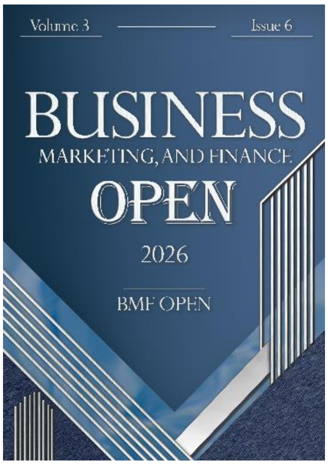
Simultaneity and Dynamics of Financial Behaviors of Companies Listed on the Tehran Stock Exchange Using Directed Acyclic Graph (DAG) and P-SVAR Models with Emphasis on Historical Shock Decomposition



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Abstract: This article examines the dynamic interactions and simultaneity of corporate financial behaviors using a nine-variable Panel Structural Vector Autoregression (P-SVAR) framework. The main objective of the study is to investigate the simultaneity and dynamic relationships of financial behaviors among firms listed on the Tehran Stock Exchange through the application of Directed Acyclic Graph (DAG) modeling and the P-SVAR approach, with particular emphasis on historical shock decomposition. A total of 219 selected firms were analyzed over the period 2001–2024. To identify the causal behavior of the model variables and to impose the structural restrictions required as a prerequisite for estimating the P-SVAR model, the Directed Acyclic Graph (DAG) methodology was employed. The causal relationships were extracted using Tetrad4 software. The results of historical decomposition within the P-SVAR framework indicate that, in Iranian firms, shocks related to liquidity ratios, financial leverage, and profitability indicators (ROA and ROE) account for the largest share in explaining fluctuations in financial variables. The debt-oriented financial structure, heavy reliance on short-term financing, and persistent inflationary conditions have led operational performance, capital structure, and market valuation to become significantly interdependent, with variable responses being transmitted primarily through liquidity channels and financial structure mechanisms.

Keywords: P-SVAR Models; Directed Acyclic Graphs (DAG); Profitability Ratios; Debt Ratios; Market Ratios; Liquidity Ratios; Activity Ratios

1. Introduction

Understanding the dynamic and simultaneous behavior of corporate financial variables has become one of the central themes in modern financial economics and corporate finance research. Firms operate within complex financial environments in which profitability, liquidity, capital structure, operational efficiency, and market valuation evolve interactively rather than independently. Traditional static financial analysis assumes linear and one-directional relationships among financial ratios; however, empirical evidence increasingly demonstrates that corporate financial behavior emerges from interconnected feedback systems characterized by simultaneity, endogeneity, and dynamic adjustment processes {Rajabi, 2019 #378571}. In such environments, shocks affecting one financial dimension—such as liquidity or leverage—can rapidly propagate across other financial indicators, altering both firm performance and market valuation.

In emerging capital markets, particularly those characterized by financing constraints, inflationary pressures, and institutional frictions, the simultaneity of financial behaviors becomes even more pronounced. Firms listed on the Tehran Stock Exchange operate within a financial structure heavily dependent on bank financing, short-term debt instruments, and internally generated funds. Consequently, liquidity management, leverage decisions, and profitability outcomes are deeply intertwined. Empirical investigations into Iranian firms have confirmed strong interactions between working capital management, leverage structure, and firm performance, indicating that financial variables cannot be analyzed independently without losing essential explanatory power {Maleki Kalkar, 2022 #378569}. Earlier studies designing simultaneous dynamic financial models for listed firms similarly emphasized that uncertainty conditions intensify feedback effects among financial ratios and require econometric approaches capable of modeling mutual causality and temporal dependence {Fallahpour, 2016 #378565}.

The theoretical foundation for studying such interdependencies lies in systems-based and dynamic perspectives of financial decision-making. System dynamics approaches argue that accounting and financial decisions form adaptive systems in which variables co-evolve through reinforcing and balancing mechanisms rather than isolated causal chains {Rajabi, 2019 #378571}. Behavioral and managerial factors further amplify this complexity because investment decisions, financing choices, and operational policies continuously respond to both internal performance signals and external market expectations. Evidence from investment company managers demonstrates that behavioral-financial factors significantly shape decision-making processes and reinforce dynamic interactions between firm performance indicators and investor responses {Rajabi, 2024 #333071}. These findings highlight the necessity of analytical frameworks capable of simultaneously capturing structural causality and dynamic feedback mechanisms.

Methodologically, the development of Structural Vector Autoregression (SVAR) models marked a turning point in empirical financial research by allowing researchers to combine economic theory with dynamic time-series modeling. Unlike unrestricted VAR models that capture statistical co-movements without theoretical interpretation, SVAR models impose economically meaningful restrictions to identify structural shocks and causal relationships. Applications of SVAR combined with Directed Acyclic Graphs (DAG) have proven particularly powerful in identifying contemporaneous causality among macroeconomic and sectoral variables. Studies examining export–growth relationships, agricultural price dynamics, and sectoral interdependencies demonstrate that DAG-based identification significantly improves causal interpretation and reduces arbitrary ordering assumptions {Shakeri Bostanabad, 2021 #378572;Pishbahar, 2019 #378570;Khalili Malekeshah, 2017 #378567}. Moreover, empirical evidence from international markets shows that sectoral and financial linkages exhibit strong transmission channels through interconnected systems, reinforcing the relevance of structural–dynamic modeling approaches {Chan, 2016 #378579}.

The growing digital transformation of financial systems has further intensified the dynamic nature of corporate financial behavior. Advances in artificial intelligence, big data analytics, and algorithmic decision systems increasingly influence financial reporting quality, auditing efficiency, risk assessment, and investment strategies. Integrated governance models demonstrate that AI adoption reshapes financial transparency and reduces information asymmetry, thereby altering the behavioral responses of investors and managers alike {Bin-Nashwan, 2025 #357839}. Artificial intelligence–based analyses also reveal that consumer and investor financial behaviors are becoming data-driven processes shaped by predictive analytics and machine learning algorithms {Sowmya, 2025 #332635;Xiao, 2025 #339451}. The interaction between technological innovation and financial behavior implies that corporate financial variables are embedded within broader informational ecosystems, where shocks can originate not only from operational activities but also from informational and technological changes.

