Chinese Integrating Factors

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Abstract

This paper explores asset-pricing model uncertainty in China's A-share market by applying an integrated Bayesian Model Averaging framework across $2^{26} \approx 67.1$ million model specifications. It incorporates mispricing, time-varying factor exposures, and evolving risk premia with 15 tradable and 11 non-tradable factors. Our key findings are as follows: (1) Model uncertainty in China's stock market is much higher than that in mature markets. (2) Posterior analysis supports time-varying models. (3) The Sharpe ratio and downside risk of the BMA model significantly outperform other benchmark models. (4) Variance decomposition, covariance entropy, and model divergence reveal uncertainty intensifies out-of-sample and peaks during stress episodes. These results underscore the importance of risk management and highlight the need to monitor uncertainty indicators and to anticipate systemic vulnerabilities.

Keywords: Factor Zoo; Bayesian Model Averaging; Chinese Stock Market

JEL Classification Codes: G11 G12

1 Introduction

Financial economics has identified a wide array of firm characteristics and macro predictors that seem to forecast cross-sectional stock returns (e.g.Cochrane (2011); Harvey et al. (2016)). But in China's A-share market, these established predictive logics have seen limited practical application. As the world's second largest equity market, China's A-share market has stagnated over the past two decades, its volatility a lingering puzzle for both academia and investors. Over the same period, China's economy surged in the first decade, then slowed in the next, yet growth has stayed generally robust. This disconnect between economic vitality and market inertia lies at the heart of its enigma, with the forces shaping its pricing dynamics still elusive.

To navigate this expanding set of predictors, researchers have pursued two main strategies: one rooted in economic theory such as present-value logic and q-theory; the other in statistical tools such as shrinkage or machine learning to extract insights from numerous predictors. While such approaches work reasonably well in mature markets, yet neither strategy fully addresses model uncertainty, a gap especially sharp in China's market. Extant abundant literature on emerging markets, China in particular, lists factors like retail investor dominance, excessive policy intervention, and market immaturity as key features. Could these features hold the key to its prolonged stagnation?

As highlighted by Harvey (2017)'s AFA presidential address, Bryzgalova et al. (2023a), whose work shows Bayesian Model Averaging (BMA) outperforms prominent models like Kozak et al. (2020) and KNS, BMA framework offers three key strengths. First, it reliably identifies a small set of observable factors. Second, it aggregates multiple imperfect risk measures. Third, it employs a novel prior driven by Sharpe ratio beliefs, enabling direct SDF estimation. These strengths make BMA an ideal fit for studying China's stock market, as it accounts for model uncertainty and reduces overreliance on a single model.

This paper follows Avramov et al. (2023) by employing a comprehensive Bayesian framework to address factor-model uncertainty in the Chinese stock market. Candidate models vary across three dimensions: the choice of cross-sectional risk factors, macroeconomic predictors, and whether pricing errors that may be time-varying are allowed. Unlike prior studies that impose priors selectively, our approach specifies economically meaningful priors over all pricing parameters, balancing prior beliefs with evidence from macroeconomic predictability and pricing performance. This yields posterior model probabilities that favor simpler models with strong pricing ability. Such a flexible framework is especially relevant for the China A-share market, where static models often overlook complexities such as mispricing, time-varying exposures, and fluctuating risk premia factors that hinder accurate risk assessment and policy formulation. Our approach prioritizes powerful models, aiming to provide a more nuanced understanding of asset pricing in this context and new insights into emerging market dynamics.

Our main findings are as follows. First, model uncertainty in China's A-share market is significantly higher than in other mature markets, with no single model or small subset able to capture its complex pricing dynamics. Second, the data favor models allowing for time-varying factor exposures and risk premia: size (SMB) and idiosyncratic volatility (STD) stand out as the most robust tradable factors, while industrial production and the El Niño index carry substantial explanatory weight among macroeconomic predictors. Furthermore, the Bayesian Model Averaging framework outperforms standard benchmarks including the CAPM, Fama-French three-factor model, Fama-French five-factor model, Fama-French six-factor model, and the DHS model in both in-sample and out-of-sample tests, delivering stronger risk-adjusted returns and lower downside risk. Finally, model uncertainty intensifies out of sample and peaks during market stress, as revealed through variance decomposition, covariance entropy, and measures of model divergence, highlighting its critical role in risk assessment for China's stock market.

Our contribution can be summarized in three dimensions. First, extending the BMA method to China's A-share market, we derive a closed-form solution, whereas prior work relied on algorithmic estimation. Second, we employ a broader dataset than most existing literature, incorporating 15 tradable and 11 non-tradable factors alongside macro predictors (e.g., industrial production, El Niño index). Third, our robust findings provide clear policy implications for China's stock market development and enrich emerging market financial regulation literature.

Our paper is related to several strands of literature. Our paper is naturally connected to the literature on the "factor zoo." Existing studies have sought to explore this phenomenon from three perspectives. First, leveraging the property of rotation invariance, (Giglio and Xiu, 2021; Giglio et al., 2025; Mao and Xia, 2023; Nucera et al., 2024) employ the three-pass method to accurately recover the risk premia of observable factors even when the true factors themselves are unobservable. Second, Feng et al. (2020) integrate cross-sectional pricing with the double-selection LASSO method proposed by Belloni et al. (2014), enabling valid inference on a small set of candidate factors from a large pool. Third, Bryzgalova et al. (2023a) develop the Bayesian Model Averaging (BMA) method to address model uncertainty.

Our paper is also related to the literature on Bayesian Model Averaging (BMA), which has found wide application in various research areas. These include asset allocation (Avramov and Zhou, 2010), volatility prediction (Liu and Maheu, 2009; Mao and Zhang, 2018), model selection (Chib et al., 2020a), and performance evaluation (Baks et al., 2001; Pástor and Stambaugh, 2000; Harvey and Liu, 2019).

Additionally, our paper is naturally linked to the asset pricing literature focused on Chinese financial markets. For instance, Liu et al. (2019) find that the well-known Fama-French five-factor model is not suitable for China's financial market and propose a three-factor model specifically tailored to it.Mao et al. (2025) study Chinese market latent factors via RP-PCA, outperforming traditional methods. Other relevant studies include Cheema et al. (2020), Lin et al. (2023), and Chen et al. (2021).

The remainder of the paper proceeds as follows. In Section 2, we present the empirical framework, including the foundational asset-pricing models, the Bayesian Model Averaging methodology, and our approach to specifying economically meaningful priors and updating them with data to obtain posterior distributions. Section 3 provides a concise overview of the data—comprising factor returns and macroeconomic variables, including their sources and preprocessing procedures. Section 4 details our empirical analysis. Section 5 concludes.

2 Asset Pricing with Model Uncertainty

2.1 Asset Pricing with Model Uncertainty

We model excess returns and factors within a framework that accounts for time-varying parameters and model uncertainty. Let $\mathbf{r}_{t+1}$ denote an $N \times 1$ vector of excess returns on test assets, $\mathbf{f}_{t+1}$ a $K \times 1$ vector of factor returns, and $\mathbf{z}_t$ an $M \times 1$ vector of lagged macro predictors. The time series length is T, with t indexing time.

Factors are modeled via a predictive regression:

$$\mathbf{f}_{t+1} = \alpha_f + a_F \mathbf{z}_t + \mathbf{u}_{f,t+1}, \tag{1}$$

where α_f is the factor intercept, a_F captures factor sensitivity to macro variables, and $\mathbf{u}_{f,t+1}$ is a mean-zero error term.

The time-varying components decompose as:

$$\alpha(\mathbf{z}_t) = \alpha_0 + \alpha_1 \mathbf{z}_t, \quad \beta(\mathbf{z}_t) = \beta_0 + \beta_1 (I_K \otimes \mathbf{z}_t)$$

where α_0 (fixed mispricing), α_1 (time-varying mispricing), β_0 (fixed loadings), and β_1 (time-varying loadings) are parameters; I_K is a $K \times K$ identity matrix, and $\otimes$ denotes the Kronecker product.

