

Examining the Impulse Effects of Economic Uncertainty Oil Price Shocks and Governance Quality on the Stock Performance of Banks Listed on the Tehran Stock Exchange Using Structural Models



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Abstract: This study examined the impulse effects of economic uncertainty, oil price shocks, and governance quality on the stock performance of banks listed on the Tehran Stock Exchange using a Bayesian panel vector autoregressive approach. The study population comprised 12 listed banks operating during the period from March 2013 to March 2024, selected through systematic elimination. To obtain precise estimates of the variables, Iranian crude oil price shocks were extracted using an exponential generalized autoregressive conditional heteroskedasticity model, while the economic policy uncertainty index was constructed by aggregating the interest rate, monetary base, budget deficit, tax revenues, and exchange rate using principal component analysis. The results of this stage indicated that exchange rate and monetary base fluctuations accounted for the largest shares of the uncertainty index. After the stationarity of the variables was confirmed using the Levin–Lin–Chu unit root test and cointegration and long-run equilibrium relationships among the variables were established through the Kao and Johansen–Juselius tests, the optimal lag length was determined to be one, and the F-Limer test supported the use of a panel data structure. The model estimation results indicated that oil price shocks and the economic uncertainty index had negative and significant effects on bank stock performance, whereas improvements in governance quality and bank size had direct, positive effects on bank stock returns and performance. The interaction variables further indicated that higher governance quality moderated the adverse effects of oil shocks and economic uncertainty and enhanced the resilience of the banking system to macroeconomic fluctuations. The estimated error correction model, with a negative coefficient of -0.097 , indicated that approximately 10% of short-run disequilibria were dynamically adjusted toward long-run equilibrium each year. In addition, the impulse response functions indicated that bank stock returns increased in response to a positive oil shock, with the effect dissipating over time, whereas an economic uncertainty shock produced a transitory positive response followed by a deterioration in performance over the medium term. The variance decomposition results showed that, in the short run, most changes in the dependent variable were attributable to its own innovations; however, over a 10-year horizon, oil shocks and economic uncertainty accounted for approximately 17% and 8%, respectively, indicating a satisfactory model fit. Finally, the inverse-root unit-circle test showed that all roots lay within the unit circle, confirming the structural stability of the model.

Keywords: bank stock performance, economic uncertainty, oil price shock, governance quality, structural cycles.

1. Introduction

Banks occupy a central position in the relationship between macroeconomic conditions and financial market performance because they simultaneously intermediate funds, allocate credit, manage liquidity, and transmit monetary and financial disturbances. Their stock performance therefore reflects expectations about profitability and the perceived sustainability of the wider economic environment. When economic conditions become uncertain, investors reassess banks' prospective earnings, asset quality, funding costs, and capacity to withstand adverse developments. These assessments are particularly consequential in economies where government finances, exchange rates, and business activity are closely connected to commodity revenues. In such settings, oil price movements and economic policy uncertainty can influence bank valuations through several overlapping channels, making their effects difficult to isolate within a static analytical framework. Research addressing the relationship between macroeconomic variables and stock prices in the Tehran Stock Exchange provides a domestic basis for investigating these connections, while studies of global crises underscore the relevance of external disturbances to equity market behavior [1, 2]. Understanding bank stock performance consequently requires attention to the interactions between macroeconomic shocks, institutional conditions, and bank characteristics.

Economic uncertainty concerns the difficulty of forming reliable expectations about future economic outcomes, whereas economic policy uncertainty specifically involves ambiguity surrounding the direction, timing, implementation, or consequences of public policies. These concepts are related but should not be treated as interchangeable. Uncertainty may emerge from fiscal decisions, monetary interventions, exchange rate management, geopolitical developments, or changing regulatory priorities. For banks, uncertainty can affect both sides of the balance sheet: borrowers may delay investment and experience weaker cash flows, while depositors and wholesale creditors may alter their funding decisions. Investors may consequently demand higher compensation for bearing bank equity risk. However, these responses need not occur immediately or uniformly. Some banks may temporarily benefit from repricing opportunities, changes in financial margins, or increased demand for financial services, even as uncertainty creates longer-term vulnerabilities. The literature addressing heterogeneous relationships between economic policy uncertainty and financial performance supports examining these effects across organizational contexts rather than assuming a universally identical response [3].

The relationship between uncertainty and equity performance also extends beyond contemporaneous profitability. Stock prices incorporate expectations about future cash flows, discount rates, and the allocation of financial resources, meaning that uncertainty can influence valuations before its consequences become visible in financial statements. The connection between aggregate corporate savings, economic uncertainty, and future stock returns offers a relevant framework for considering how precautionary financial decisions may interact with subsequent market performance [4]. Banks are directly exposed to such decisions because changes in corporate saving and investment influence deposits, loan demand, and transaction activity. Meanwhile, international research on stock price synchronicity and economic policy uncertainty highlights the importance of examining whether equity movements reflect common economic information or institution-specific developments [5]. This distinction is essential for banking research: an increase in common exposure may produce correlated stock movements even when banks differ in size, lending behavior, and operational resilience.

Oil price shocks introduce an additional source of complexity because they influence financial performance through mechanisms that depend on the economic structure of the country and the origin of the shock. Higher oil prices may increase export revenues and fiscal resources in an oil-dependent economy, potentially supporting

public expenditure, liquidity, and business activity. Nevertheless, the same movement may coincide with inflationary pressures, exchange rate adjustments, or heightened geopolitical risk. Lower oil prices may constrain government revenue and weaken demand, while also altering expectations about future policy interventions. Thus, neither the direction nor the persistence of the relationship between oil prices and bank stock performance can be inferred solely from the sign of a price change. Domestic research on the interrelationships between oil shocks and stock market fluctuations provides a basis for examining these transmission mechanisms, while research on economic policy uncertainty and oil prices in OPEC countries draws attention to the potential interdependence of commodity markets and policy conditions [6, 7].

Banks may experience oil-related disturbances indirectly through their borrowers, investment portfolios, and interactions with government finances. Firms exposed to energy production, petroleum exports, or oil-linked expenditure can transmit changes in revenues and investment to the banking system through credit demand and repayment capacity. Research examining oil prices and the stock returns of Tehran-listed petrochemical companies during the COVID-19 pandemic offers sector-specific context for considering this exposure, although relationships observed in petrochemical firms cannot automatically be generalized to banks [8]. Broader energy-market research also emphasizes the relevance of uncertainty when studying volatility connections between energy indices and stock markets [9]. Together, these perspectives suggest that oil shocks should be analyzed alongside uncertainty and institutional conditions, since a bank's market response may depend on the wider financial environment through which the initial disturbance is transmitted.

The Iranian setting provides a relevant context for examining these interacting channels. Oil-related revenue, fiscal financing requirements, monetary conditions, and exchange rate movements form a connected environment within which banks operate. A change in one policy domain may alter expectations in another, affecting borrowing costs, liquidity availability, and asset valuations. Research on fiscal policy and economic growth provides a conceptual basis for considering expenditure and revenue decisions as components of the macroeconomic environment confronting financial institutions [10]. Similarly, work on exchange rate changes and non-oil exports illustrates the relevance of currency movements to the operating conditions of firms that may depend on bank financing [11]. Political uncertainty adds another dimension by influencing expectations about investment conditions and the predictability of economic decisions [12]. These relationships support an integrated approach to uncertainty measurement that recognizes several policy channels while maintaining a clear distinction between policy indicators and the uncertainty associated with their behavior.

