



The Effects of Capital Structure Complexity on Adjustment Speed Across Business Cycles

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ABSTRACT

In constrained emerging markets, capital structure complexity remains a critical yet under-explored determinant of financial flexibility. This study examines how three complexity dimensions—number of components (NumComp), concentration (HHI), and maturity dispersion (DMD)—interact with business cycles in shaping the speed of adjustment (SOA). Using two-step System GMM for 143 non-financial firms listed on the Tehran Stock Exchange (2016–2021) and Hamilton’s (1989) Markov-switching filter, we analyze the “concentration–flexibility” nexus. Contrary to developed markets where variety typically underpins flexibility, results indicate that in Iran’s volatile, bank-dominated system, financing concentration is the key adjustment accelerator. Specifically, higher HHI—reflecting deep relationships with core creditors—noticeably increases adjustment speeds in expansions, whereas instrument quantity and maturity dispersion have no robust effect. Complementary K-means clustering reveals structural fragmentation: equity and trade credit dominate in expansions, while firms shift to loan-dependent clusters in recessions, highlighting a “flight to banking relationships” under stress. These findings challenge the “more is better” view, suggesting that in constrained systems, strategic relationship depth offers greater agility than diversification.

Keywords: Capital structure complexity; Speed of adjustment; Business cycle

1. Introduction

Strategic capital structure adjustment in response to macroeconomic fluctuations is central to modern corporate finance. Capital structure complexity embodies a fundamental trade-off: while diverse financing sources may broaden access and enhance flexibility, they also increase coordination frictions and agency costs that hinder timely rebalancing. Prior studies document this tension in developed markets (Orlova et al., 2020; Drobetz et al., 2015), yet little is known about how these mechanisms operate in bank-based emerging systems, where institutional constraints and volatility interact with financing structure. The net effect of complexity is inherently state-dependent: expansionary phases may facilitate rapid adjustment, whereas recessions magnify the frictions generated by fragmented financing arrangements. We examine this dynamic interplay within the distinct institutional context of the Iranian market. Characterized by relationship-based banking, underdeveloped corporate debt markets, and heightened macroeconomic uncertainty (Vega-Gutiérrez et al., 2025), Iran offers a compelling laboratory to examine how institutional constraints shape leverage dynamics. Although our sample period (2016–2021) is relatively short, it coincides with an episode of pronounced volatility, providing a “compressed” environment in which regime shifts can be sharply identified. The paper makes three related contributions. First, we decompose complexity into three dimensions—number of components (NumComp), concentration (HHI), and debt maturity diversity (DMD)—to examine their distinct impacts on SOA. Second, we identify economic regimes using Hamilton’s (1989) Markov-switching model. Third, we employ the two-step System GMM estimator to address endogeneity and dynamic panel bias, complemented by exploratory K-means clustering to reveal structural heterogeneity.

2. Research Background & Literature Review

Capital structure dynamics are traditionally viewed through the lens of Trade-Off and Pecking Order theories, emphasizing the balance between tax shields, distress costs, and information asymmetry (Myers & Majluf, 1984). Central to dynamic models is the speed

of adjustment (SOA) toward target leverage. While foundational theories explain target existence, recent empirical surveys (Hegde et al., 2023; Nguyen et al., 2023) and behavioral studies (Carvalho et al., 2024) document heterogeneity in SOA, driven by transaction costs and managerial traits.

2.1. Theoretical Foundations of Capital Structure

One critical yet under-explored source of heterogeneity in adjustment speed is capital structure complexity. Orlova et al. (2020) describe complexity as a double-edged phenomenon, characterized by the number of financing sources (NumComp) and financing concentration (HHI). While broader funding access may enhance flexibility (Gan et al., 2021), complexity simultaneously raises coordination costs and agency conflicts, particularly in credit-constrained environments (Kochhar, 1996). Consequently, the net effect of complexity on leverage adjustment is inherently state-dependent. Dynamic models further highlight asymmetric adjustment over the business cycle. Drobetz et al. (2015) show faster leverage adjustment during expansions and slower adjustment during recessions as credit tightens. In bank-based systems, relational banking can provide liquidity insurance during downturns relative to arm’s-length debt (Demirgüç-Kunt et al., 2020), sharpening the trade-off between financing variety and funding concentration.

2.2. The Dynamics of Capital Structure Adjustment

In developed markets, variety typically underpins flexibility. The Iranian market, however, represents a distinct context: it is bank-dominated, with shallow corporate debt markets, limited Sukuk issuance, and high macroeconomic volatility (Vega-Gutiérrez et al., 2025). In this environment, coordination costs may outweigh diversification benefits. Prior research emphasizes that the effectiveness of financial architectures depends on underlying institutional structures rather than variety alone (Ghazinoori et al., 2017). Accordingly, standardized models from developed markets fail to capture local frictions in bank-dominated systems (Mohebalizadeh & Ghazinoori, 2021). We therefore expect capital

structure complexity to affect SOA in a state-dependent manner, with financing concentration (higher HHI)—rather than instrument variety—acting as the primary accelerator of adjustment in favorable economic regimes.

2.3. Capital Structure Complexity: A Double-Edged Sword

Consistent with this framework, capital structure complexity shapes adjustment primarily through coordination and substitution channels. Fragmented financing structures may intensify agency frictions in constrained states, whereas in favorable macroeconomic conditions, limited diversification can facilitate substitution across funding sources and support faster adjustment (Byoun, 2008; Orlova et al., 2020).