Substituting these into the previous equation, excess returns become:

$$\mathbf{r}_{t+1} = \alpha_0 + \alpha_1 \mathbf{z}_t + \beta_0 \mathbf{f}_{t+1} + \beta_1 (I_K \otimes \mathbf{z}_t) \mathbf{f}_{t+1} + \mathbf{u}_{r,t+1}. \tag{2}$$

Under model uncertainty, expected returns integrate over candidate models weighted by posterior probabilities:

$$\mathbb{E}[\mathbf{r}_{t+1} | \mathcal{D}] = \sum_{l=1}^{L} \mathbb{P}(M_l | \mathcal{D}) \mathbb{E}[\mathbf{r}_{t+1} | M_l, \mathcal{D}], \tag{3}$$

where $\mathcal{D}$ represents observed panel data (test asset returns, factors, macro predictors), M_l denotes the l-th candidate model, and $\mathbb{P}(M_l|\mathcal{D})$ is its posterior probability. The covariance matrix of returns under model uncertainty decomposes into two components: the first captures average model-specific variances, and the second reflects disagreement across models about expected returns:

$$V_t = \sum_{l=1}^{L} \mathbb{P}(M_l|\mathcal{D})\text{Var}(\mathbf{r}_{t+1}|M_l, \mathcal{D}), \tag{4}$$

$$\Omega_t = \sum_{l=1}^{L} \mathbb{P}(M_l|\mathcal{D})(\mathbb{E}[\mathbf{r}_{t+1}|M_l, \mathcal{D}] - \mathbb{E}[\mathbf{r}_{t+1}|\mathcal{D}])(\mathbb{E}[\mathbf{r}_{t+1}|M_l, \mathcal{D}] - \mathbb{E}[\mathbf{r}_{t+1}|\mathcal{D}])^\top. \tag{5}$$

2.2 Deriving Posterior Probabilities

Let θ be the vector of parameters in model M_l, with prior density $\pi(\theta|M_l)$ and likelihood $\mathcal{L}(\mathcal{D}|\theta, M_l)$. The marginal likelihood is

$$m(\mathcal{D}|M_l) = \int \mathcal{L}(\mathcal{D}|\theta, M_l)\pi(\theta|M_l)d\theta, \tag{6}$$

which, following Chib et al. (2020b), can be computed via

$$m(\mathcal{D}|M_l) = \frac{\mathcal{L}(\mathcal{D}|\hat{\theta}_l, M_l)\pi(\hat{\theta}_l|M_l)}{\pi(\hat{\theta}_l|\mathcal{D}, M_l)}, \tag{7}$$

where $\hat{\theta}_l$ is the posterior mode.

Then, the posterior probability of model is

$$\mathbb{P}(M|\mathcal{D}) = \frac{m(\mathcal{D}|M)\mathbb{P}(M)}{\sum_{l=1}^{L} m(\mathcal{D}|M_l)\mathbb{P}(M_l)}. \tag{8}$$

In our baseline analysis, we assume $\mathbb{P}(M_l) = 1/L$ for all M_l, unless otherwise justified by economic theory.

Specifically, we adopt an empirical Bayes approach. For each model, we assume prior moments are centered on their sample counterparts, but priors on α, β, and a_F are centered at zero to reflect skepticism toward mispricing and time-varying loadings. The tightness of priors is governed by a hypothetical sample size T_0, which we calibrate using bounds on the Sharpe ratio.

Let the total prior variance of mispricing (including time variation) be

$$\mathrm{Var}(\alpha|\Sigma_{RR}, \mathcal{D}) = \frac{\Sigma_{RR}}{T_0}\left(1 + SR^2_{\max} + m(1 + SR^2_{\max})\right), \tag{9}$$

where $SR_{\max}$ is the squared Sharpe ratio upper bound and m is the number of predictors.

Define a target prior variance as

$$\mathbb{E}(\alpha'\Sigma^{-1}_{RR}\alpha|\Sigma_{RR}, \mathcal{D}) = \eta(N + K - k), \tag{10}$$

where η is determined by

$$\eta = \frac{(\tau^2 - 1)SR^2_{\mathrm{mkt}}}{N + K - k}, \tag{11}$$

and equating with the previous expression yields

$$T_0 = \frac{(N + K - k)(1 + SR^2_{\max} + m(1 + SR^2_{\max}))}{(\tau^2 - 1)SR^2_{\mathrm{mkt}}}. \tag{12}$$

This choice of T_0 ensures consistency with beliefs about maximum Sharpe ratios and penalizes unnecessary complexity, as adding predictors increases T_0, reducing T_0 and tightening priors.

3 Data

Our data primarily originate from the China Stock Market and Accounting Research (CSMAR) database, with supplementary macroeconomic indicators sourced from the CEIC China Economic Database and Wind. The dataset spans the period from July 2007 to January 2024 and includes all A-share listed firms, encompassing those on the STAR Market and ChiNext Market [1]. Factor data consist of monthly returns on long-short portfolios with annual rebalancing conducted on July 1st each year.

We examine 14 widely recognized factors from the existing literature. These include the six-factor model of Fama and French (2018), which extends the classic three-factor

[1] The STAR Market (Science and Technology Innovation Board) is a Nasdaq-style exchange launched in 2019 by the Shanghai Stock Exchange to support high-tech and innovative enterprises. The ChiNext Market, operated by the Shenzhen Stock Exchange, is designed to promote the development of emerging industries and startups with high growth potential.

specification, market (MKT), size (SMB), and value (HML) as proposed in Fama and French (1993) by incorporating the investment (CMA) and profitability (RMW) factors, as well as the momentum factor (MOM) from Carhart (1997). In addition, we include the betting-against-correlation (BAC) and betting-against-volatility (BAV) factors following the methodology of Asness et al. (2020); the idiosyncratic volatility factor (STD) of Ang et al. (2006); the idiosyncratic skewness (SKEW) and kurtosis (KURT) factors proposed by Amaya et al. (2015); the liquidity beta factor (LIQ) of Pastor and Stambaugh (2003); and the behavioral factors FIN and PEAD developed by Daniel et al. (2020). Finally, we include the expected growth factor (Eg) introduced by Hou et al. (2021). We omit the remaining q-factor model components due to their competitive overlap with the Fama-French framework.

For most long-short factor portfolios, we adopt a 2×3 double-sorting procedure by size, consistent with the Fama-French empirical convention. For the construction of test assets, we follow the "relative model tests" framework introduced by Barillas and Shanken (2018), which posits that excluded factors from a given model should themselves be priced by the model. Accordingly, the factor-mimicking portfolios of the omitted factors serve as test assets for model evaluation. This approach improves upon traditional model comparison methods while significantly reducing computational complexity, and has been widely adopted in subsequent studies in Chib et al. (2020b) and Avramov and Chao (2006).

According to Consume and CrudeOil factors in Giglio and Xiu (2021) and Mao and Xia (2023), we include macroeconomic information in our analysis by conducting principal component analysis (PCA) on 90 Chinese macro indicators sourced from CEIC. The top three principal components are extracted and their residuals obtained through a vector autoregression (VAR). Additional macroeconomic variables—such as retail sales of Industry, consumer goods, crude oil import prices, industrial employment, and policy uncertainty (proxied by the China Economic Policy Uncertainty Index constructed from articles in People's Daily and Guangming Daily)—are filtered using first-order autoregressive models to remove persistence and isolate exogenous shocks. We also incorporate several natural environmental variables, including the monthly Niño 3.4 sea surface temperature index (El Niño), the average monthly temperature in Shanghai, and the average monthly sunspot count.

4 Empirical Analysis

This section conducts an empirical assessment of multiple asset pricing models within the context of the Chinese stock market. The evaluation emphasizes both in-sample and out-of-sample performance metrics. We compare the Bayesian Model Averaging (BMA) approach against established benchmark models, including the Capital Asset Pricing Model (CAPM), Fama-French 3-factor model (FF3), Fama-French 5-factor model (FF5), Fama-French 6-factor model (FF6), and the DHS model. Our analysis employs a variety of metrics such as cumulative excess returns, annualized Sharpe ratios, downside risk measures, variance decomposition, and factor contributions to gauge the effectiveness of each model.

4.1 Model Uncertainty and Posterior Inference

The initial step of our empirical investigation addresses the importance of model uncertainty. We compute posterior model probabilities by exhaustively traversing the entire model space. If one or a small subset of models captures an overwhelming share of the posterior mass, model uncertainty is negligible and conventional model selection is sufficient to recover the ”true” specification. Conversely, when the posterior mass is widely dispersed, model uncertainty remains a first-order concern and Bayesian Averaging is a better choice.