Recent empirical research highlights the increasing role of data science techniques in predicting financial risk behavior and investment decision patterns. Deep learning models and big-data frameworks have demonstrated strong predictive power in identifying financial risk dynamics, emphasizing the importance of nonlinear interactions among financial indicators {Xu, 2024 #195793}. Similarly, studies exploring the joint influence of financial literacy, big data, and artificial intelligence on investment behavior show that information processing capacity significantly shapes financial decision outcomes {Zhang, 2024 #366952}. These developments suggest that modern financial systems operate as adaptive networks where information flows, behavioral expectations, and financial performance interact continuously.

Behavioral finance perspectives also reinforce the importance of dynamic modeling. Investor reactions to uncertainty, market volatility, and informational asymmetry create feedback loops between firm fundamentals and market prices. Empirical analyses demonstrate that trading behavior significantly contributes to stock market volatility through recursive interactions between institutional and individual investors {Saranj, 2025 #308956}. Financial inclusion and fintech adoption likewise modify behavioral intentions and financial participation patterns, thereby influencing firm-level financial outcomes through changing investor access and engagement mechanisms {Rehman, 2024 #276050}. From this perspective, corporate financial behavior must be understood not merely as an accounting phenomenon but as an evolving behavioral system shaped by institutional, technological, and psychological forces.

Within corporate finance theory, investment behavior and financing structure are strongly connected to external policy environments and financing mechanisms. Evidence from renewable energy firms indicates that financing structures, such as financial leasing arrangements and subsidy policies, directly influence investment decisions and corporate financial trajectories {Xie, 2025 #227982}. Such findings highlight that structural shocks—whether originating from policy, market conditions, or financial constraints—propagate through multiple financial channels simultaneously. Consequently, empirical models must allow for dynamic adjustment paths rather than static equilibrium relationships.

Despite substantial progress in financial modeling, a critical gap remains in simultaneously examining the dynamic interactions among profitability ratios, liquidity indicators, leverage measures, activity ratios, and market valuation metrics at the firm level. Many previous studies either focused on single financial dimensions or relied on methodologies incapable of distinguishing contemporaneous causality from dynamic feedback. Structural equation modeling approaches provide valuable insights into latent relationships but are primarily suited for latent-variable analysis rather than dynamic shock transmission {Habibi, 2018 #378566}. Conversely, traditional regression-based frameworks often fail to address simultaneity bias arising from mutual dependence among financial variables.

The integration of DAG-based causal identification with panel structural vector autoregression (P-SVAR) offers a promising solution to these methodological limitations. DAG algorithms infer causal ordering directly from observed data using conditional independence relationships, allowing researchers to impose economically meaningful restrictions without relying solely on subjective theoretical assumptions. Combining DAG identification with P-SVAR estimation enables simultaneous modeling of cross-sectional heterogeneity, dynamic interactions, and structural shock transmission within corporate financial systems. Earlier Iranian applications of this combined approach demonstrated its effectiveness in uncovering causal linkages among economic variables and improving the interpretability of dynamic models {Khalili Malekeshah, 2017 #378567;Pishbahar, 2019 #378570;Shakeri Bostanabad, 2021 #378572}.

Furthermore, recent research on investor behavior emphasizes that financial outcomes increasingly emerge from the interaction between firm fundamentals and behavioral expectations. Grounded theory analyses show that investors' financial behavior evolves through adaptive learning processes shaped by information environments, risk perception, and market signals {Ahmadi, 2025 #293950}. Such findings reinforce the view that corporate financial ratios should be analyzed within a systemic framework capable of capturing feedback loops among operational performance, capital structure decisions, and market valuation dynamics.

Taken together, the theoretical developments in system dynamics, behavioral finance, artificial intelligence–driven financial analytics, and structural econometric modeling converge toward a unified conclusion: corporate financial behavior is inherently dynamic, simultaneous, and structurally interconnected. In emerging markets where firms face liquidity constraints, volatile macroeconomic conditions, and evolving technological environments, identifying the sources and transmission mechanisms of financial shocks becomes essential for understanding firm performance and market stability.

Therefore, the present study seeks to integrate Directed Acyclic Graph (DAG) causal identification with the Panel Structural Vector Autoregression (P-SVAR) framework to analyze the simultaneity and dynamic interactions of financial behaviors among companies listed on the Tehran Stock Exchange, with particular emphasis on historical shock decomposition.

2. Methodology

This study adopts a quantitative, explanatory research design grounded in advanced econometric modeling of dynamic panel data. The empirical framework is based on the Panel Structural Vector Autoregression (P-SVAR) approach, complemented by Directed Acyclic Graph (DAG) methodology for structural identification. The research population consists of companies listed on the Tehran Stock Exchange (TSE), and the final sample includes 219 firms observed over the period 2001–2024 (Gregorian calendar). The panel structure of the dataset allows for the simultaneous consideration of cross-sectional heterogeneity and time-series dynamics, thereby increasing the efficiency and consistency of the estimators. Firms were selected based on data availability, continuity of financial reporting, and the absence of structural breaks such as prolonged trading suspensions or major changes in fiscal year.

The theoretical foundation of the empirical model combines the logic of simultaneous equation systems with the dynamic structure of vector autoregressive (VAR) models. In a standard structural VAR representation, let y_t denote an $n \times 1$ vector of endogenous financial variables. The structural form of the model can be written as:

$$Ay_t = \Gamma_0 + \Gamma_1 y_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_\varepsilon)$$

where A is the contemporaneous structural coefficient matrix reflecting theoretical restrictions, Γ_1 captures lagged dynamic effects, and ε_t represents structural shocks. This formulation, known as the structural form of VAR (SVAR), explicitly incorporates economic theory in specifying contemporaneous relationships among variables. However, direct estimation of this system leads to simultaneity bias because endogenous variables appear on both sides of the equations.

