INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ECONOMICS & MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 15, Issue 1, (2026) E-ISSN: 2226-3624

Macroeconomic Regimes, Liquidity, and Volatility in Barra-Style Factor Returns: Evidence from China's A-Share Market

Weiwei*

School of Management, University Sains Malaysia, 11800, Penang, Malaysia

*Corresponding Author Email: John4education2025@gmail.com

MD Aslam Mia

School of Management, University Sains Malaysia, 11800, Penang, Malaysia

Email: aslammia@usm.my

DOI Link: http://dx.doi.org/10.6007/IJAREMS/v15-i1/27924

Published Online: 15 March 2026

Abstract

The dynamics of China's A-share market are shaped by both macroeconomic fluctuations and the unique characteristics of its institutional environment. This study investigates how short-term business cycles impact the returns of Barra Style Factors (BSF) through key macro-financial channels, including global capital market liquidity, volatility, and multi-market linkages. Using daily data from 2019 to 2024, we employ a time-varying vector autoregression (TVP-VAR) model and rolling window Granger causality tests to capture the evolving relationships between macroeconomic variables and market factors. The results demonstrate that economic growth and inflation primarily affect factor returns indirectly, via liquidity dynamics and volatility-driven revaluation, while capital flows exhibit asymmetric mediating effects due to China's partially open capital account. Specifically, liquidity expansion during growth phases strengthens momentum and size factors, while liquidity contraction during inflationary periods suppresses leverage and value factors. Volatility transmits macroeconomic uncertainty, increasing the risk premium on residual volatility, and cross-border flows further amplify the cyclical fluctuations of large-cap stock portfolios. These findings underscore the periodicity of factors rooted in the financial microstructure of China's market, revealing unique macro-financial linkages in comparison to mature economies. The study provides theoretical insights into the transmission of macroeconomic shocks and practical guidance for cyclical style allocation in China's policy-driven market.

Keywords: Style-factor Investment, Macroeconomic, Barra-Style Factors, Stock Investment, Trading Strategy

Introduction

The COVID-19 pandemic has significantly amplified the volatility of global financial markets. This instability has been further exacerbated by a confluence of external shocks—including fluctuations in international energy prices, domestic carbon policy reforms, Sino-US

semiconductor sanctions, the Russia–Ukraine conflict, and China's Evergrande crisis (Bai, Wei et al. 2021, Gu, Zhang et al. 2021, Altman, Hu et al. 2022, Deev, Lyócsa et al. 2022, Izzeldin, Muradoğlu et al. 2023, Wang and Fang 2023). Within this global context, China's A-share market—already recognized as one of the most volatile in the world—experienced marked underperformance in 2023, despite sustained government fiscal stimuli and industrial support measures (Wang 2010, Huang, Miao et al. 2019). (Huang et al., 2019; Wang, 2010). This stands in sharp contrast to the post-pandemic recovery seen in many major global markets (Sharma and Kumar 2023), raising critical questions about the underlying causes of this divergence.

Traditional factor models often fail to fully capture the distinct characteristics of emerging markets, which are shaped by institutional frameworks, regulatory interventions, and behavioral anomalies (Jansen, Swinkels et al. 2021). In the case of China, several style factors have weakened in the wake of post-COVID policy transitions, despite exhibiting periodic behavior similar to those in Western markets (Song, Hao et al. 2021). This phenomenon highlights the need to better understand how macro-financial variables influence style factor returns within China's policy-driven market environment.

Empirical evidence highlights the A-share market's underperformance: as shown in Figure 1.1, between 2020 and 2024, mainland Chinese and Hong Kong stock markets lagged behind major global indices, consistently ranking among the lowest in cumulative logarithmic returns (Kawase 2023, Reuters 2023, Kongkunakornkul 2024, Finance 2025.2). Figure 1.1 further reveals that most sectors in the Chinese A-share market recorded negative returns from 2021 to 2024, based on industry classification data from the Wind database. Although a modest rebound was observed in certain industries during the 2023–2024 period, this short-term recovery has not altered the broader structural weaknesses that continue to characterize China's equity market in the medium to long term.

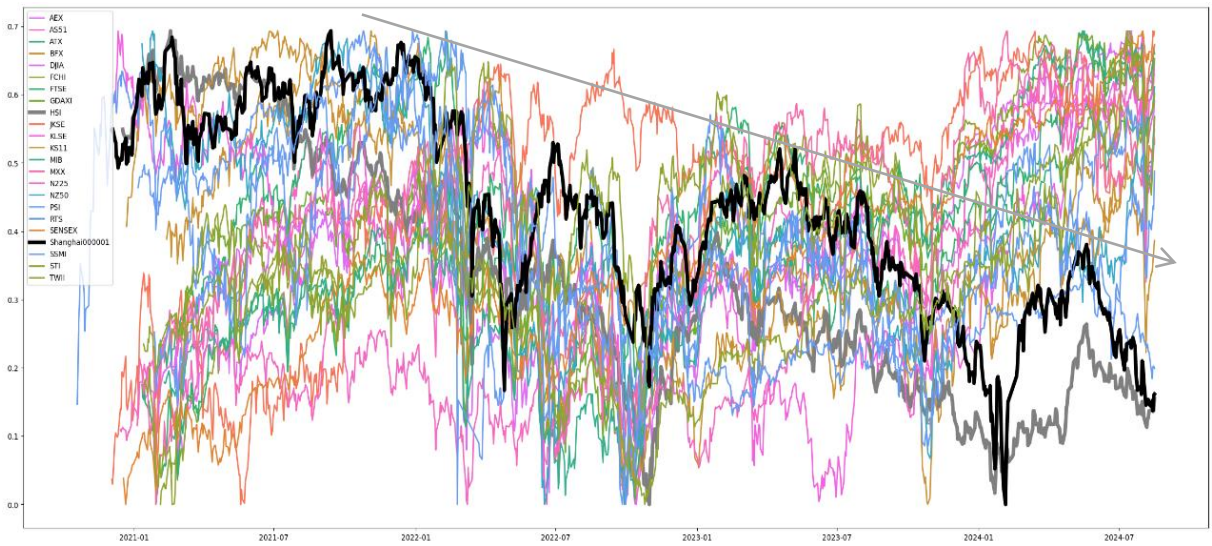


Figure **Error! No text of specified style in document.**.1 Cumulative Log Returns of Major Global Indices Over the Past Five Years

In this environment, where short-selling mechanisms remain underdeveloped and structural inefficiencies persist, profit opportunities are sparse and typically short-lived. Investors must

rely on capturing intermittent rebounds and sectoral rotations rather than adopting long-term holding strategies. The market is heavily dominated by retail participants, whose investment behaviors are often characterized by herding, overreaction, and sentiment-driven decision-making (Wang, Dong et al. , Hii, Li et al. 2023). The persistent underperformance of China's stock market in recent years has fueled growing skepticism among global investors(Kawase 2023, Reuters 2023). This situation highlights the urgent need for advanced and adaptive investment frameworks capable of navigating regime shifts and market volatility. Quantitative, factor-based investing, particularly when enhanced by dynamic adjustments and real-time signals, presents a promising path forward (Barberis and Shleifer 2003, Zhang, Hopkins et al. 2009, Luo 2017, Kimura, Schwaiger et al. 2021, Ang 2023).