Figure 1 illustrates cumulative posterior probabilities for the four model families M_1 through M_4, ordered from lowest to highest posterior probability, under alternative hyper-parameter settings for the prior Sharpe ratio τ. Across the full universe of 2^{26} = 67,108,864 candidate models, no single specification—or even a small handful—accounts for a meaningful portion of the posterior mass. Using the benchmark prior ($\tau = 1.5$), the ten highest-probability models collectively explain only 0.0047 % of the total posterior mass. Expanding this to the top 100 and top 500 models raises the cumulative posterior probability to just 0.0365 % and 0.1433 %, respectively. In fact,

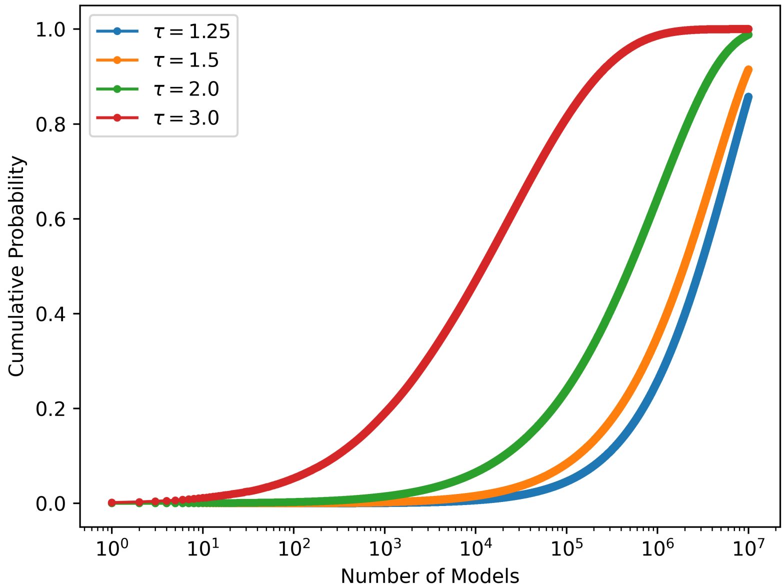

Figure 1: Cumulative posterior probabilities of asset pricing models

meaningful accumulation of posterior mass does not begin until the number of models reaches the range of 10^3 to 10^7. When the prior Sharpe ratio is increased to the unrealistically optimistic level of $\tau = 3$, the posterior mass becomes even more dispersed, concentrating further in the long tail of the model space. This dispersion is far greater than the pattern documented by Avramov and Chao (2006) for the U.S. market, indicating that model uncertainty is markedly more pronounced in the Chinese setting. In other words, the explanatory power of the leading models weakens further in the A-share market, underscoring the need for BMA.

4.2 Posterior Inclusion Probabilities

Panel (a) of Table 5 presents the posterior inclusion probabilities (PIPs) for each pricing factor and macroeconomic variable in the Chinese market under different values of the prior Sharpe ratio τ. Apart from the market factor (MKT), which is fixed by design, the idiosyncratic volatility factor (STD) consistently achieves a 100% inclusion probability across all τ settings. This indicates that STD is universally recognized as a core risk factor across nearly all models in the specification space. Following closely is

Table 1: Posterior Probabilities of Factors and Macroeconomic Variables by τ Values

Panel (a):Factor Posterior Probabilities

Factor	τ			
	1.25	1.5	2.0	3.0
MKT	1.00	1.00	1.00	1.00
SMB	0.91	0.91	0.91	0.91
HML	0.43	0.37	0.26	0.13
CMA	0.77	0.71	0.57	0.19
RMW	0.63	0.60	0.51	0.33
MOM	0.41	0.34	0.20	0.03
BAC	0.47	0.42	0.36	0.21
BAV	0.61	0.57	0.53	0.67
STD	1.00	1.00	1.00	1.00
SKEW	0.45	0.37	0.24	0.07
KURT	0.58	0.55	0.50	0.32
LIQ	0.47	0.42	0.37	0.26
PEAD	0.53	0.47	0.37	0.39
FIN	0.62	0.58	0.51	0.36
Eg	0.49	0.46	0.43	0.34

Panel (b): Macroeconomic variables

macroeconomic information	τ			
	1.25	1.5	2.0	3.0
Macro1	0.51	0.51	0.49	0.55
Macro2	0.49	0.46	0.39	0.28
Macro3	0.54	0.56	0.59	0.66
Consume	0.46	0.42	0.33	0.24
CrudeOil	0.45	0.42	0.40	0.38
Industry	0.61	0.70	0.82	0.92
employ	0.45	0.42	0.40	0.38
Uncertainty	0.48	0.44	0.37	0.31
Nino	0.57	0.61	0.67	0.77
Temp	0.51	0.51	0.49	0.45
Sunspot	0.53	0.54	0.57	0.70

Panel (c): Model Mispricing and Hypothetical Sample

	τ			
	1.25	1.5	2.0	3.0
Conditional Model Probability	1.000	1.000	1.000	1.000
Mispricing Probability	0.469	0.428	0.320	0.087
Average T_0	5385	2423	1009	378
Average $\frac{T_0}{T_0+T}$	0.973	0.941	0.871	0.723

the size factor (SMB), which maintains a stable inclusion probability of approximately 91% across all four τ configurations. This confirms the robustness of the small-cap effect, consistent with the classical Fama-French model.

Unlike the size factor (SMB), the remaining components of the Fama-French six-factor model—namely the value (HML), investment (CMA), and profitability (RMW) factors—struggle to gain posterior support in the Chinese market. As the degree of regularization increases, the posterior inclusion probability of HML declines from 43% to 13%, while that of CMA falls from 77% to 19%. These patterns indicate that the explanatory power of traditional value and profitability-based factors is highly sensitive to the strength of the prior. The momentum factor (MOM) exhibits even greater redundancy. When the prior Sharpe ratio is raised to $\tau = 3$, its cumulative posterior probability drops to merely 3%, echoing the findings of Zhu et al. (2024) that momentum may not represent an independent source of systematic risk, but rather a premium arising from market frictions.

The long-short behavioral model provides two factors—post-earnings announcement drift (PEAD) and financial distress (FIN). Similar to the expected growth factor (Eg) and the liquidity beta factor (LIQ), these two variables display moderate explanatory power under $\tau = 1.25$ but are gradually excluded as the prior becomes more stringent. Their relevance therefore depends heavily on the assumed prior Sharpe ratio. Higher-order moment factors show a similar sensitivity: while idiosyncratic volatility (STD) remains fundamental, idiosyncratic skewness (SKEW) and kurtosis (KURT) are sharply affected by the prior. Under $\tau = 3$, the posterior inclusion probability of SKEW falls to just 7%. By contrast, the betting-against-correlation factor (BAC) is progressively incorporated as τ increases, and once included, maintains a relatively stable probability of selection.

Panel (b) reports posterior inclusion probabilities for macroeconomic predictors. Industrial value added (*Industry*) rises from an inclusion probability of 61% to 92% as τ increases, making it the most reliable macro predictor—likely due to its direct link to real economic activity. The El Niño index (*Nino*) and the sunspot number (*Sunspot*) also gain importance: at $\tau = 3$ their posterior probabilities reach 77% and 70%, respectively, suggesting that climate-induced macro shocks help explain asset returns.

Other macro variables exhibit more average probabilities. Among all predictors, the leading set comprises STD, SMB, FIN, *Industry*, *Nino*, and *Sunspot*, a combination not previously examined in the Chinese market. Notably, our posterior results closely mirror those of Mao et al. (2024), who sample a far larger model space, lending further support to the effectiveness of these factors in China.

Panel (c) summarizes additional model characteristics. Regardless of how strongly the prior penalizes time-varying factor loadings, model families M_3 and M_4 unanimously support interactions between factor portfolios and macro variables, each with a posterior probability of 100%. Regarding potential mispricing, the posterior probability of a non-zero intercept is 0.469, 0.428, and 0.320 after excluding the strong priors $\tau = 1.25$, 1.5, and 2.0, respectively. This indicates that, unless the prior heavily discourages mispricing, the intercept cannot be ignored.

4.3 Out-of-Sample Portfolio Performance

We conduct out-of-sample tests of the integrated model. The mean-variance portfolios derived from model selection fully account for both parameter uncertainty and model uncertainty. We evaluate two performance metrics—Sharpe ratio and downside risk—and benchmark our results against four established factor models: **(i)** the single-factor CAPM (MKT); **(ii)** the Fama-French three-factor model (MKT, SMB, HML); **(iii)** the extended Fama-French six-factor model (MKT, SMB, HML, RMW, CMA, MOM); and **(iv)** the Daniel-Hirshleifer-Subrahmanyam long-short behavioral model (MKT, FIN, PEAD).

