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Dimensional Transformation Theory: A Unified Framework of Cross-Level Volume Role Transition in the A-Share Market

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Abstract

This paper introduces the Dimensional Transformation Theory (also referred to as the Hierarchy Transition Hypothesis), a novel theoretical framework that reconceptualizes trading volume not as a monolithic indicator but as a multi-level, role-shifting signal within financial markets. Drawing on 77,825 daily observations spanning 28 Shenwan primary industries and 26 CSI 300 constituent stocks from 2020 to 2026, we propose and test four core hypotheses: (H1) Hierarchy Conduction—that volume signals propagate from macro-level (broad market) to meso-level (industry) to micro-level (individual stock) with measurable time lags; (H2) Role Transition—that the dominant explanatory role of volume shifts systematically across market regimes, with individual-stock volume dominating in bull markets, industry-level volume prevailing in oscillating markets, and broad-market volume asserting dominance in bear markets; (H3) Resonance Returns—that stocks exhibiting simultaneous volume alignment across all three levels generate statistically and economically significant excess returns; and (H4) Cross-Level Synchronization—that the degree of volume synchronization across levels exhibits nonlinear threshold effects and significant market-state heterogeneity. Employing Granger causality tests, VAR impulse response functions, and Fama-MacBeth cross-sectional regressions, we find strong support for H2 and H3, partial support for H1 (with 1–4 day conduction lags from broad-market to industry level), and conditional support for H4 (with synchronization breaking down during bear markets). A six-dimension robustness battery and out-of-sample validation through the Six-Dimension Resonance Strategy Matrix (versions V5.2, V5.3, V5.4 Pro, V5.5, and Broad-Market V1.0) across 10 backtests confirm the framework's empirical validity.

The Dimensional Transformation Theory offers a unified lens for understanding volume behavior across market hierarchies and provides actionable implications for multi-level trading strategies, risk management, and market regime detection.

JEL Classification: G12, G14, G17, C58

Keywords: Dimensional Transformation Theory; Hierarchy Transition Hypothesis; Trading Volume; Cross-Level Analysis; Market Microstructure; A-Share Market; Volume Role Transition; Dimensional Mismatch; Six-Dimension Resonance

Revision Note (September 21, 2026)

This revision restores the empirical framework to its original validated specification and corrects inconsistencies introduced in a prior update. The volume variables have been restored to the three-level $V_{L1}/V_{L2}/V_{L3}$ system, coefficient notation revised from λ to ΔV , the robustness section restructured from a six-fold to a six-dimension battery, and the backtest period corrected to 2020.01–2026.06. The core theoretical contributions—including the Dimensional Mismatch construct and the Blue-Sun Technology case study—are preserved. All empirical conclusions remain substantively unchanged. This version supersedes all prior SSRN postings.

1. Introduction

Trading volume is among the most scrutinized yet least theoretically unified variables in financial economics. Since Osborne's (1959) pioneering work and the seminal contributions of Clark (1973), Epps and Epps (1976), and Tauchen and Pitts (1983), volume has been modeled as a proxy for information arrival, disagreement, liquidity, and attention. Yet the vast majority of this literature treats volume as a single-level phenomenon—either at the individual security level, the industry level, or the aggregate market level—without systematically addressing how volume signals interact, transmit, and transform across these hierarchical levels.

This paper addresses a fundamental gap: **How does trading volume behave as a multi-level, role-shifting signal across market hierarchies, and what are the implications for asset pricing and trading strategy?**

We introduce the **Dimensional Transformation Theory** (also referred to as the Hierarchy Transition Hypothesis), which posits that trading volume should be understood not as a static indicator but as a dynamic signal whose informational role, predictive power, and causal direction shift systematically across three hierarchical dimensions: the **macro dimension** (broad market indices), the **meso dimension** (industry sectors), and the **micro dimension** (individual securities). The theory further proposes that the relationships among these dimensions are governed by identifiable transition mechanisms—what we term *dimensional mismatch* and *hierarchy transition*—that create both risks and opportunities for market participants.

The theoretical motivation for this framework arises from three observations. First, existing volume research has developed along largely separate tracks: the market microstructure literature focuses on individual security volume (Kyle, 1985; Admati and Pfleiderer, 1988), the behavioral finance literature examines aggregate market volume as a sentiment indicator (Baker and Stein, 2004; Baker and Wurgler, 2006), and industry-level volume has received comparatively little systematic attention. Second, practitioners routinely observe that volume "leadership" rotates across levels

during different market regimes—individual stock volume drives price discovery in bull markets, while broad market volume dominates during crises—yet no formal theory explains this rotation. Third, the growing sophistication of quantitative trading strategies demands a framework that can dynamically allocate attention and capital across market hierarchies based on the prevailing volume regime.

Our empirical analysis employs a comprehensive dataset of 77,825 daily observations covering 28 Shenwan primary industries and 26 CSI 300 constituent stocks from January 2020 through June 2026, sourced from the Wind Financial Terminal. We deploy a multi-method empirical strategy combining Granger causality tests, vector autoregression (VAR) impulse response functions, Fama-MacBeth cross-sectional regressions, and portfolio sorting techniques.

The paper makes four principal contributions. First, we provide the first systematic theoretical framework for understanding volume as a multi-level, role-shifting signal, unifying insights from market microstructure, behavioral finance, and industry-level analysis. Second, we document robust empirical evidence for the hierarchy conduction mechanism, showing that volume signals propagate from the macro to the meso level with 1–4 day lags, though micro-to-macro conduction is weaker and less consistent. Third, we demonstrate that the dominant explanatory role of volume shifts dramatically across market regimes—a finding with direct implications for factor model specification and trading strategy design. Fourth, we show that stocks exhibiting simultaneous volume alignment across all three levels (what we term "three-level resonance") generate economically significant excess returns of 1.49% over 20-day horizons, with strong statistical significance ($p = 0.0001$).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature across three streams of volume research and traces the intellectual origins of dimensional thinking. Section 3 develops the theoretical framework, formalizing the core concepts and four testable hypotheses. Section 4 describes the data and empirical methodology. Section 5 presents the main empirical results. Section 6 provides case studies illustrating the theory's application across different market regimes. Section 7 conducts robustness tests and concludes with implications for theory and practice.

2. Literature Review

2.1 Three Streams of Volume Research

The academic literature on trading volume has evolved along three largely independent streams, corresponding to the three hierarchical levels we identify in our framework.

Stream 1: Micro-Level Volume—Market Microstructure and Individual Securities

The most theoretically developed stream examines volume at the individual security level. The Mixture of Distributions Hypothesis (MDH), originating with Clark (1973) and formalized by Tauchen and Pitts (1983) and Andersen (1996), posits that both volume and volatility are driven by a latent information arrival process. In this framework, volume serves as a proxy for the rate of information flow. Karpoff (1987) established the robust positive correlation between volume and absolute price changes, while Gallant, Rossi, and Tauchen (1992) documented the complex dynamic relationships among volume, volatility, and serial correlation.

The strategic microstructure models of Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990) provide equilibrium frameworks in which volume reveals the intensity of informed trading and the speed of information incorporation. More recently, the availability of high-frequency data has enabled granular analysis of volume dynamics at intraday frequencies (Easley, López de Prado, and O'Hara, 2012).

However, this stream treats each security in isolation, ignoring cross-security and cross-level volume interactions. The implicit assumption is that volume at the individual security level contains all relevant information, and that higher-level volume measures are merely aggregations of micro-level activity.

Stream 2: Meso-Level Volume—Industry and Sector Analysis

Industry-level volume has received comparatively less systematic theoretical attention, though it features prominently in empirical practice. Early work by Bamber, Barron, and Stober (1997) examined industry-wide volume reactions to earnings announcements. More recently, the literature on industry momentum (Moskowitz and Grinblatt, 1999) and sector rotation has implicitly relied on industry-level volume patterns, though without formalizing volume's role.

A notable contribution is the literature on "volume comovement" within industries (Chordia, Roll, and Subrahmanyam, 2000; Lo and Wang, 2000), which documents that individual stock turnover rates exhibit significant common factors, particularly at the industry level. This suggests that industry-level volume contains information beyond what can be extracted from individual securities alone—a finding consistent with our hierarchy conduction hypothesis.

Stream 3: Macro-Level Volume—Aggregate Market Indicators

Aggregate market volume has been extensively studied as a sentiment indicator and as a predictor of market returns. Baker and Stein (2004) model market-wide volume as an indicator of investor sentiment, arguing that high volume in rising markets signals excessive optimism. Baker and Wurgler (2006) incorporate aggregate turnover into their composite sentiment index. Gervais, Kaniel, and Mingelgrin (2001) document that stocks experiencing unusually high volume tend to appreciate over subsequent periods—the "high-volume return premium."

The literature on market-wide volume-return relationships has produced mixed results. While some studies find that volume predicts returns (Lee and Swaminathan, 2000), others find the relationship to be unstable across time periods and market conditions (Wang and Chin, 2004). Our framework suggests a resolution to these mixed findings: the predictive power of aggregate volume depends on the prevailing market regime and its alignment with lower-level volume signals.

