

Asset Characteristics and Volume-Price Dynamics: Cointegration and Causality Analysis of Cyclical Versus Consumer Core Assets

Jinghan Chang

*Paul H. Nitze School of Advanced International Studies (SAIS), Johns Hopkins University,
Washington, USA
jchan155@jh.edu*

Abstract. The classic debate over the dynamic relationship between trading volume and asset prices centers on the Sequential Information Arrival Hypothesis (SIAH) and the Mixture of Distributions Hypothesis (MDH). Existing literature generally aggregates all asset categories into a single analysis, which obscures heterogeneous pricing mechanisms across industries. To fill this gap, this paper examines the heterogeneous volume-price dynamics between strong-cycle assets and weak-cycle core consumer assets in China's A-share market. Using weekly trading data of China Shenhua (601088.SH) and Kweichow Moutai (600519.SH) from 2018 to 2025, this study investigates the long-run equilibrium and short-run causal linkages between stock returns and trading volume via the ADF test, Johansen cointegration test, vector error correction model (VECM), and Granger causality test. It also evaluates whether the well-known Wall Street adage "volume trumps price" holds universally across asset classes. The empirical results reveal significant structural differences between the two assets: the weekly error correction speed of the VECM is 28.36% for China Shenhua and 50.17% for Kweichow Moutai. Specifically, China Shenhua exhibits a long-run cointegration relationship but no significant short-run causality, consistent with macro fundamental anchoring. In contrast, Kweichow Moutai shows a pronounced "price leads volume" causal pattern, which can be explained by liquidity premiums and institutional herding behavior. These findings highlight the necessity of incorporating asset characteristics into market microstructure analysis and provide targeted strategic guidance for investors across different economic cycles.

Keywords: Turnover-return dynamics, Cointegration, Granger causality, Cyclical assets, Consumer stocks

1. Introduction

The relationship between trading volume and asset prices remains one of the most fundamental yet contentious topics in financial market microstructure research [1]. Although the classic Wall Street maxim holds that "it takes volume to move prices", empirical studies across broad market indices have yielded highly inconsistent findings. Some research supports the Sequential Information

Arrival Hypothesis (SIAH), while others align with the Mixture of Distributions Hypothesis (MDH) [2]. Specifically, proponents of SIAH argue that information disseminates sequentially across market participants, generating predictable lead-lag patterns. By contrast, advocates of MDH contend that a latent common factor drives both volume and price simultaneously, producing only contemporaneous correlation rather than predictive causal linkages [3].

A key limitation of extant literature is its tendency to pool diverse assets together, which masks the heterogeneous pricing mechanisms inherent to specific industries. In particular, it remains unclear whether assets driven by global macroeconomic cycles (e.g., strong-cycle stocks) and those driven by institutional liquidity premiums (e.g., defensive consumer staples) exhibit identical volume-price dynamics.

This study addresses this core question by examining the distinct cointegration and causal patterns across these two fundamentally different asset types. This paper conducts a comparative empirical analysis of this structural heterogeneity using weekly data from China's A-share market, with China Shenhua as a representative cyclical asset and Kweichow Moutai as a benchmark consumer core asset. The empirical framework combines the Augmented Dickey-Fuller (ADF) test, Johansen cointegration test, vector error correction model (VECM), and Granger causality test to characterize long-run equilibrium and short-run lead-lag relationships. Theoretically, this study extends the scope of classic market microstructure models by demonstrating how volume-price causality manifests differently across asset types—either as a significant "price leads volume" pattern or as the complete absence of sequential causality [4]. Practically, the findings deliver granular, industry-specific insights for market participants, supporting more informed investment decision-making across varying economic cycles.

