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Analyzing the Interaction Between Leading Stocks and Exchange Rate Shocks Using Network Analysis and VAR-GARCH: Evidence from the Tehran Stock Exchange

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Abstract

Identifying leading stocks is critical for investors, particularly in markets lacking comprehensive analytical tools. Effective stock selection necessitates an integrated approach that combines financial network analysis, performance evaluation, and predictive modeling. This study examines firm-level interconnections within the Tehran Stock Exchange, focusing on the implications of exchange rate shocks. A dual-phase analytical framework is applied: first, Minimum Spanning Tree network analysis identifies leading stocks and quantifies the effects of exchange rate fluctuations; second, VAR-GARCH models assess volatility dynamics of leading stocks, while the iterated cumulative sum of squares method detects structural breaks in market behavior. The dataset includes daily returns of 50 top-performing stocks and the free-market USD exchange rate across two periods: pre-shock (March 24, 2016–April 3, 2018) and post-shock (April 4, 2018–July 21, 2020). Pre-shock, Pars Khodro, Foulad, and Kegol dominated the market. Post-shock, export-driven sectors such as metals retained leadership due to competitive advantages, while import-dependent industries like automotive declined significantly. Later, stocks including Veghadir, Foulad, Sharak, and Tipico emerged as new leaders, reflecting structural realignments driven by currency volatility. The findings highlight the efficacy of network-driven methodologies in portfolio optimization and risk management, offering empirical clarity on sectoral dependencies and exchange rate sensitivities in emerging economies.

Highlights

- MST, VAR-GARCH, and ICSS models identify pre/post-currency crisis leaders on TSE.
- Export-oriented sectors assumed a more prominent leading role post-crisis.
- Network analysis highlights systemic risk mitigation and portfolio strategies under FX volatility.

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1. Introduction

The Iranian capital market, a cornerstone of the national economy, remains highly vulnerable to both macroeconomic fluctuations and domestic policy interventions. In recent years, the economy has faced severe instability, characterized by inflation exceeding 40%, sharp currency depreciation, and volatile asset markets. Structural weaknesses—including heavy reliance on oil revenues, import dependency, and international sanctions—amplify the disruptive effects of exchange rate shocks on production costs, corporate profitability, and stock price dynamics. These disruptions cascade through intricate inter-firm linkages, distorting capital allocation and investor behavior (Cheshmi & Osmani, 2022). Notably, the periods under study (2016–2018 and 2018–2020) coincided with aggressive government policies to stimulate the stock market, such as tax exemptions for equity investments, public campaigns to attract retail investors, and liquidity injections into the Tehran Stock Exchange. While currency shocks remain a central focus, these policy measures likely interacted with exchange rate fluctuations, complicating the isolation of purely market-driven responses and necessitating a nuanced analytical approach.

Existing literature has extensively examined sectoral disparities in exchange rate exposure, distinguishing export-oriented industries (e.g., petrochemicals) that benefit from depreciation from import-dependent sectors (e.g., pharmaceuticals) burdened by rising costs. However, prior studies overlook two critical dimensions: first, the systemic propagation of shocks through price-leading firms, and second, the confounding effects of government interventions that artificially influenced market behavior during currency crises. Conventional methodologies, relying on static sectoral classifications and linear econometric models (Sensoy & Tabak, 2014; Coletti, 2016), fail to disentangle these overlapping forces. This study addresses these gaps by integrating network theory with advanced econometrics, explicitly accounting for policy-driven distortions while analyzing shock transmission mechanisms.

The exchange rate-stock market nexus has been theorized through frameworks such as Purchasing Power Parity (PPP) and corporate cash flow models (Dornbusch & Fischer, 1980), emphasizing macroeconomic transmission channels. Empirical studies confirm that currency depreciation asymmetrically impacts exporters and importers (World Bank, 2020; Feng & Bessler, 2017)), yet few explore how state interventions—such as liquidity injections or retail investor mobilization—amplify or dampen these effects. Recent advances in network science, including hierarchical clustering and contagion mapping (Wang et al., 2016), offer tools to analyze such complexities but remain underexplored in Iran's context. This research bridges this gap by employing Minimum Spanning Trees (MST) to map inter-firm linkages and VAR-GARCH models to quantify volatility spillovers, while controlling for policy variables like liquidity inflows and retail trading activity. By comparing pre-shock (2016–2018) and post-shock (2018–2020) periods, the study disentangles the interplay between currency devaluations, government stimulus measures, and investor herding beh avior, offering insights into how policy-driven optimism interacts with structural vulnerabilities. While the primary focus of this study is on the effects of currency devaluations on the stock market, it is important to acknowledge that government policies aimed at stimulating the stock market and encouraging investment during the periods under consideration may have also influenced market dynamics. The potential impact of these policies, however, was not directly accounted for in this analysis. This could be seen as a limitation of the study, as the interaction between policy-driven market optimism and currency shocks might provide additional insights into market behavior. Future research could explore these factors more explicitly to better understand the combined effects of government interventions and currency fluctuations on market volatility.

The proposed framework acknowledges inherent limitations. Iran's opaque financial reporting under sanctions constrains data granularity, potentially affecting network accuracy. Additionally, while VAR-GARCH models capture linear volatility transmission, nonlinear interactions between policy shifts and currency shocks may remain underrepresented. Although the study controls for liquidity inflows and retail investor activity, the psychological impact of state-led market promotion campaigns—difficult to quantify—may residualize in error terms. Future research could integrate sentiment analysis or machine learning to address these complexities. Nevertheless, this research advances understanding of crisis dynamics in sanctioned economies, highlighting the unintended consequences of policy measures designed to stabilize markets. For policymakers, the findings underscore the risks of artificial market stimulation during currency crises, such as inflated valuations decoupled from fundamentals. For investors, the study provides a framework to distinguish policy-induced volatility from structural risks, supporting more resilient portfolio strategies. Subsequent sections elaborate on methodological innovations, empirical validations, and policy implications, emphasizing the need for coordinated responses to enhance financial stability in Iran's evolving market landscape.

2.Theoretical Framework

This study's theoretical framework integrates capital market dynamics, leading firms, and stock network analysis to examine systemic interactions and shock propagation. Economic theories, network methodologies, and financial models elucidate structural shifts in network topology during pre-/post-crisis periods, explaining price behavior under currency crises.

2.1 The Role of Capital Markets in the Economy

Financial markets serve as a cornerstone of the economy, providing a crucial platform for investment and capital allocation. A key concern for policymakers in these markets is to establish favorable conditions for investors seeking to maximize returns while minimizing risk (Esmaili & Eyhami, 2023). This enhances productivity, employment, and ultimately economic growth (Ross et al., 2021). By channeling surplus capital toward productive sectors and efficient firms, capital markets facilitate optimal resource allocation via price mechanisms, where high-performing firms attract more capital while inefficient ones are marginalized (Mishkin & Eakins, 2018). The expansion of capital markets can alleviate pressure on banking systems, foster competition in the financial sector, and promote innovative financial instruments (Levine, 2005).

Capital markets also serve as tools for monetary and fiscal policies, aiding in inflation control and liquidity management. Policymakers can incentivize investments in stock markets to direct liquidity toward productive activities, curbing runaway inflation (Bernanke & Gertler, 1999). Furthermore, domestic capital markets are interconnected with global markets. Foreign investors can bolster domestic investment and strengthen national currencies, while international volatility, such as financial crises, may spill over into local markets (Obstfeld & Rogoff, 1995).

2.2 Exchange Rate Effects on Stock Markets

The relationship between exchange rates and stock markets has been a key topic in financial economics, with various theoretical frameworks attempting to explain this dynamic. Flow-oriented models, such as those proposed by Dornbusch and Fischer (1980), suggest that a depreciation of the currency improves export competitiveness, which boosts corporate earnings and stock prices. This effect is especially significant for firms with substantial international exposure, as currency depreciation makes their products cheaper abroad, thus driving up demand and profitability.

Stock-oriented models, however, offer a more nuanced view, suggesting that exchange rate fluctuations may affect stock markets indirectly through investor sentiment and expectations. A sharp depreciation may signal economic instability, raising concerns about inflation and reducing investor confidence, which could lead to falling stock prices (Branson, 1983). Portfolio balance models, also developed by Branson (1983), propose an inverse relationship, where falling stock prices lead to capital outflows, putting downward pressure on the domestic currency and causing depreciation. Conversely, rising stock prices attract foreign capital inflows, leading to currency appreciation.

Monetary models, such as those proposed by Gavin (1989), argue that exchange rates are primarily influenced by macroeconomic factors such as interest rates and inflation expectations, with no direct relationship to stock prices. In this view, exchange rates are largely determined by central bank policies and broader economic conditions, rather than movements in the stock market.

Empirical studies on this relationship show mixed results, with some research indicating a positive link between currency depreciation and stock prices, particularly for export-oriented firms (Aggarwal, 1981), while others suggest that exchange rate volatility can negatively impact stock markets, especially during times of economic uncertainty (Fama & French, 1988).

