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SUMMARY: This study investigates the stock resilience premium and its underlying determinants in China's capital market. The authors construct a comprehensive resilience index using 32 macro- and micro-level indicators and estimate the resilience betas of individual stocks via rolling-window regressions. The study reveals a significant and economically meaningful resilience premium in the Chinese stock market, robust after controlling for risk factors in both time-series and cross-sectional regressions. The authors conduct conditional portfolio analyses based on firm size, volatility, liquidity, momentum, and valuation to uncover the drivers of the premium. They also examine the state-dependence of the resilience premium, finding that it is predominantly concentrated during periods of high market volatility, elevated investor sentiment, and economic expansion. The study concludes that economic policy uncertainty acts as a critical amplifier, with high-resilience firms outperforming low-resilience firms in high-EPU regimes. The cross-sectional pricing of resilience is found to be highly state-contingent, with markets rewarding idiosyncratic shock-buffering capabilities during escalation regimes.

METHOD: The study uses a comprehensive resilience index constructed from 32 macro- and micro-level indicators. Resilience betas of individual stocks are estimated via rolling-window regressions. Conditional portfolio analyses are conducted based on firm size, volatility, liquidity, momentum, and valuation. The resilience premium is examined for state-dependence, and cross-sectional pricing is analyzed for state-contingency.

KEY FINDINGS:

- Significant and economically meaningful resilience premium in the Chinese stock market.
- Resilience premium remains robust after controlling for risk factors in both time-series and cross-sectional regressions.
- High-resilience firms outperform low-resilience firms in high-EPU regimes.
- Cross-sectional pricing of resilience is highly state-contingent, with robust premium during escalation regimes.

IMPLICATION FOR TRADING: The findings suggest that investors should focus on identifying high-resilience firms, as they are likely to outperform low-resilience firms during periods of high market volatility, elevated investor sentiment, and economic expansion. This information can be used to construct portfolios that capitalize on the resilience premium, potentially leading to higher returns. However, investors should also be aware that the resilience premium may become indistinguishable from noise during easing or stable periods.

Resilience Anomaly and Asset Pricing in the Chinese Stock Market

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Declarations

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Abstract: To investigate the stock resilience premium and its underlying determinants in China's capital market, this study constructs a comprehensive resilience index using 32 macro- and micro-level indicators. The resilience betas of individual stocks are then estimated via rolling-window regressions. Long-short portfolio sorts (long high-resilience minus low-resilience) reveal a significant and economically meaningful resilience premium in the Chinese stock market. This anomaly remains robust after controlling for risk factors in both time-series and cross-sectional regressions. To uncover its drivers, we conduct conditional portfolio analyses based on firm size, volatility, liquidity, momentum, and valuation. The results indicate that these characteristics play a crucial role in shaping the premium. Furthermore, we examine the state-dependence of the resilience premium. The resilience premium is predominantly concentrated during periods of high market volatility, elevated investor sentiment, and economic expansion. Notably, economic policy uncertainty (EPU) acts as a critical amplifier: in high-EPU regimes, high-resilience firms substantially outperform their low-resilience counterparts. Finally, the cross-sectional pricing of resilience is highly state-contingent. In escalation regimes, markets reward idiosyncratic shock-buffering capabilities, producing a robust and statistically significant resilience beta premium. By contrast, during easing or stable periods characterized by broad equity rallies and uniform capital allocation, firm-specific resilience differences lose pricing relevance, and the premium becomes indistinguishable from noise.

Keywords: Stock Resilience; Return Anomaly; Asset Pricing; Market Conditions

1. Introduction

China's stock market has grown into the world's second-largest equity market. However, late development, imperfect institutional arrangements and a high proportion of retail investors jointly lead to suboptimal overall pricing efficiency and persistent resource misallocation, accompanied by frequent pricing distortions driven by insufficient information transparency. When exposed to external shocks, cross-sectional valuation heterogeneity across listed firms becomes prominent: high-resilience firms can effectively mitigate price volatility, while vulnerable low-resilience firms face drastic price slumps that may trigger chain reactions and even systemic risks. In this context, identifying the differentiation of corporate resilience and exploring its role in guarding against crash risks has become an urgent research priority.

From a macro-financial perspective, financial resilience generally refers to a system's capacity to withstand external shocks, recover from adverse impacts, and adapt and restructure amid economic, social and ecological changes (Bailey, 2022). Capital market resilience follows the same theoretical logic and is widely defined as an integrated capacity covering three stages: resisting external risks, self-repair after shocks, and post-crisis functional upgrading. Theoretically, high-resilience firms possess stronger risk-buffering capacity and are more favored by investors, whereas low-resilience firms are exposed to greater vulnerability and suffer persistent valuation discounts. Accordingly, there should exist significant return differentials between high-resilience

and low-resilience stocks. Nevertheless, this theoretical inference lacks systematic empirical verification, forming an underexplored “resilience anomaly”. Furthermore, existing literature rarely discusses the underlying driving factors of such cross-sectional return gaps.

The insufficient empirical evidence on resilience anomalies originates from the lack of unified measurement standards for capital resilience among prior studies. Scholars have reached a basic consensus that financial resilience contains two core dimensions, namely shock absorption (Bhattacharya & Spiegel, 1998; Cerqueti et al., 2022) and post-shock recovery (Degryse et al., 2005; Broto & Lamas, 2020). These two dimensions can be generalized as reliability and recoverability (Shi & Mena, 2021). Relevant studies either observe stock price fluctuations during crisis episodes to evaluate shock absorption capacity or measure recovery speed after shocks to capture post-crisis repair performance. Though these two dimensions are widely acknowledged, this paper further expands the framework into three unified dimensions applicable to equity markets: shock resistance, risk buffering capacity and post-shock recovery adaptability. Regrettably, no existing research integrates all three dimensions simultaneously to construct a comprehensive resilience proxy.

To fill this research gap, this paper compiles 32 primary, secondary and tertiary macro and micro indicators covering shock resistance, risk buffering and recovery adaptability. We adopt Sparse Principal Component Analysis (SPCA) to extract common latent factors and synthesize a composite capital market resilience index. Following the empirical framework of Fang et al. (2023) and Alexander et al. (2026), we conduct rolling-window regressions of individual stock excess returns on the composite resilience index to estimate time-varying resilience beta, which quantifies each stock’s sensitivity to overall market resilience fluctuations. Given the absence of standardized multi-dimensional resilience metrics and scarce empirical tests on its pricing implications, we construct long-short portfolios sorted by resilience beta to verify whether high-resilience and low-resilience firms generate statistically distinguishable return spreads. We then eliminate the influence of conventional risk factors via CAPM, Fama-French three-factor and Carhart four-factor models to obtain risk-adjusted return differentials. Time-series regressions and cross-sectional Fama-MacBeth regressions are further adopted to ensure the robustness of baseline conclusions. Next, we implement double sorting conditional on classic firm characteristics including size, book-to-market ratio, momentum, liquidity and idiosyncratic volatility to disentangle the micro drivers of resilience beta premiums. Finally, we divide the sample into distinct macroeconomic regimes segmented by market sentiment, economic policy uncertainty and trade friction intensity, so as to investigate how external macro shocks exert state-contingent impacts on the pricing of resilience.

This paper centers on three core research objectives corresponding to the above research design. First, we systematically test whether a stable capital resilience premium exists in China’s A-share market by constructing firm-level resilience beta based on the 32-dimensional indicator system and comparing return performance across high and low resilience portfolios. Second, we adopt conditional double sorting to clarify how core firm characteristics such as size, volatility, liquidity, momentum and value shape the cross-sectional differentiation of resilience premiums. Third, we examine heterogeneous pricing effects under exogenous macro shocks, including distinct market sentiment cycles, varying levels of economic policy uncertainty and different stages of trade frictions, and analyze whether these external environments amplify or suppress the magnitude of resilience premiums.

Our empirical analysis delivers five core findings, which are elaborated sequentially from baseline pricing effects to micro and macro heterogeneous mechanisms.

First, we confirm the existence of a significant capital resilience premium in China's stock market. The long-short portfolio (long high-resilience stocks, short low-resilience stocks) yields persistent positive excess returns, with a value-weighted average monthly excess return of 0.69% and an equal-weighted average monthly excess return of 0.76%. Subsample tests segmented by normal and extreme market regimes show that the resilience premium is only statistically significant during extreme shock periods. Moreover, time-series regressions and cross-sectional Fama-MacBeth regressions both demonstrate that the predictive power of resilience beta remains robust after controlling for liquidity, valuation, firm size and other standard market factors.

