Investment Factor Reconstruction and Pricing Efficiency in China*

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Abstract

We examine why the Fama-French five-factor model underperforms in China's equity market, focusing on the misalignment between its investment factor, asset growth (AG), and the theoretical notion of investment grounded in the dividend discount model. Motivated by China's fixed-asset-intensive corporate sector and collateral-based financial system, we construct alternative investment factors from cash, account receivables, inventory, and property, plant, and equipment (PPE). Using Sharpe ratio tests, GRS tests, and anomaly pricing analysis, we find that PPE growth delivers significantly stronger pricing performance than AG or other components, consistent with its role in capturing financing shocks through collateralizability in China's institutional environment.

Keywords: Fixed Assets Growth, Investment Effect, Asset Pricing

JEL Codes: G12, G14, G20

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1 Introduction

Recent advances in empirical factor models, most notably the four-factor model of Hou et al. (2015) and the five-factor model of Fama & French (2015), emphasize the role of investment in asset pricing by explicitly incorporating an investment factor. By doing so, both models substantially improve the ability to explain the cross-section of stock returns and to account for a wide range of market anomalies. In the Chinese market, the Fama-French five-factor model (FF5F) has been widely adopted (Lin, 2017).[1] However, existing evidence shows that the five-factor model provides little incremental explanatory power for cross-sectional returns in China (Huang, 2019), and the investment factor is redundant for average returns (Lin, 2017).

We argue that this underperformance reflects a potential misalignment between the empirical construction of the investment factor and its theoretical foundations. In Fama & French (2015), the profitability and investment factors are derived by applying the dividend discount model (DDM) to factor construction. Notably, the investment factors employed in the empirical analyses of FF5F do not rely on conventional proxies for corporate investment—such as capital expenditures or the growth rate of property, plant, and equipment (PPE)—which would align more directly with their theoretical frameworks. Rather, Fama & French (2015) adopt the asset growth (AG) factor, defined as the year-over-year percentage change in total book assets, following Cooper et al. (2008). Without a theoretical justification for this non-traditional metric, the applicability of the extant FF5F model to China warrants closer scrutiny.

From an empirical perspective, these concerns are amplified by China's distinctive macroeconomic and institutional environment. China's dynamic economic evolution—including structural transformation, deepening financial reforms, and continuous capital market liberalization—highlights the necessity of empirically validating the AG proxy. While Cooper et al. (2024) demonstrate the effectiveness of AG in the United States (U.S.) market, the distinct investment environment in China may weaken its relevance. Figure 1 illustrates the ratio of gross fixed capital formation (GFCF) to GDP from 1960 to 2024 in both China and the U.S. The Chinese GFCF/GDP ratio has consistently exceeded that of the U.S. since 2000, primarily

[1] China's equity market ranks as the world's second-largest, underpinning an economy projected to become the global leader within a decade (Liu et al., 2019).

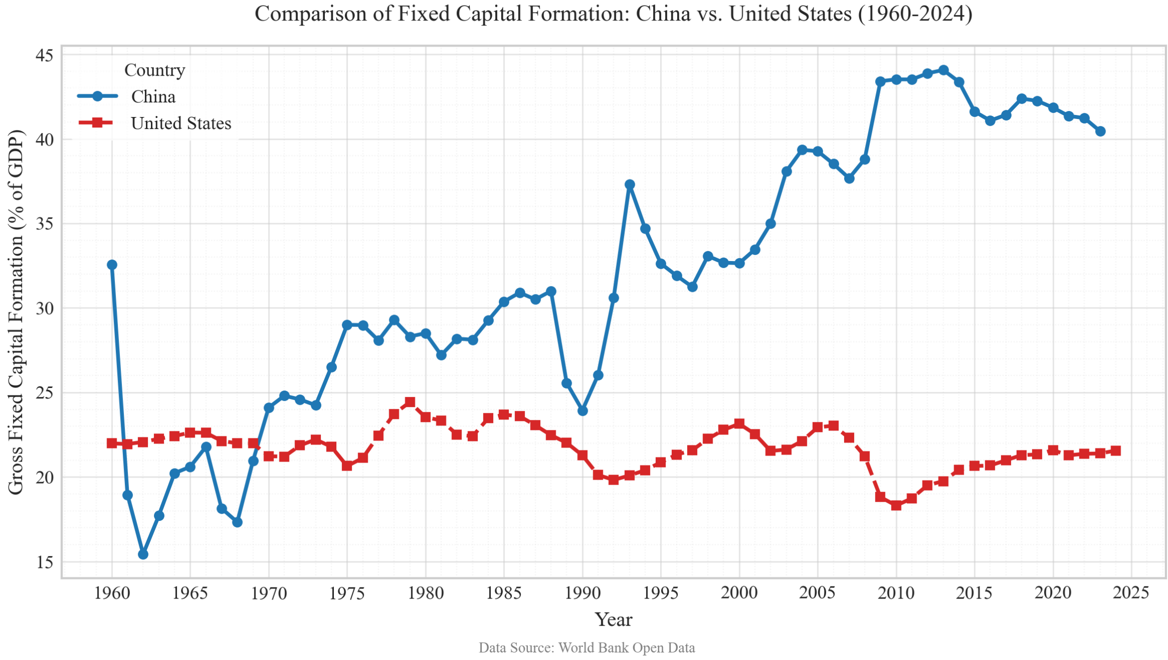

Figure 1: Comparison of Fixed Capital Formation: China vs. United States (1960-2024)

due to China's state-led infrastructure investment and policy intervention, in contrast to the U.S.'s reliance on private sector investment and financial market-driven dynamics. [2] The ratio peaked at 43.9% during 2012–2013, far surpassing the 18.3% level observed in the U.S. over the same period.[3] Compared with the U.S., China's GFCF/GDP ratio exhibits far greater volatility, driven largely by policy-induced infrastructure booms and contractions. This highlights the predominance of long-term fixed investment in shaping China's corporate investment cycles.[4] Because the AG measure combines expansions in both short-term working-capital assets and long-term fixed-capital assets, it conflates two economically distinct forms of investment and thereby obscures the pricing signal associated with long-lived, pledgeable capital. Consequently, relying on AG as the investment proxy in the FF5F model within China introduces

[2]A typical example of China's fixed asset expansion is the RMB 4 trillion stimulus plan launched in response to the 2008 Global Financial Crisis, which focused on infrastructure investment in high-speed rail, highways, and affordable housing. By 2020, China had built the world's largest high-speed rail network, exceeding 35,000 kilometers. This distinctive investment pattern not only reflects the rapid growth phase of the Chinese economy but also underscores the state-driven nature of capital allocation.

[3]Data obtained from the World Bank, available at `https://data.worldbank.org/indicator/NE.GDI.FTOT.ZS?locations=CN-US`.

[4]By contrast, evidence from the U.S. equity market suggests that investment dynamics are driven more by short-term working-capital fluctuations—such as changes in cash, receivables, or inventories—that reflect liquidity management and timing effects rather than long-term fixed-capital accumulation. Consistent with this view, Aktas et al. (2015) show that effective working capital management significantly enhances firm value across U.S. companies, underscoring the critical pricing role of short-term asset fluctuations.

both theoretical and empirical challenges.

Motivated by this distinction between short-term and long-term assets, we refine the investment channel by decomposing corporate assets into categories that more cleanly separate transitory working-capital adjustments from durable fixed-capital accumulation. To implement this approach, we follow Cooper et al. (2024) and construct investment proxies from four key asset categories on the balance sheet—cash (CASH), accounts receivable (RECE), inventory (INVT), and property, plant, and equipment (PPE). We then develop four alternative versions of the FF5F model in China's equity market by replacing the AG factor with factors based on the growth of each category. CASH reflects strategic flexibility under policy uncertainty (Han & Wang, 2023); RECE captures liquidity risks arising from payment delays in China's credit environment (Yan et al., 2024); INVT signals resilience to consumption shocks within supply chains (Shan & Zhu, 2013); and PPE embodies cyclical capacity shifts driven by policy interventions (Qin & Song, 2009). These dimensions highlight fundamental contrasts in return behavior between short-term assets, such as INVT, and long-term assets, such as PPE, reflecting their differing roles in firms' operations and exposure to macroeconomic and policy-related risks.

Our model comparison yields two key findings. First, replacing AG with INVT or RECE produces performance that is statistically indistinguishable from that of the baseline AG-FF5F specification. Second, relative to the original AG-FF5F model, specifications incorporating investment proxies more closely aligned with the traditional concept of corporate investment—particularly those based on the growth of PPE—exhibit superior asset pricing performance. These results hold in model comparisons based on the Sharpe ratio tests. Given the unique institutional features of China's capital market, and to rigorously assess whether the PPE factor materially enhances the model's pricing ability, we follow the approach of Stambaugh & Yuan (2017); Liu et al. (2019) and employ the Gibbons, Ross, and Shanken (1989) (GRS) test, in addition to evaluating the model's ability to explain returns on well-documented anomalies. The GRS test results indicate that, among the five models considered, the PPE-based five-factor model generates the lowest mean absolute alpha and the lowest GRS statistic. Moreover, this model delivers superior explanatory power for a broad set of established anomaly returns in the Chinese market. Consistent with the theoretical critique of the AG measure, our evidence shows that replacing AG with a PPE-based proxy—one that better reflects the economic concept of investment—substantially enhances the pricing performance of the five-factor model in China's equity market.

Our findings indicate that the explanatory power of the FF5F model (when using AG as the investment factor) is highly sensitive to the specific construction of the investment proxy. In the Chinese market, the factor constructed from PPE growth demonstrates significantly greater ability to explain the cross-section of returns. This suggests that the PPE factor captures a systematic risk component that is not effectively reflected by alternative investment proxies such as INVT or RECE. However, this advantage is not observed in developed markets such as the U.S., where analogous tests find no significant improvement from replacing AG with PPE (Cooper et al., 2024). To identify the nature of this risk, we select macroeconomic state variables that prior research has shown to drive cross-sectional return differences and that have proven effective and widely used in empirical applications to the Chinese equity market.[5] We then apply the generalized method of moments (GMM) to test whether these variables can price the returns of portfolios sorted on AG, INVT, RECE, and PPE growth, after adjusting for market exposure. Our GMM analysis yields the following insights: The only state variable that significantly prices all three non-PPE portfolios (AG, INVT, and RECE) is the Baker & Wurgler (2006) investor sentiment index (BW). Furthermore, shocks related to financial intermediation are found to have significant explanatory power for the PPE-sorted portfolios, whereas their influence is statistically insignificant for portfolios sorted by AG, INVT, or RECE. These findings support the hypothesis that the pricing power of the PPE factor stems from its exposure to systematic financing shocks, especially those driven by fluctuations in investor sentiment.

