Which Factor Model Performs Best: No One-Size-Fits-All Evidence from the Chinese Stock Market

Xinyu Wang, Shaoping Wang, Hao Feng

School of Economics
Huazhong University of Science and Technology

1 Introduction

2 Characteristics of Chinese Stock Market

3 Data

4 Empirical results

5 Conclusions

Motivation

- The Chinese stock market has emerged as the world's second-largest → its growing importance in global finance.
- Relatively low correlation with global markets → international diversification (Hou et al., 2023)
- Characterized by a predominance of retail investors and an opaque information environment → unique challenges for understanding the cross-sectional return pattern within this market.

Prominent Multi-Factor Models in Literature

Factor models play a pivotal role in understanding the cross-sectional return patterns and asset pricing mechanisms in stock markets

Table 1: The list of prominent factor models

Model	Citation	Factors
FF3	Fama and French (1993)	Market, Size, Value
FFC	Carhart (1997)	Market, Size, Value, Momentum
HXZ4	Hou et al. (2015)	Market, Size, Profitability, Investment
FF5	Fama and French (2015)	Market, Size, Value, Profitability, Investment
FF6	Fama and French (2018)	Market, Size, Value, Profitability, Investment, Momentum
DHS3	Daniel et al. (2020)	Market, Long-horizon factor, Short-horizon factor
LSY3	Liu et al. (2019)	Market, Size, Value
LSY4	Liu et al. (2019)	market, Size, Value, Sentiment

Motivation: No One-Size-Fits-All Asset Pricing

- **Non-stationarity of asset returns:** Much of the literature seeks a universal asset pricing mechanism and implicitly assumes stable return dynamics, despite well-documented non-stationarity in returns and risk exposures (Pukthuanthong et al., 2019).
- **Time-varying factor relevance:** Moskowitz (2003) shows that covariance structures shift substantially over time, implying that the importance of risk factors is inherently time-varying.
- **State-dependent SDF:** Multi-factor models represent empirical approximations of the SDF, which evolves with business-cycle conditions (Fama and French, 1993). Hence, factor performance should be state-dependent rather than universal.
- **Regime-specific systematic risk:** Systematic risks themselves change across market regimes, undermining the validity of a single pricing framework that applies uniformly across bubbles, normal periods, and downturns (Cerniglia and Fabozzi, 2018).

Research Gaps

- **Market susceptibility to regime shifts:** The Chinese stock market exhibits recurrent bubbles and prolonged downturns (Chen et al., 2021), offering a setting where systematic risk undergoes fundamental structural shifts.
- **Narrow model focus in prior studies:** Existing empirical work (e.g., Horvath and Wang, 2021; Wang et al., 2021; Yu and Li, 2023) concentrates mainly on Fama–French style models, which are rooted in the Efficient Market Hypothesis (EMH).
- **Challenges to EMH in real markets:** The EMH presumes random-walk behavior and unpredictable returns, a premise that breaks down during bubble episodes (Phillips et al., 2015), calling into question the universal applicability of traditional factor models.

Questions?

- Is there truly a kind of universal asset pricing mechanism that effectively reflects diverse market conditions?
- Can any specific factor model consistently outperform others across various market scenarios?
- Will the recurrent bubbles and extended downturns in the Chinese market undermine the effectiveness of models based on the EMH?
- Can the four-factor model, tailored for the Chinese market by Liu et al. (2019), consistently demonstrate superiority across different market conditions as previously documented? If not, which model performs the best?

Sketch of this Research

Characterizing the Chinese Stock Market:

- Employed the modified Backward Sup Dickey-Fuller method (mBSADF) by Wang et al., (2023) to detect bubble periods
- Used the ADF test on GLS-detrended data (DF-GLS) by Elliott et al. (1996) to identity efficient periods

Comparing the performance of prominent factor models:

- Implemented the wild-bootstrap GRS test to address the issues of time-varying volatility
- Applied the spanning test to analyze the relative performance of those factor models

Contributions and Main Results

Provide the first systemic identification and classification of the market regimes in the Chinese stock market:

- Three bubble periods (2014-15; 2017-18; 2020-21); Two efficient periods (2015-17; 2018-20); An extended downturn period (2021-22)
- The alternate emergence of the bubble and random walk periods
- The downward trend during the post COVID-19 pandemic era dominated the market dynamics

Possibly explains why the heterogeneity in sample period choices contribute to the ongoing lack of consensus regarding the best-performing factor model in this market (Jansen et al., 2021)

Contributions and Main Results

Demonstrate the empirical limitations of universal factor models through regime-conditional evaluation and uncover the different underlying asset pricing mechanism:

- No factor model dominates universally, hence there is no universal asset pricing mechanism that consistently outperforms across different market conditions in China
- The behavioral factor model by Daniel et al. (2020) (DHS3) outperformed others during bubble episodes
- The *q*-factor model by Hou et al. (2015) (HXZ4) demonstrated superior performance under efficient market conditions
- All prominent asset pricing model lost their pricing power during the 2021/02/22-2022/12/31.