Governance quality may influence how these macroeconomic disturbances translate into financial outcomes. At the national level, governance concerns the institutional arrangements through which policies are formulated, implemented, enforced, and made predictable. The reliability of legal protections, credibility of monetary arrangements, consistency of regulation, and conditions governing economic exchange can affect investors' confidence and banks' capacity to plan. More predictable institutions may reduce ambiguity about policy responses and facilitate the adjustment of financial contracts following a shock. Conversely, weak institutional arrangements may intensify uncertainty by making enforcement, intervention, or regulatory treatment less foreseeable. Governance should therefore be considered both as a potential determinant of bank stock performance and as a condition that changes banks' exposure to oil-related and uncertainty-related disturbances. The distinction between national governance and internal bank governance is particularly important: although they may interact, they represent different analytical levels and require different operational measures.

Recent financial research increasingly considers institutional and sustainability-related conditions alongside conventional market risks. Studies of geopolitical risks and ESG bonds address the implications of uncertainty for investment allocation, while work on ESG stock volatility explicitly incorporates asymmetric responses to uncertain conditions [13, 14]. These studies concern different assets and should not be interpreted as direct evidence about Iranian banks, but they establish relevant questions about how risk perceptions and institutional considerations enter market valuations. Research on climate policy uncertainty and gold-mining stock returns similarly illustrates the need to distinguish sector-specific exposure from broader uncertainty effects [15]. In the present context, this distinction directs attention toward the mechanisms through which national governance may alter bank stock responses, rather than assuming that governance produces the same protective effect across all financial assets or economic disturbances.

Organizational characteristics may further shape the relationship between macroeconomic shocks and bank stock performance. Bank size can influence access to funding, diversification opportunities, market visibility, and the resources available for managing adverse conditions. However, greater size can also increase organizational complexity and exposure to common economic developments. Loan growth likewise has an ambiguous interpretation: expanding lending may indicate stronger demand and prospective earnings, but rapid expansion can increase future credit risk if underwriting standards weaken or borrowers' repayment capacity deteriorates. Research specifically examining economic policy uncertainty and banking stability among Tehran-listed banks, with attention to size, capital, and liquidity, provides a closely related domestic foundation for considering these characteristics [16]. More broadly, research on concentrated growth and systemic risk demonstrates the relevance of separating favorable market performance from the sustainability of underlying financial structures [17]. These considerations make it necessary to include bank-level variables when evaluating macroeconomic and governance-related effects.

The capacity to respond to uncertainty also depends on how organizations process information and direct managerial attention. Attention influences which external developments are recognized, how competing risks are evaluated, and whether resources are allocated toward adaptation or existing priorities. Research connecting responsible artificial intelligence attention with firm innovation offers an organizational perspective on the relationship between attention and strategic adjustment [18]. Its relevance here is conceptual rather than evidential: it does not establish a relationship between national governance and Iranian bank stock returns. Nevertheless, it helps explain why institutions operating under similar macroeconomic conditions may differ in their responses. For banks, the identification and interpretation of oil-price developments, policy changes, and credit-market signals can affect operational adjustments. National governance may influence the predictability of the external environment within which these organizational decisions occur, while bank characteristics influence the resources available for responding.

A dynamic framework is required because the effects of shocks may unfold across several periods and differ between their initial and subsequent consequences. A disturbance may trigger an immediate change in investor expectations, followed by adjustments in lending, funding, borrower performance, and profitability. Static coefficients alone cannot describe these temporal patterns or reveal how the relative contributions of different shocks change across forecasting horizons. Research applying time-varying parameter VAR methods to connectedness among BRICS markets during the pandemic illustrates the value of examining evolving relationships within financial systems [19]. International research using a TVP-VAR approach to investigate portfolio diversification similarly provides methodological context for analyzing interconnected financial

responses [20]. Although these approaches differ from Bayesian panel VAR estimation, they reinforce the relevance of modeling joint dynamics rather than interpreting each source of disturbance in isolation.

The present study brings these considerations together by examining oil price shocks, an economic uncertainty index, national governance quality, and selected bank characteristics within a common empirical framework. A panel approach allows observations from several banks to be considered jointly, while a vector autoregressive structure captures lagged relationships among the modeled variables. Bayesian estimation provides a framework for incorporating prior information, although the resulting interpretations depend on the specification of priors, the treatment of bank heterogeneity, and the identification of innovations. Modeling oil-price volatility through EGARCH recognizes the potential relevance of asymmetric volatility responses, while constructing a composite uncertainty index through principal component analysis addresses the multidimensional nature of the selected policy indicators. Governance interactions permit an explicit examination of whether institutional quality changes the relationship of oil shocks and uncertainty with stock performance. Impulse response functions and forecast error variance decomposition then provide complementary information about the direction, persistence, and relative contribution of disturbances. The aim of this study is to examine the dynamic effects of economic uncertainty and Iranian crude oil price shocks on the stock performance of banks listed on the Tehran Stock Exchange from March 2013 to March 2024, assess the direct and moderating roles of national governance quality, and account for bank size and loan growth using a Bayesian panel vector autoregressive framework.

2. Methods and Materials

The present study was applied in purpose, descriptive–analytical in nature, and classified as ex post facto research using historical information. It examined the impulse effects of economic uncertainty, oil price shocks, and governance quality on the stock performance of banks listed on the Tehran Stock Exchange using structural models. A Bayesian panel VAR model was employed to estimate stock performance in selected listed banks. The Bayesian panel VAR model was also used to identify the effects of positive or negative oil shocks and economic uncertainty on the stock performance of listed banks, taking into account the moderating role of national governance.

The left-hand side of the above equation represents the differenced logarithms of the dependent variables. On the right-hand side, $A(L)$ is a square matrix containing polynomials in the lag operator. For example, the entry in row i and column j of $A(L)$ is $a_{ij}(L)$, which represents the response of the i th variable to the j th structural variable. The vector $E = [U_{ij}]$ contains the structural disturbances, defined as follows:

Shocks associated with oil prices.

Shocks associated with economic uncertainty.

Shocks associated with governance quality.

Shocks associated with the moderating effect of governance quality on oil shocks.

Shocks associated with the moderating effect of governance quality on economic uncertainty.

Shocks associated with bank loan growth.

Shocks associated with bank size.

Shocks associated with bank stock performance.

Operational Definitions of the Study Variables

Y: Bank stock performance. This indicator was measured using the stock returns of the selected banks listed on the Tehran Stock Exchange.

OILSH: Iranian crude oil price shocks, to be calculated using an EGARCH model.