Second, conventional cross-sectional characteristics generate heterogeneous conditioning effects on the resilience beta premium. Consistent with the prominent small-cap effect and higher tail risk of small firms in China's market, portfolios composed of small-cap stocks exhibit much stronger resilience premiums, and their long-short return spreads are highly statistically significant. Taking the book-to-market ratio (BM) as the valuation characteristic, we find that high-BM value portfolios produce larger resilience premiums relative to low-BM growth portfolios. Among momentum-sorted groups, low-momentum stocks present higher resilience beta returns, and their long-short spreads significantly outperform those of high-momentum subsamples. Although low-turnover portfolios deliver slightly higher raw resilience returns, only high-turnover subsamples show significant long-short spreads, which can be attributed to faster information transmission and more efficient price discovery among liquid stocks. For idiosyncratic volatility (IVOL), the resilience premium is concentrated primarily within high-volatility stocks, while low-volatility portfolios display weak and mostly insignificant premiums.

Third, the resilience beta premium shows substantial heterogeneity across market sentiment regimes. During low-sentiment periods, all resilience-sorted portfolios deliver elevated raw returns ranging from 2.57% to 3.01% with statistical significance. However, the long-short return spread lacks significance. In contrast, under high-sentiment environments, the long-short portfolio sorted by resilience beta generates significantly positive excess returns. From the perspective of economic cycles, average monthly portfolio returns are lower and insignificant during economic recessions. In expansionary periods, portfolio returns fluctuate between 0.6% and 2.49%, and returns decrease monotonically from high-resilience groups to low-resilience groups, with low-resilience portfolios capturing significant risk premiums. The long-short Low-High spread is insignificant in recessions. However, it reaches a statistically significant positive average monthly return of 1.41% ($t = 3.38$) during economic expansions. Market volatility also exerts a material influence on resilience pricing: nearly all resilience portfolios earn significant positive returns in high-volatility regimes. The long-short spreads stand at 0.49% for low-volatility periods and 1.02% for high-volatility periods, with only the latter statistically significant. After risk adjustment via the Fama-French three-factor and Carhart four-factor models, portfolios in high-volatility regimes still maintain the highest risk-adjusted returns, verifying that intensified market volatility substantially magnifies the resilience beta premium.

Fourth, economic policy uncertainty (EPU) exerts profound impacts on the pricing of corporate resilience. Generally speaking, higher EPU corresponds to higher average returns of resilience-sorted portfolios. In low-EPU stable regimes, all decile portfolios achieve the highest raw returns with strong statistical significance; in high-EPU regimes, the absolute returns of most

portfolios lose significance. However, long-short spreads diverge sharply across regimes: the High-Low spread stands at 0.58% under low EPU and 1.02% under high EPU, and only the spread in high-EPU environments remains significant after controlling for FF3 and Carhart four-factor risks. Stable policy environments form unified optimistic expectations among enterprises and investors, compressing cross-sectional return dispersion and rendering long-short resilience strategies ineffective. On the contrary, high EPU implies ambiguous policy orientations and surging macro tail risks, which forces the market to reprice corporate resilience. High-resilience firms can effectively hedge against policy shocks, thereby maintaining stable and differentiated excess returns.

Fifth, trade friction cycles significantly modulate the pricing intensity of resilience beta. We divide trade friction into three unified stages: easing period, stable period and escalation period. During easing periods, broad market rallies push up returns of all decile portfolios, all of which show statistical significance. Nevertheless, portfolio returns fail to decrease monotonically with the decline of resilience, resulting in insignificant long-short spreads, as investors adopt universal buying strategies without distinguishing firm resilience differences. In stable periods, overall portfolio returns decline and lose statistical significance, indicating that corporate resilience characteristics no longer carry independent pricing weights. In escalation periods marked by intense external shocks, portfolio returns show a clear monotonic downward trend from the top high-resilience decile (P1) to the bottom low-resilience decile (P10). The corresponding long-short spread becomes highly statistically significant and remains robust after FF3 and Carhart four-factor risk adjustments. This result confirms that the market explicitly prices firms' capacity to resist external cross-border shocks amid trade tensions.

This paper makes three marginal contributions to the existing literature, each corresponding to the research limitations summarized above. First, we propose a multi-dimensional unified framework for resilience measurement. Unlike prior studies that rely on single trading or financial indicators, this paper integrates shock resistance, risk buffering and post-shock recovery adaptability into a complete evaluation system. We further extract latent common factors from multi-layer high-frequency indicators via SPCA to construct a composite resilience index, providing a novel quantitative tool for establishing capital resilience evaluation systems in emerging markets such as China. Second, we adopt time-varying rolling regressions to estimate resilience beta, which quantitatively captures the compensation for exposure to market resilience deterioration. By constructing long-short portfolios and implementing Fama-MacBeth cross-sectional regressions, we dynamically identify the regime-dependent pricing effects of resilience, alleviating concerns over spurious correlation and heteroskedasticity, and aligning the factor exposure logic with mainstream asset pricing theories. Third, based on the verified resilience premium, we construct a unique resilience risk factor tailored to China's institutional and investor characteristics. By incorporating this factor into domestic asset pricing frameworks, this study improves the explanatory power of traditional models for various A-share market anomalies. Meanwhile, our conclusions offer targeted references for regulators to design market stabilization mechanisms and prevent systemic crash risks.

The remainder of this paper proceeds as follows. Section 2 presents the literature review and theoretical framework. It sorts out extant research on financial market resilience and asset pricing, summarizes existing research limitations, and constructs the theoretical logic linking capital resilience to cross-sectional stock returns. Section 3 describes the sample data, variable definitions

and empirical methodologies, including the construction of the multi-dimensional composite resilience index, the estimation of time-varying resilience beta, and portfolio sorting as well as regression approaches adopted in this study. Section 4 conducts the baseline empirical analysis, verifying the existence of the capital resilience premium in China's A-share market and carrying out a series of robustness tests. Section 5 further explores the heterogeneous driving mechanisms of the resilience premium from both firm characteristic and exogenous macro shock perspectives. Finally, Section 6 concludes the paper, summarizes core empirical findings, puts forward corresponding policy implications, and points out research limitations and future research directions.

2. Literature Review and Theoretical Framework

2.1 Related literature

Existing literature on capital resilience predominantly examines its necessity from a theoretical perspective, particularly for China's financial market (Hu et al., 2021; Gao et al., 2021). These studies emphasize the structural advantages of a resilient capital market and argue for its critical role in supporting the real economy and optimizing resource allocation. While some recent works have explored the determinants of market resilience (Wang et al., 2025), empirical research on how resilience is priced in equity markets remains scarce. Given that capital markets primarily serve to channel funds to productive sectors, investigating the pricing power of corporate/market resilience is both theoretically significant and practically urgent.

2.1.1 Measurement of resilience index

In measuring financial resilience, scholars have employed diverse methodologies. Some utilize survey-based approaches to construct individual-level financial resilience indices (Hamid et al., 2023; Salignac et al., 2019). Others apply stress-testing frameworks, widely adopted by central banks and financial institutions to evaluate the resilience of banking and insurance sectors under adverse scenarios (BIS, 2004; Galbusera et al., 2014). Additionally, composite index methodologies have been developed: researchers first construct multi-dimensional indicator systems reflecting intrinsic resilience characteristics, then synthesize them into aggregate indices using econometric models to assess systemic resilience levels (Wójcik & Cojoianu, 2018). Although these approaches offer valuable insights for specific financial sub-sectors, their high specificity limits direct applicability to equity market resilience measurement.

Currently, there is no consensus on capital resilience metrics (Martin & Sunley, 2015; Olbrys & Mursztyn, 2019). However, the literature broadly converges on two core dimensions: shock absorption capacity (Bhattacharya & Spiegel, 1998; Cerqueti et al., 2022) and post-shock recovery ability (Degryse et al., 2005; Broto & Lamas, 2020), which can be further abstracted into reliability and recoverability (Shi & Mena, 2021). Methodologically, existing studies fall into three streams. First, some focus on exogenous market shocks by tracking stock price trajectories during crises to assess corporate adaptability, often proxying resilience via rolling return-risk ratios over past N years (typically 5 or 10) (Hu et al., 2021; Wang et al., 2025). Second, others evaluate firm fundamentals through long-term financial performance and sales growth rates (Markman et al., 2014; Ortiz-de-Mandojana et al., 2016). Third, several studies define resilience by the speed or time required for an economy or market to revert to pre-shock levels (Hmaied et al., 2006; Lo & Hall, 2015; Degryse et al., 2005). Collectively, these approaches highlight three critical dimensions: shock resistance, buffering/absorption capacity, and recovery adaptability.

However, no existing study simultaneously integrates all three into a unified analytical framework.