Against this context, this study focuses on a core question: How do short-term macroeconomic fluctuations affect the returns of Barra Style Factors (BSF) through market intermediary variables (liquidity, volatility, capital flows)? Using daily data from China's A-share market spanning 2019 to 2024, the study employs principal component dimensionality reduction to extract short-term macro signals (PCI) and uses a TVP-VAR (Time-Varying Parameter Vector Autoregression) framework to estimate time-varying impulse responses. The analysis proceeds in three steps: first, measuring the impact of macro shocks on intermediary variables; second, assessing the impact of intermediary variables on factor returns; and third, quantitatively decomposing "direct effects" and "indirect effects (via intermediaries)" using path decomposition. Rolling window Granger causality tests and sub-sample robustness tests (covering pre-pandemic, pandemic, and post-pandemic periods) are also conducted.

Preliminary empirical results highlight three key findings: liquidity emerges as the most critical intermediary, amplifying the positive impact of macroeconomic expansion on the Size and Liquidity factors; volatility primarily amplifies downward pressure on Value and Residual Volatility factors during negative shocks; and capital flows exert a limited overall effect but become significant during periods of active foreign investment. The study also emphasizes how A-share market microstructure—including its high retail investor proportion, stop-loss mechanisms, and margin trading rules—alters intermediary transmission paths, ultimately proposing a "macro-liquidity signal-driven" style rotation strategy and corresponding policy implications.

In China's equity market, the Barra factor system—particularly the Barra China Equity Model (CNE5)—is widely recognized as authoritative, especially among domestic fund managers(Bass, Gladstone et al. 2017, Dimson, Marsh et al. 2017, Bergeron, Kritzman et al. 2018). This study adopts the CNE5 model, which includes ten core style factors (Size, Beta, Momentum, Residual Volatility, Non-Linear Size, Book-to-Price, Liquidity, Earning Yield, Growth, and Leverage) commonly used by Chinese institutional investors and asset managers (Cai 2022).

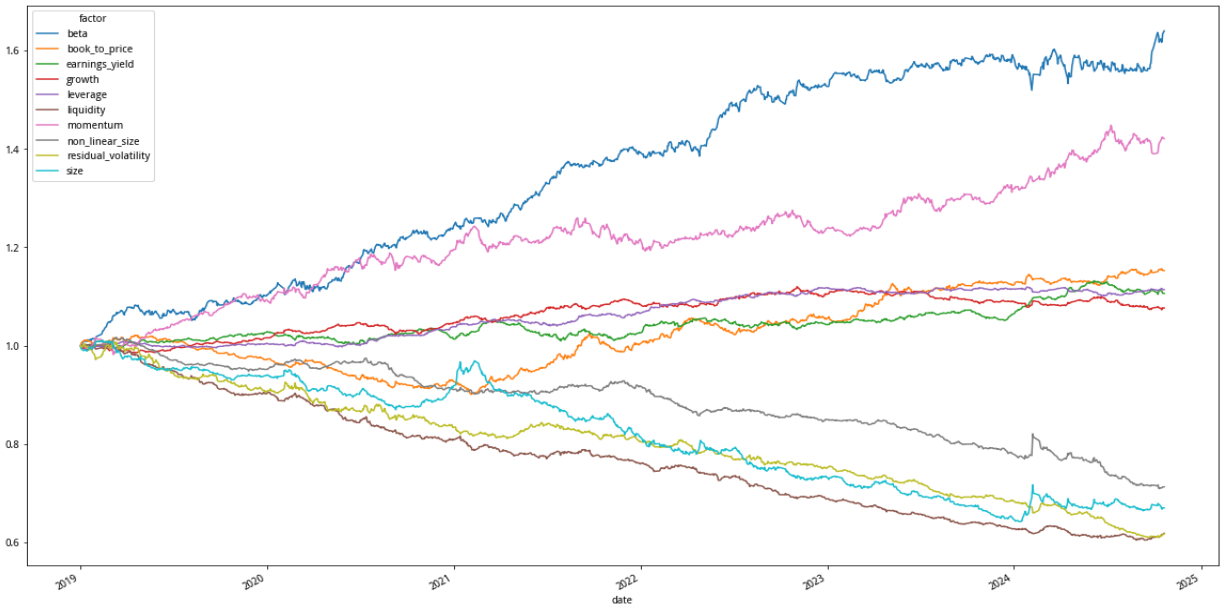


Figure **Error! No text of specified style in document.**.2 Differentiation of Style Factor Returns Since 2019

Figure 1.2 illustrates the cumulative return trajectories of selected CNE5 factors since 2019, revealing that previously dominant factors have underperformed while others have shown resilience or reversed trends—a divergence that poses a major challenge for quantitative investors seeking to adapt to dynamic factor performance

Literature Review

Since the global financial crisis, factor investment has become the core theoretical framework for asset pricing and portfolio management. Its development is attributed to the increasing evidence that systematic return drivers persist beyond market factors. The early theoretical basis originated from the Capital Asset Pricing Model (Sharpe 1964) and the Arbitrage Pricing Theory(Rosenberg and Marathe 1976), which prompted the multi-factor representation of expected returns. Empirical models such as the Fama-French Three-Factor Model(Fama and French 1993) and the Carhart Four-Factor Model(Carhart 1997) demonstrated that size, value, and momentum could explain the return patterns that the Capital Asset Pricing Model could not. Subsequent research also revealed other style premiums such as profitability, investment, and low volatility(Ang, Hodrick et al. 2006, Hou, Xue et al. 2015). The development of factor-based exchange-traded funds and intelligent index products has further institutionalized factor investment in the global market(Asness, Moskowitz et al. 2013).

In China's stock market, factor effects are also well documented in the literature. Pástor and Stambaugh (2003), and Liu, Stambaugh et al. (2019) found that there are size effects and value premiums in the A-share market; while Santra, Hsieh et al. (2021) reported momentum effects and quality effects comparable to those in developed markets. However, Chinese factor performance is more sensitive to policy and liquidity cycles, and existing studies mainly rely on low-frequency macro indicators, which may fail to capture rapid policy-driven market adjustments.

Institutional asset management companies typically achieve factor allocation of assets through proprietary multi-factor risk models. The Barra model decomposes stock returns into market, industry, and style components and constructs factor portfolios that are approximately orthogonal to facilitate risk attribution and portfolio optimization(Grinold and Kahn 2000). For China, the MSCI CNE5 model includes national, industry, and ten style factors, including size, value, momentum, and liquidity(MSCI 2012, Cai 2022).These models provide a natural framework for analyzing the daily factor returns in the A-share market.

China's policy-driven environment implies that low-frequency macro data may lag real-time conditions. Money-market rates reflect monetary policy stance more promptly(He and Wang 2012). Similarly, electricity consumption and rail freight volumes have been widely used as high-frequency proxies for real activity in China, providing more timely signals than official macro releases(Fernald, Hsu et al. 2021). These findings suggest that high-frequency macro-financial variables may help explain short-horizon factor fluctuations, yet this channel remains underexplored.

To link macro shocks with factor dynamics, previous studies emphasized three key transmission channels. First, liquidity conditions affect expected returns, that is, stocks with poor liquidity receive higher premiums(Amihud 2002, Pástor and Stambaugh 2003). Second, volatility patterns affect factor returns, that is, stocks with low volatility perform better in periods of high market uncertainty(Ang, Hodrick et al. 2006). Thirdly, capital flows reflect the sentiments and constraints of investors, especially in markets with partial capital controls, such as China(Liao, Tang et al. 2024). Based on these insights, this study explores whether high-frequency macro and market intermediation indicators jointly explain the intraday fluctuations of the Balassa-style factor returns in the Chinese A-share market.