2.4. The Business Cycle as a Critical Moderator

Drobtz et al. (2015) demonstrate that firms adjust more slowly in recessions, especially if financially constrained, and faster in expansions—an asymmetry consistent with the interaction of adjustment costs and capital supply. Within expansions, high liquidity and favorable sentiment reduce transaction frictions, allowing the flexibility benefits of capital structure complexity to dominate (Gan et al., 2021). In recessions, tighter credit and uncertainty amplify coordination problems, meaning complexity can become a liability (Demirgüç-Kunt et al., 2020). Nguyen et al. (2023) note that macroeconomic state variables and institutional context (market-based vs bank-based systems) materially alter SOA estimates and should be embedded in empirical models.

2.5. Hypothesis Development

How capital structure complexity influences leverage adjustment depends on the interaction between institutional frictions, macroeconomic conditions, and behavioral factors such as managerial overconfidence. Complexity may raise coordination costs and hinder rebalancing, yet it may also expand access to alternative funding channels (Orlova et al., 2020). Importantly, while Orlova et al. (2020) and Drobtz et al. (2015) establish the complexity–SOA relationship in developed markets, they do not account for the

institutional constraints of bank-dominated emerging economies. This gap motivates a tailored framework for the Iranian context.

Conceptual Mechanism. Drawing on Agency and Dynamic Trade-Off theories, the effect of capital structure complexity on SOA can be explained by two opposing channels. Under Agency Theory, fragmented creditor structures exacerbate coordination and free-rider problems, slowing renegotiation and increasing adjustment inertia. By contrast, financing concentration reduces these frictions and strengthens creditor monitoring—a “discipline-through-concentration” mechanism. Within the Dynamic Trade-Off framework, concentrated relationships can therefore operate as a flexibility tool in bank-based systems where alternative instruments lack depth and liquidity. This mechanism provides the theoretical foundation for our empirical expectations.

Given the distinctive features of the Iranian capital market—its relationship-based banking system, shallow corporate debt market, and limited Sukuk issuance—we propose the following context-specific sub-hypotheses:

H1a :Financing concentration (HHI) increases the speed of leverage adjustment, particularly during expansions, consistent with relationship banking theory.

H1b :Instrument variety (NumComp) has a weak or negligible effect on the speed of adjustment, due to the limited substitutability and liquidity of corporate debt instruments in Iran.

H1c :Debt maturity dispersion (DMD) has no systematic impact on the speed of adjustment, reflecting structural constraints that limit the availability of genuine long-term corporate debt.

3. Methodology

3.1. Empirical Model

We employ a dynamic partial-adjustment framework to examine how capital structure complexity—measured by the number of components (NumComp), concentration (HHI), and debt maturity dispersion (DMD)—affects the speed of adjustment (SOA) across business cycles. Consistent with Fama and French (2002) and Flannery and Rangan (2006), we estimate a

baseline leverage-based model (Equation 1) and an alternative direct SOA specification.

3.1.1 Empirical Model

In the baseline specification, the dependent variable is book leverage ($Lev_{i,t}$). The dynamic panel model is:

$$\begin{aligned} Lev_{i,t} = & \alpha_0 + \phi Lev_{i,t-1} + \beta_1 NumComp_{i,t} \\ & + \beta_2 HHI_{i,t} + \beta_3 DMD_{i,t} + \beta_4 EXP_t \\ & + \beta_5 (EXP_t \times NumComp_{i,t}) \\ & + \beta_6 (EXP_t \times HHI_{i,t}) \\ & + \beta_7 (EXP_t \times DMD_{i,t}) \\ & + \beta_8 (NumComp_{i,t} \times Lev_{i,t-1}) \\ & + \beta_9 (HHI_{i,t} \times Lev_{i,t-1}) \\ & + \beta_{10} (DMD_{i,t} \times Lev_{i,t-1}) \\ & + \beta_{11} (EXP_t \times Lev_{i,t-1}) \\ & + \beta_{12} (EXP_t \times NumComp_{i,t} \\ & \times Lev_{i,t-1}) \\ & + \beta_{13} (EXP_t \times HHI_{i,t} \times Lev_{i,t-1}) \\ & + \beta_{14} (EXP_t \times DMD_{i,t} \times Lev_{i,t-1}) \\ & + \sum_k \gamma_k Controls_{k,i,t} + \mu_i + \lambda_t \\ & + \varepsilon_{i,t}, \end{aligned}$$

Equation (1)

where:

where $Lev_{i,t}$ is total debt to total assets (Rajan & Zingales, 1995; Lemmon & Zender, 2010), and ϕ captures leverage persistence (reported as L_Lev in Table 1). Complexity variables are defined as follows: $NumComp_{i,t}$, the count of distinct financing instruments (Orlova et al., 2020); $HHI_{i,t}$, the concentration of funding sources (Orlova et al., 2020); and $DMD_{i,t}$, debt maturity dispersion (Chiu et al., 2021; Wang et al., 2018). EXP_t is a binary business cycle indicator (1 = expansion, 0 = recession) following Korajczyk and Levy (2003). The vector Controls includes firm size, market-to-book ratio, tangibility, profitability, dividend payout, cash flow volatility, and R&D intensity (Frank & Goyal, 2009). μ_i and λ_t denote firm and year fixed effects, respectively.