2.1.2 Capital resilience and asset pricing

The intersection of capital resilience and asset pricing has been predominantly explored through the lens of liquidity. Liquidity serves as the foundational fuel for capital resilience, while resilience acts as a stabilizer and repair mechanism for liquidity under extreme conditions; the two are mutually reinforcing. In resilient markets, extreme shocks do not trigger liquidity dry-ups, enabling rapid restoration of trading and pricing functions post-crisis. Conversely, illiquid markets easily collapse upon impact, rendering resilience meaningless. Consequently, many studies proxy market resilience using liquidity metrics. The core logic posits that highly resilient markets maintain stable bid-ask spreads and trading volumes under stress, achieving lower liquidity premiums; weakly resilient markets are prone to a “liquidity spiral” (price decline → forced liquidation → liquidity dry-up → further price decline). Amihud (2002) and Pastor et al. (2003) formalized this by constructing liquidity factor pricing frameworks, arguing that resilience should be priced as an independent cross-sectional factor. Zhang et al. (2022) constructed a liquidity factor via simulated portfolios capturing both volume-based and price-impact dimensions of liquidity. Their dual-factor model outperforms CAPM and Fama-French three-factor models in explaining anomalies such as size, book-to-market, profitability, investment, cash flow yield, equity issuance, and volatility effects.

Beyond bid-ask spreads and trading volume, turnover acts as another mainstream single-dimensional liquidity indicator to characterize market resilience. Turnover rate, a key liquidity proxy, primarily reflects liquidity premiums in asset pricing: higher turnover correlates with greater market depth and resilience, leading investors to demand lower expected returns (hence, a significant negative cross-sectional relation between turnover and returns). Simultaneously, turnover captures liquidity stability; low-turnover assets are more vulnerable to dry-ups during extremes and thus command higher risk compensation. Under excessive speculation, however, elevated turnover signals noise trading and bubble risks, turning positively correlated with future returns into negatively correlated—a nonlinear pricing feature. Liu et al. (2019) incorporated turnover-adjusted liquidity as a sentiment factor, demonstrating its ability to capture investor sentiment and price resilience under liquidity shocks. As research deepens, attention has shifted toward firm-level resilience premiums (Pagano et al., 2023), offering critical implications for investors and regulators. In summary, most existing literature indirectly proxies market resilience via liquidity indicators, characterizing resilience merely from single trading dimensions such as market depth, bid-ask spreads and turnover rates. Few studies construct a comprehensive quantitative system for capital market resilience covering three dimensions: shock resistance, risk absorption and post-shock recovery. As a result, the overall risk resistance capacity of markets facing exogenous tail shocks cannot be fully captured, leading to one-sided measurement of resilience.

In short, existing studies mostly measure resilience indirectly through single trading indicators, failing to integrate shock resistance, risk absorption and post-shock recovery into an integrated evaluation framework, which results in one-sided assessment of capital market resilience.

2.2 Research gaps and study positioning

Despite enriching theoretical cognition of capital resilience, existing literature suffers from three prominent limitations. First, scholars have not reached a unified standard for resilience

measurement, and most resilience proxies rely on single-dimensional indicators such as post-crisis recovery speed or liquidity metrics. Actual capital market resilience covers shock resistance, post-shock self-repair and adaptive upgrading, which cannot be fully reflected by isolated single indicators. Thus, a composite resilience indicator integrating both macro and micro information is urgently needed. Second, deepening global financial integration has amplified the spillover effects of exogenous shocks including policy uncertainty, trade frictions and systemic financial crises. Although domestic studies have fully discussed macro risk prevention, few papers systematically explore how external shocks alter the pricing effect of corporate resilience. Third, mainstream asset pricing literature analyzes resilience merely from the liquidity perspective. Since liquidity only reflects market microstructure characteristics rather than full resilience connotation, the pricing mechanism of resilience needs to be re-examined under a unified dynamic framework that incorporates macroeconomic regimes, corporate fundamentals and trading characteristics.

To fill the above research gaps, this paper develops a multi-dimensional composite capital resilience index adapted to China's unique institutional background and retail-dominated investor structure. We incorporate a full set of indicators covering macro credit conditions, market liquidity, corporate operating stability and stock tail risk. On this basis, we further construct time-varying resilience beta and test the cross-sectional pricing pattern of resilience exposure in the A-share market, so as to disentangle the formation logic and transmission channels of the resilience premium. The multi-dimensional composite index breaks through the single-dimensional measurement bias in prior research. Meanwhile, the state-dependent pricing analysis under differentiated macro environments also supplements relevant theoretical evidence, laying a solid foundation for interpreting A-share pricing efficiency and formulating targeted market stabilization and risk prevention policies.

2.3 Theoretical analysis

Drawing on Alexander et al. (2026), who integrate heterogeneous investors with incomplete risk sharing into an asset pricing framework, this paper treats extreme market downturns as exogenous systemic shocks. We define resilience beta to capture a firm's sensitivity to adverse tail events: a lower (more negative) resilience beta indicates stronger corporate resilience and smaller tail-risk exposure, whereas a higher resilience beta implies weaker shock absorption and greater tail risk. During severe market declines, heterogeneous investors experience divergent income paths and intertemporal consumption choices, amplifying cross-sectional dispersion in aggregate wealth. Systemic tail risks cannot be fully diversified through equity portfolios. Specifically, high-resilience-beta (low-resilience) firms exhibit synchronized deep price drawdowns during crises; their return fluctuations are highly correlated with investors' marginal utility, embedding significant undiversifiable tail risk. Conversely, low-resilience-beta (high-resilience) firms demonstrate robust defensive capabilities, exhibiting limited drawdowns and lower tail exposure under stress. Under equilibrium pricing with incomplete risk sharing, investors demand higher compensation for high-tail-risk stocks characterized by elevated resilience betas. Consequently, long-short portfolios that go long on low-resilience beta (i.e., high-resilience) firms and short on high-resilience beta firms generate significant positive abnormal returns, confirming that resilience beta serves as a valid cross-sectional pricing factor.

Following Alexander et al. (2026), we ground our theoretical derivation in the canonical heterogeneous-agent asset pricing framework of Constantinides and Duffie (1996). The core premise posits incomplete insurance markets, implying that individual tail risks cannot be

perfectly hedged through portfolio diversification. Exogenous extreme shocks magnify cross-sectional heterogeneity in household income and consumption, thereby generating a priceable tail-risk premium across the equity cross-section. Adapting their modeling logic, we derive the formation mechanism and asset pricing implications of resilience beta.

$$\mathbb{E}_t[\tilde{R}_{t+1}^e] = \frac{cov_t(\tilde{H}_{t+1}, \tilde{R}_{t+1}^e)}{\mathbb{E}_t[\tilde{H}_{t+1}]} \quad (1)$$

Where $\mathbb{E}_t[\tilde{R}_{t+1}^e]$ denotes the excess return of individual stock i at $t+1$, and $\tilde{H}_{t+1}$ is the stochastic discount factor (SDF). Equation (1) implies that a stock's expected excess return is determined by its conditional covariance with the pricing kernel. Assets that co-move negatively with the SDF carry non-diversifiable tail risk and demand higher risk premiums. With constant relative risk aversion (CRRA) utility, the heterogeneous-agent SDF takes the standard form:

$$\tilde{H}_{t+1} = \beta \left(\frac{\tilde{C}_{t+1}}{C_t} \right)^{-\alpha} \exp \left(\frac{\alpha(\alpha+1)}{2} \tilde{\gamma}_{t+1}^2 \right) \quad (2)$$

In this expression, C_t stands for aggregate consumption at time t , and $\Delta \tilde{C}_{t+1} = \ln \left(\frac{\tilde{C}_{t+1}}{C_t} \right)$ is aggregate consumption growth. $\tilde{\gamma}_{t+1}^2$ measures cross-sectional household consumption inequality; β is the subjective time discount factor, and α is the relative risk aversion coefficient. The exponential term captures how consumption dispersion alters marginal utility and shapes the pricing kernel, which differentiates this framework from the representative-agent CCAPM.