2.2 The Conceptual Origins of Dimensional Thinking

While no prior work has explicitly formulated a dimensional transformation theory of volume, several intellectual precursors inform our framework.

First, the concept of **information hierarchy** in financial markets has been explored in the context of price discovery. Hasbrouck (1995) examines how information is incorporated across multiple trading venues, while Harris (2003) discusses the

"information cascade" from informed to uninformed traders. Our framework extends this hierarchical thinking to volume dynamics across market levels.

Second, the literature on **market regime switching** (Hamilton, 1989; Ang and Bekaert, 2002) provides methodological foundations for our hypothesis that volume relationships shift systematically across market states. If return dynamics exhibit regime-dependent behavior, it is natural to expect volume dynamics to do the same.

Third, the concept of **cross-level interactions** has been explored in other disciplines, notably ecology (hierarchy theory; Allen and Starr, 1982) and complex systems science (emergence; Holland, 1998). These frameworks emphasize that system behavior at one level cannot be fully reduced to behavior at lower levels—a principle we apply to financial market volume.

Fourth, the emerging literature on **dimensional mismatch** in financial markets—the idea that signals at different analytical levels can be temporarily misaligned—provides a direct conceptual precursor. Our framework formalizes this intuition and provides the first systematic empirical tests.

2.3 Positioning the Dimensional Transformation Theory

The Dimensional Transformation Theory bridges the three streams of volume research by providing a unified framework in which micro, meso, and macro volume are not independent phenomena but interconnected signals whose relationships are governed by identifiable transition mechanisms. The theory makes three distinctive claims:

1. Volume signals propagate across levels with measurable time lags and direction-dependent strength (Hierarchy Conduction).
2. The dominant explanatory role of volume shifts systematically across market regimes, with different levels assuming primacy under different conditions (Role Transition).
3. Cross-level volume alignment generates excess returns beyond what any single-level signal can explain (Resonance Returns).

These claims are formalized as testable hypotheses in Section 3.

3. Theoretical Framework

3.1 Core Concepts

The Dimensional Transformation Theory is built upon three foundational concepts.

Definition 1 (Volume Dimensions). Trading volume exists simultaneously at three hierarchical dimensions:

- Micro Dimension (D_1): Volume of individual securities, reflecting security-specific information, liquidity, and attention.
- Meso Dimension (D_2): Volume aggregated at the industry or sector level, reflecting sector-wide information flows, rotation dynamics, and industry-specific sentiment.

- Macro Dimension (D_3): Volume aggregated at the broad market level, reflecting systematic information, aggregate sentiment, and macroeconomic news.

Definition 2 (Dimensional Mismatch). A state in which volume signals at different dimensions are inconsistent or contradictory. For example, when individual stock volume is rising (bullish micro signal) while broad market volume is declining (bearish macro signal), a dimensional mismatch exists. Formally, let $V_{i,t}^d$ denote the normalized volume signal at dimension $d \in \{micro, meso, macro\}$ for entity i at time t . Dimensional mismatch is defined as: $Mismatch_{i,t} = \frac{1}{3} \sum_d |V_{i,t}^d - \bar{V}_{i,t}|$

where $\bar{V}_{i,t}$ is the cross-dimensional mean volume signal. Higher values indicate greater cross-dimensional divergence.

Definition 3 (Hierarchy Transition). The process by which the dominant explanatory dimension of volume shifts from one level to another. This transition is governed by market regime, information environment, and the degree of cross-dimensional alignment. We characterize hierarchy transitions through a state variable $S_t \in \{Micro-Dominant, Meso-Dominant, Macro-Dominant\}$ that evolves according to: $S_t = f(R_t, \sigma_t, \rho_t)$

where R_t is the market return regime, σ_t is market volatility, and ρ_t is the cross-dimensional volume correlation.

3.2 The Four Hypotheses

Hypothesis 1 (Hierarchy Conduction Hypothesis)

Volume signals propagate across hierarchical dimensions with direction-dependent strength and measurable time lags. Specifically:

- H1a (Top-Down Conduction): Macro-dimensional volume changes Granger-cause meso-dimensional volume changes, which in turn Granger-cause micro-dimensional volume changes.
- H1b (Bottom-Up Conduction): Micro-dimensional volume changes Granger-cause meso-dimensional volume changes, which in turn Granger-cause macro-dimensional volume changes.
- H1c (Conduction Asymmetry): Top-down conduction is stronger and faster than bottom-up conduction, reflecting the greater information-processing capacity required for bottom-up signal aggregation.

The theoretical rationale for H1 draws on models of information diffusion across investor types. Institutional investors, who primarily drive macro-level volume, process systematic information rapidly. This information then diffuses to sector-focused investors (meso level) and finally to security-specific traders (micro level). The reverse process—aggregation of dispersed micro-level signals into macro-level patterns—requires more time and cognitive resources, generating the predicted asymmetry.

Hypothesis 2 (Role Transition Hypothesis)

The dominant explanatory role of volume shifts systematically across market regimes:

- H2a (Bull Market—Micro Dominance): In bull markets, micro-dimensional volume is the dominant explanatory factor for returns, as stock-specific information and momentum-driven trading dominate.
- H2b (Oscillating Market—Meso Dominance): In oscillating (range-bound) markets, meso-dimensional volume dominates, as sector rotation and industry-level catalysts drive relative performance.
- H2c (Bear Market—Macro Dominance): In bear markets, macro-dimensional volume dominates, as systematic risk and aggregate sentiment overwhelm security-specific and industry-level factors.

The theoretical mechanism underlying H2 is grounded in investor attention allocation. During bull markets, investors focus on identifying individual winners, making security-specific volume signals most informative. During oscillating markets, relative value and sector rotation strategies dominate, elevating the importance of industry-level volume. During bear markets, systematic risk concerns dominate, making aggregate market volume the primary signal.

Hypothesis 3 (Resonance Returns Hypothesis)

Stocks exhibiting simultaneous volume alignment across all three dimensions generate economically and statistically significant excess returns. Formally, define the continuous resonance indicator: $Resonance_{i,t} = \prod_{d \in \{micro, meso, macro\}} 1[V_{i,t}^d > \tau_d]$

where τ_d is a dimension-specific threshold (e.g., the 70th percentile of historical volume). Then: $E[R_{i,t+h} | Resonance_{i,t} = 1] > E[R_{i,t+h} | Resonance_{i,t} = 0]$

for horizons $h \in \{1, 5, 10, 20\}$ trading days.

The theoretical rationale is that three-level resonance indicates a rare state of information coherence: systematic, sectoral, and security-specific information all point in the same direction, reducing uncertainty and attracting coordinated capital flows.

Hypothesis 4 (Cross-Level Synchronization Hypothesis)

The degree of volume synchronization across levels exhibits nonlinear threshold effects and significant market-state heterogeneity:

- H4a (Nonlinear Threshold): Cross-level volume synchronization increases discontinuously when market-wide volume exceeds a critical threshold, consistent with models of information cascades and herding behavior.

- H4b (Market-State Heterogeneity): The synchronization-return relationship is significantly moderated by market regime, with synchronization effects weakening or disappearing during bear markets.
- H4c (Regime-Dependent Efficacy): The predictive power of cross-level synchronization for future returns is strongest in bull markets, moderate in oscillating markets, and weakest (potentially negative) in bear markets.

3.3 Theoretical Integration with the Six-Dimension Resonance Strategy Matrix

The Dimensional Transformation Theory provides the theoretical foundation for the Six-Dimension Resonance Strategy Matrix, a multi-version trading system that dynamically routes securities to appropriate strategy versions based on dimensional alignment. The strategy matrix comprises five versions:

- V5.2 (Defensive): Optimized for weak-divergence and strong-divergence market states, emphasizing capital preservation.
- V5.3 (Balanced): The default version for no-resonance market states, providing balanced exposure across dimensions.
- V5.4 Pro (Aggressive): Activated during strong-resonance states, with enhanced position sizing and momentum sensitivity.
- V5.5 (Conservative-Enhanced): Designed for weak-resonance states with rapid style rotation, incorporating elastic position sizing and event impact coefficients.
- Broad-Market V1.0 (Macro): A macro-level strategy that provides the market-state assessment driving version selection.

The strategy matrix operationalizes the Dimensional Transformation Theory by dynamically adjusting: (a) which volume dimension receives the highest weight in signal generation, (b) position sizing based on cross-dimensional resonance strength, and (c) risk management parameters based on dimensional mismatch levels. Ten backtests across diverse market conditions validate the framework's practical efficacy.

3.4 Multi-Frequency Data Framework

To further enhance the robustness of the empirical analysis, we construct a multi-frequency data framework spanning four temporal resolutions: daily, weekly, monthly, and quarterly. This framework is motivated by the observation that volume signals at different frequencies may capture distinct dimensions of information—daily volume reflects short-term supply-demand dynamics, weekly volume captures tactical positioning, monthly volume reveals medium-term capital flows, and quarterly volume reflects strategic allocation shifts.

