Proceedings of ICFTBA 2026 Symposium: Digital Government, Finance, Accountability, and Sustainable Economic Development
DOI: 10.54254/2754-1169/2026.AB39344

Construction and Evaluation of a Simplified Barra Multi-factor Risk Model for the Chinese A-Share Market

Hao Wu

Tandon School of Engineering, New York University, New York, USA
hw3700@nyu.edu

Abstract. The Barra multi-factor risk model is a core tool in quantitative investing. First proposed by Barr Rosenberg, it has been widely applied to risk analysis, portfolio management, and performance attribution. The model decomposes stock returns into common risk factors and idiosyncratic components via style and industry factors, enabling investors to systematically identify the sources and structure of portfolio returns. Although MSCI has developed dedicated Barra models for the Chinese stock market, such as the CNE5, CNE6, and CNE7 series, these commercial frameworks generally operate as black-box tools with limited public disclosure of their specific construction details. Grounded in the principles of feasibility and transparency, this paper constructs a simplified Barra multi-factor risk model for the Chinese A-share market. Book equity is derived from raw financial data and strictly aligned with financial report announcement dates, and factor returns are estimated through monthly cross-sectional regressions. Finally, the model is evaluated across three dimensions: explanatory power measured by 12-month rolling adjusted R-squared, factor return volatility, and the performance of major style factors. The assessment verifies whether the model can capture core style and industry risk exposures in the Chinese A-share market and provide a reliable foundation for follow-up research.

Keywords: Barra model, Multi-Factor risk model, Style factors, Industry factors, Chinese A-share market

1. Introduction

The theoretical foundation of the modern multi-factor risk model was laid by Barr Rosenberg in the early 1970s. Its core formulation expresses individual stock returns as the sum of factor exposures to style and industry factors multiplied by corresponding factor returns, plus an idiosyncratic residual term [1]. After Barra was acquired by MSCI in the early 2000s, the CNE series of models for the Chinese equity market were subsequently developed [2].

Although these commercial models are widely adopted in practice, they typically function as black boxes. As a result, their factor construction methodologies and data alignment rules remain largely opaque to end users. In the Chinese A-share market, a distinctive challenge arises from the structure of financial disclosure: corporate reports tend to be released within concentrated time windows, and reporting lags vary substantially across firms and fiscal periods [3]. To address this limitation, this study proposes a transparent factor modeling framework that explicitly specifies

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factor construction rules and point-in-time data alignment mechanisms, overcoming the information constraints of existing commercial models. Against this background, this paper builds a simplified yet fully transparent Barra-style multi-factor risk model. Book equity is computed directly from raw accounting data and strictly aligned with announcement dates to avoid look-ahead bias. A set of factors is constructed using CITIC Level-1 industry dummy variables, and factor returns are estimated monthly via square-root market-capitalization-weighted cross-sectional regressions [4-6]. The empirical analysis centers on two core questions: first, to what extent do style and industry factors explain cross-sectional return variation in the A-share market? Second, what risk-return characteristics do major style factors exhibit over the sample period?

2. Data sources and factor construction

2.1. Data source

All data are used from the Chinese A-share market. Stock returns are calculated from the daily adjusted closing prices. Market capitalization data are used both for constructing Size factor and determining the weights in the cross-sectional regressions. The earning related factors such as earning- to-price(EP) are based on the net income figures. Fundamental information are aligned with the actual public released time according to the announcement dates of the financial reports to avoid forward-looking statements. Industry classifications are followed by the CITIC Level 1 classification standard [7]. In addition,the data like share capital,capital reserve, surplus reserve, retained earnings, and special reserve from financial statements are collected to build the book equity measure required for the Book-to-Price (BP) factor.