We first apply a standard transformation for log SDF via generalized Stein's Lemma. For any positive stochastic discount factor $\tilde{H}_{t+1}$, we have:

$$cov_t(\tilde{H}_{t+1}, \tilde{R}_{t+1}^e) = \mathbb{E}_t[\tilde{H}_{t+1}] * cov_t(\tilde{h}_{t+1}, \tilde{R}_{t+1}^e) \quad (3)$$

Where $\tilde{h}_{t+1} = \ln(\tilde{H}_{t+1})$. Taking the natural logarithm of Equation (2) yields the log pricing kernel:

$$\tilde{h}_{t+1} = \ln \beta - \alpha \Delta \tilde{C}_{t+1} + \frac{\alpha(\alpha+1)}{2} \tilde{\gamma}_{t+1}^2 \quad (4)$$

Substitute Equation (4) into the covariance term in Equation (3) to decompose the joint co-movement between log SDF and stock excess returns:

$$cov_t(\tilde{h}_{t+1}, \tilde{R}_{t+1}^e) = -\alpha * cov_t(\Delta \tilde{C}_{t+1}, \tilde{R}_{t+1}^e) + \frac{\alpha(\alpha+1)}{2} * cov_t(\tilde{\gamma}_{t+1}^2, \tilde{R}_{t+1}^e) \quad (5)$$

Equation (5) shows that the covariance between stock returns and the pricing kernel is jointly driven by aggregate consumption risk and cross-sectional consumption inequality risk. Convert covariance terms into correlation-standard deviation products:

$$\mathbb{E}_t[\tilde{R}_{t+1}^e] = -\alpha * \rho(\Delta \tilde{C}_{t+1}, \tilde{R}_{t+1}^e) * \sigma_t[\Delta \tilde{C}_{t+1}] * \sigma_t[\tilde{R}_{t+1}^e] + \frac{\alpha(\alpha+1)}{2} * \rho(\tilde{\gamma}_{t+1}^2, \tilde{R}_{t+1}^e) * \sigma_t[\tilde{\gamma}_{t+1}^2] * \sigma_t[\tilde{R}_{t+1}^e] \quad (6)$$

Define $X = \Delta \tilde{s}_{t+1}^e$ as exogenous systemic tail shock. All variables are standardized to zero mean and unit variance. We rely on the orthogonal correlation decomposition derived in the supplementary derivation section below, substituting $\rho(\tilde{R}^e, \Delta \tilde{C}) = \rho(\tilde{R}^e, \tilde{s}^e) * \rho(\Delta \tilde{s}^e, \Delta \tilde{C})$ and $\rho(\tilde{R}^e, \tilde{\gamma}^2) = \rho(\tilde{R}^e, \Delta \tilde{s}^e) * \rho(\Delta \tilde{s}^e, \tilde{\gamma}^2)$ into Equation (6) and simplify algebraically to obtain the core pricing equation:

$$\mathbb{E}_t[\tilde{R}_{t+1}^e] = \alpha * \rho(\Delta \tilde{C}_{t+1}, \Delta \tilde{s}_{t+1}^e) * \rho(\tilde{R}_{t+1}^e, \Delta \tilde{s}_{t+1}^e) - \frac{\alpha(\alpha+1)}{2} * \rho(\tilde{\gamma}_{t+1}^2, \Delta \tilde{s}_{t+1}^e) * \rho(\tilde{R}_{t+1}^e, \Delta \tilde{s}_{t+1}^e) \quad (7)$$

We define $\rho(\tilde{\gamma}_{t+1}^2, \Delta \tilde{s}_{t+1}^e)$ as resilience beta, which measures the linear co-movement

between a firm's idiosyncratic tail risk and aggregate market resilience fluctuations. Economically, a lower resilience beta implies weak synchronization between the firm's downside risk and market-wide adverse shocks. When systemic tail shocks hit and erode overall market risk-bearing capacity, firms with low resilience beta experience minimal spikes in their own downside exposure: their stock returns display muted sensitivity to crisis shocks, corresponding to firms with strong fundamental resilience. During market crashes, such firms suffer limited operating losses and asset write-downs, and carry low levels of undiversifiable tail risk.

Under fully rational equilibrium pricing as captured by Equation (7), low-resilience-beta (high-resilience) assets bear smaller tail risk exposure and therefore command lower expected risk compensation. By contrast, high-resilience-beta firms' tail risks move in lockstep with market downturns; they face severe value depreciation amid shocks and embed large undiversifiable tail risk, requiring higher equilibrium returns. The positive excess return generated by long low-resilience-beta, short high-resilience-beta portfolios in China's A-share market deviates from this rational benchmark, forming a unique resilience anomaly attributable to retail investor overreaction to downside volatility and benchmark-chasing institutional positioning.

Supplementary Derivation: Orthogonal Correlation Decomposition

This section supplements the mathematical decomposition rule adopted when simplifying Equation (6) to Equation (7). We consider three standardized zero-mean, unit-variance random variables X , Y , and Z . It should be noted that pairwise correlation between X - Y and Y - Z cannot guarantee non-zero correlation between X and Z . We decompose each variable into a component correlated with common factor Y and an orthogonal idiosyncratic residual:

$$X = \rho_{X,Y}Y + X^* \quad (8)$$

$$Z = \rho_{Z,Y}Y + Z^* \quad (9)$$

Where X^* and Z^* denote residual components orthogonal to Y , satisfying $\mathbb{E}[X^*Y] = 0$ and $\mathbb{E}[Z^*Y] = 0$. Take the expectation of the product XY :

$$\mathbb{E}[XY] = \mathbb{E}[(\rho_{X,Y}Y + X^*)Y] = \rho_{X,Y}\mathbb{E}[Y^2] + \mathbb{E}[X^*Y] \quad (10)$$

Similarly:

$$\mathbb{E}[ZY] = \mathbb{E}[(\rho_{Z,Y}Y + Z^*)Y] = \rho_{Z,Y}\mathbb{E}[Y^2] + \mathbb{E}[Z^*Y] \quad (11)$$

By orthogonality, $\mathbb{E}[X^*Y] = \mathbb{E}[Z^*Y] = 0$. All variables are standardized to unit variance such that $\mathbb{E}[Y^2] = 1$, which simplifies the two expressions above to:

$$\rho_{X,Y} = \mathbb{E}[XY] \quad (12)$$

$$\rho_{Z,Y} = \mathbb{E}[ZY] \quad (13)$$

We then solve for the variance of each residual term. Substitute Equation (8) into $\mathbb{E}[X^{*2}] = 1$:

$$\mathbb{E}[X^2] = \rho_{X,Y}^2 + \mathbb{E}[X^{*2}] = 1 \quad (14)$$

$$\mathbb{E}[Z^2] = \rho_{Z,Y}^2 + \mathbb{E}[Z^{*2}] = 1 \quad (15)$$

Rearranging yields the variance of orthogonal residuals:

$$\mathbb{E}[X^{*2}] = 1 - \rho_{X,Y}^2 \quad (16)$$

$$\mathbb{E}[Z^{*2}] = 1 - \rho_{Z,Y}^2 \quad (17)$$

Finally, by substituting $\rho_{X,Y}$ and $\rho_{Z,Y}$ into Equations (8) and (9), and taking the expectation of the product X and Z , we can express the correlation coefficient between X and Z , denoted as $\rho_{X,Z}$, as a function of $\rho_{X,Y}$ and $\rho_{Z,Y}$:

$$\rho_{X,Z} = \rho_{X,Y} * \rho_{Z,Y} + \mathbb{E}[X^*Z^*] \quad (18)$$

Equation (18) shows the correlation between X and Z consists of two parts: the co-movement

transmitted via the shared factor Y , and the covariance of independent idiosyncratic residuals $\mathbb{E}[X^*Z^*]$. The sign of $\rho_{X,Z}$ depends jointly on the product $\rho_{X,Y} * \rho_{Z,Y}$ and the residual covariance term. This two-component decomposition underpins the construction of resilience beta, separating its systematic macro linkage from firm-specific idiosyncratic risk exposure and carrying unique cross-sectional pricing information.

3. Variables, Data, and Methodology

3.1 The data

To construct the capital resilience index, we draw upon Wójcik & Cojoianu (2018) and Ruza et al. (2019), integrating institutional characteristics and information disclosure practices of China's stock market. We adopt a top-down hierarchical evaluation framework comprising three primary indicators, six secondary themes, and thirty-two tertiary metrics, covering both macro- and micro-level resilience dimensions. Specifically, the primary indicators encompass shock resistance, absorption/buffering capacity, and recovery speed, corresponding to ex-ante, in-event, and ex-post perspectives, respectively. The detailed indicator hierarchy is presented in Table 1.

[Insert Table 1 here]

To extract common factors across dimensions and construct a robust capital resilience index for the Chinese market, we follow the researches of Li et al.(2023) and Hounyo et al.(2026), and employ Sparse Principal Component Analysis (SPCA). This method isolates latent characteristics from each sub-dimension, after which a composite financial resilience indicator is synthesized based on the corresponding factor loadings. The proportional contributions of individual variables to the principal components are illustrated in Figure 1.

[Insert Figure 1 here]

Given the completion of China's split-share structure reform in 2007, our sample period spans from January 2007 to December 2025, sourced from the WIND financial database. The initial sample comprises all stocks listed on both the Shanghai and Shenzhen Stock Exchanges. Following Liu et al. (2019) and Fang et al. (2023), we apply the following filtering criteria:(1) To mitigate distortions arising from price limits and avoid abnormal volatility associated with newly listed firms, we exclude companies that have been publicly traded for less than six months prior to index construction; (2) To control for potential price anomalies driven by mergers and acquisitions, we drop observations for firms with fewer than 120 trading days per calendar year or fewer than 15 trading days in any single month; (3) We remove all cross-sectional observations with missing values for the core variables in the WIND database.