Updates capital market research concerning the COVID-19 pandemic:

- DHS3 demonstrates superior performance during the pandemic's early phase
- All candidate factor models exhibit limitations in capturing market dynamics during its later stages

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How to Identify Bubble Periods

modified Backward Sup Augmented Dickey-Fuller method

A price series $\{y_t\}$ under efficient market conditions:

$$y_t = dT^{-\eta} + y_{t-1} + u_t, t = 1, 2, \dots T \tag{1}$$

A price series containing one bubble:

$$y_t = \begin{cases} dT^{-\eta} + y_{t-1} + u_t, & t \in N^0 \\ \delta_T y_{t-1} + u_t, & t \in B \\ dT^{-\eta} + y_{t-1} + u_t, & t \in N^1 \end{cases}, \tag{2}$$

$B = [Tf_o, Tf_c]$ represent the bubble period. f_o and f_c denote the (fractional) date of the bubble origination and termination, respectively

How to Identify Bubble Periods

modified Backward Sup Augmented Dickey-Fuller method

Perform the following DF regression on the sub-samples for each observation of interest $t := \lfloor Tf \rfloor$:

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{j=1}^{k} \theta_j \Delta y_{t-j} + u_t, t = \lfloor Tf_1 \rfloor, ..., \lfloor Tf \rfloor, \quad (3)$$

The *BSADF* statistic:

$$BSADF(f_0, f) = \sup_{f_1 \in [0, f - f_0]} ADF(f_1, f), f \in [f_0, 1]. \quad (4)$$

The *mBSADF* statistic:

$$mBSADF(f_0, f) = \sup_{f_1 \in [0, f - f_0]} ADF(f_1, f) + \frac{C}{K} \sum_{t = \lfloor fT \rfloor - K + 1}^{\lfloor fT \rfloor} m_t, f \in [f_0, 1], \quad (5)$$

where $m_t = \Delta y_t / \sigma_{\Delta y_t}$

How to Identify Bubble Periods

modified Backward Sup Augmented Dickey-Fuller method

Obtain the estimates of f_o and f_c by comparing $mBSADF(f_0, f)$ and it correspond right side critical values

$$\hat{f}_o = \inf_{f \in [f_0, 1]} \{f : mBSADF(f_0, f) > mscv^{\theta_T}(f)\}, \tag{6}$$

$$\hat{f}_c = \inf_{f \in [\hat{f}_o + L_b, 1]} \{f : mBSADF(f_0, f) < mscv^{\theta_T}(f)\}, \tag{7}$$

Why mBSADF?

- Improve the differentiation between genuine bubbles and mere data fluctuations
- Minimize the estimated bias

How to Identify Bubble Periods

modified Backward Sup Augmented Dickey-Fuller method

We apply mBSADF method on CSI 300 index from January 2011 to December 2023.

Why this period?

- The post-2007 sub-sample period could provide a better playing field for factor model comparison in China due to the completion of the split-share structure reform and the implementation of new accounting standards.
- Begin our analysis in 2011 to exclude the global financial crisis (2007-2010), as data from that period, particularly during the bubble phase, may be incomplete or unrepresentative of typical market dynamics.

Which Periods Have Been Identified as Bubble Periods

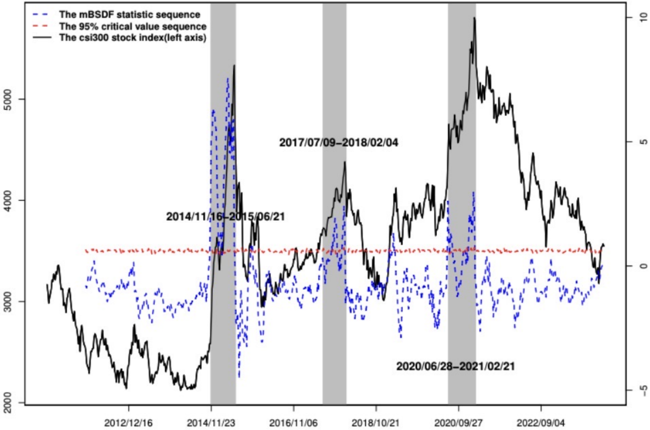

Figure 1: The bubble periods in the CSI300 index

How to Identify Efficient (Random Walk) Periods

Augmented Dickey-Fuller test on Generalized Least Squares-detrended data(DF-GLS)

