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Investigating Multidimensional Spatial Patterns of the Relationship between Financial Stress and Financial Market Growth: A Hybrid MSPAHM Model Approach[1]

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Highlights

- **Development of MSPAHM model analyzing financial stress-firm growth across spatial, network, and sectoral dimensions.**
- **Identification of spatial spillover effects with significant cross-industry vulnerability variation to financial shocks.**
- **Comparative analysis across policy periods revealing intensified impacts during crisis periods.**

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Abstract

This study investigates the multidimensional spatial patterns characterizing the relationship between financial stress and financial market growth among companies listed on the Tehran Stock Exchange. The research incorporates three critical dimensions: spatial interdependencies, network structures, and inter-sectoral interactions. The analytical framework employs the innovative Multidimensional Spatial Panel Autoregressive Hybrid Model (MSPAHM), which facilitates simultaneous examination of temporal dynamics, spatial dependencies, and sectoral heterogeneity across the economic landscape. The empirical analysis encompasses a comprehensive dataset of Tehran Stock Exchange-listed companies spanning 2010 to 2024, capturing multiple economic cycles and policy regimes. The findings reveal that financial stress exerts a significant negative impact on firms' financial growth, with effects propagating through spatial spillover mechanisms to interconnected companies within the broader economic network. This transmission occurs across both direct and indirect channels, creating cascading effects throughout the market structure. Notably, the analysis identifies substantial sectoral variation in vulnerability patterns. Capital-intensive and import-dependent industries demonstrate heightened susceptibility to financial stress shocks, with effect magnitudes intensifying markedly during periods of economic sanctions and maximum pressure policies. These results underscore the dynamic and networked nature of financial stress, emphasizing its dependence on sectoral characteristics and temporal contexts. The study concludes that effective policy intervention requires adopting a systemic approach grounded in comprehensive network analysis, enabling policymakers to anticipate spillover effects and design targeted interventions that account for the interconnected nature of firm-level financial distress within the broader economic ecosystem.

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1. Introduction

The financial market plays a key role in mobilizing and efficiently allocating financial resources, serving as the driving engine of economic growth and development (Fengju & Wubishet, 2024; Shirzadi et al., 2022). The performance of stock markets is widely regarded as a barometer of overall economic health (Li et al., 2024), yet financial stress can severely disrupt this function, triggering recession and unemployment (Heydarian et al., 2019). The global financial crises of 2007–2009 illustrated how stress in financial markets can destabilize production, employment, and welfare across entire economies (van Roye, 2014).

macroeconomic level, Cardarelli et al. (2009) showed that banking-sector stress produces deeper and longer recessions, while Cevik et al. (2016) and Ferrer et al. (2018) confirmed significant negative effects of financial stress on economic activity in emerging Asian economies and the United States, respectively. At the market level, Xu et al. (2023) demonstrated the superior predictive power of financial stress indices for Chinese stock returns, and Mezghani and Boujelbène-Abbes (2023) and Mezghani et al. (2024) documented stress-driven risk transmission across Gulf Cooperation Council markets. In the Iranian context, studies have identified financial stress as a significant driver of business cycle fluctuations (Ebrahimi Shaghaghi et al., 2022), mutual fund return asymmetries (Bakhshor et al., 2024), monetary instability (Abdollahzade & Zare, 2022), speculative price bubbles (Asadi et al., 2019), and heightened systemic risk under macroeconomic uncertainty (Zare & Zare, 2019; Zare et al., 2020; Zare, 2021). Yet these studies share a common limitation: they focus on aggregate macroeconomic or fund-level outcomes, leaving the firm-level spatial transmission of financial stress within Iran's stock exchange largely unexamined.

This study addresses that gap by modeling the multidimensional spatial relationship between financial stress and financial market growth at the firm level for companies listed on the Tehran Stock Exchange. The main innovation lies in applying a hybrid Multidimensional Spatial Panel Autoregressive Hybrid Model (MSPAHM) that simultaneously captures direct effects, spatial spillovers, and cross-sectoral interactions — dimensions that prior research has not jointly addressed in the Iranian context. The findings can inform macroprudential policy, early warning systems, and capital market regulation aimed at strengthening the stability of Iran's financial system.

The remainder of this article is organized as follows: Section 2 presents the theoretical foundations and empirical literature. Section 3 describes the model and methodological framework. Section 4 reports the empirical analyses, and Section 5 concludes.

2. Literature Review

2.1 Theoretical Foundations

Financial stress refers to conditions in which instability and inability to meet debt obligations — or investors' distorted expectations — create serious disruptions at the level of firms, households, and the broader financial system (Oet et al., 2011;

Monin, 2017). It is conceptually distinct from macroeconomic instability, which originates in supply and demand shocks at the national level; financial stress is rooted in financial intermediary markets and is characterized by high frequency, persistence, and broad coverage spanning stock, bond, foreign exchange, banking, and housing markets (Semmler & Chen, 2014; Vdovychenko & Oros, 2014).

Traditional Measurement Models. Hakkio and Keeton (2009) constructed the Kansas City Financial Stress Index as a linear combination of eleven financial variables — including stock market volatility, interest rate spreads, and asset return correlations — grounded in the premise that stress rises when uncertainty about fundamental asset values increases (Caporin et al., 2024). Cardarelli et al. (2011) extended this by conceptualizing financial stress as a function of four core components — banking, bond, stock, and currency market stress — and explaining its negative effects on market growth through credit risk, reduced liquidity, risk aversion, and information asymmetry (Elsayed et al., 2023). Aboura and van Roye (2017) further introduced a latent-variable framework using factor analysis to capture nonlinear and threshold effects of stress on market growth dynamics.

Contagion and Network Models. Allen and Gale (2000) demonstrated that interbank network structures critically shape financial shock propagation: highly connected networks may be resilient to localized shocks yet amplify systemic vulnerability. Acharya and Yorulmazer (2008) introduced the concept of endogenous systemic risk, showing that correlated investment strategies during tranquil periods intensify collective fragility during downturns (de Bandt & Hartmann, 2002). Diebold and Yilmaz (2014) operationalized these insights through forecast-error variance decompositions, highlighting the directional and spatial nature of stress spillovers across markets (Glasserman & Young, 2016).

Behavioral Models. Baker and Wurgler (2006) showed that financial stress drives pessimistic investor sentiment, shifting portfolios toward safer assets and reducing market liquidity and growth. Shiller (2015) emphasized that stress is shaped not only by economic fundamentals but also by widely shared economic narratives. Bollerslev et al. (2008) demonstrated that stress affects market growth through time-varying variance risk premia, serving as a nonlinear predictor of stock returns.

Spatial and Multidimensional Models. Anselin (2010) established the theoretical foundation for spatial dependence modeling through spatial lag, spatial error, and spatial Durbin specifications (Anselin & Florax, 2004). Baltagi et al. (2013) extended this to dynamic spatial panel models that simultaneously account for temporal persistence and spatial interdependence. Billio et al. (2012) introduced dynamic financial network frameworks showing that network topology generates complex, heterogeneous stress propagation patterns (Chen et al., 2022).

Taken together, these theoretical streams converge on a key insight: analyzing financial stress and market growth requires an integrated framework that simultaneously captures measurement, behavioral, network, and spatial dimensions. A substantial gap remains in developing such a unified framework for emerging markets, where institutional characteristics and shock transmission mechanisms differ significantly from developed economies.

2.2 Empirical Evidence

International studies consistently document the negative macroeconomic effects of financial stress. Cardarelli et al. (2009) showed that banking-sector stress produces deeper and longer recessions; Hubrich and Tetlow (2014) confirmed regime-dependent stress transmission in the United States; Cevik et al. (2016) and Ferrer et al. (2018) documented significant stress-driven contractions in emerging Asian economies and the United States, respectively; and Polat and Ozkan (2019) confirmed similar dynamics in Turkey. At the market level, Zhou et al. (2021) linked financial stress to mutual fund returns in China, Xu et al. (2023) demonstrated its superior return predictability, and Mezghani and Boujelbène-Abbes (2023) and Mezghani et al. (2024) documented stress-driven risk transmission in Gulf Cooperation Council markets. Soltani and Abbes (2025) further confirmed bidirectional relationships between financial stress, oil, and GCC stock markets. Alavitabar et al. (2023) showed that financial stress indices in Iran, Kuwait, Qatar, and Saudi Arabia positively affect crude oil prices, with causal linkages existing specifically between Iran and Saudi Arabia. Kasal (2023) further confirmed that financial stress negatively affects economic activity and increases government debt in emerging economies.

In Iran, Touhidi et al. (2021) found that despite severe stress episodes, the impact on sectoral growth was largely negligible, while Ebrahimi Shaghaghi et al. (2022) demonstrated significant negative effects on economic growth using Markov-switching models. Bakhshor et al. (2024) confirmed regime-dependent effects on mutual fund returns. These domestic studies, while valuable, share a common limitation: they operate at the macroeconomic or fund level and do not examine firm-level spatial transmission patterns within the stock exchange.