2.2. Style and industry factor construction and standardization

Table 1. Factor definitions and construction methodology

Category	Factor	Construction Method
Style factors	Size	Natural logarithm of market capitalization
	Non-Linear Size	Square of raw Size, orthogonalized to Size, then standardized
	Book-to-Price (BP)	Book equity / Market capitalization (Book equity = share capital + capital reserve + surplus reserve + retained earnings + special reserve)
	Earning-to-price (EP)	Net income / Market capitalization
	Growth	Year-over-year growth rate of net income
	Momentum	Cumulative return over the past 12 months, excluding the most recent month
	Beta	Slope from a trailing regression of daily stock returns on market returns (≈12-month window)
	Residual Volatility (ResVol)	Residual standard deviation from the same regression used for Beta

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Table 1. (continued)

Industry factor	Industry dummies	CITIC Level-1 industry dummy variables (one category dropped to avoid multicollinearity)

The style and industry construction method are listed in the table 1 above. BP, EP, and Growth use only data already announced by month-end. All continuous style factors are processed in two steps within each cross-section. First, extreme values are adjusted using the median absolute deviation (MAD) method, with a threshold of 3*MAD. And then each factor is standardized to have a mean of 0 and a standard deviation of 1.

3. Methodology

3.1. Cross-sectional regression framework

The risk model follows the standard Barra multi-factor specification. For each stock i in month t, the return is expressed as:

$$r_i = \sum_k X_{ik} f_k + \varepsilon_i \tag{1}$$

$$r_{i,t} = \sum_k X_{ik,t} f_{k,t} + \varepsilon_{i,t} \tag{2}$$

where is the monthly return of stock i, is the exposure of stock i to factor k (style factors and industry dummies), is the factor return to be estimated, and is the residual return.

3.2. Research method

Factor returns are estimated each month by a square-root market-cap weighted least squares (WLS) regression. The weight for stock i is defined as:

$$w_i = \frac{\sqrt{MarketCap_i}}{\sum_j \sqrt{MarketCap_j}} \tag{3}$$

The regression includes an intercept (market factor), the eight style factors, and the CITIC Level-1 industry dummy variables (with one industry dropped to avoid perfect multicollinearity). After estimation, the adjusted R-squared of each monthly cross-sectional regression is recorded to measure the model's explanatory power [8].

4. Evaluation

4.1. Model explanatory power

Figure 1 reports the 12-month rolling adjusted R-squared of the cross-sectional regressions that include both style factors and industry dummies. Over the sample period the rolling adjusted R-

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squared fluctuates between approximately 0.11 and 0.36. It declines to a relatively low level around 2017, then gradually rises and reaches its peak near 0.35 in 2022, before moderating slightly toward the end of the sample.

The 2017 trough coincides with a period of elevated policy uncertainty and regulatory tightening in the A-share market (including intensified deleveraging and stricter financial supervision). During such episodes, firm-specific and event-driven shocks tend to dominate, temporarily weakening the explanatory power of systematic style and industry factors. The subsequent recovery and 2022 peak occur against a backdrop of more pronounced sector rotation, stronger style differentiation (especially around residual-volatility and size effects), and relatively clearer macroeconomic and policy signals. These conditions appear to have amplified the common-component contribution of the style-plus-industry specification.

Overall, within the sample period, style and industry factors together capture a meaningful portion of return variation in the A-share market, and the model's explanatory power strengthened in the later years of the sample. It should be noted that the observed time variation in adjusted R-squared is specific to the sample window examined; different sample intervals may yield different magnitudes and timing of peaks and troughs.

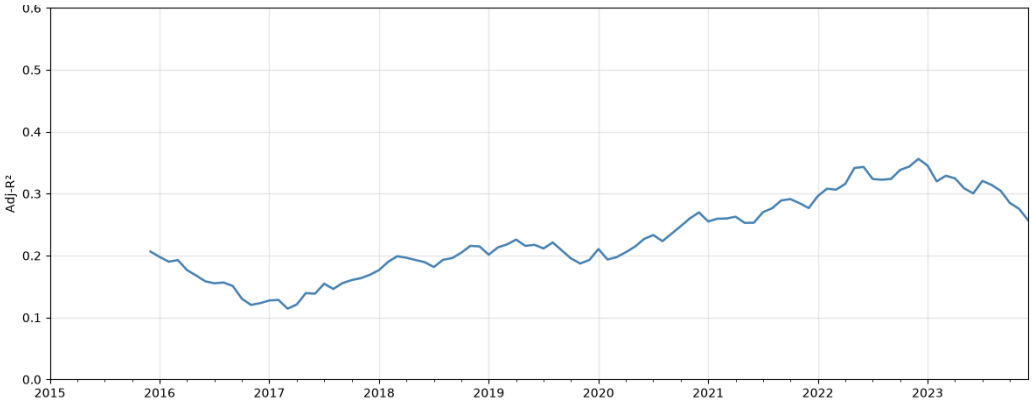

Figure 1. 12-month rolling adjusted R-square (style + industry, √cap weighted)

