007/s11356-024-33430-7.
11. Nuta AC. The significance of economic complexity and renewable energy for decarbonization in Eastern European countries. Energies. 2024;17(21):5271.
12. Agu C, Ogbuabor JE, Onah BU. How are economic governance institutions moderating the effect of economic complexity on trade, FDI inflow, environmental degradation, and economic growth in Africa? Journal of the Knowledge Economy. 2024:1-32.
13. Song A, Rasool Z, Nazar R, Anser MK. Towards a greener future: how green technology innovation and energy efficiency are transforming sustainability. Energy. 2024;290:129891.
14. Dogan B, Nketiah E, Ghosh S, Nassani AA. The impact of green technology on renewable energy innovation: Fresh evidence under the role of research and development and the digital economy. Renewable and Sustainable Energy Reviews. 2025;210:115193.
15. Kumar PH, Alluraiah NC, Gopi P, Bajaj M, Kumar PS, Kalyan CNC, et al. Techno-economic optimization and sensitivity analysis of off-grid hybrid renewable energy systems: A case study for sustainable energy solutions in rural India. Results in Engineering. 2025;25:103674.
16. Xinxin C, Umair M, Rahman Su, Alraey Y. The potential impact of digital economy on energy poverty in the context of Chinese provinces. Heliyon. 2024;10(9):e30140. doi: 10.1016/j.heliyon.2024.e30140.