2.3 Research Gap and Innovation

The empirical literature reveals three interconnected gaps. First, existing studies both international (Cardarelli et al., 2009; Cevik et al., 2016; Ferrer et al., 2018) and domestic (Touhidi et al., 2021; Ebrahimi Shaghaghi et al., 2022; Bakhshor et al., 2024) focus on country-level or fund-level outcomes, leaving firm-level spatial transmission of financial stress within stock exchanges largely unexplored. Second, although spatial econometric frameworks (Anselin, 2010; Baltagi et al., 2013; Billio et al., 2012) have established the theoretical importance of spillover effects, their empirical application to financial stress transmission in developing economies remains limited. Third, Iran’s specific institutional context — prolonged sanctions, oil revenue dependence, and a distinct capital market structure — creates transmission mechanisms that differ fundamentally from those studied in mainstream literature, yet no study has comprehensively modeled these dynamics at the firm level. This study addresses these gaps through a hybrid Multidimensional Spatial Panel Autoregressive Hybrid Model (MSPAHM) that simultaneously integrates: (i) spatial dependence modeling to capture geographic and network-based spillovers among listed firms; (ii) temporal dynamics to account for persistence in financial stress and market growth; and (iii) cross-sectoral heterogeneity to identify differential transmission mechanisms across industries. Unlike conventional approaches that treat financial stress as a uniform macroeconomic shock, the MSPAHM framework decomposes effects into direct impacts on individual firms, indirect spillovers through spatial linkages, and total cumulative effects across the financial system providing a more precise and policy-relevant picture of stress transmission in Iran's capital market.

3. Methods

In the present study, to derive empirical results and analyze the effects of financial stress on the growth of Iran's capital market, we employ a Hybrid Multidimensional Spatial Panel Autoregressive Hybrid Model (MSPAHM). This methodological choice is motivated by the need to overcome fundamental limitations of conventional spatial econometric models when applied to complex, highly volatile emerging markets operating under severe institutional and macroeconomic constraints.

3.1 Theoretical and Methodological Justification of the MSPAHM Framework

Traditional spatial econometric models—such as the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Spatial Autoregressive Combined Model (SAC)—have been widely used to capture spatial dependencies in cross-sectional and panel data (Anselin, 2004). However, these models typically impose restrictive assumptions that limit their applicability in contexts characterized by multidimensional interdependencies, regime-switching dynamics, and heterogeneous transmission channels.

The MSPAHM framework addresses these limitations through four key innovations:

First, while standard spatial models rely on a single, pre-specified weight matrix (typically based on geographic proximity or sectoral classification), MSPAHM incorporates multiple, theoretically motivated weight matrices simultaneously. This allows the model to disentangle distinct channels of financial stress transmission—namely, sectoral linkages (supply chain and industry-specific shocks), financial similarity networks (balance sheet contagion), and information networks (behavioral and sentiment-driven spillovers). The use of multiple matrices is not merely an ad hoc extension but is grounded in the financial contagion literature, which emphasizes that shocks propagate through heterogeneous channels (Allen & Gale, 2000; Billio et al., 2012).

Second, MSPAHM integrates both spatial lag dependence (in the dependent variable) and spatial error dependence in a unified framework, while also allowing for spatially lagged independent variables (as in the SDM specification). This nested structure enables rigorous testing of whether spillovers operate through direct market linkages, common unobserved shocks, or both. Formally, the model can be expressed as:

$$G_{i,t} = \alpha + \rho \sum_{j=1}^{N} w_{ij} G_{j,t} + \beta_1 FSI_{i,t} + \beta_2 X_{i,t} + \theta_1 \sum\nolimits_{j=1}^{N} w_{ij} FSI_{j,t} + \theta_2 \sum\nolimits_{j=1}^{N} w_{ij} X_{j,t} + \phi Z_t + \mu_i + \lambda_t + u_{i,t} \quad (1)$$

$$u_{i,t} = \delta_j \sum\nolimits_{j=1}^{N} m_{ij} u_{j,t} + \epsilon_{i,t} \quad (2)$$

where $G_{i,t}$ is the financial growth of firm i at time t, $FSI_{i,t}$ is the firm-level financial stress index, $X_{i,t}$ represents firm-level controls, Z_t denotes macroeconomic variables, w_{ij} and m_{ij} are elements of spatial weight matrices, ρ and δ capture spatial autocorrelation in the dependent variable and error term respectively, μ_i and λ_t are firm and time fixed effects, and $\epsilon_{i,t}$ is the idiosyncratic error term.

Third, the hybrid approach systematically tests for and models nonlinear and threshold effects using Spatial Smooth Transition Regression (STR) and spatial threshold panel techniques. This is critical for capturing regime-dependent dynamics—for instance, the impact of financial stress on firm growth may differ fundamentally during periods of severe sanctions versus relative stability, or when stress exceeds critical thresholds that trigger liquidity crises or credit crunches.

Fourth, MSPAHM addresses endogeneity concerns through a combination of spatial instrumental variables (using spatially lagged exogenous variables as instruments) and spatial system GMM estimation. This is essential because financial stress and firm growth are likely jointly determined, and the inclusion of a lagged dependent variable with firm fixed effects induces Nickell bias in short panels (Nickell, 1981).

Table 1 below provides a systematic comparison of MSPAHM with standard spatial econometric models:

Table 1. Comparison of MSPAHM with Standard Spatial Econometric Models

Feature	SAR	SEM	SDM	SAC	MSPAHM
Spatial lag of dependent variable	✓	✗	✓	✓	✓
Spatial error autocorrelation	✗	✓	✗	✓	✓
Spatial lags of independent variables	✗	✗	✓	✗	✓
Multiple weight matrices	✗	✗	✗	✗	✓
Threshold/regime-switching	✗	✗	✗	✗	✓
Endogeneity correction (GMM)	Limited	Limited	Limited	Limited	✓
Direct/indirect effects decomposition	✓	✗	✓	✓	✓

This nested structure allows MSPAHM to encompass standard models as special cases while providing a more flexible and comprehensive framework for analyzing financial stress transmission in complex market environments.

3.2 Data and Sample

The dataset consists of financial market and economic information for all listed manufacturing firms in Iran's capital market over the period 2010–2024, collected from official sources including the Comprehensive Database of All Listed Firms (CODAL), the Tadbir Pardaz Capital Market Database, the Tehran Stock Exchange (TSE), Iran Fara Bourse (IFB), the Securities and Exchange Organization of Iran (SEO), and the Central Securities Depository of Iran (CSDI).

Sample selection and potential biases: Following standard practice in financial stress research (Cardarelli et al., 2011), we exclude financial firms (banks, insurance companies, investment firms) because their balance sheet structures and regulatory environments differ fundamentally from non-financial corporations. While this exclusion enhances sample homogeneity, it may introduce sample selection bias if financial firms play a disproportionate role in stress transmission. However, given that Iran's banking sector operates under distinct regulatory constraints and state ownership structures, we believe this exclusion improves the internal validity of our estimates for the manufacturing sector, which constitutes the core of the real economy. The final sample comprises [X] firm-year observations across [Y] firms and [Z] two-digit ISIC industry groups.

3.3 Research Model and Variable Definitions

Dependent Variable: Firm Financial Growth

The dependent variable, firm financial growth ($G_{i,t}$), is measured as the total stock return, calculated as:

$$G_{i,t} = \frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} - 1 \tag{3}$$

where $P_{i,t}$ is the closing stock price of firm i at the end of period t, $D_{i,t}$ is the cash dividend paid per share, and $P_{i,t-1}$ is the closing price at the end of the previous period (Francis et al., 2016; Sharpe et al., 1999; Easterbrook, 1984; Fama & French, 1992).

3.3.1 Main Independent Variable: Firm-Level Financial Stress Index

The construction of a firm-level financial stress index is a cornerstone of our analysis. We follow the composite index approach used in the literature (Bollerslev, 1986; Altman, 1968; Opler et al., 1999; Banz, 1981; Cardarelli et al., 2011; Chao et al., 2022) but adapt it to the firm level. The FSI aggregates six sub-indices capturing distinct dimensions of financial vulnerability:

1. Systematic Risk (β_i): Estimated using a rolling 24-month window (not 36 months, to avoid excessive look-ahead bias) via the market model: $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ is the firm's monthly return and $R_{m,t}$ is the market return. To further mitigate look-ahead bias, we use only backward-looking data up to period $t-1$ when constructing $\beta_{i,t}$.

$$r_{i,\tau} = \alpha_i + \beta_i r_{m,\tau} + \epsilon_{i,\tau} \ , \qquad \tau = t-35, \dots, t \tag{4}$$

2. Stock Return Volatility: Measured as the monthly standard deviation of daily returns (rather than annual volatility) to capture intra-year stress events. For robustness, we also estimate conditional volatility using a GARCH (1,1) model.

$$\sigma_{i,t}^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

3. Financial Leverage: Calculated as the ratio of total debt to total assets at the end of period $t - 1$.

$$Lev_{i,t} = \frac{Total\ Debt_{i,t}}{Total\ Assets_{i,t}} \tag{6}$$

4. Interest Coverage Ratio: Earnings before interest and taxes (EBIT) divided by interest expense.

$$ICR_{i,t} = \frac{EBIT_{i,t}}{Interest\ Expense_{i,t}} \tag{7}$$

5. Current Ratio: Current assets divided by current liabilities.

$$CR_{i,t} = \frac{Current\ Assets_{i,t}}{Current\ Liabilities_{i,t}} \tag{8}$$

6. Liquidity Pressure: Operating cash flow divided by total assets.

$$LIQ_{i,t} = \frac{Operating\ Cash\ Flow_{i,t}}{Total\ Assets_{i,t}} \tag{9}$$

Aggregation via Principal Component Analysis (PCA): Following Illing and Liu (2006) and Park and Mercado (2014) , we use PCA to aggregate these six sub-indices into a single composite FSI. Before applying PCA, all sub-indices are standardized to have zero mean and unit variance. The first principal component is extracted and used as the FSI.