Our results are consistent with the debt-equity substitution mechanism proposed by Belo et al. (2019).[6] If PPE represents a firm's primary collateralizable asset base (see Rampini &

[5]We use the following additional macroeconomic variables: an investor sentiment index constructed via principal component analysis (PCA) of margin trading data, following Baker & Wurgler (2006); a financial leverage shock proxied by the leverage ratio of financial intermediaries, as in Adrian et al. (2014); a consumption shock measured by the year-over-year growth in CPI-adjusted retail sales, based on the methodology of Yu & Yuan (2011); and a total factor productivity (TFP) shock estimated from Solow residuals, following the quarterly series constructed by Fernald (2014).

[6]They argue that high-investment firms (as proxied by capital expenditures, CAPX) are less sensitive to fluctuations in equity financing costs due to their relatively low collateral constraints. These firms are more

Viswanathan, 2013), then the PPE factor's significant exposure to financing shocks—particularly via the equity financing channel—can be interpreted as capturing this collateralizability premium. Consequently, portfolios sorted on PPE growth exhibit stronger asset pricing explanatory power due to their differential sensitivity to refinancing shocks, especially those affecting equity issuance capacity. Supporting this mechanism, we find empirical evidence that during periods of sharply declining BW sentiment (indicative of deteriorating equity financing conditions), firms with high PPE growth exhibit a significantly stronger substitution effect from equity to debt financing compared to low-PPE-growth firms. No comparable substitution pattern is observed among firms sorted by AG, INVT, or RECE growth.

We document a pronounced cross-country contrast: in China, PPE growth is the dominant driver of the investment effect, whereas in the U.S., inventory and receivables account for most of the pricing power (Cooper et al., 2024). We attribute this divergence to institutional differences: China's fixed-asset-intensive corporate structure and collateral-based lending system render PPE a central channel for financing shocks (Kermani & Ma, 2023), while the prevalence of asset-light business models in the U.S. elevates liquidity-based measures such as CASH or RECE in capturing refinancing shocks (Crouzet et al., 2022; Cooper et al., 2024).

Recent research has advanced investment-based asset pricing by refining factor construction and incorporating new empirical tools. Building on the dividend discount model, Fama & French (2015) introduce profitability and investment factors, while Hou et al. (2015) develop a q-theory-based specification. Subsequent studies refine the investment proxy—from aggregate asset growth (Cooper et al., 2008) to intangible-adjusted measures (Peters & Taylor, 2017) and decompositions highlighting the role of short-term working capital (Cooper et al., 2024)—with interpretations grounded in financing constraints (Belo et al., 2019) and collateralizability (Ai et al., 2020). Parallel work applies machine learning (ML) to capture high-dimensional interactions and state dependence in returns, with methods ranging from tree-based predictors (Gu et al., 2020) to deep-SDF estimation under no-arbitrage constraints (Chen et al., 2024). While we do not claim to employ the most advanced ML techniques here,

capable of substituting equity for debt financing during economic downturns, thereby better hedging against systematic equity financing shocks. This mechanism aligns with the theory of Ai et al. (2020), which posits that higher collateral value allows firms to circumvent financing constraints during recessions and commands a negative risk premium (i.e., the "collateralizability premium").

these developments underscore a broader point: simplified theoretical models, when mapped to noisy empirical proxies, often face limits in establishing robust links to underlying economic mechanisms. Because of these limitations, we may prefer statistically driven methods such as Kozak et al. (2020) or Kelly et al. (2019).

Recent China-focused evidence shows that directly importing the FF5F model yields mixed results and, in particular, the conventional investment factor based on total asset growth (AG) is often weak or redundant in A-shares once other characteristics are controlled. Using long samples of Chinese equities, studies document that FF5F sometimes improves upon FF3F but fails to price key portfolios, with value and profitability remaining salient while the investment leg underperforms (Lin, 2017; Huang, 2019). This attenuation is consistent with China's institutional features—a fixed-asset-intensive corporate sector, collateral-based intermediation, and policy-driven investment cycles—which shift the relevant risk margin toward pledgeable, long-lived capital rather than short-term working capital (Qin & Song, 2009). To address these limitations, a growing stream of literature proposes alternative specifications of the investment factor that, while developed in broader contexts, offer conceptual avenues for refinement within China's distinctive institutional environment. For instance, Gulen et al. (2025) demonstrates that incorporating intangibles significantly enhances the performance of both FF5F and Q-factor models in emerging markets. A complementary perspective is offered by Feng et al. (2020), who develop a robust statistical framework to evaluate a large cross-section of proposed asset pricing factors and identify those with persistent explanatory power across diverse settings.

Building on these insights, our study refines the investment channel in a manner consistent with both the institutional critiques and methodological advances highlighted above. Specifically, we construct alternative investment factors from four balance-sheet components and evaluate their performance through Sharpe ratio tests, GRS tests, and anomaly pricing analysis. Our results show that PPE growth—unlike in the U.S.—emerges as a materially superior proxy for investment in China, aligning with the economy's fixed-asset-intensive corporate structure and collateral-based financial system.

The paper proceeds as follows: Section 2 provides a detailed introduction to the data and methods. Section 3 provides a detailed introduction to the empirical testing methods and results. Section 4 attempts to verify economic mechanisms from both macro and micro perspectives. Section 6 summarizes the insights into theory and practice.

2 Sample Selection and Factor Construction

2.1 Sample Selection and Data Processing

This study selects the sample period from December 2007 to September 2022. Data on interbank lending rates, monthly returns of the CSI 300 Index, and monthly returns, float market capitalization, shareholders' equity, operating profits, total assets, monetary funds, net accounts receivable, net inventory, and fixed assets of all A-share listed companies in Shanghai and Shenzhen stock markets are collected from the China Stock Market and Accounting Research (CSMAR) database. The 30-day weighted average interbank lending rate serves as the risk-free rate (r_f), while the monthly realized return of the CSI 300 Index represents the market return (r_m). The initial sample comprises all non-financial A-share listed companies as of December of the year $(t-1)$.

Following Liu et al. (2019), we implement the following data filters for the Chinese market: (i) stocks must have been listed for at least six months; (ii) have experienced fewer than five trading suspensions in the past month; (iii) have been suspended for fewer than 120 trading days over the preceding year; (iv) be excluded if halted during portfolio formation; (v) and remove the smallest 30% of stocks by market capitalization to mitigate shell company effects. Companies delisted as ST/*ST during May of year t to April of year $(t+1)$, those with negative shareholders' equity, and firms with missing data are excluded to form the final sample. The final processed data is briefly summarized in the table below. Firm characteristics are measured as follows: Size is defined as float market capitalization at the end of year $(t-1)$; Book-to-market ratio (B/M) is calculated as shareholders' equity divided by float market capitalization at the end of year $(t-1)$; Profitability (OP) equals operating profit divided by shareholders' equity at the end of year $(t-1)$; Five investment proxies are constructed using year-on-year growth rates of total assets (AG), cash (CASH), accounts receivable (RECE), inventory (INVT), and property, plant, and equipment (PPE) at the end of year $(t-1)$.

Table 1: Summary statistics

Year	Firms	Market Value (Trillion)	Average Market Value	Market Return
2007	1090	243.19	0.22	2.22
2008	1202	117.92	0.10	-0.55
2009	1232	225.77	0.18	1.16
2010	1475	236.93	0.16	0.07
2011	1851	206.69	0.11	-0.17
2012	2070	224.28	0.11	0.14
2013	2150	232.70	0.11	0.16
2014	2198	360.99	0.16	0.73
2015	2508	516.99	0.21	0.65
2016	2466	461.70	0.19	-0.04
2017	2760	425.09	0.15	0.14
2018	3060	328.13	0.11	-0.20
2019	3166	440.29	0.14	0.45
2020	3405	615.96	0.18	0.57
2021	3919	749.07	0.19	0.42
2022	4209	621.71	0.15	-0.10

Table 1 reports the evolution of China's A-share market from 2007 to 2022. Market breadth expanded substantially, with the number of listed firms increasing from 1090 to 4209 (a 286% increase), consistent with the deepening of equity financing during the economic transition.

Macroeconomic variables are collected from multiple sources: Monthly total retail sales of consumer goods from CSMAR, month-on-month CPI data from the China Statistical Yearbook, and annual national population statistics from the National Bureau of Statistics website. Following (Yu & Yuan, 2011), the consumption growth factor (CS) is constructed by first converting nominal retail sales to real terms using CPI data, then estimating monthly population through an exponential growth model, and finally calculating real per capita consumption growth (Δc). Three additional factors are developed with methodological improvements: 1) The investor sentiment index (IS) adapts Baker and Wurgler's (Baker & Wurgler, 2006) approach, employing principal component analysis (PCA) on margin trading balances, IPO volumes, turnover rates, and market volatility from CSMAR; 2) Total factor productivity (TFP) follows Fernald and JohnZhang's (Fernald, 2014) framework using Solow Residual method on labor, capital, and output data from CSMAR and statistical yearbooks; 3) Financial intermediary leverage (LEV) adopts Adrian and Etula's (Adrian et al., 2014) formula: Total Financial Assets/(Total Financial Assets - Total Financial Liabilities), computed from CSMAR's sectoral balance sheet data. All factors are converted to monthly frequency to ensure temporal alignment with stock return data.

2.2 Factor Construction

This study adopts the 2×3 sorting approach following Fama and French methodology (Fama & French, 1993) to construct factor portfolios. Specifically, we first sort all valid sample firms from July of year t to June of year t+1 into two size groups (Big [B] and Small [S]) based on market capitalization at the end of year t-1, and three book-to-market (B/M) groups (High [H], Neutral [N], Low [L]) using 30th and 70th percentile breakpoints. The intersection of size and B/M sorts yields six portfolios: SH, SN, SL, BH, BN, and BL. We then repeat this procedure substituting B/M with operating profitability (OP) and total asset growth (AG), generating twelve additional portfolios: SR (Robust Profitability), SN, SW (Weak Profitability), BR, BN, BW, SC (Conservative Investment), SN, SA (Aggressive Investment), BC, BN, and BA. Monthly value-weighted returns are calculated for each portfolio. Four factors are constructed as return differentials:

$$
\begin{aligned}
SMB_{BM} &= \frac{1}{3}(SH + SN + SL) - \frac{1}{3}(BH + BN + BL) \\
SMB_{OP} &= \frac{1}{3}(SR + SN + SW) - \frac{1}{3}(BR + BN + BW) \\
SMB_{INV} &= \frac{1}{3}(SC + SN + SA) - \frac{1}{3}(BC + BN + BA) \\
SMB &= \frac{1}{3}(SMB_{BM} + SMB_{OP} + SMB_{AG}) \\
HML &= \frac{1}{2}(SH + BH) - \frac{1}{2}(SL + BL) \\
RMW &= \frac{1}{2}(SR + BR) - \frac{1}{2}(SW + BW) \\
CMA &= \frac{1}{2}(SC + BC) - \frac{1}{2}(SA + BA),
\end{aligned}
$$

where *SMB* represents the average return difference between six small and six big portfolios, *HML* captures the value premium between high and low B/M stocks, and *RMW* measures profitability effects through robust versus weak OP portfolios. The investment factor in the original FF5F model, denoted *CMA*, is constructed as the return spread between firms with low and high asset growth (AG).