Following Fama and French (2002), leverage dynamics can be written as:

$$Leverage_{i,t} - Leverage_{i,t-1} = \delta (Leverage_{i,t}^* - Leverage_{i,t-1}) + \varepsilon_{i,t} \quad \text{Equation (2)}$$

where target leverage ($Leverage_{i,t}^*$) is modeled as a function of lagged firm characteristics (Lemmon & Zender, 2010). The implied SOA is:

$$SOA = \delta = 1 - \phi$$

Equation (3)

Since SOA is the complement of persistence (ϕ), a coefficient ϕ close to one implies high inertia. Consequently, the interaction terms involving $Lev_{i,t-1}$ in Equation (1) (e.g., β_{13} for $HHI \times EXP \times Lev$) capture shifts in this persistence. A negative interaction coefficient signifies reduced inertia and, therefore, a faster speed of adjustment.

3.2. Alternative specification: direct SOA model

For robustness, we estimate an alternative specification in which the firm-year adjustment speed, $SOA_{i,t}$, computed from Equations (1) and (2) following Flannery and Rangan (2006), serves directly as the dependent variable. This dynamic model mirrors the baseline leverage specification, with two modifications: the dependent variable is replaced by $SOA_{i,t}$, and the lagged dependent variable becomes $SOA_{i,t-1}$ (reported as L_SOA in Table 4) to capture persistence in adjustment behavior. All explanatory variables, interaction terms, and controls remain unchanged. This approach functions solely as a robustness check and is interpreted separately from the leverage-based System GMM model.

3.3. Independent Variables – Capital Structure Complexity:

Capital Structure Complexity (Independent Variables). Following Orlova et al. (2020), we quantify complexity based on seven financing categories: Equity, Sukuk, Long-Term Loans, Long-Term Payables, Short-Term Loans, Trade Payables, and Other Liabilities. We construct three measures:

1- Number of Components (NumComp): The count of distinct financing instruments employed by the firm from the categories listed above.

2- Concentration (HHI): This index measures the concentration of financing shares relative to total capital (SCS). Following standard methodology (e.g., Orlova et al., 2020), we use the normalized specification in Equation (4), where the value

approaches one as the capital structure becomes concentrated and zero as diversification increases:

$$HHI_{i,t} = \frac{\left(\frac{CP}{scs}\right)^2 + \left(\frac{DC}{scs}\right)^2 + \left(\frac{TL}{scs}\right)^2 + \dots + \left(\frac{Other}{scs}\right)^2}{1 - \frac{1}{\text{total of capital structure}}}$$

Equation (4)

3- Debt Maturity Dispersion (DMD): Following Chiu et al. (2021), we measure the diversity of debt tenors. Let p_i denote the share of short-term (≤ 1 year), medium-term (1–5 years), and long-term (> 5 years) debt in total debt. Dispersion is defined as the complement of maturity concentration:

$$DMD = 1 - \sum_i p_i^2$$

Equation (5)

Moderating Variable:

We identify business cycle phases using Hamilton's (1989) Markov-switching filter applied to quarterly real GDP growth, which classifies each period into a high-growth (expansion) or low-growth (recession) state based on smoothed regime probabilities. This approach captures nonlinear transitions in a short, volatile sample, providing a more reliable state variable than traditional filtering methods.

3.4. Capital Structure Composition and Adjustment Behavior (Exploratory Analysis)

Beyond the econometric analysis, we apply a data-mining framework to examine how the composition of firms' capital structures evolves during periods of differing SOA. The focus lies on changes in the relative shares of the key financing instruments—Equity, Sukuk, Long-Term Payables, Long-Term Loans, Trade Payables, Short-Term Loans, and Other Liabilities—between fast- and slow-adjusting firms. Conducted separately from the regression model, this exploratory analysis aims to identify financing patterns associated with adjustment behavior. Specifically, it assesses whether particular capital components gain or lose importance depending on (i) adjustment speed and (ii) the prevailing macroeconomic state. These descriptive insights reveal how firms reconfigure their financing mix under pressure, helping to detect structural shifts in funding preferences that are not captured by parametric models.

3.5 Control Variables

Following Orlova et al. (2020), we include several standard firm-specific controls to isolate the effects of complexity and business cycles. These are: Size (ln Total Assets), Market-to-Book Ratio, Tangibility (Fixed/Total Assets), Profitability (EBIT/Assets), Dividend Payout, Cash Flow Volatility (5-year standard deviation of cash flows), and R&D Intensity (R&D/Sales).

3.6. Estimation Method

To address potential endogeneity and dynamic panel bias arising from the lagged dependent variable, we employ the two-step System GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998). This estimator is appropriate for small-T, large-N panels and is widely applied in recent studies of capital structure dynamics (e.g., Choi et al., 2024). This estimator is particularly suitable for panels with small T and large N. We use Windmeijer's (2005) finite-sample correction for the two-step standard errors and apply the 'collapse' option to mitigate instrument proliferation, which could otherwise weaken the Hansen J-test. Capital structure complexity measures (NumComp, HHI, and DMD) are treated as potentially endogenous and instrumented with their internal lags. Model validity is assessed using the Hansen J-statistic for over-identifying restrictions and the Arellano–Bond AR(2) test for serial correlation; our baseline models satisfy both criteria. For robustness, we employ two complementary procedures. First, we re-estimate the baseline specifications using Fixed-Effects OLS (Table 3) to check coefficient consistency, while acknowledging the known dynamic panel bias of this estimator. Second, we estimate a direct SOA specification (Tables 4 and 5) and assess its stability via a firm-clustered bootstrap (Table 6). However, given the limitations of OLS in dynamic settings and the sensitivity of direct SOA models, our primary inferences rely on the statistically robust leverage-based System GMM estimates.