Justification and variance explained: Justification, variance explained, and PCA loadings: The first principal component explains [X]% of the total variance in the six sub-indices (to be reported in the results section), consistent with the financial stress literature where the first PC typically captures 40–60% of variance Cardarelli et al., 2011; Valizadeh and Hayati, 2025). To enhance transparency and interpretability, Table A1 in the Appendix reports the full PCA loading matrix, eigenvalues, and the proportion of variance explained by each component. The loadings on the first PC confirm that all six sub-indices contribute meaningfully and with theoretically consistent signs: systematic risk (β_i), return volatility ($\sigma_{i,t}$), and financial leverage ($Lev_{i,t}$) load positively (higher values indicate greater stress), while the interest coverage ratio ($ICR_{i,t}$), current ratio ($CR_{i,t}$), and liquidity pressure ($LIQ_{i,t}$) load negatively (higher values indicate lower stress). The relative magnitude of the loadings identifies which dimension contributes most to financial stress in Iran's capital market a finding with direct policy implications discussed in Section 4. Nevertheless, we acknowledge that a single dimension cannot fully capture the multifaceted nature of financial stress. As a robustness check, we also estimate models using individual sub-indices separately and a two-component FSI (reported in the robustness section).

Addressing measurement error: The use of a 24-month rolling window for beta and monthly volatility (rather than annual) significantly reduces, though does not entirely eliminate, look-ahead bias and temporal aggregation issues. In sensitivity analyses, we also construct an alternative FSI using only lagged values ($FSI_{i,t-1}$) as the main regressor to ensure that all information used to construct the stress measure predates the growth outcome.

3.3.2 Firm-Level Control Variables

Followin Chen et al., 2012; Frank & Goyal, 2009; Jolliffe, 2005; Titman et al., 2004; Deaton et al., 2002; Chao et al. (2022) and Bakhshor et al. (2024), we include the following firm-level controls (all measured at $t-1$to mitigate reverse causality):

- Firm Size: Natural logarithm of total assets.
- Profitability (ROA): Return on assets, calculated as net income divided by total assets.

$$\text{ROA} = \frac{\text{Net Income}}{\text{Total Assets}} \tag{10}$$

- Asset Growth: Year-on-year percentage change in total assets.

$$\text{Growth} = \frac{\text{Asset}_t - \text{Assets}_{t-1}}{\text{Assets}_{t-1}} \tag{11}$$

- Market-to-Book Ratio (MB): Market value of equity divided by book value of equity.

$$\text{MB} = \frac{\text{Market Equity}}{\text{Book Equity}} \tag{12}$$

- Capital Expenditure Intensity (CapEx): Capital expenditures divided by total assets.

$$\text{CapEx} = \frac{\text{Capital Expenditures}}{\text{Total Assets}} \tag{13}$$

3.3.3 Macroeconomic and Market Variables

Exchange Rate Shock ($\Delta\ln EX_t$): First difference of the natural logarithm of the official Rial/Dollar exchange rate (Eichengreen et al., 1996).

$$\Delta EX = Ln(EX_t) - Ln(EX_{t-1}).$$

Inflation Rate (INF_t): Year-on-year percentage change in the Consumer Price Index (CPI).

$$\text{INF} = \frac{(\text{CPI}_t - \text{CPI}_{t-1})}{\text{CPI}_{t-1}} \tag{14}$$

Bank Interest Rate (IR_t): Interest rate on one-year deposits announced by the Central Bank of Iran.

Gold Price ($\ln Gold_t$): Natural logarithm of the global gold price per ounce (in dollars), converted to Rials.

Sanction Intensity Index ($Sanction_t$): A weighted event-based index assigning scores (0 = no serious sanctions, 1 = moderate, 2 = severe) to major international sanctions episodes (Peksen, 2019).
Market Return ($MktRet_t$): Monthly return of the Tehran Stock Exchange total price index (TEDPIX).
Oil Price (ln Oil_t): Natural logarithm of Brent crude oil price (in dollars), converted to Rials (Hamilton, 1983).

3.4 Spatial Weight Matrix (W)

A key innovation of the MSPAHM framework is the use of multiple, theoretically motivated spatial weight matrices to capture distinct channels of financial stress transmission. We construct three matrices:

- **Sector Weight Matrix (W_{Sector})**

This binary adjacency matrix captures intra-industry linkages. If firms iand jbelong to the same two-digit ISIC industry group, $\mathrm{w}_{\mathrm{ij}}^{\mathrm{Sector}} = 1$; otherwise, $\mathrm{w}_{\mathrm{ij}}^{\mathrm{Sector}} = 0$. The matrix is then row-normalized so that $\sum_{\mathrm{j}} \mathrm{w}_{\mathrm{ij}}^{\mathrm{Sector}} = 1$((Ellerton et al., 2015).
This specification assumes that firms within the same industry are more likely to experience correlated shocks due to common supply chains, regulatory environments, and demand conditions.

- **Financial Similarity Weight Matrix ($W_{Financial}$)**

This matrix captures balance sheet contagion by defining weights as the inverse of the standardized Euclidean distance between firms' financial characteristics. Specifically:

$$w_{ij}^{Financial} = \frac{1}{1 + d_{ij,t-1}} \tag{15}$$

were

$$d_{ij,t-1} = \sqrt{\sum_{k=1}^{K} (z_{ik,t-1} - z_{jk,t-1})^2} \tag{16}$$

and $z_{ik,t-1}$represents the standardized value of financial characteristic k(firm size, leverage, profitability) for firm $i$at time $t-1$. The use of lagged values $(t-1)$ mitigates endogeneity concerns (Billio et al., 2012). The matrix is then row-normalized.
Justification and robustness: The choice of Euclidean distance and the specific set of financial characteristics (size, leverage, profitability) follows Billio et al. (2012) and reflects the hypothesis that firms with similar balance sheet structures are more vulnerable to common shocks and contagion. However, we acknowledge that this specification is not unique. In robustness checks (Section 4.5), we test alternative definitions:

Correlation-based similarity: $w_{ij}^{Financial} = |\operatorname{corr}(X_i, X_j)|$, where $X$is the vector of financial characteristics.
Mahala Nobis distance: To account for correlations among financial variables.
Different lag structures: Using $t-2$or a three-year average to reduce sensitivity to transitory shocks.

- **Information Network Weight Matrix (W_{Info})**

This matrix captures behavioral and sentiment-driven spillovers by defining weights as the absolute value of the correlation of daily stock returns over a rolling window:

$$w_{ij}^{Info} = |\operatorname{corr}(R_{i,daily}, R_{j,daily})|_{t-12:t} \tag{17}$$

where the correlation is calculated using daily returns over the preceding 12 months. The matrix is then row-normalized (Diebold & Yılmaz, 2014).
Justification and robustness: High return correlation suggests that investors treat firms as informationally linked, either because they respond to common news or because trading in one firm's stock triggers trading in another's (behavioral herding). The 12-month window balances the need for sufficient observations (approximately 250 trading days) with the desire to capture time-varying network structures. In robustness checks, we vary the window length (6, 18, and 24 months) and also construct an alternative matrix based on news co-mentions (the frequency with which two firms are mentioned together in financial news), though data availability limits this analysis to recent years.

- **Combined Weight Matrix**

In the baseline MSPAHM estimation, we combine the three matrices using a linear weighting scheme:

$$W_{Combined} = \omega_1 W_{Sector} + \omega_2 W_{Financial} + \omega_3 W_{Info} \tag{18}$$

where $\omega_1 + \omega_2 + \omega_3 = 1$. The optimal weights are determined via a grid search that maximizes the log-likelihood of the spatial panel model, subject to the constraint that all weights are non-negative. This data-driven approach allows the relative importance of each transmission channel to be determined empirically. As a robustness check, we also estimate models using each matrix separately and report the results in Section 4.5.

3.5 Estimation Strategy and Addressing Endogeneity

3.5.1 Endogeneity Concerns

A critical challenge in estimating the relationship between financial stress and firm growth is the potential for simultaneous causality: financial stress may reduce growth, but poor growth performance may also increase financial stress (e.g., by reducing cash flows and increasing leverage). Moreover, the inclusion of a lagged dependent variable ($G_{i,t-1}$) in a fixed-effects panel model with a relatively short time dimension ($T \approx 15$ years) induces Nickell bias (Nickell, 1981), whereby the within-group transformation causes the lagged dependent variable to be correlated with the transformed error term.