IQ: Average governance quality index. Governance quality was measured by combining five distinct groups or subindices: (1) size of government, (2) legal system and property rights, (3) sound money, (4) freedom to trade internationally, and (5) regulation of credit, labor, and business. These five areas contain major components, which in turn include subcomponents that contribute to the overall index of the independent variables. The Fraser Institute assigns a score to each category and calculates the average of these five indices to obtain a comprehensive index for each country. In this index, zero indicates the lowest governance score, and 10 represents the highest governance quality.

LoanG: Bank loan growth, measured as the percentage change in bank lending.

Size: Bank size, measured as the logarithm of total bank assets.

Given the prevailing economic conditions in Iran, where government budgetary requirements have consistently been associated with exchange rate changes, growth in the money supply, inadequate economic growth, and dependence on oil revenues that has reduced attention to tax revenues, an index specific to the Iranian economy is required to capture its policy uncertainty. Accordingly, following Louni et al. (2021), fluctuations in fiscal, monetary, and exchange rate policy indicators were used to construct an economic uncertainty index through principal component analysis (PCA). PCA reduces the dimensionality of observations using a composite index and groups similar observations. In this method, correlated variables in a multidimensional space are summarized into a set of uncorrelated components, each of which is a linear combination of the original variables. The resulting uncorrelated components, referred to as principal components (PCs), are obtained from the eigenvectors of the covariance or correlation matrix of the original variables. Reducing the number of variables and identifying the structure of relationships among them are among the most important applications of PCA. Its main advantage in econometrics is the elimination of multicollinearity in models containing numerous influential variables.

Table 1. Economic policy uncertainty index

Policy	Abbreviation	Operational definition
Monetary policy: The set of factors and mechanisms that enables the central bank to regulate the quantity of money in the economy to achieve price stability and sustainable economic growth. Its instruments generally include open market operations, changes in banks' required reserve ratios, and changes in the rediscount rate.	IR	Interest rate: The cost of borrowing money that must be paid by the borrower. In other words, it is the opportunity cost incurred by the lender by lending money instead of using it to earn a return.
Monetary policy	M	Monetary base: The total highly liquid money created by the central bank. More specifically, it comprises cash, including banknotes and coins held by the public and in general circulation, together with a portion of the public's money deposited in banks and all funds held by commercial banks at the central bank.
Fiscal policy: The set of policies that changes government expenditure or revenue and thereby affects output. Fiscal policy was first proposed by Keynes, and its instruments include government expenditure and tax rates.	BD	Budget deficit: The excess of government expenditure over government revenue. This policy is generally used when the economy is in recession.
Fiscal policy	TAX	Taxation: The transfer of a portion of society's income to the government, or the share of profits from economic activities accruing to the government. Tax revenues are generally generated in two ways. The first involves changes in tax rates, which governments reduce during recessions and increase during

		economic expansions. The second involves the tax base, namely, levying taxes on goods and economic entities that were previously untaxed.
Exchange rate policy: The mechanism through which the exchange rate is determined in an economy is referred to as the exchange rate system or policy. Two prevailing arrangements are the fixed exchange rate system, in which the central bank intervenes to support an officially established rate, and the floating exchange rate system, in which no officially established rate applies and market mechanisms determine the exchange rate.	ER	Exchange rate: The rate at which the domestic currency is valued and exchanged against a foreign currency. In other words, it is the amount of national currency required to obtain one unit of another country's currency.

The study population consisted of data on the Iranian economy and selected listed banks during the period from March 2013 to March 2024. The sample was selected through systematic elimination according to the following criteria:

The banks must have been listed on the Tehran Stock Exchange before March 2013.

All required information must have been available.

Their fiscal year-end must have corresponded to March 19 or 20, depending on the year.

They must not have experienced an interruption in operations exceeding three months during any fiscal period.

Based on these criteria, the banks included in this study were Bank Eghtesad Novin, Bank Parsian, Bank Pasargad, Bank Karafarin, Bank Saman, Bank Sina, Bank Sarmayeh, Bank Dey, Bank Saderat, Bank Mellat, Bank Tejarat, and Bank Iran Zamin.

3. Findings and Results

First, the oil price shock was measured and extracted.

To calculate the oil price shock in accordance with the existing literature on volatility models, oil prices must first be modeled using ARMA models, and the relevant lags must be identified. The Box–Jenkins methodology was used for this purpose. The results of oil price modeling are presented in the following table.

Table 2. Estimation of the oil price model

Variable	Coefficient	Std. error	z statistic	p value
AR(1)	1.014930	0.011936	85.03441	0.0000
MA(1)	-0.275550	0.037883	-7.273665	0.0000

According to the above model, the government debt-to-GDP ratio is related to its own value in the preceding period, AR(1), and to its disturbance term in the preceding period, MA(1).

ARCH Test

The ARCH test must be used to examine the presence of conditional heteroskedasticity in oil prices. The results are presented in Table 3.

Table 3. ARCH test

Heteroskedasticity test: ARCH

Statistic	Value	Probability measure	p value
F statistic	2.214044	F(1, 80)	0.0364
Observations $\times$ R-squared	2.218810	Chi-square(1)	0.0363

Given the reported probability values, the null hypothesis of no conditional heteroskedasticity in oil prices is rejected. Thus, oil prices exhibit conditional heteroskedasticity.

Finally, the EGARCH model introduced by Nelson (1991) was used to obtain the oil price shock. An important limitation of ARCH and GARCH models is their symmetry: negative and positive shocks of equal magnitude are assumed to have the same effect on volatility. However, fluctuations in the government debt ratio do not respond identically to different types of news, that is, negative and positive shocks. An asymmetric model is therefore required to address this limitation and analyze the volatility behavior of the series (Verbeek, 2005).

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

$$\alpha_0 = \omega - \alpha \sqrt{\frac{2}{\pi}}, \quad \alpha_1 = \alpha$$

This model has several advantages. First, the dependent variable, σ_t^2 , is expressed in logarithmic form. Consequently, the coefficients of the right-hand-side variables may be positive or negative, while σ_t^2 remains positive in either case. Thus, nonnegativity restrictions on the coefficients are unnecessary. Second, the model accounts for asymmetric shock effects because γ is the coefficient of u_{t-1} , which can be either positive or negative. The coefficient γ captures the effects of positive and negative shocks, whereas α is associated only with the absolute value, $|u_{t-1}|$. If $\gamma = 0$, the model is symmetric; otherwise, it is asymmetric. The effect of positive shocks is $\alpha + \gamma$, and that of negative shocks is $\alpha - \gamma$. A negative γ indicates that negative shocks have a greater effect than positive shocks, and vice versa.

Table 4. EGARCH model for oil prices

Dependent variable: OIL

Method: Maximum likelihood ARCH, normal distribution, BFGS/Marquardt steps.

$$\ln h_t = C(3) + C(4) \left| \frac{u_{t-1}}{\sqrt{h_{t-1}}} \right| + C(5) \frac{u_{t-1}}{\sqrt{h_{t-1}}} + C(6) \ln h_{t-1}$$

Variable	Coefficient	Std. error	z statistic	p value
AR(1)	1.014930	0.011936	85.03441	0.0000
MA(1)	-0.275550	0.037883	-7.273665	0.0000
Variance equation				
C(3)	-1.460988	0.302531	-4.829211	0.0000
C(4)	-0.557479	0.164041	-3.398404	0.0007
C(5)	0.118678	0.138461	0.857123	0.3914
C(6)	-0.842610	0.171831	-4.903725	0.0000

At this stage, the estimated volatility of oil prices was calculated. To use this measure in the main model, estimated using panel data, it was converted into a variable. For this purpose, the “Make variance GARCH” command was used to generate an independent variable from the estimated volatility.