In conclusion, the relationship between exchange rates and stock markets is complex, with different models offering varying perspectives. While flow-oriented models emphasize the positive impact of currency depreciation on stock prices through trade competitiveness (Dornbusch & Fischer, 1980), portfolio balance models highlight an inverse relationship due to capital flows (Branson, 1983). Monetary models, on the other hand, suggest that exchange rates are more closely tied to macroeconomic factors than to stock market movements (Gavin, 1989). Empirical studies provide mixed evidence, with some research indicating a positive link between currency depreciation and stock prices, particularly for export-oriented firms (Aggarwal, 1981), while others suggest that exchange rate volatility can negatively impact stock markets, especially during times of economic uncertainty (Fama & French, 1988).

2.3 Graph Theory and Financial Markets

Network theory, rooted in Euler's (1736) graph theory, has become a vital tool in modeling financial markets. Networks consist of nodes (entities) and edges (relationships), with financial applications focusing on stock correlations (Mantegna, 1999). Graph theory analyzes complex interconnections, enabling the study of systemic risk, shock propagation, and market centrality (Strogatz, 2001). Metrics like centrality identify influential nodes, aiding in portfolio optimization and risk management (Newman, 2010).

2.4 Minimum Spanning Tree (MST)

The Minimum Spanning Tree (MST), a foundational concept in graph theory, represents an optimal network structure that connects all nodes (e.g., financial assets) using edges with the minimum total weight while eliminating cyclic connections (Kruskal, 1956; Prim, 1957). In financial contexts, MSTs simplify complex interdependencies by transforming correlation matrices—quantitative measures of pairwise asset price movements—into sparse, hierarchical networks. This method filters redundant or weak correlations, retaining only the most significant linkages to reveal systemic relationships (Mantegna, 1999). Centrality metrics, which quantify the topological importance of nodes within the MST, further enable the identification of systemically influential entities that disproportionately drive market dynamics (Montasheri & Sadeghi, 2018). By combining algorithmic efficiency with structural clarity, MSTs provide a robust framework for analyzing market interconnectedness, offering insights into risk propagation, portfolio optimization, and the stability of financial systems.

2.5 Leading Firms in Stock Markets

Under the framework of degree centrality, a node's importance increases with the number of adjacent connections it holds (Uddin & Jakobsen, 2013). When a stock establishes numerous linkages within a network, it forges extensive relationships with other stocks, thereby qualifying as a leading share. In financial network analysis, Minimum Spanning Trees (MSTs) enable the identification of central nodes that exert the greatest influence on others—these nodes represent market-leading firms. It is critical to emphasize that, in this study, "leading shares" are not defined as index-weighted constituents but as firms occupying central network positions that confer structural influence over the market ecosystem. MSTs and complex network models serve as vital tools for dissecting inter-firm relationships and the behavioral dynamics of market leaders (Albert & Barabási, 2002). Leading firms situated at central nodes within MSTs wield significant influence over peers. For instance, a sudden decline in a leading firm's stock price may cascade to other firms through network spillover effects, illustrating how shocks propagate in complex systems. This phenomenon underscores that price fluctuations in structurally influential firms can rapidly disseminate across the network. During economic or political crises, such firms may amplify market-wide volatility, as their price movements reverberate through interconnected sectors (George et al., 2017).

Leading firms, often large-cap entities in key industries, significantly influence market indices and set behavioral benchmarks for smaller firms (Baker & Wurgler, 2006). Their strategic decisions and price movements shape market trends and investor sentiment (Merton, 1987). Network analysis reveals their central roles in shock transmission and market stability (Granovetter, 1985).

2.6 Behavioral Finance and Market Psychology

Behavioral economics merges cognitive psychology with finance to explain irrational decision-making. Key biases: herding (investors follow trends, Shiller, 2000), anchoring (reliance on past prices, Tversky & Kahneman, 1974), overconfidence (excessive trading, Barber & Odean, 2001). Crises amplify fear-driven selling (tightening market networks) and optimism-driven risk concentration. Dominant firms exploit asymmetric information, centralizing market influence (Fama & French, 1997). Biases and structural factors shape crisis dynamics.

2.7 Integration of Network and Econometric Models

The integration of network theory and econometric models offers a sophisticated approach to dissecting financial market dynamics, merging the temporal rigor of econometrics with the topological depth of network science. While traditional econometric tools like VAR and GARCH capture time-dependent volatility and interdependencies, network metrics—such as Minimum Spanning Trees (MSTs) and centrality measures—uncover structural relationships, such as systemic risk pathways and spillover effects (Diebold & Yılmaz, 2014). For instance, network-weighted GARCH models enhance volatility forecasts by embedding inter-firm connectivity into weighting schemes, demonstrating improved predictive accuracy in interconnected markets (Diebold & Yılmaz, 2014). Similarly, hierarchical clustering tools like dendrograms reveal post-crisis market reconfigurations, supplementing VAR frameworks in identifying regime shifts (Mantegna, 1999).

However, this synthesis is not devoid of methodological trade-offs. A critical limitation lies in the linear assumptions underpinning conventional network metrics (e.g., correlation-based edges), which may inadequately represent non-linear contagion mechanisms during market turmoil (Battiston et al., 2016). Static network representations further clash with the dynamic nature of financial systems, as econometric models prioritize temporal evolution, creating a mismatch that hybrid frameworks (e.g., time-varying network GARCH) struggle to resolve computationally (Ahelegbey et al., 2016). Additionally, reliance on correlation matrices risks conflating causal linkages with spurious associations, potentially distorting policy insights (Billio et al., 2012).

Emerging methodologies aim to reconcile these tensions. Causal networks, integrating Granger causality with topological metrics, refine shock transmission analysis by distinguishing direct influences from incidental correlations (Eichler, 2012). Machine learning-augmented models, such as neural network-enhanced GARCH, detect non-linear dependencies in volatility clustering, addressing the rigidity of linear assumptions (Gu et al., 2020). Adaptive weighting techniques, including Bayesian-updated networks, dynamically align structural connectivity with temporal econometric parameters, mitigating static biases. Despite these advances, the field must prioritize empirical validation to ensure methodological transparency. As Billio et al. (2012) caution, interdisciplinary models risk theoretical overreach without rigorous grounding in empirical data. Future research should thus focus on adaptive, causal frameworks that harmonize network granularity with econometric rigor, advancing robust insights into the non-linear, interconnected nature of modern financial systems.

3. A Review of the Related Literature

Dolfin et al. (2024), in "Investor Behavior and Multiscale Correlations: Detecting Regime Shifts in Global Markets", demonstrated MST’s efficacy in identifying market instability. During crises, MSTs shortened, reflecting intensified market linkages.

Nabavi Qaedi et al. (2024), in their study titled "Monetary Policy and Crisis Contagion to Stock Markets: An Application of Minimum Spanning Tree (MST)", investigated the role of monetary policy in transmitting the 2008 U.S. financial crisis to selected global markets using graph theory and MST analysis. Monthly stock indices and real interest rates (2004–2021) for Iran, China, Russia, Germany, the Netherlands, the UK, Brazil, South Korea, Japan, and France were analyzed. Findings reveal financial contagion from the U.S. through trade, financial linkages, and investor sentiment shifts. Despite Iran’s limited direct exposure, contagion occurred via domestic channels (e.g., oil markets), intermediary countries (e.g., China), and domestic investor behavior. Monetary policy interventions mitigated contagion costs, reduced investment risks, and promoted productive investments globally.

Taghizadeh & Abdzadeh Kanafi (2023), in "An Analysis of the Capital Market Using a Network Approach", examined Iran’s capital market structure based on stock prices, returns, and trading volumes (2017–2020) using network analysis. They found that higher correlation thresholds reduced network connectivity and increased disorder, while key nodes (central firms) exerted greater influence on price dynamics. Network fragmentation intensified in late 2020, suggesting that network-based analysis enhances transparency, risk management, and policymaking.

Namaki et al. (2022), in "Analyzing Systemic Risk in Tehran Stock Exchange Firms Using Complex Systems", applied MST to study systemic risk and local topology. Results confirmed a significant relationship between firms' systemic risk and their closeness centrality in the financial network, highlighting topology's role in risk propagation.

Sadeghi (2022), in "A Second-Order Hierarchical Clustering of Selected Cryptocurrencies", clustered 30 cryptocurrencies using MST and centrality metrics. The study revealed shifts in clustering structures pre- and post-COVID-19, emphasizing MST's utility in dynamic asset classification.

Ebrahimi and Rajabi (2024), in "A Portfolio Optimization Model Using Network Theory in Iran's Stock Market", designed a two-stage MST-based portfolio model. Central and peripheral portfolios outperformed the market index, with peripheral portfolios excelling during bullish trends.

Kalyagin et al. (2022), in "Reliability of Maximum Spanning Trees in Correlation-Based Networks", compared similarity metrics for MST construction, finding minimal theoretical differences despite observational variability.

Marti et al. (2021), in "Two Decades of Financial Networks: Correlations, Hierarchies, and Clustering", reviewed network applications in finance, emphasizing their utility in risk assessment and market analysis.

Millington and Niranjan (2021), in "MSTs Using Rank Correlations in Financial Returns", showed rank-based MSTs (Spearman, Kendall) outperformed Pearson in stability and edge retention, particularly in larger markets.