We test four benchmark models and BMA's annualized Sharpe ratio for the sample period of T,T/2 and 2/3 T. For T period, the model does not exist; conversely, for the other two instances, we use in-sample data to determine the weight.In our Figure 2 ($\tau = 1.5$), the market's cumulative excess returns are depicted by a black line. Two blue lines illustrate the in-sample and out-of-sample cumulative returns for portfolios characterized by negative or delayed maturities, respectively. To ensure comparability, the volatility of the BMA-derived portfolio returns is calibrated to align with that of the benchmark models, maintaining uniform leverage ratios across both in-sample and out-of-sample datasets. Meanwhile, we also examined the portfolio returns established

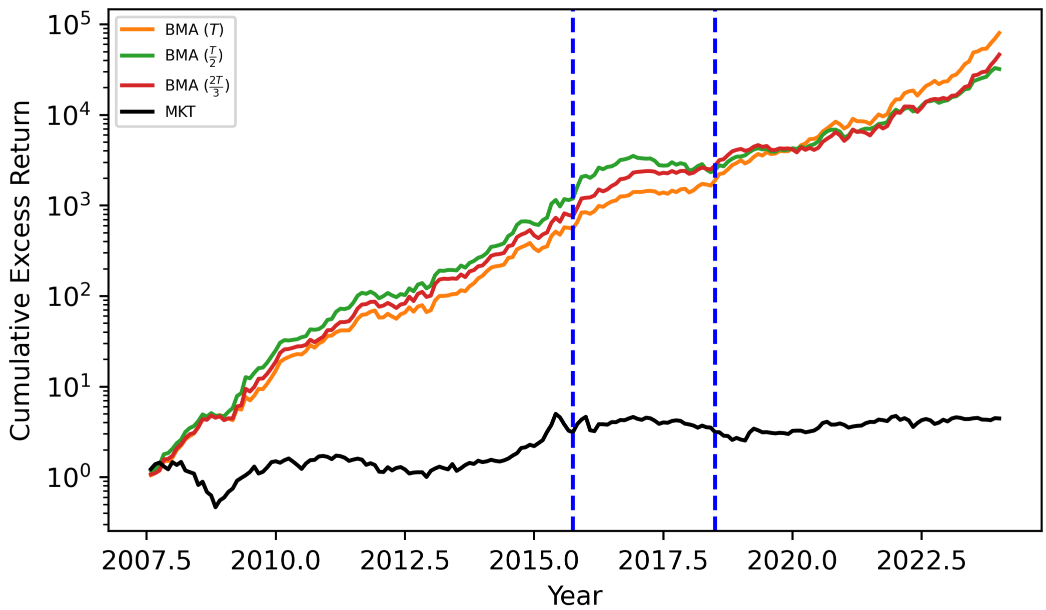

Figure 2: Cumulative Excess Return

under the T-Regulation (T-Reg) denoted by the restriction on leverage ratios, where the net long position of the portfolio cannot exceed twice the available capital.It imposes restrictions on the leverage level of the portfolio, prohibiting free adjustments.For the weights w of all factor assets, we require the inclusion of the constraint $1^T w \leq 2$ in the quadratic programming of the optimal portfolio, prohibiting the model from the leverage exceeding two times.

Table 2 presents the annualized Sharpe ratios for the BMA and benchmark models. The BMA model demonstrates exceptional performance, with an in-sample Sharpe ratio of 2.558 and an out-of-sample Sharpe ratio of 1.565, markedly surpassing the CAPM's in-sample value of 0.445. Notably, approximately two-thirds of the sample, with a Sharpe ratio of 1.853, exhibits statistical significance across all evaluated characteristics, reinforcing the robustness of the BMA approach. While models such as FF5 and FF6 exhibit competitive in-sample performance in unconstrained scenarios, their out-of-sample results lag behind BMA.

After the imposition of the T-Regulation, the in-sample and out-of-sample performance of all models generally weakened. The BMA model exhibited a significant decline in its Sharpe ratio across all scenarios, yet it retained a relative advantage over bench-

Table 2: In-sample and out-of-sample BMA annualized Sharpe ratios with benchmark

	T	$\frac{T}{2}$		$\frac{2T}{3}$	
Model	EST	EST	OOS	EST	OOS
CAPM	0.445	0.557	0.297	0.471	0.403
FF3	0.972	1.251	0.669	1.052	0.771
FF6	1.319	1.913	0.560	1.432	0.924
DHS	0.527	1.079	-0.398	0.834	-0.393
BMA	**2.358**	**2.516**	**1.565**	**2.214**	**1.853**
FF3 T-Reg	0.691	0.952	0.384	0.730	0.629
FF6 T-Reg	0.838	1.207	0.476	0.930	0.597
DHS T-Reg	0.493	0.718	0.188	0.597	0.234
BMA T-Reg	**1.366**	**1.315**	**0.970**	**1.196**	**1.495**

Note: This table presents the annualized Sharpe ratios of the BMA model and four benchmark models under different sample lengths, where we consider three sample lengths: T, $\frac{T}{2}$, and $\frac{2T}{3}$. "EST" denotes the in-sample Sharpe ratio, and "OOS" denotes the out-of-sample Sharpe ratio. "T-Reg" refers to restricting the leverage level of the portfolio to be less than or equal to 2 times

mark models, such as the Fama-French 3-factor (FF3), Fama-French 6-factor (FF6), and DHS models. While the in-sample estimates (EST) for FF3, FF6, and DHS declined, some models demonstrated improved out-of-sample (OOS) performance.

4.4 Downside Risk

Table 3: Out-of-sample downside risk performance of the model

Model	Risk downward Indicators					
	Mean	Standard Deviation	Sharpe Ratio	Skewness	Excess Kurtosis	Maximum Drawdown
Tangent Portfolio						
CAPM	0.705	6.056	0.403	0.525	1.926	24.419
FF3	1.481	6.656	0.771	-0.100	0.394	40.058
FF6	1.663	6.239	0.924	-0.198	-0.181	34.213
DHS	-0.241	2.123	-0.393	0.339	0.620	27.098
BMA	0.599	1.186	1.749	0.329	0.020	**2.826**
T-Reg						
CAPM T-Reg	1.410	12.113	0.403	0.525	1.926	45.636
FF3 T-Reg	0.948	5.218	0.629	0.365	0.917	19.369
FF6 T-Reg	0.781	4.535	0.597	0.211	-0.441	16.926
DHS T-Reg	0.368	5.454	0.234	0.291	1.463	24.797
BMA T-Reg	2.403	5.618	1.482	0.284	-0.076	**11.908**

Table 3 presents the baseline case with a sample length of $2T$ and $\tau = 1.5$, aligning with the benchmark settings established by Barillas and Shanken (2018) and Avramov and Chao (2006). In contrast to the previous section, the analysis of downside risk places particular emphasis on adverse economic conditions. Accordingly, in addition to reporting Sharpe ratios, skewness, and kurtosis, we examine the maximum drawdown, defined as the maximum difference in cumulative excess returns between any two time points t_0 and t_1, where $t_0 \leq t_1$, i.e., $\max(R_{t_0} - R_{t_1})$. Consistent with the prior analysis, we evaluate four benchmark models under the scenarios of the T-Regulation. As previously noted, BMA model achieved the highest Sharpe ratio among all models, underscoring its superiority over other benchmark models in risk-adjusted terms. In terms of standard deviation, the CAPM tangency portfolio exhibited lower volatility than FF3 and FF6, yet the BMA tangency portfolio recorded a standard deviation of only 1.186, reflecting its exceptional risk management capabilities. Regarding excess kurtosis, the BMA tangency portfolio approached zero, indicating the lowest tail risk among the models, particularly when compared to the CAPM tangency portfolio's excess kurtosis of 1.926. Furthermore, after evaluating all time points, the BMA tangency portfolio's maximum drawdown was a mere 2.826, starkly contrasting with 40.058 for the FF3 model and 34.213 for the FF6 model. This highlights the BMA model's remarkable resilience to downside risk, maintaining robustness both in-sample and out-of-sample, with downside risk several times lower than that of all benchmark models. A review of Figure 2 reveals that during periods of significant market distress, such as the 2008 financial crisis, the 2015 stock market crash, and the COVID-19 pandemic around 2021, the BMA model consistently demonstrated strong resistance to downside risk.