A central limitation of the conventional *CMA* factor lies in its reliance on AG as a proxy for corporate investment. While Fama & French (2015) theoretically ground the investment factor in the dividend discount model (DDM), their empirical implementation follows Cooper et al. (2008) in adopting AG—the year-over-year change in total assets. This choice diverges from conventional measures of corporate investment such as capital expenditures or the growth of property, plant, and equipment (PPE), which more closely align with the DDM's emphasis on expected future cash flows (see detailed derivations in Appendix A). The theoretical inconsistency arises because the DDM links expected returns to earnings, book equity growth, and investment through changes in book equity, thereby highlighting long-term capital accumulation as the relevant channel. By contrast, AG mechanically aggregates short-term working-capital adjustments (e.g., cash, receivables, inventories) with long-term fixed-capital growth (e.g., PPE). As a result, it conflates two economically distinct forms of investment and dilutes the pricing signal associated with pledgeable, long-lived capital. This theoretical misalignment is particularly consequential in China, where corporate financing depends heavily on the collateral value of fixed assets, making AG an especially noisy and potentially misleading proxy for investment risk.

To address these concerns, we extend the standard 2×3 sorting procedure following Cooper et al. (2024) by replacing the AG with four asset-specific growth rates. In particular, we construct investment proxies from four key asset categories reported on the balance sheet: cash (CASH), accounts receivable (RECE), inventory (INVT), and PPE. Specifically, the four disaggregated proxies capture distinct dimensions of firms' investment dynamics. First, CASH reflects precautionary saving and strategic liquidity management, serving as a hedge against policy uncertainty and financing shocks (Han & Wang, 2023). Second, RECE captures risks in trade credit and payment delays, which are particularly salient in China's relationship-based credit system (Yan et al., 2024). Third, INVT reflects firms' resilience to demand fluctuations and supply-chain disruptions, and thus proxies exposure to consumption-related shocks (Shan & Zhu, 2013). Finally, PPE embodies long-term capital accumulation, capturing cyclical expansions in productive capacity and collateral value that are closely tied to China's credit allocation and policy interventions (Qin & Song, 2009).

This decomposition allows us to sharpen the interpretation of the investment factor: while short-term components such as CASH, RECE, and INVT primarily capture liquidity management and working-capital adjustments, PPE isolates the role of durable, collateralizable capital in amplifying financing shocks. By constructing CMA_{CASH}, CMA_{RECE}, CMA_{INVT}, and CMA_{PPE} (abbreviated as CASH, RECE, INVT, PPE) within the same 2×3 framework, we can systematically evaluate which dimensions of investment risk are most relevant for pricing the cross-section of returns in China's equity market. This approach not only addresses the theoretical inconsistency of AG but also aligns the empirical design more closely with the institutional realities of China's corporate sector, where fixed assets dominate both firm balance sheets and collateral-based lending practices.

Table 2: Descriptive Statistics of Investment Factors

Statistic	AG	CASH	RECE	INVT	PPE
Mean	0.02	0.01	0.01	0.00	0.01
Std. Dev.	0.05	0.03	0.02	0.03	0.04
Minimum	-0.23	-0.07	-0.06	-0.09	-0.08
Maximum	0.32	0.13	0.17	0.13	0.15
Median	0.01	0.01	0.01	0.00	0.01

Table 2 reports descriptive statistics for the investment factors. All factors have means close to zero, consistent with standardized factor construction. The PPE factor exhibits slightly lower volatility relative to AG, as indicated by its smaller standard deviation (0.04 vs. 0.05). Its distribution is also less dispersed, with a range of $[-0.08, 0.15]$ compared to AG's wider spread of $[-0.23, 0.32]$. These patterns indicate that PPE is less sensitive to extreme realizations, whereas AG displays greater exposure to outliers. Median values are similar across factors, suggesting broadly symmetric distributions.

Table 3 presents the correlation structure across investment factors. The high correlation between PPE and AG ($\rho = 0.76$) indicates that these measures capture overlapping eco-

Table 3: Correlation Matrix of Investment Factors

	AG	CASH	RECE	INVT	PPE
AG	1.00	0.71	0.46	0.66	0.76
CASH	0.71	1.00	0.32	0.72	0.83
RECE	0.46	0.32	1.00	0.37	0.46
INVT	0.66	0.72	0.37	1.00	0.73
PPE	0.76	0.83	0.46	0.73	1.00

nomic information, consistent with their shared dependence on firm-level investment dynamics. Importantly, PPE is more highly correlated with other proxies than AG: its correlation with CASH (0.83) exceeds AG–CASH (0.71), and its correlation with INVT (0.73) surpasses AG–INVT (0.66). This stronger comovement suggests that PPE aggregates signals from different dimensions of corporate investment more effectively, thereby serving as a broader representation of firms' investment activities.

3 Empirical Results and Analysis

Recent evidence suggests that the performance of investment-based factor models is highly sensitive to how the investment factor is empirically constructed. While the FF5F model employs AG as its investment proxy (Cooper et al., 2008; Fama & French, 2015), subsequent studies show that alternative measures, such as capital expenditures or growth in PPE, may better align with the theoretical underpinnings of the investment channel (Peters & Taylor, 2017; Cooper et al., 2024). In emerging markets like China, where corporate financing is closely tied to collateralizable fixed assets, reliance on AG may obscure the role of long-term capital formation in asset pricing (Qin & Song, 2009; Kermani & Ma, 2023). To address this concern, we construct investment factors from distinct balance-sheet components—including CASH, RECE, INVT, and PPE—and evaluate whether models based on these proxies deliver superior explanatory power relative to the AG-based specification.

To benchmark the relative performance of these alternative specifications, we employ a battery of standard asset pricing diagnostics. Specifically, we use the Sharpe ratio test of Barillas & Shanken (2017); Barillas et al. (2020) to assess improvements in the investment opportunity set, the Gibbons et al. (1989) (GRS) statistic to evaluate model-level pricing errors, and an anomaly-based analysis to test explanatory power across a broad cross-section of return patterns, following the approach of Stambaugh & Yuan (2017) and Liu et al. (2019), who compare factor models across anomalies to highlight the importance of model specification in reducing unexplained returns. Together, these tests allow us to quantify whether investment proxies grounded in fixed-capital growth—most notably PPE—deliver economically and statistically meaningful improvements in the Chinese equity market.

3.1 Cross-Model Comparison Framework

We begin by evaluating the performance of our reconstructed investment factors using the maximum Sharpe ratio, a foundational test for assessing risk-adjusted returns. This initial analysis provides critical insights into whether our factors effectively enhance returns per unit of volatility. Establishing the risk-adjusted performance of the factor model sets the stage for more complex evaluations, as we first need to ensure that the proposed factors outperform conventional metrics in terms of risk management and return optimization. This test thus serves as a preliminary validation before delving into more nuanced tests of pricing efficiency.

The cross-model comparison framework proposed by Barillas & Shanken (2017); Barillas et al. (2020) demonstrates a core advantage: by comparing the maximum squared Sharpe ratio ($maxSR^2$) implied by competing models, it circumvents debates over test asset selection and directly identifies the theoretical pricing upper bound of factor portfolios. This approach is particularly well suited to the complexity of China's capital market, where policy shocks (such as the split-share structure reform) simultaneously alter risk factor structures and return distributions. The resulting $\Delta maxSR^2$ metric isolates institutional noise and precisely measures intrinsic model improvements.

3.1.1 Theoretical Foundation

Following Barillas & Shanken (2017), when comparing two factor models f_1 and f_2 (both containing tradable factors), their relative pricing power is determined by:

$$\Delta maxSR^2 = maxSR^2(f_2) - maxSR^2(f_1), \tag{1}$$

This framework eliminates dependence on test assets X, as model rankings depend solely on $maxSR^2$ differences. The mispricing degree is quantified through Sharpe ratio improvements:

$$\Delta_1 = maxSR^2(f_1, f_2, X) - maxSR^2(f_1). \tag{2}$$

Similarly, the pricing error of model f_2 is measured by the following formula: Similarly, the pricing error of model f_2 is measured by the following formula:

$$\Delta_2 = maxSR^2(f_2, f_1, X) - maxSR^2(f_2). \tag{3}$$

Equivalent simplification is (1).

These formulations are algebraically equivalent, and importantly, the relative ranking of models does not depend on the particular choice of test assets X. The advantage of this framework lies in its independence from traditional reliance on specific test portfolios, thereby mitigating biases from asset selection. By directly comparing Sharpe ratio boundaries, this method provides a theoretically rigorous and computationally efficient paradigm for assessing the validity of alternative investment factor structures. In practice, it not only identifies models with superior explanatory power but also reveals the relative contributions of distinct factors within pricing mechanisms. Accordingly, we use this framework to contrast the AG-based specification with proxies grounded in traditional measures of corporate investment, highlighting the pricing advantages of the latter in China's capital markets.

3.1.2 Key Findings

Table 4 reports formal model comparison tests based on the maximum squared Sharpe ratio framework. Each entry in the table represents the difference in $\max SR^2$ between a model that substitutes the conventional AG-based investment factor with a disaggregated proxy and the benchmark specification. This design allows us to directly assess whether alternative measures of firm investment improve the risk–return tradeoff embedded in factor portfolios.

Table 4: Maximum Sharpe Ratio Difference Tests for Investment Factors

	CASH	RECE	INVT	PPE
$\Delta \max SR^2$	-0.03	-0.08	-0.08	0.07
p-value	0.18	0.11	0.39	0.01
Significance	Insignificant	Insignificant	Insignificant	***

The results highlight a clear contrast across proxies. The most notable finding is the statistically significant improvement delivered by the PPE-based factor: replacing AG with PPE raises the maximum Sharpe ratio by 0.07, with a p-value of 0.01. Economically, this translates into a 7% increase in attainable risk-adjusted return per unit of volatility, suggesting that long-term fixed-capital investment conveys information more closely aligned with systematic risks. In contrast, models employing short-term asset components show no incremental explanatory power. The CASH factor even slightly reduces the maximum Sharpe ratio ($\Delta \max SR^2 = -0.03$, p-value $= 0.18$), while RECE exhibits a larger negative effect (-0.08) that also lacks statistical significance (p-value $= 0.11$). The INVT factor also fails to pass conventional significance thresholds (p-value = 0.39).