Finally, we apply K-means clustering to detect structural patterns in financing composition, selecting the optimal number of clusters via the Calinski–Harabasz index.

3.7 Sample and Data

Our sample comprises 143 non-financial firms listed on the Tehran Stock Exchange (TSE) from 2016 to 2021. This window captures a period of intense macroeconomic volatility in Iran, serving as a high-frequency “stress test” for corporate financing architectures. Rather than a long, low-frequency cycle, the period features sharp regime shifts that are well suited for examining leverage adjustment under stress. Firm-level data are obtained from Codal and Rahavard365, while macroeconomic indicators come from the Central Bank of Iran and the Statistical Centre of Iran. To ensure data consistency, we exclude financial institutions, firms with inconsistent fiscal year-ends, firms with negative shareholder equity at any point during the sample period, and firms with trading halts exceeding six months. These filters yield a final dataset of 858 firm-year observations, which we winsorize at the 1st and 99th percentiles to mitigate the influence of outliers. Crucially, as shown in Figure 1, the Hamilton (1989) filter successfully identifies distinct regimes of expansion and contraction within this short window, validating the sample’s suitability for cyclical analysis. All estimations are performed using Stata.

4. Empirical Results

4.1 Business Cycle Identification

Using the Hamilton (1989) Markov-switching filter on real GDP, we identify 2016, 2018, and 2020 as recession years ($EXP = 0$) and the remaining years as expansions ($EXP = 1$). This binary indicator serves as the key moderator in our regression analysis.

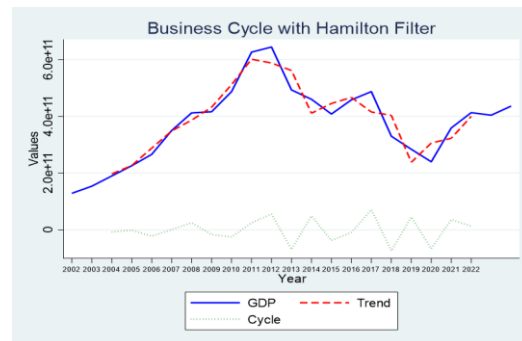


Figure 1. Iran's Business Cycle (Hamilton -filtered GDP).

4.2 Cluster Analysis of Capital Structure Composition

K-means clustering reveals clear structural shifts across business-cycle regimes. During expansion periods (Figure 2), firms split into two clusters: Cluster 1 ($N=225$) is equity-dominated, with equity accounting for roughly 67% of financing, while Cluster 2 ($N=204$) relies more heavily on supply-chain credit, with trade payables averaging 35%. During recessions (Figure 3), the structure fragments into four clusters. A notable loan-heavy cluster emerges—Cluster 3 ($N=87$)—where short-term bank loans constitute 39% of financing. This contrasts with other recessionary clusters, such as the trade-credit-intensive Cluster 4 ($N=59$, 54% trade payables) and the equity-heavy Cluster 2 ($N=143$, 80% equity). These quantitative patterns reinforce the “flight to banking relationships” mechanism, showing firms pivoting toward loan-dependent configurations that are consistent with the slower adjustment speeds observed in our regressions.

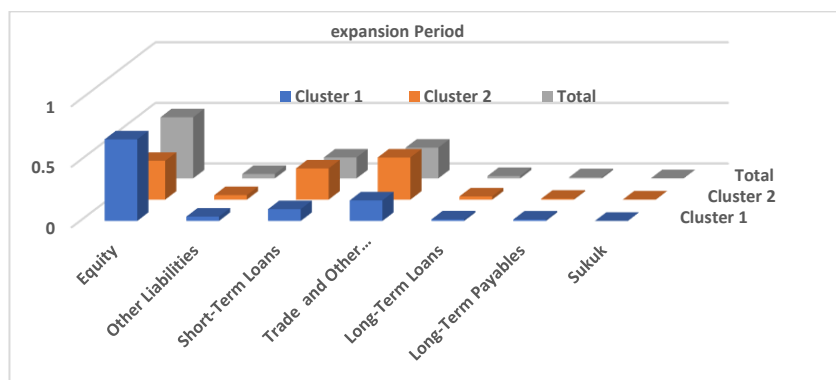


Figure 2. Capital Structure Composition during Expansion Periods ($K=2$). Capital structures converge into two dominant clusters—equity-focused and trade-credit-focused—consistent with financing concentration patterns discussed in Hypothesis H1a.