4.5 Model Uncertainty Analysis

This subsection employs a variance decomposition framework based on an integrated model to examine the impact of model uncertainty on the risk structure of factors. As previously discussed, $V_t + \Omega_t$ represents the sum of the conditional variance mean and the model disagreement of the integrated model, while OBS denotes the historical sample variance, which does not account for model uncertainty risk. The comparison between these two measures is grounded in the law of total variance, which states that the unconditional variance equals the expected conditional variance plus the variance of

Table 4: In-sample and out-of-sample model estimated variance and actual sample variance

	T In-sample			$\frac{T}{2}$ In-sample			$\frac{T}{2}$ Out-of-sample			$\frac{2T}{3}$ In-sample			$\frac{2T}{3}$ Out-of-sample		
Factor	$\overline{V_t + \Omega_t}$	$\overline{\Omega_t}$	OBS	$\overline{V_t + \Omega_t}$	$\overline{\Omega_t}$	OBS	$\overline{V_t + \Omega_t}$	$\overline{\Omega_t}$	OBS	$\overline{V_t + \Omega_t}$	$\overline{\Omega_t}$	OBS	$\overline{V_t + \Omega_t}$	$\overline{\Omega_t}$	OBS
MKT	84.510	0.001	84.604	119.023	0.002	119.577	119.283	0.007	49.824	108.468	0.002	108.858	108.651	0.007	36.680
SMB	8.566	0.004	8.560	14.587	0.102	10.684	25.113	0.498	6.301	9.751	0.003	9.769	9.767	0.003	6.207
HML	3.705	0.001	3.718	17.982	0.192	2.972	26.444	0.276	4.481	2.810	0.000	2.816	2.816	0.000	5.586
CMA	2.344	0.001	2.345	27.585	0.184	2.961	40.109	0.263	1.702	2.561	0.003	2.572	2.568	0.003	1.766
RMW	5.825	0.005	5.798	56.134	0.196	5.313	80.349	0.280	6.060	5.378	0.004	5.341	5.392	0.004	6.774
MOM	8.724	0.003	8.755	16.686	0.092	11.342	32.121	0.436	6.022	9.586	0.002	9.620	9.618	0.002	6.966
BAC	5.089	0.001	5.088	7.746	0.006	6.721	11.730	0.012	3.501	6.102	0.002	6.110	6.104	0.002	3.060
BAV	5.791	0.003	5.827	7.755	0.007	6.827	11.781	0.007	4.634	6.202	0.003	6.247	6.227	0.003	5.011
FIN	5.226	0.001	5.225	32.147	0.306	4.821	47.297	0.443	5.680	4.578	0.001	4.578	4.603	0.001	6.572
LIQ	2.871	0.001	2.859	4.176	0.006	3.206	7.907	0.018	2.488	2.658	0.001	2.645	2.668	0.001	3.146
PEAD	2.654	0.002	2.645	3.475	0.005	3.321	3.633	0.006	1.881	2.644	0.002	2.628	2.647	0.002	2.571
STD	9.393	0.000	9.404	11.528	0.001	11.570	11.571	0.001	7.204	9.723	0.000	9.759	9.739	0.000	8.767
SKEW	3.415	0.001	3.416	16.599	0.117	5.004	22.902	0.168	1.769	3.979	0.001	3.983	3.994	0.001	2.183
KURT	4.835	0.003	4.844	7.047	0.005	6.832	7.599	0.010	2.751	5.491	0.002	5.507	5.498	0.002	3.471
FIN	4.735	0.002	4.747	5.852	0.006	5.633	6.246	0.007	3.664	5.297	0.003	5.320	5.331	0.003	3.490

the conditional expectation. Consequently, the inequality $\mathrm{Var}(r_{t+1}) > E(\mathrm{Var}(r_{t+1}|z_t))$ holds strictly. However, $E(\mathrm{Var}(r_{t+1}|z_t))$ does not incorporate model uncertainty. Therefore, when applying the Bayesian Model Averaging (BMA) method, we perceive additional risk stemming from model uncertainty. To assess this, we compare $\mathrm{Var}(r_{t+1})$ with $E(\mathrm{Var}(r_{t+1}|D))$. If the time-series average of the integrated model's variance exceeds that of the historical sample variance, it suggests that accounting for model uncertainty enables investors to perceive additional risk.

Table 4 reports the comparison between the variance $V + \Omega$ and the sample variance (OBS) across different sample periods. Among the 15 factors, 6 exhibit an integrated model variance greater than the sample variance. Overall, within the full sample, model parameter uncertainty adequately reflects the uncertainty in BMA, indicating a limited impact of model uncertainty. However, this changes when considering half-sample and two-thirds sample scenarios. In the in-sample half-sample case, the integrated model variance exceeds the sample variance for 13 factors, with some variances expanding significantly. For instance, the CMA factor's sample variance is only 2.961, but for investors considering model uncertainty, the model variance rises to 27.585. When examining the out-of-sample performance, the model variance often exceeds the sample variance by several multiples. In the out-of-sample half-sample, the model variance is significantly larger than the historical sample variance for all 15 factors, with the integrated model variance averaging 6.19 times the sample variance, compared to 3.16 times in-sample. This disparity underscores that investors face uncertainty not only regarding model parameters but also concerning the true model itself. Particularly in out-of-sample contexts, the influence of model uncertainty on risk perception is substantial in the Chinese market.

4.6 Factor Pricing Divergence

Table 5 provides a detailed decomposition of each factor's contribution. Panel (a) reports the *average* contribution of individual factors, whereas Panel (b) documents the *maximum* contribution observed over the entire sample period. On average, SMB, CMA, RMW and BAV exhibit the most stable contributions among all factors. In the full-sample estimation, their mean contributions are 8.62%, 7.38%, 12.57% and 9.65%, re-

Table 5: Factor covariance contribution

Factor	T	$\frac{T}{2}$ In-sample	$\frac{T}{2}$ Out-of-sample	$\frac{2T}{3}$ In-sample	$\frac{2T}{3}$ Out-of-sample
Panel (a): Average Factor's Relative Contribution to Entropy (%)					
MKT	0.388	0.041	0.101	0.536	1.536
SMB	8.621	14.160	25.377	6.288	5.702
HML	3.892	20.511	15.171	2.215	2.542
CMA	7.382	12.149	8.548	18.579	17.245
RMW	12.573	6.745	4.731	9.810	9.739
MOM	4.557	11.279	18.578	3.009	3.442
BAC	5.092	1.535	1.553	5.042	5.536
BAV	9.647	1.598	0.803	9.171	8.152
EG	4.053	16.589	12.131	3.466	3.954
LIQ	4.081	2.322	2.803	6.446	6.802
PEAD	11.331	1.947	1.480	10.906	10.007
STD	1.959	0.143	0.146	1.223	1.743
SKEW	6.737	8.020	5.669	5.882	6.287
KURT	10.506	1.527	1.775	7.613	7.519
FIN	9.181	1.433	1.133	9.813	9.793
Panel (b): Maximum Factor's Relative Contribution to Entropy (%)					
MKT	1.887	0.158	0.462	3.124	7.092
SMB	10.871	41.019	50.826	8.212	7.513
HML	7.457	31.038	29.126	5.342	4.624
CMA	9.041	17.691	15.282	23.064	21.747
RMW	17.016	10.468	8.380	12.027	12.791
MOM	7.212	33.763	32.822	4.694	8.488
BAC	10.677	4.562	4.734	6.936	10.537
BAV	13.084	5.740	5.377	13.123	11.412
EG	8.830	24.430	22.492	4.325	6.051
LIQ	7.246	6.045	6.342	8.421	8.414
PEAD	16.015	7.116	5.768	13.305	12.474
STD	13.368	0.775	0.774	7.412	10.270
SKEW	9.818	13.157	12.006	8.628	9.127
KURT	14.797	6.874	5.628	11.732	11.063
FIN	15.156	4.881	4.198	13.291	12.764

spectively, together accounting for 32–41% of the total increase in entropy, underscoring their persistent influence on model divergence.

Notably, the contribution of SMB rises sharply in the half-sample scenario: its in-sample share jumps from 8.62% in the full sample to 14.16%, and further to 25.38% out-of-sample, indicating that the risk premium on small-cap stocks in the A-share market is highly sensitive to model specification. Other factors, such as LIQ and FIN, each contribute less than 5% on average and fluctuate only modestly between the in-sample and out-of-sample periods, suggesting a stronger consensus on the pricing of these risks.

As noted above, we observe a surge in model divergence during certain special events; consequently, we devote additional attention to tail outcomes. Panel (b) of Table 5 documents the maximum entropy contribution delivered by each factor. SMB stands out, with a maximum out-of-sample contribution of 50.83% under the half-sample setting, confirming that SMB accounts for a large share of model disagreement when entropy rises rapidly and reinforcing the conclusions drawn from the average results. Mao and Xia (2023) report that SMB behaves oppositely in the Chinese market relative to the evidence in Bryzgalova et al. (2023b) for the U.S. market. They argue that, during market crashes, the government's primary objective is to preserve financial stability through fiscal support and preferential policies targeted at large, state-owned enterprises (SOEs). Liquidity therefore flows first to SOEs, driving up their prices and eroding, if not reversing the small-firm premium underlying SMB. Our findings further demonstrate, from the perspective of model uncertainty, that SMB is a major driver of model disagreement during extreme events.

Figure 3 plots the time-series evolution of the entropy contributions of all factors. We again find that SMB, CMA and RMW contribute materially to the entropy of the covariance matrix. In addition, the influence of FIN, PEAD and SKEW varies with the sample length employed.