2. Literature review

2.1. Sequential Information Arrival Hypothesis (SIAH)

The Sequential Information Arrival Hypothesis (SIAH) was originally proposed to provide a basic framework for understanding the lead-lag causal relationship in financial markets [2]. SIAH believes that new information is not disseminated simultaneously to all market participants, but reaches investors in a sequential manner. Therefore, as information flows in the market, sequential trading reactions will generate a series of transitional price balances [2]. This theoretical mechanism naturally allows for the existence of sequential causality, and the predicted lagging trading volume may contain predictive information about the current stock returns, and vice versa [2]. Later empirical extensions further demonstrated how sequential information flow induces structural lead-lag patterns in equity trading [5]. Therefore, SIAH provides a theoretical framework explaining the sequential lead-lag relationships between trading volume and stock returns.

2.2. Mixed distribution hypothesis (MDH)

On the contrary, the mixed distribution hypothesis (MDH) questions the sequential causality [6]. MDH believes that price fluctuations and trading volume are jointly driven by an unobservable potential common variable, usually the rate at which new information flows into the market [6]. Because these two variables react to news in the same period, MDH is the same as correlation, but not a lead-lag relationship with predictive power [7]. In this stringent context, historical trading volume should not be able to predict future price movements, which, in theory, diminishes the power of technical analysis using trading volume indicators. Later elaborations of MDH added the arrival

rates of news to account for the joint probability distribution of price changes and volume [8]. The basic distinction between the two hypotheses is the speed and the time dimension of the diffusion of information: whereas SIAH suggests sequential price discovery, with lead-lag causality, MDH suggests immediate joint price adjustment, with contemporaneous correlation.

2.3. Limitations and marginal contributions of existing empirical research

There have been numerous studies on SIAH and MDH, but the empirical findings are very divergent and unclear [1]. The major drawbacks of the previous works lie in over-focusing on the overall macro-market indices (e.g., S&P 500 or Shanghai-Shenzhen 300), which inevitably weakens the microstructure noise of each industry and also weakens the unique pricing anchor of the same asset class. In particular, the literature is missing a comparative approach in order to distinguish between assets that are fundamental and assets that are liquidity-driven. Therefore, the academic marginal contribution of this article is to prove that the applicability of SIAH or MDH is not universal. This study empirically demonstrates that the volume-price transmission mechanism varies based on the characteristics of the asset using a comparison between strong cyclical assets and defensive consumer assets. In order to fill this research gap, this paper chooses two typical A-share stocks to construct comparative cointegration and causality tests.

3. Data and methodology

3.1. Sample selection and weekly data processing

This study selects two representative leading stocks in China's A-share market to illustrate the differences between different asset classes: China Shenhua (601088.SH) is used as an agent variable for strong cyclical assets, while Kweichow Moutai (600519.SH) is chosen as a representative of core defensive consumption assets. This sample selection is mainly based on the different pricing mechanisms of these two asset classes. The valuation performance of China Shenhua is highly correlated with the global macroeconomic cycle and commodity prices, and its stock price fluctuations are more influenced by changes in coal market supply and demand and industrial cycles. In contrast, Kweichow Moutai, with its high brand premium, has unique core asset attributes in the A-share market and has gradually become an important liquidity allocation object for institutional investors. Therefore, there are significant differences in fundamental driving factors and investor structures between the two—specifically, China Shenhua's investor base is dominated by state-owned, industrial, and value-oriented capital focusing on cyclical fundamentals, whereas Kweichow Moutai is heavily held by active mutual funds, foreign institutional capital (e.g., Northbound capital), and core-asset growth funds seeking liquidity premiums. This distinction provides a good comparative basis for studying the volume-price transmission mechanism under different asset classes.

3.2. Econometric model construction

This empirical study covers the period from January 2018 to the beginning of 2025. To reduce the microstructure noise in intraday trading, this paper converts the daily closing prices and trading volume data into weekly frequency data. Among them, the explained variable is the logarithmic weekly return rate $R_t = \Delta \ln P_t$, and the explanatory variable is the logarithmic turnover rate $V_t = \ln \text{Turn}_t$. Furthermore, for the small number of missing values in the data, this paper

employs the linear interpolation method (ipolate) for processing, in order to ensure the continuity of the time series and meet the requirements of subsequent VAR modelling for complete time series data.