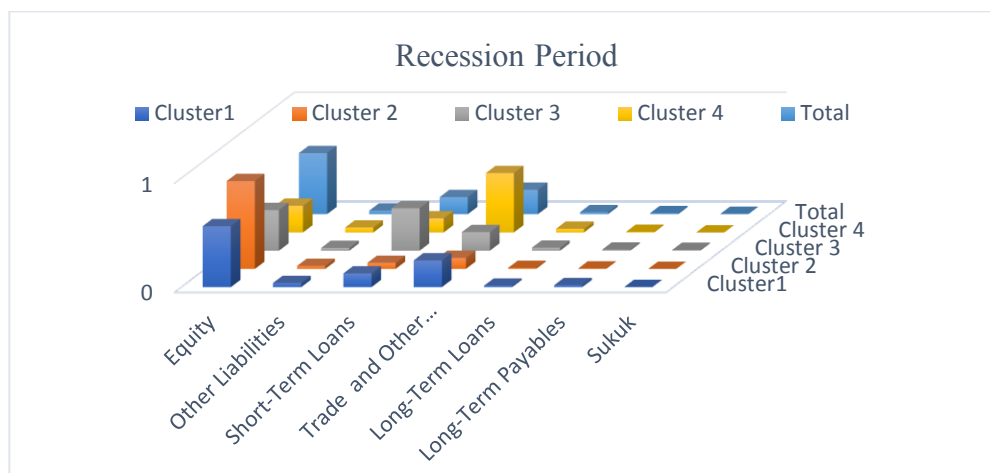


Figure 3. Capital Structure Composition during Recession Periods (K=4). Financing structures become more fragmented during recessions with the emergence of loan-dependent clusters, reflecting the “flight to banking relationships” pattern.

4.3 Empirical Results: Dynamic Panel Model

The System GMM results in Tables 1 and 2 indicate that financing concentration plays a meaningful cyclical role. The triple interaction between HHI, the business cycle, and lagged leverage is negative in the HHI specification, suggesting that firms with more concentrated financing structures face less inertia and

adjust more quickly during expansions. By contrast, interaction terms involving NumComp and DMD are consistently insignificant, indicating that neither instrument variety nor maturity dispersion meaningfully enhances adjustment flexibility in the Iranian context. Control variables follow expected patterns, supporting the internal validity of the model.

Table 1 – Dynamic Panel Estimation of Capital Structure Adjustment Speed: The Role of Complexity and Business Cycles, Main Results

Variable	NumComp Model	HHI Model	DMD Model	Combined Model
$(\phi) \text{ L_Lev}$	0.052 (0.934)	0.074 (0.625)	0.410*** (0.000)	0.066 (0.864)
NumComp (β_1)	-0.033 (0.662)	-	-	-0.006 (0.891)
HHI (β_2)	-	0.194 (0.325)	-	0.331** (0.024)
DMD (β_3)	-	-	-0.036 (0.804)	0.187 (0.244)
Exp (β_4)	0.034 (0.246)	0.012 (0.392)	0.003 (0.869)	-0.033 (0.756)
NumComp * Exp (β_5)	-0.006 (0.345)	-	-	0.001 (0.980)
HHI * Exp (β_6)	-	-0.017 (0.759)	-	0.072 (0.381)
DMD * Exp (β_7)	-	-	-0.054 (0.125)	-0.143 (0.295)
NumComp * L_Lev (β_8)	0.101 (0.465)	-	-	0.006 (0.942)
HHI * L_Lev (β_9)	-	0.477 (0.148)	-	0.384 (0.137)
DMD * L_Lev (β_{10})	-	-	0.204 (0.484)	-0.423 (0.206)
Exp * L_Lev (β_{11})	0.003 (0.925)	0.009 (0.884)	0.021 (0.476)	0.212 (0.414)

Variable	NumComp Model	HHI Model	DMD Model	Combined Model
NumComp * Exp * L_Lev (β_{12})	0.005 (0.911)	-	-	-0.006 (0.904)
HHI * Exp * L_Lev (β_{13})	-	-0.392* (0.051)	-	-0.304 (0.111)
DMD * Exp * L_Lev (β_{14})	-	-	0.107 (0.703)	0.291 (0.271)
Cash Flow Volatility (β_k)	-0.001 (0.991)	0.018 (0.826)	-0.101 (0.277)	-0.013 (0.880)
Size (β_k)	0.009** (0.023)	0.007** (0.013)	0.010** (0.011)	0.008** (0.011)
Profitability (β_k)	-0.503*** (0.000)	-0.312*** (0.000)	-0.529*** (0.000)	-0.296*** (0.000)
Tangible Assets Ratio (β_k)	-0.239*** (0.000)	-0.172*** (0.000)	-0.226*** (0.000)	-0.178*** (0.000)
Market to Book Value (β_k)	0.002*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.003*** (0.000)
Dividends (β_k)	-0.012 (0.612)	-0.022 (0.285)	-0.011 (0.609)	-0.025 (0.267)
R&D (β_k)	0.359 (0.285)	-0.147 (0.724)	0.225 (0.527)	-0.225 (0.640)
Constant	0.449 (0.173)	0.228** (0.006)	0.341*** (0.000)	0.189 (0.312)

*** p<0.01, ** p<0.05, * p<0.10

Table 2– Model Statistics and Diagnostic Tests– Dynamic Panel Estimation, Main Results

Test / Statistic	NumComp Model	HHI Model	DMD Model	Combined Model
Observations	715	715	714	714
Number of groups	143	143	143	143
(#) Instruments	26	26	26	51
F-statistic	1173.17***	1382.74***	934.64***	845.21***
AR(1) p-value	0.008	0.003	0.011	0.007
AR(2) p-value	0.649	0.240	0.772	0.189
Sargan χ^2 (p-value)	32.66 (0.001)	27.01 (0.008)	29.47 (0.003)	43.21 (0.033)
Hansen χ^2 (p-value)	17.45 (0.133)	12.31 (0.421)	16.92 (0.153)	39.26 (0.077)
Diff-Hansen p-value (L_Lev)	0.578	0.553	0.275	0.024
Diff-Hansen p-value (Controls)	0.552	0.675	0.319	0.120