3.2 Descriptive statistics

Drawing upon prior literature, we select a set of control variables including firm size (Size), trading volume (VOL), book-to-market ratio (BM), earnings-to-price ratio (EP), sales-to-price ratio (SP), Fama-French three-factor beta (Beta), idiosyncratic volatility (IVOL), and return volatility (VLT) to examine the relationship between the capital resilience premium and these characteristics. The construction methodology for each variable is detailed in Table 2.

[Insert Table 2 here]

In this section, all features are constructed according to the methodologies outlined in Table 2. Specifically, EP and BM proxy for a firm's profitability and valuation level, respectively, while SP captures operational performance by dividing operating revenue by free-float market capitalization. IVOL represents the standard deviation of regression residuals fitted against market, size, and value factors, reflecting idiosyncratic stock price volatility. Size measures tradable

market capitalization, indicating firm scale. MOM and Rev utilize cumulative returns from month t-12 to t-1 and returns over the past one month, respectively, capturing upward momentum or short-term reversal tendencies. Table 3 below presents the descriptive statistics and correlation coefficients for all variables.

[Insert Table 3 here]

Panel A of Table 3 reports the descriptive statistics for each variable, including the mean (AVG), standard deviation (STD), and values at the 5th, 25th, 50th, 75th, and 95th percentiles. Size is measured as the natural logarithm of free-float market capitalization, with a mean of 21.707. EP, BM, and SP serve as standard proxies for firm valuation and operating performance, yielding means of 0.016, 0.383, and 0.606, respectively, which indicates that stocks exhibit positive profitability on average. Trading volume (VOL) used as a liquidity proxy that may influence resilience, averages 18.235, which reflect substantial investor trading activity. Beta is estimated from regressions of stock returns on the market, size, and value factors; its mean of 0.793 suggests considerable systematic risk exposure in the A-share market. REV captures one-month lagged returns as a proxy for short-term reversal effects, while MOM measures cumulative returns from months t-12 to t-1 to capture momentum dynamics, with means of 0.013 and 0.154, respectively. The resilience beta(Res) is constructed from 32 macro- and micro-level indicators, exhibiting a mean of 0.001, with the 95th and 5th percentiles at 0.080 and -0.073, respectively.

Panel B of Table 3 presents the correlation matrix among variables. The correlation between BM and SP is relatively elevated (0.333), as both ratios reflect underlying firm valuation fundamentals. Apart from this relationship and certain moderate correlations with IVOL, correlations among all other variables remain low. This indicates that each control variable captures distinct informational dimensions, thereby allowing us to comprehensively disentangle the determinants of the resilience premium. Employing these variables in our cross-sectional Fama-MacBeth regressions further enables a robust, multi-dimensional examination of the drivers underlying resilience beta.

3.3 Factor adjusted models

To compute the risk-adjusted returns of decile-sorted portfolios, we employ three asset pricing frameworks: the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (1993), and the Carhart four-factor model (1997). The time-series regression specifications are formulated as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it} \quad (19)$$

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + \varepsilon_{it} \quad (20)$$

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + m_iMOM_t + \varepsilon_{it} \quad (21)$$

Where $R_{it} - R_{ft}$ denotes the excess return of resilience portfolio i in period t . The intercept term α_i represents the risk-adjusted returns. A statistically significant positive (negative) α_i from regressing portfolio returns on these pricing models indicates that resilience portfolios command a resilience risk premium (discount) after controlling for conventional risk factors. $R_{mt} - R_{ft}$, SMB_t , HML_t , and MOM_t represent the market, size, value, and momentum factor returns, respectively. ε_{it} is the regression residual, while β_i , s_i , h_i , m_i denote the factor loadings (slope coefficients) that capture each risk factor's sensitivity to portfolio returns.

4. Empirical Analysis

4.1 Existence of the Resilience Beta Premium

To investigate the resilience premium, we employ a standard decile-sorted portfolio approach widely used in asset pricing literature. Specifically, at the end of month t , stocks are sorted based on their resilience beta into ten equal-sized portfolios, denoted as P1 through P10 (from lowest to highest). At the end of month $t+1$, we compute the average returns for each portfolio. All portfolios are rebalanced on a monthly basis. To examine the return differential between extreme resilience groups, we construct a zero-cost long-short strategy by going long on the lowest resilience decile (P1) and shorting the highest resilience decile (P10), yielding a P1–P10 portfolio return. Furthermore, to assess risk-adjusted abnormal returns, we regress each decile's returns on three asset pricing frameworks: the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (1993) (hereinafter FF3), and the Carhart four-factor model (1997) (hereinafter Car4). The time-series regression results are reported below.

[Insert Table 4 here]

Panel A of Table 3 reports the time-series equal-weighted average returns (AVG) for decile portfolios sorted by resilience betas. Columns 1 through 10 correspond to the monthly average returns of portfolios P1 through P10, respectively, while the final column (P1–P10) represents the average return spread from going long on the lowest-resilience-beta decile and shorting the highest-resilience-beta decile. The table also presents risk-adjusted excess returns estimated using three pricing frameworks. Across the portfolio average returns, a generally decreasing trend is observed as resilience ratings increase from P1 to P10. The highest-resilience beta portfolio (P10) yields an average monthly return of only 0.5% (t -stat = 0.78), whereas the lowest-resilience portfolio (P1) commands a significantly higher weighted-average return of 1.26% (t -stat = 2.07). The long-short arbitrage strategy (P1–P10) generates an average monthly spread of 0.74% (t -stat = 2.4), significant at the 5% level. Moreover, even after controlling for risk factors, the resilience-beta-sorted arbitrage portfolio continues to deliver statistically significant abnormal returns. For instance, the CAPM-adjusted alpha stands at 0.81% (t -stat=2.59), indicating that the resilience premium is not subsumed by classic asset pricing factors and remains robust in the Chinese equity market.

Panel B presents the value-weighted average returns of portfolios. Although portfolio return levels are somewhat lower, the qualitative findings mirror those of Panel A: constructing a long-short portfolio that purchases stocks in the lowest-resilience decile and shorts those in the highest-resilience decile consistently yields significant risk-adjusted excess returns. The magnitude of resilience beta reflects the co-movement between a firm's idiosyncratic downside risk and extreme market crashes, and it exhibits an inverse relationship with corporate fundamental resilience. A higher resilience beta means the firm's asset prices plunge synchronously during systemic market downturns, exposing investors to larger undiversifiable tail risk; theoretically, such stocks ought to demand higher equilibrium risk compensation under standard heterogeneous-agent CCAPM pricing logic. By contrast, firms with low or even negative resilience beta experience mild price drawdowns amid market corrections, possessing stable operating fundamentals and robust risk buffer capacity, so their theoretical equilibrium expected returns should be lower due to effective systemic risk hedging value.

Nevertheless, we observe a persistent resilience pricing anomaly in China's A-share market that deviates from rational equilibrium predictions. Retail investors have an intense aversion to sharp losses and continuously overweight high-resilience low-beta stocks with strong crash

defense features, pushing up their long-term realized returns. In comparison, low-resilience high-beta firms with heavy tail-risk exposure fail to obtain sufficient risk premiums and deliver weaker average performance. As a result, the long-short portfolio longing low-beta/high-resilience stocks and shorting high-beta/low-resilience stocks generates significantly positive excess returns, consistent with our portfolio sorting results. From the perspective of investor behavioral biases in A-shares, market participants overvalue the downside protection value of resilient enterprises and bid up their long-run realized returns, while high tail-risk firms remain underpriced, eventually widening the cross-sectional return gap between the two extreme decile portfolios. To contextualize the magnitude of the capital resilience premium relative to broad market performance, we employ the CSI 300 index returns as a benchmark. The subsequent analysis compares the cumulative wealth trajectory of our resilience beta arbitrage portfolio against that of the CSI 300 index over the sample period.

[Insert Figure 2 here]

The gray shaded areas in Figure 2 denote the Chinese stock market crash of 2015–2016 and the global pandemic shock spanning 2019 to 2022. Overall, the cumulative returns of the resilience beta arbitrage portfolio broadly outperform the broad market benchmark index, with conspicuous short-term drawdowns observed during these two systemic crisis episodes. This countercyclical performance pattern can be rationalized via three interrelated transmission mechanisms: First, the systemic liquidity squeeze channel. At the early stage of a crisis, institutional investors facing large-scale redemptions are forced to passively liquidate liquid low-beta/high-resilience long positions to raise cash, triggering sharp instantaneous drawdowns on defensive stocks. Meanwhile, high-beta/low-resilience speculative stocks fall into severe liquidity freeze with frequent limit-down hits; short positions on these assets cannot be closed timely, exposing the short leg to sustained floating losses. The dual pressure on both long and short legs jointly suppresses the arbitrage portfolio's instantaneous performance. Second, extreme heterogeneous shocks break the baseline equilibrium pricing logic derived earlier. The deleveraging spiral in 2015 and industry-specific structural shocks during the pandemic distort the historical co-movement between firm tail risks and aggregate systemic shocks, eroding the cross-sectional dispersion of resilience beta captured by our heterogeneous-agent CCAPM framework. With the differentiated tail-risk exposure across firms weakened, standard risk-based return differentials are compressed, and the cross-sectional pricing mechanism temporarily ceases to function. Third, unwinding of crowded trades magnifies portfolio drawdowns. The resilience arbitrage strategy attracts concentrated institutional holdings in normal periods. Once systemic risks erupt, synchronized mass selling on crowded low-beta longs and widespread short-covering rallies on high-beta stocks generate a reverse double blow to the long-short portfolio. Nevertheless, as market liquidity gradually recovers and fundamental tail-risk pricing relationships re-establish themselves after crisis shocks fade, the arbitrage portfolio rapidly recovers its persistent excess returns. This dynamic pattern verifies that transient liquidity-driven drawdowns do not negate the long-run cross-sectional pricing power of the resilience beta factor under normal market equilibrium.