3.3. Augmented Dickey-Fuller (ADF) stationarity test

To avoid the occurrence of spurious regression problems, it is necessary to determine the order of integration of the time series variables first. This paper uses the ADF test to test the stationarity of each variable. Considering that the series may have both intercept terms and linear time trends, this paper sets an ADF model that includes the constant term and the linear time trend, and the specific form is as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-i} + \varepsilon_t \quad (1)$$

where y_t represents the asset series (R_t or V_t), and p is the lag length. The null hypothesis is that there is a unit root, that is:

$$[H_0 : \gamma = 0] \quad (2)$$

If a variable reaches a stationary state after being subjected to first-order differencing, then this variable is classified as an $I(1)$ sequence. Since the establishment of the cointegration relationship requires that the variables have the same order of integration, $I(1)$ is a strict prerequisite for conducting the cointegration test.

3.4. Johansen cointegration test

For $I(1)$ variables that have reached stationarity after first-order differencing, this paper further employs the Johansen maximum likelihood method to test whether there is a long-term equilibrium relationship among the variables. This method is based on the vector autoregression (VAR) framework and determines the existence of long-term stable relationships by analyzing the cointegration rank among the variables.

Specifically, the VAR model can be expressed as:

$$\Delta Y_t = \alpha (\beta' Y_{t-1}) + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

Here, the error correction term $ECT_{t-1} = \beta' Y_{t-1}$ measures the deviation from the long-term equilibrium, while the coefficient α acts as a self-correction mechanism, indicating the speed at which the system returns to the equilibrium state.

3.5. Vector error correction model (VECM)

When it is confirmed that there is a cointegration relationship (that is, Π has a reduced rank of $0 < r < n$), it can be decomposed as $\Pi = \alpha\beta'$. Subsequently, the VECM is estimated to capture the short-term dynamics and adjustment speed:

$$R_t = c_1 + \sum_{i=1}^p \phi_i R_{t-i} + \sum_{i=1}^p \theta_i V_{t-i} + u_{1t} \quad (4)$$

$$V_t = c_2 + \sum_{i=1}^p \lambda_i V_{t-i} + \sum_{i=1}^p \omega_i R_{t-i} + u_{2t} \quad (5)$$

To test whether volume Granger-causes returns, the null hypothesis $H_0 : \theta_i = 0$ for all i is examined using a chi-square (χ^2) statistic. Rejecting H_0 implies a "volume leads price" mechanism.

4. Empirical results

4.1. Stationarity test and lag selection

Before analyzing the relationship between price and volume, it is necessary to test the stationarity of the time series to prevent spurious regression [1]. The Augmented Dickey-Fuller (ADF) test indicates that the level series of the logarithmic closing prices and the logarithmic turnover rates of China Shenhua and Kweichow Moutai are all non-stationary. However, after performing the first-order difference, the absolute value of the ADF test statistic exceeds the strict critical value of 1% and the p value is 0.0000. As shown in Table 1, this confirms that all variables are integrated of order one, $I(1)$, meeting the prerequisite conditions for cointegration analysis.

Table 1. Augmented Dickey-Fuller (ADF) unit root test results

Variables	Test Statistic	1% Critical Value	5% Critical Value	MacKinnon p-value	Conclusion
$\Delta \ln(\text{Close})$ - Shenhua	-16.630***	-3.447	-2.874	0.0000	Stationary, $I(1)$
$\Delta \ln(\text{Turnover})$ - Shenhua	-17.432***	-3.465	-2.883	0.0000	Stationary, $I(1)$
$\Delta \ln(\text{Close})$ - Moutai	-20.865***	-3.448	-2.874	0.0000	Stationary, $I(1)$
$\Delta \ln(\text{Turnover})$ - Moutai	-15.242***	-3.447	-2.874	0.0000	Stationary, $I(1)$

Note: *** denotes statistical significance at the 1% level.