The principal direction of dispersion of the observations lies along neither X_1 nor X_2 nor any other individual variable, but between them, primarily along the major axis of the ellipse. This axis is called PC1, the first principal component of the variability in X_1 , X_2 , and the other variables. The second component, PC2, lies along the minor axis of the ellipse, exactly perpendicular to PC1, and explains the remaining variation in X_1 , X_2 , and the other variables. PC1, PC2, and the other components constitute new axes for describing X_1 , X_2 , and the remaining

variables. Thus, X_1 , X_2 , and the other variables through X_5 can be expressed as linear combinations of PC1, PC2, ..., PC5:

$$X_i = a_{i1}PC_1 + a_{i2}PC_2 + a_{i3}PC_3 + a_{i4}PC_4 + a_{i5}PC_5$$

The principal component scores can also be obtained using the following equations:

$$PC_1 = W_1X_1 + W_2X_2 + W_3X_3 + W_4X_4 + W_5X_5$$

$$PC_2 = W_6X_1 + W_7X_2 + W_8X_3 + W_9X_4 + W_{10}X_5$$

⋮

$$PC_5 = W_{20}X_1 + W_{21}X_2 + W_{22}X_3 + W_{23}X_4 + W_{24}X_5$$

Here, W_i denotes the regression coefficient of the principal components on the variables.

Principal components can be calculated from the original dataset or, when the original data are unavailable, from the covariance or correlation matrix. The correlation matrix is generally used when the dataset contains variables measured in different units or variables with different variances. Using the correlation matrix effectively means using standardized variables with a mean of zero and a standard deviation of one.

The number of components extracted in each model equals the number of variables examined. However, a specified number of these components can be selected. The first two or three components generally account for a substantial proportion of data dispersion. Accordingly, selecting the first two or three components is usually sufficient for further analysis. In some cases, however, other criteria must also be considered to determine the required number of components. These criteria are as follows:

First criterion, the scree test: Plotting the eigenvalues against the corresponding principal components produces a scree plot. This plot shows changes in the importance of the eigenvalues for each principal component. Figure 1 presents a hypothetical scree plot. As shown, the eigenvalue of the first vector, representing the variance explained by that vector, is approximately 1.2; the eigenvalue of the second vector is approximately 0.9; and that of the third vector is below 0.9. The initial decline in importance is therefore rapid, after which the rate of decline levels off. The elbow indicates the maximum number of principal components to retain. Retaining one fewer PC than the number indicated by the elbow may also be appropriate. Accordingly, in Figure 1, either the first component or the first three components may be selected.

Second criterion, eigenvalues: Components with eigenvalues greater than one are retained, and the remaining components are disregarded.

Third criterion, variance: Components that explain a larger proportion of data dispersion are sufficient for further analysis. The first component generally accounts for the greatest proportion of variance.

Scree Plot (Ordered Eigenvalues)

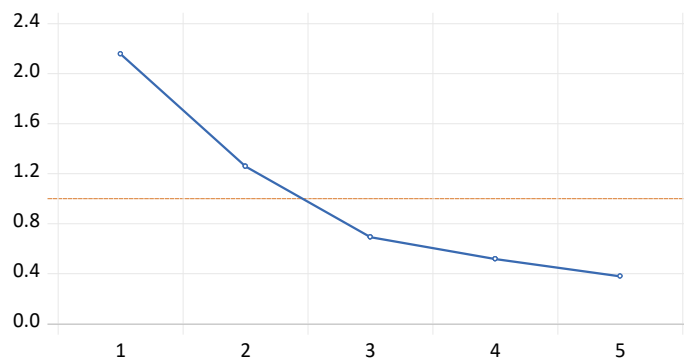


Figure 1. Eigenvalues of the principal components

Five variables—interest rate, monetary base, budget deficit, taxation, and exchange rate—were used to extract the economic uncertainty index.

Table 5. Correlation matrix of economic uncertainty indicators

	IR	M	BD	TAX	ER
IR	1.000000				
M	0.442958	1.000000			
BD	-0.238077	0.194274	1.000000		
TAX	-0.277098	-0.433110	-0.200485	1.000000	
ER	-0.240710	-0.319965	-0.257410	0.487120	1.000000

Table 5 indicates relatively high correlations among the above indicators. Consequently, the economic uncertainty index was extracted through dimensionality reduction using PCA.

Table 6 shows that the eigenvalue of the first component exceeds one and that approximately 43% of the dispersion in the dataset is explained by this component. Therefore, this component was considered the best choice for the index.

Table 6. PCA estimation results for the composite economic uncertainty index

Eigenvalues: Sum = 5; average = 1.

Component	Eigenvalue	Difference	Proportion	Cumulative eigenvalue	Cumulative proportion
1	2.156439	0.899970	0.4313	2.156439	0.4313
2	1.256470	0.564386	0.2513	3.412909	0.6826
3	0.692084	0.175020	0.1384	4.104993	0.8210
4	0.517064	0.139120	0.1034	4.622057	0.9244
5	0.377943	—	0.0756	5.000000	1.0000
Eigenvectors (loadings):					
Variable	PC1	PC2	PC3	PC4	PC5
IR	0.387918	0.618616	0.112783	0.319848	0.593136
M	0.521743	0.115009	0.633411	-0.043667	-0.558069
BD	0.211096	-0.748055	0.378247	0.211935	0.455923
TAX	-0.534374	0.087095	0.294306	0.759848	-0.207059
ER	-0.497179	0.192133	0.596979	-0.522976	0.293274

The relationships between the observed variables and the principal components can be expressed using factor loadings as follows:

$$\begin{aligned}
 IR &= 0.38PC_1 + 0.61PC_2 + 0.11PC_3 + 0.31PC_4 + 0.59PC_5 \\
 M &= 0.52PC_1 + 0.11PC_2 + 0.63PC_3 - 0.04PC_4 - 0.55PC_5 \\
 BD &= 0.21PC_1 - 0.74PC_2 + 0.37PC_3 + 0.21PC_4 + 0.45PC_5 \\
 TAX &= -0.53PC_1 + 0.08PC_2 + 0.29PC_3 + 0.75PC_4 - 0.20PC_5 \\
 ER &= -0.49PC_1 + 0.19PC_2 + 0.59PC_3 - 0.52PC_4 + 0.29PC_5
 \end{aligned}$$

An estimate of the principal components using factor scores can also be expressed as follows:

$$PC_1 = 0.38IR + 0.52M + 0.21BD - 0.53TAX - 0.49ER$$

Thus, the linear combination of the first component, PC1, used for the economic uncertainty index is as specified above.

Finally, the weight of each subindex in the composite economic uncertainty index is presented in the following table.