Sadaqati et al. (2020), in "Portfolio Management Based on Stock Market Network Topology", mapped Iran's market correlations across daily, seasonal, and annual scales. Centrality metrics identified influential sectors, aiding investors and regulators in risk-aware decision-making.

Monteshri and Sadeghi (2020), in "Typology of Financial Networks Based on Topological Features", analyzed Iran's top 100 firms (2009–2019) using centrality metrics. Key firms (e.g., Sepahan Cement, Ghadir Investment) dominated network influence, while greedy clustering algorithms revealed 11 tightly connected clusters.

Azarpeykan (2020), in "Hierarchical Stock Trees in Tehran's Capital Market", applied hierarchical clustering to 30 top firms (2015). Reliable correlations and nested factor models improved network analysis precision.

Zięba et al. (2019), in "Shock Transmission in Cryptocurrency Markets: Is Bitcoin Dominant?", analyzed 30 cryptocurrencies via MST and VAR models. Bitcoin's price changes showed no significant spillover effects, challenging its perceived market dominance.

Li et al. (2019), in "Network-Based Portfolio Optimization", proposed machine learning strategies using volatility networks. Network metrics improved regional allocation and crisis-period predictions.

Khoojine and Han (2019), in "Network Analysis of China's 2015–2016 Market Turbulence", constructed MSTs from returns and volumes, revealing fragmented post-crisis networks vulnerable to node attacks.

Stosic et al. (2018), in "Collective Behavior in Cryptocurrency Price Dynamics", identified hierarchical clusters in cryptocurrency markets using MSTs, highlighting stable structures useful for portfolio diversification.

Francés et al. (2018), conducted a study titled "Digital Currency Market: A Network Analysis," employing minimum spanning tree analysis and hierarchical clustering (dendrogram) to study the digital currency market. Their findings reveal a network structure among cryptocurrencies, suggesting that network analysis can assist investors in optimizing their investment strategies.

Eng (2018), in "Stock Market Predictions: Does Network Topology Matter?", linked network topology to systemic risk, showing centrality metrics enhance return predictability.

Brida et al. (2016), in "Cross-Sector Linkages in China's Stock Market", analyzed Euro Stoxx indices, revealing post-2008 geographic clustering and sectoral fragmentation.

Sadeghi and Sharifi Samani (2016), in "Topological Features of Tehran's Stock Network Post-JCPOA", used MST to analyze market indices pre- and post-JCPOA. MST effectively captured structural shifts, with central nodes maintaining critical roles.

SoltaniNejad and Dawallou (2016), in "Portfolio Optimization via Clustering Methods", reduced noise in correlation matrices using clustering techniques. Bootstrapping validated improved portfolio performance across varying market conditions.

Teh et al. (2015), in "Hierarchical Shifts During China's 2007 Market Correction", used hierarchical clustering to detect weakening inter-cluster correlations pre-crisis, with localized shocks dominating.

Yang et al. (2014), in "Industry Linkages in China's Stock Market", identified central industries (e.g., finance, IT) via MSTs, emphasizing regulator focus on key nodes for stability.

Onnela et al. (2003), in "Market Correlation Dynamics and Portfolio Analysis", introduced "asset trees" using MSTs, observing topology shifts during crashes (e.g., reduced mean occupation layers).

Mantegna (1999), in "Hierarchical Structures in Financial Markets", pioneered MST-based ultrametric clustering for stocks, revealing economically meaningful groupings in DJIA and S&P 500.

This study advances financial network analysis by addressing critical limitations in prior scholarship, which has predominantly relied on traditional econometric models and pairwise linear frameworks, thereby overlooking the dynamic interdependencies inherent in stock market structures. Existing approaches have insufficiently captured how external macroeconomic shocks—such as exchange rate volatility—interact with internal network structures to reshape price leadership hierarchies, particularly in key sectors like petrochemicals.

To bridge these gaps, we propose an integrative methodological framework that synthesizes topological network analysis with regime-sensitive econometrics. First, advanced clustering algorithms and dependency models are employed to map latent inter-firm connections and identify systemic vulnerabilities that conventional methods may overlook. Second, dynamic network centrality metrics, coupled with VAR-GARCH models, are deployed to analyze market fluctuations and trace the evolution of price leadership under structural breaks detected via the ICSS algorithm.

This dual-phase approach demonstrates that sustained market dominance is achieved not merely through sectoral advantages but also through adaptive positioning within evolving financial networks. By integrating clustered breakpoint analysis with real-time price co-movement tracking, the framework disentangles the combined effects of exchange rate fluctuations and network reconfigurations on market hierarchies. The resulting paradigm shift—from static, sector-centric analyses to dynamic, network-aware modeling—provides investors and policymakers with actionable tools to anticipate leadership transitions, assess risk dynamics, and optimize resilience strategies in volatile emerging markets.

In summary, the synthesis of structural break detection, dependency mapping, and topology-driven volatility modeling offers a refined perspective for analyzing crisis-driven market restructuring. This approach moves beyond conventional sector-based assessments by prioritizing the role of endogenous network mechanics and firm-level adaptability in shaping financial stability.

4. Data and Methodology

This applied, descriptive-analytical study examines behavioral patterns of top-performing stocks in Iran's capital market, analyzes structural network changes induced by the currency crisis, and investigates the role of leading stocks. Focusing on price dynamics in the Tehran Stock Exchange (TSE), the research assesses stock network shifts before and after the crisis. The statistical population includes all active TSE-listed firms, with a purposive sample of 50 top-performing companies[1], regularly indexed by the TSE, selected for analysis. The list of 50 top-performing companies analyzed in this study was curated and published by the Iranian Securities and Exchange Organization (SEO) based on standardized criteria, including liquidity, trading volume, frequency of transactions, and market influence. These firms were selected due to their distinct characteristics, such as

[1] The selected stocks in the study sample are as follows: Befajr, Beterans, Dejaber, Fameli, Fars, Fasemin, Febahonar, Fekhas, Fekhooz, Fenval, Fouland, Hamrah, Hekashti, Jam, Kechad, Kegol, Kenoor, Keroy, Khebahman, Khepars, Khezamia, Khodro, Kasra, Mobin, Pakshoo, Parsan, Reanfor, Retap, Sefars, Sharak, Shebandar, Shebharn, Shekhark, Shepaksa, Shapdis, Shapna, Shiran, Shiraz, Tipico, Veati, Vebank, Vekhavar, Velsapa, Veniki, Verna, Vesanat, Vghadir, Vmaden, Veomid, Vesandogh

active market participation and high liquidity, which align with the analytical objectives of this research. This methodological approach ensures that the findings accurately reflect the operational dynamics of the Tehran Stock Exchange (TSE) and provide actionable insights into market trends. By focusing on companies with systemic importance and robust market activity, the analysis captures critical interdependencies and volatility patterns, enhancing the validity of conclusions drawn for investors and policymakers.

Daily closing prices of sampled stocks were obtained from the TSE database[1] to calculate returns, while free-market USD exchange rate data were sourced from licensed exchange offices. Cross-correlation matrices of daily returns were used to construct Minimum Spanning Trees (MSTs) for two periods: pre-crisis (March 24, 2016–April 3, 2018) and post-crisis (April 4, 2018–July 21, 2020), simplifying complex correlations into hierarchical structures to visualize network topology changes. Leading stocks were identified based on degree centrality, highlighting the most connected nodes in MSTs.

While this purposive sampling ensures analytical focus on high-impact, systemically important companies—critical for understanding market stability and leadership dynamics—it inherently limits representativeness, as smaller or less liquid firms, which may exhibit distinct crisis-response behaviors, are excluded. Additionally, free-market USD exchange rate data, though sourced from licensed offices, may reflect transient volatility or regulatory distortions during crises, despite cross-verification with central bank benchmarks to enhance reliability. These limitations are counterbalanced by the sample's unique advantages: the 50 firms act as market bellwethers, offering insights into structural interdependencies and resilience patterns that disproportionately shape TSE behavior. Their high liquidity and active participation also ensure robust correlation analyses, minimizing noise in network modeling.

Temporal dynamics were analyzed using optimal lags for leading stock returns, determined via AIC/BIC criteria for Vector Autoregression (VAR) models. Volatility clustering was validated through ARCH tests, followed by GARCH(1,1) modeling to estimate volatility dynamics. Granger causality tests examined directional relationships among leading stocks, while the ICSS test detected structural breaks, confirming crisis-induced regime shifts. This integrated approach, combining network theory, econometric modeling, and structural break analysis, provides a comprehensive framework for understanding crisis-driven market reconfigurations in Iran's capital market.

5. Empirical model

5.1 Minimum Spanning Tree (MST) in Financial Markets

The MST is a concept in graph theory. A random graph can be defined by the triplet $G =< V, E, F >$, where $V = \{v_1, v_2, \dots, v_n\}$ is the set of vertices, and $E \subseteq V \times V = \{e_1, e_2, \dots, e_n\}$ is the set of edges. The matrix $F_{n\times n}$ represents

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[1] fipiran.com

the probability distributions for a characteristic of the graph's edges (e.g., edge length). The entry f_{ij} in this matrix represents the probability distribution of the characteristic for the edge (v_i, v_j).