*** p<0.01, ** p<0.05, * p<0.10

4.4 Robustness Checks and Methodological Analysis

We conduct two robustness checks to validate the main findings. Fixed-Effects OLS results (Table 3) broadly confirm the directional effects identified in the System GMM models, alleviating concerns about estimator dependence. In addition, we estimate a direct SOA specification (Tables 4–6). Consistent with

recent evidence on the instability of direct SOA models in short and volatile panels (Nguyen et al., 2023), this specification yields weaker significance yet preserves the qualitative patterns observed in the baseline results. Taken together, these robustness checks reinforce that financing concentration—rather than instrument variety or maturity dispersion—is the primary driver of state-dependent adjustment speed.

Table3 – Fixed-Effects OLS Estimation of Capital Structure Adjustment Speed: Robustness Check for Complexity and Business Cycles

Variable	NumComp Model	HHI Model	DMD Model	Combined Model
(ϕ) L_Lev	0.3653** (0.006)	0.1524 (0.112)	0.3132*** (0.000)	0.0195 (0.886)
NumComp (β_1)	0.0350** (0.030)	—	—	-0.0173 (0.307)
HHI (β_2)	—	0.3440*** (0.000)	—	0.3221*** (0.000)
DMD (β_3)	—	—	0.2352	0.2647** (0.036)

Variable	NumComp Model	HHI Model	DMD Model	Combined Model
			(0.108)	
Exp (β_4)	0.0559 (0.332)	0.0484 (0.170)	0.0629*** (0.009)	0.0436 (0.463)
NumComp * Exp (β_5)	-0.0028 (0.842)	—	—	-0.00043 (0.978)
HHI * Exp (β_6)	—	0.0057 (0.916)	—	0.0549 (0.300)
DMD * Exp (β_7)	—	—	-0.1512 (0.293)	-0.1320 (0.326)
NumComp * L_ Lev (β_8)	-0.0246 (0.396)	—	—	0.0364 (0.231)
HHI * L_ Lev (β_9)	—	0.0305 (0.838)	—	0.1009 (0.543)
DMD * L_ Lev (β_{10})	—	—	-0.3576 (0.167)	-0.5809*** (0.008)
Exp * L_ Lev (β_{11})	0.0607 (0.658)	0.0835 (0.507)	-0.0196 (0.627)	0.1606 (0.323)
NumComp * Exp * L_ Lev (β_{12})	-0.0125 (0.679)	—	—	-0.0154 (0.589)
HHI * Exp * L_ Lev (β_{13})	—	-0.1093 (0.477)	—	-0.1830 (0.205)
DMD * Exp * L_ Lev (β_{14})	—	—	0.1989 (0.427)	0.2878 (0.198)
Cash Flow Volatility (β_k)	-0.0097 (0.911)	-0.0122 (0.881)	-0.0108 (0.901)	-0.00035 (0.997)
Size (β_k)	0.0457*** (0.009)	0.0665*** (0.000)	0.0492*** (0.005)	0.0733*** (0.000)
Profitability (β_k)	-0.6414*** (0.000)	-0.5030*** (0.000)	-0.6414*** (0.000)	-0.4942*** (0.000)
Tangible Assets Ratio (β_k)	-0.4842*** (0.000)	-0.4158*** (0.000)	-0.4729*** (0.000)	-0.4073*** (0.000)
Market to Book Value (β_k)	0.00229*** (0.001)	0.00256*** (0.000)	0.00223*** (0.001)	0.00261*** (0.000)
Dividends (β_k)	0.00435 (0.803)	-0.00753 (0.683)	0.00124 (0.946)	-0.00966 (0.603)
R&D (β_k)	0.4493 (0.430)	0.2723 (0.579)	0.4293 (0.441)	0.2809 (0.566)
Constant	0.0382 (0.804)	-0.1701 (0.185)	0.1287 (0.379)	-0.1737 (0.169)

Table 4. Alternative Specification: two-step System GMM Estimation using Direct Speed of Adjustment (SOA)