Model the CSI300 series:

$$y_t = \delta_0 + \delta_1 t + y_t^*, \tag{8}$$

where $y_t^* = \alpha y_{t-1}^* + u_t$ (a near-integrated or random walk process).
Employ the GLS estimation:

$$(1-\alpha L)y_t = (1-\alpha L)\delta_0 + (1-\alpha L)\delta_1 t + u_t, \tag{9}$$

with $\alpha = 1 - (13.5/T)$.
With the OLS estimates $\hat{\delta}_0$ and $\hat{\delta}_1$, remove the trend from y_t:

$$y_t^* = y_t - (\hat{\delta}_0 + \hat{\delta}_1 t) \tag{10}$$

Apply the standard ADF test to the detrended variable:

$$\Delta y_t^* = \alpha + \beta y_{t-1}^* + \sum_{j=1}^{k} \xi_j \Delta y_{t-j}^* + \epsilon_t, \tag{11}$$

$$H_0 : \beta = 0, \quad \text{i.e., the CSI300 series as a random walk process}$$

Which Periods has been Identified as Efficient (Random Walk) Periods

Table 2: The test results of random walk periods for CSI300 index from June 2015 to December 2022

	2015/06/22 - 2017/07/08	2018/02/05 - 2020/06/27	2021/02/22 - 2022/12/31
ADF statistics	-1.493	-1.688	-3.249**

To What Extent Can the Extended Downward Trends Explain the Market Dynamics?

GLS estimation during the detected stationary period:

$$y_t = 5648.3 - 20.55t + y_t^*. \tag{12}$$

The modified version of R^2:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 81.75\%, \tag{13}$$

where $SS_{res} = \sum_t (y_t - \hat{\delta}_1 t)^2$

To What Extent Can the Extended Downward Trends Explain the Market Dynamics?

Figure 2: The CSI300 stock index and its declining trend from February 2021 to December 2022

Characteristics of Chinese Stock Market

1. A substantial dominance of retail investors and developing trading mechanisms, which means low-quality information and less sophisticated investors
2. Bubbles are unambiguously a persistent characteristic of this emerging market
3. The alternate emergence of bubble and market efficiency
4. The persistent downward trend dominated the market dynamics during the post-COVID-19 pandemic

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Data Process

Why weekly data sample

- The monthly frequency data in our subsamples is too scarce, potentially leading to unreliable conclusions
- Daily data often exhibits excessive volatility, which can also undermine reliability (Fama, 1965)

Data source

- All A-shares listed on the SSE and SZSE
- Exclude "special treatment" (ST) stocks
- Removed stocks
  - Listed for less than six months or
  - trading days fewer than 120 in the last year or 15 in the last month
- When constructing factors proposed by Liu et al. (2019), eliminate the bottom 30% of stocks ranked by market value

Factor Construction

2×3 sort (value-weighted):

		Firm Characteristics		
		High (30%)	Middle (40%)	Low (30%)
Size	Small (50%)	S/H	S/M	S/L
	Big (50%)	B/H	B/M	B/L

$$SMB = \frac{1}{3}(S/H + S/M + S/L) - \frac{1}{3}(B/H + B/M + B/L)$$

$$Other\ factors = \frac{1}{2}(S/H + B/H) - \frac{1}{2}(S/L + B/L)$$

Factor Construction

Firm characteristics of each non-Fama-French Factor

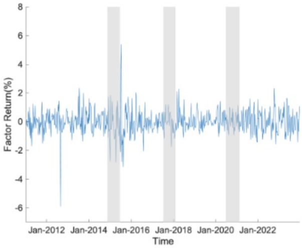
- *VMG* (value): firm's earnings/ market capitalization
- r_{ROE} (profitability): return on equity.
- *PMO* (sentiment): the ratio of the average daily turnover over the past 20 trading days to the average daily turnover over the 250 trading days; reflecting the high trading intensity of a stock
- *FIN* (overconfidence): the average of the 1-year net-share-issuance (NSI) and the 5-year composite-share-issuance (CSI).
  - $NSI_t = log \frac{split\ adjusted\ shares\ outstanding_t}{split\ adjusted\ shares\ outstanding_{t-1}}$.
  - $CSI_t = log(ME_t / ME_{t-5}) - r(t-5, t)$
  - Well-informed managers exploit market timing opportunities through share issues or repurchases
  - Investor often overlooked it due to their overconfidence
- *PEAD* (post-earnings announcement drift): $CAR_i = \sum_{d=-2}^{d=1}(R_{i,d} - R_{m,d})$ Cumulative Abnormal Return around the latest quarterly earnings announcement date; Investors often respond to earning surprises sluggishly due to limited attention