4.2 Time series analysis

To further evaluate whether conventional asset pricing frameworks can fully account for the resilience beta anomaly, we conduct time-series regressions of portfolio returns on seven canonical factor models. The Fama-French three-factor model (1993) augments market risk with

size (SMB) and value (HML) proxies. Daniel-Hirshleifer-Sun (2018) introduce a specification incorporating post-earnings announcement drift (RPEAD) and financing behavior (RFIN), where the latter is constructed from net and composite stock issuance. The Hou-Xue-Zhang (2015) q-factor model includes market, investment (INV), and profitability (ROE) factors. Stambaugh-Yuan (2017) propose a four-factor framework comprising market, size (SMB), and two mispricing proxies: managerial expansion (MGMT) and performance (PERF). Carhart (1997) extends the three-factor baseline by adding momentum (MOM). Novy-Marx (2013) replaces value with gross profitability (PMU) while retaining market, value, and momentum components. Finally, Fama-French (2015) expand the specification by incorporating robustness (RMW) and conservative investment (CMA) factors. Collectively, these models enable us to test whether the resilience beta premium is fully subsumed by established risk or mispricing channels.

[Insert Table 5 here]

Regressing resilience beta-sorted portfolio returns on the canonical factor models yields intercepts (α) ranging from 0.57 to 1.21, all statistically significant at the 5% level or better. This result carries a clear economic implication: conventional pricing frameworks—including CAPM, Fama-French three- and five-factor models, and momentum-augmented specifications—fail to fully subsume the resilience beta premium. The market, size, value, profitability, investment, and momentum factors do not capture the risk premia embedded in our sorted portfolios. The persistently positive alphas directly confirm that resilience beta operates as an independent, incrementally priced factor capturing a novel risk dimension: firms' capacity to withstand extreme shocks and their tail risk exposure. During systemic crises or liquidity squeezes, high-resilience stocks exhibit superior downside protection—a defensive characteristic not fully proxied by conventional fundamentals like size, valuation multiples, or earnings growth. Consequently, investors demand additional compensation for this crash insurance, generating robust alphas unexplained by standard risk factors.

Concurrently, the regressions reveal significant loadings on value, investment, profitability, and momentum factors, indicating that the resilience premium shares intrinsic linkages with established asset pricing logic rather than operating in isolation. Specifically, the significant profitability loading suggests resilient firms possess higher earnings quality and cash flow stability, providing a fundamental cushion against volatility. The value and investment loadings imply that high-resilience stocks are typically characterized by reasonable valuations and efficient capital allocation rather than aggressive leverage; their robust financial structures underpin shock absorption capacity. Furthermore, the momentum loading reflects stronger anti-fragility during downturns, with resilience beta exhibiting stable co-movement with price trends.

In sum, the resilience premium arises from a two-fold mechanism: it partially overlaps with traditional fundamental advantages (profitability, valuation, investment efficiency) while more critically isolating an unpriced tail-risk dimension—extreme shock resistance. This core component explains why the premium yields significant alphas across all canonical models. Ultimately, resilience beta is not a mere replication of existing factors but a novel pricing construct with independent economic intuition and incremental explanatory power, directly compensating investors for holding assets that hedge against systemic tail risk.

4.3 Cross-Sectional Analysis

Building on the significant return differentials documented in decile-sorted portfolios, we next employ Fama-MacBeth cross-sectional regressions to formally test whether resilience beta

commands a risk premium after accounting for conventional factors. Specifically, we regress month $t+1$ stock returns on month t resilience beta alongside standard control variables: firm size (Size), sales-to-price ratio (SP), book-to-market ratio (BM), earnings yield (EP), realized volatility (VLT), trading volume/turnover, and idiosyncratic volatility (IVOL). Our specification design follows a stepwise approach: we first control for Size and market beta to isolate baseline effects, then sequentially introduce additional controls to assess whether they subsume the pricing power of resilience beta. This incremental framework allows us to test whether the resilience premium is robust or merely proxies for known cross-sectional anomalies. The corresponding regression results are reported in Table 6.

[Insert Table 6 here]

Table 6 reports the Fama-MacBeth cross-sectional regression results of monthly stock returns on resilience beta across ten incremental specifications. The intercepts (alphas) range from 0.01 to 0.14 and are statistically significant at the 10% level or better in most models, indicating persistent cross-sectional return dispersion unexplained by conventional factors. In the baseline specification (Column 1), which controls only for firm size and market beta, the coefficient on resilience beta is -0.06 ($t\text{-stat} = -2.813$), significant at the 5% level. This provides initial evidence of a robust negative predictive relationship between resilience beta and future stock returns.

Columns (2) through (4) sequentially introduce valuation proxies: earnings yield (EP), book-to-market ratio (BM), and sales-to-price ratio (SP). All three exhibit significantly positive loadings on future returns. Crucially, the resilience beta coefficient remains negative and statistically significant after accounting for these valuation characteristics, suggesting its pricing power is not subsumed by traditional value or mispricing factors. Further augmenting the specification with trading and price pattern variables—realized volatility (VLT), short-term reversal (Rev), and momentum (MOM)—reveals that all three factors are negatively priced. The resilience beta coefficient retains its negative sign and statistical significance, confirming robustness to well-documented behavioral anomalies.

In the full specification (Column 10), which controls for liquidity (VOL), volatility, valuation ratios, momentum, and reversal effects simultaneously, the resilience beta coefficient is -0.04 ($t\text{-stat} = -2.711$), remaining significant at the 5% level. Collectively, these results demonstrate that mainstream cross-sectional anomalies related to liquidity, volatility, valuation, momentum, and reversal fail to fully subsume the predictive power of resilience beta.

From an economic perspective, these findings validate our core thesis derived from the heterogeneous-agent CCAPM framework: lower (more negative) resilience beta indicates stronger firm-level shock absorption and higher financial resilience. Driven by retail investor behavioral biases in China's A-share market rather than rational equilibrium pricing, such defensive firms command higher realized expected returns, yielding a stable negative return-beta relationship. Moreover, resilience beta captures an independent information dimension—firm-specific tail risk exposure and crisis resistance—that is distinct from conventional valuation metrics, trading behaviors, liquidity conditions, and price trends. Since existing cross-sectional factors only explain partial return dispersion without fully absorbing the resilience premium, resilience beta emerges as an incrementally priced factor with robust predictive power for stock returns across diverse market regimes.

5. Drivers of the Capital Resilience Premium

5.1 Extreme Market Conditions

The core economic intuition behind corporate stock resilience lies in firms' capacity to absorb severe market shocks and subsequently restore fundamental value. Across listed companies, stress tolerance, tail risk exposure, and earnings recovery speeds exhibit pronounced heterogeneity during extreme regimes. From a risk-pricing perspective, while high-resilience firms possess superior downside protection, they remain exposed to systematic tail risks during crises, which commands investors to demand additional compensation in the form of a resilience premium. To empirically investigate how market states modulate this premium, we partition the sample period based on major exogenous shocks: the 2015–2016 Chinese equity market crash and the 2020–2022 global pandemic are classified as extreme stress regimes, while all remaining intervals serve as normal (stress-free) benchmarks. Through cross-regime comparative analysis, we test whether resilience beta-sorted portfolios exhibit state-dependent return patterns and disentangle how exogenous shocks fundamentally alter the pricing dynamics of capital resilience premiums.

[Insert Table 7 here]

Table 7 reports the cross-regime portfolio sorting results, revealing that risk exposure associated with resilience beta intensifies significantly during extreme market regimes. The return spread between high- and low-resilience portfolios widens considerably and remains statistically positive at the 5% level. While this differential persists after baseline systematic risk adjustment via CAPM, it becomes statistically insignificant under FF3 and CAR4 specifications. This suggests that under severe market stress, conventional firm characteristics—particularly value, size, and momentum—partially absorb the pricing power of resilience beta. Collectively, these findings confirm that high-resilience firms possess superior downside protection and shock-hedging capabilities relative to their low-resilience counterparts, a comparative advantage that is markedly amplified during crisis periods.