Table 7. Relative importance of variables in the composite economic uncertainty index

Variable	Relative importance
Interest rate	21
Monetary base	24
Budget deficit	17
Taxation	11
Exchange rate	27
Total	100

Table 7 presents the relative importance of the components of the overall index, disaggregated by the variables selected using the rotated-component regression method. Based on the estimated weights, the exchange rate has the greatest contribution to the composite economic uncertainty index. The monetary base and budget deficit have the next greatest effects. Economic uncertainty is calculated as the weighted sum of the five variables using the weights reported in Table 7.

Finally, the “Make Principal Component Analysis” command was used to extract the composite economic uncertainty index for inclusion in the final research model.

The stationarity of the variables was then examined. According to the Levin et al. unit root test, if the probability associated with the test statistic is below the selected significance level, 0.05 in this study, the independent, dependent, and control variables are stationary over the study period.

Table 8. Stationarity test results

Variable	Method	Statistic	p value	Integration order
EMPU	Levin–Lin–Chu t	–4.09173	0.0000	I(0)
IQ	Levin–Lin–Chu t	–15.3721	0.0000	I(0)
LOANG	Levin–Lin–Chu t	–4.15208	0.0000	I(0)
OILSH	Levin–Lin–Chu t	–6.73904	0.0000	I(0)
SIZE	Levin–Lin–Chu t	–2.37116	0.0089	I(0)
Y	Levin–Lin–Chu t	–2.34508	0.0095	I(0)

The null hypothesis of the Levin–Lin test is that the variables under examination are nonstationary. The hypotheses can be stated as follows:

H_0 : The variable under examination is nonstationary.

H_1 : The variable under examination is stationary.

As shown in Table 8, the calculated probability values for the independent variables are below 0.05, indicating that the variables are stationary. This means that their means and variances are constant over time and that their covariances across different years remain constant.

Most economic theories express long-run relationships between variables in level form. To establish a long-run relationship among the variables in a model, the variables must be stationary or, if nonstationary, integrated of the same order. Accordingly, their stationarity or cointegration must be examined using appropriate tests to determine whether a long-run relationship exists. If the residuals from the estimated regressions are found to be I(0), or stationary, the existence of a long-run relationship among the variables can be established. In this study, the Kao panel cointegration test was used to verify the existence of a long-run equilibrium relationship.

Table 9. Panel cointegration test results

Kao test		
Test	t statistic	p value
ADF	-2.470113	0.0068

As shown in Table 9, the panel cointegration test for the estimated variables confirms the existence of a relationship among the variables in the estimated regression.

The hypotheses of the cointegration test are defined as follows:

H_0 : No cointegration.

H_1 : Cointegration exists among the variables.

Because the significance level is below 0.05, the null hypothesis of no cointegrating relationship among the variables can be rejected. The variables are therefore cointegrated in the long run, and a long-run relationship exists among them.

To estimate the model using panel VAR, the optimal lag length was first examined. Determining the optimal number of lags is particularly important in a VAR model. Accordingly, the Akaike information criterion, Hannan–Quinn criterion, Schwarz criterion, and final prediction error criterion were used to identify the optimal lag length for the vector autoregressive model. The Schwarz Bayesian criterion is considered more reliable for determining the optimal lag length in a VAR model. The results obtained using these criteria for the study regressions are presented in the following table.

Table 10. Selection of the optimal lag length for the regression model

VAR lag order selection criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	12.16220	NA	3.39e-08	-0.171172	0.018550	-0.095643
1	143.3406	236.8499	2.42e-09*	-2.815017*	-1.486961*	-2.286314*
2	160.5302	28.17178	4.17e-09	-2.292504	0.173884	-1.310628
3	177.4939	24.97443	7.46e-09	-1.763720	1.841001	-0.328670
4	195.5305	23.54779	1.36e-08	-1.264737	3.478318	0.623487
5	243.7855	54.95708*	1.16e-08	-1.605153	4.276234	0.736244

The asterisk indicates the optimal lag.

According to the results presented in the above table, all criteria support an optimal lag length of one for the regression model. This optimal lag will therefore be used to estimate the long-run relationship in the vector autoregressive model.

Following Johansen's proposed method, the trace test, λ_{trace} , and the maximum eigenvalue test, λ_{max} , were used to determine the cointegrating vectors. As shown in the table, the trace test rejects the null hypothesis that no cointegrating vector exists and accepts the alternative hypothesis indicating more than one cointegrating vector. At the second level, the hypothesis of at least four cointegrating vectors is tested against six vectors, and the test statistic exceeds the critical value. Consequently, the existence of four cointegrating vectors is confirmed. Finally, the maximum eigenvalue test confirms the existence of three cointegrating vectors. Rejection of the null hypothesis $r = 0$ at the 5% significance level indicates the existence of a cointegrating vector, or $r = 1$. The distinction between the maximum eigenvalue and trace statistics is that the alternative hypothesis is explicitly specified in the maximum eigenvalue test. The two tests may yield conflicting results. The maximum eigenvalue test has a more specific and

clearly defined alternative hypothesis. Nevertheless, when the results conflict, selecting the smaller number of cointegrating vectors is preferable (Enders, 2007). The results are presented in the following table.

Table 11. Trace and maximum eigenvalue tests for the regression model

Hypothesized number of cointegrating equations	Eigenvalue	Trace statistic	0.05 critical value	p value
None*	0.569325	334.8859	159.5297	0.0000
At most 1*	0.557128	243.9066	125.6154	0.0000
At most 2*	0.410547	155.9434	95.75366	0.0000
At most 3*	0.319399	98.85882	69.81889	0.0001
At most 4*	0.207241	57.30270	47.85613	0.0051
At most 5*	0.161738	32.22114	29.79707	0.0258
At most 6	0.084636	13.16733	15.49471	0.1088
At most 7	0.032931	3.616469	3.841466	0.0572

The trace test indicates six cointegrating equations at the 0.05 level.

Unrestricted cointegration rank test, maximum eigenvalue:

Hypothesized number of cointegrating equations	Eigenvalue	Maximum eigenvalue statistic	0.05 critical value	p value
None*	0.569325	90.97933	52.36261	0.0000
At most 1*	0.557128	87.96320	46.23142	0.0000
At most 2*	0.410547	57.08460	40.07757	0.0003
At most 3*	0.319399	41.55612	33.87687	0.0050
At most 4	0.207241	25.08156	27.58434	0.1012
At most 5	0.161738	19.05381	21.13162	0.0953
At most 6	0.084636	9.550862	14.26460	0.2431
At most 7	0.032931	3.616469	3.841466	0.0572

The maximum eigenvalue test indicates four cointegrating equations at the 0.05 level.

Based on the results of the cointegration tests, both tests confirm the existence of at least four cointegrating vectors for the study regression. Thus, the existence of a long-run equilibrium relationship among the variables in the regression model is confirmed.

Various tests are used to determine the optimal model type for pooled cross-sectional and time-series data. The most common are the Chow test, which compares a panel data model with a pooled data model, and the Lagrange multiplier (LM) test, which compares a random-effects model with a pooled data model.