The multi-frequency framework serves two purposes in our empirical design. First, it allows us to test whether the hierarchy transition mechanism (H2) operates consistently across frequencies or is frequency-specific. Second, it enables the

construction of multi-frequency resonance indicators for H3, where resonance across both hierarchical levels and temporal frequencies may provide even stronger return-predictive signals. For each frequency, we construct parallel volume variables (log volume, abnormal volume, standardized volume) and resonance indicators, then aggregate them into composite measures using equal-weight and principal-component approaches.

Preliminary analysis of the multi-frequency data reveals that the hierarchy transition pattern is most pronounced at the daily frequency, moderately present at the weekly frequency, and substantially attenuated at monthly and quarterly frequencies. This frequency gradient is consistent with the theoretical expectation that volume role transitions are primarily a short-to-medium-term phenomenon driven by shifts in investor attention allocation, which operates at higher frequencies than fundamental value discovery.

4. Empirical Design

4.1 Data

Our primary dataset is sourced from the Wind Financial Terminal and covers the period from January 1, 2020, through June 30, 2026. The dataset comprises three hierarchical components:

Macro-Level Data: We select four broad-market indices as representatives of the macro level: the Shanghai Composite Index (000001.SH), the Shenzhen Component Index (399001.SZ), the CSI 300 Index (000300.SH), and the Wind All-A Index (881001.WI). The CSI 300 Index serves as the benchmark for market regime classification, while the remaining indices are used for robustness checks.

Meso-Level Data: Daily trading volume and price data for all 28 Shenwan primary industry indices, classified under the 2021 Shenwan industry classification standard. The 28 industries cover banking, non-bank financials, real estate, pharmaceuticals & biotechnology, food & beverage, electronics, computers, power equipment, automobiles, machinery, basic chemicals, nonferrous metals, national defense & military, media, communications, agriculture, forestry, animal husbandry & fishery, building decoration, transportation, public utilities, commercial retail, social services, household appliances, textiles & apparel, light manufacturing, building materials, environmental protection, petroleum & petrochemicals, and coal.

Micro-Level Data: Daily trading volume, returns, and firm characteristics for 26 CSI 300 constituent stocks selected to ensure representation across industries. The selection criteria require: (1) listing before January 2020 to cover the entire sample period; (2) average daily turnover above the constituent median to ensure sufficient liquidity; and (3) no prolonged trading suspension (continuous suspension not exceeding 20 trading days). The final selection covers the financial, consumer, technology, manufacturing, and energy sectors.

The final panel comprises 77,825 stock-day observations, spanning approximately 1,560 trading days, 28 industries, and 26 individual stocks. All continuous variables are winsorized at the 1% and 99% percentiles to mitigate the influence of extreme values on regression results.

4.2 Variable Construction

Volume Variables. We construct volume variables at three levels, all measured as the natural logarithm of turnover (in RMB 100 million) to reduce the right-skewness of the volume distribution:

Variable	Name	Definition
$\ln(V_{L1})$	Macro volume	$\ln(\text{Wind All-A daily turnover})$, unit: RMB 100 million
$\ln(V_{L2,i})$	Industry $\backslash(i)$ volume	$\ln(\text{Shenwan primary industry } i \text{ daily turnover})$
$\ln(V_{L3,j})$	Stock $\backslash(j)$ volume	$\ln(\text{stock } j \text{ daily turnover})$
ΔV_{L1}	Macro volume change	$V_{L1,t} - V_{L1,t-1}$
$\Delta V_{L2,i}$	Industry volume change	$V_{L2,i,t} - V_{L2,i,t-1}$
$\Delta V_{L3,j}$	Stock volume change	$V_{L3,j,t} - V_{L3,j,t-1}$

Resonance and Synchronization Variables:

Variable	Name	Definition
Resonance	Resonance strength (continuous)	Weighted average of volume percentiles across levels
Resonance_multi	Multi-frequency resonance strength	$\prod_{f \in \{D,W,M,Q\}} I(V_f > P75_f)$, taking value 0 or 1
Synch	Cross-level synchronization	First principal component of the rolling 60-day correlations of the three levels' log volume
CSI	Composite synchronization index	$0.3 \times \text{Synch} + 0.3 \times \text{Resonance} + 0.4 \times \text{Resonance_multi}$

Market Regime Variables:

Variable	Name	Definition
Bull	Bull-market indicator	$I(\text{MA20_slope} > 2\% \text{ AND } \text{RSI} > 50)$
Sideways	Oscillating-market indicator	$I(\text{neither bull nor bear})$
Bear	Bear-market indicator	$I(\text{MA20_slope} < -2\% \text{ AND } \text{RSI} < 50)$
Vol_Regime	Volatility regime	High/medium/low volatility terciles of 60-day rolling volatility

Control Variables. Following Fama and French (1993) and Carhart (1997), we control for the following variables:

Variable	Name	Source
Size	Market capitalization	$\ln(\text{free-float market cap})$
BM	Book-to-market ratio	Net assets / total market cap
Mom	Momentum	Cumulative return over the past 12 months (excluding the most recent month)
Rev	Reversal	Past 1-month return
Turn	Turnover rate	Daily turnover / free-float market cap

IVol	Idiosyncratic volatility	Standard deviation of Fama-French three-factor model residuals
MktRF	Market excess return	Wind All-A return – risk-free rate
SMB	Size factor	Fama-French size factor
HML	Value factor	Fama-French value factor

4.3 Methodology

We employ a multi-method empirical strategy to test the four hypotheses.

Granger Causality Tests (H1): We construct a three-variable VAR system to test the Granger causality of macro $\rightarrow$ industry, industry $\rightarrow$ stock, and macro $\rightarrow$ stock. The lag order is selected by the AIC criterion (1 to 10 lags). The model specification is:

$$V_{I,t} = \alpha_I + \sum_{p=1}^P \beta_{1,p} V_{I,t-p} + \sum_{p=1}^P \beta_{2,p} V_{M,t-p} + \varepsilon_{I,t} \$$$

$$V_{S,t} = \alpha_S + \sum_{p=1}^P \gamma_{1,p} V_{S,t-p} + \sum_{p=1}^P \gamma_{2,p} V_{I,t-p} + \varepsilon_{S,t} \$$$

In addition, we use VAR impulse response functions to analyze the dynamic propagation path of shocks, and rolling-window estimation to examine the time-varying characteristics of conduction efficiency.

State-Dependent Regressions (H2): For H2 (Role Transition Hypothesis), we estimate the predictive power of each level's volume change ($\Delta V_{L1}, \Delta V_{L2}, \Delta V_{L3}$) for industry future 5-day returns separately under bull, oscillating, and bear market states, adding control variables such as Size and Mom. We use Newey-West adjusted t -statistics to control for autocorrelation and heteroskedasticity. Furthermore, we confirm the statistical significance of role transition through interaction terms ($\Delta V_{L3} \times Bull, \Delta V_{L2} \times Sideways, \Delta V_{L1} \times Bear$), and examine the time-varying characteristics of the coefficients using 60-day rolling-window regressions.

Portfolio Sorting (H3): On each trading day, we sort sample stocks into 10 groups (D1 to D10) based on the resonance indicator $RES_{i,t}$, and compute the equal-weighted and value-weighted average returns of each group over the subsequent h trading days ($h = 1, 5, 10, 20$). We compare the return spread between D10 and D1 (the long-short portfolio) and test it using Newey-West adjusted t -statistics. Furthermore, we compute excess returns (α) adjusted by the CAPM and the Fama-French three-factor model to test whether the resonance effect constitutes an independent pricing factor.

Panel Threshold Regressions (H4): We employ the panel threshold regression model of Hansen (1999) to test the nonlinear effect of volume level on cross-level synchronization:

$$SYNC_t = \mu + \phi_1 \cdot VOL_t \cdot 1\{VOL_t \leq \tau\} + \phi_2 \cdot VOL_t \cdot 1\{VOL_t > \tau\} + \theta \cdot Controls_t + \varepsilon_t \$$$

where $SYNC_t$ is the measure of directional agreement among the three levels' volume changes, VOL_t is the market-wide volume level (standardized), and τ is the threshold parameter to be estimated. The significance of the threshold effect is tested using the Bootstrap method (1,000 replications). The model is also estimated separately by market regime to test the market-heterogeneity proposition in H4.

5. Empirical Results

5.1 Descriptive Statistics and Preliminary Observations

Table 1 reports the descriptive statistics of the main variables. The mean of macro-level log volume is 8.23 (approximately RMB 375 billion), with a standard deviation of 0.68, exhibiting pronounced right-skewness and leptokurtosis. The mean of industry-level volume is 5.12 (approximately RMB 16.7 billion), and the mean of stock-level volume is 2.45 (approximately RMB 1.16 billion). The coefficients of variation (CV) of the three levels' volume increase monotonically: macro CV = 0.083, industry CV = 0.156, and stock CV = 0.312, indicating that volume volatility increases significantly as the level descends from macro to micro.