Taken together, these patterns suggest that the source of investment measurement is critical. Short-term working-capital adjustments—whether through cash, receivables, or inventories—do not appear to improve the pricing kernel, consistent with their role in liquidity management rather than long-term capital formation. By contrast, PPE captures durable, collateralizable commitments that likely interact more strongly with financing frictions and macroeconomic shocks. While the precise mechanism will be probed in subsequent sections, these findings provide preliminary evidence that investment factors rooted in fixed capital accumulation deliver superior risk-adjusted performance relative to those based on short-term asset fluctuations.

3.2 GRS Test Results

Following the Sharpe ratio tests, a natural next step is to examine whether the apparent improvements in model performance translate into statistically meaningful reductions in pricing errors. While the Sharpe ratio provides a useful measure of risk-adjusted efficiency, it does not directly address whether factor models eliminate systematic mispricing in the cross-section of returns. To provide this stronger benchmark, we employ the joint test of asset-pricing errors developed by Gibbons et al. (1989) (the GRS test), which evaluates whether the intercepts from factor regressions are jointly equal to zero.

Table 5 and Table 6 present the GRS statistics for equally-weighted and value-weighted test portfolios, respectively. The results reinforce our earlier findings: models constructed with short-term asset-based factors (CASH, RECE, and INVT) fail to deliver significant improvements over the AG-FF5F specification, as their pricing errors remain jointly significant. In contrast, the PPE-based specification yields the lowest GRS statistic and the smallest mean absolute alpha across portfolios, indicating a substantial enhancement in pricing efficiency. Moreover, the PPE model demonstrates stronger explanatory power for anomaly returns, confirming that long-term fixed-capital investment captures systematic risk information that AG and short-term components overlook. These findings establish the PPE-based factor as a more valid proxy for corporate investment risk in China's equity market.

Table 5: GRS Test Results: Equally-Weighted Portfolios

Factor	GRS Statistic	p-value	Average Alpha	Average |t-stat|
AG	5.78	5.44e-15	0.0198	5.85
CASH	6.29	3.33e-16	0.0208	6.34
RECE	6.37	2.22e-16	0.0208	6.31
INVT	6.82	1.11e-16	0.0199	6.23
PPE	4.61	4.29e-12	0.0188	5.26

For equally-weighted portfolios in Table 5, the results highlight two key findings. First, all models exhibit highly significant GRS statistics ($p < 10^{-11}$), decisively rejecting the null that pricing errors are jointly equal to zero. This indicates that none of the specifications can fully span the cross-section of returns, consistent with prior evidence on the limitations of standard multifactor models in China's equity market. Second, relative performance across models reveals that the PPE-based specification achieves the lowest GRS statistic (4.61) and the smallest average alpha (0.0188), both marked in red to underscore their significance. This improvement, though not eliminating mispricing altogether, implies that incorporating long-term fixed-capital investment meaningfully reduces the joint magnitude of pricing errors compared to both the benchmark AG factor and short-term asset components such as CASH, RECE, and INVT. The smaller average |t-stat| further suggests that PPE captures risk exposures more aligned with systematic return variation, reinforcing its role as a superior investment proxy.

Table 6: GRS Test Results: Value-Weighted Portfolios

Factor	GRS Statistic	p-value	Average Alpha	Average |t-stat|
AG	5.54	1.97e-14	0.0199	5.91
CASH	6.41	2.22e-16	0.0209	6.41
RECE	6.27	4.44e-16	0.0209	6.37
INVT	6.79	1.11e-16	0.0200	6.30
PPE	5.03	3.52e-13	0.0189	5.32

Turning to value-weighted portfolios in Table 6, the broad conclusions remain intact. While the overall level of GRS statistics declines relative to the equally-weighted case—a pattern consistent with the attenuation of pricing anomalies in larger firms documented by Stambaugh & Yuan (2017)—the PPE-based model again dominates, producing the lowest GRS statistic (5.03) and smallest average alpha (0.0189). Importantly, these results are robust to the inclusion of an additional intangible-capital proxy, which performs no better than the AG baseline. The persistence of statistically significant GRS values across all models ($p < 10^{-12}$) confirms that no single specification fully resolves pricing errors. Nevertheless, the consistent relative advantage of PPE across weighting schemes underscores its robustness as the most economically meaningful replacement for AG in China's equity market. This evidence motivates further tests on anomaly portfolios, where the distinction between short-term and long-term investment channels becomes even more salient.

3.3 Anomaly Pricing Power

After establishing relative performance through Sharpe ratio and GRS tests, we turn to anomaly pricing as a more stringent benchmark for evaluating factor models. While the GRS test assesses whether average pricing errors are jointly significant, anomaly-based tests directly evaluate whether a model can account for well-documented cross-sectional return patterns. As emphasized by Liu et al. (2019), the ability to explain anomaly returns is a defining criterion for a model's empirical validity. This is particularly relevant in China's equity market, where prior studies have identified a wide range of anomalies spanning size, value, profitability, volatility, reversal, turnover, investment, and illiquidity. In line with this literature, we compile 12 representative anomalies (listed in Appendix B) to test the explanatory power of our models.[7] This approach allows us to assess not only whether the PPE-based five-factor model improves upon the traditional AG specification in reducing mispricing, but also whether it captures the fundamental sources of risk that drive return anomalies in China.

Table 7 and Table 8 present the comparative pricing power of investment factors AG and PPE in explaining prominent asset pricing anomalies under unconditional and size-neutral portfolio sorts. Following Fama & French (2015)'s methodology, we estimate the following specification for each anomaly portfolio i:

$$R_{i,t} = \alpha_i + \beta_i F_t + \epsilon_{i,t}, \tag{4}$$

where F_t represents the respective investment factor.

Table 7 reports unconditional portfolio sorts, which provide a first test of the models' anomaly-pricing power without controlling for firm size. The results show that the PPE-based specification delivers systematically lower alphas and stronger beta loadings relative to the AG benchmark in anomalies tied to firms' investment intensity. For example, in the Total Assets anomaly, the PPE model produces a more negative and statistically significant alpha (-1.71, $t = -2.99$ versus -1.59, $t = -2.53$ under AG), highlighting its superior ability

[7] In addition to the traditional asset growth (AG) measure, we extend the investment-related anomalies by constructing counterparts based on specific balance-sheet components, including cash holdings, holding receivables, inventories, PPE, and intangibles. This extension allows us to disentangle the distinct pricing implications of short-term working-capital adjustments versus long-term fixed-capital accumulation.

to eliminate mispricing in balance-sheet-driven portfolios. Similarly, in Cash Holdings and Intangibles, the PPE factor not only reduces residual mispricing but also strengthens the link between anomalies and systematic risk exposures. Importantly, beta estimates provide additional economic insight: PPE's coefficients on Book-to-Market (-40.02, $t = -2.45$) and Total Assets (37.02, $t = 2.00$) are far larger in magnitude and more statistically reliable than those of AG. These stronger loadings indicate that PPE better captures the underlying risk premia associated with value-related anomalies—risks that are muted when investment is measured by aggregate asset growth.

Table 7: Unconditional Portfolio Sorts: Pricing Power Comparison

	AG				**PPE**			
Anomaly	α	t_α	β	t_β	α	t_α	β	t_β
Book-to-Market	0.48	0.87	-23.57	-1.53	0.45	0.89	-40.02	-2.45
Operating Profit	0.39	1.02	27.87	2.65	0.69	1.95	17.06	1.50
Total Assets	-1.59	-2.53	11.72	0.67	-1.71	-2.99	37.02	2.00
Cash Holdings	-1.00	-2.19	-5.26	-0.41	-1.19	-2.84	12.55	0.93
Receivables	-0.48	-1.71	-3.79	-0.49	-0.50	-1.96	-2.45	-0.30
Inventories	-0.52	-1.36	5.63	0.53	-0.50	-1.43	9.26	0.82
PPE	-1.60	-3.10	18.47	1.29	-1.55	-3.28	30.78	2.02
Intangibles	0.80	2.00	-2.64	-0.24	0.89	2.40	-14.40	-1.21
Volatility (1m)	-0.35	-0.68	13.29	0.94	-0.15	-0.31	0.50	0.03
Volatility (max)	0.02	0.05	-0.02	0.00	0.04	0.10	-3.75	-0.33
Liquidity	2.18	4.12	-24.82	-1.68	2.20	4.58	-47.63	-3.07
Turnover (12m)	-0.05	-0.10	4.33	0.33	-0.05	-0.12	9.97	0.70
Turnover (1m)	-0.50	-1.13	8.46	0.69	-0.39	-0.96	2.73	0.21
Reversal	0.18	0.42	-14.47	-1.20	-0.05	-0.12	-4.28	-0.33

Notes: This table presents the results of unconditional portfolio sorts. Alpha and beta coefficients are estimated for both AG (Asset Growth) and PPE (Property, Plant, and Equipment) portfolios. Significant coefficients at the 5% level are marked in red.

Turning to size-neutral sorts in Table 8, the advantages of PPE remain robust even after controlling for the confounding role of firm size. The PPE specification effectively neutralizes spurious alpha in several anomalies: for example, the Total Assets alpha becomes indistinguishable from zero under PPE (-0.07, $t = -0.15$), whereas AG continues to exhibit unexplained returns. Similarly, the Fixed Assets anomaly shows a substantial reduction in alpha magnitude, confirming that PPE's investment proxy better aligns with systematic risks rather than idiosyncratic mispricing. On the beta side, PPE's loadings strengthen markedly for Book-to-Market (-34.39, $t = -2.38$ versus AG's -17.88, $t = -1.31$) and Operating Profit

(20.62, t = 2.40 versus 17.07, t = 2.12). These enhanced exposures underscore PPE's role in capturing policy- and capacity-driven investment risks that are central to the Chinese market, where collateralizability and government intervention shape firms' fixed-asset accumulation.