Suppose the linear panel regression is specified as follows:

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k Z_{kit} + e_{it}$$

Here, Y_{it} is the value of the dependent variable for unit i in period t , and X_{jit} is the value of explanatory variable j for unit i in period t . Cross-sectional differences are represented by α_i , which is assumed to remain constant over time. If the null hypothesis states that α_i is the same for all banks, OLS yields efficient and consistent estimates of α and β . However, if differences exist across cross-sectional units, the panel data method is used for estimation. The hypotheses are stated as follows:

H_0 : The intercept is identical across all cross-sectional units.

H_1 : At least one cross-sectional unit has a different intercept.

The following F statistic is used to determine whether a separate intercept exists for each cross-sectional unit. This is a simple Chow test.

$$F_0 = \frac{(RRSS - URSS)/(\text{missing term})}{URSS/(NT - N - K)}$$

In the above expression, UR denotes the unrestricted model, and R denotes the restricted model with a common constant term for all groups. K is the number of explanatory variables included in the model, n is the number of cross-sectional units, and t denotes the time period. If the calculated F statistic exceeds the tabulated F value with degrees of freedom $N - 1$ and $N(T - 1) - K$, the null hypothesis is rejected. Consequently, the restricted regression is invalid, and different intercepts must be included in estimation. A further fundamental question is whether the differences in intercepts operate as fixed effects or whether differences in performance can explain the variation across units more clearly (Ashrafzadeh & Mehrgan, 2010, p. 103). The results of the F-Limer test are presented in Table 12.

Table 12. Model specification test results

Test	Test statistic	Degrees of freedom	p value	Selected model
F-Limer	5.111631	(11, 113)	0.0000	Panel data
F-Limer	53.309355	11	0.0000	Panel data

Because the calculated probability values in the above table are below 0.05, the null hypothesis that the model should be estimated using pooled data is rejected. The panel data model is therefore selected.

After determining the optimal lag, performing the diagnostic test, and establishing the existence of a long-run relationship among the variables in the regression models, the model was estimated using panel VAR. The results are presented in the following table.

Table 13. Bayesian panel VAR model estimation results

Response variable: Bank stock performance.

Explanatory variable	Effect coefficient	Standard deviation	Test statistic
OILSH	-0.326912	(0.11156)	-2.930369
EMPU	-0.261852	(0.10288)	-2.545218
IQ	0.526557	(0.20156)	2.61241
IQ × EMPU	0.625156	(0.15312)	4.082785
IQ × OILSH	0.363486	(0.12838)	2.831329
SIZE	0.256156	(0.10226)	2.50495
LOANG	0.067273	(0.14806)	0.454363

The t statistic was then used to examine the significance of the coefficients of the independent variables in each model.

The long-run equilibrium relationship can be used to estimate short-run relationships, referred to as error correction models. These models capture short-run fluctuations in the variables and their relationships with long-run equilibrium values. The estimated error correction coefficient for the study regression model is presented below.

Table 14. Estimated error correction model coefficients

Model	ECM(-1)	Standard deviation	Statistic
Regression model	-0.097247	(0.03558)	[-2.73325]

The coefficient of ECM(-1) is the central element of the error correction model because it indicates the speed of adjustment from disequilibrium. The error correction coefficient in the model specification is approximately -0.09 and is statistically significant. Its negative value and magnitude below one indicate that short-run disequilibria

move toward long-run equilibrium. Because the data in this study are annual, approximately 0.09 of the short-run disequilibrium is adjusted each year to achieve long-run equilibrium in the study regression model.

In a VAR model, tests of coefficients estimated using the optimal lags do not provide sufficient information about the dynamic relationships among the variables. Impulse response analysis is used to examine the system's response to conventional random shocks that produce a positive residual equal to one standard deviation in each equation of the system. In 1980, Sims proposed using impulse responses and variance decomposition to obtain an interpretable VAR model. Consider the following bivariate VAR(1) model:

$$\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \end{bmatrix} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

An innovation in e_{1t} has an immediate, direct effect on x_{1t} . In period $t + 1$, the disturbance in x_{1t} affects $x_{1,t-1}$ through the first equation and $x_{1,t-2}$ through the second equation. These effects also operate in period $t + 2$ and continue in subsequent periods. Thus, a random shock to one variable in a VAR generates a chain reaction over time across all VAR variables. An impulse response function calculates these chain reactions. Impulse response functions have a limitation: a disturbance to one variable cannot be isolated contemporaneously from the other variables in the model, although it generates a chain reaction over time in each variable. The assumption that one variable in the above bivariate model receives a disturbance while the other does not is therefore questionable. One solution is to transform the variables into orthogonal variables that are pairwise uncorrelated and have unit variance. In other words, this analysis shows how bank stock performance responds to a one-standard-deviation shock or sudden change in economic uncertainty, oil market shocks, or the other explanatory variables.