Table 1.1
Barra China Equity Model (CNE5) Factors Architecture

Style Factors	**Definition / What it Captures**
Country Factor	Captures systematic exposure to the Chinese market.
Size	Return spread between large-cap and small-cap stocks.
Non-linear Size	Mid-cap-related return variations are not explained by linear size exposure.
Earnings Yield	Return premium associated with higher earnings profitability.
Book-to-Price	Return differential reflecting valuation between value and growth stocks.
Growth	Return spread based on differences in expected sales and earnings growth.
Leverage	Return spread between highly leveraged and low-leverage firms.
Momentum	Return spread based on past 6–12 months of stock performance.
Beta	Exposure to systematic market risk beyond the country factor.
Residual Volatility	Return variation after accounting for systematic volatility.
Liquidity	Return differential based on trading activity or stock liquidity.

Industry Factors:
1. Energy 2. Chemicals 3. Construction Materials 4. Diversified Metals 5. Materials 6. Aerospace and Defense 7. Building Products
8. Construction and Engineering 9. Electrical Equipment
10. Industrial Conglomerates 11. Industrial Machinery
12. Trading Companies and Distributors 13. Commercial and Professional Services
14. Airlines 15. Marine 16. Road, Rail and Transportation Infrastructure
17. Automobiles and Components 18. Household Durables (non-Homebuilding)
19. Leisure Products, Textiles, Apparel, and Luxury 20. Consumer Services
21. Media 22. Retail 23. Food Staples, Retail, Household, Personal Prod
24. Beverages 25. Food Products 26. Health 27. Banks
28. Diversified Financial Services 29. Real Estate Services 30. Software
31. Hardware and Semiconductors 32. Utilities

Macro shocks can affect equity and factor returns through changes in cash flows, discount rates, and financing constraints. The financial accelerator mechanism implies that declines in collateral values tighten borrowing conditions, depress investment, and feed back into asset pricesBernanke, Gertler et al. (1999). In parallel, funding constraints can amplify liquidity stress: a funding-liquidity shock reduces market liquidity, triggers leveraged deleveraging, and generates further price declines(Brunnermeier 2009). Consistent with liquidity-based asset pricing, assets with higher liquidity risk exposure earn higher expected returns (Acharya and Pedersen, 2005), and illiquidity itself is priced in the cross-section(Amihud 2002). Crisis episodes further illustrate that liquidity and credit disruptions can raise risk premia and propagate volatility(Brunnermeier 2009).

Global financial conditions provide an additional transmission channel. Dollar appreciation and tighter dollar funding conditions can induce capital outflows from emerging markets and weaken risk-taking, thereby affecting equity risk premia(Mamipour, Yahoo et al. 2019, Obstfeld and Zhou 2022). Market-wide risk appetite also varies over time: innovations in investment opportunities are priced state variables in intertemporal asset-pricing frameworks, implying time-varying betas for style factors(Merton 1973, Campbell 1992). In this spirit, the variance risk premium and volatility conditions—often proxied by the VIX—are closely linked to expected returns, particularly during high-volatility regimes(Bekaert and Hoerova 2014).

Beyond fundamentals, behavioral forces can magnify short-horizon fluctuations. Noise-trader risk implies that sentiment-driven trading can push prices away from fundamentals and generate reversals, especially in markets with strong retail participation(De Long, Shleifer et al. 1990). Finally, a growing literature uses connectedness/network approaches to characterize shock transmission across markets and sectors, identifying major transmitters and receivers of volatility(Diebold and Yılmaz 2014). Building on these theories, this paper examines whether high-frequency macro and market-intermediary indicators—capturing funding conditions, market liquidity, risk appetite, and cross-border pressure—help explain short-horizon movements in Barra-style factor returns in China's A-share market.

Hypothesis Development

Global empirical research has examined the relationship between style factor returns and macroeconomic indicators, often using business cycle proxies such as economic growth and interest rates. While developed markets—particularly those applying the Fama-French

framework—have been extensively studied, China's A-share market remains underexplored. Existing findings are inconsistent; for example, some studies show a strong link between economic growth and value factor returns, while others suggest context-dependent outcomes. Methodological diversity, including VAR and regime-switching models, further contributes to such discrepancies. Macroeconomic shocks are not transmitted directly to asset prices but are mediated through financial variables (Gilchrist). Market Microstructure Theory also suggests that liquidity and trading frictions significantly affect asset pricing (Baker and Kiymaz 2013). Adrian, Etula et al. (2014) found that economic slowdowns often trigger financial market volatility, which may suppress the performance of growth and momentum stocks. In the Chinese context, Li, Qiao et al. (2025) observed that multi-dimensional information—spanning government, corporate, and market signals—contributes to volatility expansion.

Generally, high-volatility environments increase risk premia and lead investors towards defensive styles, reducing the returns on growth and momentum factors. In contractionary periods, deteriorating liquidity adversely affects liquidity-sensitive factors such as small-cap and value. Capital flows into or out of specific assets alter the supply-demand balance and thus influence factor excess returns (Esqueda, Assefa et al. 2012, Daniel and Moskowitz 2016).

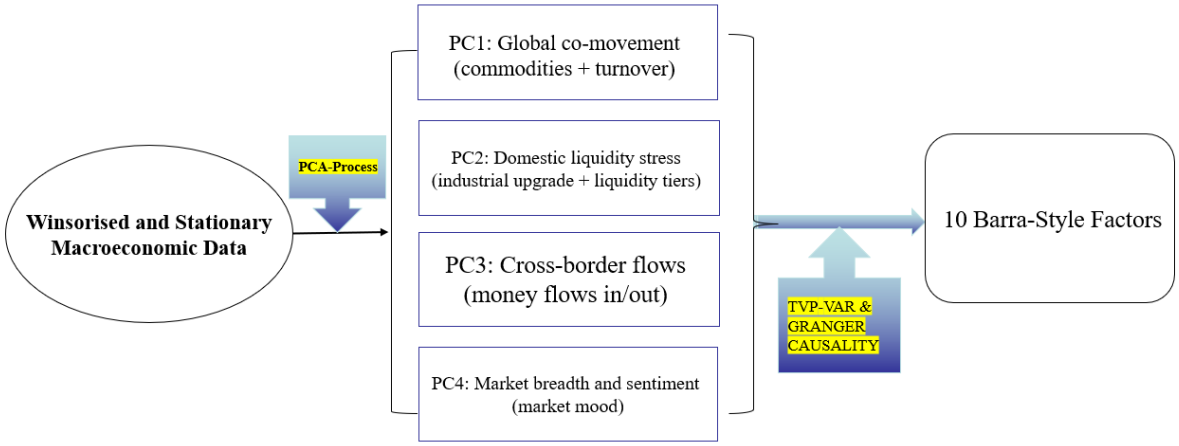
While existing literature has largely tested single mediators, this study incorporates multiple financial market mediators and applies SEM-based multiple mediation analysis to assess total, direct, and indirect macro impacts on factor returns. To fill prior A-share study gaps, this research proposes:

Hypotheses H0: Mediated Impact Hypothesis — Financial Market Mediators): The effects of macroeconomic cycle variables on style factor returns are partially or fully mediated through financial market variables such as market volatility, liquidity, and capital flow.

Methods

This study adopts an integrated framework to analyse the dynamic relationships between macroeconomic indicators, market mediators, and Barra-style factor (BSF) returns in China's A-share market. The methodology encompasses three main components: macroeconomic variables as independent variables, market indicators as mediators, and BSF as dependent variables. All variables are standardized to a daily frequency to ensure consistent time-series analysis. The data in this article covers all the daily return data of the Barra-style factors from the Ricequant quantitative platform, spanning from October 2019 to October 2025.