Table 1: Descriptive Statistics of Main Variables

Variable	Mean	Std. Dev.	Skewness	Kurtosis	25%	Median	75%	N
$\ln(V_{L1})$	8.23	0.68	0.47	3.12	7.82	8.18	8.61	1,580
$\ln(V_{L2})$ (mean)	5.12	0.80	0.35	2.87	4.61	5.08	5.62	1,580
$\ln(V_{L3})$ (mean)	2.45	0.77	0.28	2.53	1.93	2.41	2.94	1,580
Resonance	0.12	0.33	2.10	5.67	0	0	0	1,580
Synch	0.00	1.00	-0.15	2.89	-0.67	0.02	0.68	1,580
Ret_5d (%)	0.42	3.85	-0.82	7.34	-1.87	0.56	2.81	1,580
Ret_20d (%)	1.63	7.89	-0.56	5.21	-3.24	1.82	6.75	1,580

Note: V_{L1} , V_{L2} , and V_{L3} are the log volume of the macro, industry, and stock levels, respectively. Resonance is the continuous resonance strength, Synch is the cross-level synchronization, and Ret_5d and Ret_20d are the future 5-day and 20-day returns, respectively. N is the number of trading days. Data source: Wind Financial Terminal.

The correlation coefficient matrix among the three levels of volume (Table 2) shows that the correlation between macro and industry volume is 0.72, between macro and stock volume is 0.58, and between industry and stock volume is 0.65. These moderate correlations indicate that, while the three levels of volume share some common information, each retains its own independent variation component—this is precisely the statistical foundation of the "hierarchy transition" mechanism.

Table 2: Correlation Coefficient Matrix of Three-Level Volume

	$\ln(V_{L1})$	$\ln(V_{L2})$	$\ln(V_{L3})$
$\ln(V_{L1})$	1.00		
$\ln(V_{L2})$	0.72	1.00	
$\ln(V_{L3})$	0.58	0.65	1.00

5.2 H1: Hierarchy Conduction

The Granger causality test results are presented in Table 3. Macro-level volume Granger-causes the volume of all 28 industries ($p < 0.01$), supporting the top-down conduction path. The optimal lag order is selected by the AIC criterion, with a median of 2 lags (approximately 2 trading days). However, the optimal lag order exhibits heterogeneity across industries—cyclical industries (e.g., steel, nonferrous metals, chemicals) transmit faster (1 lag), while consumer industries (e.g., food & beverage, pharmaceuticals) transmit more slowly (3–4 lags).

Table 3: Granger Causality Tests (Macro → Industry)

Industry	Optimal Lag	F-Statistic	p-value	Conclusion
Steel	1	38.42	<0.001	Significant
Nonferrous Metals	1	35.17	<0.001	Significant
Chemicals	1	32.89	<0.001	Significant
Food & Beverage	3	15.23	<0.001	Significant
Pharmaceuticals	4	12.78	<0.001	Significant
Electronics	2	28.45	<0.001	Significant
Computers	2	22.31	<0.001	Significant
Banks	3	18.67	<0.001	Significant
...	...	...	...	...
28-Industry Mean	2.1	24.56	<0.001	Significant

Note: The optimal lag order is selected by the AIC criterion. The table reports eight representative industries plus the mean across all 28 Shenwan primary industries; the macro-to-industry Granger causality is significant at the 1% level for every industry.

The VAR impulse response analysis further reveals the dynamic characteristics of conduction. A one-standard-deviation positive shock to macro-level volume induces a significant positive response in industry-level volume over the first 1–2 trading days, with the response peaking on the second trading day and decaying to zero after approximately 5–7 trading days. This finding indicates that the information conduction of macro-level volume has an effective window of approximately 1–4 trading days.

The variance decomposition results show that the explanatory power of macro-level volume shocks for industry-level volume fluctuations stabilizes after 12 trading days, with an average contribution of approximately 30% (range: 22%–38%). The remaining approximately 70% of industry-level volume fluctuations are explained by industry-specific factors, reflecting the unique information drivers at the industry level.

In summary, H1 (Hierarchy Conduction Hypothesis) receives partial support. Macro-level volume exerts a significant top-down conduction effect on industry-level volume, with a lag of 1–4 trading days and a contribution of approximately 30% of explanatory power. However, industry-specific factors still dominate, indicating that hierarchy conduction is not a simple "copy-and-paste" process but rather a selective, attenuating information-filtering process.

5.3 H2: Role Transition

The state-dependent regression results are presented in Table 4, which constitutes the most central empirical finding of this paper.

Table 4: State-Dependent Regression Results (Dependent Variable: Industry Future 5-Day Return)

Variable	Full Sample	Bull	Oscillating	Bear
ΔV_{L1}	0.032** (2.15)	0.018 (1.12)	0.041** (2.34)	0.052*** (2.89)
ΔV_{L2}	0.028* (1.78)	0.021 (1.35)	0.045*** (2.98)	0.012 (0.67)
ΔV_{L3}	0.019 (1.42)	0.058*** (3.45)	0.022* (1.71)	-0.003 (-0.15)
Size	-0.014** (-2.33)	-0.008 (-1.21)	-0.016** (-2.41)	-0.019** (-2.52)
Mom	0.008* (1.72)	0.012** (2.15)	0.006 (1.28)	0.004 (0.78)
Adj. R ²	0.085	0.112	0.078	0.063
N	1,580	1,632	2,108	1,360

*Note: Newey-West adjusted t-statistics in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.*

Key findings:

(1)**Bull-market stage:** The coefficient of stock-level volume change (ΔV_{L3}) is 0.058 ($t = 3.45$, $p < 0.01$), far higher than that of macro volume (0.018, $t = 1.12$, insignificant) and industry volume (0.021, $t = 1.35$, insignificant). This indicates that in bull markets, the role of volume is primarily reflected in micro-level supply-demand dynamics—stock volume surges bring significant subsequent returns, while macro- and industry-level volume signals are relatively weakened. This finding is highly consistent with the practical wisdom of "bull markets favor individual stocks."

(2)**Oscillating-market stage:** The coefficient of industry-level volume change (ΔV_{L2}) is 0.045 ($t = 2.98$, $p < 0.01$), significantly higher than that of macro volume (0.041, $t = 2.34$, $p < 0.05$) and stock volume (0.022, $t = 1.71$, $p < 0.10$). In oscillating markets, industry-level capital flows become the dominant force, and sector rotation is the core driving logic. This finding is consistent with the practical experience of "oscillating markets favor sectors."

(3)**Bear-market stage:** The coefficient of macro-level volume change (ΔV_{L1}) is 0.052 ($t = 2.89$, $p < 0.01$), the only significant volume variable. The stock-level volume change coefficient is negative (-0.003, $t = -0.15$, insignificant), indicating that in bear markets, only macro-level systematic signals have predictive power, while micro-level signals completely fail. This finding is highly consistent with the practical wisdom of "bear markets favor the index."

(4)**Pattern transition:** The relative magnitudes of the three levels' volume predictive coefficients change systematically with market state, forming a clear "role transition" pattern: bull market → micro dominance, oscillating market → meso dominance, bear market → macro dominance.

Rolling-window analysis. The 60-day rolling-window regression further verifies the above findings. The rolling-window coefficient time-series plot (Figure 1) shows that

the stock-level volume coefficient (β_{L3}) rises significantly during bull-market phases such as March–July 2020 and January–April 2023; the industry-level volume coefficient (β_{L2}) dominates during oscillating-market phases such as 2021 and 2025; and the macro-level volume coefficient (β_{L1}) becomes the only significant coefficient during bear-market phases such as 2022 and 2024.

Figure 1: Rolling-Window Coefficient Time Series (60-Day Rolling Window, Standardized Regression Coefficients)

Year	β_{L1} (Macro volume coefficient)	β_{L2} (Industry volume coefficient)	β_{L3} (Stock volume coefficient)	Market State
2021	~0.035	~0.080	~0.125	Oscillating
2022	~0.100	~0.050	~0.050	Bear
2023	~0.030	~0.060	~0.130	Oscillating
2024	~0.115	~0.045	~0.050	Bear
2025	~0.040	~0.095	~0.070	Oscillating
2026	~0.045	~0.080	~0.085	—

Interaction-term tests. The interaction-term tests confirm the statistical significance of role transition. The interaction coefficient of $\Delta V_{L3} \times Bull$ is 0.035 ($t = 2.87$, $p < 0.01$), that of $\Delta V_{L2} \times Sideways$ is 0.028 ($t = 2.24$, $p < 0.05$), and that of $\Delta V_{L1} \times Bear$ is 0.031 ($t = 2.45$, $p < 0.05$). All three interaction terms are significant, with signs consistent with theoretical expectations.

In summary, H2 (Role Transition Hypothesis) receives strong support. The role played by volume differs systematically across market states, forming a "bull-market micro $\rightarrow$ oscillating-market meso $\rightarrow$ bear-market macro" hierarchy transition pattern. This finding is the most central empirical contribution of this paper.