4.2. Comparison of long-term cointegration

In order to study the long-term equilibrium between stock yield and trading volume, we conducted the Johansen trace test (Table 2). The empirical findings indicate that at the long-term level there are considerable similarities in structure. Whether it is a strong cyclical Chinese Shenhua or a weak cyclical consumer Kweichow Moutai, their trace statistics significantly reject the zero hypothesis of no co-integration at a critical value of 5% (the trace statistics when $r=0$ are respectively 48.225 and 82.066, both of which are greater than 15.41). It can be seen that the long-term binding force of price and trading volume of Kweichow Moutai is far greater than that of China Shenhua, as its larger trace statistic shows that it has a stronger and tighter long-term equilibrium binding force. Economically, this means that Moutai, a high-concentration institutional core asset, is more tightly connected with its price discovery and turnover in the long run by continuous institutional liquidity

allocation and valuation re-anchoring. While both assets have long-term equilibrium, this is not a direct confirmation of MDH. Rather, it gives evidence of the long-run market relationship between price and volume [6].

Table 2. Johansen cointegration test (trace statistic)

Asset	Null Hypothesis	Trace Statistic	5% Critical Value	Conclusion
China Shenhua	$r = 0$	48.2253	15.41	Reject H0
	$r \leq 1$	0.0166*	3.76	Accept H0
Kweichow Moutai	$r = 0$	82.0665	15.41	Reject H0
	$r \leq 1$	2.9591*	3.76	Accept H0

Note: * indicates the selected cointegration rank based on the trace statistic at 5% significance level.

4.3. VECM error correction mechanism analysis

We estimated the VECM (vector error correction model) and analyzed the speed of the adjustment of the system to short-term shocks, due to identification of the co-integration vector (Table 3). The adjustment speed is amazing! In these two types of assets, the Error Correction Term (ECT, α) in the turnover rate equation is highly significant ($p < 0.01$), but the ECT coefficient in the price equation is statistically insignificant. This shows that when the system deviates from equilibrium, price does not adjust to trading volume, rather, trading volume actively adjusts to eliminate deviations and restore long-term equilibrium. In particular, Moutai's ECT coefficient is -0.5017, that is, the speed of adjustment of the weekly rate is as fast as 50.17% to the long-term equilibrium. On the contrary, the adjustment speed of Shenhua is quite slow, 28.36%. The difference indicates that consumer core assets are far more liquidity sensitive than the former because institutional investors will readily move in response to the pricing signals [8].

Table 3. VECM Error Correction Term (ECT) estimation result

Asset	Dependent Variable	ECT Coefficient (α)	Std. Err.	P-value	Adjustment Speed
China Shenhua	$\Delta \ln(\text{Turnover})$	-0.2836***	0.0402	0.000	28.36% / week
	$\Delta \ln(\text{Close})$	-0.0009	0.0039	0.818	Insignificant
Kweichow Moutai	$\Delta \ln(\text{Turnover})$	-0.5017***	0.0541	0.000	50.17% / week
	$\Delta \ln(\text{Close})$	-0.0017	0.0062	0.781	Insignificant

Note: *** denotes statistical significance at the 1% level.

4.4. Granger causality contrast analysis

Both are coherent in the long term, but the difference between the two in the dynamics of short-term microstructure is evident in the Granger causality test (Table 4). Kweichow Moutai case stock returns are highly Granger-causative of the turnover rate ($\chi^2=7.504, p=0.006$), while the trading volume is not Granger-causative of the stock returns. This finding is consistent with the "Price leads Volume" mechanism that is well developed in the short term and corresponds very well with the theoretical expectations of the SIAH hypothesis. This hypothesis suggests that institutional investors will trade serially according to the price trend, which means that the price signal should be created first, and then the trading behavior of institutional investors should be triggered [2]. From an economic point of view, this "Price leads Volume" mechanism means that rising prices of core consumer assets create a bullish consensus among institutional investors, which attracts further trend-following investments and market attention and causes turnover rates to rise and a "Price-driven trading volume" trend to be formed on the market. In contrast, China Shenhua did not exhibit any significant short-term Granger causality relationship. The effects of price on trading volume and of trading volume on price were not significant ($p > 0.10$). This difference in structure is also evidence that the nature of the assets themselves and the liquidity condition are important in the information transmission mechanism between quantity and price [9]. In other words, the different characteristics of investors' structure, market attention, and information response speed in different categories of assets will create separate volume and price transmission mechanisms.