Table 8: Size-Neutral Portfolio Sorts: Pricing Power Comparison

	AG				PPE			
Anomaly	α	t_α	β	t_β	α	t_α	β	t_β
Book-to-Market	0.52	1.06	-17.88	-1.31	0.54	1.21	-34.39	-2.38
Operating Profit	-0.38	-1.33	17.07	2.12	-0.29	-1.09	20.62	2.40
Total Assets	-0.28	-0.53	30.81	2.13	-0.07	-0.15	33.24	2.15
Cash Holdings	0.17	0.55	12.20	1.39	0.29	1.00	7.92	0.84
Receivables	0.24	1.13	3.11	0.53	0.32	1.66	-3.60	-0.58
Inventories	0.02	0.06	15.13	1.56	0.17	0.53	10.19	0.98
Fixed Assets	-0.64	-1.35	30.29	2.30	-0.39	-0.90	29.17	2.07
Intangibles	0.13	0.41	-12.17	-1.34	0.07	0.22	-15.15	-1.57
Volatility (1m)	-0.14	-0.29	15.46	1.18	0.10	0.23	0.59	0.04
Volatility (max)	0.25	0.72	-3.83	-0.39	0.31	0.97	-15.09	-1.46
Liquidity	0.99	2.19	-42.81	-3.38	0.64	1.53	-39.40	-2.89
Turnover (12m)	-0.71	-1.71	-0.42	-0.04	-0.87	-2.27	18.04	1.46
Turnover (1m)	-0.53	-1.36	3.74	0.35	-0.52	-1.46	4.76	0.41

Notes: This table presents the results of size-neutral portfolio sorts. Alpha and beta coefficients are estimated for both AG (Asset Growth) and PPE (Property, Plant, and Equipment) portfolios. Significant coefficients at the 5% level are marked in red.

Taken together, the anomaly pricing evidence indicates that replacing AG with PPE significantly reduces unexplained returns and strengthens the economic linkage between anomalies and risk factors. In contrast, the AG-based specification leaves systematic mispricing unresolved, particularly in investment-sensitive anomalies. This motivates the next step of our analysis: while GRS and anomaly pricing tests document PPE's statistical superiority, they remain reduced-form evaluations. To uncover the underlying economic mechanisms, we extend our investigation to macroeconomic factor tests, examining whether PPE-based returns co-move with shocks that are theoretically relevant to China's investment environment, such as productivity, credit conditions, and policy-driven capacity cycles.

4 Investment Factors and Macroeconomic Drivers

Although the above sections establish the excellent pricing power of PPE, its economic principles need more in-depth analysis: why does the fixed asset based investment factor (PPE) produce a sustained risk premium in China's capital market? Does this reflect a unique macroeconomic transmission channel? We solve this problem through the macro and micro framework: (i) construct a random discount factor (SDF) model to identify the macroeconomic risk exposure of PPE, and (ii) analyze the micro mechanism of PPE adjustment.

4.1 Macroeconomic Risk Identification

The literature on macroeconomic shocks that generate cross-sectional risk dispersion is extensive, and we do not claim to have exhaustively covered it in the tests below. However, in the context of China's capital market, certain macroeconomic channels stand out as particularly relevant. We therefore assemble a representative set of variables that capture the key drivers of systematic risks in this environment. As summarized in Table 9, our analysis focuses on shocks to productivity, consumption, financing costs, and market sentiment—dimensions that are especially important in China, where state-led growth strategies, credit-driven investment cycles, and policy-sensitive demand fluctuations jointly shape firms' risk exposures.

Table 9: Representative Macroeconomic Indicators

Variable	Description
Investor Sentiment (IS)	Composite index using margin trading and PCA (Baker & Wurgler, 2006)
Financial Leverage (LEV)	Financial sector leverage ratio (Adrian et al., 2014)
Consumption (CS)	CPI-adjusted retail sales growth (Yu & Yuan, 2011)
TFP	Solow residual-based productivity (Fernald, 2014)

4.1.1 SDF Model Specification

We estimate SDF models incorporating macroeconomic factors:

$$m_t = 1 - b_{\mathrm{MKT}}\mathrm{MKT}_t - b_{\mathrm{MACRO}}\mathrm{MACRO}_t \tag{5}$$

where MACRO_t denotes IS, LEV, CS, or TFP. Test assets comprise 25 portfolios double-sorted on profitability and investment factors (AG/CASH/RECE/INVT/PPE), controlling for profitability-investment interactions (Papanikolaou, 2011; Kogan, 2004).

In order to measure the goodness of fit of the model, this article reports the implied mean absolute pricing error (MAPE) of each model, which is the average absolute deviation between the predicted and actual values of the model's excess returns on test assets. The calculation formula for MAPE is:

$$\text{MAPE} = \sum \left| r_{i,t}^{e} - \hat{r}_{i,t}^{e} \right|, \tag{6}$$

where $r_{i,t}^{e}$ denotes the actual excess return of test asset i at time t, $\hat{r}_{i,t}^{e}$ represents the model-predicted excess return, and N is the number of test assets ($N = 25$ in this study). The mean absolute pricing error (MAPE) decreases with smaller values, indicating lower pricing errors and stronger model fit.

4.1.2 Empirical Results

The test assets comprise four sets of portfolios double-sorted on profitability and investment factors (AG, CASH, RECE, INVT, PPE). Following Kogan (2004), we first partition firms into high/low profitability groups, then further split each group into high/low investment subgroups using factor medians, yielding 25 portfolios per set. This design controls for profitability-investment interactions, ensuring that investment factor pricing reflects genuine risk exposure rather than profitability confounders.

Table 10 reports first-stage GMM estimates of factor loadings (β_{MKT}, β_{MACRO}) using identity weighting. The moment conditions follow:

$$E[M_t r_{i,t}^{e}] = 0, \tag{7}$$

where $r_{i,t}^{e}$ denotes excess returns of test asset i. Each column represents a distinct model specification varying by macroeconomic factor (IS, LEV, CS, TFP) in Equation (5). Panels A–E correspond to test assets constructed from CMA, CASH, RECE, INVT and PPE double-sorts, respectively.

Each column in Table 10 corresponds to a different model, and the differences are mainly reflected in the selection of macro factors in Equation (5). For example, the first column of the model only includes market factors, while subsequent columns introduce different macro factors (such as IS, LEV, CS, or TFP) as explanatory variables. In addition, each panel uses a different set of test assets to estimate each model. Specifically, each panel is priced based on 25 investment portfolios constructed from dual grouping of profitability and different investment factors (AG, CASH, RECE, INVT, or PPE). The specific steps are as follows:

- **Panel A**: 25 AG-Profitability portfolios
- **Panel B**: 25 CASH-Profitability portfolios
- **Panel C**: 25 RECE-Profitability portfolios
- **Panel D**: 25 INVT-Profitability portfolios
- **Panel E**: 25 PPE-Profitability portfolios

Table 10 reports first-stage GMM estimates of SDF loadings with unit weighting. For brevity, we present only macro factor coefficients (market factor loadings are included but suppressed). Table 10 highlights how alternative investment-based factors capture distinct macroeconomic risk exposures, with PPE-based portfolios standing out for their unique sensitivity to financing constraints and sentiment-driven fluctuations. Both PPE and aggregate asset growth (AG) display positive and significant loadings on investor sentiment shocks (IS: PPE $b = 0.916$, $t = 2.41$; AG $b = 1.855$, $t = 2.18$), indicating that equity returns in China are strongly influenced by waves of optimism and pessimism in capital markets. However, only PPE portfolios exhibit significant exposure to financial leverage shocks (LEV: $b = 0.877$, $t = 2.26$), while AG portfolios remain largely unresponsive ($b = 0.084$, $t = 0.19$). This contrast underscores the fact that fixed-asset-intensive firms in China are directly tied to the availability and cost of collateralized credit, making their returns systematically sensitive to fluctuations in financial intermediary balance sheets.

The differentiated risk profiles across investment factors have several implications. First,

Table 10: Estimation of SDF Model with Macroeconomic Factors

Investment Factor	Macroeconomic Factor			
	CS	IS	LEV	TFP
Panel A: Total Asset Growth (AG)				
Coefficient	−1.008	1.855*	0.084	−0.056
	(−1.516)	(2.183)	(0.185)	(−0.142)
SSQE	157.850	101.579	19.766	19.108
MAPE	14.118	10.288	5.404	4.964
Panel B: Cash Investment (CASH)				
Coefficient	−1.454	1.388*	−0.504	−1.303**
	(−2.066)	(2.253)	(−1.147)	(−3.108)
SSQE	139.756	86.560	13.898	12.338
MAPE	14.247	10.637	4.444	4.122
Panel C: Receivables Investment (RECE)				
Coefficient	0.351	0.733*	0.432	−0.059
	(1.251)	(2.108)	(0.995)	(−0.160)
SSQE	77.989	69.957	14.638	18.212
MAPE	10.198	8.815	4.653	4.917
Panel D: Inventory Investment (INVT)				
Coefficient	−0.654*	1.347*	−0.581	1.001**
	(−2.481)	(2.719)	(−1.604)	(2.937)
SSQE	65.167	41.466	11.011	9.329
MAPE	9.637	7.490	3.827	3.366
Panel E: PPE Investment (PPE)				
Coefficient	0.032	0.916*	0.877*	0.339
	(0.086)	(2.408)	(2.255)	(0.812)
SSQE	134.049	115.672	17.994	22.318
MAPE	13.754	11.805	5.193	5.507

Notes: Coefficients report SDF loadings for macroeconomic factors. t-statistics in parentheses. Significance levels: *p<0.1, **p<0.05, ***p<0.01. SSQE = sum of squared pricing errors; MAPE = mean absolute percentage error (%). Market factor (MKT) included in all specifications.

the dual loadings of PPE on sentiment and leverage shocks reflect the institutional reality of China's credit system, where tangible capital serves as the main pledgeable collateral in corporate borrowing. As financing conditions tighten, firms with high PPE intensities face higher marginal costs of external capital, which are subsequently priced into their equity returns. Second, PPE's consistent sentiment loading—with stable significance across specifications—suggests that fixed asset growth is a reliable barometer of policy-driven credit cycles and market sentiment, while AG's noisier exposure reflects the heterogeneity of short-term asset fluctuations (e.g., cash or receivables) that are less tied to long-lived investment commitments. Importantly, the magnitude of PPE's leverage exposure—over ten times larger than that of AG—demonstrates that financing frictions, rather than pure productivity shocks, are a central channel in explaining cross-sectional returns in China. This finding aligns with recent theories emphasizing the role of collateral constraints in shaping risk premia in emerging markets.

4.2 Microeconomic Transmission

These macro-level findings raise an important follow-up question: through which firm-level mechanisms are financing frictions and sentiment shocks transmitted into returns? Prior research has emphasized the central role of financing constraints and collateralizability in shaping investment-based risk premia. For instance, Belo et al. (2019) highlight that high-investment firms are systematically exposed to equity financing costs, while Ai et al. (2020) argue that assets with greater collateral value provide a hedge against financing shocks, thereby commanding a negative premium. Similarly, Rampini & Viswanathan (2013) show that tangible capital, such as PPE, is more pledgeable and thus directly tied to firms' borrowing capacity. Building on these insights, we examine whether the explanatory power of PPE in China reflects its role in facilitating debt substitution when equity financing conditions deteriorate. In particular, we investigate whether fluctuations in investor sentiment (proxied by IS) induce systematic shifts between equity and debt financing across firms with different asset compositions.