Variable	NumComp Model	HHI Model	DMD Model	Combined Model
L SOA (ρ)	-2.7861 (0.181)	-4.7557** (0.040)	-0.6279 (0.475)	-3.9815* (0.085)
NumComp (β_1)	0.6281* (0.086)	—	—	0.5863 (0.204)
HHI (β_2)	—	-1.0823 (0.575)	—	-0.5986 (0.732)
DMD (β_3)	—	—	-1.3744 (0.591)	-1.9555 (0.434)
Exp (β_4)	0.1315 (0.933)	-0.0013 (0.999)	-0.6695 (0.180)	0.1123 (0.940)
NumComp * Exp (β_5)	-0.1258 (0.706)	—	—	-0.0722 (0.855)
HHI * Exp (β_6)	—	-0.3657 (0.767)	—	-1.0799 (0.501)
DMD * Exp (β_7)	—	—	2.6061 (0.383)	2.4324 (0.364)
NumComp * L SOA (β_8)	0.6471 (0.161)	—	—	0.6819 (0.138)
HHI * L SOA (β_9)	—	7.5831** (0.040)	—	2.2919 (0.156)
DMD * L SOA (β_{10})	—	—	3.3476 (0.526)	-3.4499 (0.183)
Exp * L SOA (β_{11})	3.0071 (0.112)	4.5750** (0.036)	0.6222 (0.481)	4.0906 (0.104)
NumComp * Exp * L SOA (β_{12})	-0.7091* (0.092)	—	—	-0.7344 (0.155)
HHI * Exp * L SOA (β_{13})	—	-7.3565** (0.037)	—	-2.1768 (0.184)
DMD * Exp * L SOA (β_{14})	—	—	-3.4304 (0.516)	3.3235 (0.199)
Cash Flow Volatility (β_k)	12.0829** (0.042)	9.9157 (0.194)	9.7064 (0.338)	12.2503* (0.068)
Size (β_k)	-0.0272 (0.825)	0.1136 (0.523)	0.0501 (0.700)	0.0607 (0.678)
Profitability (β_k)	-1.2056 (0.299)	-3.2966 (0.242)	-2.1705 (0.308)	-1.9176 (0.244)
Tangible Assets Ratio (β_k)	-0.5753 (0.656)	-0.1466 (0.920)	-0.1742 (0.921)	0.1756 (0.878)
Market to Book Value (β_k)	0.0052 (0.809)	-0.0036 (0.885)	0.0153 (0.498)	0.0041 (0.847)
Dividends (β_k)	-0.2144 (0.783)	0.5558 (0.503)	0.6536 (0.428)	0.0840 (0.935)
R&D (β_k)	176.8799* (0.058)	104.9613 (0.100)	143.1826 (0.148)	275.1659** (0.047)
Constant	-2.7835 (0.223)	-0.7674 (0.722)	-1.2698 (0.455)	-3.1763 (0.356)

*** p<0.01, ** p<0.05, * p<0.10

Table 5. Diagnostic Tests for the Alternative Direct SOA Specification

Test / Statistic	NumComp Model	HHI Model	DMD Model	Combined Model
Observations	715	715	714	714
Number of groups	143	143	143	143
(#) Instruments	28	28	29	51
F-statistic	2.08**	1.19	0.91	3.43***
Prob > F	0.016	0.288	0.552	0.000
AR(1) p-value	0.098	0.083	0.127	0.082
AR(2) p-value	0.252	0.541	0.224	0.352
Sargan χ^2 (p-value)	4.71 (0.981)	7.94 (0.847)	11.92 (0.613)	26.29 (0.557)
Hansen χ^2 (p-value)	9.82 (0.709)	9.43 (0.740)	17.26 (0.243)	22.44 (0.761)
Diff-Hansen p-value (L.SOA)	0.353	0.563	0.908	0.177
Diff-Hansen p-value (Controls)	0.874	0.730	0.372	0.528

Table 6. Robustness Check: Firm-Clustered Bootstrap Analysis of Direct SOA Estimates

Variable	NumComp Model	HHI Model	DMD Model	Combined Model
L_SOA	-0.7115 (1.3855)	0.6893 (2.5077)	-0.3509 (0.4609)	-1.4695 (3.0764)
NumComp	-0.0374 (0.4510)	—	—	0.3463 (0.9832)
HHI	—	-1.8241 (2.9054)	—	-2.6804 (5.2972)
DMD	—	—	5.1071 (3.8690)	4.2652 (8.2158)
Exp	-1.7618 (1.6376)	-0.5697 (0.8419)	0.4106 (0.4715)	-1.5721 (2.5755)
NumComp * Exp	0.3431 (0.3312)	—	—	0.5448 (0.8004)
HHI * Exp	—	0.4496 (1.2239)	—	-0.8653 (2.2787)
DMD * Exp	—	—	-4.7274 (3.8178)	-5.6037 (7.3198)
NumComp * L_SOA	0.0891 (0.3407)	—	—	0.5100 (0.8658)
HHI * L_SOA	—	-0.7701 (4.0018)	—	-1.7689 (3.9903)
DMD * L_SOA	—	—	3.0539 (2.3241)	1.5743 (4.3949)
Exp * L_SOA	-0.9687 (1.8422)	-0.2806 (2.7496)	0.3051 (0.4663)	0.6479 (3.7272)
NumComp * Exp * L_SOA	0.2886 (0.4083)	—	—	-0.2712 (1.0049)
HHI * Exp * L_SOA	—	0.0493 (4.2446)	—	1.5193 (4.1747)
DMD * Exp * L_SOA	—	—	-3.5150 (2.1943)	-1.9471 (5.0584)
Cash Flow Volatility	7.2874 (4.5085)	8.6749 (4.7676)	9.4893 (5.1716)	11.1513 (7.7957)
Size	0.0455 (0.0780)	0.0563 (0.0892)	0.0154 (0.0853)	0.0010 (0.1832)
Profitability	-1.5396 (0.8916)	-2.7874 (2.1794)	-2.0756 (1.1520)	-3.3125 (3.9083)
Tangible Assets Ratio	-1.0060 (1.1792)	-0.2347 (1.1794)	-0.8328 (1.0632)	-2.5897 (3.2568)
Market to Book Value	0.0146 (0.0191)	0.0173 (0.0177)	0.0139 (0.0253)	0.0020 (0.0292)
Dividends	0.1218 (0.6115)	0.0316 (0.5566)	0.3502 (0.5965)	-0.0182 (1.0564)
R&D	120.0251 (94.0444)	119.0684 (81.4392)	128.7303 (91.3375)	162.4194 (128.1543)
Constant	-0.2590 (2.0888)	0.6647 (2.3255)	-1.0955 (1.0500)	0.2142 (4.6565)
Hansen p-value	0.3822 [0.2142]	0.6320 [0.2940]	0.5430 [0.2492]	0.3553 [0.3313]
AR(2) p-value	0.3141 [0.1723]	0.5040 [0.2143]	0.3235 [0.2121]	0.2207 [0.1994]