4.2. Factor volatility analysis

Figure 2 presents the annualized volatility of all estimated factor returns. Industry factors generally exhibit substantially higher volatility than style factors. The most volatile factors include Non-Bank Finance, Conglomerate, and Defense, with annualized volatilities exceeding 25%. In contrast, most style factors display much lower volatility. Among the style factors, Momentum, Residual Volatility, and Beta show relatively higher volatility (around 7–9%), while Size, BP, EP, Growth, and NonLinearSize remain at lower levels (mostly below 5%).

The elevated industry volatilities are consistent with the well-documented sector-driven character of the A-share market, where policy, regulatory, and thematic shocks frequently produce large and persistent industry returns. Style-factor volatilities are comparatively muted, reflecting the more gradual and mean-reverting nature of characteristic-based premia in this market. These results indicate that, within the sample period, industry exposures constitute an important source of return fluctuation. The ranking of factor volatilities may differ outside the present sample window.

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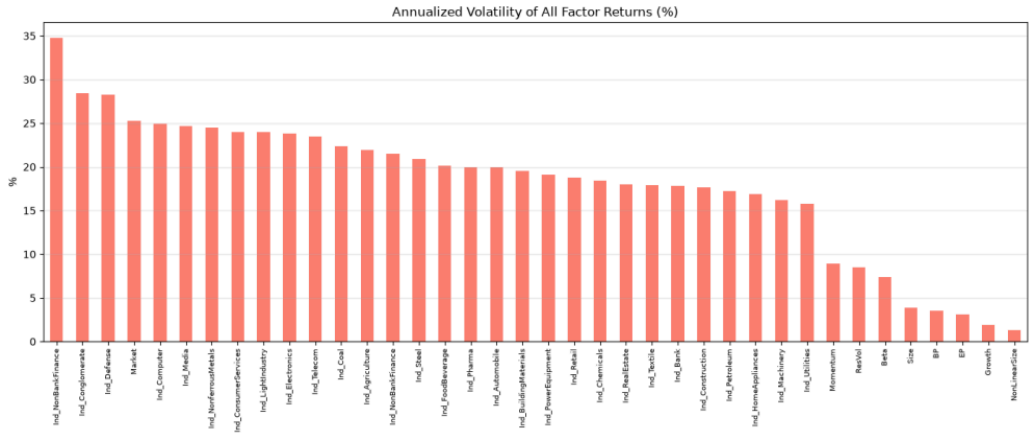

Figure 2. Annualized volatility of all factor returns (%)

4.3. Style factor performance

Figure 3 shows the cumulative net value of the style factors, and Table 2 reports their annualized returns, annualized volatilities, and information ratios (IR). In Figure 3, Residual Volatility (ResVol) records the strongest performance, with its cumulative value rising steadily to around 3 by the end of the sample. Size and EP generate moderate positive cumulative returns. NonLinearSize stays close to 1. In contrast, BP and Momentum exhibit persistent underperformance, with cumulative net values declining well below 1. Growth and Beta remain relatively flat and close to the benchmark line of 1.

Table 2 confirms these patterns: Residual Volatility achieves the highest annualized return (12.63%) and the highest IR (1.48). EP and Size also produce positive returns with relatively high IRs. BP and Momentum record notably negative returns and low (negative) IRs, while Growth and Beta remain close to zero or slightly negative.