Table 11: Financing Structure Changes Across Sentiment Regimes by Asset Group

	Total Asset		**Cash**		**Receivable**		**Inventory**		**PPE**	
Portfolio	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*
Equity Financing										
High BW	29.13	0.91	27.47	1.34	23.46	3.90	27.54	2.85	28.14	1.19
Low BW	36.71	0.73	22.71	6.68	34.25	2.58	16.00	9.31	20.45	8.51
Change Rate	0.26	-0.19	-0.17	3.98	0.46	-0.34	-0.42	2.27	-0.27	6.17
Debt Financing										
High BW	52.85	0.34	49.24	0.96	41.16	4.43	51.13	3.25	50.17	0.66
Low BW	251.84	0.43	48.93	87.05	256.58	6.98	29.14	109.85	30.95	106.79
Change Rate	3.77	0.26	-0.01	89.86	5.23	0.57	-0.43	32.82	-0.38	161.83

Notes: Reports financing values (equity/debt) for high/low sentiment periods. Change rate = (Low BW - High BW)/High BW. PPE portfolios show most pronounced equity-debt substitution. Red values highlight critical substitution effects.

As shown in Table 11, the financing structure changes across sentiment regimes reveal a pronounced substitution effect for PPE-intensive firms. During low-BW periods, low-PPE portfolios increase debt financing by 161.83 (ΔDebt = 106.13) while expanding equity only modestly by 6.17 (ΔEquity = 7.32). By contrast, working-capital-oriented firms exhibit much weaker or even opposite patterns: cash-intensive firms display virtually no debt substitution (ΔRate = -0.01), while receivables-focused firms experience an outright contraction in equity financing (ΔRate = -0.34). These results underscore that the ability to substitute between equity and debt financing is most pronounced among firms with higher tangible capital intensity, consistent with PPE's superior collateral value.

As tangible assets, PPE's superior collateral value (Rampini & Viswanathan, 2013) fundamentally drives financing substitution dynamics during market downturns. When investor sentiment declines, firms exhibit divergent financing behaviors based on asset composition: low-PPE firms aggressively leverage fixed assets to secure debt financing, evidenced by their debt-to-PPE ratio surging from 0.013 to 3.45, while high-PPE firms maintain remarkably stable financing structures with minimal debt adjustment (debt change rate = -0.38). This bifurcation aligns with China's bank-dominated financial architecture where tangible assets command loan-to-value ratios three times higher than working capital (Yeung, 2009), creating distinct refinancing capacities across asset profiles.

The dramatic 161.83 debt increase among low-PPE firms signals a critical financing regime shift below sentiment thresholds. These firms cross an inflection point where debt becomes the marginal financing source during distress periods, confirmed by highly asymmetric sensitivity: debt exhibits strong negative sensitivity to business conditions while equity shows only mild responsiveness. This refinancing risk channel—uniquely captured by PPE-based factors but missed by working-capital measures—explains PPE's dominance in asset pricing models, particularly during market stress when refinancing constraints bind most severely.

Ai et al. (2020) argue that asset collateralizability should command a negative premium and they show empirical evidence consistent with this idea. They point out that many macroeconomic models featuring financing frictions predict that financial constraints are more binding in recessions and therefore can worsen economic downturns. Through their ability to relax financial constraints, collateralizable assets should provide a hedge against the risk of becoming financially constrained in recessions. Hence, firms with more collateralizable assets should be less exposed to aggregate financing shocks. If, consistent with Rampini & Viswanathan (2013), PPE, As tangible assets, provide a better proxy for the firms' collateralizable capital, then the results in Ai et al. (2020) could explain why we find a stronger link between financing shocks and PPE. In the Ai et al. (2020)'s framework, the PPE factors would simply be better proxies for the collateralizability premium.

4.3 Comparison with the Literature

Overall, the PPE-based five-factor model delivers strong pricing performance in China, capturing most documented anomalies and exhibiting robust sensitivity to macro-financing shocks. By contrast, U.S. evidence from Cooper et al. (2024) shows that the explanatory power of investment-based models hinges on the choice of proxy: INVT and RECE carry much of the pricing information, while PPE-based measures contribute relatively little to explaining the cross-section of returns. This contrast suggests that in developed markets, short-term working-capital adjustments, rather than fixed-capital accumulation, represent the dominant margin of investment-related risk premia.

We attribute this cross-country divergence to fundamental differences in corporate asset structures and institutional arrangements. Both theory and empirical evidence indicate that when PPE exhibits high asset specificity and low redeployability, its exposure to macro-financing shocks intensifies—capital expenditures become particularly sensitive to uncertainty shocks when fixed assets cannot be easily liquidated or reallocated (Kermani & Ma, 2023). In China, firms have historically emphasized fixed-asset-intensive investment, resulting in large tangible capital stocks that serve as a stable collateral base. Combined with a credit system centered on collateralized lending against PPE, this environment amplifies the pricing role of fixed-asset growth, making it a key driver of debt–equity substitution dynamics.

In contrast, U.S. firms increasingly operate under asset-light business models, with a greater reliance on liquid assets such as cash and receivables. These assets are more easily redeployed and directly reflect firms' refinancing flexibility, particularly in equity and short-term credit markets. As a result, liquidity-based proxies such as CASH or RECE growth become more relevant indicators of systematic risk exposure in developed markets, while PPE growth plays a comparatively muted role in asset pricing (Cooper et al., 2024; Crouzet et al., 2022).

5 Heterogeneity test

This section evaluates alternative investment-factor specifications using industry portfolios as test assets. We construct, for each month t, both *fine industries* and *broad industries* from individual stocks, following the official Chinese National Industry Classification (GB/T 4754) summarized in Appendix D. Specifically, fine industries correspond to three-digit categories within each industrial sector, while broad industries refer to the aggregated first-level divisions such as Manufacturing (C), Mining (B), or Finance (J). Unless otherwise noted, industry returns are value-weighted using previous-month float market capitalization. Let $R^{\text{ind}}_{i,t}$ denote the excess return of industry i at t and F_t the $K \times 1$ vector of common factors.

5.1 Time-Series Pricing Tests

For each industry i, we estimate the linear factor model

$$R^{\text{ind}}_{i,t} = \alpha_i + \beta_i^{\top} F_t + \varepsilon_{i,t}, \qquad \mathbb{E}[\varepsilon_{i,t} | F_t] = 0. \tag{8}$$

The intercept α_i measures the industry pricing error (Jensen's alpha) under the candidate factor model. We estimate (8) by OLS with Newey–West (HAC) standard errors using monthly data and four lags.[8] For model fit we report the sample R^2, $t(\alpha_i)$, and the share of industries with statistically insignificant alphas.

We benchmark five unified models that differ only in the investment proxy used to construct the investment factor: aggregate asset growth (AG), cash (CASH), receivables (RECE),

[8]HAC lags of 3–6 are common at monthly frequency; our main results use four lags.

inventories (INVT), and property, plant, and equipment (PPE). Other factors are held fixed across specifications. The goal is to compare cross-sectional pricing performance at the industry level.

Dates are aligned to month-end and stored as Period(M) to ensure exact merging with factor files. We exclude month–industry cells with fewer than three constituent stocks. For insignificance counts we use two-sided 5% tests for $\alpha_i = 0$ with HAC standard errors; the critical value is based on average degrees of freedom across industries.[9]

5.2 Results

Table 12 reports, for each model, the number and percentage of industries whose pricing errors are statistically indistinguishable from zero. Higher percentages indicate better overall pricing at the industry level (fewer unexplained alphas).

Table 12: Industry Time-Series Pricing: Share of Insignificant Alphas

	Fine Industries			Broad Industries		
Model	Count	Total	% Insignificant.	Count	Total	% Insignificant.
AG	57	73	78.08	12	18	66.67
CASH	44	73	60.27	7	18	38.89
RECE	44	73	60.27	9	18	50.00
INVT	43	73	58.90	7	18	38.89
PPE	50	73	68.49	13	18	72.22

Notes: "Fine industries" correspond to three-digit categories under the GB/T 4754 classification, whereas "broad industries" refer to first-level divisions such as Agriculture (A), Mining (B), and Manufacturing (C). Percentages denote the fraction of industries with $|t(\alpha_i)| < t_{0.975}$ under HAC–NW standard errors (lag 4). Larger values indicate fewer pricing errors under the candidate factor specification.

From the results summarized in Table 12, three main findings emerge that highlight how industry aggregation and investment-proxy choice shape model performance.

First, at the fine-industry level—corresponding to three-digit categories under the GB/T 4754 classification—the AG specification attains the highest share of insignificant alphas (78.08%), followed by PPE (68.49%). In contrast, at the broad-industry level—referring to first-level di-

[9]Using industry-specific degrees of freedom yields nearly identical qualitative rankings.

visions such as Agriculture (A), Mining (B), and Manufacturing (C)—PPE leads with 72.22%, exceeding AG (66.67%). This pattern suggests that when industries are aggregated into higher-level sectors, the explanatory power of long-lived capital investment (PPE) becomes more pronounced. The result is consistent with fixed-asset intensity being a key driver of systematic sectoral risk in China's real economy.

Second, comparing across investment proxies, working-capital-based factors (CASH, RECE, and INVT) show markedly weaker performance, with insignificance shares of roughly 39–60%. These results imply that short-term asset fluctuations leave greater unexplained variation in industry returns. In other words, transitory working-capital adjustments are less directly connected to the systematic risk components that drive expected returns across sectors.

Finally, synthesizing these patterns reveals a coherent economic interpretation. Fewer significant alphas imply a closer alignment between factor exposures and realized industry returns. The superior broad-industry performance of PPE aligns with China's collateral-based financial environment, in which fixed-asset intensity loads on priced shocks such as financing-cost or investment-specific technology shocks. Meanwhile, AG's advantage at the fine-industry level suggests that total asset growth captures both working- and fixed-capital dynamics relevant to narrowly defined industries.

Overall, the evidence underscores that the construction of the investment factor materially affects industry-level pricing performance. The PPE-based specification excels when industries are aggregated—consistent with fixed-capital intensity being a structural, sector-wide attribute—whereas AG performs best for fine industries, likely because it reflects a broader range of firm-level adjustments. These complementary patterns support a mechanism in which collateralizable capital (PPE) serves as a priced state variable for sectoral risk, while working-capital proxies remain weaker in explaining systematic return variation across industries.