Furthermore, in spatial models, endogeneity can arise from three sources (Anselin, 2010):

1. Simultaneity: The spatial lag of the dependent variable ($\sum_j w_{ij} G_{j,t}$) is endogenous by construction.
2. Omitted variables: Unobserved spatial shocks may be correlated with both the dependent variable and the regressors.
3. Measurement error: Errors in constructing the FSI or weight matrices can bias estimates.

3.5.2 Estimation Methods

To address these concerns, we employ a two-pronged estimation strategy:

Maximum Likelihood Estimation (MLE): We first estimate the MSPAHM model using MLE with firm and time fixed effects. Under the assumption that the error term is normally distributed and that the weight matrices are exogenous (conditional on fixed effects), MLE provides consistent and efficient estimates.

However, MLE does not fully address endogeneity arising from simultaneity or measurement error.

Spatial System GMM: To address endogeneity more rigorously, we employ a spatial system GMM estimator. This approach combines the difference GMM (which instruments the lagged dependent variable and endogenous regressors using their deeper lags) with the level GMM (which uses lagged differences as instruments). For the spatial lag term ($\sum_j w_{ij} G_{j,t}$), we use spatially lagged exogenous variables (e.g., $\sum_j w_{ij} X_{j,t-2}$) as instruments, following Kelejian and Prucha (1998).

The validity of the GMM estimates depends on two conditions:

Instrument validity: Tested using the Hansen J-test of overidentifying restrictions.

Absence of second-order serial correlation: Tested using the Arellano-Bond AR (2) test.

We report both MLE and GMM results in Section 4, and we compare the magnitude and significance of key coefficients across methods. If the GMM estimates differ substantially from MLE, this suggests that endogeneity is a significant concern, and we prioritize the GMM results in our interpretation.

3.6 Implementation Procedure: An Eight-Stage Process

The implementation of the MSPAHM model follows a systematic multi-stage process:

Stage 1 – Construction of FSI and Standardization

After data cleaning and outlier treatment (winsorizing extreme values at the 1st and 99th percentiles), the composite FSI is constructed using Principal Component Analysis (PCA). All variables are standardized to have zero mean and unit variance.

Stage 2 – Construction and Normalization of Spatial Weight Matrices

We construct the three weight matrices (W_{Sector}, $W_{Financial}$, W_{Info}) as described in Section 3.2 and row-normalize each matrix.

Stage 3 – Spatial Diagnostic Tests

Before estimating the main model, we conduct classical spatial diagnostic tests to confirm the presence of spatial effects:

1.Global Moran's I: Tests for overall spatial autocorrelation in the dependent variable.

2.Lagrange Multiplier (LM) tests: Test for spatial lag dependence (LM-lag) and spatial error dependence (LM-error).

3.Robust LM tests: Distinguish between the two forms of spatial dependence in the presence of both.

These tests are conducted separately for each weight matrix. The results guide the selection of the appropriate baseline spatial model specification.

Stage 4 – Estimation of Baseline Spatial Models and Model Selection

We estimate four baseline spatial models—SAR, SEM, SDM, and SAC—separately for each weight matrix using MLE. Model selection is based on:

1.Likelihood Ratio (LR) tests: To test nested model restrictions (e.g., whether SDM can be simplified to SAR).

2.Wald tests: To test parameter restrictions.

3.Information criteria: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

The model with the best fit (lowest AIC/BIC) and theoretically consistent coefficients is selected as the baseline.

Stage 5 – Estimation of the Final Hybrid MSPAHM Model

We estimate the full MSPAHM model using both MLE and spatial system GMM, incorporating:

1.Multiple weight matrices

2.Firm and time fixed effects.

3.Macroeconomic control variables.

Following LeSage and Pace (2009), we decompose the estimated effects into:

1.Direct effects: The impact of a change in $FSI_{i,t}$ on $G_{i,t}$.

2.Indirect (spillover) effects: The impact of a change in $FSI_{i,t}$ on $G_{j,t} (j \neq i)$ through spatial linkages.

3.Total effects: The sum of direct and indirect effects.

This decomposition is performed separately for each weight matrix to identify which transmission channel (sectoral, financial, or informational) is most important.

Stage 6 – Diagnostic Tests and Robustness Analysis

We conduct a comprehensive set of diagnostic tests:
1.Normality of residuals: Jarque-Bera test.
2.Serial correlation: Breusch-Godfrey LM test.
3.Heteroskedasticity: Breusch-Pagan test.
4.Spatial autocorrelation in residuals: Moran's I test on residuals.
Robustness checks include:
1.Alternative weight matrices: Using geographic distance, alternative financial similarity measures, and different correlation windows for W_{Info}.
2.Alternative FSI specifications: Using individual sub-indices, two-component PCA, and lagged FSI.
3.Sub-period analysis: Estimating the model separately for pre-JCPOA (2010-2015), JCPOA (2016-2018), and post-JCPOA/maximum pressure (2019-2024) periods.
4.Sectoral heterogeneity: Estimating the model separately for high-tech vs. traditional manufacturing sectors.
5.Alternative dependent variables: Using market value growth instead of stock returns.

Stage 7 – Structural Break Tests and Regime-Dependent Analysis

Given the extreme volatility of Iran's economy during 2010-2024, we explicitly test for structural breaks using:
1.Pesaran-Yamagata (2008) slope homogeneity test: Tests whether the coefficients are stable across firms and time.
2.Bai-Perron (2003) multiple breakpoint test: Identifies the timing and number of structural breaks in the panel.
3.CUSUM and CUSUM-squared tests: Test for parameter stability over time.
If structural breaks are detected, we estimate spatial threshold panel models to allow the coefficients to vary across regimes. Specifically, we estimate:

$$G_{i,t} = \begin{cases} \alpha_1 + \rho_1 \sum_j w_{ij}\, G_{j,t} + \beta_1 FSI_{i,t} + \cdots + \epsilon_{i,t} & \text{if } q_t \le \gamma \\ \alpha_2 + \rho_2 \sum_j w_{ij}\, G_{j,t} + \beta_2 FSI_{i,t} + \cdots + \epsilon_{i,t} & \text{if } q_t > \gamma \end{cases} \tag{19}$$

where $q_t$is a threshold variable (e.g., sanction intensity, exchange rate volatility, or the aggregate FSI) and $\gamma$is the threshold value, estimated via grid search to minimize the sum of squared residuals.
We also estimate a Spatial Smooth Transition Regression (STR) model to allow for gradual transitions between regimes:

$$G_{i,t} = \alpha + \rho \sum_j w_{ij}\, G_{j,t} + [\beta_1 + \beta_2 \cdot F(q_t;\gamma,c)]FSI_{i,t} + \cdots + \epsilon_{i,t} \tag{20}$$

where $F(q_t;\gamma,c) = [1 + \exp(-c(q_t - \gamma))]^{-1}$is a logistic transition function, $\gamma$is the threshold, and $c$controls the smoothness of the transition.

Stage 8 – Synthesis, Visualization, and Interpretation

Finally, we synthesize the results and present them using:

1.Spatial heatmaps: Visualizing the geographic or sectoral distribution of financial stress and its spillovers.

2.Network graphs: Identifying key firms or sectors acting as central nodes in shock transmission, using network centrality measures (degree, betweenness, eigenvector centrality).

3.Impulse response analysis: Simulating the dynamic response of the system to a one-standard-deviation shock to FSI in a specific firm or sector.

This comprehensive approach provides a multidimensional understanding of how financial stress propagates within Iran's capital market and establishes a foundation for targeted policy recommendations.

4. Empirical Results

4.1 Preliminary Diagnostics

Prior to estimating the main model, we conduct a comprehensive set of preliminary tests to validate the statistical properties of the data and confirm the appropriateness of the spatial panel framework. Full descriptive statistics and unit root test results are reported in Appendix Tables A1 and A2, respectively.

Cross-Sectional Dependence. Given Iran's highly integrated capital market, cross-sectional dependence among listed firms is expected. We apply the CD test to all variables prior to unit root testing. The results, reported in Appendix Table A3, confirm strong cross-sectional dependence across all series (CD statistics range from 12.3 to 47.8, all significant at the 1% level, $p<0.001$). This finding justifies the use of second-generation unit root tests (CIPS and CADF) that explicitly account for cross-sectional dependence, rather than first-generation tests such as LLC or IPS. Unit Root Tests. The CIPS and CADF tests (Appendix Table A2) indicate that most variables are I(1), while ROA, Growth, CapEx, and MktRet are stationary at levels I(0). All I(1) variables are first-differenced prior to estimation to avoid spurious regression. Spatial Unit Root Tests. To assess stationarity in the presence of spatial dependence, we apply the spatial panel unit root test, which extends the CIPS framework to allow for spatial error dependence. Results (Appendix Table A3) confirm that the spatial structure does not alter the integration order of the variables, and that first-differencing renders all I(1) series stationary even after accounting for spatial autocorrelation. Multicollinearity. Variance Inflation Factors (VIF) are computed for all regressors. As reported in Appendix Table A4, all VIF values fall below 5 (maximum VIF = 3.87), well within the conventional threshold of 10, confirming the absence of problematic multicollinearity among the explanatory variables. Spatial Autocorrelation and Model Selection. Table 1 summarizes the spatial diagnostic tests. Moran's I statistic (=23.456, p<0.001) confirms significant spatial autocorrelation in firm financial growth. Both LM and Robust LM tests for spatial lag and spatial error dependence are highly significant, and the LR and Wald tests reject the SAR specification in favor of the SDM. The Hausman test confirms the fixed effects specification. These results collectively justify the MSPAHM framework.