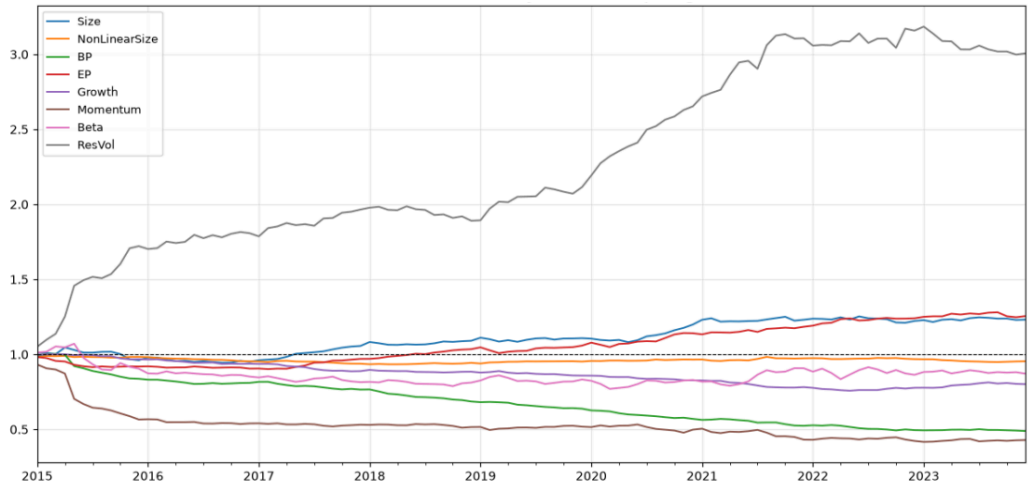

Figure 3. Cumulative net value of style factors(√cap weighted)

The pronounced low-residual-volatility effect is consistent with several A-share-specific features observed over the sample: retail-investor dominance and preference for high-volatility "concept" stocks tend to leave lower-volatility names relatively under-owned and, on average, better compensated; periods of risk-off sentiment and deleveraging further amplified the outperformance

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of low-ResVol stocks. The weak performance of the traditional value (BP) factor aligns with the prolonged growth- and policy-driven regime that characterized much of the sample, during which high book-to-price stocks were frequently associated with cyclicals or financially constrained firms that underperformed. Momentum's poor performance is consistent with the frequent policy interventions, abrupt sector rotations, and relatively short investment horizons typical of the A-share market, all of which tend to disrupt trend persistence [9].

These performance differentials are specific to the sample period examined. Different sample intervals—especially those encompassing distinct policy or market-structure regimes—may produce materially different factor rankings and IRs.

Table 2. Performance of style factors (market capitalization weighted)

Style factor	Annualized return (%)	Annualized volatility (%)	Information ratio (IR)
Residual Volatility (ResVol)	12.63	8.53	1.48
Earnings-to-Price (EP)	2.58	3.14	0.82
Size	2.39	3.91	0.61
Beta	-1.26	7.34	-0.17
Non-Linear Size	-0.51	1.33	-0.39
Momentum	-8.94	8.92	-1
Growth	-2.44	1.94	-1.26
Book-to-Price (BP)	-7.86	3.5	-2.25

Note. All indicators are annualized over the sample period. The information ratio is defined as the ratio of annualized factor return to annualized volatility. Factor returns are estimated from monthly square-root market-cap weighted cross-sectional regressions.

5. Conclusion

This paper constructs a simplified Barra-style multi-factor risk model for the Chinese A-share market. Starting from raw financial statement data, book equity is aggregated from share capital, capital reserve, surplus reserve, retained earnings, and special reserve, and aligned with announcement dates to eliminate look-ahead bias. Eight style factors, together with CITIC Level-1 industry dummy variables, are then constructed and estimated monthly through square-root market-cap-weighted cross-sectional regressions.

Over the sample period, empirical results show that style and industry factors jointly explain a meaningful share of A-share return variation. The 12-month rolling adjusted R-squared ranges from approximately 0.11 to 0.36, and the model's explanatory power strengthens in the later years of the sample. The 2017 dip and subsequent recovery align with episodes of elevated policy uncertainty followed by clearer sector rotation and style differentiation. Industry factors display markedly higher volatility than most style factors, underscoring that industry exposure represents a major source of systematic risk in the A-share market. Among style factors, residual volatility delivers the strongest performance with high annualized returns and information ratios, while book-to-price and momentum factors underperform. These patterns align with retail-driven preference for volatile

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stocks, the growth-oriented policy regime, and frequent policy-induced sector rotations observed over the sample window.

Overall, the simplified model provides a transparent and replicable framework for decomposing A-share returns into style and industry components. It offers a practical reference for risk analysis and can serve as a basis for further research on factor investing in the Chinese equity market. All conclusions regarding performance and explanatory power are bounded by the sample period studied; results may differ across alternative time intervals. Future work can refine the model by incorporating point-in-time industry classifications, expanding the set of style factors, and applying the risk framework to portfolio construction and performance attribution.

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