6 Conclusion

Uncovering why factor models succeed or fail in different institutional settings is central to understanding the forces behind expected returns. We show that the Fama–French five-factor model (FF5F), though widely used globally, underperforms in China because its investment factor—asset growth (AG)—does not align with the fixed-asset-intensive corporate structure and collateral-based credit system that characterize the Chinese market.

By decomposing aggregate assets into CASH, RECE, INVT, and PPE, we find that only PPE-based factors materially improve model performance. Across Sharpe ratio tests, GRS statistics, and anomaly pricing benchmarks, PPE growth consistently outperforms AG and other short-term asset proxies. This advantage is not mechanical: macroeconomic SDF tests reveal that PPE portfolios load strongly on financing-cost and sentiment shocks, while AG fails to capture leverage exposures. At the micro level, PPE-intensive firms exhibit pronounced equity–debt substitution during sentiment downturns, consistent with the role of collateralizable capital in relaxing financing frictions.

The cross-country contrast reinforces this institutional dependence. In the U.S., working-capital proxies like inventories and receivables capture most of the investment effect (Cooper et al., 2024), while PPE contributes little. In China, the opposite holds, reflecting its bank-financed, asset-heavy corporate sector. Thus, the economic meaning of the "investment factor" is not universal but shaped by institutional context.

Overall, our findings caution against mechanically importing reduced-form proxies across markets. While AG performs well in developed economies, it obscures the distinction between short- and long-term assets in China and fails to capture collateral-based financing frictions. Substituting PPE restores both theoretical consistency with the dividend discount model and empirical relevance for China. Future research should integrate collateral constraints explicitly into macro-finance models, examine the state dependence of PPE's pricing role, and extend the analysis to other emerging markets with similar credit structures. More broadly, factor models must be interpreted in light of the institutional foundations that shape balance sheets, financing channels, and, ultimately, expected returns.

References

Adrian, T., Etula, E., & Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *The journal of Finance*, 69(6), 2557–2596.

Ai, H., Li, J. E., Li, K., & Schlag, C. (2020). The collateralizability premium. *The Review of Financial Studies*, 33(12), 5821–5855.

Aktas, N., Croci, E., & Petmezas, D. (2015). Is working capital management value-enhancing? evidence from firm performance and investments. *Journal of Corporate Finance*, 30, 98–113.

Baker, M. & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, 61(4), 1645–1680.

Barillas, F., Kan, R., Robotti, C., & Shanken, J. (2020). Model comparison with sharpe ratios. *Journal of Financial and Quantitative Analysis*, 55(6), 1840–1874.

Barillas, F. & Shanken, J. (2017). Which alpha? *The Review of Financial Studies*, 30(4), 1316–1338.

Belo, F., Lin, X., & Yang, F. (2019). External equity financing shocks, financial flows, and asset prices. *The Review of Financial Studies*, 32(9), 3500–3543.

Cakici, N., Chan, K., & Topyan, K. (2017). Cross-sectional stock return predictability in china. *The European Journal of Finance*, 23(7-9), 581–605.

Carpenter, J. N., Lu, F., & Whitelaw, R. F. (2021). The real value of china's stock market. *Journal of Financial Economics*, 139(3), 679–696.

Chen, L., Pelger, M., & Zhu, J. (2024). Deep learning in asset pricing. *Management Science*, 70(2), 714–750.

Chen, X., Kim, K. A., Yao, T., & Yu, T. (2010). On the predictability of chinese stock returns. *Pacific-basin finance journal*, 18(4), 403–425.

Cooper, M., Gulen, H., & Ion, M. (2024). The use of asset growth in empirical asset pricing models. *Journal of Financial Economics*, 151, 103746.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *the Journal of Finance*, 63(4), 1609–1651.

Crouzet, N., Eberly, J. C., Eisfeldt, A. L., & Papanikolaou, D. (2022). The economics of intangible capital. *Journal of Economic Perspectives*, 36(3), 29–52.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds.

Journal of financial economics, 33(1), 3–56.

Fama, E. F. & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, 116(1), 1–22.

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the factor zoo: A test of new factors. *The Journal of Finance*, 75(3), 1327–1370.

Fernald, J. (2014). *A quarterly, utilization-adjusted series on total factor productivity*. Working paper, Federal Reserve Bank of San Francisco.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, (pp. 1121–1152).

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), 2223–2273.

Gulen, H., Li, D., Peters, R. H., & Zekhnini, M. (2025). Intangible capital in factor models. *Management Science*, 71(2), 1756–1778.

Guo, B., Zhang, W., Zhang, Y., & Zhang, H. (2017). The five-factor asset pricing model tests for the chinese stock market. *Pacific-Basin Finance Journal*, 43, 84–106.

Han, H. & Wang, X. (2023). Monetary policy uncertainty and corporate cash holdings: Evidence from china. *Journal of Financial Stability*, 67, 101138.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), 650–705.

Hsu, J., Viswanathan, V., Wang, M., & Wool, P. (2018). Anomalies in chinese a-shares. *Journal of Portfolio Management*, 44(7), 108–123.

Hu, G. X., Chen, C., Shao, Y., & Wang, J. (2019). Fama–french in china: size and value factors in chinese stock returns. *International Review of Finance*, 19(1), 3–44.

Huang, T.-L. (2019). Is the fama and french five-factor model robust in the chinese stock market? *Asia Pacific Management Review*, 24(3), 278–289.

Kelly, B. T., Pruitt, S., & Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics*, 134(3), 501–524.

Kermani, A. & Ma, Y. (2023). Asset specificity of nonfinancial firms. *The Quarterly Journal of Economics*, 138(1), 205–264.

Kogan, L. (2004). Asset prices and real investment. *Journal of Financial Economics*, 73(3), 411–431.

Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross-section. *Journal of Financial Economics*, 135(2), 271–292.

Lin, Q. (2017). Noisy prices and the fama–french five-factor asset pricing model in china. *Emerging Markets Review*, 31, 141–163.

Liu, J., Stambaugh, R. F., & Yuan, Y. (2019). Size and value in china. *Journal of financial economics*, 134(1), 48–69.

Miller, M. H. & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *the Journal of Business*, 34(4), 411–433.

Papanikolaou, D. (2011). Investment shocks and asset prices. *Journal of Political Economy*, 119(4), 639–685.

Peters, R. H. & Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123(2), 251–272.

Qin, D. & Song, H. (2009). Sources of investment inefficiency: The case of fixed-asset investment in china. *Journal of Development Economics*, 90(1), 94–105.

Rampini, A. A. & Viswanathan, S. (2013). Collateral and capital structure. *Journal of Financial Economics*, 109(2), 466–492.

Shan, J. & Zhu, K. (2013). Inventory management in china: An empirical study. *Production and Operations Management*, 22(2), 302–313.

Stambaugh, R. F. & Yuan, Y. (2017). Mispricing factors. *The review of financial studies*, 30(4), 1270–1315.

Yan, B., Chen, Z., Yan, C., Zhang, Z., & Kang, H. (2024). Evolutionary multiplayer game analysis of accounts receivable financing based on supply chain financing. *International Journal of Production Research*, 62(22), 8110–8128.

Yeung, G. (2009). How banks in china make lending decisions. *Journal of Contemporary China*, 18(59), 285–302.

Yu, J. & Yuan, Y. (2011). Investor sentiment and the mean–variance relation. *Journal of Financial Economics*, 100(2), 367–381.

A The DDM in FF5F model

The theoretical foundation for including book-to-market equity (B/M), profitability, and investment in asset pricing models can be derived from the dividend discount model. Let m_t denote the market value of a stock at time t, and $E(d_{t+\tau})$ be the expected dividend at time $t+\tau$. The model states that the price is the discounted sum of expected future dividends:

$$m_t = \sum_{\tau=1}^{\infty} \frac{E(d_{t+\tau})}{(1+r)^{\tau}},$$

where r denotes the expected long-run return. Miller & Modigliani (1961) show that, under standard accounting identities, the market value M_t of equity equals the present value of expected future earnings net of changes in book equity:

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - \Delta B_{t+\tau})}{(1+r)^{\tau}},$$

where $Y_{t+\tau}$ is total earnings and $\Delta B_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$ is the change in book equity. Normalizing by B_t, the current book equity, gives:

$$\frac{M_t}{B_t} = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - \Delta B_{t+\tau})}{(1+r)^{\tau} B_t}.$$

This formulation implies that, holding all else constant, a higher B_t/M_t (i.e., a higher book-to-market ratio) signals higher expected returns. Moreover, higher expected earnings increase expected returns, while higher expected investment (i.e., book equity growth) reduces expected returns, justifying the use of profitability and investment factors in explaining the cross-section of returns. See Fama & French (2015) for a full discussion.

B Anomaly Portfolios

Table B1: Chinese Anomalies and References

Anomaly	References
Market cap (Size)	Hsu et al. (2018) and Hu et al. (2019)
BM (Value)	Cakici et al. (2017) and Hsu et al. (2018)
ROE (Profitability)	Guo et al. (2017)
1-Mo. vol. (Volatility)	Cakici et al. (2017) and Hsu et al. (2018)
MAX (Volatility)	Carpenter et al. (2021)
1-Month return (Reversal)	Cakici et al. (2017),Hsu et al. (2018) and Carpenter et al. (2021)
12-Month turn. (Turnover)	Stambaugh & Yuan (2017)
1-Mo. abn. turn. (Turnover)	Stambaugh & Yuan (2017)
Asset growth (Investment)	Chen et al. (2010)
Amihud illiq. (Illiquidity)	Carpenter et al. (2021) and Hsu et al. (2018)

1. Size. The stock's market capitalization is used in this category. It is computed as the previous month's closing price times total A shares outstanding, including nontradable shares.[10]

2. Value. Book-to-market ratio (BM) is used: Book equity equals total shareholder equity minus the book value of preferred stocks. A stock's BM is the ratio of book equity to the product of last month-end's close price and total shares.

3. Profitability. Firm-level ROE at the quarterly frequency is used. The value of ROE equals the ratio of a firm's earnings to book equity, with earnings and book equity defined in the Value category.

4. Volatility. Two variables are used:

- *One-month volatility*: A firm's one-month volatility is calculated as the standard devia-

[10]In China's stock market, a firm can issue three types of share classes: A, B, and H shares. Domestic investors can trade only A shares, while foreign investors can trade only B shares. H shares are issued by domestic companies but traded on Hong Kong exchanges. We measure size based on total A shares but compute valuation ratios by scaling with total shares, including B and H shares (treating earnings and book-values of a firm as applying to all shareholders, including foreign and Hong Kong investors).

tion of daily returns over the past 20 trading days.

- *MAX*: MAX equals the highest daily return over the past 20 trading days.