A random spanning tree $G' =< V', E', F >$ of the graph $G =< V, E, F >$ is a connected random subgraph of G such that $V' = V$ and $E' \subseteq E$. If $T = \{\tau_1, \tau_2, \ldots, \tau_n\}$ is the set of spanning trees of the random graph $G =< V, E, F >$, and $\bar{L}_{\tau_i}$ is the average weight of the spanning tree $\tau^* \in T$ is called the Minimum Spanning Tree (MST) of the random graph $G =< V, E, F >$ if $\bar{L}\tau^* = min_{\forall_{\tau_{i \in T}}}\{\bar{L}\tau_i\}$ (Al-Taie & Kadri, 2017).

In this method, an MST with (*N−1*) nodes is constructed for *N* variables. In stock market analysis, edge weights are derived from the cross-correlation of stock returns, highlighting key relationships. A symmetric distance matrix *D* is computed, where the distance between stocks is defined as one minus their correlation. Higher correlations correspond to shorter distances, ensuring that the MST captures the most significant connections (Ziba et al., 2019).

To calculate the distance between stocks, the return of each stock is first computed using the following relationship (Bazrayi et al., 2021):

$$S_i \equiv \ln Y_i(t) - \ln Y_i(t-1) \tag{1}$$

Where Y_i is the Closing Price of the stock at time *t.*

The correlation coefficient can be expressed as follows (Montashari & Sadeghi, 2020):

$$\rho_{ij} = \frac{\langle S_i S_j \rangle - \langle S_i \rangle \langle S_j \rangle}{\sqrt{\langle S_i^2 - \langle S_i \rangle^2 \rangle \langle S_j^2 - \langle S_j \rangle^2 \rangle}} \tag{2}$$

ρ_{ij} represents the correlation between variable *i* and variable *j*.

In the next step, we compute the adjacency matrix *DD* based on the metric distance between all pairs of stocks. This distance is calculated using the following equation (Mantegna, 1999):

$$d(i,j) = \sqrt{2(1 - \rho_{i,j})} \tag{3}$$

Centrality, particularly degree centrality, is a crucial concept in network analysis, referring to the number of connections a node (vertex) has. In stock networks, degree centrality indicates a stock's immediate influence based on its connectivity, with more connected stocks having higher centrality, reflecting extensive relationships with other stocks (Montasheri & Sadeghi, 2020). Stocks with high degree centrality are considered influential and pivotal within the network, often serving as market leaders. The degree centrality of a vertex v_i in a graph *G=(V,E)* with $|v|$ vertices and $|E|$ edges is defined as the number of edges incident to v_i representing its level of connectivity (Uddin & Jacobsen, 2013):

$$\grave{C}_D(v_i) = \frac{d(v_i)}{|v| - 1} \tag{4}$$

D, represents the degree, and $d(v_i)$ denotes the number of vertices connected to vertex v_i.

In the framework of Minimum Spanning Trees (MST), the selection of the correlation coefficient can significantly influence the network structure (Mantegna, 1999). Additionally, data quality issues such as noise, outliers, and missing observations can negatively impact the accuracy of correlation estimates, thereby affecting the stability of the MST configuration. Nevertheless, these limitations are acknowledged as inherent challenges and have not hindered the widespread application of MST in studies and research. Through comprehensive sensitivity analyses and the use of complementary validation techniques, researchers have effectively managed these constraints, utilizing MST as a valuable tool in the analysis of financial networks.(Onnela et al., 2003).

At the same time, it is important to recognize certain assumptions and potential biases inherent to the MST methodology. For instance, one assumption often made in MST applications is that the underlying data are independent and identically distributed (i.i.d.). However, in financial networks, where temporal dependencies and autocorrelation might be present, this assumption could be relaxed (Mantegna, 1999). Additionally, the choice of the correlation coefficient, whether Pearson or Spearman, can influence the resulting network structure. Although the current approach takes this into account, variations in network construction based on different correlation methods highlight the sensitivity of the model to such decisions (Onnela et al., 2003). Furthermore, issues like missing data or outliers may affect correlation estimates, which, if not properly addressed, could introduce biases into the MST configuration. While these challenges are inherent to the methodology, the use of sensitivity analyses and robust validation techniques, as described in existing literature, helps to mitigate their impact and ensure the reliability of the results (Onnela et al., 2003). These considerations underscore the importance of careful data handling and model validation to maintain the robustness and accuracy of MST-based analyses.

5.2 Vector Autoregressive Model with Conditional Heteroskedasticity

The VAR-GARCH model combines Vector Autoregressive (VAR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to capture cross-correlation and conditional volatility in financial and economic time series. It is used for dynamic correlation analysis, risk assessment, and volatility modeling, particularly in financial markets and macroeconomics, by structuring the conditional variance-covariance of VAR equation errors. The general form of the model is as follows:

$$\mathcal{N}(0, H_t) \sim \varepsilon_t,\ y_t = A_0 + A_i \sum_{i=1}^{p} y_i + \varepsilon_t \qquad (5)$$

In this model, the conditional variance-covariance matrix H_t is modeled as follows:

$$H_t = CC' + \sum_{i=1}^{q} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{j}^{p} B_j' H_{i-j} B_j \qquad (6)$$

In this model, C is the constant term matrix, A_i are the matrices associated with the effects of past shocks, and B_j are the matrices associated with the influence of past conditional variances (Bollerslev, 1986).

While the VAR-GARCH model provides a flexible framework for capturing dynamic correlations and conditional volatility, it is important to consider the risk of overfitting, particularly when selecting lag lengths in the VAR component and the structure of the conditional variance-covariance matrix. Overfitting can occur when an excessive number of parameters are estimated relative to the available data, leading to models that fit historical noise rather than genuine patterns in the time series (Lütkepohl, 2005). To mitigate this risk, model selection criteria such as the Akaike (1974) Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are commonly used to balance model complexity and predictive performance. Furthermore, out-of-sample validation and robustness checks can help ensure that the estimated model generalizes well beyond the sample data (Engle, 2001). These considerations are particularly crucial in financial applications, where structural changes and regime shifts may affect the stability of estimated relationships.

Additionally, the VAR-GARCH framework requires weak stationarity of all variables, verified via Augmented Dickey-Fuller tests and addressed through differencing or cointegration if violated (Lütkepohl, 2005). Moreover, the model assumes normality of residuals, which can be problematic in financial data due to

heavy tails and skewness. To account for this, alternative distributions such as the Student's t-distribution are used when needed (Bollerslev, 1986). The model also assumes independence of residuals; however, if unaccounted-for structural breaks are present, regime-switching models can be used to address such issues (Hamilton, 1994).

6. Empirical Results

6.1 Iterated cumulative sum of squares

The ICSS algorithm detects structural breaks in the variance of time series volatility. However, the test by Iklan and Tiao for identifying unconditional variance changes in financial data has significant limitations, and results from the IT-based method should be interpreted with caution.and the results derived from the IT-based method should be interpreted with caution. Consequently, a new test, $\boldsymbol{\kappa_2}$, has been introduced, which accounts for variance heterogeneity within the process itself. The use of ICSS in conjunction with $\boldsymbol{\kappa_2}$ is therefore recommended (Sensoy et al., 2003).

Based on the results of the structural break test, the currency crisis in 2018 is identified as having commenced on April 4, 2018.

Table1. Results of the structural break test for exchange rates

ICSS($\boldsymbol{\kappa_1}$)		ICSS($\boldsymbol{\kappa_2}$)	
(2252)	07/04/2018	(2253)	04/04/2018
(2432)	30/12/2018		

Source: *results of paper*

6.2 Minimum Spanning Tree

After identifying the start of the currency crisis, the time period was divided into the pre-crisis period (24/03/2016 to 03/04/2018) and the crisis period (04/04/2018 to 21/07/2020). The minimum spanning tree was then constructed based on Pearson correlation for both periods.

In the pre-crisis period (Figure 1), stocks like Khepars (Pars Khodro), Foulad (Isfahan Steel), and Kegol (Gol Gohar) showed the highest correlation with others, marking them as central in the stock network. Khepars, with the most direct connections, had the greatest influence, and clusters centered around Pars Khodro and Foulad highlighted the dominance of the automotive and metal sectors before the currency crisis. Additionally, Vesanat and Veniki, investment group stocks, were closely tied to these sectors.