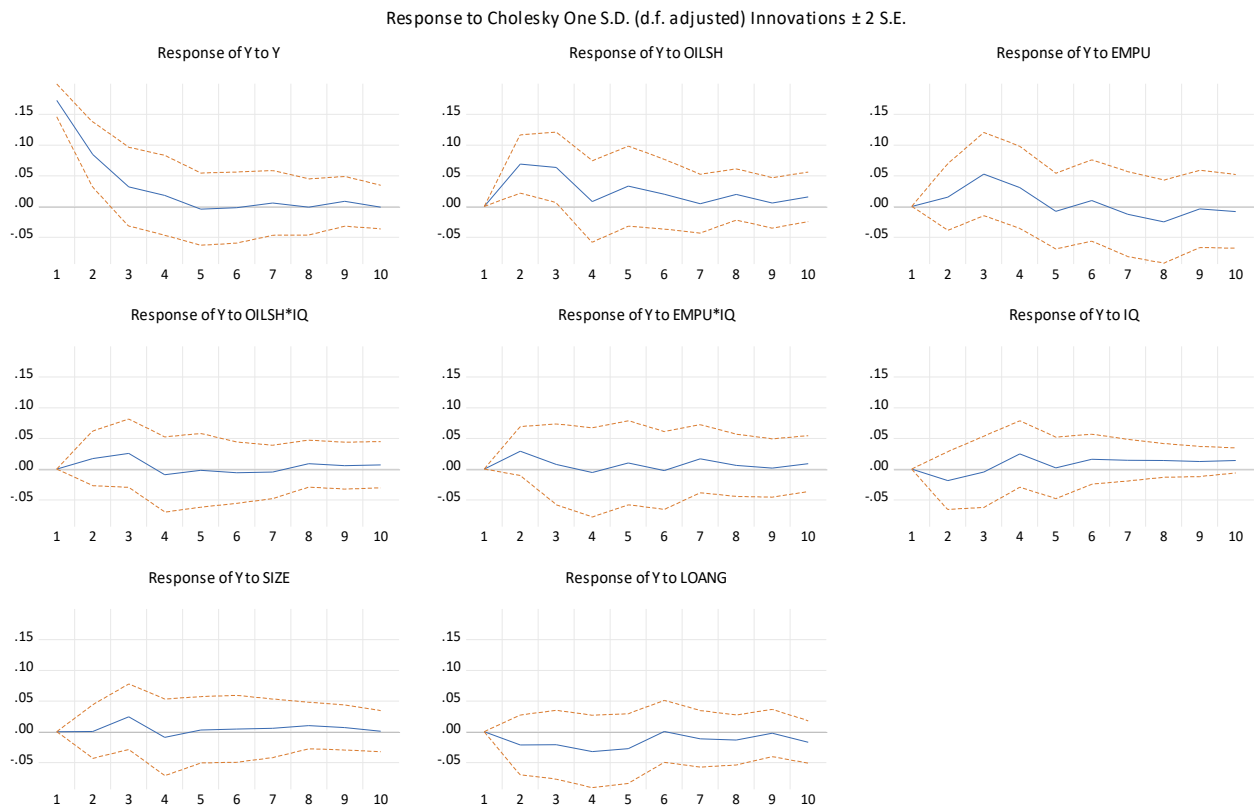


Figure 2. Impulse response functions

As shown in the graph above, the responses of the stock performance of the selected banks to the explanatory variables are illustrated. The results indicate that, following a one-standard-deviation shock to crude oil prices, bank stock performance begins to increase, and the shock gradually dissipates over time. A one-standard-deviation

shock to economic uncertainty initially increases bank stock performance for two periods, after which bank performance begins to decline.

Because unrestricted VAR models contain an excessive number of parameters, they cannot be used for short-run forecasting. Variance decomposition makes it possible to examine the extent to which changes in a series are attributable to its own components and to the disturbance components of other variables in the system (Enders, 2007). It separates the variation in an endogenous variable attributable to shocks in the other endogenous variables. In this method, the contributions of shocks to the different variables in the model are allocated across the forecast error variance of the variable responding to those shocks. This allows the contribution of each variable to changes in the other variables to be measured over time. In effect, variance decomposition identifies the contribution of each shock to the forecast of a particular variable. The variance decomposition for the stock performance index of the selected banks is presented below. Variance decompositions are defined such that, in the first period, or short run, fluctuations in each variable are generally explained by its own innovations. At longer horizons, however, the contribution of the other variables to forecasting the behavior of a given variable increases according to their importance.

Table 15. Variance decomposition of the stock performance index of the selected banks

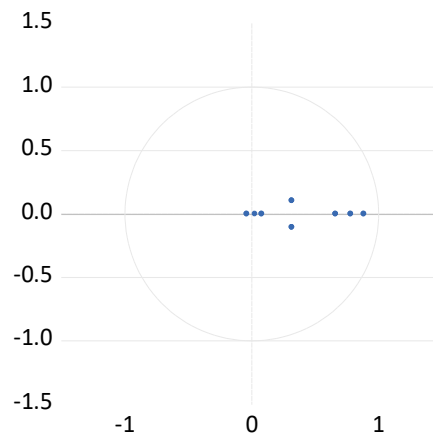
Period	S.E.	Y	OILSH	EMPU	OILSH × IQ	EMPU × IQ	IQ	SIZE	LOANG
1	0.172694	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.209762	84.13090	10.86994	0.532360	0.690634	1.947913	0.787086	1.040746	0.000422
3	0.231612	70.93637	16.45147	5.605365	1.801861	1.708605	0.682387	1.690413	1.123523
4	0.238395	67.52980	15.64489	6.984561	1.842196	1.666079	1.715995	3.411809	1.204669
5	0.242662	65.20734	16.96008	6.841803	1.785038	1.786986	1.662875	4.577179	1.178698
6	0.244337	64.32236	17.39188	6.904697	1.818452	1.772112	2.076589	4.515358	1.198553
7	0.246159	63.42585	17.16744	7.057618	1.827247	2.217303	2.400898	4.671292	1.232348
8	0.249387	61.79586	17.34220	7.871656	1.908512	2.222778	2.656299	4.836347	1.366350
9	0.250105	61.55462	17.29441	7.851712	1.948206	2.214624	2.885168	4.816148	1.435115
10	0.251952	60.65721	17.42811	7.840591	1.998867	2.306858	3.156722	5.195791	1.415853

As shown in the above table:

In the first period, 100% of the changes in the bank stock performance index are explained by the variable itself. As previously noted, variance decompositions are defined such that, in the first period, or short run, fluctuations in each variable are generally explained by its own innovations. In subsequent periods, however, this explanatory share decreases, reaching approximately 60% in the tenth period, or long run. This indicates that the contribution of the other variables to explaining changes in the bank stock performance index increases over the long run, suggesting a good model fit.

Finally, the stability of the regression model was examined using the unit-circle root test.

Inverse Roots of AR Characteristic Polynomial

**Figure 3. Unit-circle root test for the regression model**

If a panel VAR model is unstable, its results are unreliable. The AR root plot was therefore used to assess the stability of the estimated model. This plot displays the inverse characteristic roots of an AR process. If the absolute values of all these roots are below one and they lie within the unit circle, the estimated Bayesian panel VAR model is stable. The AR root plot shows that all inverse characteristic roots lie within the unit circle. Therefore, the estimated panel VAR models satisfy the stability condition.

4. Discussion and Conclusion

The findings indicate that bank stock performance is associated with economic uncertainty, oil price disturbances, and governance quality through both direct and conditional relationships. The estimated coefficients for oil price shocks and economic uncertainty were negative, whereas governance quality and bank size exhibited positive coefficients. Positive interaction terms further suggest that governance quality changes the relationship between macroeconomic disturbances and bank stock performance. These findings support an interpretation in which bank equity valuations reflect the combined influence of external economic conditions, institutional arrangements, and organizational characteristics. This perspective is consistent with the analytical focus of research examining macroeconomic variables and stock prices in the Tehran Stock Exchange and economic policy uncertainty and banking stability among Iranian listed banks [1, 16]. However, the estimated relationships should be interpreted within the model specification rather than treated as unrestricted causal effects.

Economic uncertainty exhibited a negative coefficient of -0.261852 , with a reported test statistic of -2.545218 . This result suggests that less predictable economic conditions are associated with weaker bank stock performance, conditional on the other modeled variables. A plausible explanation is that uncertainty increases the difficulty of forecasting borrowers' cash flows, future credit demand, funding costs, and policy responses. Investors may consequently revise expected bank earnings downward or require higher compensation for holding bank equity. The relationship may also operate through delayed investment and precautionary saving, which alter banks' lending opportunities and liability structures. These mechanisms are conceptually aligned with research addressing heterogeneous relationships between economic policy uncertainty and financial performance and the connections among economic uncertainty, corporate savings, and future stock returns [3, 4]. Research on political uncertainty and foreign investment provides an additional perspective on how uncertain conditions can influence the allocation of financial resources [12].

The construction of the uncertainty index highlights the relevance of exchange rate and monetary conditions in the Iranian setting. The reported relative weights assigned the largest contributions to the exchange rate and monetary base, at 27% and 24%, respectively. These components can affect banks through asset revaluation, borrowers' financing requirements, liquidity conditions, and expectations about inflation and policy intervention. Fiscal conditions may reinforce these channels when budgetary pressures influence monetary financing or exchange rate management. The economic relevance of these relationships is supported by the subject matter of research on exchange rate changes and non-oil exports and fiscal policies and economic growth [10, 11]. Nevertheless, the index requires careful interpretation: the relative weights differ from the absolute PCA coefficients, and movements in policy variables do not automatically represent uncertainty. The results therefore concern the constructed composite measure rather than every dimension of economic policy uncertainty.