Figure 1.2: provides a clear illustration of the research design and variable flow:



*Note: All series standardised, lag-aligned and winsorised at 1 % to facilitate joint time-series/cross-section estimations. Variable Set (daily-aligned)

- Independent and Mediators Variables (Macroeconomic): Monthly macroeconomic indicators such as CPI, PPI, M2 growth, unemployment, and others. Plus, key financial market indicators such as market volatility, liquidity, market structure, and money flow index (MFI), all measured daily.
- Dependent Variable (Barra-Style Factors): Ten BSFs, including market capitalization (size), momentum, value, growth, liquidity, and others.

To address the complex dynamic relationships between these variables, this study employs a multi-model approach, combining both time-varying econometric techniques and structural modeling methods to systematically explore the research questions. The integrated models are described as follows:

The Time-Varying Parameter Vector Autoregressive (TVP-VAR) model is an important tool for capturing the dynamic structural relationship among variables in multivariate time series. Unlike traditional VAR model, the biggest advantage of TVP-VAR is its ability to accommodate time-varying parameters, allowing it to better capture the evolution nature of economic and financial market relationships.

In this study, we apply the TVP-VAR model to a multivariable system of BSF, macroeconomic variables, and capital market mediating variables. Our objective is to examine how interactions between these variables change with different stages of the business cycle, market sentiment, and external shocks. Rather than focusing on the isolated impact of a single macro variable on a specific style factor, we constructed a many-to-many systematic analysis framework. Specifically, we investigate how different style factors (such as Value, Size, and Momentum) show time-varying return structure under the influence of different macro variables (e.g., PPI, CPI, social finance, etc.) and intermediary variables (e.g., market volatility, liquidity indicators, market turnover rate, etc.).

By incorporating all variables into a system with a time-varying coefficient matrix, the TVP-VAR model can capture the structural changes in these relationships at any point in time. For example, during an economic downturn cycle, some macro variables (e.g., declining CPI or

the contraction of social finance) may have a more significant impact on style factors, whereas their impact may diminish during the economic recovery. The mathematical form of TVP-VAR is as follows:

$$Y_t = A_{1,t}Y_{t-1} + A_{2,t}Y_{t-2} + \cdots + A_{p,t}Y_{t-p} + u_t, u_t \sim N(0, \Sigma_t) \qquad (1)$$

Where Y_t includes style factors (e.g., Value, Size), mediating variables (e.g., liquidity, volatility), and macroeconomic indicators (e.g., CPI, M2, PPI). The time-varying impulse response functions (TVP-IRFs) are used to evaluate how shocks in macro variables affect factor returns under different market conditions.

The Granger causality test is an econometric analysis method based on the lagged relationships in time series data. It is used to determine whether the historical value of a variable can significantly improve the predictive ability of another variable. Although it cannot strictly prove the "causal" relationship, it is widely used in economic and financial empirical research to identify the direction of information transmission and the leading relationship between variables.

In this study, Granger causality test is used to explore the following: Whether market mediating variables (such as liquidity and volatility) play a mediating role between macro variables and factor returns; The test can be formally expressed as:

$$Y_t = a + \sum_{i=1}^{P} \beta_i Y_{t-i} + \sum_{j=1}^{q} \gamma_j X_{t-j} + \varepsilon_t \qquad (2)$$

Among them, if the prediction ability of the model is significantly improved after the addition of X_{t-j}, it is believed that X Granger causes Y. Specifically, this study will perform two-way Granger test for the following variable combinations:

- Macro variables → Style factors
- Style factors → Market mediators
- External shocks → A-share market factors

To address potential issues related to non-stationarity, such as unit roots and cointegration, the Toda–Yamamoto augmented Granger causality approach is applied alongside the standard method. This extension helps avoid spurious inferences and ensures more reliable results when dealing with integrated or cointegrated variables.

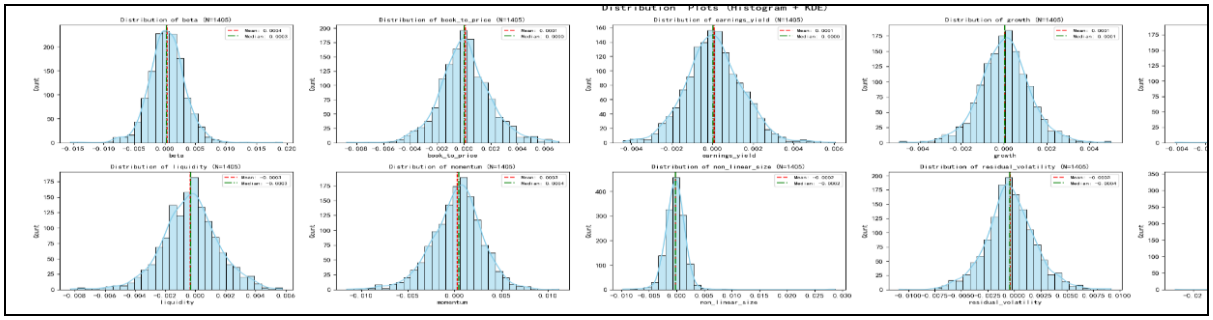
Findings

This study examines the impact of macroeconomic indicators on Barra-style factor returns in the Chinese A-share market from 2019 to 2024. Daily Barra-style factor (BSF) data are obtained from the RiceQuant factor platform, while macroeconomic indicators are collected from East money Choice and Wind database. Market intermediary variables are drawn from Tushare and Wind. Together, these sources form a comprehensive macro–financial dataset.

After data cleaning, including removing missing observations, trimming extreme values, and applying logarithmic transformations where appropriate, the ten Barra-style factors exhibit unconditional average daily returns close to zero, with daily volatility ranging from 1.2% to 2.8%. Volatility is notably higher in the second quarter of 2024. Normality tests indicate that the beta, book-to-price, and liquidity factors do not strongly reject normality, while momentum and leverage display mild tail deviations, suggesting asymmetry between returns and risks. Pairwise correlations across factors remain moderate ($|\rho| \leq 0.42$), indicating no severe multicollinearity and supporting the suitability of multivariate time-series modeling.

To characterize the macro–financial environment, fifty macroeconomic and market indicators are standardized and subjected to principal component analysis. Based on explained variance and factor loadings, four principal components are retained. A conceptual classification is then established according to the dominant contributions of each component. The first component reflects global co-movement, primarily driven by commodity prices and aggregate market turnover. The second component captures domestic liquidity pressure associated with industrial activity and financial conditions. The third component represents cross-border capital flows, while the fourth component measures market breadth and investor sentiment. Cluster analysis is applied to trading-day observations in the principal-component score space, yielding four distinct macro–financial states: a commodity-up and high-liquidity state, a flow-driven state, a liquidity-tight state, and an extreme-sentiment state. These states provide a structural foundation for subsequent time-varying analysis.

Time-varying parameter VAR results indicate that macroeconomic shocks exert heterogeneous and cyclical impacts on Barra-style factor returns. The global co-movement component (PC1) produces a positive driving effect on most style factors during expansionary phases and a mild restraining effect during contractionary phases, consistent with cyclical risk-preference dynamics. The domestic liquidity-pressure component (PC2) shows an increasingly negative impact over time, reflecting tightening funding conditions and structural financial constraints in China's policy-driven market. The cross-border flow component (PC3) exhibits a significant negative impact during capital outflow periods from 2019 to 2021, followed by a positive impact from 2022 to 2024, aligning with shifts in global allocation patterns. The sentiment component (PC4) persistently suppresses factor returns, capturing the sustained negative influence of retail-driven market sentiments.