Factor Performance Across Various Phases

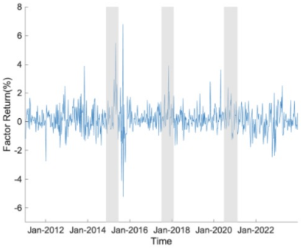
Table 3: Descriptive statistics of the factor returns (%)

Statistics	MKT	SMB	HML	VMG	RMW	r_{ROE}	CMA	UMD	PMO	FIN	PEAD
Panel A: Bubble Period I (2014/11/16 - 2015/06/21) (B1)											
Mean	2.72	0.46	-0.19	-1.04	-0.32	-0.17	-0.21	-0.26	0.35	0.24	0.63
St. Dev.	4.61	3.64	2.51	3.39	1.51	1.65	1.24	2.82	2.81	1.11	1.34
t-Stats	4.43**	0.41	-0.38	-1.22	-1.21	-0.91	-0.65	-1.01	0.52	3.18**	1.14
Panel B: Bubble Period II (2017/07/09 - 2018/02/04) (B2)											
Mean	0.34	-0.81	0.25	0.56	0.10	0.32	0.11	0.01	-0.65	0.12	0.48
St. Dev.	1.48	1.63	1.48	1.67	1.19	0.85	0.93	1.63	1.70	0.72	1.00
t-Stats	2.19	-1.75	0.58	1.25	0.35	1.57	0.43	0.05	-3.64**	-0.57	3.25**
Panel C: Bubble Period III (2020/06/28 - 2021/02/21) (B3)											
Mean	1.01	-0.52	-0.30	0.35	0.35	0.32	0.34	0.23	-0.86	0.00	0.28
St. Dev.	2.86	1.77	1.32	1.66	1.66	0.85	1.63	2.19	1.62	0.58	0.84
t-Stats	-1.07	-1.75	-2.35*	1.49	1.77	2.10	1.21	1.55	-3.83**	-0.08	3.86**
Panel D: Random Walk Period I (2015/06/22 - 2017/07/08) (R1)											
Mean	0.05	-0.52	0.13	-0.06	-0.08	0.12	-0.04	-0.70	-0.64	-0.06	0.12
St. Dev.	4.05	1.77	3.13	3.36	0.83	1.46	0.94	2.28	2.95	1.11	1.22
t-Stats	0.36	-1.75	0.17	-0.16	-0.45	0.92	-0.31	-1.75	-7.20***	-1.81	1.44
Panel E: Random Walk Period II (2015/06/22 - 2017/07/08) (R2)											
Mean	0.21	0.07	0.13	-0.35	0.17	0.27	0.19	-0.18	-0.48	0.05	0.16
St. Dev.	2.86	1.45	1.13	1.78	1.14	1.17	1.00	1.52	1.65	0.59	0.70
t-Stats	0.73	-1.75	-2.13	-3.19**	0.74	1.52	0.83	-1.14	-2.51*	0.70	3.69**
Panel F: Extended Downturn Period (2021/02/22 - 2022/12/31) (SP)											
Mean	0.15	0.36	-0.04	-0.67	-0.16	-0.22	-0.24	-0.29	-0.81	-0.03	-0.10
St. Dev.	2.14	1.63	1.58	1.88	1.25	1.38	1.38	2.11	1.75	0.77	0.90
t-Stats	0.55	5.28**	-0.25	-2.45*	-1.14	-1.43	-1.84	-1.35	-2.92*	-0.46	-0.88

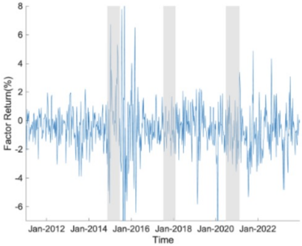
Selected Factor Performance Across Various Phases



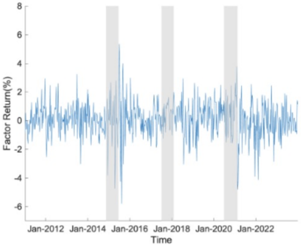
(a) FIN



(b) PEAD



(c) PMO



(d) r_{ROE}

Performance of Factors Across Various Phases

1. **Speculative nature inherent in bubble conditions**
   - Both *PEAD* and *PMO*, especially *PMO*, display elevated volatility during the bubble periods in Figures
   - The *PEAD*, *FIN*, and *PMO* factors demonstrated consistent significant premiums across all bubble periods
2. The speculative transactions become particularly pronounced during bubble periods & ROE is an ideal proxy
   - The *PMO* and r_{ROE} factors dominated with regard to the significance of premiums across our sub-samples
   - These two factors maintained pronounced volatility throughout the full sample period, more so during bubble periods.
   - The magnitude of volatility for *PMO* was substantially greater than that of r_{ROE}
   - *PMO*'s premium is statistically significant across all sub-samples compared to five for r_{ROE}
3. Short-horizon mispricing phenomena may be more common during bubble periods: Compared with the performance of *PMO* and R_{ROE}, the fluctuations of *PEAD* were less pronounced during non-bubble periods