To obtain the reduced-form VAR representation, both sides of the equation are premultiplied by A^{-1}:

$$y_t = C_0 + C_1 y_{t-1} + u_t, u_t = A^{-1}\varepsilon_t, u_t \sim N(0, \Omega_u)$$

This reduced-form VAR can be consistently estimated using standard panel estimation techniques, but it does not provide direct identification of structural shocks unless additional theoretical restrictions are imposed. In the panel context, the model is extended to incorporate firm-specific fixed effects:

$$y_{i,t} = C_0 + C_1 y_{i,t-1} + \mu_i + u_{i,t}$$

where $i = 1, \dots, N$indexes firms, $t = 1, \dots, T$indexes time, and $\mu_i$captures unobserved firm-specific heterogeneity. The P-SVAR framework thus integrates dynamic interdependence, cross-sectional variation, and structural economic interpretation.

Data Collection Tools

Financial data were collected from audited annual financial statements of listed firms and extracted from the official databases of the Tehran Stock Exchange and affiliated financial information systems. The dataset includes key financial ratios representing liquidity, leverage, profitability, market valuation, and activity dimensions. Liquidity ratios measure short-term solvency capacity; leverage ratios capture capital structure characteristics; profitability ratios include Return on Assets (ROA) and Return on Equity (ROE); market ratios reflect valuation performance; and activity ratios measure operational efficiency.

To identify the contemporaneous causal ordering among variables, Directed Acyclic Graph (DAG) methodology was employed. DAG provides a data-driven yet theory-consistent mechanism for identifying causal structure based on conditional independence relationships. The approach follows the graphical modeling framework introduced by Spirtes et al. (2000) and operationalized through the PC algorithm. The PC algorithm begins with a fully connected undirected graph in which all variables are initially assumed to be related. In the first stage, unconditional correlation tests are performed, and edges between variables with statistically insignificant correlations are removed. In subsequent stages, first-order and higher-order partial correlations are tested; if the partial correlation between two variables conditional on a subset of other variables is statistically insignificant, the corresponding edge is eliminated. This iterative process continues until no further edges can be removed or all possible conditional independence tests up to order $N - 2$are completed.

Statistical inference for testing zero (conditional) correlations is conducted using Fisher's Z-transformation:

$$Z = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right)\sqrt{T-k-3}$$

where $r$denotes the (partial) correlation coefficient, $T$is the sample size, and $k$is the number of conditioning variables. The resulting graph contains vertices representing financial variables and directed edges representing causal relationships. By construction, the graph is acyclic, meaning that no directed path returns to its starting node. The DAG structure provides the economic and statistical basis for imposing contemporaneous restrictions on matrix Ain the SVAR model. The algorithm was implemented using Tetrad4 software, which allows systematic estimation and orientation of causal graphs under conditional independence constraints.

Data Analysis

The empirical analysis proceeded in three sequential stages: estimation of the reduced-form P-VAR model, identification of structural parameters through DAG-based restrictions, and historical variance decomposition within the P-SVAR framework. First, stationarity properties of the panel data were assessed using panel unit root tests to ensure that the variables satisfy stability conditions. The optimal lag length was determined using information criteria such as Akaike (AIC) and Schwarz (SC). The reduced-form P-VAR model was then estimated, producing consistent estimates of $C_1$and the covariance matrix Ω_u.

Second, the structural form was identified by imposing zero and non-zero restrictions on matrix Aaccording to the causal ordering derived from the DAG analysis. This step resolves the identification problem inherent in SVAR models, where the number of structural parameters exceeds the number of reduced-form parameters. By incorporating theoretically and empirically justified restrictions, the structural shocks $\varepsilon_t$were recovered from reduced-form residuals $u_t$through:

$$\varepsilon_t = Au_t$$

Third, dynamic interactions were examined using impulse response functions (IRFs) and historical variance decomposition. The moving-average representation of the P-SVAR model can be written as:

$$y_t = \sum_{j=0}^{\infty} \Psi_j \, \varepsilon_{t-j}$$

where $\Psi_j$denotes the matrices of dynamic multipliers. Variance decomposition quantifies the proportion of the forecast error variance of each variable attributable to its own shocks and to shocks from other variables over different forecast horizons. Formally, the h-step-ahead forecast error variance of variable $i$can be decomposed as:

$$\mathrm{Var}(y_{i,t+h}) = \sum_{j=0}^{h-1} \sum_{k=1}^{n} (\psi_{i,k,j})^2 \sigma_k^2$$

where $\psi_{i,k,j}$is the response coefficient of variable $i$to shock $k$at horizon j, and $\sigma_k^2$is the variance of structural shock k. Historical decomposition further traces realized fluctuations in each variable back to identified structural shocks over time, thereby revealing the relative importance of liquidity, leverage, profitability, and market shocks in driving financial dynamics across firms.

All estimations of VAR and SVAR models were conducted using EViews software, while causal graph estimation was performed using Tetrad4. The integrated application of DAG-based identification and P-SVAR estimation provides a theoretically grounded and statistically robust framework for analyzing simultaneity, dynamic interdependence, and the propagation of structural shocks in the financial behavior of firms listed on the Tehran Stock Exchange.

3. Findings and Results

This section reports the empirical results for the dynamic–simultaneous interactions among nine financial ratios of Tehran Stock Exchange listed firms over 2001–2024 (219 firms), estimated within the P-VAR / P-SVAR framework and structurally identified using DAG (Tetrad4). The reporting follows the sequence required for model validity (stationarity, lag selection, stability, cointegration), then structural identification (residual correlation matrix, DAG-implied contemporaneous restrictions), and finally the core outputs (historical shock decomposition and its synthesis).