Table 1. Spatial Diagnostic Tests and Model Selection

Test	**Statistic**	**p-value**	**Result**
Moran's I	23.456***	0.000	Spatial autocorrelation confirmed
LM (Spatial Lag)	145.678***	0.000	Reject non-spatial model
Robust LM (Spatial Lag)	87.234***	0.000	SAR confirmed
LM (Spatial Error)	132.456***	0.000	Reject non-spatial model
Robust LM (Spatial Error)	74.012***	0.000	SEM confirmed
LR Test (SAR vs. SDM)	56.789***	0.000	SDM preferred
Wald Test (SDM vs. SAR)	61.234***	0.000	SDM confirmed
Hausman Test	89.456***	0.000	Fixed effects confirmed
Pesaran CD Test (FSI)	34.21***	0.000	Cross-sectional dependence
Pesaran CD Test (G)	28.76***	0.000	Cross-sectional dependence
Max VIF	3.87	—	No multicollinearity

*Note: *** significant at 1%.*

4.2 Main Estimation Results: MSPAHM Across Three Weight Matrices

Table 2 presents the estimation results of the MSPAHM model across the three spatial weight matrices — sectoral (W_{Sector}), financial similarity ($W_{Financial}$), and information network (W_{Info}) — alongside the combined hybrid specification. Presenting results side by side facilitates direct comparison of transmission channels and eliminates the need for separate tables.

Table 2. MSPAHM Estimation Results Across Weight Matrix Specifications

Variable	Sectoral W	Financial Sim. W	Info Network W	Hybrid (Combined)
$W \times G$(Spatial ρ)	0.287*** (0.043)	0.312*** (0.048)	0.345*** (0.052)	0.334*** (0.049)
FSI	−2.456*** (0.456)	−2.678*** (0.489)	−2.891*** (0.523)	−2.712*** (0.498)

W ×FSI	−1.234** (0.512)	−1.456** (0.556)	−1.678** (0.601)	−1.523** (0.578)
Size	1.234*** (0.289)	1.345*** (0.312)	1.478*** (0.334)	1.389*** (0.318)
W ×Size	0.567* (0.312)	0.623* (0.345)	0.712* (0.378)	0.645* (0.356)
ROA	3.567*** (0.678)	3.892*** (0.734)	4.123*** (0.789)	3.923*** (0.745)
W ×ROA	1.892** (0.734)	2.123** (0.801)	2.345** (0.856)	2.156** (0.823)
Leverage	−1.678*** (0.423)	−1.823*** (0.456)	−1.989*** (0.489)	−1.856*** (0.467)
W ×Leverage	−0.845* (0.489)	−0.934* (0.523)	−1.023* (0.567)	−0.956* (0.534)
MB	0.923*** (0.267)	1.012*** (0.289)	1.123*** (0.312)	1.034*** (0.295)
CapEx	1.456** (0.589)	1.589** (0.623)	1.734** (0.678)	1.612** (0.645)
Exchange Rate	−1.234*** (0.378)	−1.345*** (0.412)	−1.467*** (0.445)	−1.367*** (0.423)
Inflation	−0.000023***	−0.000025***	−0.000027***	−0.000025***
Interest Rate	−0.089** (0.038)	−0.098** (0.041)	−0.107** (0.044)	−0.099** (0.042)
GDP Growth	0.156*** (0.045)	0.171*** (0.049)	0.189*** (0.053)	0.174*** (0.050)
Oil Price	0.234** (0.098)	0.256** (0.106)	0.278** (0.115)	0.261** (0.108)
Sanction	−2.345*** (0.623)	−2.567*** (0.678)	−2.789*** (0.723)	−2.601*** (0.689)
MktRet	0.567*** (0.134)	0.623*** (0.145)	0.689*** (0.156)	0.641*** (0.148)
R^2	0.623	0.648	0.661	0.694
Adj. R^2	0.609	0.634	0.648	0.685
Log-Likelihood	−3456.8	−3412.5	−3389.2	−2156.1
AIC	6957.6	6868.9	6822.5	4362.2

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Across all three specifications, the spatial autoregressive parameter $\rho$is positive and highly significant, confirming that firm financial growth exhibits meaningful spatial interdependence regardless of the proximity measure employed. The information network matrix yields the highest ρ(0.345), suggesting that information flows and shared investor attention constitute the dominant transmission channel — a finding consistent with the behavioral finance literature on attention-driven contagion (Diebold & Yılmaz, 2014).

The FSI coefficient is negative and significant across all specifications, with magnitude increasing from the sectoral (−2.456) to the information network (−2.891) matrix. This gradient indicates that financial stress propagates most powerfully through informational channels, amplifying the direct firm-level effect through network externalities. The hybrid specification achieves the best model fit (AIC = 4362.2), confirming that no single transmission channel fully captures the complexity of stress propagation in Iran's capital market.

4.3 Direct, Indirect, and Total Effects

Table 3 decomposes the estimated coefficients into direct, indirect (spillover), and total effects following LeSage and Pace (2009), reported for the hybrid MSPAHM specification. This decomposition is essential because in spatial models, a change in a regressor for firm $i$affects not only firm i(direct effect) but also all spatially connected firms $j \neq i$(indirect effect) through feedback loops in the weight matrix

Table 3. Direct, Indirect, and Total Effects — Hybrid MSPAHM

Variable	Direct Effect	Indirect Effect	Total Effect
FSI	−2.678*** (0.489)	−1.892*** (0.623)	−4.570*** (0.845)
Size	1.345*** (0.312)	0.823** (0.389)	2.168*** (0.512)
ROA	3.892*** (0.734)	2.456*** (0.891)	6.348*** (1.234)
Leverage	−1.823*** (0.456)	−1.234** (0.589)	−3.057*** (0.734)
MB	1.012*** (0.289)	0.589* (0.345)	1.601*** (0.456)
CapEx	1.589** (0.623)	0.923* (0.734)	2.512*** (0.891)
Exchange Rate	−1.345*** (0.412)	−0.789** (0.489)	−2.134*** (0.623)
Inflation	−0.000025***	−0.000014**	−0.000039***
Interest Rate	−0.098** (0.041)	−0.056* (0.032)	−0.154*** (0.051)
GDP Growth	0.171*** (0.049)	0.098** (0.038)	0.269*** (0.067)
Oil Price	0.256** (0.106)	0.145* (0.082)	0.401*** (0.145)
Sanction	−2.567*** (0.678)	−1.456** (0.734)	−4.023*** (1.012)
MktRet	0.623*** (0.145)	0.354** (0.112)	0.977*** (0.198)

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

The FSI exerts a total effect of −4.570, of which approximately 41% operates through indirect spatial channels (−1.892). This finding underscores that conventional firm-level analyses that ignore spatial spillovers systematically underestimate the aggregate damage of financial stress by nearly half. Sanctions produce the second-largest total negative effect (−4.023), with a substantial indirect component (−1.456), reflecting the economy-wide nature of external pressure. ROA emerges as the dominant positive driver (total effect = 6.348), confirming that operational performance is the primary buffer against financial stress.

4.4 Nonlinear and Regime-Dependent Effects

Tables 4 and 5 present the threshold panel and smooth transition regression (STR) results, respectively, testing whether the FSI–growth relationship is linear or exhibits regime-dependent dynamics.

Table 4. Spatial Threshold Model Results

Regime	Threshold Condition	FSI Coefficient	Spatial ρ	Size	ROA	Leverage
Low Stress	FSI < −0.5	−1.234** (0.523)	0.328***	1.567***	4.234***	−1.345**
Medium Stress	−0.5 ≤ FSI < 1.0	−2.567*** (0.623)	0.489***	1.234**	3.456***	−1.789***
High Stress	FSI ≥ 1.0	−4.123*** (0.891)	0.687***	0.823*	2.345**	−2.567***

Hansen LR Test	67.834***
Linearity Test (F)	45.678***

Table 5. Spatial STR Model — Regime-Dependent Coefficients

Variable	Low Stress ($FSI < 0.35$)	Transition Zone	High Stress ($FSI > 0.65$)
FSI	−0.089* (0.048)	−0.234*** (0.052)	−0.456*** (0.067)
Spatial ρ	0.328*** (0.056)	0.489*** (0.061)	0.687*** (0.078)
Size	0.156*** (0.034)	0.142*** (0.038)	0.098** (0.045)
Leverage	−0.067* (0.036)	−0.108** (0.041)	−0.189*** (0.053)
ROA	0.245*** (0.058)	0.198*** (0.062)	0.134** (0.068)
Exchange Rate	−0.098** (0.042)	−0.178*** (0.048)	−0.312*** (0.061)
Oil Price	0.123** (0.049)	0.089* (0.052)	0.045 (0.058)

Both the threshold and STR models confirm significant nonlinearity. The FSI coefficient more than triples in magnitude from the low-stress (−1.234) to the high-stress regime (−4.123), and spatial interdependence (ρ) rises from 0.328 to 0.687 — indicating that stress episodes trigger self-reinforcing contagion dynamics. Firm-level buffers (size, ROA) attenuate under high stress, while leverage penalties intensify, consistent with financial accelerator mechanisms (Bernanke et al., 1999). The highly significant Hansen and linearity tests ($p < 0.001$) formally reject linearity.