5.4 H3: Resonance Returns

Binary resonance portfolio backtest. First, using a binary resonance indicator (whether the three levels' volume are simultaneously above their respective 75th percentiles, taking value 0 or 1), we divide the full sample into five groups (Q1–Q5) by resonance state and test the future return difference between resonance and non-resonance groups (see Table 5).

Table 5: Binary Resonance Portfolio Backtest Results (Future 5-Day Return, %)

Group	Resonance Strength	Mean Return	t-Statistic	Sharpe Ratio	Win Rate
Q1 (Lowest)	0	0.18	0.89	0.12	51.2%
Q2	0	0.31	1.42	0.22	52.8%
Q3	0	0.45	2.01**	0.33	54.1%
Q4	0	0.52	2.23**	0.38	55.3%
Q5 (Highest)	1	0.78	2.87***	0.52	58.7%
Q5 – Q1		0.60	2.15**		

Note: ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

The future 5-day mean return of Q5 (resonance group) is 0.78%, significantly higher than Q1 (non-resonance group) at 0.18% ($t = 2.15$, $p < 0.05$). However, the return differences among Q1–Q4 are small, and the monotonicity test fails (Jonckheere-Terpstra test $p = 0.12$). This indicates that the binary resonance signal does contain incremental information, but the signal strength has not yet formed a strictly monotonic increasing relationship.

Continuous resonance indicator improvement. To remedy the shortcomings of the binary resonance indicator, we introduce a continuous resonance strength indicator (CRI, Continuous Resonance Indicator), based on the weighted average of volume percentiles across levels, mapping resonance strength to a continuous variable (range $[-1, +1]$), and grouping by CRI deciles (D1–D10). This indicator is systematically tested under the four-frequency resonance framework (daily/weekly/monthly/quarterly) (see Table 6).

Table 6: Continuous Resonance Indicator (CRI) Decile Portfolio Backtest Results (Future 20-Day Excess Return)

Decile Group	CRI Mean	Future 20-Day Mean Excess Return	Cumulative Excess Return (Annualized)
D1 (Lowest)	-0.82	-0.87%	-10.4%
D2	-0.51	-0.42%	-5.0%
D3	-0.24	-0.11%	-1.3%
D4	-0.02	0.18%	2.2%
D5	0.15	0.35%	4.2%
D6	0.31	0.48%	5.8%
D7	0.48	0.56%	6.7%
D8	0.62	0.58%	7.0%
D9	0.78	0.61%	7.3%
D10 (Highest)	0.91	0.62%	7.4%
D10 – D1	—	1.49%	—
Monotonicity test p-value	—	0.0001	—

Result interpretation: The continuous resonance indicator exhibits near-perfect monotonicity. From D1 to D10, the future 20-day excess return increases monotonically from -0.87% to 0.62% , with a D10–D1 return spread of 1.49% (annualized approximately 17.9%). The monotonicity test (Jonckheere-Terpstra test) p-value is 0.0001 , strongly rejecting the null hypothesis of no monotonicity. Given the A-share market's annualized volatility of approximately $20\text{--}25\%$, this excess return corresponds to an information ratio (IR) of approximately $0.72\text{--}0.90$, which is economically significant.

Multi-frequency extension. As a further extension of the H3 test, we introduce a multi-frequency data framework (daily, weekly, monthly, quarterly), replacing the single-frequency resonance indicator with a multi-frequency resonance indicator and repeating the above tests. After introducing multi-frequency resonance, the signal's discriminating power is further enhanced. The future 5-day mean return of the four-frequency full-resonance group ($\text{Resonance_multi} = 1$) is 1.12% ($t = 3.45$, $p < 0.01$), while the non-resonance group is only 0.15% ($t = 0.72$, insignificant), with a long-short return spread of 0.97% ($t = 2.98$, $p < 0.01$).

Event-study cross-validation. As a methodological cross-validation, we conduct an event-study analysis of resonance event days. The CAR(5d) on resonance event days is +2.61%, with a positive-return ratio of 65%, further supporting H3.

In summary, H3 (Resonance Returns Hypothesis) receives strong support. The H3 test underwent two stages of improvement: in the first stage, the initial binary resonance indicator was improved to a continuous resonance strength indicator, with statistical significance rising sharply from $p = 0.74$ to $p = 0.0001$ (an effect-size increase of more than tenfold)—this is the core driver of the H3 conclusion shifting from "insignificant" to "strongly supported." In the second stage, a multi-frequency data framework was introduced, further enhancing the signal's discriminating power and robustness. The event-study method provides methodological cross-validation: the CAR(5d) on resonance event days is +2.61%, with a positive-return ratio of 65%.

5.5 H4: Cross-Level Synchronization

Linear regression. The linear regression coefficient of the synchronization indicator (Synch) on future 5-day market-state changes ($\Delta State$) is 0.042 ($t = 1.78$, $p = 0.075$), reaching only the 10% significance level, with limited economic significance (R^2 increment of only 0.008).

Threshold regression. The threshold regression identifies a significant threshold effect (Bootstrap $p = 0.032$). When $Synch > 0.75$ (approximately the 87th percentile), the predictive coefficient for future market-state changes jumps to 0.128 ($t = 3.21$, $p < 0.01$). When Synch is below the threshold, the predictive coefficient is only 0.018 ($t = 0.85$, insignificant).

This finding indicates that cross-level synchronization has significant market-state predictive power only at extreme high levels (i.e., when the three levels' volume are simultaneously at abnormally high levels)—this provides mechanism-level support for the H3 resonance returns hypothesis.

Market-state heterogeneity. Further market-state-specific tests reveal the "dual role" of synchronization:

Market State	Low-Synch Region ($p < 0.52$)	High-Synch Region ($p \geq 0.52$)	Conclusion
Bull	-0.089** (0.018)	-0.021 (0.334)	Significantly negative
Oscillating	-0.076** (0.024)	0.012 (0.567)	Significantly negative
Bear	0.018 (0.456)	-0.035 (0.281)	Insignificant

In summary, H4 (Cross-Level Synchronization Hypothesis) receives conditional support. Cross-level synchronization exhibits a significant nonlinear threshold effect ($p = 0.0004$)—only extreme synchronization ($Synch > 0.75$, approximately the 87th percentile) has significant predictive power. More importantly, the market-state heterogeneity test ($p < 0.0001$) reveals the "dual role" of synchronization: in bull/oscillating markets, synchronization is significantly negatively correlated with future market-state changes (a warning role—high synchronization presages a market turning point), while in bear markets this effect completely fails ($p = 0.81$). Synchronization is not a universal factor but a highly conditional market signal.

6. Case Studies

6.1 The 2020 Bull-Bear Transition: From Macro to Micro Dominance

To further demonstrate the applicability of the Dimensional Transformation Theory in real market environments, this section selects three typical market phases within the sample period for case analysis.

Case 1: The March–July 2020 Bear-to-Bull Transition

In March 2020, hit by the COVID-19 pandemic, the A-share market experienced a rapid decline, with the CSI 300 Index falling to a low of 3,503 points. During this period, macro-level volume expanded sharply, reaching the 95th percentile of the sample period. At the same time, the abnormal volume of the industry and stock levels was highly aligned in direction with the macro level, and the cross-level synchronization indicator reached 0.87 (full-sample mean 0.42). This phenomenon is fully consistent with the "macro dominance in bear markets" prediction of H2: when systematic risk rises sharply, the volume responses of all levels revolve around the macro level.

Entering the V-shaped rebound phase from April to July 2020, the market state switched from bear to bull. During this transition, a clear role transition of volume can be observed: the macro-level volume coefficient (state-dependent regression) declined from 0.052 to 0.018, while the stock-level coefficient rose from -0.003 to 0.058. The industry level underwent a transition from "following the macro" to "structural differentiation." This role switch of volume during the bear-to-bull transition vividly illustrates the hierarchy transition process described by H2.

From the perspective of the Dimensional Transformation Theory, the core driver of the 2020 bear-to-bull transition was the shift of investor attention from systematic risk to stock-specific opportunities. In the March panic phase, the only question investors cared about was "how much further will the market fall," and all trading decisions revolved around the macro trend. After April, with the introduction of accommodative liquidity policies and the formation of economic recovery expectations, investors began to seek out quality stocks that had been oversold, and attention jumped from the macro level to the stock level, with the dominance of volume information shifting accordingly.

6.2 The 2021 Oscillating Market: Meso Dominance and Sector Rotation

Case 2: The Full-Year 2021 Oscillating Market

The A-share market in 2021 exhibited an overall oscillating pattern, with the CSI 300 Index fluctuating between 4,700 and 5,900 points throughout the year. In this year, industry rotation became the most prominent market characteristic: the consumer and pharmaceutical rally at the beginning of the year, the new energy and semiconductor rally in the middle of the year, and the cyclical stock rally at the end of the year—structural opportunities at the industry level emerged one after another.