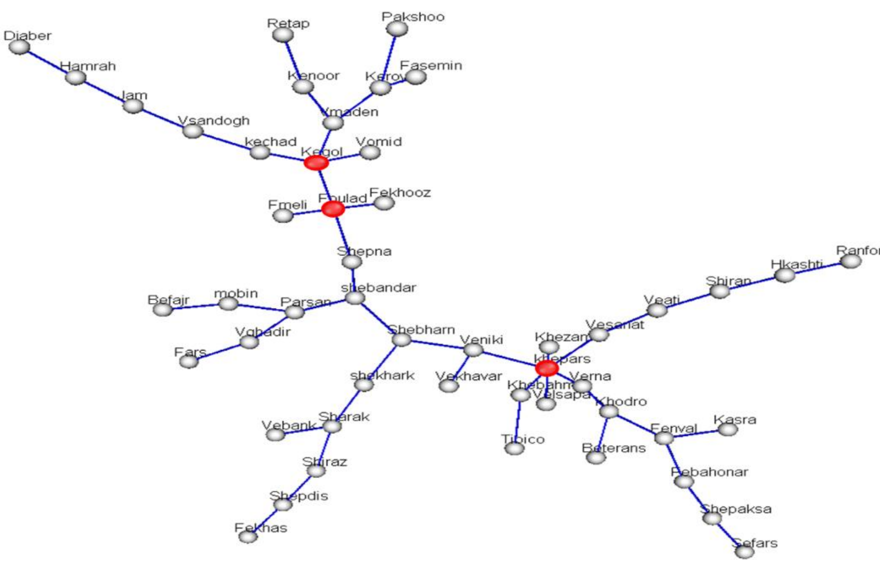


Figure 1. MST of stocks (24/03/2016 to 03/04/2018)
Source: *results of paper*

Post-currency surge (April 4, 2018–July 21, 2020), as shown in Figure (2), the network analysis revealed that Veghadir and Foulad had the highest connectivity, with Veghadir, a diversified industrial company, emerging as the primary node. It clustered with stocks from the petrochemical, refining, and basic metals sectors, underscoring the increased influence of export-oriented companies. Foulad remained central, linking to stocks in metal ore extraction and basic metals.

The findings indicate that the metal industries retained leadership post-crisis, while the automotive sector's influence waned, giving way to petrochemical and refining companies. The MST (Figure 2) revealed that Veghadir, with the highest number of connections, led the market, followed by Foulad, Sharak, and Tipico. These stocks became the primary market leaders, reflecting the shift in market dynamics toward petrochemical and export-oriented industries.

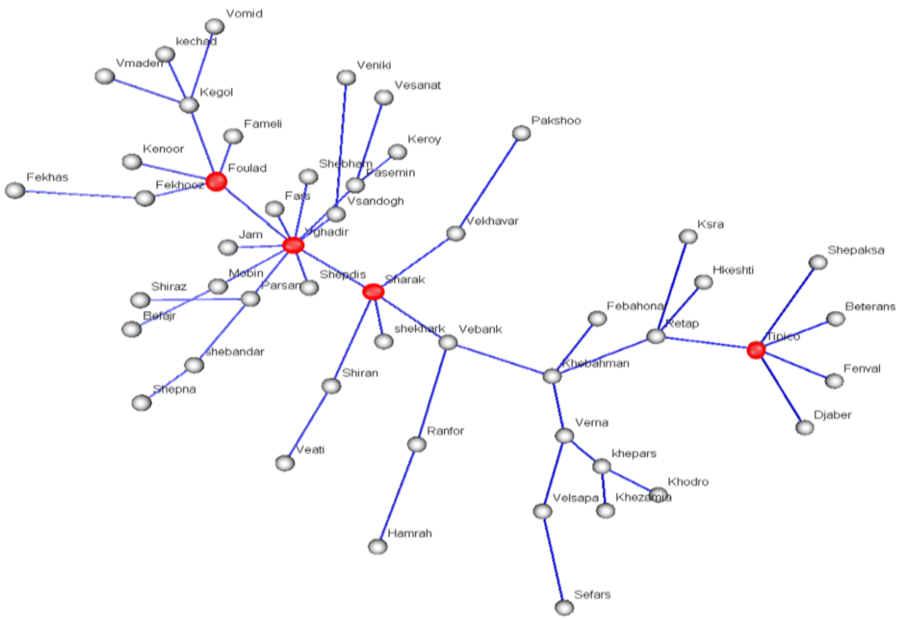


Figure 2. MST of stocks (04/04/2018 to 21/07/2020)
Source: *results of paper*

Another significant cluster revolves around Foulad, encompassing Fameli, Fakhooz, Kgl, Kenur, and Vaghdir. A third cluster, centered on Sharak (chemical products), includes Shiraz, Shkharak, Vebank, Veghadir, and Vekhavar (banks and credit institutions). A fourth cluster, led by Tipico (pharmaceutical products), comprises Retap (computer-related activities), Djaber (pharmaceuticals), Fenval (basic metals), Betrans (electrical machinery), and Shepaksa (chemical products).

An examination of the investment portfolios of Veghadir (investment company), Vesandogh (Investment Company), Vebank (National Development Group Investment Company), and Bank Khavarmiane (Vekhavar) reveals a predominant focus on metal ore extraction and chemical product industries. This portfolio composition likely explains the high correlation between these firms and the metal and chemical sectors.

6.3 Data Stationarity Test

Stationarity is a fundamental concept in time series analysis, ensuring that key statistical properties, such as mean, variance, and autocovariance, remain constant over time (Hamilton, 1994; Box et al., 2015). Many econometric models, including ARIMA and GARCH, assume stationarity for reliable forecasting. To assess stationarity, statistical tests such as the Dickey-Fuller (1979) (DF) and Phillips-Perron (PP) tests are commonly used, with the Augmented Dickey-Fuller (ADF) test offering robustness in detecting unit roots while accounting for trends (Dickey & Fuller, 1979; Phillips & Perron, 1988; Elliott et al., 1996). In this study, the ADF test was applied to key stock indices, including Foulad, Kegol, and Khepars, to examine the stationarity of stock return series before the currency crisis.

Table2. Results of the Unit Root Test for Variables First Time Period (24/03/2016 to 03/04/2018)

Probability	Generalized Dickey-Fuller Statistic	Variables
0.0000	-19.58980	Foulad
0.0000	-18.83169	Kegol
0.0000	-16.73256	Khepars

Critical Values (99%) = -3.442437
Source: *results of paper*

Table (3) reports test statistics of -10.02042 for Foulad, -15.50538 for Sharak, -16.37807 for Tipico, and -16.52270 for Veghadir, each with a p-value of 0.000. These results confirm the absence of a unit root, ensuring that these time series remain stationary even post-currency Shock.

6.4. Optimal Lag Selection

Optimal lag selection in VAR models is crucial to balance model accuracy and complexity. Statistical criteria such as AIC, SC, FPE, and HQ guide this process by penalizing excessive parameters while maintaining explanatory power.

Table 4. Results of the Optimal Lag Test for VAR (First and Second Periods)

(24/03/2016 to 03/04/2018)						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	12811.50	NA	4.81	-54.38855	-54.36209	-54.37814
1	13918.57	2195.324	4.54*	-59.05124*	-58.94539*	-59.00960*
2	13923.95	10.60263	4.61	-59.03588	-58.85063	-58.96300
(04/04/2018 to 21/07/2020)						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	17025.95	NA	7.15	-64.96926	-64.93673	-64.95653
1	19014.56	3939.274	3.84	-72.49832	-72.33567*	-72.43462*
2	19037.76	45.59659	3.74*	-72.52579*	-72.23301	-72.41114

(* indicates the optimal lag)
Source: *results of paper*

For pre-crisis data, all criteria unanimously suggested a single lag, indicating a parsimonious structure was sufficient to capture variable interactions. AIC, emphasizing predictive accuracy, tolerated complexity for better out-of-sample performance, while SC and HQ prioritized simplicity to avoid overfitting. FPE balanced forecast error variance and model complexity. Post-crisis, increased lag length (two lags) was necessary, as endorsed by AIC and FPE, to capture enhanced interdependencies and nonlinear feedback effects induced by the shock. This change highlights the adaptive nature of VAR models in response to structural breaks, ensuring that delayed spillovers are captured without introducing noise. Proper lag selection ensures robustness and reliable forecasting, crucial in volatile macroeconomic environments where structural shifts alter variable relationships (Akaike, 1974; Anderson & Burnham, 2004; Lütkepohl, 2005).

6.5. ARCH Effects Tests

An ARCH model assumes that error variance depends on past errors, which is key for analyzing volatility dynamics. The ARCH test detects hidden variance patterns, and when identified, advanced models like GARCH offer greater precision. This is particularly useful in risk management and market volatility forecasting, where variance fluctuates over time (Engle, 1982).

Table 5. ARCH Test Results for the First Period (24/03/2016 to 03/04/2018)

Variable/Statistic	Foulad	Kegol	Khepars
F-statistic	11.30343 (0.0000)	16.27238 (0.0000)	6.967425 (0.0010)
Obs*R-squared	21.71252 (0.0000)	30.64280 (0.0000)	13.62192 (0.0011)

Source: *results of paper*

Table (5) presents the results of the ARCH test for the period before the currency rate surge, analyzing price return time series for "Foulad," "Kegol," and "Khepars." The test statistics for Foulad (11.30343) and Kegol (16.27238) are significant, with probabilities near zero, while Khepars shows an F-statistic of 6.967425 and an LM statistic of 13.62192, both with probabilities below 0.01. These results reject the null hypothesis of no ARCH effect at the 99% significance level, confirming the presence of conditional heteroskedasticity and justifying the use of ARCH-family models for volatility analysis.

Table 6. ARCH Test Results for the second Period (24/03/2016 to 03/04/2018)

Variable/Statistic	Veghadir	Tipico	Sharak	Foulad
F-statistic	30.29074 (0.0000)	19.19381 (0.0000)	7.801634 (0.0000)	11.32134 (0.0000)
Obs*R-squared	54.63453 (0.0000)	35.98069 (0.0000)	15.24017 (0.0000)	21.83202 (0.0000)

Source: *results of paper*

In the post-surge period, the stocks of "Veghadir," "Foulad," "Sharak," and "Tipico" were tested for ARCH effects. Table (6) shows that Foulad’s test statistics (11.32134 and 21.83202 for F-statistic and LM statistic, respectively) both have probabilities near zero, confirming the presence of the ARCH effect.