Variations in Excess Returns of Test Assets Across Market Conditions

Limitations of traditions:

- **The standard** 5×5 **portfolio sorts:** a pronounced factor structure and a loss of vital cross-sectional information; Fama-French three-factor model outperforms with size-BM sorted portfolios as the test assets, it underperforms when applied to industry-sorted portfolios
- **Individual stocks:** errors in variables

Employ **10 sector indices** of the CSI300 as our test assets

1. The mean value of test assets across different phases:
   - **Significant positive excess returns during bubble periods:** speculation likely drives the market valuations above their fundamental economic values
   - Excess returns **hover around zero during random walk periods**: market efficiency
   - **Excess returns were predominantly negative in the SP period:** broad economic downturns
2. **The standard deviations of excess returns during the bubble periods were nearly double:** increased volatility and risk
3. **A pronounced ARCH effect in bubble periods:** volatility clustering & herding behavior and momentum trading

Variations in Excess Returns of Test Assets Across Market Conditions

Statistics	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecommunication Service	Utilities
Panel A: Bubble Period I (2014/11/16 - 2015/06/21) (B1)										
Mean	1.50	1.95	2.62	1.98	1.59	1.44	1.95	2.37	2.26	2.23
St. Dev.	5.35	4.62	6.23	4.11	4.21	3.46	6.35	4.78	6.36	5.03
Jarque-Bera	0.33	9.02***	1.54	12.52***	40.56***	37.04***	0.86	19.73***	18.20***	0.54
Q(10)	20.59***	42.68***	25.96***	94.91***	27.05***	41.80***	10.40	35.84***	46.06***	13.43
Panel B: Bubble Period II (2017/07/09 - 2018/02/04)										
Mean	0.68	0.69	0.07	0.47	1.35	0.22	0.64	0.23	-0.02	-0.17
St. Dev.	2.27	2.25	1.43	2.57	3.51	2.01	2.11	2.78	3.25	1.27
Jarque-Bera	2.60	1.28	0.16	1.15	1.50	0.84	0.05	0.09	1.29	0.75
Q(10)	17.35*	12.51	15.21	19.89**	18.42**	22.64***	16.42*	16.10	31.30***	14.86
Panel C: Bubble Period III (2020/06/28 - 2021/02/21)										
Mean	0.56	2.01	1.37	1.52	1.65	0.97	0.57	0.42	-0.27	0.24
St. Dev.	2.81	4.63	3.44	3.60	3.88	4.64	3.40	4.39	4.01	2.36
Jarque-Bera	1.44	1.01	0.68	1.29	1.58	2.10	0.86	0.38	0.01	2.63
Q(10)	19.40**	11.51	28.59***	14.43	13.31	43.57***	14.47	11.21	14.79	10.17
Panel D: Random Walk Period I (2015/06/22 - 2017/07/08) (R1)										
Mean	-0.34	-0.26	-0.42	-0.20	0.23	0.07	-0.10	-0.33	-0.15	-0.38
St. Dev.	3.61	3.94	4.27	3.59	3.06	2.95	3.28	4.63	3.87	3.36
Jarque-Bera	45.80***	35.33***	68.42	49.33***	14.46***	44.38***	25.66***	24.04	4.24	179.33***
Q(10)	9.87	16.96*	7.09	9.26	8.09	17.91*	6.67	12.22	5.00	12.69
Panel E: Random Walk Period II (2015/06/22 - 2017/07/08)										
Mean	-0.51	-0.20	-0.13	-0.03	0.42	0.34	-0.10	0.29	0.09	-0.11
St. Dev.	2.89	3.48	2.93	3.37	3.64	3.67	3.09	4.52	4.58	2.02
Jarque-Bera	75.25***	0.81	4.51*	8.47***	2.73	2.03	5.75*	0.25	14.73***	8.25**
Q(10)	4.54	3.51	6.04	4.56	10.62	10.62	5.36	3.21	10.79	6.55
Panel F: Extended Downturn Period (2021/02/22 - 2022/12/31) (SP)										
Mean	0.28	-0.40	-0.31	-0.52	-0.38	-0.58	-0.35	-0.51	-0.24	0.15
St. Dev.	3.86	3.71	3.09	3.22	4.13	3.80	2.73	3.11	2.78	3.09
Jarque-Bera	7.94**	0.83	1.98	4.75*	16.50***	0.12	0.22	1.61	0.43	2.96
Q(10)	13.83	9.55	14.11	6.54	6.85	7.57	15.41	5.24	7.36	8.45

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How to Compare Prominent Factor Models?