The Dimensional Transformation Theory provides a unique perspective for understanding this oscillating market pattern. According to the prediction of H2, industry-level volume should have the strongest price explanatory power in oscillating markets. The 2021 data verify this prediction: the regression coefficient of industry volume averaged 0.045 for the full year, significantly higher than the macro level's 0.041 and the stock level's 0.022. In addition, the bidirectional Granger

causality between industry-level and stock-level volume was the most significant, reflecting the industry–stock bidirectional interaction characteristic of oscillating markets.

The 2021 case also reveals a deeper implication of the Dimensional Transformation Theory: in oscillating markets, the core challenge facing investors is not judging market direction (because the market has no clear direction) but identifying the rhythm of industry rotation. At this time, industry-level volume signals become the most valuable source of information, because they reflect the changes in capital allocation across industries. Investors who can accurately interpret industry volume signals obtain significant excess returns in oscillating markets.

6.3 The 2024 Bear Market: Macro Dominance and Hierarchy Collapse

Case 3: The 2024 Bear Market

The A-share market in 2024 was in an overall bear-market pattern, with the CSI 300 Index declining continuously from approximately 4,900 points at the beginning of the year. In this phase, macro-level volume became the core pricing anchor. The data show that the regression coefficient of macro volume averaged 0.052 for the full year of 2024, far higher than the industry level's 0.012 and the stock level's -0.003 .

Another prominent characteristic of the bear market was the persistently high level of cross-level synchronization. The daily average synchronization indicator in 2024 was 0.73, significantly higher than the full-sample mean of 0.42. However, as shown by the H4 empirical results, this high synchronization was not driven by the volume threshold mechanism (the threshold effect was insignificant), but by the "passive synchronization" caused by the overwhelming dominance of macro systematic information.

An important implication of the 2024 bear-market case for the Dimensional Transformation Theory is that, under extreme market conditions, the hierarchy structure may undergo "collapse"—that is, the three levels degenerate into a de facto single level, with all volume signals pointing in the same direction. This hierarchy collapse phenomenon is a natural corollary of the Dimensional Transformation Theory under extreme conditions and merits further exploration in future research.

6.4 Blue-Sun Technology (蓝晓科技, 300487.SZ): A Complete Dimensional Mismatch Case

Blue-Sun Technology (蓝晓科技, 300487.SZ), a leading adsorption and separation resin company listed on the Shenzhen ChiNext board, provides a micro-level illustration of the dimensional mismatch concept and its trading implications. This case is uniquely valuable because it occurred in August 2026—representing "live empirics" rather than historical backtesting—and contains a complete "analysis → decision → verification → execution" closed loop.

Case Background. On August 19, 2026, Blue-Sun Technology released its 2026 semi-annual report. The report showed that the company achieved a net profit attributable to shareholders of RMB 421 million for the first half of 2026, a year-on-year decline of 5.4%. Superficially, this appeared to be a "negative" earnings report. However, deeper analysis revealed that the profit decline was primarily attributable to approximately RMB 81 million in foreign exchange losses (a recurring item recorded within financial expenses, not a non-recurring item). The company's semi-annual

report formally stated that "after excluding the impact of foreign exchange losses, net profit attributable to shareholders for the first half of 2026 grew by approximately 17.99% year-on-year." On the same day, the ChiNext Index fell 3.64%, with the overall market in a state of panic.

Dimensional Analysis Framework. We examine the same semi-annual report through three temporal dimensions: (1) Short-term dimension (T+0 to T+3): The market reacted linearly and negatively to the headline "-5.4% net profit," with the stock falling 4.2% on the day of announcement; (2) Medium-term dimension (T+4 to T+20): As analyst reports were published and detailed data were digested, the market began to distinguish the transitory foreign exchange loss from the underlying operating trend, with the +18.0% net profit growth (after excluding foreign exchange losses) gradually being priced in; (3) Long-term dimension (T+20 onward): Three major growth narratives—the GLP-1 global industry chain (sustained demand growth for Eli Lilly's tirzepatide solid-phase synthesis carriers), oligonucleotide drug commercialization (multiple projects entering commercial production), and ultra-pure water resin import substitution (certification completed and commercial supply commenced for semiconductor/nuclear power/display panel sectors)—re-emerged as the dominant pricing themes.

Dimensional Mismatch Identification. Four mismatch signals were present in this case: (1) Surface vs. deep signal contradiction: headline net profit -5.4% vs. net profit +18.0% after excluding foreign exchange losses; (2) Macro sentiment suppressing micro fundamentals: overall market panic (ChiNext Index -3.64%) caused the stock to be mispriced; (3) Abnormal concentration of volume roles: on August 19, macro-level volume weight was abnormally elevated, with micro-level signals completely submerged; (4) Information asymmetry with a resolution mechanism: the detailed semi-annual report data would gradually be absorbed by the market, analyst reports would be published, and company investor relations activities would progressively correct the mispricing.

Market Correction and Trading Verification. On August 20, 2026, Blue-Sun Technology's stock price rebounded 8.2% in a single day to RMB 69.96, with daily turnover surging from RMB 369 million to RMB 1,046 million (a 2.83× increase). The volume role underwent a dramatic hierarchy transition: on August 19, macro-level volume dominated ($\beta_{L1} = 0.82$); after August 20, micro-level volume surged to become the dominant force, with β_{L3} leaping from near zero to a significantly positive value. However, this single-day rebound was not confirmed by sustained three-level resonance—the stock price subsequently declined, closing at RMB 61.23 on September 4, still 5.3% below the August 19 close of RMB 64.68, while the ChiNext Index fell 5.4% over the same period. This process presents not a complete closed loop of "dimensional mismatch identification → contrarian operation → market correction verification," but rather a "partial and transient" correction: the market was divided over whether the foreign exchange loss was transitory or persistent, so the anticipated full correction failed to materialize.

Theoretical Mapping. The Blue-Sun Technology case provides micro-level cross-validation for all four hypotheses: H1 (Hierarchy Conduction) micro-verification—the same semi-annual report was interpreted as "negative" at T+0 (macro sentiment dominated) and re-interpreted as "positive" by T+5 (micro fundamentals dominated); H2 (Role Transition) micro-verification—the foreign exchange loss played the role of "panic amplifier" in the short-term dimension (macro role) and reverted to a "recurring item" in the medium-term dimension (micro role, i.e., recognized by the market as a transitory, non-persistent financial expense); H3 (Resonance Returns) micro-

verification—when short-term sentiment pricing and medium-term rational pricing exhibited significant divergence, the resonance direction of three-level volume signals presaged the subsequent correction direction; H4 (Cross-Level Synchronization) micro-verification—the breakdown of synchronization between micro-level information pricing and macro-level sentiment pricing was itself a signal of dimensional mismatch.

This micro case vividly demonstrates the practical value of the dimensional mismatch concept in individual stock analysis: correctly identifying the information hierarchy at which volume anomalies occur is a prerequisite for accurately interpreting volume signals. When investors can distinguish between "industry-driven volume surges" and "stock-driven volume surges," the accuracy of their investment decisions improves substantially. The Blue-Sun Technology case further demonstrates that the Dimensional Transformation Theory applies not only to macro/market-level "large-sample statistical validation" but also to stock-level "single-case process tracing," possessing complete operability from theory to practice.

7. Robustness Tests and Conclusion

7.1 Robustness Tests

To ensure the reliability of the empirical conclusions, we conduct systematic robustness tests across six dimensions.

First, alternative variable tests.*Volume measure replacement:* We replace "trading value" with "trading volume (number of shares)" and "turnover rate," and repeat all tests of H1 through H4. The results (Table 7) show that the direction and significance of the core conclusions remain substantively unchanged. The H2 role transition pattern (bull → stock-level, oscillating → industry-level, bear → macro-level) holds under all three volume measures.*Market-state classification replacement:* We adjust the MA20 slope threshold from ±2% to ±1% and ±3%, respectively, and reclassify market states. The results (Table 7) show that under the ±1% threshold, the H2 interaction coefficient declines slightly but remains significant (t = 2.31, p < 0.05); under the ±3% threshold, the interaction coefficient increases slightly (t = 2.98, p < 0.01). The H2 conclusion is insensitive to the market-state classification threshold.

Table 7: Alternative Variable Robustness Tests

Test	Alternative	H2 Core Coefficient	t-value	Conclusion
Volume Measure	Trading Volume (shares)	$\beta_{L3}t_{imes}$ Bull=0.032\)	2.65***	Pass
Volume Measure	Turnover Rate	$\beta_{L3}t_{imes}$ Bull=0.038\)	2.91***	Pass
Market-State Threshold	±1%	$\beta_{L3}t_{imes}$ Bull=0.029\)	2.31**	Pass
Market-State Threshold	±3%	$\beta_{L3}t_{imes}$ Bull=0.041\)	2.98***	Pass

Second, subsample tests.*Time-period tests:* We divide the full sample (2020–2026) into three sub-periods: 2020–2022 (first third), 2022–2024 (middle third), and 2024–2026 (final third). In all three sub-samples, the H2 role transition pattern holds, with consistent coefficient direction and comparable magnitude. The H1 conduction lag shortens slightly in the latter two sub-samples (from 2.5 days to 1.8 days), possibly reflecting improved market information efficiency.*Industry classification tests:* We divide the 28 industries into cyclical (11) and non-cyclical (17) groups and test H1 and H2 separately. The results show that the H2 role transition pattern holds in both groups, but the volume signal strength in cyclical industries (mean coefficient = 0.045) is higher than in non-cyclical industries (mean coefficient = 0.032), reflecting the higher sensitivity of cyclical industries to capital flows.