Similarly, for Sharak, Tipico, and Veghadir, the test statistics indicate conditional heteroskedasticity, as the associated probabilities are all below 0.01. This confirms the presence of volatility clustering in these time series and necessitates the use of advanced models like GARCH for more accurate volatility modeling and forecasting.

6.6. Granger Causality Test Among Leading Stocks in the Pre-Currency Surge Period

In this study, prior to conducting the Granger causality test, the data were tested for stationarity, and the results of the unit root tests confirmed that the time series (daily stock returns) are stationary. Therefore, the issue of non-stationarity-induced errors is ruled out. Additionally, for selecting the optimal lag length in the VAR model, commonly used criteria such as AIC and BIC were employed, ensuring that the model correctly captures the causal relationships between the variables.

In the selection of the model and variables, the principle of parsimony has been adhered to. This means that efforts were made to keep the models as simple as possible while still preserving the key information and necessary causal relationships. This approach helps ensure that the selected models are both more interpretable and generalizable, while eliminating unnecessary complexity (Greene, 2018). However, it is important to acknowledge that there may be other confounding variables in the economic environment that have not been included in this model. These variables could include external economic shocks, such as financial crises, major shifts in global market conditions, or policy changes like adjustments in monetary and fiscal policies. Such factors can influence stock returns and the causal relationships between them, potentially affecting the final analysis. By openly recognizing this limitation, the study demonstrates an active acceptance of potential research constraints and maintains scientific transparency.

When interpreting the results of the Granger causality test, it is important to acknowledge that, even though the data are stationary and the optimal lag length has been chosen, the results may still be subject to spurious correlations. In other words, there may be a relationship observed between two variables (e.g., stock returns) that is driven by temporal correlation or shared external factors, rather than a true causal relationship. This is particularly relevant when stock returns are influenced by common or similar factors, such as macroeconomic trends or external shocks, which could lead to the emergence of spurious correlations.

This study investigates Granger causality among the return volatilities of three leading industrial stocks—Foulad, Kegol, and Khepars—during the pre-currency surge period, with a focus on volatility spillovers within the industrial supply chain context. The results indicate that there is no Granger causality from Foulad's volatility to Kegol ($p > 0.10$), but unidirectional causality is found from Khepars' volatility to Kegol's ($p = 0.0745$) and from a combination of Foulad and Khepars' volatilities to Kegol's ($p = 0.0257$), suggesting that fluctuations in automotive demand (Khepars) reduce the demand for raw materials (Kegol).

Additionally, significant one-way causality from Foulad's volatility to Khepars ($\chi^2 = 3.94$, $p < 0.05$) is observed, implying that rising steel prices increase automotive production costs, contributing to higher stock volatility for Khepars. However, no Granger causality is found from Kegol's volatility to Khepars ($p = 0.5610$), although joint volatility with Foulad does show predictive effects. The absence of bidirectional causality suggests a hierarchical volatility structure, where shocks propagate from upstream sectors (raw materials) to downstream sectors (end-users), highlighting the susceptibility of downstream industries to upstream cost shocks during currency-induced macroeconomic instability.

Methodologically, conditional volatilities derived from GARCH(1,1) models and a VAR framework with optimal lag 1 (Table 7) provide robust quantification of regime-specific spillovers. The findings align with Granger's (1969) predictive causality paradigm, emphasizing temporal precedence over structural causation. Practically, these results inform risk mitigation strategies for investors and policymakers, particularly in managing exposure to sectoral interdependencies during currency shocks. For example, hedging against steel price volatility may buffer downstream automotive equities, while raw material producers like Kegol must anticipate demand-side shocks from end-user industries.

Table 7. Granger Causality Test for Leading Stocks in the First Period

Dependent Variable	Excluded	χ^2	Degrees of Freedom	Probability
Foulad	Kegol	7.286732	1	0.0069
	Khepars	0.545792	1	0.4600
	All	8.612821	2	0.0135
Kegol	Foulad	2.510807	1	0.1131
	Khepars	3.182022	1	0.0745
	All	7.325021	2	0.0257
Khepars	Foulad	3.941570	1	0.0471
	Kegol	0.338055	1	0.5610
	All	4.614922	2	0.0995

Source: *results of paper*

This analysis advances understanding of volatility transmission in industrial supply chains, demonstrating how sectoral positioning and input-cost dependencies shape financial market dynamics in emerging economies. The absence of bidirectional feedback, as shown in Table 7, further validates the linearity of shock propagation in hierarchical production networks, offering a framework for anticipating spillover effects during exogenous macroeconomic disruptions.

6.7. Impulse Response Functions of Leading Stocks in the Pre-Currency Surge Period

Impulse response functions (IRFs) are a key tool in analyzing economic and financial systems through vector autoregressive (VAR) models, capturing how variables react dynamically to exogenous shocks over time. These functions reveal the propagation mechanisms and interdependencies among variables within a system, enabling the study of both short- and long-term interactions (Lütkepohl, 2005). The VAR framework, introduced by Sims (1980), provides a statistical basis for modeling temporal interdependencies among multiple variables, where each variable depends on its own lagged values and those of other system variables. When a shock is introduced to one variable, its effects ripple through the entire system, with IRFs quantifying the magnitude, direction, and duration of these spillover effects.

According to Figure (3), Kogel's return volatility responds positively and significantly to Foulad shocks in the short term, with a peak between 5 and 10 days before gradually dissipating. This rapid response reflects Kogel's position as a key raw material supplier to the steel industry, where price fluctuations quickly affect upstream suppliers. In contrast, shocks from Khepars have a negligible and transient effect on Kogel due to the lack of direct industrial linkage between the automotive and mining sectors. Over the medium term (50–150 days), the influence of Foulad shocks diminishes as new market information and fundamental analyses adjust investor expectations, while Khepars' impact completely vanishes. In the long term (beyond 150 days), the residual effects of Foulad fade to near zero, with Kogel's valuation increasingly driven by macroeconomic variables rather than short-term sectoral shocks.

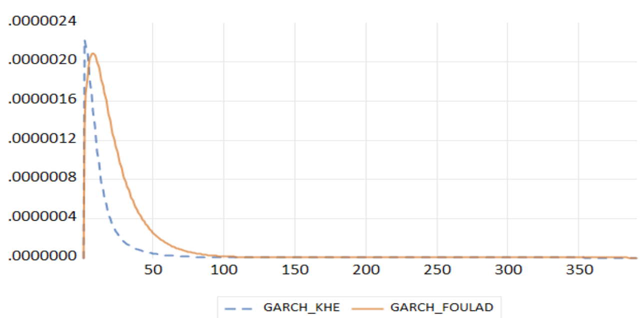


Figure 3. Impulse Response Function of Kegol's Return Volatility to Shocks in Khepars' and Foulad's Return Volatilities
Source: *results of paper*

Figure (4) depicts the impulse response of Foulad's return volatility to shocks from Khepars and Kogel. In the short term (up to 5 days), Foulad exhibits a strong positive reaction to Kogel's shocks, highlighting the mining sector's critical role as an upstream supplier, with peak effects within the first week. Conversely, Khepars' impact is minimal, as the downstream automotive sector has limited short-term influence on steel prices. Over the medium term (50–100 days), Kogel's impact gradually declines, approaching neutrality, while Khepars' effects stabilize, reflecting weakened cross-sectoral linkages. In the long run, both shocks converge to a steady state, with Foulad's volatility increasingly driven by macroeconomic fundamentals, strategic shifts, and structural supply-demand dynamics. This underscores the dominance of upstream supply chain effects in the short run and the transition towards fundamental market drivers over extended horizons.

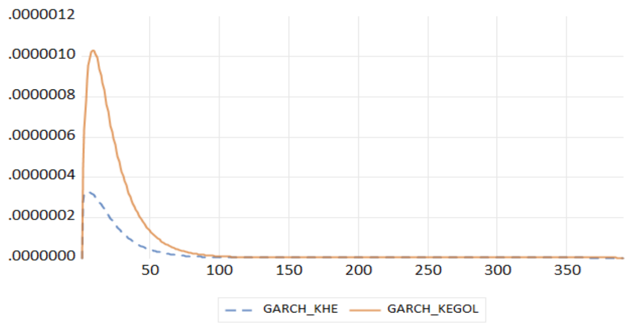


Figure 4. Impulse Response Function of Fouladl's Return Volatility to Shocks in Khepars' and Kegol's Return Volatilities
Source: *results of paper*

Figure (5) illustrates that Khepars' return volatility responds significantly and positively to Foulad's volatility shocks in the short term, reflecting the automotive sector's sensitivity to steel price fluctuations as steel is a key input.