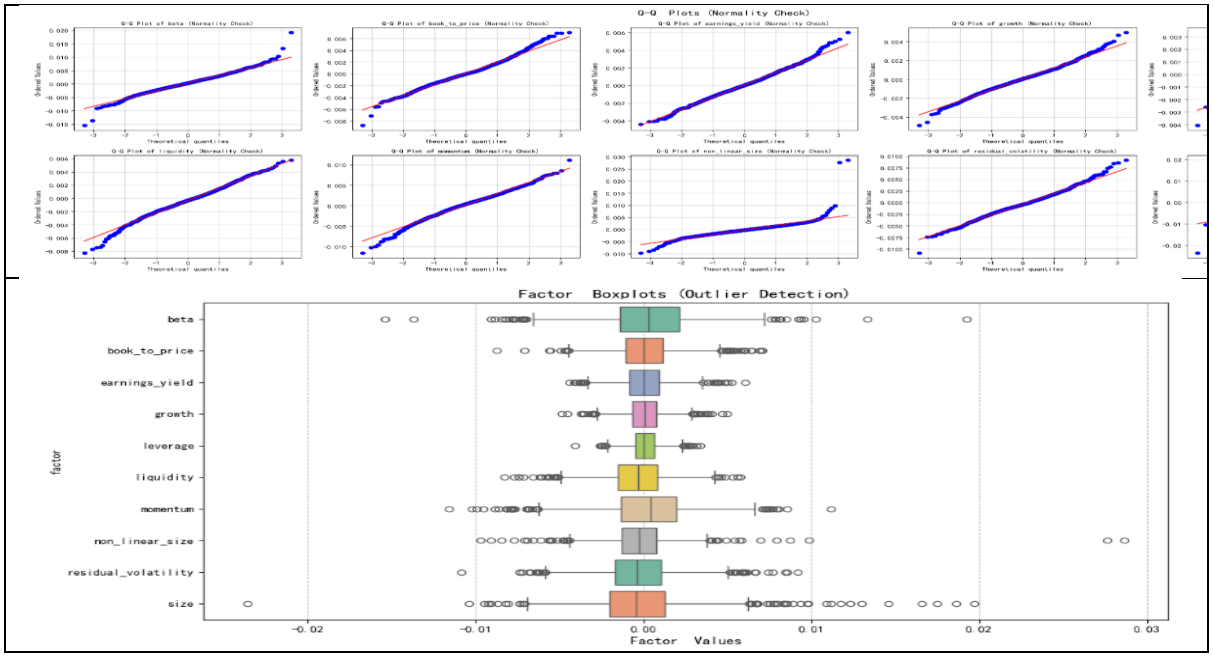


Figure1.2 Daily and Cumulative Log Return of BSF and Correlations

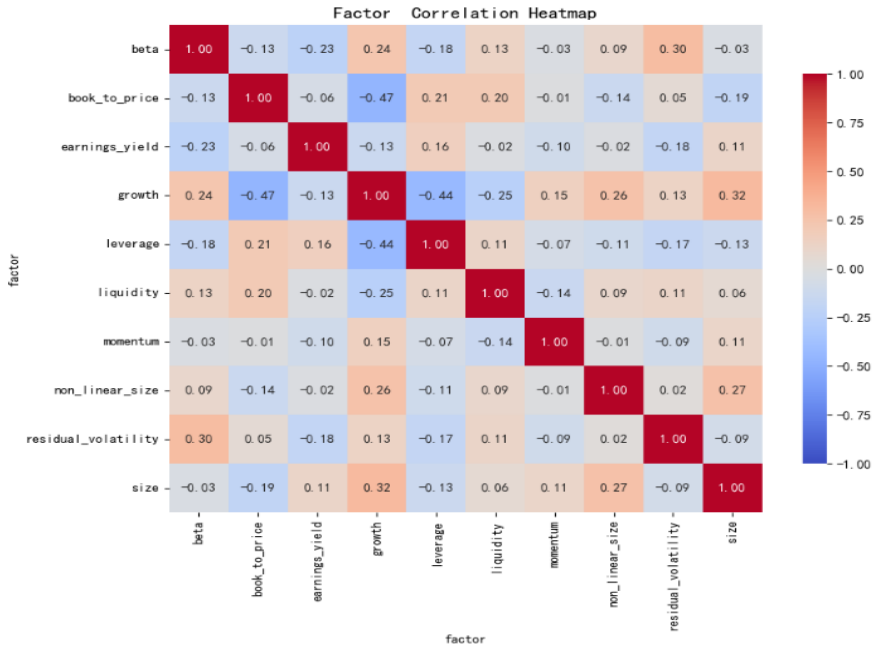


Figure 1.3 PCA Clusters for Financial and Economic Indicators Using Silhouette and Elbow Method

Table 1.2
Summary table of average effects of principal components on style factors and core feature

Style Factor	PC1 Coefficient (Average Impact)	PC2 Coefficient (Average Impact)	PC3 Coefficient (Average Impact)	PC4 Coefficient (Average Impact)	Core Feature Summary
beta	0.04 (Weak Positive)	-0.18 (Moderate Negative)	0.04 (Weak Positive)	-0.14 (Weak Negative)	PC2 and PC4 are dominated by negative impacts; the positive impacts of PC1 and PC3 are weak, and the overall correlation is not prominent.
Book to price	0.12 (Moderate Positive)	-0.07 (Weak Negative)	-0.17 (Moderate Negative)	-0.34 (Relatively Strong Negative)	PC1 drives positively, while PC3 and PC4 inhibit negatively (PC4 has the most significant negative impact).
Earnings yield	0.12 (Moderate Positive)	-0.08 (Weak Negative)	-0.18 (Moderate Negative)	0.02 (Weak Positive)	PC1 drives positively, PC3 inhibits negatively, and the impact of PC4 is extremely weak.
Growth	0.10 (Weak Positive)	-0.16 (Moderate Negative)	-0.07 (Weak Negative)	0.35 (Relatively Strong Positive)	PC4 has a significant positive impact (serving as the core driver), and the negative impact of PC2 is relatively prominent.
leverage	0.16 (Moderate Positive)	-0.09 (Weak Negative)	-0.06 (Weak Negative)	-0.13 (Weak Negative)	PC1 drives positively, and the negative impacts of other PCs are all weak.
liquidity	0.19 (Relatively Strong Positive)	0.02 (Weak Positive)	-0.04 (Weak Negative)	-0.53 (Very Strong Negative)	PC1 has a strong positive impact and PC4 has a strong negative impact (both are core driving dimensions).
momentum	0.09 (Weak Positive)	-0.14 (Moderate Negative)	0.05 (Weak Positive)	0.12 (Weak Positive)	PC1, PC3, and PC4 are all weakly positive, while PC2 is moderately negative.
Nonlinear size	0.25 (Relatively Strong Positive)	-0.13 (Moderate Negative)	-0.07 (Weak Negative)	-0.23 (Moderate Negative)	PC1 drives strongly positively, while PC2 and PC4 inhibit moderately negatively.
Residual volatility	0.15 (Moderate Positive)	-0.06 (Weak Negative)	-0.19 (Moderate Negative)	-0.21 (Moderate Negative)	PC1 drives positively, and PC3 and PC4 inhibit moderately negatively.
Size	0.07 (Weak Positive)	-0.02 (Weak Negative)	-0.16 (Moderate Negative)	-0.22 (Moderate Negative)	PC3 and PC4 inhibit moderately negatively, and PC1 is weakly positive.