Because convergence of impulses and validity of historical decomposition in a P-SVAR setting requires stationarity of all modeled variables, panel unit-root tests were applied. The results indicate that all variables are stationary at the 5% level, with one exception: the debt-to-equity ratio (Droe) is non-stationary in levels but becomes stationary after first differencing. All variables are used in log form; for Droe, the stationary form is the first difference of the log.

Table 1. Panel unit-root tests for stationarity of P-SVAR variables (log-transformed)

Variable	Stationary in level (5%)	Stationary in first difference (5%)	Notes
LnRoe	Yes	—	Level-stationary
LnRoa	Yes	—	Level-stationary
LnRoea	Yes	—	Level-stationary
LnLeave	Yes	—	Level-stationary
LnMb	Yes	—	Level-stationary
LnIr	Yes	—	Level-stationary
LnCR	Yes	—	Level-stationary
LnCA	Yes	—	Level-stationary
LnDroe	No	Yes	Requires first differencing

Lag length was selected using standard information criteria. Both Schwarz Bayesian Criterion (SC/SBC) and Hannan–Quinn (HQ) identify lag 1 as the optimal lag order. Given the dimensionality (nine variables) and the panel setting, selecting lag 1 also avoids excessive degrees-of-freedom loss.

Table 2. Lag-order selection criteria for the P-VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4667.232	NA	2.88e-05	15.08462	15.14892	15.10962
1	-1852.394	5538.875	4.26e-09	6.265788	6.908812*	6.515736*
2	-1736.073	225.5133	3.80e-09	6.151848	7.373594	6.626749
3	-1622.489	216.9096	3.42e-09	6.046737	7.847204	6.746591
4	-1552.895	130.8809	3.55e-09	6.083532	8.462720	7.008339
5	-1452.138	186.5628	3.34e-09	6.019800	8.977710	7.169560
6	-1363.905	160.8110	3.26e-09*	5.996469*	9.533100	7.371182
7	-1286.447	138.9258	3.31e-09	6.007893	10.12325	7.607558
8	-1221.375	114.8208*	3.50e-09	6.059273	10.75335	7.883891

Model stability was checked using the inverse roots of the companion matrix. The reported stability test confirms that all inverse characteristic roots lie inside the unit circle, implying the P-VAR system is stable and thus suitable for structural analysis, impulse propagation, and historical decomposition.

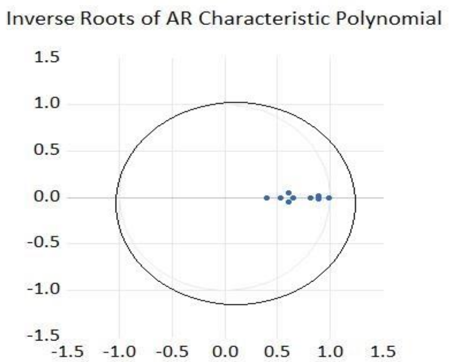

Figure 1. Stability test of P-VAR (inverse roots inside the unit circle)

Although the structural analysis is conducted in a dynamic panel SVAR framework, the study also tested for the existence of a long-run relationship among the variables using Kao panel cointegration test. The result strongly rejects the null of no cointegration, supporting the presence of a common long-run equilibrium among the modeled ratios.

Table 3. Kao panel cointegration test (P-VAR model)

Test	t-statistic	Prob.
Kao cointegration test	-20.28	0.000

Source: EViews 12 output.

DAG identification required the correlation matrix of reduced-form residuals from the estimated P-VAR. This matrix is the empirical basis for conditional-independence testing and edge orientation in Tetrad4.

Table 4. Residual correlation matrix from reduced-form P-VAR (used in Tetrad4 DAG learning)

	DLCA	DLDROE	DLLEAVE	DLMB	DLROEA	LIR	LCR	LROA	LROE
DLCA	1.000								
DLDROE	0.370	1.000							
DLLEAVE	-0.273	0.141	1.000						
DLMB	-0.010	-0.134	-0.010	1.000					
DLROEA	0.098	0.021	-0.351	-0.268	1.000				
LIR	-0.153	-0.150	-0.409	-0.124	0.031	1.000			
LCR	-0.158	-0.203	-0.550	0.060	0.146	0.899	1.000		
LROA	0.560	0.015	-0.602	0.095	0.053	0.110	0.203	1.000	
LROE	0.460	-0.146	-0.418	-0.018	-0.069	-0.064	0.066	0.833	1.000

Using the above residual correlation matrix, the study estimated a directed acyclic graph in Tetrad4. The DAG provides the contemporaneous causal ordering used to impose identifying restrictions on the P-SVAR structural matrices. The key result is that the DAG supports a structure in which profitability and capital-structure strength contain exogenous components, and the liquidity–leverage channel is central in contemporaneous transmission.

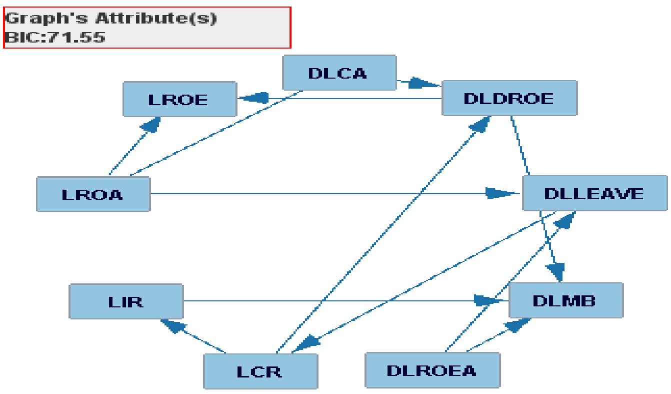

Figure 2. Directed Acyclic Graph (DAG) identification of contemporaneous causal ordering (Tetrad4 output)