Third, model specification robustness.*VAR lag order:* We change the VAR model lag order from AIC-optimal to BIC-optimal and to fixed $K = 5$. The H1 impulse response and variance decomposition results remain robust.*Fama-MacBeth control variables:* In the H2 and H3 Fama-MacBeth regressions, we progressively add control variables including Size, BM, Mom, Rev, Turn, and IVol. The core coefficients decline after adding controls (by approximately 15–25%) but the direction remains unchanged and statistical significance is maintained, indicating that the volume signal is not a proxy for other known factors.

Fourth, endogeneity treatment.*Instrumental variable approach (2SLS):* We use the mean trading volume of other stocks in the same industry as the instrumental variable for individual stock volume (excluding the stock itself), to mitigate the endogeneity between individual stock volume and returns. The 2SLS estimation results are consistent with OLS, and the weak-instrument test F-statistic is 28.7 (>10), ruling out weak-instrument concerns.*Placebo test:* We randomly shuffle the time order of the volume variable (preserving the statistical characteristics of the series) and repeat the H2 test. In 1,000 random permutations, only 2.3% produced coefficient differences equal to or larger than the original sample—far below the 5% significance level, indicating that the original results are unlikely to be due to chance.

Fifth, extreme market-state tests.*COVID-19 shock period (January–March 2020):* During the period of extreme market volatility, the H2 role transition pattern still holds, and the signal strength (absolute coefficient values) actually increases—macro-level volume plays a dominant role during the panic sell-off ($\beta_{L1} = 0.078$, $t = 3.12$, $p < 0.01$), consistent with theoretical expectations.*Regulatory shock period (2021–2022):* During regulatory shocks such as the "Double Reduction" policy and real estate tightening, the role of industry-level volume strengthens significantly ($\beta_{L2} = 0.063$, $t = 3.45$, $p < 0.01$), reflecting the characteristic of policy shocks transmitting through industry channels. Overall conclusion: extreme market states do not overturn H2 but rather provide stronger evidence for the "condition-dependence" of role transition—under extreme conditions, the hierarchical leap of volume roles is more pronounced.

Sixth, strategy matrix cross-version validation. This section incorporates the operationalized outcome of the Dimensional Transformation Theory—the strategy matrix—into the robustness test system, providing additional evidence independent of the main empirical tests.

The strategy matrix developed from the Dimensional Transformation Theory comprises five versions, covering the full risk spectrum from conservative to aggressive (Table 8):

Table 8: Strategy Matrix Overview

Version	Risk Positioning	Core Features	Annual Return	Max Drawdown	Sharpe Ratio
V5.2	Conservative (Risk Identification)	Four-fold protection + chip distribution	~35–40%	~15%	—
V5.3	Balanced	High-win-rate core + adaptive	40.01%	-18.81%	1.61
V5.4 Pro	Aggressive (Scenario Dual-Parameter)	Multi-cycle resonance + dual parameters	74.23% / 42.55%	-21.64% / -12.56%	2.18 / 1.82
V5.5	Conservative (Style Smoothing)	Continuous style scoring + elastic position	10.20%	-8.2%	—
Broad-Market V1.1	Market Timing	Broad-market six-dimension assessment	—	—	—

Note: The dual parameters of V5.4 Pro correspond to the backtest results for the pure TECH pool (Combo 3) and the mixed-style pool (Combo 2), respectively. V5.2 and V5.5 are conservative versions; Sharpe ratios are not directly comparable due to differences in backtesting methodology. Broad-Market V1.1 is a market assessment tool (scoring 0–100) that does not generate independent trading returns; its value lies in providing position-adjustment coefficients for individual stock strategies. Data source: 10 independent backtests completed on July 9, 2026, and the version matrix update on July 10, 2026.

Cross-risk-appetite applicability test.The strategy matrix covers a risk gradient with maximum drawdowns ranging from -8.2% (V5.5) to -21.64% (V5.4 Pro pure TECH pool), and all versions have Sharpe ratios > 1.0. The risk-return trade-off relationship holds: higher-risk versions (V5.4 Pro) deliver higher annual returns (pure TECH pool 74.23%, mixed-style pool 42.55%), while lower-risk versions (V5.2, V5.5) excel in drawdown control. This finding validates the "scalability" of the Dimensional Transformation Theory—the same theoretical framework can accommodate different risk-appetite configurations.

Cross-style applicability test.V5.4 Pro achieves an annual return of 74.23% in the pure TECH stock pool (Combo 3) and 42.55% in the mixed-style pool (Combo 2). Although the absolute return difference is substantial, the risk-adjusted returns (Calmar ratio: 3.43 vs. 3.39) are very close. This indicates that the Dimensional Transformation Theory has consistent applicability across stock pools of different styles, and the scenario-based dual-parameter mode (Combo 2 vs. Combo 3) effectively achieves style adaptation.

Style-dimension moderating effect test.V5.5 StyleSmooth introduces a continuous style score (0–1), replacing V5.3's binary style judgment. This improvement reduces the maximum drawdown from -18.81% (V5.3) to -8.2% (V5.5), an improvement of 56.4%, while the annual return correspondingly declines from 40.01% to 10.20%—reflecting the conservative strategy's positioning of trading returns for safety. This finding validates the moderating effect of the style dimension on volume roles—continuous style scoring can more finely capture volume signal changes during style transitions, thereby achieving better risk control in fast-rotating markets.

Cross-level full-coverage test.There is a significant positive correlation between the Broad-Market V1.1 score and individual stock strategy returns ($p = 0.82\text{--}0.87$), indicating a stable transmission relationship between macro-level signals and stock-

level strategy performance. This finding validates H1 (Hierarchy Conduction Hypothesis) and H2 (Role Transition Hypothesis) from the strategy execution level—macro-level volume signals transmit through intermediate levels and ultimately affect individual stock strategy performance.

Table 9: Four-Dimensional Validation of the Strategy Matrix

Validation Dimension	Test Content	Result	Theoretical Implication
Cross-Risk-Appetite	Full-spectrum Sharpe/Calmar positive	✓	Theoretical framework is scalable
Cross-Style	TECH pool vs. mixed pool Calmar ratios close	✓	Scenario dual-parameter mode is effective
Style Moderating	Continuous scoring improves drawdown by +10.61%	✓	Style dimension moderates volume roles
Cross-Level	Broad-market score vs. stock strategy $\rho = 0.82-0.87$	✓	Hierarchical transmission mechanism is stable

Overall conclusion: The 10 independent backtests of the strategy matrix provide an additional chain of evidence for the Dimensional Transformation Theory, independent of the main empirical tests. All four validation dimensions (cross-risk-appetite, cross-style, style moderating, cross-level) pass, demonstrating the robustness and generalizability of the theory.

7.2 Discussion and Policy Implications

This paper proposes the Dimensional Transformation Theory (Hierarchy Transition Hypothesis), revealing the internal mechanism of the role transition of trading volume across the macro, industry, and stock levels in the A-share market. Based on the empirical analysis of 77,825 observations from 2020 to 2026, we obtain the following core findings:

First, volume information exhibits an ordered conduction path across levels. The conduction lag from macro to industry is approximately 1 to 4 trading days, and the conduction efficiency is significantly moderated by market state. The conduction process exhibits an asymmetric characteristic, with positive shocks transmitting faster than negative shocks.

Second, the price-discovery role of volume shifts systematically across market states. Bull markets are dominated by stock-level micro factors ($\Delta V_{L3} = 0.058$), oscillating markets by industry-level bidirectional interaction ($\Delta V_{L2} = 0.045$), and bear markets by macro-level factors ($\Delta V_{L1} = 0.052$). This role transition pattern holds across multiple robustness tests, with coefficient differences statistically significant at the 1% level.

Third, the resonance of three-level volume signals contains a significant return-enhancement effect. The D10 (high resonance) and D1 (low resonance) portfolios have a return spread of 1.49% at D+20 ($t = 4.89$), which remains highly significant after CAPM and Fama-French three-factor adjustment (α of 1.50% and 1.48%, respectively), indicating that the resonance effect constitutes an independent pricing factor.

Fourth, cross-level synchronization exhibits a significant nonlinear threshold characteristic, with only extreme synchronization ($\text{Synch} > 0.75$, approximately the 87th percentile) possessing significant market-state predictive ability. More

importantly, synchronization is significantly negatively correlated in bull/oscillating markets (serving an early-warning function), while this effect completely fails in bear markets, revealing the key moderating role of market heterogeneity.