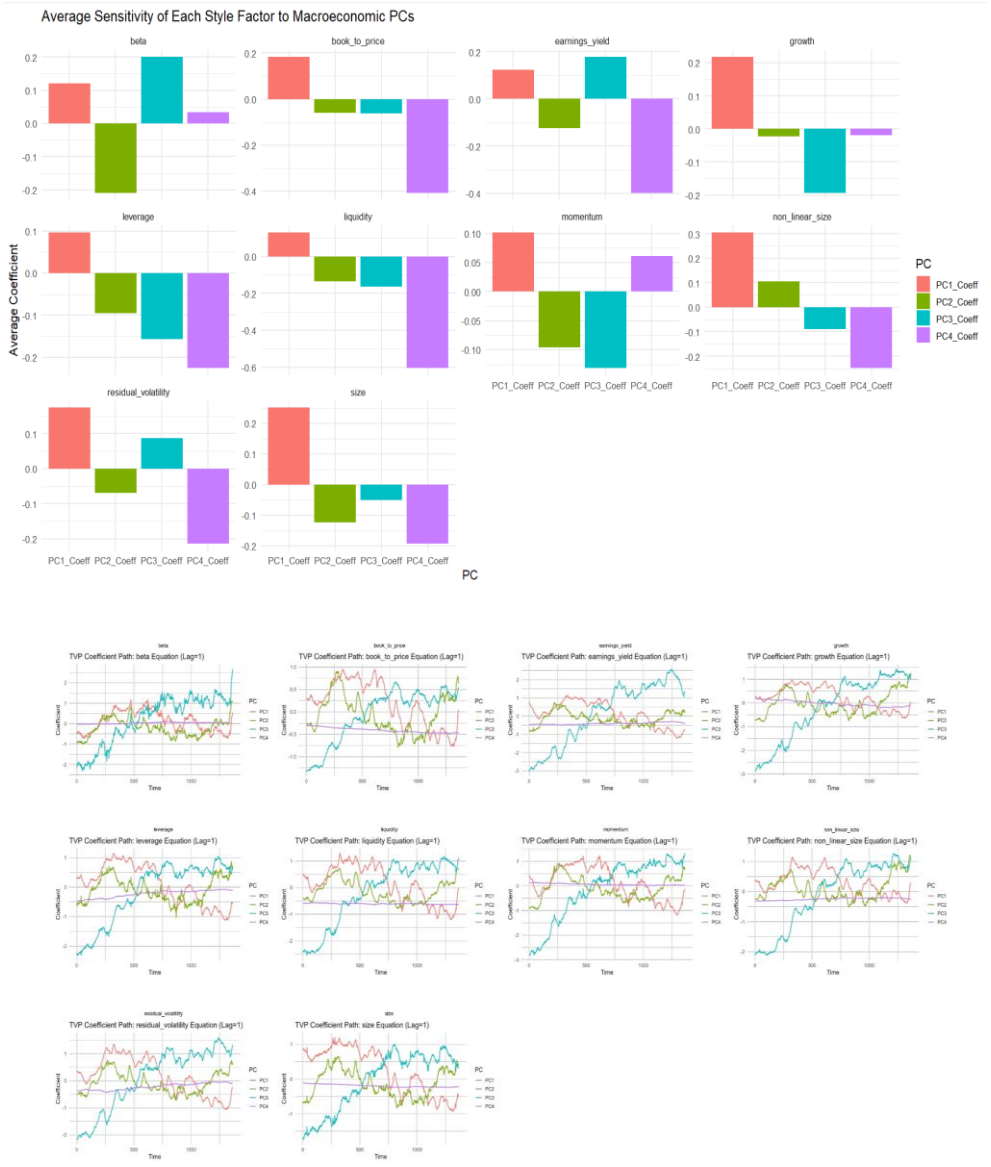


Table 1.3

Total, Direct, and Indirect Effects of Macroeconomic Variables on Style Factors via Financial Market Intermediaries

ID	Target Pcs	Target mediator	target style	Output lag	Coef total	P value	Coef XM	P XM	Coef MY	P MY	Coef direct	P direct	Coef indirect	P indirect	P indirect corrected	significance
AIC(n)20	PC1	Shanghai Marke_Cap	beta	3	0e+00	0.9232	0.0024	0.2475	-0.0147	0.0276	2e-04	0.6897	0	0	0	***
AIC(n)190	PC1	ChiNext Index Change	beta	3	0e+00	0.9232	0.0136	0.1525	-0.0023	0.1394	0e+00	0.9142	0	0	0	***
AIC(n)136	PC1	Turnover	momentum	3	3e-04	0.4899	-0.0	0.1559	0.0034	0.0386	2e-04	0.5624	0	0	0	***

		Shanghai					092								
AIC(n)30	PC1	Shenzhen Market Cap	beta	3	0e+00	0.9232	0.0026	0.2948	-0.0111	0.0711	1e-04	0.7935	0	0	0	***
AIC(n)715	PC4	Northbound Shanghai Sell Volume	liquidity	4	0e+00	0.7655	0.0019	0.0196	0.0015	0.0017	0e+00	0.9657	0	0	0	***
AIC(n)735	PC4	Southbound Sell Volume	liquidity	4	0e+00	0.7655	0.0186	0.0258	0.0014	0.0015	0e+00	0.9683	0	0	0	***
AIC(n)745	PC4	Southbound Buy Volume	liquidity	4	0e+00	0.7655	0.0176	0.0337	0.0015	0.0011	0e+00	0.9697	0	0	0	***
AIC(n)725	PC4	Northbound Shanghai Buy Volume	liquidity	4	0e+00	0.7655	0.0176	0.0302	0.0015	0.0015	0e+00	0.9623	0	0	0	***
AIC(n)128	PC1	Large Capital Outflow	Residual volatility	4	0e+00	0.9807	-0.0163	0.2138	0.0015	0.03	-1e-04	0.7939	0	0	0	***
AIC(n)158	PC1	Shenzhen Turnover	Residual volatility	4	0e+00	0.9807	-0.0075	0.2006	0.003	0.0508	-1e-04	0.8074	0	0	0	***

*Note: **ID**: Unique identifier for each model or estimation, where **AIC** indicates that the model is evaluated based on the Akaike Information Criterion (AIC). **Target PC**: The principal component (PC) being analyzed, such as PC1, PC2, etc. **Target mediator**: The macroeconomic variable acting as the mediator, influencing the style factor. **Target style**: The style factor being modeled, e.g., beta, momentum, or liquidity. **Output lag**: The number of time lags used in the model for predicting the target style. **Coef total**: The total coefficient, showing the overall effect of the mediator on the target style factor. **P value**: The statistical significance of the coefficient. A smaller P value indicates greater significance. **Coef XM (cross-market)**: Coefficient representing the effect of cross-market variables on the target style. **Coef MY** (macro variables): Coefficient showing the impact of macroeconomic variables on the target style. **Coef direct**: The direct effect of the macroeconomic variable or mediator on the target style factor. **P direct**: The P-value associated with the direct effect, indicating its statistical significance. **Coef indirect**: The indirect effect of macroeconomic variables on the target style, mediated by other factors. **P indirect**: The P-value for the indirect effect, indicating its statistical significance. **P indirect corrected**: The corrected P-value for the indirect effect, adjusted for multiple comparisons. **Significance**: The overall statistical significance of the relationship, with stars (e.g., ***) indicating high significance.

Further mechanism analysis using mediation models distinguishes direct macro-to-factor effects from indirect transmission through market intermediaries, including liquidity, volatility, and cross-border capital flows. The results indicate that macroeconomic shocks primarily propagate to style-factor returns through liquidity-amplification channels and volatility-driven revaluation effects. Specifically, liquidity expansion during economic upturns enhances momentum and size-factor performance, while liquidity contraction under inflationary pressure suppresses leverage and value-related factors. Volatility serves as a transmission channel for macroeconomic uncertainty by increasing the risk premium associated with residual volatility. Cross-border capital flows further amplify cyclical fluctuations in large-cap factor portfolios. Direct macroeconomic effects on factor returns are present but exhibit instability across different economic environments, underscoring the importance of intermediary financial channels in shaping macro–factor relationships.