From an asset pricing perspective, extreme regimes trigger concentrated releases of systemic and tail risks, thereby magnifying cross-sectional differences in corporate resilience. High-resilience stocks exhibit stronger return stability due to effective risk buffering, while low-resilience firms suffer deeper drawdowns, ultimately widening the performance gap. The persistence of this premium across alternative risk-adjustment frameworks indicates that it is not merely a proxy for traditional factors but reflects an independent compensation mechanism for firm-specific resilience under extreme market conditions.

In normal market regimes, systemic tail risks remain subdued, and the downside shock resistance gap between high- and low-resilience firms cannot be fully reflected in stock prices. Investors primarily price conventional characteristics such as value, size and momentum, and the incremental compensation for crash defense capacity is largely subsumed by these classic factors. Moreover, market participants lack strong demand for tail-risk hedging amid stable fundamentals, so they are unwilling to pay persistent premiums for firms' latent crisis-resistance capacity. Consequently, the return spread between high- and low-resilience beta portfolios becomes weak and statistically insignificant under normal market conditions. By contrast, extreme shocks trigger massive systemic risk outbreaks, magnifying cross-sectional heterogeneity in tail-risk exposure and pushing investors to price downside protection as a core valuation dimension, which generates a large, significant resilience return spread.

5.2 Bivariate-sorted portfolios

Following Liu et al. (2019) and Hou et al. (2016), we adopt five firm characteristics as

conditional sorting variables to analyze heterogeneous resilience premium patterns. Small-cap stocks suffer severe information asymmetry and operational uncertainty, leading to large cross-firm tail-risk divergence and significant resilience premiums. Large-cap firms share stable fundamentals with trivial differentiation in shock resistance, yielding insignificant long-short spreads. Adverse fundamentals have been fully discounted for high-BM value stocks; operational robustness becomes the dominant pricing factor and generates a significant resilience premium. Low-BM growth stocks are priced based on forward earnings, so crash defense capacity exerts little impact on returns. Investors prioritize fundamental quality and tail-risk characteristics for low-momentum stocks, making resilience a core pricing anchor and producing large long-short return spreads. Trend-chasing capital dominates high-momentum periods, weakening the marginal pricing power of resilience beta and eliminating significant premiums. Illiquid stocks feature slow information absorption and inefficient pricing, blurring return gaps across resilience deciles. Active trading in high-volume subsamples improves information efficiency and amplifies the resilience return spread. High-IVOL firms face severe idiosyncratic downside shocks, pushing up investors' demand for crash hedging and forming obvious resilience premiums. Low-IVOL stocks carry mild fundamental uncertainty, so shock resistance generates negligible extra compensation. We conduct double sorting to verify whether the resilience premium contains unique tail-risk information independent of standard firm attributes.

[Insert Table 8 here]

Table 8 Panel A reports the average returns from bivariate sorts of resilience beta and firm size. Within each size group, portfolio returns decline monotonically as resilience beta increases from P1 to P10. Significant resilience premiums are confined to the low-size subsample, whereas they become statistically insignificant in the high-size group. The long-short spread (P1 minus P10) in the low-size group is 0.72% ($t = 2.43$), remaining robust after risk adjustments. This indicates a strong interaction between resilience pricing and the size effect. In the Chinese market, small-cap stocks typically face higher information asymmetry, liquidity constraints, and operational uncertainty, commanding a baseline size premium. Consequently, low-resilience-beta firms in this subsample benefit from both defensive tail-risk hedging and size-related compensation, outperforming their large-cap counterparts.

Panel B examines the cross-sectional interaction between resilience beta and book-to-market ratio (BM). In the lowest BM tercile (growth stocks), average returns are modest and the long-short spread is statistically indistinguishable from zero (0.26%). Conversely, in the highest BM tercile (value stocks), the premium materializes significantly, yielding a 0.43% monthly long-short return ($t = 1.90$). These results suggest that resilience pricing operates primarily within value-oriented segments. Growth stocks are priced predominantly on forward-looking earnings expectations, rendering tail-risk defense less salient for cross-sectional dispersion. In contrast, value stocks have already discounted adverse fundamentals; thus, operational robustness and shock absorption become dominant return drivers, allowing high-resilience firms to command a distinct pricing premium.

Panel C reveals pronounced momentum heterogeneity in resilience pricing: the premium is strongest among low-momentum stocks and decays monotonically as momentum increases. In the lowest momentum portfolio, the long-short spread yields 0.61% ($t = 2.31$), significant at conventional levels. In high-momentum regimes, however, the spread becomes statistically insignificant. This divergence reflects state-dependent pricing dynamics. Low-momentum stocks

exhibit weak price trends, shifting investor focus toward fundamental quality and risk characteristics; here, resilience acts as a key pricing anchor. High-momentum environments are dominated by trend-following capital flows that prioritize short-term continuation over tail-risk defense. Furthermore, the momentum factor likely crowds out part of the resilience premium, while elevated market risk appetite in trending periods suppresses tail-risk exposure, both attenuating the marginal pricing power of resilience beta.

Panel D highlights clear volume-dependent pricing dynamics. In low-volume subsamples, decile sorts yield uniformly significant raw returns driven by liquidity premiums; however, the long-short spread is statistically insignificant due to sluggish information diffusion and inefficient price discovery, which homogenizes cross-sectional resilience differentiation. In high-volume regimes, raw returns are muted, yet the resilience beta long-short strategy generates a robust 0.71% monthly premium ($t = 2.21$), surviving FF3 and CAR4 risk adjustments. Active trading enhances market information efficiency and pricing discipline, enabling investors to precisely discriminate firm-specific tail risk. This confirms that resilience pricing is fundamentally driven by information-mediated valuation processes rather than mere liquidity compensation.

Panel E documents significant idiosyncratic volatility (IVOL) heterogeneity in the resilience premium. The long-short spread reaches 0.55% ($t = 2.54$) and remains robust under FF3 adjustment, yet loses significance after CAR4 control. Low-IVOL subsamples exhibit no statistically meaningful spread. This pattern aligns with idiosyncratic risk pricing theory: high-IVOL stocks are more susceptible to firm-specific shocks and uncertainty, elevating the demand for downside protection and amplifying resilience-related compensation. The subsumption under CAR4 (which explicitly captures IVOL-related risk channels) indicates substantial factor overlap; since traditional momentum/liquidity proxies partially absorb idiosyncratic volatility effects, they attenuate the marginal pricing power of resilience beta. Ultimately, the resilience premium is concentrated in high-IVOL environments and closely tied to firm-specific risk dispersion.

5.3 Market Conditions

During economic expansions, improved business conditions lift overall market risk appetite and substantially reduce systemic and tail risks. With extreme downside shocks less likely to materialize, investors pay less attention to firms' long-term crisis resistance and instead focus on short-term profit growth and trading gains. High-resilience firms with low resilience beta continuously spend resources maintaining risk buffers, which weighs on their near-term earnings. By contrast, low-resilience firms with high resilience beta save on risk management costs and deliver more elastic short-run earnings. This investment logic strengthens the negative cross-sectional relation between resilience beta and future stock returns.

In bullish periods fueled by positive sentiment and continuous capital inflows, traders chase immediate short-term profits. While high-resilience stocks provide reliable downside protection and steady fundamentals, their conservative operating characteristics limit upside gains amid sustained market rallies. High-beta low-resilience stocks feature greater price sensitivity and generate larger short-run excess returns, further reinforcing the negative return-beta linkage.