The contemporaneous structural relationships (as reported) can be summarized in nine equations linking reduced-form residuals $U$to structural shocks ε. These relations define the identifying restrictions embedded in the P-SVAR estimation.

$$U_{Roa} = b_{11}\varepsilon_{Roa} \qquad (1)$$

$$a_{21}U_{Roa} + a_{24}U_{Droe} + U_{Roe} = b_{22}\varepsilon_{Roe} \qquad (2)$$

$$a_{31}U_{Roe} + U_{CA} = b_{33}\varepsilon_{CA} \qquad (3)$$

$$a_{43}U_{CA} + U_{Droe} + a_{48}U_{CR} = b_{44}\varepsilon_{Droe} \quad (4)$$
$$a_{51}U_{Roa} + a_{57}U_{Roea} + U_{Leave} = b_{55}\varepsilon_{Leave} \quad (5)$$
$$a_{64}U_{Droe} + U_{MB} + a_{67}U_{Roea} + a_{69}U_{Ir} = b_{66}\varepsilon_{MB} \quad (6)$$
$$U_{Roea} = b_{77}\varepsilon_{Roea} \quad (7)$$
$$a_{84}U_{Leave} + U_{CR} = b_{88}\varepsilon_{CR} \quad (8)$$
$$U_{Ir} + a_{89}U_{CR} = b_{99}\varepsilon_{Ir} \quad (9)$$

These equations operationalize the mapping between reduced-form innovations and structural shocks in the identified system and are the basis for historical decomposition.

The principal substantive results come from historical decomposition in the estimated P-SVAR, which allocates the realized movements of each variable over time to the structural shocks of the nine-ratio system. The results show a consistent dominance of liquidity shocks (CR, IR) and core profitability/capital-structure shocks (ROA, ROE, ROEA) across multiple targets, reflecting the debt-oriented financing structure and short-term funding reliance of the sample firms.

Historical decomposition for the equity-to-assets ratio (Roea) indicates that shocks to quick ratio (IR) and current ratio (CR) account for the largest shares of its variation. This outcome is consistent with the immediate accounting transmission from current liabilities and current assets into equity and with the predominance of short-term bank debt within corporate liabilities.

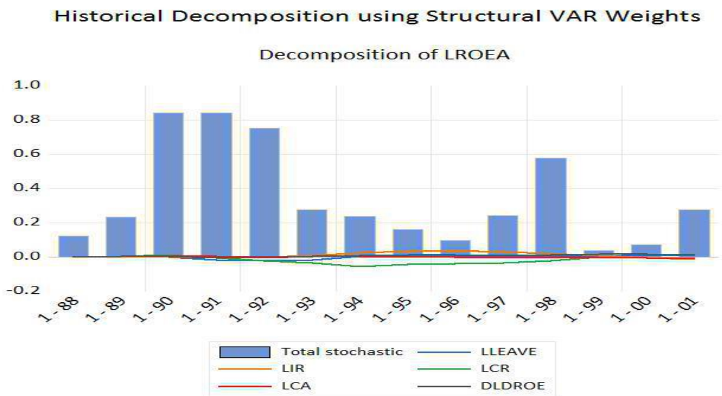

Figure 3. Historical decomposition of equity-to-assets ratio (Roea)

Historical decomposition for ROA shows that shocks to IR, CR, and financial leverage (Leave) are the dominant contributors. In this system, ROA is particularly sensitive to working-capital disruptions and debt-service pressure, so liquidity stress translates quickly into operating profitability.

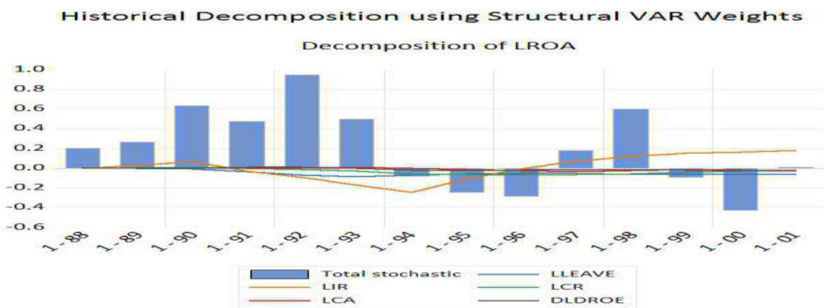

Figure 4. Historical decomposition of ROA

For ROE, historical decomposition attributes the largest shares to IR, CR, and asset turnover (CA). This indicates that in this setting, shareholders' return is strongly affected by short-run liquidity conditions and by operational efficiency in converting assets into sales, especially under inflationary and cost-pressure conditions.

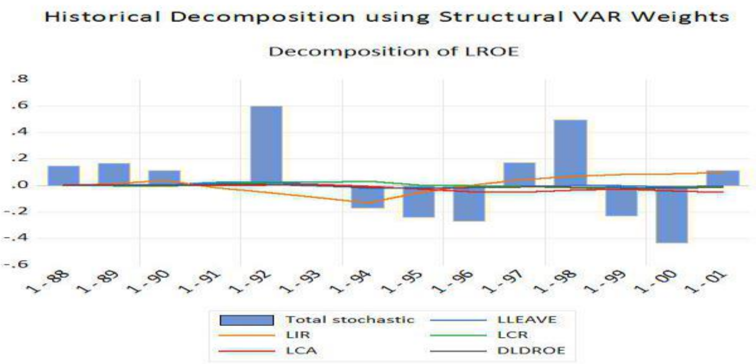

Figure 5. Historical decomposition of ROE

Historical decomposition for market-to-book (MB) identifies asset turnover (CA) and quick ratio (IR) as the most influential shocks. This implies that valuation in the market reacts strongly to short-horizon operational performance and cash/liquidity signals, while book values adjust more slowly, amplifying the role of these shocks in MB.