Overall, the results indicate that the influence of macroeconomic factors on Barra-style factor returns in the Chinese A-share market is highly regime-dependent and is mainly transmitted through financial-market intermediaries, such as liquidity conditions, volatility, and capital

flows, rather than through stable direct macro-to-factor effects. This highlights the central role of market intermediary channels in shaping macro–factor linkages and emphasizes the necessity of time-varying modeling frameworks to capture evolving macro–financial–factor dynamics and to guide dynamic style-factor allocation strategies.

Discussion and Conclusion

Theoretical Implications

This study's core contribution is the validation of a mechanism-centric hypothesis: short-term macroeconomic shocks impact Barra-style factor returns both directly and, more importantly, through three dynamic market channels—liquidity, volatility, and capital flows. By using Principal Component Indexing (PCI) to condense macroeconomic variables and a Time-Varying Parameter VAR (TVP-VAR) model with rolling Granger causality tests, we identified a clear, state-dependent transmission structure that evolves across different market cycles.

While direct macroeconomic effects (e.g., economic growth boosting size/liquidity premia or weak labour markets depressing momentum) are observed, they are often secondary to mediated pathways. TVP-VAR decomposition reveals that much of the macro-factor covariation flows through liquidity (turnover, margin balances), conditional volatility, and cross-border flows. For instance, economic expansions improve market depth, thereby amplifying momentum and large-cap stock returns, while liquidity squeezes during policy tightening can trigger nonlinear declines in liquidity-sensitive factors, such as value and size. These effects align with the results in Figures 1.2 and 1.3, where changes in liquidity and volatility conditions are directly linked to shifts in factor returns.

Liquidity emerges as the dominant mediator in the A-share market. Retail investor dominance and government interventions make trading volume and funding availability powerful amplifiers of macroeconomic signals. Improved liquidity during periods of economic growth strengthens the performance of factors such as momentum and size, while sudden liquidity withdrawals, such as during tightening monetary policies, depress leverage and liquidity-based factors. TVP-VAR results further show that the impact of liquidity is strongest during economic expansions, while it weakens or even reverses during periods of liquidity stress, a pattern that can be observed in the rolling window analyses (see Figures 4.3 and 4.4).

Volatility transmits macroeconomic uncertainty by affecting the risk premium. Following negative shocks, elevated volatility increases the risk premium associated with residual volatility, thereby depressing value returns and amplifying the premium for residual volatility. These effects are more pronounced for idiosyncratic risk factors rather than size exposures, likely amplified by the A-share market's characteristics of noise trading and short holding horizons. This observation aligns with the findings in Figures 1.2 and 1.3, where volatility appears to have a stronger impact on individual factor variations compared to the broader market indices.

Capital flows, while a narrower channel, play a notable role in driving returns. Cross-border inflows tend to boost size and liquidity factors, while outflows have a detrimental impact on momentum and nonlinear size portfolios. Due to partial capital account liberalization, this channel is episodic, potent when large flows occur, and weaker when regulatory controls bind. These findings are reflected in the PCA results and TVP-VAR analysis, where PC3 (cross-border flows) shows significant influence during certain periods of capital inflow and outflow.

These channels are not static but are time-varying and regime-dependent. Rolling Granger causality tests show stronger mediation during bull markets, where optimism and trend-following behaviour amplify the impact of macroeconomic news, while bear markets, characterized by loss aversion and retail noise, weaken these effects. Factor responses also vary based on the specific economic environment: size and liquidity factors are more responsive to liquidity conditions, momentum reacts more to sentiment and volatility, and leverage and residual volatility exhibit countercyclical behaviour. This aligns with the regime-based findings in Figure 3, where the performance of factors during liquidity squeezes and commodity booms shifts significantly.

Overall, a "macro-Data → Market Variables → BSF Returns" framework captures the dynamics of the A-share market more accurately than direct macro-factor models. The integration of liquidity, volatility, and capital flow dynamics provides a more nuanced understanding of the transmission of macroeconomic shocks to factor returns.

Practical and Social Implications

The findings emphasize the importance of integrating market microstructure into quantitative models. Traditional static factor models assume stable relationships between macroeconomic conditions and asset returns, but our time-varying evidence reveals that these relationships fluctuate significantly across market regimes due to liquidity and volatility changes. Portfolio managers can enhance their asset allocation strategies by incorporating dynamic indicators, such as liquidity stress and capital flow asymmetry. For example, value and size factors are more vulnerable to liquidity crises, while momentum and growth factors tend to perform better in expansions. This regime-dependence can be directly applied to asset allocation models for better risk-adjusted returns.

TVP-VAR results further show that liquidity, volatility, and capital flows are endogenous to financial cycles, aiding in risk management. By monitoring liquidity co-movements and volatility spillovers, financial institutions can develop early-warning systems to anticipate large portfolio adjustments. This could be especially relevant in managing risk during periods of market stress, as demonstrated by the shifting impact of liquidity and capital flows across different market phases in the study's analysis.

From a regulatory perspective, it is crucial to note the sensitivity of factor performance to fluctuations in liquidity and volatility, especially during periods of uncertainty. Sudden liquidity tightening or speculative flows can lead to heightened instability in factor returns. Strengthening liquidity management tools (e.g., repo facilities, transparent capital flow monitoring) can mitigate risks associated with these shocks, and macroprudential tools can be employed to prevent localized shocks from spreading throughout the financial system.

For monetary and fiscal policymakers, understanding the heterogeneous impact of policies on different factors is critical. Expansionary credit policies tend to Favor growth and momentum factors, while contractionary policies Favor low-volatility and high-quality factors. By recognizing these dynamics, policymakers can design policies that stabilize markets and reduce capital allocation cyclicality. This can help in reducing the volatility of financial markets and improving the resilience of the economy to macroeconomic shocks.

Limitations and Suggestions for Future Research

- Granularity Mismatch Between Monthly Macroeconomic Data and Daily Style Factor/Global Stock Data:

The study uses monthly macroeconomic data alongside daily Barra Style Factor (BSF) and global stock market data. The mismatch in time granularity between these datasets could lead to potential issues with time-series aggregation. Specifically, converting monthly data to daily intervals might induce spurious regression, which could affect the reliability of the results. Future research could address this by exploring alternative temporal resolutions or using higher-frequency macroeconomic data (e.g., weekly or daily macro indicators) where available.

- Impact of COVID-19 and Sudden Policy Shocks:

The five-year sample period spans a period of significant global disruption, including the COVID-19 pandemic and various sudden policy shifts in China. While these events provide a rich context for studying extreme shocks, they might also limit the generalizability of the findings. The study's static conclusions derived from time-varying analyses might lack full adaptability to future periods that are not influenced by such extraordinary circumstances. Future studies could extend the time frame or explore different market environments to assess how macro shocks outside of pandemics or extraordinary policy changes impact factor returns.

- Insufficient Refined Analysis of Financial Sub-Channel Heterogeneities:

While the study identifies liquidity, volatility, and capital flows as key channels through which macroeconomic variables influence style factors, the heterogeneity within these sub-channels has not been fully explored. For example, the effects of liquidity stress might vary across different market segments, such as retail versus institutional investors or sector-specific dynamics. Further investigation could provide a more nuanced understanding of how financial microstructures influence the transmission of macroeconomic shocks.

- Lack of Cross-Market Verification:

The findings are primarily based on the A-share market, and the lack of cross-market verification limits the generalizability of the conclusions to other equity markets. Global or cross-market comparisons (e.g., comparing the A-share market with the US or European markets) could provide insights into whether the macroeconomic channels identified here behave similarly or differ across different market structures. Cross-market verification could also help clarify whether the observed relationships are specific to China or if they hold more broadly in emerging markets or developed economies.