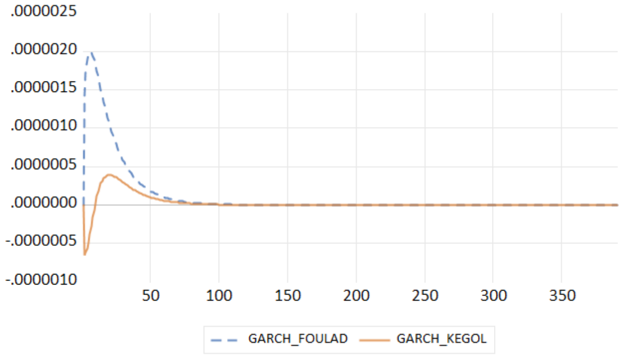


Figure 5. Impulse Response Function of Khapars' Return Volatility to Shocks in the Return Fluctuations of Kegol and Foulad
Source*: results of paper*

This immediate response, driven by abrupt commodity market shifts and demand-supply imbalances, peaks rapidly and underscores the impact of short-term economic disruptions on operational costs and pricing strategies. Over the medium term, the initial effects attenuate as markets adjust and investor focus shifts toward long-term profitability, demand trends, and macroeconomic stability, thereby reducing the direct influence of steel volatility on automotive returns. In the long term, the system converges to equilibrium with residual shocks dissipating, indicating that persistent steel price dynamics or supply chain issues no longer significantly affect automotive valuations, and that the steel-automotive linkage transitions from short-term volatility spillovers to alignment with enduring industrial fundamentals.

6.8. Granger Causality Testing Between Leading Stocks in the Post-Currency Rate Shock Period

Table (8) presents the results of Granger causality tests between leading stocks' GARCH-based return volatility series—Foulad, Sharak Tipico, and Veghadir—following a currency rate shock.

Table 8. Granger Causality Test Results Between Leading Stocks second period

Dependent Variable	Excluding	χ^2	Degrees of Freedom	Probability
Foulad	Sharak	4.259341	2	0.1189
	Tipico	1.364686	2	0.5054
	Veghadir	3.418684	2	0.1810
	All Variables	15.09764	6	0.0195
Sharak	Foulad	5.116401	2	0.0774
	Tipico	0.076496	2	0.3541
	Veghadir	8.575034	2	0.0137
	All Variables	32.19793	6	0.0000
Tipico	Foulad	3.666608	2	0.1599
	Sharak	0.017870	2	0.9911
	Veghadir	1.644383	2	0.4395
	All Variables	10.51063	6	0.1047
Veghadir	Foulad	8.320884	2	0.0156
	Sharak	12.21104	2	0.0022
	Tipico	11.01029	2	0.0041
	All Variables	32.44352	6	0.0000

Source: *results of paper*

With an optimal lag of 2 in the post-shock period, individual causality tests from Sharak, Tipico, and Veghadir to Foulad yielded insignificant results, indicating no direct causality. This suggests that sector-specific factors, such as petrochemicals' dependence on oil prices and pharmaceuticals' sensitivity to healthcare policies, decouple these industries from steel market volatility in isolation. However, the joint effect of Sharak, Tipico, and Veghadir significantly predicts Foulad's volatility (p=0.0195), revealing latent economic interdependencies intensified by macroeconomic shocks.

Bidirectional causality emerged only between Veghadir and Sharak, reflecting their shared exposure to input price volatility and operational linkages, while Tipico remained isolated due to its reliance on healthcare demand and regulatory frameworks. Moreover, Foulad, Sharak, and Veghadir showed no predictive power over Tipico's returns, reinforcing the sector's idiosyncratic drivers. However, aggregated volatility shocks from Foulad, Sharak, and Tipico had persistent causal effects on Veghadir, indicating cross-sectoral spillovers in multisectoral firms.

These findings highlight the complexity of post-shock market linkages: direct bilateral causality is limited, but systemic interactions emerge through sectoral overlaps. Petrochemicals and multisectoral industrials exhibit mutual reinforcement via input cost sensitivities, while pharmaceuticals remain structurally insulated. The results emphasize that currency shocks reshape market dynamics through networked economic exposures rather than isolated sectoral channels, underscoring the need for a systemic approach in volatility forecasting and policy design.

6.9. Impulse Response Functions of Leading Stocks in the in the Post-Currency Rate Shock Period

To utilize impulse response functions in analyzing the interdependent behavior of leader stocks and their reaction to immediate shocks in the period following an exchange rate surge, the return volatilities of Ghadir, Foulad, Sharak, and Tipico—considered as leader stocks during this period—were selected as the variables for analysis.

Figure (6) shows that volatility shocks from Sharak, Foulad, and Tipico initially exert a strong and positive impact on Veghadir's return volatility, with Sharak's shock being notably more pronounced in the very short term. Over a short-term horizon (up to 50 days), these shocks quickly influence Veghadir's conditional variance, reflecting the immediate effects of investor sentiment and macroeconomic variables such as exchange rate movements, global oil prices, and key commodity prices. In the medium term (50–150 days), the intensity of these responses diminishes, although the impact from Tipico remains the most persistent. By the long term (150–200 days), the initial shock effects fade to near zero, indicating that the market gradually absorbs these disturbances and reverts to an equilibrium where fundamental factors dominate valuation.

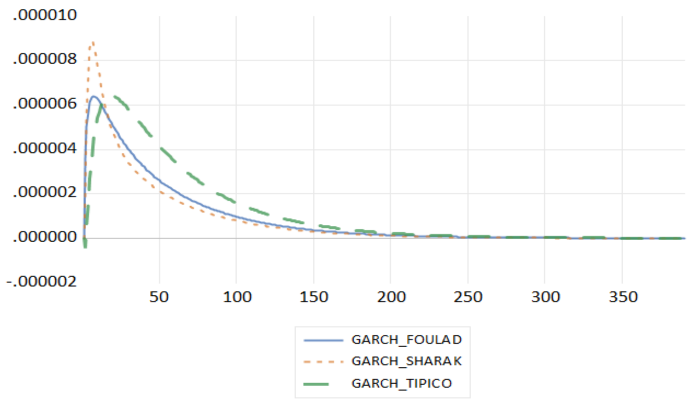


Figure 6. Impulse Response Function of Veghadir's Return Volatility to Shocks in the Return Fluctuations of Tipico, Sharak and Foulad
***Source:** results of paper*

Figure (7) illustrates Foulad's return volatility response to shocks from Veghadir, Sharak, and Tipico post-exchange rate surge. In the very short term, Foulad reacts strongly and positively to Sharak and Veghadir but initially negatively to Tipico (1–5 days), before turning positive. These reactions peak quickly in both directions. The negative response to Tipico suggests sectoral rotation, as investors shift between steel and pharmaceutical stocks. Investor behavior and market liquidity can create short-term correlations between unrelated industries, such as pharmaceuticals (Tipico) and steel (Foulad). In the short term (0-50 days), Foulad reacts negatively to Tipico's volatility but becomes positive after a few days. Sharak shows a strong response to Veghadir's volatility, while Foulad and Tipico have weaker immediate impacts. Sector rotation occurs as investors adjust to pharmaceutical fluctuations, affecting stocks like Sharak. In the medium term (50-150 days), market reactions stabilize, with Tipico's influence on Foulad and Sharak remaining stronger. Investors shift focus to fundamentals, and indirect correlations weaken due to macroeconomic factors. In the long term (150-200+ days), the shock effects dissipate, with industries regaining independent trends. The market adjusts to past fluctuations, focusing on company fundamentals and macroeconomic trends, while investor sensitivity to past shocks fades.

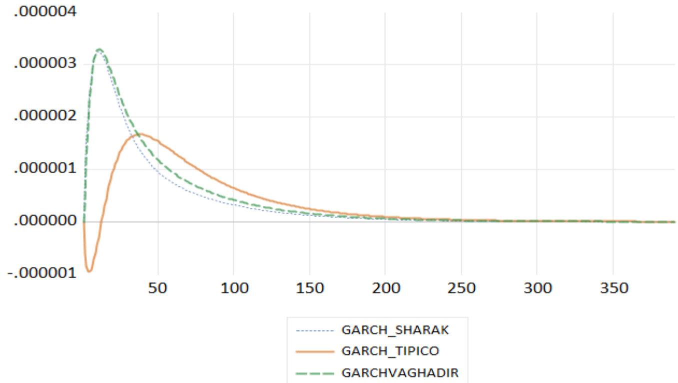
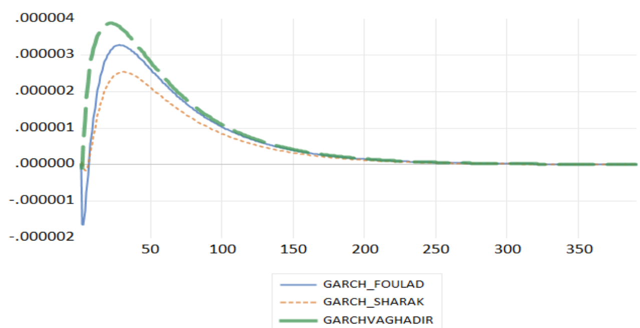


Figure 7. Impulse Response Function of Fould's Return Volatility to Shocks in the Return Fluctuations of Tipico, Sharak and Veghadir
Source: *results of paper*

figure(8) illustrates the impulse response of Tipico's return volatility to shocks from Foulad, Sharak, and Veghadir.