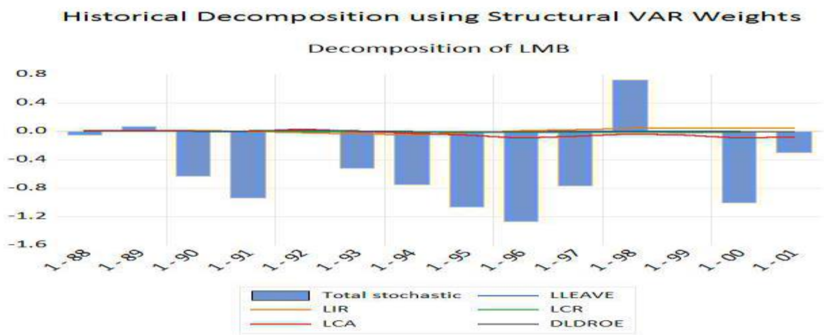

Figure 6. Historical decomposition of market-to-book ratio (MB)

For financial leverage (Leave), the dominant contributors are shocks to IR and CR. This reflects the mechanical linkage between liquidity ratios and current liabilities, and the fact that leverage in the sample firms is largely determined by short-term debt dynamics.

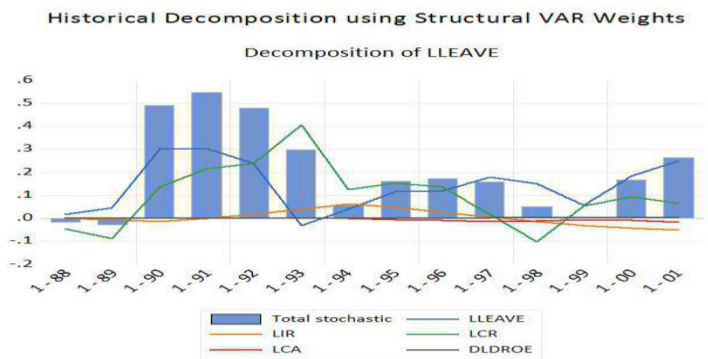

Figure 7. Historical decomposition of financial leverage (Leave)

For the quick ratio (IR) itself, the strongest contributor is the current ratio (CR) shock, consistent with their shared balance-sheet base and the relatively slower adjustment of inventories compared with other current components.

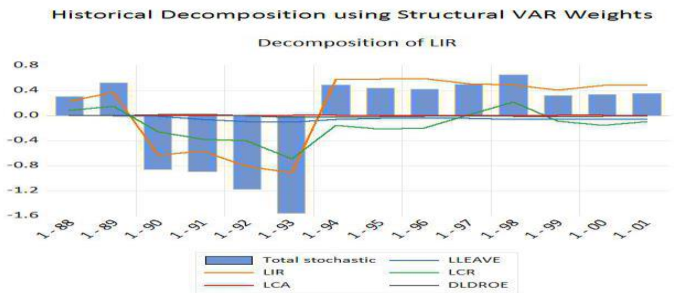

Figure 8. Historical decomposition of quick ratio (IR)

For the current ratio (CR), the decomposition is dominated by IR shocks and leverage (Leave) shocks, capturing the two principal channels: liquid current assets and short-term debt.

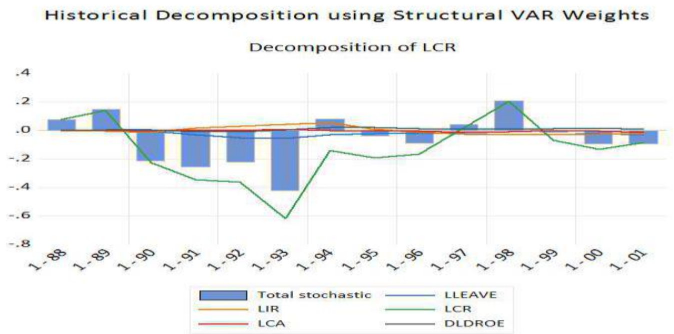

Figure 9. Historical decomposition of current ratio (CR)

For asset turnover (CA), historical decomposition indicates dominant effects from CR (working-capital capacity) and Leave (debt pressure), consistent with operational scaling decisions being constrained by liquidity and financing pressure.

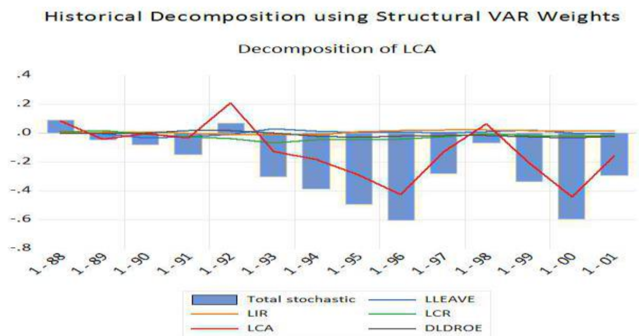

Figure 10. Historical decomposition of asset turnover (CA)

For debt-to-equity (Droe), the decomposition shows the strongest influences coming from CR, IR, Leave, and CA, reflecting that debt-to-equity acts primarily as a reactive capital-structure outcome that adjusts in response to liquidity stress, leverage shifts, and operational contraction/expansion.

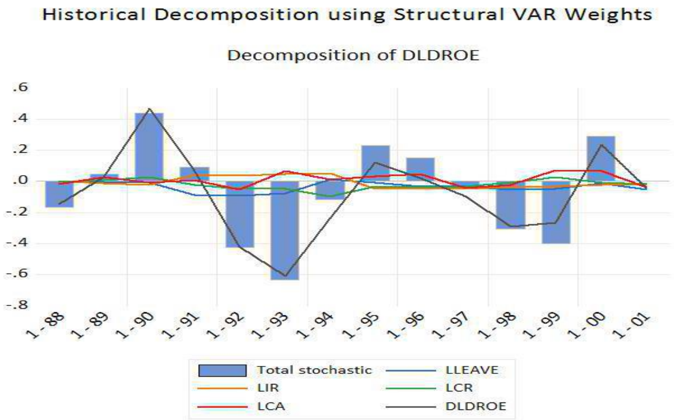

Figure 11. Historical decomposition of debt-to-equity ratio (Droe)

To summarize the historical decomposition evidence across the system, the study reports a frequency-based aggregation of which shocks most often appear as major contributors. The distribution is clearly uneven: ROA shocks and Roea shocks have the highest relative frequencies (19.04% each), followed by IR (16.6%), CR and MB (14.28% each). Lower frequencies are reported for Leave (9%), CA (7%), and ROE (4%). The shock attributed to Droe has 0% frequency, indicating that its independent structural shock does not meaningfully explain the variation of other variables once ROA, Roea, liquidity ratios, and market valuation are accounted for.