The Wild Bootstrapped GRS test

Consider the following factor model in the cross-sectional specification:

$$r_{it} - r_{ft} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_t + u_{it},\ for\ \ i = 1, 2, \dots, N; t = 1, 2, \dots, T, \tag{14}$$

If the m factors are correctly priced, the intercepts α_i should be zero for all

$$H_0 : \alpha_i = 0, \quad \forall i = 1, \dots, N. \tag{15}$$

$$GRS = \frac{T - N - K}{N} [1 + \bar{f}' \hat{\Omega}^{-1} \bar{f}]^{-1} \hat{\alpha}' \hat{\Sigma}^{-1} \hat{\alpha} \sim F_{N, T-N-K} \tag{16}$$

- Estimated the parameters of the unrestricted model and retained these estimated parameters
- Generated the bootstrap residuals $\mathbf{u}_t^b := \hat{\mathbf{u}}_t \omega_t$
- constructed the bootstrap sample $\mathbf{y}_t^b = \hat{\boldsymbol{\beta}}_i' \mathbf{f}_t + u_{it}^b$ and calculated the wild bootstrap GRS test statistics
- Computed the p^b-value by determining the proportion of bootstrapped GRS statistics that exceed the statistic calculated by actual data

Primarily relied on the p^b-value, since the factor number of candidate

Which Factor Model Performs Best During Bubble Periods?

	FF3	FFC	HXZ4	FF5	FF6	LSY3	LSY4	DHS3
Panel A: Bubble Period I (2014/11/16 - 2015/06/21) (B1)								
GRS statistics	2.24	2.33	2.03	1.88	1.84	2.72	2.44	1.04
p^b value	0.02	0.02	0.09	0.06	0.12	0.02	0.02	0.42
$A\|a\|$	0.39	0.47	0.39	0.41	0.50	0.46	0.53	0.53
$A\|t\|$	0.89	1.03	0.90	1.01	1.22	0.84	1.74	0.84
Mean adj. R^2	0.77	0.77	0.80	0.83	0.83	0.73	0.75	0.69
Panel B: Bubble Period II (2017/07/09 - 2018/02/04) (B2)								
GRS statistics	1.43	1.69	2.54	3.15	3.54	1.58	2.04	0.68
p^b value	0.17	0.12	0.02	0.01	0.01	0.15	0.06	0.72
$A\|a\|$	0.39	0.38	0.42	0.42	0.37	0.37	0.44	0.33
$A\|t\|$	1.19	1.13	1.27	1.46	1.29	1.29	1.04	0.82
Mean adj. R^2	0.48	0.48	0.53	0.65	0.65	0.65	0.36	0.34
Panel C: Bubble Period III (2020/06/28 - 2021/02/21) (B3)								
GRS statistics	2.00	2.24	2.16	2.02	2.38	2.19	1.80	1.38
p^b	0.06	0.03	0.05	0.06	0.05	0.04	0.14	0.14
$A\|a\|$	0.43	0.43	0.46	0.38	0.42	0.43	0.32	0.50
$A\|t\|$	1.08	1.06	1.19	0.97	1.07	0.94	0.75	1.06
Mean adj. R^2	0.65	0.65	0.62	0.69	0.69	0.57	0.57	0.56

Why DHS3 Outperforms Others During Bubble Periods?

DHS3 model consistently outperforms others during bubble periods

- The DHS3 model effectively captures mispricing due to investor overconfidence and limited attention, prevalent during bubble periods.
  - **Evidence of Overconfidence:** Trading volumes surge, indicating overconfidence (Grinblatt and Keloharju, 2009; Liao et al., 2022)
  - **Demand for Speculative Assets:** Overconfidence leads to abnormal demand for speculative assets (Han et al., 2020)
  - **Limited attention Caused by High-Risk Preferences:** During volatile periods, investors favor high-risk stocks, ignoring fundamental data (Kumar, 2009)
- The dominating retail investor activities further amplify
  - **Preference for Lottery-Type Stocks:** Retail investors are drawn to high-gain, high-risk investments (Kumar, 2009)
  - **Sensitivity to News:** More likely to react to sensational news
  - **Investor Proficiency and Mispricing:** Lower proficiency correlates with more pronounced (Shu and Tan, 2022)
  - **Heterogeneous Beliefs:** Overconfidence among retail investors leads to diverse expectations and severe mispricing (Xiong and Yu, 2011; Shu and Tan, 2022)
- Retail investor activities will intensify during bubble periods (An et al., 2022). The explosive price behaviors and the dominance of retail investors work in tandem, magnifying these mispricing effects

Which Factor Model Performs Best During Periods of Market Efficiency?