5. Discussion and Conclusion

5.1. Summary of Main Findings

This study investigates how capital structure complexity interacts with business cycles to shape the speed of adjustment (SOA) on the Tehran Stock Exchange. Three main findings emerge. First,

consistent with dynamic trade-off theory (Fama & French, 2002), Iranian firms actively rebalance toward target leverage despite a volatile, bank-dominated environment. Second, among complexity dimensions, only financing concentration (HHI) exerts a state-dependent effect on SOA. Specifically, higher

concentration reduces inertia and accelerates adjustment during expansions, whereas instrument variety (NumComp) and maturity dispersion (DMD) show no robust moderating effects. Third, cluster analysis reveals a structural pivot: firms rely on equity and trade credit in expansions, shifting to loan-dependent configurations in recessions. These patterns suggest that in Iran's constrained setting, "relationship depth trumps instrument variety": depth in core relationships, not instrument proliferation, underpins adjustment speed.

5.2. Economic Interpretation

These findings refine Hypothesis H1 and contribute to the SOA literature (Nguyen et al., 2023).

Complexity versus Concentration in Bank-Based Systems. In developed markets, complexity is often associated with financial flexibility (Orlova et al., 2020). By contrast, our evidence shows that in a bank-based emerging market, higher HHI—reflecting deep relationships with core banks and suppliers—drives adjustment agility. This aligns with the relationship-banking view (Demirgüç-Kunt et al., 2020), according to which concentrated ties reduce information asymmetry and renegotiation costs, enabling faster SOA.

State-Dependent Flexibility. The benefits of concentration are asymmetric. During expansions, liquidity allows concentrated firms to exploit banking relationships to close leverage gaps. In economic terms, a one-standard-deviation increase in financing concentration (0.176) during expansions raises the annual adjustment speed by about 6.9 percentage points, indicating a sizable and economically meaningful effect. In recessions, however, systemic credit tightening constrains firms, rendering complexity measures largely ineffective for SOA. Complexity in Iran is thus constrained, with its potential benefits muted by the limited depth and substitutability of domestic debt instruments.

Maturity Dispersion and Structural Constraints. The insignificance of DMD is consistent with the institutional reality that genuinely long-term corporate debt is scarce, and many bank facilities are effectively short- or medium-term loans that are repeatedly rolled over. Observed dispersion in stated maturities therefore fails to translate into meaningful variation in rollover risk or renegotiation options, limiting its scope to affect SOA.

Behavioral and Agency Channels. From an agency perspective (Jensen & Meckling, 1976), our results fit a "discipline-through-concentration" mechanism. Core creditors monitor closely and can pressure managers to correct leverage deviations, mitigating behavioral biases such as overconfidence (Carvalho et al., 2024). Broader complexity (high NumComp), however, may dilute this discipline without providing independent funding alternatives in Iran's shallow capital markets.

5.3. Managerial and Policy Implications

For managers, financing architecture is a strategic lever for flexibility. In Iran's volatile environment, over-engineering capital structures with many small, thinly used instruments adds friction without enhancing SOA. Cultivating deep relationships with a limited set of core banks and trade creditors appears more effective for timely rebalancing. For policymakers, the findings highlight the need for targeted financial regulation and debt market development. The insignificance of NumComp and Sukuk underscores a structural weakness: complexity cannot generate flexibility if instruments are not substitutable and supported by liquid secondary markets. To convert "variety" into a practical tool, reforms should prioritize deepening corporate bond and Sukuk markets and improving secondary market liquidity. Furthermore, corporate governance reforms that enhance transparency are essential to reduce the systemic reliance on bank-based monitoring. As shown by international evidence (Drobetz et al., 2015), such integrated developments would allow complexity to play a more constructive role in SOA.

5.4. Limitations and Directions for Future Research

This study has several limitations. The 2016–2021 sample period is short and marked by high volatility, so findings are conditional on a high-stress environment. Longer panels would help disentangle cyclical from structural effects. We also focus on book leverage; future work should analyze market leverage in a high-inflation context and control for valuation effects. Furthermore, our structural complexity measures do not capture contractual features like covenants. Loan-level studies could directly test the "concentration effect" through renegotiation processes (Devos et al., 2017). Finally, future research could

examine whether managerial traits (e.g., overconfidence) moderate the concentration–SOA nexus (Carvalho et al., 2024). Comparative analyses across other bank-based MENA markets would also clarify the generalizability of our results.

5.5. Concluding Remarks

Our evidence shows that capital structure complexity is not uniformly beneficial. In a volatile, bank-based emerging market with shallow debt markets, strategic concentration in core financial relationships—not instrument variety—is the primary driver of faster capital structure adjustment during expansions. These findings challenge the “more is better” view of complexity and highlight the need to incorporate institutional constraints into models of capital structure dynamics.

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