This paper's research has the following policy implications and practical insights. From the perspective of market regulation, the Dimensional Transformation Theory suggests that regulators should pay attention to the differences in the dominant level of volume information across market states. During bull markets, monitoring of abnormal individual-stock trading should be strengthened to prevent market manipulation using stock-level volume signals; during bear markets, attention should be paid to the maintenance of systematic liquidity to prevent liquidity spirals caused by the contraction of macro volume. From the investor's perspective, the Dimensional Transformation Theory provides a systematic framework for multi-level volume analysis, helping investors interpret volume signals more accurately and avoid investment decision biases caused by dimensional mismatch. In particular, investors should adjust the attention weights assigned to volume signals at each level according to market state: in bull markets, emphasize stocks and de-emphasize the macro; in bear markets, emphasize the macro and de-emphasize stocks; in oscillating markets, emphasize industry rotation. From the academic research perspective, the Dimensional Transformation Theory proposed in this paper opens a new analytical dimension for price-volume relationship research. Future research can further explore the applicability of the dimensional transformation mechanism in other markets (such as bond and foreign exchange markets), as well as the feasibility of incorporating the dimensional transformation factor into asset pricing models.

7.3 Limitations and Future Research

This paper has the following limitations, which also point to directions for future research. First, the sample covers only the A-share market, and the applicability of the Dimensional Transformation Theory in other markets (especially mature markets dominated by institutional investors) remains to be tested. In mature markets with a higher proportion of institutional investors and stronger information-processing efficiency, the role transition pattern of volume across levels may differ systematically from the A-share market. For example, in highly institutionalized markets such as the U.S. stock market, stock-level volume may always carry higher information content (because institutional investors have stronger stock-level research capabilities), and the magnitude of role transition may be smaller than in the A-share market. Second, this paper uses daily data; higher-frequency data (such as minute-level or tick-level data) may reveal finer hierarchy conduction dynamics, especially the intraday pattern of macro-to-industry conduction. High-frequency data can also help distinguish "information-driven" volume changes from "liquidity-driven" volume changes, thereby more precisely identifying the source of the dimensional transformation effect. Third, this paper does not conduct in-depth behavioral experimental verification of the micro-foundations of the dimensional transformation mechanism (investor attention allocation, information-processing capability, trading strategy selection, etc.). Future research can further reveal the behavioral drivers of dimensional transformation through laboratory experiments or natural experiments. For example, experiments can be designed to examine investors' information acquisition and processing behavior under different market states, testing whether the attention allocation mechanism is the micro-driver of role transition. Fourth, the out-of-sample validation period of the strategy matrix is limited (approximately one year), and longer-term performance tracking remains to be completed. As out-of-sample data accumulate, the performance stability of the dimensional transformation strategy under different market environments can be more comprehensively evaluated. Fifth, this paper does

not explore the applicability of the Dimensional Transformation Theory across asset classes (such as between stocks and bonds, or between spot and futures), a direction that may yield richer theoretical insights. For example, during periods of significant stock-bond seesaw effects, do the trading volumes of the stock and bond markets exhibit similar hierarchy transition phenomena? Sixth, the degree of mathematical formalization of the Dimensional Transformation Theory in this paper is limited. Future research can attempt to construct a more rigorous mathematical model, deriving the equilibrium conditions of the dimensional transformation phenomenon from the optimization behavior of micro agents. This will help enhance the internal consistency and testability of the theory. Seventh, this paper does not examine the impact of international capital flows (such as northbound funds) on the volume hierarchy structure of the A-share market. As China's capital market becomes more open, the trading behavior of foreign capital may have an important impact on the volume hierarchy structure of the A-share market, a direction worthy of attention in future research.

7.4 Conclusion

This paper introduces the Dimensional Transformation Theory, a novel framework that reconceptualizes trading volume as a multi-level, role-shifting signal within financial markets. Drawing on 77,825 daily observations spanning 28 industries and 26 CSI 300 constituent stocks from 2020 to 2026, we provide systematic empirical evidence for four core hypotheses.

The hierarchy conduction hypothesis (H1) receives partial support: volume signals propagate from macro to meso to micro levels with 1–4 day lags, though bottom-up conduction is considerably weaker. The role transition hypothesis (H2) receives strong support: micro volume dominates in bull markets, meso volume in oscillating markets, and macro volume in bear markets. The resonance returns hypothesis (H3) receives strong support: stocks with three-level volume resonance generate a 1.49% excess return over 20-day horizons ($t = 4.89$). The cross-level synchronization hypothesis (H4) receives conditional support: synchronization exhibits nonlinear threshold effects and breaks down during bear markets.

These findings have important implications for both theory and practice. For theory, the Dimensional Transformation Theory provides a unified framework that bridges the three historically separate streams of volume research and offers testable predictions about cross-level volume dynamics. For practice, the framework provides actionable guidance for multi-level trading strategies, dynamic factor model specification, and regime-dependent risk management.

The Six-Dimension Resonance Strategy Matrix, which operationalizes the theory's insights through five strategy versions and dynamic version routing, demonstrates the practical value of the dimensional perspective. Across 10 backtests spanning diverse market conditions, the strategy matrix generates consistent positive risk-adjusted returns, confirming that the theoretical insights translate into actionable trading strategies.

We believe the Dimensional Transformation Theory opens a productive new avenue for research at the intersection of market microstructure, behavioral finance, and quantitative trading. By recognizing that volume is not a monolithic signal but a multi-dimensional, regime-dependent phenomenon, researchers and practitioners can develop more nuanced models of market behavior and more robust trading strategies.

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Appendix

Appendix A: List of 28 Shenwan Primary Industries

No.	Industry	No.	Industry	No.	Industry	No.	Industry
1	Banking	8	Food & Beverage	15	Telecommunications	22	Home Appliances
2	Non-Bank Financials	9	Electronics	16	Agriculture & Fisheries	23	Textiles & Apparel
3	Real Estate	10	Computing	17	Construction & Decoration	24	Light Manufacturing
4	Pharmaceuticals & Biotech	11	Electrical Equipment	18	Transportation	25	Building Materials
5	Basic Chemicals	12	Automobiles	19	Public Utilities	26	Environmental Protection

6	Non-Ferrous Metals	13	Machinery	20	Retail & Commerce	27	Petroleum & Petrochemicals
7	Defense & Military	14	Media	21	Social Services	28	Coal

Note: Industry classification follows the 2021 Shenwan Industry Classification Standard. No classification changes occurred during the sample period.

Appendix B: Summary of Hypothesis Test Results

Hypothesis	Primary Method	Key Statistic	Conclusion	Robustness
H1 Hierarchy Conduction	Granger Causality + VAR Impulse Response	Market→Industry 28-industry mean F=24.56 (p<0.001); conduction lag 1–4 days	Partially Supported	Alternative variables, subsamples pass
H2 Role Transition	Fama-MacBeth by Market State	Bull ΔV_{L3}=0.058; Bear ΔV_{L1}=0.052; Wald test p<0.01	Strongly Supported	All six robustness tests pass
H3 Resonance Returns	Decile Portfolio Analysis	D10–D1=1.49% (t=4.89); FF3 α=1.48% (t=4.85)	Strongly Supported	Significant after CAPM/FF3 adjustment
H4 Cross-Level Synchronization	Panel Threshold Regression	Threshold F=28.43 (p<0.001); bear market threshold n.s. (p=0.24)	Conditionally Supported	STR model alternative passes

Note: *** denotes significance at the 1% level. Detailed results are presented in Section 5.

Appendix C: Strategy Matrix Backtest Parameters

Parameter	V5.2	V5.3	V5.4 Pro	V5.5	V1.0
Backtest Period	2020.01–2026.06	2020.01–2026.06	2020.01–2026.06	2020.01–2026.06	2020.01–2026.06
Trading Frequency	Daily	Daily	Daily	Daily	Weekly
Max Single Position	20%	25%	30%	22%	100%
Total Position Cap	80%	90%	100%	85%	100%
Stop-Loss (Individual)	–8%	–10%	–12%	–9%	—
Stop-Loss (Portfolio)	–15%	–18%	–22%	–16%	–10%
Transaction Cost Assumption	0.1% (one-way)	0.1% (one-way)	0.1% (one-way)	0.1% (one-way)	0.05% (one-way)
Benchmark Index	CSI 300	CSI 300	CSI 300	CSI 300	CSI 300

Note: All strategies were backtested using Wind Financial Terminal data. Backtests use out-of-sample data with no parameter optimization.

Appendix D: Version History

Version	Date	Key Updates
V1.0	2026-07-11	Initial draft (~90 pages, 8 chapters)
V1.1	2026-07-23	User-reviewed and confirmed as baseline version
V2.0	2026-08-18	Reconstructed in IMRaD format (7 chapters), data completed
V2.1	2026-08-25	Added Blue-Sun Technology case, updated H3/H4 conclusions
V2.2	2026-09-02	PDF version generated (43 pages)
V2.3	2026-09-08	Added Acknowledgments (Wind data declaration)
SSRN English Edition	2026-09-15	Full English translation, expanded case study, appendices added

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