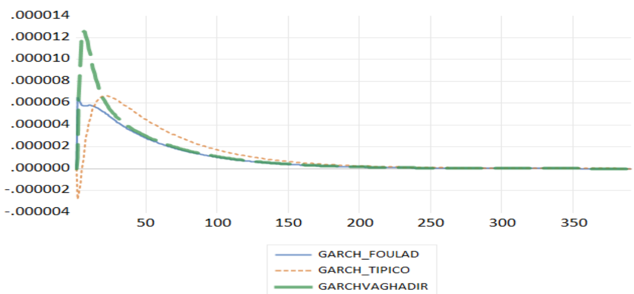


Figurre 8. illustrates the impulse response of Tipico's return volatility to shocks from Foulad, Sharak, and Ghadir.
Source: *results of paper*

In the short term, Tipico's return volatility responds positively to fluctuations in the returns of Veghadir, Foulad, and Sharak, reflecting the transmission of volatility shocks across sectors. The strongest reaction is observed with Veghadir, a multi-sector investment firm whose diversified portfolio facilitates the indirect transmission of volatility to the pharmaceutical sector, including Tipico. Tipico's moderate response to Foolad's volatility suggests that common macroeconomic

factors—such as significant exchange rate fluctuations—can simultaneously impact seemingly unrelated sectors like steel and pharmaceuticals, thereby inducing correlations between them.

In contrast, the weakest response is associated with Sharak, likely due to the minimal direct economic linkage between the petrochemical and pharmaceutical industries. These short-term inter-industry relationships persist for up to 50 days, during which Tipico remains responsive to external shocks. Over time, as market participants absorb new information and initial reactions to news and sentiment wane, the influence of these shocks diminishes. In the long term, approximately 150 days post-shock, the impact of these volatility transmissions becomes negligible, with fundamental factors such as profitability, production, and research and development assuming a more dominant role in determining Tipico's returns.



Figurre 9. illustrates the impulse response of Tipico's return volatility to shocks from Foulad, Sharak, and Ghadir.
***Source:** results of paper*

Figure (9) illustrates Sharak's return volatility response to shocks from Foulad, Tipico, and Veghadir, with Veghadir exerting the strongest short-term influence due to its diversified portfolio and industrial linkages, particularly in petrochemicals. These volatility linkages remain stable over approximately 50 days, though towards the end of this period, Tipico's impact increases, reflecting sectoral asset reallocations driven by pharmaceutical market fluctuations and macroeconomic factors such as exchange rate policies.

In the medium term (50–150 days), the influence of these shocks on Sharak's volatility gradually declines as market participants shift from sentiment-driven reactions to fundamental analysis. This transition reflects a weakening of short-term volatility interdependencies, with investors prioritizing sector-specific and macroeconomic fundamentals. Over the long term (up to 200 days), the impact of these shocks approaches neutrality as the market absorbs past volatility, and investor behavior increasingly aligns with fundamental drivers, such as corporate profitability and global oil and petrochemical price trends, reducing the relevance of historical inter-stock volatility correlations.

7. Conclusions and Suggestions

This study focuses on market-leading stocks based on their centrality in the stock correlation network, rather than on index-driving stocks. While index-driving stocks are typically large-cap firms, market leaders are identified by their systemic influence and interconnections with other stocks. The absence of certain index-driving stocks in the results is due to the network-based methodology, which highlights firms with key network positions rather than those with high market capitalization. This approach better captures leadership shifts, especially during economic shocks.

This research uses hierarchical clustering and the Minimum Spanning Tree (MST) approach to analyze stock relationships, identify market leaders, and assess the impact of exchange rate fluctuations on these leaders. Market leadership within an MST is determined by centrality, where stocks with more connections are considered more influential. Prior to the exchange rate shock (April 3, 2016 – April 3, 2018), Khepars, Foulad, and Kegol were identified as leading stocks. However, after the currency shock (April 5, 2018–July 22, 2020), Vegadir, Foulad, Sharak, and Tipico emerged as the most interconnected, indicating a shift in market leadership from automotive to petrochemical, multi-industry, and pharmaceutical sectors, while metal industries retained their dominance. This shift highlights how exchange rate shocks enhance the leadership of export-oriented firms.

The results of this study are consistent with prior research in the field. Specifically, they align with the findings of Marti et al. (2021), Francis & Ariano (2018), Onnela et al. (2003), and Montashri and Sadeghi (2020), who underscored the significance of structural relationships among shares and the application of inter-share network analysis for stock market evaluation. These results are further corroborated by Mantegna (1999) and Sadeghi and Sharifi Samani (2016), who identified cluster formation based on specific attributes and highlighted the dynamic nature of market structures over time. Additionally, they resonate with Sedaghati et al. (2022), who advocated for network-driven methodologies to pinpoint pivotal companies within market ecosystems. Collectively, these studies reinforce the critical role of structural and network-based frameworks in understanding market dynamics and organizational interdependencies.

The findings align with prior research on stock network structures and clustering evolution. Stock return volatility analysis confirmed the stationarity of leading stocks' returns in both periods, with ARCH tests revealing conditional heteroscedasticity. Granger causality tests before the exchange rate shock showed a cyclic dependency between Kegol, Foulad, and Khepars, with short-term volatility reactions sharp but diminishing over time, while long-term fluctuations were driven by fundamental changes.

Post-currency shock analysis of stock relationships indicated no significant impact of Sharak on Foulad or Tipico, but a bidirectional causality between Sharak and Veghadir. Sharak's short-term influence on Tipico was negative, with its impact on Foulad diminishing over time. These results underscore the complexity of economic interdependencies, with different industries reacting differently to macroeconomic shifts, such as exchange rate fluctuations, and highlight the prominence of export-driven firms during such periods. This study offers valuable insights for investors and policymakers in understanding how external shocks affect financial markets.

While the findings are empirically robust, several confounding factors may influence the results. For instance, during the study period, structural shifts in the equity network could have been driven not only by exchange rate fluctuations but also by concurrent macroeconomic policies and exogenous economic shocks. The absence of direct controls for these variables may introduce bias in interpreting causal relationships. Additionally, while Granger causality tests identified directional linkages between specific stocks, as with any econometric analysis, the risk of **omitted variable bias** remains a concern. Nevertheless, the integration of network-based methods with high-frequency, granular data enabled a more comprehensive examination of market structural relationships, aligning the findings with prior research on financial contagion and systemic risk transmission.

Furthermore, the study's exclusive focus on a domestic market constrains its **external validity**. Generalizing these insights to other emerging markets necessitates further empirical validation, as divergent economic structures, exchange rate regimes, and policy frameworks may yield heterogeneous outcomes. A key limitation is the exclusion of broader macroeconomic factors—such as monetary and fiscal policies—that could modulate network dynamics. Despite these constraints, the proposed methodology provides a scalable **analytical framework** for emerging markets, particularly those characterized by high exchange rate sensitivity and export dependency (e.g., commodity-driven economies). Comparative studies across diverse emerging markets could disentangle universal network dynamics (e.g., shock propagation pathways) from context-specific structural dependencies (e.g., regulatory environments), offering nuanced insights into both shared and idiosyncratic market behaviors.

Recommendations

Managing Exchange Rate Shocks Through Targeted Policy Interventions: Policymakers should leverage the role of leading industries—such as metals, petrochemicals, and investment sectors—in transmitting exchange rate shocks. To mitigate volatility, tools such as futures contracts, derivative markets, and trade policy adjustments can be deployed to buffer systemic risks.

Enhancing Transparency and Supply Chain Resilience: The strong interdependencies observed between firms like *KGL*, *Foulad*, and *Kahaz* underscore the vulnerability of raw material supply chains. Policymakers should prioritize building transparent infrastructure for sustainable resource procurement. Long-term supplier contracts and financial support mechanisms for raw material providers should be strengthened to insulate supply chains from exchange rate-driven disruptions.

Designing Risk Hedging Strategies for Investors: Investors and mutual funds can reduce exposure to volatility in leading firms by diversifying portfolios. A balanced allocation of shares in exchange rate-sensitive industries (e.g., metals) and sectors with lower currency dependency (e.g., technology or consumer goods) may optimize risk-adjusted returns.

Curbing Extreme Price Volatility in Mining and Steel Industries: Sharp fluctuations in mineral and steel prices risk amplifying causal feedback loops, destabilizing production chains. Governments can deploy measures such as calibrated export-import tariffs, producer subsidies, and targeted support for downstream industries (e.g., manufacturing) to dampen excessive price swings. These interventions would reduce the cascading effects of exchange rate shocks while enhancing economic stability.

This study advances a novel framework for market structure analysis by emphasizing equity correlation networks as a tool to identify systemic market leaders. Findings demonstrate that mapping network dynamics enables investors and policymakers to craft adaptive strategies for economic shock absorption. Further comparative research across emerging markets could disentangle universal trends (e.g., resource dependency) from context-specific factors (e.g., regulatory regimes), offering actionable insights for context-specific policy design. Such cross-market benchmarking would strengthen the generalizability of network-based approaches to financial stability and risk governance.

Author Contributions

Conceptualization, all authors; methodology all authors; formal analysis, all authors; resources, all authors; writing—original draft preparation, all authors; writing—review and editing, all authors; supervision, Emamverdi, Gh. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data used in the study were taken from https:// tsetmc.ir

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