4.7 Model Decomposition Divergence

We disentangle each component of our pricing model into seven terms. The constant pricing error, α_0, captures time-invariant mispricing. The interaction between time-varying pricing errors and lagged macroeconomic variables, $Z_{t-1}\alpha_1$, represents the portion of mispricing that can be explained by the macro state z_t. The term $F\beta_0'$ combines fixed factor loadings with constant risk premia, where α_f is fixed and the factor loading matrix β_0 is time-invariant. The product $Z_{t-1}\beta_0 a_F z_t'$ allows risk premia to vary with z_t while holding factor loadings constant. The component $\beta_1(I \otimes z_t)\alpha_f$ introduces time variation in

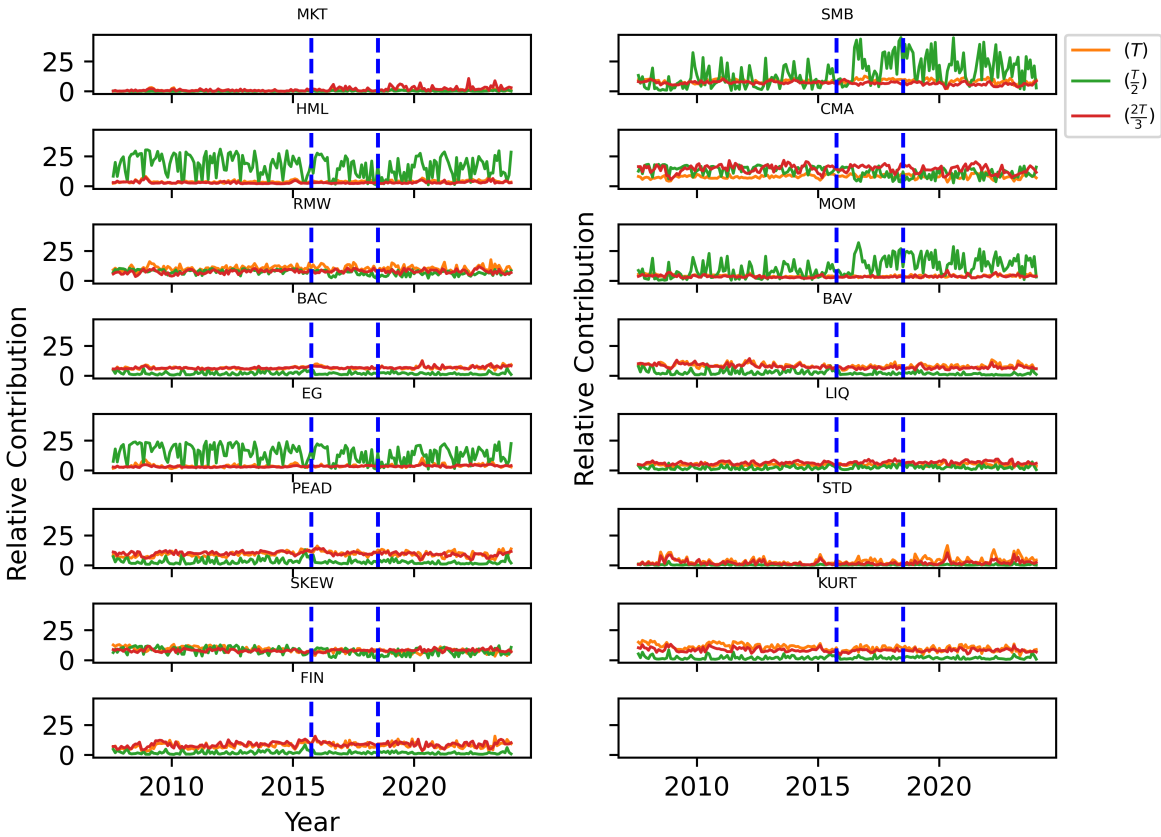

Figure 3: Relative Contribution to Factor Entropy Increase

factor loadings through interactions with z_t, while keeping risk premia constant. Allowing both loadings and premia to vary simultaneously yields $\beta_1(I \otimes z_t)a_F z_t'$, where both β_1 and α_f interact with the macro state. Finally, the stand-alone term $a_F z_t'$ reflects the direct interaction between factor risk premia and the macro variables.

Table 6 and Table 7 summarize factor-specific model divergence for each component, with separate reporting for the in-sample and out-of-sample segments. Model-component dispersion is defined as the standard deviation across all candidate models of the respective component, reweighted by the posterior model probabilities. Mirroring the U.S. evidence, the maximum of each component markedly exceeds its mean, a pattern that is more pronounced out-of-sample, where the maxima often reach more than three times the mean. For the components incorporating both time-varying loadings and risk premia, the maximum can be 13 to 14 times larger than the average.

Figure 4 affords a clearer view of the time-series behavior of model-component dispersion. Following the third blue vertical line denoting the start of the out-of-sample period model component disagreement rises sharply. Its shape resembles that of the entropy plot: during special events, extreme outcomes become frequent, the variance of each model component comoves, and maxima far exceed means, creating a pronounced imbalance.

4.8 Portfolio-Choice Divergence

In our framework, the factors that do not enter the right-hand side of the pricing equation serve as test assets. If a factor is not selected by a given model, the model is expected to explain its returns. Each pricing model therefore yields a tangency portfolio formed from the unselected test-factor assets, assigning weights determined by the model. This section investigates the dispersion in weights across a broad set of pricing models and the resulting variation in returns.

As described in the previous section, in Table 8 we measure divergence in the choice of test assets as the standard deviation of the tangency portfolio weights implied by each model, weighted by the posterior model probabilities. Divergence in portfolio performance is constructed analogously.

Figure 4: Model Component Dispersion by Factor

The dispersion of factor asset portfolios shows a skewed distribution similar to the previous experiments. Within the sample, the dispersion of factor test assets is generally between 0.031 and 0.805. However, at the 95th percentile (99th percentile, maximum value), this range changes to 0.153-4.212 (0.317-8.099, 0.733-15.463), and the overall distribution is skewed. This indicates in extreme scenarios, the divergence in allocation weights for the same factor test asset among different models increases significantly.

Comparison of in-sample and out-of-sample data shows that the average out-of-sample dispersion of most factors exceeds that of in-sample. The average dispersion of 15 factors is 0.878, while that in the US market is 0.025, with the Chinese market being 34 times higher. Our US data are from Avramov et al. (2023). Additionally, out-of-sample divergence of 12 out of 15 factors is higher than in-sample, with an average increase of 12.23%. Compared with the US market data, the average out-of-sample of 14 factors in the US market is 6.63% higher than in-sample, indicating a more significant increase in the divergence of factor assets in the Chinese market out-of-sample.

From panel (b), the mean out-of-sample return dispersion is 1.842, nearly matching the in-sample 1.846, but with significantly higher extremes. The 95th percentile is 6.628 (vs. in-sample 5.860), and the maximum reaches 33.024 (vs. in-sample 31.779). While average return divergence is similar in-sample and out-of-sample, model performance differences widen in extreme markets, confirming that model uncertainty strongly impacts portfolio choices and performance in such cases. Figure 5 and Figure 6 further illustrate the time-series performance of the two indicators, showing peaks consistent with prior experiments.

5 Conclusion

This paper conducts an empirical investigation into model uncertainty in the Chinese stock market, by employing a Bayesian Model Averaging (BMA) framework that integrates over 60 million candidate asset pricing models.Our findings reveal that model uncertainty is particularly pronounced in China's A-share market. In the full-sample analysis, the cumulative posterior probability of the top ten models is extremely low, substantially lower than the levels reported in comparable studies of the U.S. market.

This suggests that the pricing structure in China cannot be adequately captured by any single model or small set of models, necessitating the use of model aggregation to accommodate multi-source uncertainty. The posterior results strongly support time-varying specifications and also allow for the presence of mispricing. Among the risk factors, SMB (size) and STD (return volatility) are identified as the most robust. In addition, certain macroeconomic variables—such as industrial production (Industry), the El Niño index (Nino), and sunspot numbers (Sunspot)—exhibit notable posterior explanatory power.Out-of-sample evaluations show that the BMA model maintains strong robustness in the Chinese market and significantly outperforms benchmark factor pricing models. These results underscore the importance of explicitly addressing model uncertainty in empirical asset pricing.

To further understand the implications of model uncertainty, we compare the variance from the integrated model to the sample variance. For out-of-sample, the integrated model variance is significantly larger for most factors, indicating that model uncertainty materially affects perceived risk. We then introduce an entropy augmentation index to quantify the additional dispersion in the covariance matrix caused by divergence across models. This index shows that SMB, CMA, RMW, and BAV are the most influential in terms of both average and maximum entropy contributions. Notably, entropy rises substantially during periods of market stress, a pattern that differs from the U.S. market, where entropy tends to react only to conventional economic events.