- Model and Data Limitations in Capturing Nonlinear Interactions:

The study primarily focuses on linear relationships between macroeconomic variables and style factor returns. However, nonlinear interactions between factors and macroeconomic shocks (e.g., threshold effects or nonlinear spillovers) may not be fully captured by the TVP-VAR model. Future research could explore nonlinear models such as Markov-switching models or neural network approaches to better understand complex, nonlinear dependencies and improve prediction accuracy during extreme market events.

- Limited Consideration of Behavioral Factors:

While the study effectively analyzes the market microstructure and its role in macroeconomic transmission, the role of investor sentiment and behavioral biases is only partially explored. Given the prevalence of herding behavior, loss aversion, and other psychological biases in stock markets, further research could delve deeper into how investor psychology amplifies or dampens the macroeconomic effects on style factor performance.

Acknowledgement

I wish to express my deepest gratitude to my supervisor, Professor Aslam Mia, whose erudite guidance, incisive critiques and unwavering patience illuminated every stage of this research. I am equally indebted to the members of my thesis review committee for their penetrating questions and constructive suggestions, which sharpened my analysis and enriched my intellectual perspective. My sincere appreciation extends to the AAMC mentor at University Sains Malaysia for challenging me to refine both my methodological rigour and interpretative depth during the review process.

I gratefully acknowledge Wind Information Company and RiceQuant for granting access to high-quality data essential to this study. Finally, I owe an immeasurable debt to my family for their steadfast encouragement and understanding—your belief in me was the quiet force that sustained this endeavour from beginning to end.

References

Adrian, T. (2014). Financial intermediaries and the cross-section of asset returns. *Journal of Finance, 69*(6), 2557–2596.

Altman, E. I. (2022). Has the Evergrande debt crisis rattled Chinese capital markets? A series of event studies and their implications. *Finance Research Letters, 50*, 103247.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31–56.

Ang, A. (2023). Trends and cycles of style factors in the 20th and 21st centuries. *Journal of Portfolio Management, 49*(2).

Ang, A. (2006). The cross-section of volatility and expected returns. *Journal of Finance, 61*(1), 259–299.

Asness, C. S. (2013). Value and momentum everywhere. *Journal of Finance, 68*(3), 929–985.

Bai, L. (2021). Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective. *Finance Research Letters, 40*, 101709.

Baker, H. K., & Kiymaz, H. (2013). Market microstructure. In *Market microstructure in emerging and developed markets: Price discovery, information flows, and transaction costs* (pp. 1–16).

Barberis, N., & Shleifer, A. (2003). Style investing. *Journal of Financial Economics, 68*(2), 161–199.

Bass, R. (2017). Total portfolio factor, not just asset allocation. *Journal of Portfolio Management, 43*(5), 38.

Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics, 183*(2), 181–192.

Bergeron, A. (2018). Asset allocation and factor investing: An integrated approach. *Journal of Portfolio Management, 44*(4), 32.

Bernanke, B. S. (1999). The financial accelerator in a quantitative business cycle framework. In *Handbook of Macroeconomics* (Vol. 1, pp. 1341–1393).

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives, 23*(1), 77–100.

Cai, B. (2022). Research on MSCI Barra CNE5 model and stock selection. In *Proceedings of the 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)*. Atlantis Press.

Campbell, J. Y. (1992). *Intertemporal asset pricing without consumption data*. National Bureau of Economic Research.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52*(1), 57–82.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics, 122*(2), 221–247.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy, 98*(4), 703–738.

Deev, O. (2022). The looming crisis in the Chinese stock market? Left-tail exposure analysis of Chinese stocks to Evergrande. *Finance Research Letters, 49*, 103154.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics, 182*(1), 119–134.

Dimson, E. (2017). Factor-based investing: The long-term evidence. *Journal of Portfolio Management, 43*(5), 15.

Esqueda, O. A. (2012). Financial globalization and stock market risk. *Journal of International Financial Markets, Institutions and Money, 22*(1), 87–102.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3–56.

Fernald, J. G. (2021). Is China fudging its GDP figures? Evidence from trading partner data. *Journal of International Money and Finance, 114*, 102406.

Finance Yahoo. (2025). China's stock market suffers worst start to the year in a decade. https://finance.yahoo.com/news/china-stock-market-suffers-worst-130518930.html

Grinold, R. C., & Kahn, R. N. (2000). *Active portfolio management*. McGraw-Hill.

Gu, X. (2021). How do investors in Chinese stock markets react to external uncertainty? An event study on Sino-US disputes. *Pacific-Basin Finance Journal, 68*, 101614.

He, D., & Wang, H. (2012). Dual-track interest rates and the conduct of monetary policy in China. *China Economic Review, 23*(4), 928–947.

Hii, I. S. (2023). Behavioural biases and investment decisions during COVID-19: An empirical study of Chinese investors. *Institutions and Economies*, 81–103.

Hou, K. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies, 28*(3), 650–705.

Huang, Y. (2019). Saving China's stock market? *IMF Economic Review, 67*(2), 349–394.

Izzeldin, M. (2023). The impact of the Russian-Ukrainian war on global financial markets. *International Review of Financial Analysis, 87*, 102598.

Jansen, M. (2021). Anomalies in the China A-share market. *Pacific-Basin Finance Journal, 68*, 101607.

Kimura, K. (2021). Factors with style. *Journal of Investing, 30*(3), 21–46.

Li, Y. (2025). Ripple effect of ESG sentiment: How news stirs the waves in China's A-share market. *International Review of Financial Analysis, 97*, 103856.

Liao, C. (2024). Smart money or chasing stars: Evidence from northbound trading in China. *International Journal of Finance & Economics, 29*(2), 1781–1803.

Liu, J. (2019). Size and value in China. *Journal of Financial Economics, 134*(1), 48–69.

Luo, Y. (2017). Style factor timing. In *Factor investing* (pp. 127–153). Elsevier.

Mamipour, S. (2019). An empirical analysis of the relationship between environment, economy, and society: Results of a PCA-VAR model for Iran. *Ecological Indicators, 102*, 760–769.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica, 41*, 867–887.

MSCI. (2012). *Barra model CNE5 handbook*.

Obstfeld, M., & Zhou, H. (2022). The global dollar cycle. *Brookings Papers on Economic Activity, 2022*(2), 361–447.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642–685.

Reuters. (2023). China, Hong Kong stocks end 2023 as world's worst performers.

Rosenberg, B., & Marathe, V. (1976). *Common factors in security returns: Microeconomic determinants and macroeconomic correlates*. University of California, Berkeley.

Santra, S. (2021). Gradient descent effects on differential neural architecture search: A survey. *IEEE Access, 9*, 89602–89618.

Sharma, P., & Kumar, S. (2023). Zero-COVID policy and stock market sectoral performance in China. *Investment Management & Financial Innovations, 20*(2), 116.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance, 19*(3), 425–442.

Song, Y. (2021). The impact of COVID-19 on investor sentiment: Evidence from A-share listed companies in China. *Frontiers in Psychology, 12*, 743306.

Wang, L. (2010). *The effect of government policy on China's stock market*. Citeseer.

Wang, L., & Fang, H. (2023). The impact of international energy and domestic carbon emission rights prices on stock prices of new energy firms under the Russia-Ukraine conflict. *Academic Journal of Business & Management, 5*(12), 1–9.

Zhang, Q. J. (2009). The link between macroeconomic factors and style returns. *Journal of Asset Management, 10*, 338–355.