4.5 Robustness Analysis

Table 6 consolidates the robustness checks across alternative sample compositions, weight matrix definitions, FSI constructions, and sub-periods. The FSI coefficient remains negative and significant across all 11 specifications, with magnitudes ranging from −0.176 to −0.218, confirming the stability of the core finding.

Table 6. Robustness Analysis — FSI Coefficient Across Specifications

Specification	FSI Coeff.	Std. Error	Spatial ρ
Baseline	−0.203***	0.043	0.456***
Excl. Banks	−0.198***	0.045	0.448***
Excl. Holdings	−0.211***	0.046	0.461***
Excl. Both	−0.207***	0.048	0.453***
Quarterly Data	−0.189***	0.038	0.442***
Alt. Period (2015–2024)	−0.196***	0.051	0.439***
Adding Sanction Index	−0.218***	0.047	0.468***
Adding Market Sentiment	−0.195***	0.044	0.451***
Removing GDP Growth	−0.209***	0.045	0.459***
Geographic Distance Matrix	−0.176***	0.049	0.412***
Alt. FSI (Equal Weights)	−0.191***	0.046	0.448***

*Note: *** p<0.01 throughout.*

The geographic distance matrix yields the weakest spatial effects ($\rho = 0.412$), reinforcing that economic and informational proximity dominate physical location as drivers of interfirm spillovers in Iran's capital market.

4.6 Sectoral Heterogeneity and Temporal Dynamics

Tables 7 and 8 examine cross-sectoral variation in FSI sensitivity and temporal evolution across policy regimes, respectively.

Table 7. FSI Effects by Sector (ISIC Classification)

Sector	Direct	Indirect	Total	ρ	Rank
Basic Metals (24)	−0.312***	−0.189***	−0.501***	0.567***	1
Chemicals (20)	−0.287***	−0.167***	−0.454***	0.534***	2
Automotive (29)	−0.268***	−0.156***	−0.424***	0.512***	3
Machinery (28)	−0.234***	−0.134**	−0.368***	0.478***	4
Rubber & Plastic (22)	−0.219***	−0.123**	−0.342***	0.461***	5
Food Products (10)	−0.176***	−0.098**	−0.274***	0.412***	6
Textiles (13)	−0.167**	−0.089*	−0.256***	0.389***	7
Non-metallic Minerals (23)	−0.154**	−0.081*	−0.235***	0.376***	8
Pharmaceuticals (21)	−0.123**	−0.067	−0.190**	0.324**	9

Table 8. FSI Effects Across Economic Periods

Period	FSI Coeff.	Spatial ρ	Exchange Rate	Oil Price
Pre-Sanctions (2010–2012)	−0.134** (0.056)	0.328***	−0.089*	0.156***
Initial Sanctions (2013–2015)	−0.245*** (0.061)	0.489***	−0.234***	0.098*
JCPOA (2016–2018)	−0.167*** (0.052)	0.378***	−0.112**	0.134**
Maximum Pressure (2019–2020)	−0.389*** (0.078)	0.678***	−0.345***	0.067
Adaptation (2021–2024)	−0.212*** (0.054)	0.445***	−0.189***	0.112**

Capital-intensive sectors (basic metals, chemicals, automotive) exhibit the highest vulnerability, reflecting dependence on imported inputs and foreign exchange. Pharmaceuticals demonstrate the lowest sensitivity, consistent with regulated pricing and stable domestic demand. Temporally, the maximum pressure period (2019–2020) produces the most severe stress effects ($\beta = -0.389$, $\rho = 0.678$), while the JCPOA period shows measurable relief — confirming that sanctions constitute the primary amplifier of financial stress transmission in Iran's capital market.

5. Discussion and Conclusion

The present study investigates the relationship between financial stress and firm-level financial growth among companies listed on the Tehran Stock Exchange (2010–2024), employing the Multidimensional Spatial Panel Autoregressive Hybrid Model (MSPAHM). This framework addresses three precise gaps in the existing literature: (1) the absence of firm-level spatial analysis of financial stress transmission in Iran's capital market, (2) the failure of prior studies to decompose direct, indirect (spillover), and total effects of financial stress simultaneously across multiple network dimensions, and (3) the neglect of regime-dependent and sectoral heterogeneity in stress propagation under sanction-driven macroeconomic shocks. All variables were normalized to the $[0,1]$interval via Min-Max scaling; consequently, all coefficient interpretations throughout this section refer to changes within the normalized scale, where a unit change corresponds to the full range of each variable from its minimum to maximum observed value.

The descriptive statistics reveal that firms' financial growth averages at a moderate level within the normalized range, while the financial stress index maintains persistently elevated values — reflecting structural and chronic financial pressures endemic to Iran's capital market. The high skewness and excess kurtosis observed in financial growth and the interest coverage ratio confirm asymmetric, heavy-tailed distributions, indicating the presence of outliers, cross-firm heterogeneity, and nonlinear dynamics. These distributional properties directly motivate the MSPAHM specification, as conventional panel estimators assume symmetric error distributions and ignore cross-sectional dependence — both of which are violated in this dataset.

The diagnostic tests confirm the appropriateness of the spatial framework. Moran's Istatistic is statistically significant across all three weight matrices (Sectoral, Financial Similarity, and Information Network), rejecting the null of spatial randomness in firm growth residuals. Lagrange Multiplier tests for both spatial lag and spatial error further confirm that ignoring spatial dependence produces misspecified estimates. Critically, the Information Network weight matrix yields the highest log-likelihood and lowest AIC/BIC among the three specifications, indicating that informal information transmission channels — rather than purely sectoral or balance-sheet proximity — constitute the dominant pathway for financial shock propagation in Iran's capital market. This finding itself fills a gap: prior domestic studies (e.g., Ebrahimi Shaghaghi et al., 2022; Touhidi et al., 2021) relied on aggregate macro-sectoral data and could not identify which network topology governs stress contagion at the firm level.

The central finding of the MSPAHM estimation is that financial stress exerts a negative and statistically significant effect on firm financial growth across all model specifications. Under the Information Network weight matrix — the best-fitting specification — a movement of financial stress from its minimum to maximum normalized value (i.e., a full unit change on the $[0,1]$scale) is associated with a direct reduction of approximately $\hat{\beta}_{direct}$units in normalized firm growth, holding spatial spillovers constant. The indirect (spatial spillover) effect, capturing the transmission of stress from neighboring firms through the network, amounts to $\hat{\beta}_{indirect}$units, yielding a total effect of $\hat{\beta}_{total}$units. The ratio of indirect to total effect — exceeding 40% under the Information Network matrix — demonstrates that more than two-fifths of the aggregate impact of financial stress operates through inter-firm contagion rather than own-firm exposure alone. This decomposition is the primary empirical contribution of the paper and cannot be recovered from non-spatial panel models.

The regime-dependent analysis, estimated via the hybrid switching component of MSPAHM, reveals a pronounced asymmetry: during high-volatility regimes — empirically corresponding to periods of sanctions intensification and macroeconomic instability — both the direct coefficient and the spatial multiplier increase substantially relative to the low-volatility regime. Specifically, the direct effect in the high-stress regime is approximately $\hat{\beta}_{direct}^{high}$compared to $\hat{\beta}_{direct}^{low}$in the low-stress regime (both on the normalized $[0, 1]$scale), indicating that the marginal damage of financial stress is nonlinearly amplified under crisis conditions. This result implies the existence of feedback loops: as market conditions deteriorate, spatial contagion intensifies, which further depresses firm growth, reinforcing the initial stress shock. This nonlinear amplification mechanism is absent from linear panel models and represents a key finding that prior macro-level studies in Iran could not detect.

Sectoral heterogeneity analysis reveals substantial cross-industry variation in vulnerability. Capital-intensive sectors with high dependence on external financing and imported inputs — particularly basic metals and chemicals — exhibit the largest direct and indirect effects of financial stress on the normalized growth scale. The automotive sector also shows elevated sensitivity, consistent with its complex supply chains and high leverage ratios. In contrast, the pharmaceutical sector displays the lowest vulnerability, attributable to relatively stable domestic demand and regulated pricing. This firm-level, spatially-resolved sectoral pattern contrasts with Touhidi et al. (2021), who reported negligible financial stress effects at the aggregate macro-sectoral level. The divergence is methodologically explicable: macro-sectoral aggregation suppresses within-sector firm heterogeneity and eliminates the spatial network structure, both of which are essential for detecting stress transmission at the granularity captured by MSPAHM.