References

Amaya, D., Christoffersen, P., Jacobs, K., Vasquez, C., 2015. Does realized skewness predict the cross-section of equity returns? Journal of Financial Economics 118, 135–167.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. The Journal of Finance 61, 259–299.

Asness, C.S., Frazzini, A., Gormsen, N.J., Pedersen, L.H., 2020. Betting against correlation: Testing theories of the low-risk effect. Journal of Financial Economics 135, 629–652.

Avramov, D., Chao, J.H., 2006. An exact bayes test of asset pricing models with application to international markets*. The Journal of Business 79, 293–324.

Avramov, D., Cheng, S., Metzker, L., Voigt, S., 2023. Integrating factor models. The Journal of Finance 78, 1593–1646.

Avramov, D., Zhou, G., 2010. Bayesian portfolio analysis. Annual Review of Financial Economics 2, 25–47.

Baks, K.P., Metrick, A., Wachter, J., 2001. Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation. The Journal of Finance 56, 45–85.

Barillas, F., Shanken, J., 2018. Comparing asset pricing models. The Journal of Finance 73, 715–754.

Belloni, A., Chernozhukov, V., Hansen, C., 2014. Inference on treatment effects after selection among high-dimensional controls. Review of Economic Studies 81, 608–650.

Bryzgalova, S., Huang, J., Julliard, C., 2023a. Bayesian solutions for the factor zoo: We just ran two quadrillion models. The Journal of Finance 78, 487–557.

Bryzgalova, S., Huang, J., Julliard, C., 2023b. Bayesian solutions for the factor zoo: We just ran two quadrillion models. The Journal of Finance 78, 487–557.

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

Cheema, M.A., Chiah, M., Man, Y., 2020. Cross-sectional and time-series momentum returns: Is China different? Pacific-Basin Finance Journal 64, 101458.

Chen, T.Y., Chao, C.H., Wu, Z.X., 2021. Does the turnover effect matter in emerging markets? Evidence from China. Pacific-Basin Finance Journal 67, 101551.

Chib, S., Zeng, X., Zhao, L., 2020a. On comparing asset pricing models. The Journal of Finance 75, 551–577.

Chib, S., Zeng, X., Zhao, L., 2020b. On comparing asset pricing models. The Journal of Finance 75, 551–577.

Cochrane, J., 2011. Discount rates. Journal of Finance 66, 1047 – 1108.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short- and long-horizon behavioral factors. The Review of Financial Studies 33, 1673–1736.

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

Fama, E.F., French, K.R., 2018. Choosing factors. Journal of Financial Economics 128, 234–252.

Feng, G., Giglio, S., Xiu, D., 2020. Taming the factor zoo: A test of new factors. Journal of Finance 75, 1327–1370.

Giglio, S., Xiu, D., 2021. Asset pricing with omitted factors. Journal of Political Economy 129, 1947–1990.

Giglio, S., Xiu, D., Zhang, D., 2025. Test assets and weak factors. The Journal of Finance 80, 259–319.

Harvey, C.R., 2017. Presidential address: The scientific outlook in financial economics. The Journal of Finance 72, 1399–1440.

Harvey, C.R., Liu, Y., 2019. Cross-sectional alpha dispersion and performance evaluation. Journal of Financial Economics 134, 273–296.

Harvey, C.R., Liu, Y., Zhu, H., 2016. ...and the cross-section of expected returns. Review of Financial Studies 29, 5–68.

Hou, K., Mo, H., Xue, C., Zhang, L., 2021. An augmented q-factor model with expected growth. Review of Finance 25, 1–41.

Lin, C., Chang, H.W., Chou, R.K., 2023. Overnight versus intraday returns of anomalies in China. Pacific-Basin Finance Journal 79, 102007.

Liu, C., Maheu, J.M., 2009. Forecasting realized volatility: A Bayesian model-averaging approach. Journal of Applied Econometrics 24, 709–733.

Liu, J., Stambaugh, R.F., Yuan, Y., 2019. Size and value in China. Journal of Financial Economics 134, 48–69.

Mao, G., Zhang, Z., 2018. Stochastic tail index model for high frequency financial data with Bayesian analysis. Journal of Econometrics 205, 470–487.

Mao, J., Shao, J., Wang, W., 2025. Risk premium principal components for the chinese stock market. Pacific - Basin Finance Journal 89, 102579.

Mao, J., Xia, T., 2023. The estimation of risk premia with omitted variable bias: evidence from china. Risks 11, 215.

Mao, J., Xia, X., Zhuo, H., 2024. Taming China's Factor Zoo with a Bayesian Method. Technical Report 4965590. SSRN Working Paper.

Nucera, F., Sarno, L., Zinna, G., 2024. Currency risk premiums redux. The Review of Financial Studies 37, 356–408.

Pástor, L., Stambaugh, R.F., 2000. Comparing asset pricing models: An investment perspective. Journal of Financial Economics 56, 335–381.

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Zhu, L., Jiang, F., Tang, G., et al., 2024. From macro to micro: Sparse macroeconomic risks and the cross-section of stock returns. International Review of Financial Analysis 95, 103433.

Table 6: Average Dispersion Across Model Components

Factor	$\sigma(\alpha_0)$	$\sigma(\beta_0\alpha_F)$	$\sigma(\alpha_1 z_t)$		$\sigma(\beta_0\alpha_F z_t)$		$\sigma(\beta_1(I \otimes z_t)\alpha_f)$		$\sigma(\beta_1(I \otimes z_t)\alpha_F z_t)$		$\sigma(\alpha_F z_t)$	
	EST	EST	EST	OOS	EST	OOS	EST	OOS	EST	OOS	EST	OOS
MKT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.069	0.130
SMB	0.000	0.000	0.001	0.001	0.002	0.002	0.001	0.001	0.000	0.000	0.018	0.021
HML	0.001	0.001	0.003	0.005	0.015	0.015	0.006	0.008	0.000	0.001	0.004	0.006
CMA	0.001	0.001	0.002	0.002	0.005	0.005	0.002	0.002	0.000	0.000	0.008	0.012
RMW	0.002	0.002	0.004	0.006	0.021	0.021	0.005	0.006	0.000	0.001	0.006	0.009
MOM	0.003	0.003	0.009	0.013	0.036	0.036	0.012	0.017	0.001	0.002	0.007	0.010
BAC	0.002	0.002	0.005	0.007	0.034	0.034	0.009	0.013	0.001	0.001	0.007	0.011
BAV	0.001	0.001	0.003	0.005	0.017	0.017	0.007	0.009	0.000	0.001	0.012	0.018
LIQ	0.001	0.001	0.004	0.007	0.023	0.023	0.004	0.005	0.001	0.001	0.003	0.005
EG	0.001	0.001	0.004	0.005	0.018	0.018	0.007	0.009	0.000	0.001	0.006	0.009
PEAD	0.002	0.002	0.004	0.006	0.017	0.017	0.004	0.007	0.001	0.001	0.005	0.006
SKEW	0.002	0.002	0.004	0.005	0.030	0.030	0.010	0.015	0.000	0.001	0.005	0.009
STD	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.025	0.033
KURT	0.001	0.001	0.003	0.004	0.023	0.023	0.007	0.010	0.000	0.001	0.011	0.017
FIN	0.001	0.001	0.003	0.005	0.012	0.012	0.005	0.007	0.000	0.001	0.009	0.012

Table 7: Maximum Dispersion Across Model Components

Factor	$\sigma(\alpha_0)$	$\sigma(\beta_0\alpha_F)$	$\sigma(\alpha_1 z_t)$		$\sigma(\beta_0\alpha_F z_t)$		$\sigma(\beta_1(I \otimes z_t)\alpha_f)$		$\sigma(\beta_1(I \otimes z_t)\alpha_F z_t)$		$\sigma(\alpha_F z_t)$	
	EST	EST	EST	OOS	EST	OOS	EST	OOS	EST	OOS	EST	OOS
MKT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.198	0.443
SMB	0.000	0.000	0.002	0.003	0.002	0.002	0.002	0.003	0.000	0.002	0.036	0.062
HML	0.001	0.001	0.008	0.016	0.015	0.015	0.017	0.034	0.002	0.009	0.012	0.019
CMA	0.001	0.001	0.004	0.008	0.005	0.005	0.003	0.008	0.001	0.004	0.026	0.046
RMW	0.002	0.002	0.010	0.023	0.021	0.021	0.011	0.017	0.002	0.011	0.017	0.044
MOM	0.003	0.003	0.020	0.040	0.036	0.036	0.036	0.076	0.006	0.019	0.013	0.036
BAC	0.002	0.002	0.011	0.023	0.034	0.034	0.025	0.046	0.004	0.013	0.021	0.049
BAV	0.001	0.001	0.008	0.017	0.017	0.017	0.017	0.031	0.002	0.008	0.028	0.047
LIQ	0.001	0.001	0.010	0.022	0.023	0.023	0.008	0.012	0.003	0.010	0.007	0.022
EG	0.001	0.001	0.009	0.021	0.018	0.018	0.018	0.036	0.002	0.013	0.011	0.030
PEAD	0.002	0.002	0.010	0.022	0.017	0.017	0.008	0.019	0.003	0.009	0.011	0.014
SKEW	0.002	0.002	0.009	0.019	0.030	0.030	0.020	0.037	0.003	0.009	0.014	0.026
STD	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.079	0.139
KURT	0.001	0.001	0.008	0.014	0.023	0.023	0.019	0.032	0.002	0.007	0.030	0.052
FIN	0.001	0.001	0.007	0.016	0.012	0.012	0.013	0.023	0.003	0.014	0.020	0.030