Oil price shocks had a negative coefficient of -0.326912 and a reported test statistic of -2.930369 . This association suggests that oil-related disturbances can weaken bank stock performance despite the potential revenue benefits of higher oil prices in an oil-dependent economy. The distinction between oil price levels and oil-price volatility is central because the study generated OILSH from the estimated conditional variance. Greater volatility can complicate fiscal planning, business investment, liquidity management, and assessments of borrowers' repayment capacity, irrespective of whether prices initially rise or fall. This interpretation complements research examining the interrelationships between oil shocks and stock market fluctuations and economic policy uncertainty and oil prices in OPEC countries [6, 7]. Research on oil prices and petrochemical stock returns also provides a sectoral context for understanding exposure to oil-related developments, although its implications cannot be transferred directly to banking institutions [8].

Governance quality exhibited a positive coefficient of 0.526557 , with a reported test statistic of 2.61241 . Higher institutional quality may support bank valuations by improving the predictability of regulation, the enforceability of contracts, and confidence in monetary and legal arrangements. Such conditions can reduce ambiguity surrounding banks' operating environment and facilitate adjustments following macroeconomic disturbances. However, the governance measure combines government size, legal protections, monetary conditions, international trade freedom, and regulatory arrangements. Its coefficient consequently represents an association with a broad institutional composite rather than a separately identified effect of any single governance dimension. Research examining geopolitical risks and ESG bonds and climate policy uncertainty and commodity-related stock returns provides complementary context for considering institutional and policy conditions in asset valuation [13, 15]. These studies concern different financial assets and offer conceptual comparisons rather than direct confirmation of the present governance result.

The interaction coefficients were positive for governance quality with economic uncertainty, at 0.625156 , and governance quality with oil shocks, at 0.363486 . These estimates are consistent with a buffering interpretation: stronger institutions may reduce the adverse association between macroeconomic disturbances and bank stock performance. Nevertheless, interaction models require conditional interpretation. The marginal association of uncertainty is $-0.261852 + 0.625156IQ$, while that of oil shocks is $-0.326912 + 0.363486IQ$. Accordingly, the negative main coefficients describe associations when IQ equals zero, unless the governance variable was centered before estimation. The conclusion that governance merely attenuates negative effects therefore requires examining marginal effects over the observed governance range. Research incorporating uncertainty into energy-market connectedness and asymmetric ESG stock volatility supports the broader relevance of conditional and

heterogeneous financial responses [9, 14]. It does not, however, establish the specific governance mechanism identified here.

Bank size was positively associated with stock performance, with a coefficient of 0.256156 and a reported test statistic of 2.50495. Larger banks may possess broader funding access, more diversified operations, and greater capacity to absorb adjustment costs. These advantages offer plausible explanations for the result, although size may also increase complexity and exposure to common economic risks. Loan growth, by contrast, had a coefficient of 0.067273 and a test statistic of 0.454363, providing no evidence of significance under the reported criterion. Lending expansion may therefore have offsetting consequences: additional earnings opportunities can coexist with greater credit exposure. This distinction is relevant to domestic research considering bank size, capital, and liquidity under uncertainty [16]. Research on concentrated growth and systemic risk further reinforces the need to distinguish favorable market performance from sustainable financial resilience [17].

The error correction coefficient of -0.097247 indicates that approximately 9.7% of disequilibrium is adjusted within one annual period under the estimated specification. This suggests relatively gradual adjustment rather than rapid restoration of equilibrium. Slow adjustment could reflect persistent lending commitments, delayed recognition of credit deterioration, or gradual changes in expectations, although these mechanisms were not separately tested. The impulse response results also indicate temporal differences: bank stock performance increased initially following the reported oil shock, while the uncertainty shock produced a positive response over two periods followed by deterioration. These responses should not be equated directly with the negative coefficients because regression associations and system-wide innovation responses are different quantities. Moreover, an innovation in conditional oil-price variance is not necessarily a positive oil-price-level shock. Research using dynamic connectedness frameworks provides methodological context for interpreting such evolving financial relationships [19, 20].

Variance decomposition showed that the contribution of the stock performance variable's own innovations decreased from 100% initially to approximately 60.7% in the tenth period. Oil shocks and economic uncertainty accounted for approximately 17.4% and 7.8%, respectively, at that horizon, suggesting increasing contributions from macroeconomic disturbances over time. These shares describe the allocation of forecast error variance and do not independently establish predictive accuracy or goodness of fit. Likewise, inverse roots within the unit circle support dynamic stability but do not validate every identifying assumption. Research on stock price synchronicity and policy uncertainty provides context for distinguishing common economic influences from institution-specific information [5]. Studies of global crises offer a complementary perspective on external disturbances [2]. Organizational attention may influence how banks interpret these signals, although research linking responsible artificial intelligence attention with innovation provides only a conceptual analogy rather than evidence of this mechanism in the present sample [18].

Several limitations constrain the interpretation and generalizability of the findings. The sample comprises 12 listed banks over a relatively short annual period, limiting the identification of complex dynamics and bank-specific differences. Annual observations may conceal shorter-lived responses. The uncertainty index combines policy indicators whose movements may reflect predictable changes as well as uncertainty, and the national governance measure offers limited independent variation across banks. Important estimation details, including Bayesian priors, posterior diagnostics, innovation identification, and interval estimates, require fuller documentation. Furthermore, the reported level-stationarity results should be reconciled with the cointegration and error correction

specifications, while inconsistencies between narrative interpretations and tabulated results should be resolved. The findings remain conditional on these measurement and modeling choices.

Future research should extend the observation period, incorporate higher-frequency data where available, and compare listed and unlisted banks. Alternative uncertainty measures could help distinguish policy volatility from uncertainty about future decisions. Governance dimensions should be examined separately, alongside bank-level governance, ownership, capitalization, liquidity, and asset quality. Studies should report conditional marginal effects and uncertainty intervals across the observed governance range. Alternative shock-identification schemes, variable orderings, and dynamic specifications could clarify differences between oil-price-level innovations and volatility disturbances. Explicit testing of structural breaks, cross-sectional dependence, and parameter heterogeneity would further strengthen inference. Forecast evaluation against suitable benchmarks would establish whether the dynamic relationships improve predictive performance.

For practice, the results support integrating oil-market volatility, policy uncertainty, and institutional conditions into bank risk assessment and investment analysis. Bank managers could use scenario analysis to evaluate the joint consequences of exchange rate changes, liquidity pressures, and oil-related disturbances for borrowers and funding requirements. Lending expansion should be assessed alongside credit quality and capital capacity rather than interpreted as an automatic source of stronger stock performance. Policymakers could improve policy communication, regulatory consistency, and institutional predictability to facilitate financial adjustment. Investors should evaluate bank-specific exposures and interpret governance interactions conditionally. These applications should remain proportionate to the model's annual frequency and should be supported by additional operational evidence before informing major decisions.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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