Table 4. Granger causality wald tests results

Asset	Null Hypothesis	χ^2 Statistic	p- value	Causality Direction
China Shenhua	Return does not Granger cause Turnover	0.492	0.483	None
	Turnover does not Granger cause Return	0.006	0.938	None
Kweichow Moutai	Return does not Granger cause Turnover	7.504***	0.006	Return → Turnover
	Turnover does not Granger cause Return	0.508	0.476	None

Note: *** denotes statistical significance at the 1% level.

5. Discussion and economic implications

5.1. Macro-fundamental anchoring effect: why Shenhua fits the slower adjustment model

The differences in the empirical results of the two types of assets can be essentially explained by the underlying economic anchoring factors. China Shenhua is a typical cyclical asset, whose value performance is largely related to global macroeconomics, particularly coal prices and the change of industrial cycles. In the case of these cyclical stocks, the speed of macroeconomic information diffusion across market participants is relatively slow, and there is strong symmetry of information diffusion. It is not surprising because the Mixed Distribution Hypothesis (MDH) implies that

changes in prices and trading volumes are simultaneous and the potential information flows are the factors that drive both the volume and the price changes, thus, there is no clear evidence about any short-term leading/lagging relationship between the volume and the price changes [10]. Thus, China Shenhua was not significantly short-term Granger causal, and the speed of adjustment of its VECM model was relatively moderate (28.36%). Typically, for cyclical asset investors, investment decisions are based more on long-term fundamental value judgments than on short-term market microstructure noise. As such, the trading behavior of Shenhua is more representative of the macro-induced gradual adjustment feature.

5.2. Liquidity premium and institutional herd behavior

In contrast, Kweichow Moutai is more like an important liquidity allocation pool for institutional investors as a representative consumption core asset in the A-share market. It is notable that it exhibits a "Price leads Volume" mechanism ($p = 0.006$) and a high VECM adjustment speed (50.17%), which fully demonstrates the characteristics of herd behavior of institutional investors. Institutional funds seem to make rapid adjustments to their asset allocation, and continuous trading behavior brings about rapid changes in trading volume in response to new pricing signals or liquidity shocks in the market, leading to a situation in which volume changes lag price changes [8]. This dynamic process is in line with the theoretical prediction of the Sequential Information Arrival Hypothesis (SIAH) [5]. In the consumer sector, the price change is not only the signal of change in information, but also an important signal for institutional trading. So the short-term price volume correlation of Kweichow Moutai is more affected by the liquidity premiums and the consensus of institutional funds, which can be said to indicate that the micro-structural characteristics of core assets in the capital market affect the short-term price volume correlation [11].

6. Conclusion

Based on the weekly data from 2018 to 2025, this paper compares two different asset classes, namely China Shenhua (a cyclical stock) and Kweichow Moutai (a core consumer asset), to study the heterogeneity of the dynamic relationship between the quantities and prices of different asset categories. Through methods such as Johansen cointegration test, VECM, and Granger causality test, the study found that although both asset classes have a long-term cointegration relationship, there are significant differences in their short-term microstructural transmission mechanisms.

Specifically, China Shenhua features a moderate error correction speed and no significant short-run causality, reflecting its characteristic of being anchored by macroeconomic fundamentals. By contrast, Kweichow Moutai shows a faster adjustment speed and a significant "price leads volume" causal relationship, indicating that institutional investor behavior and liquidity factors exert a pronounced influence on its short-run price-volume interaction. This study further expands the applicability of classic SIAH and MDH theories, demonstrating that the volume-price relationship is not determined by a single mechanism, but is shaped by multiple factors including asset attributes, investor structure, and market conditions.

This study has certain limitations that point to future research directions. First, the sample is limited to two representative individual stocks, future work could extend the empirical framework to broader sector-level panel datasets or additional asset classes. Second, while weekly frequency helps reduce intraday microstructure noise, subsequent research could leverage high-frequency tick data to explore intraday transmission dynamics in greater depth.

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