Table 8: Dispersion in Portfolio Choice and Performance

	EST				OOS			
	Mean	95^{th} Pctl.	99^{th} Pctl.	Max	Mean	95^{th} Pctl.	99^{th} Pctl.	Max
	(a) Dispersion in Tangency Portfolio Weights							
MKT	0.031	0.153	0.317	0.733	0.058	0.074	1.077	2.845
SMB	0.301	1.266	2.932	4.801	0.470	0.449	7.768	20.934
HML	0.360	1.890	3.977	7.511	0.411	0.694	6.388	16.767
CMA	0.713	3.458	7.975	14.520	0.583	1.439	7.632	17.885
RMW	0.503	2.842	5.996	9.134	0.298	1.210	3.186	5.652
MOM	0.150	0.737	1.259	1.645	0.177	0.378	2.149	5.042
PEAD	0.098	0.165	0.736	1.365	0.129	0.110	1.429	3.675
FIN	0.326	1.087	1.915	5.124	0.353	0.572	3.695	9.037
EG	0.170	0.804	1.527	1.569	0.193	0.547	2.371	5.165
LIQ	0.255	1.383	2.446	4.268	0.263	0.699	3.424	7.924
STD	0.449	2.175	4.977	7.950	0.492	0.745	7.446	19.245
SKEW	0.805	4.212	8.099	15.463	0.687	1.792	9.124	21.139
KURT	0.351	1.598	3.243	4.154	0.568	1.393	8.731	21.011
BAC	0.325	0.703	2.843	4.456	0.571	1.078	7.818	19.307
BAV	0.118	0.288	0.953	2.119	0.214	0.181	3.300	8.857
	(b) Dispersion in Tangency Portfolio Returns							
Return	1.846	5.860	23.014	31.779	1.842	6.628	23.014	33.024

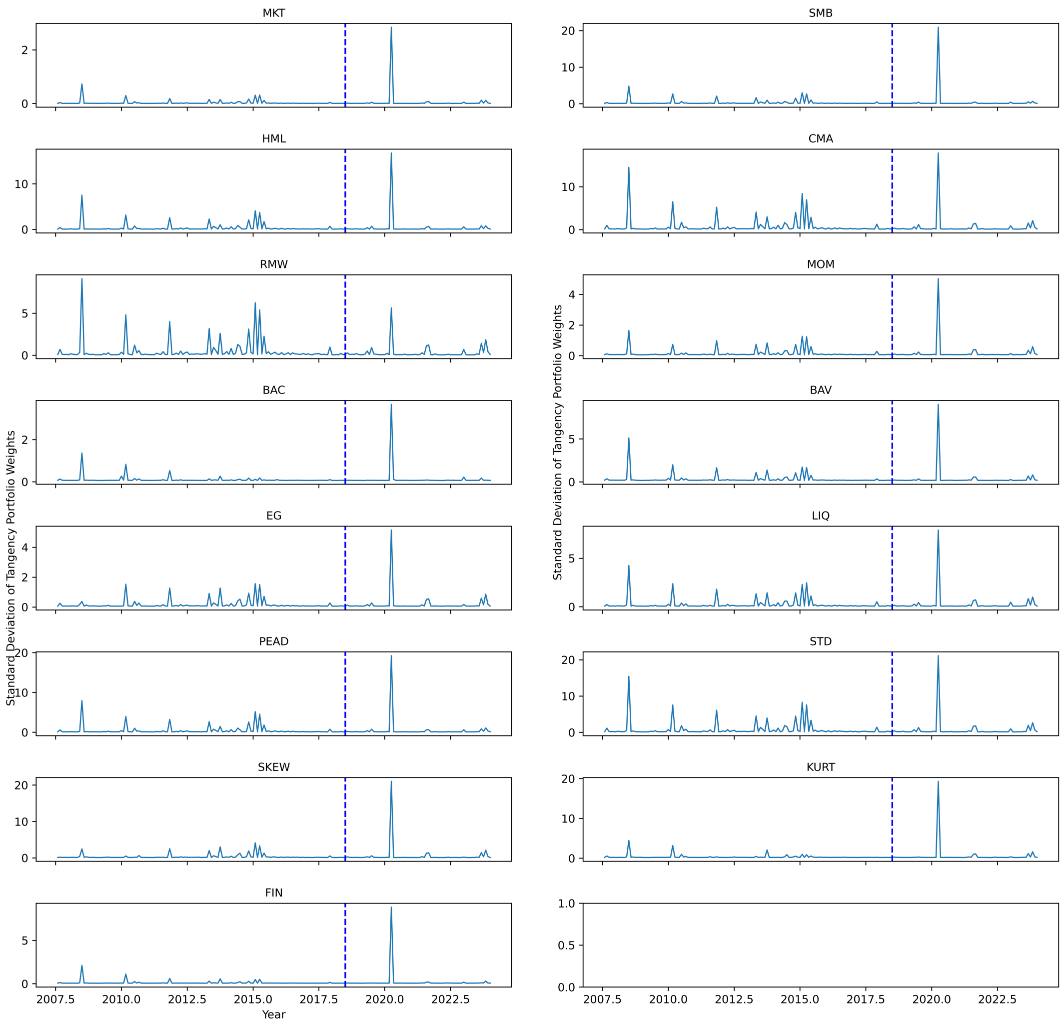

Figure 5: Std dev of tangency portfolio weights for each factor asset

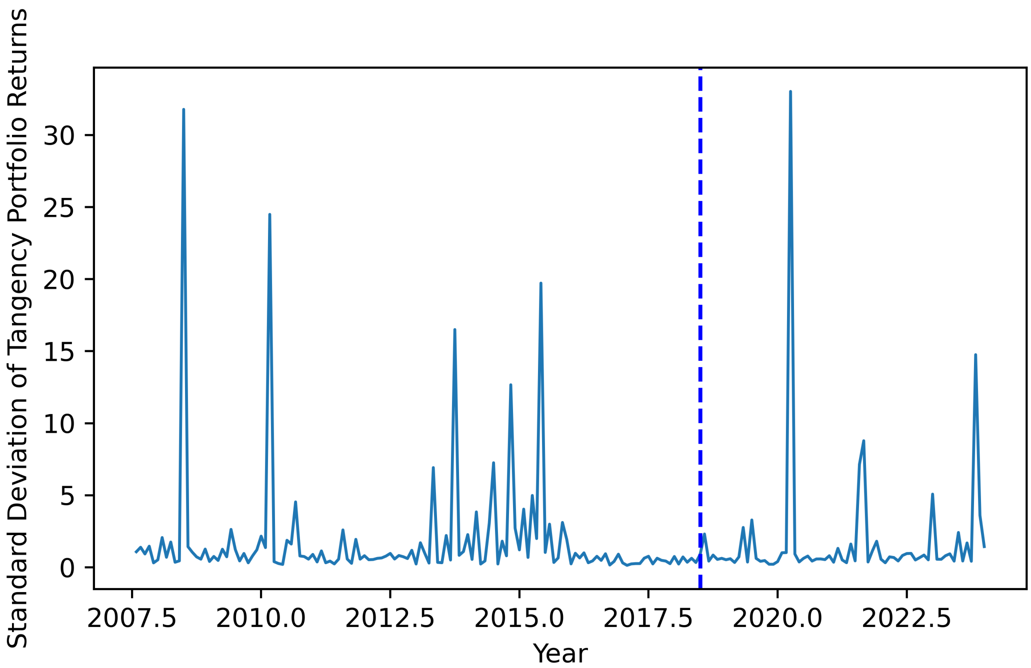

Figure 6: Standard deviation of tangency portfolio returns