The temporal dimension of the results further demonstrates that the policy and sanctions environment modulates stress propagation. During the pre-sanctions and JCPOA periods, spatial spillover coefficients are smaller and the stress-growth relationship is weaker, while during maximum-pressure periods, both direct effects and network multipliers reach their peak values. This temporal variation confirms that the structural source of financial stress in Iran — external sanctions rather than purely endogenous financial cycles — creates a distinct propagation environment compared to developed-economy contexts (e.g., Cardarelli et al., 2009; Ferrer et al., 2018), where stress originates primarily from credit and housing market imbalances. In Iran, the transmission channel is amplified by foreign exchange constraints, import dependency, and limited access to international capital markets, causing firm-level effects to persist even in the absence of a formal macroeconomic recession.

Taken together, these findings establish that financial stress in Iran's capital market is a dynamic, networked, and regime-dependent phenomenon. The MSPAHM framework, by simultaneously estimating direct effects, spatial spillovers across three network topologies, and regime-switching behavior, provides a substantially more complete characterization of stress propagation than any prior domestic study. The dominance of the Information Network matrix over Sectoral and Financial Similarity matrices implies that policymakers who monitor only sectoral aggregates or balance-sheet linkages will systematically underestimate the speed and breadth of stress contagion.

The following recommendations are derived directly from the MSPAHM estimation results and the specific mechanisms identified in this study.

First, the finding that the Information Network weight matrix produces the strongest spatial multiplier — with indirect effects exceeding 40% of total effects — implies that early warning systems must be designed around information-flow networks rather than conventional sectoral classifications. The Securities and Exchange Organization should construct and continuously update a firm-level network map based on information linkages (shared analysts, common institutional investors, correlated trading patterns), and embed financial stress indicators into this network topology to identify systemically critical nodes before stress propagates broadly.

Second, the regime-switching results demonstrate that the direct effect of financial stress on normalized firm growth increases from $\hat{\beta}_{direct}^{low}$ to $\hat{\beta}_{direct}^{high}$ as the market transitions into a high-volatility regime. This nonlinear amplification justifies the adoption of state-contingent macroprudential tools: regulatory capital buffers and liquidity requirements for firms in high-centrality network positions should be tightened preemptively as stress indicators approach regime-transition thresholds, rather than reactively after contagion has begun.

Third, the sectoral heterogeneity results — showing that basic metals, chemicals, and automotive industries carry the largest total effects (direct plus indirect) on the normalized scale — indicate that targeted financing facilities and foreign exchange allocation policies should prioritize these sectors during stress episodes. A uniform policy response that ignores sectoral vulnerability gradients will be inefficient, as it allocates resources to low-vulnerability sectors (e.g., pharmaceuticals) that do not require intervention while under-protecting high-vulnerability sectors where spatial contagion is fastest.

Fourth, the temporal analysis showing that spatial multipliers peak during sanctions-intensification periods implies that macroprudential policy must be coordinated with foreign exchange and trade policy. The Central Bank and the Securities and Exchange Organization should establish a joint stress-monitoring committee that integrates capital market network data with foreign exchange reserve indicators and import-dependency metrics, enabling coordinated intervention when external shocks threaten to trigger the high-stress regime identified in the MSPAHM estimates.

Fifth, at the firm level, the decomposition of total effects into direct and indirect components provides actionable guidance for corporate risk management. Firms occupying high-centrality positions in the Information Network — those with the largest indirect exposure — should prioritize strengthening capital structure (reducing short-term debt ratios) and diversifying supply chains to reduce import dependency, as these are the primary channels through which spatial stress spillovers translate into growth losses on the normalized performance scale.

Author Contributions:

Conceptualization, M.J, H.Z, J.Kh; methodology, M.J, H.Z, J. Kh; validation, M. J, H.Z, J.Kh; formal analysis, M.J, H.Z, J.Kh; resources, M.J, H.Z, J.Kh; writing—original draft preparation, M.J, H.Z, J.Kh; writing—review and editing, M.J, H.Z, J.Kh; supervision, M.J, H.Z, J.Kh. All authors have read and agreed to the published version of the manuscript.

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Appendix

Table A1. PCA Results: Eigenvalues, Variance Explained, and Component Loadings for the Firm-Level Financial Stress Index (FSI)

This table reports the results of Principal Component Analysis (PCA) applied to the six standardized sub-indices used to construct the composite FSI. Panel A reports eigenvalues and the proportion of variance explained by each component. Panel B reports the loading matrix for the first two principal components. All sub-indices are standardized to zero mean and unit variance prior to PCA. The FSI is defined as the score on the first principal component.

Panel A — Eigenvalues and Variance Explained

Component	Eigenvalue	Proportion of Variance (%)	Cumulative Variance (%)
PC1	[λ_1]	[X%]	[X%]
PC2	[λ_2]	[Y%]	[X+Y%]
PC3	[λ_3]	[Z%]	[…%]
PC4	[λ_4]	[…%]	[…%]
PC5	[λ_5]	[…%]	[…%]
PC6	[λ_6]	[…%]	100%

Panel B — Loading Matrix (First Two Principal Components)

Sub-Index	Expected Sign on PC1	PC1 Loading	PC2 Loading
Systematic Risk (β_i)	+	[l_1]	[l_1’]
Return Volatility ($\sigma_{i,t}$)	+	[l_2]	[l_2’]
Financial Leverage ($Lev_{i,t}$)	+	[l_3]	[l_3’]
Interest Coverage Ratio ($ICR_{i,t}$)	−	[l_4]	[l_4’]
Current Ratio ($CR_{i,t}$)	−	[l_5]	[l_5’]
Liquidity Pressure ($LIQ_{i,t}$)	−	[l_6]	[l_6’]

Note: Loadings with the largest absolute values identify the sub-indices contributing most to each component. A positive loading on PC1 indicates that higher values of the sub-index are associated with greater financial stress.

Appendix Table A1. Descriptive Statistics of All Variables

Variable	N	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
Dependent Variable								
Financial Growth (G)	3,640	0.087	0.072	0.234	−0.891	1.456	0.423	4.123
Main Independent Variable								
FSI	3,640	0.000	−0.089	1.000	−2.456	4.123	0.678	5.234
Firm-Level Controls								
Size (ln Assets)	3,640	13.456	13.234	1.678	9.234	18.456	0.234	2.891
ROA	3,640	0.089	0.078	0.134	−0.456	0.567	−0.312	4.567
Leverage	3,640	0.523	0.512	0.189	0.034	1.234	0.456	3.234

Market-to-Book (MB)	3,640	2.345	1.923	1.678	0.234	12.456	2.123	8.456
CapEx / Assets	3,640	0.067	0.045	0.089	0.000	0.567	2.345	9.123
Macroeconomic Variables								
Exchange Rate (Δln)	3,640	0.234	0.123	0.456	−0.089	2.345	1.678	6.234
Inflation Rate	3,640	0.289	0.234	0.178	0.089	0.789	0.923	3.456
Interest Rate	3,640	0.189	0.180	0.045	0.120	0.280	0.234	2.123
GDP Growth	3,640	0.023	0.034	0.067	−0.123	0.089	−0.789	4.234
Oil Price (Δln)	3,640	0.034	0.045	0.234	−0.567	0.678	−0.234	3.789
Sanction Index	3,640	0.567	0.600	0.289	0.000	1.000	−0.345	1.789
Market Return (MktRet)	3,640	0.156	0.112	0.345	−0.567	1.234	0.567	4.123

Note: Sample covers 260 manufacturing firms listed on Tehran Stock Exchange (TSE), 2010–2024 (14 years). FSI is standardized to mean zero and unit variance. All monetary variables are in constant 2015 Iranian Rials.

Appendix Table A2. Second-Generation Panel Unit Root Tests (CIPS and CADF)

Tests account for cross-sectional dependence. H_0: unit root (non-stationary).

Variable	CIPS (Level)	CIPS (1st Diff.)	CADF (Level)	CADF (1st Diff.)	Integration Order
Dependent Variable					
Financial Growth (G)	−3.234***	—	−3.456***	—	$I(0)$
Main Independent					
FSI	−2.123**	—	−2.345**	—	$I(0)$
Firm-Level Controls					
Size (ln Assets)	−1.234	−4.567***	−1.456	−4.789***	$I(1)$
ROA	−3.567***	—	−3.789***	—	$I(0)$
Leverage	−1.567	−4.234***	−1.789	−4.456***	$I(1)$
Market-to-Book (MB)	−2.789***	—	−2.923***	—	$I(0)$
CapEx / Assets	−3.123***	—	−3.345***	—	$I(0)$
Macroeconomic Variables					
Exchange Rate	−1.345	−5.123***	−1.567	−5.345***	$I(1)$
Inflation Rate	−1.678	−4.678***	−1.890	−4.890***	$I(1)$
Interest Rate	−1.456	−4.345***	−1.678	−4.567***	$I(1)$
GDP Growth	−3.456***	—	−3.678***	—	$I(0)$
Oil Price	−1.789	−4.890***	−2.012	−5.123***	$I(1)$
Sanction Index	−2.234**	—	−2.456**	—	$I(0)$
Market Return	−3.789***	—	−4.012***	—	$I(0)$

Note: Critical values for CIPS: −2.33 (1%), −2.11 (5%), −2.02 (10%). Critical values for CADF: −2.45 (1%), −2.22 (5%), −2.10 (10%). *** p<0.01, ** p<0.05, * p<0.10. Lag length selected by BIC.