	FF3	FFC	HXZ4	FF5	FF6	LSY3	LSY4	DHS3
Panel A: Random Walk Period I (2015/06/22 - 2017/07/08) (R1)								
GRS statistics	2.05	1.58	1.66	2.36	1.83	2.87	2.07	3.09
p^b value	0.06	0.10	0.15	0.04	0.07	0.01	0.05	0.00
$A\|a\|$	0.24	0.18	0.20	0.25	0.18	0.30	0.23	0.31
$A\|t\|$	1.48	1.08	1.30	1.62	1.20	1.86	1.08	1.80
Mean adj. R^2	0.79	0.81	0.81	0.82	0.83	0.78	0.79	0.75
Panel B: Random Walk Period II (2018/02/05 - 2020/06/27) (R2)								
GRS statistics	2.72	3.14	2.10	2.82	3.75	4.12	4.56	3.19
p^b value	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
$A\|a\|$	0.21	0.22	0.19	0.21	0.22	0.25	0.22	0.27
$A\|t\|$	1.29	1.36	1.24	1.41	1.51	1.52	1.56	1.77
Mean adj. R^2	0.72	0.72	0.72	0.75	0.75	0.69	0.72	0.66
Panel C: Extended Downturn Period (2021/02/22 - 2022/12/31) (SP)								
GRS statistics	5.62	6.00	5.13	5.25	5.71	7.98	6.18	4.56
p^b value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$A\|a\|$	0.36	0.36	0.31	0.35	0.36	0.50	0.44	0.47
$A\|t\|$	1.60	1.66	1.37	1.64	1.70	1.93	1.60	1.93
Mean adj. R^2	0.57	0.58	0.56	0.58	0.60	0.48	0.47	0.43

Why HXZ4 Outperforms Others During Periods of Market Efficiency

HXZ4 model consistently outperforms others during efficient periods

- **Redundancy of value factor:** First principle of real investment theory behind HXZ4 suggest that firms should continue to invest until the present value of the marginal revenue from an investment equates to its marginal cost. The marginal cost is closely related to the value of a firm; See empirical evidence in Fama and French (2015)
- **The applicability of r_{ROE}:** ROE is a critical metric for assessing firm profitability endorsed by the CSRC; consistent significant premiums
- **The increased importance of firms' growth potential and future investment prospects in pricing mechanism:** The value factor typically focuses on the return convergence of stocks, while the profitability and investment factors more directly reflect the firms' future growth and investment potential; Chinese retail investors favor growth stocks (Hsu et al., 2018)
- **Well-documented absence of a momentum effect in the Chinese equity market**: speculation-oriented retail investors prioritize short-term gains

The performance of prominent asset pricing models during periods of extended downturn period

All established factor models lost pricing ability in the SP period

- Exceptionally large GRS statistics coupled with notably low Mean adj. R^2 values
- The downward trend plays a central role in market dynamics, leading to a substantial distortions in pricing mechanisms
- The stringent restrictions implemented during this time, e.g., lockdown, likely exacerbated investor uncertainty regarding firms' financial futures

Spanning Test During Bubble Periods

	Mean	FF3	FFC	FF5	FF6	HXZ4	LSY3	LSY4
Panel A: Bubble Period I (2014/11/16 - 2015/06/21) (B1)								
FIN	0.24	0.16	0.19	0.15	0.19	0.27	0.46	0.47
	(3.18)	(0.89)	(1.15)	(0.77)	(1.11)	(3.00)	(4.35)	(2.26)
		0.44	0.33	0.50	0.35	0.06	0.02	0.11
PEAD	0.63	0.61	0.63	0.58	0.65	0.55	0.54	0.51
	(1.14)	(1.09)	(1.14)	(1.17)	(1.34)	(1.16)	(0.96)	(1.05)
		0.35	0.34	0.33	0.27	0.33	0.41	0.40
		6.86	7.66	5.57	7.23	6.73	9.16	8.83
		[0.07]	[0.06]	[0.07]	[0.07]	[0.05]	[0.01]	[0.03]
Panel B: Bubble Period II (2017/07/09 - 2018/02/04) (B2)								
FIN	0.12	0.03	-0.01	0.03	-0.02	0.04	-0.14	-0.10
	(0.57)	(0.18)	(-0.04)	(0.24)	(-0.14)	(0.28)	(-0.74)	(-0.54)
		0.87	0.97	0.83	0.90	0.80	0.51	0.63
PEAD	0.48	0.20	0.45	0.21	0.45	0.14	0.22	0.12
	(3.25)	(1.26)	(3.48)	(1.57)	(4.24)	(1.08)	(1.20)	(0.60)
		0.29	0.04	0.21	0.02	0.36	0.32	0.59
		1.75	7.95	1.87	7.55	1.13	1.64	0.68
		[0.42]	[0.01]	[0.40]	[0.03]	[0.57]	[0.41]	[0.62]
Panel C: Bubble Period III (2020/06/28 - 2021/02/21) (B3)								
FIN	0.00	0.08	0.06	0.06	0.05	0.05	0.09	0.12
	(0.08)	(1.48)	(1.35)	(1.02)	(1.02)	(0.81)	(1.62)	(2.37)
		0.24	0.27	0.38	0.38	0.48	0.20	0.10
PEAD	0.28	0.21	0.23	0.23	0.24	0.25	0.22	0.16
	(3.86)	(2.11)	(2.98)	(3.07)	(3.71)	(3.49)	(1.90)	(1.60)
		0.12	0.06	0.05	0.03	0.04	0.15	0.21