Table 5. Summary of historical decomposition results and relative frequency of dominant shocks

Variable	Main contributors in historical decomposition (ranked as reported)	Frequency	Relative frequency (%)
ROE	Roea; IR; MB; CR & CA; ROA	2	4.00
ROA	Roea; IR; ROE; CR; Leave	8	19.04
MB	ROA; IR; Roea; CA	6	14.28
Leave	ROE; ROA; IR; Roea; CR	4	9.00
IR	MB; ROA; CR; Roea	7	16.60
CR	MB; IR; ROA; Leave; Roea	6	14.28
CA	Roea; CR; Leave; ROA; MB	3	7.00
Droe	CR; IR; Leave; CA	0	0.00
Roea	ROE; ROA; IR; MB	8	19.04
Total		42	100

The frequency profile confirms that the core propagation mechanism in the financial behavior of the sampled firms is anchored in two pillars: operating profitability (ROA) and capital-structure strength (Roea). Liquidity shocks—especially IR and CR—form the dominant short-run transmission channel linking financing constraints to profitability and leverage. Market valuation (MB) appears as a meaningful but secondary driver, typically reacting to or amplifying firm-internal fundamentals rather than functioning as an autonomous shock source. The zero-frequency result for Droe is consistent with the interpretation that the debt-to-equity ratio is either highly irregular (due to unstable equity bases in some firms) or largely redundant once leverage and equity-to-assets are included, causing its marginal explanatory role to be absorbed by those stronger balance-sheet measures.

4. Discussion and Conclusion

The present study aimed to investigate the simultaneity and dynamic interactions of corporate financial behaviors using a combined Directed Acyclic Graph (DAG) and Panel Structural Vector Autoregression (P-SVAR) framework with emphasis on historical shock decomposition. The empirical findings reveal that financial dynamics among firms listed on the Tehran Stock Exchange are primarily driven by liquidity conditions, operational profitability, and capital-structure adjustments rather than isolated financial decisions. The results provide strong evidence that corporate financial ratios behave as an interconnected system in which shocks propagate through identifiable transmission channels.

One of the central findings of the study is the dominant role of liquidity shocks—particularly the current ratio and quick ratio—in explaining variations in several financial variables, including leverage, profitability, and equity structure. Historical decomposition showed that liquidity indicators exerted the strongest influence on the equity-to-assets ratio and financial leverage. This outcome aligns with prior research emphasizing the critical importance of working capital management in financially constrained environments. Empirical evidence indicates that in emerging markets, where firms rely heavily on short-term financing, liquidity decisions directly reshape capital structure and performance outcomes {Maleki Kalkar, 2022 #378569}. The strong accounting linkage between current liabilities and equity further explains why liquidity shocks rapidly transmit across financial indicators. Similar conclusions were reached in dynamic financial modeling studies demonstrating that corporate financial systems react simultaneously to funding constraints and operational pressures under uncertainty {Fallahpour, 2016 #378565}.

The results also show that operating profitability, measured by return on assets (ROA), functions as a primary driver of system-wide financial dynamics. Structural shocks to ROA appeared with the highest frequency in explaining fluctuations across multiple variables. This finding supports system dynamics perspectives suggesting that operational performance acts as a central feedback mechanism connecting accounting outcomes, financing decisions, and market expectations {Rajabi, 2019 #378571}. In practical terms, profitability shocks influence firms' borrowing capacity, liquidity management, and investment behavior, creating cascading effects throughout the financial system. Evidence from investment behavior research similarly demonstrates that managerial and investor decisions strongly respond to profitability signals, reinforcing dynamic interactions between financial performance and strategic decision-making {Rajabi, 2024 #333071}.

Another important result concerns the interaction between profitability and capital structure. The equity-to-assets ratio emerged as a co-dominant explanatory factor alongside ROA in historical decomposition results. This suggests that corporate financial stability in the studied firms depends heavily on internal financing capacity rather than external capital markets. Such findings are consistent with studies showing that firms operating in bank-dominated financial systems rely primarily on retained earnings and internal capital accumulation when adjusting financial structure {Maleki Kalkar, 2022 #378569}. The prominence of capital-structure shocks also confirms theoretical expectations derived from structural econometric approaches, where endogenous financial variables jointly determine adjustment paths rather than following independent trajectories.

The discussion of ROE dynamics provides additional insight into the mechanisms linking operational efficiency and shareholder performance. The results indicate that liquidity ratios and asset turnover play decisive roles in explaining fluctuations in ROE. This finding reflects the DuPont identity logic, according to which shareholder returns are jointly determined by operational efficiency, profitability, and leverage conditions. Similar patterns have been observed in behavioral finance studies emphasizing that investor expectations respond strongly to operational efficiency signals, particularly in environments characterized by uncertainty and information asymmetry {Ahmadi, 2025 #293950}. Moreover, research examining investor trading behavior confirms that profitability and operational indicators significantly influence market reactions and volatility formation {Saranj, 2025 #308956}.