5. Investment. In Fama and French (2015), a firm's investment is measured by its annual asset growth rate, calculated as total assets in the most recent annual report divided by total assets in the previous report. In this study, we extend the construction of the investment anomaly by decomposing total assets into several balance-sheet components. Specifically, a firm's *Cash Holdings* anomaly is measured by the year-over-year growth rate of monetary funds; the *Receivables* anomaly is measured by the growth rate of net accounts receivable; the *Inventories* anomaly is measured by the growth rate of net inventories; the *PPE* anomaly is measured by the growth rate of fixed assets; and the *Intangibles* anomaly is measured by the growth rate of intangible assets. Each measure is constructed in the same way as asset growth, namely, the value reported in the most recent annual report divided by the corresponding value in the previous annual report, minus one.

6. Illiquidity. We compute a stock's average daily illiquidity over the past 20 trading days. Following Amihud (2002), a stock's illiquidity measure for day t is calculated as:

$$\text{Illiq}_t = \frac{|ret_t|}{\text{volume}_t}$$

where $|ret_t|$ is the stock's absolute return on day t, and volume_t is the stock's dollar trading volume on day t.

7. Turnover. Two variables are used:

- *Twelve-month turnover*: Measured as the average daily share turnover over the past 250 days. A firm's daily turnover is calculated as its share trading volume divided by its total shares outstanding.
- *One-month abnormal turnover*: A firm's abnormal turnover is calculated as the ratio of its average daily turnover over the past 20 days to its average daily turnover over the past 250 days.

8. Reversal. The sorting measure used is the stock's one-month return, computed as the cumulative return over the past 20 trading days. For every anomaly except reversal, we sort the stock universe each month using the most recent month-end measures and hold the resulting portfolios for one month. For the one-month return reversal anomaly (a short-term anomaly), we sort the stock universe each day based on the most recently available 20-day cumulative return. Using this sort, we rebalance a one-fifth "slice" of the total portfolio that is held for five trading days. Each day we average the returns across the five slices, and compound these daily returns to compute the reversal anomaly's monthly return. For all anomalies, value-weighted portfolios of stocks within the top and bottom deciles are formed using the most recent month-end market capitalizations as weights.

C Factor Models' Explanatory Power for Anomalies

This appendix presents detailed results of the explanatory power of three factor models: the Fama-French three-factor model (FF3F), the five-factor model with traditional investment factor (FF5F-AG), and the five-factor model with PPE-based investment factor (FF5F-PPE) across 14 anomalies. Results are reported for both unconditional and size-neutral grouping methodologies. Alphas (monthly percentage returns) and their corresponding t-statistics are shown in Table C1 and Table C2.

Table C1: Alphas and t-statistics for Anomalies: Unconditional Grouping

Anomaly	FF3F	FF5F-AG	FF5F-PPE
Book-to-Market	0.13 (0.30)	0.48 (0.87)	0.45 (0.89)
Operating Profit	0.66 (2.13)	0.39 (1.02)	0.69 (1.95)
Total Assets	-1.45 (-2.88)	-1.59 (-2.53)	-1.71 (-2.99)
Cash	-1.17 (-3.19)	-1.00 (-2.19)	-1.19 (-2.84)
Accounts Receivable	-0.51 (-2.29)	-0.48 (-1.71)	-0.50 (-1.96)
Inventory	-0.43 (-1.42)	-0.52 (-1.36)	-0.50 (-1.43)
Fixed Assets	-1.25 (-3.00)	-1.60 (-3.10)	-1.55 (-3.28)
Intangible Assets	0.76 (2.35)	0.80 (2.00)	0.89 (2.40)
Volatility (1m)	-0.11 (-0.27)	-0.35 (-0.68)	-0.15 (-0.31)
Volatility (max)	-0.09 (-0.28)	0.02 (0.05)	0.04 (0.10)
Liquidity	1.80 (4.19)	2.18 (4.12)	2.20 (4.58)
Turnover (12m)	0.05 (0.12)	-0.05 (-0.10)	-0.05 (-0.12)
Turnover (1m)	-0.07 (-0.19)	-0.50 (-1.13)	-0.39 (-0.96)
Reversal	-0.11 (-0.31)	0.18 (0.42)	-0.05 (-0.12)

Notes: This table reports alphas (in percentage points per month) and t-statistics (in parentheses) from time-series regressions of 14 anomaly portfolios on factor models using unconditional grouping. FF3F denotes the Fama-French three-factor model, FF5F-AG the five-factor model with traditional asset growth factor, and FF5F-PPE the five-factor model with PPE-based investment factor. t-statistics are calculated using Newey-West standard errors with 6 lags.

The PPE-based investment factor (FF5F-PPE) demonstrates superior explanatory power for investment-sensitive anomalies compared to the traditional investment factor (FF5F-AG), while performing similarly to the three-factor model (FF3F). Across both grouping methodologies, FF5F-PPE generates smaller and less statistically significant alphas than FF5F-AG for anomalies directly related to corporate investment, indicating better explanatory power. Specifically:

Table C2: Alphas and t-statistics for Anomalies: Size-Neutral Grouping

Anomaly	FF3F	FF5F-AG	FF5F-PPE
Book-to-Market	0.35 (0.90)	0.52 (1.06)	0.54 (1.21)
Operating Profit	-0.26 (-1.08)	-0.38 (-1.33)	-0.29 (-1.09)
Total Assets	0.21 (0.50)	-0.28 (-0.53)	-0.07 (-0.15)
Cash	0.24 (0.93)	0.17 (0.55)	0.29 (1.00)
Accounts Receivable	0.31 (1.84)	0.24 (1.13)	0.32 (1.66)
Inventory	0.24 (0.84)	0.02 (0.06)	0.17 (0.53)
Fixed Assets	-0.05 (-0.13)	-0.64 (-1.35)	-0.39 (-0.90)
Intangible Assets	-0.15 (-0.56)	0.13 (0.41)	0.07 (0.22)
Volatility (1m)	-0.01 (-0.04)	-0.14 (-0.29)	0.10 (0.23)
Volatility (max)	0.09 (0.33)	0.25 (0.72)	0.31 (0.97)
Liquidity	0.35 (0.94)	0.99 (2.19)	0.64 (1.53)
Turnover (12m)	-0.73 (-2.17)	-0.71 (-1.71)	-0.87 (-2.27)
Turnover (1m)	-0.19 (-0.59)	-0.53 (-1.36)	-0.52 (-1.46)
Reversal	-0.01 (-0.04)	-0.04 (-0.11)	-0.15 (-0.44)

Notes: This table reports alphas and t-statistics using size-neutral grouping methodology. All specifications follow Table A1. Size-neutral portfolios are constructed by independent double sorting on size and anomaly characteristics.

- For *Fixed Assets*—the anomaly most directly related to investment behavior—FF5F-PPE produces substantially smaller alphas than FF5F-AG in size-neutral sorts (-0.39 vs -0.64) with lower statistical significance (t = -0.90 vs -1.35)
- In *Total Assets* anomalies, FF5F-PPE shows marked improvement over FF5F-AG under size-neutral grouping (-0.07 vs -0.28) with near-zero statistical significance (t = -0.15)
- For *Intangible Assets*, FF5F-PPE generates smaller alphas than FF5F-AG in unconditional sorts (0.89 vs 0.80) with comparable statistical significance

Notably, FF5F-PPE's explanatory power is comparable to FF3F across most anomalies:

- In size-neutral sorts, FF5F-PPE and FF3F produce statistically indistinguishable alphas for 10 of 14 anomalies
- For *Book-to-Market*, both models generate small, statistically insignificant alphas (FF3F: 0.35, FF5F-PPE: 0.54)
- *Cash* and *Accounts Receivable* anomalies show nearly identical alpha magnitudes and significance levels between FF5F-PPE and FF3F

Liquidity effects remain resistant to factor explanations, generating the largest and most statistically significant alphas across all specifications (1.80-2.20, t > 4.0 in unconditional sorts). Turnover anomalies show contrasting patterns: while 12-month turnover exhibits significant negative alphas in size-neutral sorts (-0.71 to -0.87), 1-month turnover effects are substantially reduced when controlling for size.

These results highlight two key insights: (1) The PPE-based investment factor provides superior explanatory power for investment-sensitive anomalies compared to the traditional AG factor, and (2) FF5F-PPE maintains explanatory power comparable to the established FF3F model across most anomaly categories, suggesting it captures similar pricing effects while improving investment-related anomaly explanations.

D Appendix: Industry Classification Codes in China

Table D1: National Industry Classification (Condensed)

Code	Category	Subcategory (abbrev.)
A	Agriculture, Forestry, Animal Husbandry and Fishery	01 Agriculture; 02 Forestry; 03 Animal Husbandry; 04 Fishery; 05 Agricultural Services
B	Mining	06 Coal Mining; 07 Oil and Gas Extraction; 08 Ferrous Metal Mining; 09 Non-ferrous Metal Mining; 10 Non-metal Mining; 11 Mining Support; 12 Other Mining
C	Manufacturing	13–43 Food, Textiles, Chemicals, Metal Products, Machinery, Transport Equipment, Electronics, etc.
D	Electricity, Heat, Gas and Water Supply	44 Electricity and Heat Supply; 45 Gas Supply; 46 Water Supply
E	Construction	47 Housing Construction; 48 Civil Engineering; 49 Installation Works; 50 Decoration and Other Construction
F	Wholesale and Retail Trade	51 Wholesale; 52 Retail
G	Transportation, Storage and Postal Services	53 Railway; 54 Road; 55 Water; 56 Air; 57 Pipeline; 58 Handling and Agency; 59 Storage; 60 Postal
H	Accommodation and Catering	61 Accommodation; 62 Catering
I	Information Transmission, Software and IT Services	63 Telecommunications; 64 Internet Services; 65 Software and IT Services

Code	Category	Subcategory (abbrev.)
J	Finance	66 Monetary Services; 67 Capital Market; 68 Insurance; 69 Other Finance
K	Real Estate	70 Real Estate
L	Leasing and Business Services	71 Leasing; 72 Business Services
M	Scientific Research and Technical Services	73 R&D; 74 Professional Technical; 75 Science Promotion and Application
N	Water Conservancy, Environment and Public Facilities	76 Water Management; 77 Ecological Protection; 78 Public Facility Management
O	Resident, Repair and Other Services	79 Resident Services; 80 Repair of Vehicles and Electronics; 81 Other Services
P	Education	82 Education
Q	Health and Social Work	83 Health; 84 Social Work
R	Culture, Sports and Entertainment	85 Publishing; 86 Broadcasting and Film; 87 Arts; 88 Sports; 89 Entertainment
S	Comprehensive Activities	90 Comprehensive

Note: Codes follow the National Industrial Classification of the People's Republic of China (GB/T 4754). The condensed version lists only major categories and abbreviated sub-categories for reference.