Spanning Test During Random Walk Periods

	mean	FF3	FFC	FF5	FF6	LSY3	LSY4	DHS3
Panel A: Random Walk Period I (2015/06/22 - 2017/07/08) (R1)								
r_{Me}	0.25	0.01	0.01	0.01	0.00	0.35	0.33	0.33
	(0.60)	(0.55)	(0.28)	(0.88)	(0.46)	(5.07)	(3.10)	(0.82)
		0.62	0.80	0.44	0.68	0.01	0.05	0.47
$r_{I/A}$	-0.04	0.02	-0.01	0.00	0.00	-0.04	-0.04	-0.02
	(-0.31)	(0.19)	(-0.07)	(-0.99)	(-1.47)	(-0.26)	(-0.28)	(-0.18)
		0.86	0.94	0.39	0.24	0.81	0.80	0.87
r_{ROE}	0.12	0.22	0.17	0.20	0.15	0.12	0.15	0.11
	(0.92)	(1.60)	(1.41)	(3.14)	(2.82)	(0.82)	(1.05)	(0.77)
		0.21	0.25	0.05	0.07	0.47	0.37	0.50
		4.64	3.08	6.21	12.10	27.55	34.44	5.85
		[0.25]	[0.44]	[0.12]	[0.02]	[0.00]	[0.00]	[0.14]
Panel B: Random Walk Period II (2018/02/05 - 2020/06/27) (R2)								
r_{Me}	0.24	0.03	0.03	0.01	0.00	0.32	0.30	0.33
	(1.72)	(1.19)	(0.93)	(0.58)	(0.41)	(3.61)	(3.96)	(2.61)
		0.32	0.42	0.60	0.71	0.04	0.03	0.08
$r_{I/A}$	0.19	-0.02	-0.01	0.00	0.00	0.11	0.09	0.08
	(0.83)	(-0.12)	(-0.05)	(0.00)	(-0.11)	(0.46)	(0.40)	(0.41)
		0.91	0.96	1.00	0.92	0.68	0.72	0.71
r_{ROE}	0.27	0.16	0.20	0.18	0.20	0.21	0.21	0.14
	(1.52)	(1.05)	(1.39)	(5.92)	(5.96)	(0.94)	(0.97)	(0.95)
		0.37	0.26	0.01	0.01	0.41	0.40	0.41
		10.84	11.54	9.13	9.61	38.64	61.10	13.46
		[0.01]	[0.01]	[0.06]	[0.22]	[0.00]	[0.00]	[0.01]

Spanning Test During Random Walk Periods

- the DHS3 factors cannot be adequately spanned by existing factor models during bubble periods, and the spanning test results reinforce our earlier findings on the distinctiveness and explanatory power of DHS3.
- the spanning test results during the random walk periods are consistent with our earlier findings, reinforcing the distinct explanatory content of the HXZ4 factors.

1. Introduction
2. Characteristics of Chinese Stock Market
3. Data
4. Empirical results
5. Conclusions

Key Takeaways

- The behavior factor model by Daniel et al. (2020) consistently outperformed other models during bubble periods
  - Increased prevalence of overconfidence and limited attention alongside the dominance of retail investors fuels bubble periods
- The *q*-factor model by Hou et al. (2015) demonstrated superior performance in efficient market
  - The redundancy of the value factor
  - The well-documented absence of momentum effects
  - The relevance of firms' future growth potential in pricing mechanisms
- All these prevalent asset pricing models struggled to capture the market dynamics during the stationary ARCH phase with a significant market decline
  - Substantial and consistent distortions in market pricing mechanisms which may be attributed to the sustained economic downturn

Thank you for listening !