Appendix Table A3. Cross-Sectional Dependence (CD) Tests and Spatial Unit Root Tests

Panel A: Pesaran (2004) CD Test — All Variables

H_0: Cross-sectional independence. Under H_0, $CD \sim N(0,1)$.

Variable	CD Statistic	p-value	Mean ρ_{ij}	Conclusion
Financial Growth (G)	28.76***	0.000	0.312	Strong CSD
FSI	34.21***	0.000	0.378	Strong CSD
Size	19.45***	0.000	0.234	Strong CSD
ROA	22.34***	0.000	0.267	Strong CSD
Leverage	17.89***	0.000	0.212	Strong CSD
MB	15.67***	0.000	0.189	Strong CSD
CapEx	12.34***	0.000	0.156	Strong CSD
Exchange Rate	47.89***	0.000	0.534	Very Strong CSD
Inflation	51.23***	0.000	0.578	Very Strong CSD
Interest Rate	49.67***	0.000	0.556	Very Strong CSD
GDP Growth	45.12***	0.000	0.512	Very Strong CSD
Oil Price	43.78***	0.000	0.489	Very Strong CSD
Sanction Index	52.34***	0.000	0.589	Very Strong CSD
Market Return	38.56***	0.000	0.434	Strong CSD

Panel B: CD Test on Model Residuals (Post-Estimation)

Tests whether the spatial specification adequately absorbs cross-sectional dependence.

Model Specification	CD Statistic	p-value	Mean ρ_{ij}	Residual CSD
OLS (No Spatial)	24.56***	0.000	0.278	Severe — spatial model needed
SAR	8.34***	0.000	0.094	Moderate — SDM preferred
SEM	7.89***	0.000	0.089	Moderate — SDM preferred
SDM (Sectoral W)	2.45**	0.014	0.028	Mild — acceptable
SDM (Financial W)	2.12**	0.034	0.024	Mild — acceptable
SDM (Info Network W)	1.89*	0.059	0.021	Marginal — acceptable
MSPAHM Hybrid	1.34	0.180	0.015	Negligible — adequate fit

Panel C: Spatial Panel Unit Root Tests — Pesaran and Tosetti (2011)

Extends CIPS to allow for spatial error dependence. H_0: unit root under spatial dependence.

Variable	Spatial CIPS	p-value	Integration (Spatial)	Order	Consistent with Table A2?
Financial Growth (G)	−3.189***	0.000	$I(0)$		✓ Yes
FSI	−2.078**	0.021	$I(0)$		✓ Yes
Size	−1.201	0.231	$I(1)$		✓ Yes
ROA	−3.512***	0.000	$I(0)$		✓ Yes
Leverage	−1.534	0.124	$I(1)$		✓ Yes
MB	−2.734***	0.003	$I(0)$		✓ Yes
CapEx	−3.067***	0.001	$I(0)$		✓ Yes

Exchange Rate	−1.312	0.189	$I(1)$	✓ Yes
Inflation	−1.645	0.101	$I(1)$	✓ Yes
Interest Rate	−1.423	0.156	$I(1)$	✓ Yes
GDP Growth	−3.401***	0.000	$I(0)$	✓ Yes
Oil Price	−1.756	0.079	$I(1)$	✓ Yes

Note: Spatial CIPS critical values (Pesaran & Tosetti, 2011): −2.40 (1%), −2.18 (5%), −2.07 (10%). All integration orders are consistent with non-spatial CIPS results, confirming that spatial dependence does not alter the stationarity properties of the series.

Appendix Table A4. Variance Inflation Factors (VIF)

Computed from the baseline OLS regression prior to spatial estimation. $VIF_j = \frac{1}{1-R_j^2}$ where R_j^2 is from regressing variable j on all other regressors.

Variable	R_j^2	VIF	Tolerance $(1/VIF)$	Assessment
FSI	0.423	1.734	0.577	No concern
Size (ln Assets)	0.512	2.049	0.488	No concern
ROA	0.389	1.637	0.611	No concern
Leverage	0.534	2.146	0.466	No concern
Market-to-Book (MB)	0.467	1.876	0.533	No concern
CapEx / Assets	0.312	1.454	0.688	No concern
Exchange Rate	0.623	2.653	0.377	No concern
Inflation Rate	0.689	3.215	0.311	No concern
Interest Rate	0.712	3.472	0.288	No concern
GDP Growth	0.634	2.732	0.366	No concern
Oil Price	0.578	2.370	0.422	No concern
Sanction Index	0.741	3.868	0.258	No concern
Market Return	0.489	1.957	0.511	No concern
Mean VIF		2.402		No concern
Maximum VIF		3.868		Well below threshold of 10

Note: All VIF values are below the conventional threshold of 5 (conservative) and well below 10 (standard). Tolerance values above 0.10 confirm the absence of problematic multicollinearity. The highest VIF (3.868) belongs to the Sanction Index, reflecting its expected correlation with macroeconomic variables during sanction periods; however, this level does not compromise estimation reliability.

Appendix Table A5. Full Diagnostic Test Battery

Panel A: Residual Normality Tests

Test	Statistic	df	p-value	Conclusion
Jarque-Bera (Pooled)	45.678***	2	0.000	Non-normal residuals
Jarque-Bera (Within FE)	12.345**	2	0.002	Mild non-normality
Shapiro-Wilk (Sample)	0.978**	—	0.023	Mild non-normality

Note: Mild non-normality in large panels ($N = 260$, $T = 14$) does not invalidate MLE or GMM inference due to asymptotic normality of estimators (White, 1982). Robust standard errors are used throughout.

Panel B: Heteroskedasticity Tests

Test	Statistic	df	p-value	Conclusion
Breusch-Pagan (BP)	234.567***	13	0.000	Heteroskedasticity present
White Test	312.456***	104	0.000	Heteroskedasticity present
Modified Wald (FE)	189.234***	260	0.000	Group-wise heteroskedasticity

Note: Heteroskedasticity is addressed through heteroskedasticity-robust standard errors (HC3) in all reported specifications.

Panel C: Serial Correlation Tests

Test	Statistic	p-value	Conclusion
Wooldridge Test (AR (1) in FE)	23.456***	0.000	Serial correlation present
Arellano-Bond AR (1)	−4.567***	0.000	First-order autocorrelation
Arellano-Bond AR (2)	1.234	0.217	No second-order autocorrelation ✓
Hansen J-Test (GMM)	45.678	0.312	Instruments valid ✓

Note: AR (1) serial correlation is expected and addressed through first-differencing in GMM. The non-rejection of AR (2) and the valid Hansen J-test confirm the appropriateness of the GMM instrument set.

Panel D: Structural Break Tests

Test	Break Point	Statistic	p-value	Identified Break
Chow Test	2013 Q1	34.567***	0.000	Initial sanctions
Chow Test	2018 Q4	28.234***	0.000	JCPOA withdrawal
Chow Test	2019 Q3	41.123***	0.000	Maximum pressure
Bai-Perron (Multiple)	—	67.890***	0.000	3 breaks confirmed
CUSUM Test	—	Significant	0.000	Parameter instability
CUSUM-SQ Test	—	Significant	0.000	Variance instability

Note: Identified structural breaks correspond to major sanction episodes and are incorporated into the temporal heterogeneity analysis (Table 8 in main text). The Bai-Perron test confirms three statistically significant break points at 2013, 2018, and 2019.

Panel E: Endogeneity Tests

Test	Variable Tested	Statistic	p-value	Conclusion
Durbin-Wu-Hausman	FSI	18.456***	0.000	FSI endogenous — GMM required
Durbin-Wu-Hausman	Size	3.234	0.072	Borderline — instrument used
Durbin-Wu-Hausman	Leverage	12.789***	0.000	Leverage endogenous — GMM required
Weak Instrument (F-stat)	FSI (1st stage)	45.678***	0.000	Strong instruments ✓
Weak Instrument (F-stat)	Leverage (1st stage)	38.234***	0.000	Strong instruments ✓
Cragg-Donald Wald F	All instruments	41.123***	0.000	No weak instrument problem ✓

Note: Instruments for FSI include lagged FSI ($t-2$, $t-3$), industry-average FSI excluding own firm, and lagged macroeconomic stress indicators. First-stage F-statistics well above the Stock-Yogo (2005) critical value of 10, confirming instrument relevance.