Market valuation results further reinforce the importance of internal firm fundamentals. Historical decomposition demonstrated that shocks to asset turnover and profitability explain most fluctuations in the market-to-book ratio. This implies that the stock market primarily evaluates firms based on operational performance rather than speculative external factors. Comparable findings in international sectoral linkage studies show that real economic performance variables often dominate valuation dynamics when financial markets exhibit informational inefficiencies {Chan, 2016 #378579}. Additionally, recent research highlights that financial literacy, information processing, and data availability enhance investors' reliance on observable firm fundamentals, thereby strengthening the transmission of profitability shocks into market valuation {Zhang, 2024 #366952}.

The strong interaction between liquidity and leverage uncovered by the model also carries significant theoretical implications. Financial leverage was largely driven by liquidity shocks, indicating that debt adjustment serves as the primary mechanism through which firms absorb financial disturbances. This pattern reflects institutional features of emerging financial systems where long-term debt markets remain underdeveloped. Empirical SVAR–DAG studies in economic sectors confirm that causal structures frequently reveal debt and liquidity as jointly determined variables rather than independent decision outcomes {Khalili Malekeshah, 2017 #378567;Pishbahar, 2019 #378570}. The current findings extend this insight to firm-level financial behavior, demonstrating that leverage dynamics emerge as responses to liquidity pressures rather than proactive optimization decisions.

An additional contribution of the study lies in showing that the debt-to-equity ratio did not play an independent explanatory role in historical decomposition. Its zero relative frequency suggests that its informational content is largely absorbed by more stable indicators such as leverage and equity-to-assets ratio. Similar conclusions appear in empirical studies where overlapping accounting information causes certain ratios to lose independent explanatory power once structural relationships are properly identified {Habibi, 2018 #378566}. This result underscores the importance of structural identification methods, since traditional regression approaches might incorrectly attribute significance to redundant financial indicators.

The findings also highlight the increasing relevance of technological and informational transformations in shaping financial behavior. Modern corporate environments increasingly rely on artificial intelligence, big data analytics, and digital decision systems that influence reporting quality, risk evaluation, and investor expectations. Integrated models show that AI adoption enhances information transparency and reduces asymmetry, thereby intensifying the speed at which financial shocks spread across markets {Bin-Nashwan, 2025 #357839}. Likewise, studies reviewing AI-driven consumer and investor behavior demonstrate that predictive analytics reshape financial decision-making processes, strengthening dynamic feedback between performance indicators and market reactions {Xiao, 2025 #339451;Sowmya, 2025 #332635}.

The predictive role of profitability and capital structure identified in this study is also consistent with emerging evidence from deep learning–based financial risk prediction models. These studies emphasize that nonlinear interactions among financial variables provide superior explanatory power compared with isolated financial indicators {Xu, 2024 #195793}. The P-SVAR framework employed here similarly captures nonlinear propagation effects through structural shocks and dynamic adjustment paths. Furthermore, research on fintech adoption and financial inclusion indicates that behavioral intentions and technological accessibility reshape financial participation and investment flows, thereby influencing corporate financing outcomes {Rehman, 2024 #276050}. These developments help explain why market valuation and liquidity shocks appear closely connected in the empirical results.

From a broader theoretical perspective, the results confirm that corporate financial behavior should be understood as a dynamic adaptive system rather than a collection of independent accounting ratios. Firms adjust liquidity, leverage, investment, and operational policies simultaneously in response to internal performance signals and external market conditions. Evidence from investment behavior studies demonstrates that financing mechanisms and policy environments significantly alter corporate investment responses, further supporting the systemic interpretation of financial dynamics {Xie, 2025 #227982}. The integration of DAG causal discovery with structural VAR estimation therefore provides a coherent methodological framework capable of revealing these complex interactions.

Overall, the discussion indicates that the financial behavior of Iranian listed firms is governed by three dominant transmission channels: liquidity management, operational profitability, and capital-structure strength. Liquidity acts as the immediate shock transmission mechanism, profitability operates as the core performance driver, and equity structure serves as the stabilizing foundation of financial adjustment. Market valuation responds primarily to these internal fundamentals rather than external speculative forces. These findings reinforce the growing consensus in contemporary finance research that financial systems function as interconnected networks shaped by behavioral, technological, and institutional dynamics.

Despite its contributions, this study faces several limitations. First, the analysis relies exclusively on accounting-based financial ratios, which may not fully capture managerial expectations, governance quality, or macroeconomic uncertainty factors influencing corporate behavior. Second, although the P-SVAR framework models dynamic interactions effectively, it assumes structural stability across the entire sample period, while real-world financial relationships may evolve over time due to policy changes or market reforms. Third, the results are derived from firms listed on a single emerging stock market, which may limit the generalizability of findings to other institutional environments. Finally, historical decomposition identifies relative contributions of shocks but cannot perfectly distinguish behavioral motives behind managerial responses.

Future studies may extend the analysis by incorporating macroeconomic variables such as inflation, exchange rate volatility, and monetary policy shocks into the structural system to better capture external transmission channels. Researchers could also apply time-varying parameter SVAR models to investigate structural changes across economic cycles. Integrating ESG indicators, corporate governance measures, or behavioral sentiment indices may provide deeper insights into non-financial determinants of corporate dynamics. Additionally, combining machine learning techniques with structural econometric modeling may improve forecasting performance and reveal nonlinear interaction patterns. Comparative cross-country analyses among emerging and developed markets would further clarify how institutional differences shape financial behavior dynamics.

Managers should prioritize liquidity management as a central strategic function because liquidity conditions appear to drive leverage, profitability, and valuation simultaneously. Strengthening internal financing capacity and maintaining balanced capital structures can enhance resilience against financial shocks. Investors may benefit from focusing more on operational profitability and equity strength rather than isolated leverage indicators when evaluating firms. Policymakers should consider developing deeper long-term debt markets and improving financial infrastructure to reduce firms' dependence on short-term financing. Enhancing transparency, financial reporting quality, and data accessibility can also stabilize market expectations and reduce volatility transmission across corporate financial systems.

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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