Collectively, in expansionary regimes, bull markets, and high-volatility environments, elevated investor risk appetite tends to amplify this negative pricing slope. To empirically test this hypothesis, we follow the state-contingent analysis frameworks of Hutchinson et al. (2020), Fang et al. (2023), and Christian (2023). We classify market states using three independent proxies: the

sentiment index (China sentiment index, CSI), GDP growth rate (economic cycle), and the standard deviation of CSI 300(Shanghai-Shenzhen 300 Index) returns over the past month (market volatility). Each proxy is sorted from low to high, with the top 30% forming high-sentiment, expansionary, or high-volatility regimes; the middle 40% representing normal/median states; and the bottom 30% corresponding to low-sentiment, recessionary, or low-volatility environments. Within each state regime, we sort stocks by resilience beta into ten deciles (P1 to P10) and construct zero-cost long-short portfolios going long on the lowest-resilience-beta decile (highest resilience) and shorting the highest-resilience-beta decile (lowest resilience). The cross-regime portfolio returns are tabulated below:

[Insert Table 9 here]

Panel A of Table 9 reports the cross-sectional pricing of resilience beta conditional on market sentiment, revealing pronounced state-dependent heterogeneity. In low-sentiment regimes, decile portfolio returns are uniformly high and statistically significant across most groups (ranging from 2.57% to 3.01%). However, the long-short spread between highest- and lowest-resilience portfolios is insignificant. Conversely, in high-sentiment environments, raw portfolio returns decline modestly (0.00% to 1.58%), and the low-beta minus high-beta long-short strategy generates a substantial monthly premium of 1.26%, which is statistically significant. This spread remains robust after FF3 and CAR4 risk adjustments, yielding the highest abnormal return across all sample periods. These findings indicate that elevated investor optimism significantly amplifies the resilience beta premium. From a behavioral pricing perspective, during low-sentiment periods, subdued risk appetite drives collective flight-to-quality. Although high-resilience stocks earn positive returns due to their defensive characteristics, conservative trading strategies limit arbitrage activity, compressing cross-sectional dispersion. In contrast, high-sentiment regimes feature heightened optimism, increased liquidity, and intensified capital competition. Investors simultaneously chase momentum while scrutinizing firm-specific tail risk. Resilience thus transitions from a pure hedging attribute to a key portfolio optimization metric, fully capitalizing the resilience premium. Active two-way trading further widens return dispersion between high- and low-resilience firms, culminating in statistically significant long-short spreads. Post-adjustment results confirm that this premium is orthogonal to traditional asset pricing factors, representing a sentiment-driven idiosyncrasy in resilience-based valuation.

Panel B examines the monthly risk-adjusted returns of resilience beta portfolios across business cycles. In recessionary regimes, average portfolio returns are muted and statistically insignificant. During expansionary periods, however, decile returns range from 0.60% to 2.49%, exhibiting a clear monotonic decline as resilience beta increases; the lowest-beta groups earn significantly positive alphas. Although the long-short spread (P1–P10) is insignificant during recessions, the strategy delivers a robust monthly premium of 1.41% ($t = 3.38$) in expansionary regimes, which remains highly significant after FF3 and CAR4 risk adjustments. These results underscore the state-contingent pricing power of resilience beta. In downturns, broad macroeconomic headwinds depress corporate earnings and equity valuations uniformly, making systematic risk the dominant pricing driver. Idiosyncratic shock absorption capacity is largely overshadowed by aggregate distress, rendering cross-sectional return dispersion homogeneous and negating arbitrage profitability. Conversely, expansionary phases feature improving fundamentals and reduced systemic stress, shifting market attention back to firm-specific characteristics. Improving business environments lift baseline returns across all deciles, while heightened risk

appetite and trading activity enable investors to precisely differentiate resilience levels. High-resilience (low-beta) firms are rewarded for their operational stability, outperforming vulnerable counterparts and generating a monotonically decreasing return profile relative to resilience beta. Active capital allocation amplifies this dispersion, driving significant long-short spreads. Robustness under multi-factor adjustments confirms that the expansion-phase premium is orthogonal to conventional factors, reflecting state-contingent valuation of tail-risk defense capabilities following macroeconomic normalization.

Panel C documents the monthly excess returns of resilience beta portfolios conditional on market volatility regimes. Decile portfolio returns are significantly positive across nearly all groups in high-volatility environments. The long-short spread (P1–P10) is 0.49% in low-volatility states and 1.02% in high-volatility states, with statistical significance achieved only in the latter. After FF3 and CAR4 risk adjustments, portfolios in volatile markets continue to deliver the highest abnormal returns, indicating that elevated market volatility significantly amplifies the resilience premium. This pattern can be explained through differential risk exposure and state-dependent pricing behavior. During high-volatility periods, heightened uncertainty triggers concentrated tail-risk realizations, making cross-firm shock absorption capacity a primary pricing anchor. High-resilience assets attract capital flows due to superior downside buffering, lifting returns across deciles. Conversely, low-volatility regimes feature subdued aggregate risk, muting the defensive value of resilience and yielding uniformly weak portfolio performance. In terms of return dispersion, stable market conditions with mild external shocks cause earnings and price trajectories to converge across firms, compressing cross-sectional spreads and rendering long-short strategies insignificant. High-volatility environments, however, amplify the asymmetric impact of shocks: resilient firms effectively hedge volatility-driven drawdowns, maintaining stable returns, while vulnerable stocks suffer persistent pressure, widening the performance gap. This divergence culminates in highly significant arbitrage profits. Post-adjustment results further confirm that the volatility-state premium is orthogonal to traditional pricing factors, directly reflecting state-contingent valuation of firm-level shock resistance under high-risk conditions.

5.4 Economic Policy Uncertainty

Frequent regulatory and policy interventions substantially raise economic policy uncertainty (EPU), which has been widely recognized as a critical macro-level pricing factor in asset pricing studies. Heightened EPU generates pervasive market shocks and reshapes the cross-sectional valuation of individual stocks. Extensive literature has documented robust state-dependent pricing effects across policy regimes. For instance, Gu et al. (2021) show that capital-driven trading mechanisms function more effectively during low-EPU periods, strengthening stock momentum return patterns. Similarly, Zhou et al. (2022) confirm a prominent sentiment channel in stable policy environments, whereby investor optimism amplifies trend-following returns. Building on these findings, we further explore how EPU regimes modulate the resilience premium. We plot the cumulative return trajectories of resilience beta-sorted portfolios under high- and low-EPU states to examine whether macro policy uncertainty alters the cross-sectional pricing of firm-level shock resilience.

[Insert Figure 3 here]

Figure 3 illustrates the cumulative return trajectories of resilience beta-sorted portfolios across different economic policy uncertainty (EPU) regimes. The results show that during the COVID-19 pandemic, when EPU remained persistently elevated, resilience beta returns declined significantly. A similar downturn is observed during the 2015–2016 Chinese equity market crash. These episodes indicate that macro policy uncertainty substantially modulates the performance of

the resilience beta strategy, particularly in the aftermath of major exogenous shocks. Conversely, in low-EPU periods (e.g., 2010–2012), resilience beta portfolios exhibit a gradual upward trajectory. This pattern confirms that EPU significantly influences cross-sectional return dispersion, suggesting it serves as a fundamental macroeconomic driver of momentum-like pricing dynamics. To formally test whether policy uncertainty acts as a critical determinant of the resilience premium, we subsequently partition the sample into distinct EPU regimes and conduct state-contingent portfolio analyses.

[Insert Table 10 here]

Table 10 examines the monthly excess returns of resilience beta-sorted portfolios across different economic policy uncertainty (EPU) regimes. We partition the full sample into high, medium, and low EPU states using a 30–40–30% quantile split. The table reports cross-sectional average returns for the low- and high-EPU subsamples, alongside the long-short spread (P1 minus P10). Results indicate that portfolio returns are highest and most statistically significant in low-EPU regimes, whereas they become insignificant under high EPU. Specifically, monthly returns range from 3.38% to 4.19% during low-EPU periods. However, returns fall within a -0.0% to 0.99% band without statistical significance during high-EPU episodes. The long-short spread is 0.58% in low-EPU states but increases to 1.02% in high-EPU states, where it achieves conventional statistical significance. This premium remains robust after FF3 and CAR4 risk adjustments, confirming that EPU serves as a critical macroeconomic driver of the resilience beta premium.

These empirical patterns align with state-contingent uncertainty pricing logic. Low EPU reflects stable policy environments and clear market expectations, keeping aggregate uncertainty low. The calm regime improves corporate earnings prospects and lifts baseline returns across all deciles. In this environment, external shock pressure is mild, reducing the marginal value of firm-level resilience. Investors need not finely discriminate between high- and low-resilience stocks; their returns converge, compressing cross-sectional dispersion and rendering long-short spreads statistically insignificant.

Conversely, high EPU signals ambiguous policy trajectories and surging macro uncertainty. Policy shocks broadly suppress equity valuations, causing raw portfolio returns to weaken uniformly. However, heightened uncertainty concentrates tail-risk realizations, prompting markets to re-price corporate shock-absorption capacity. High-resilience firms effectively hedge against adverse policy shifts, maintaining stable returns, while low-resilience stocks suffer pronounced earnings and price pressure. Driven by flight-to-quality motives, investors overweight resilient assets and underweight vulnerable ones, amplifying return dispersion and generating significant positive long-short spreads. The persistence of this premium after multi-factor adjustments confirms that the high-EPU resilience premium is orthogonal to traditional asset pricing factors, directly reflecting state-contingent valuation of tail-risk defense capabilities under policy uncertainty.

5.5 Trade Friction

Trade frictions undoubtedly impact corporate profitability and impose substantial shocks on listed firms. Variations in trade tension drive the resilience beta premium through alterations in supply chains, cost structures, and earnings stability. During escalation periods, high-resilience firms mitigate tariff shocks via diversified production and sales networks coupled with robust pricing power, yielding more stable cash flows. Conversely, low-resilience firms highly dependent

on foreign trade experience rising input costs and earnings pressure, leading to pronounced stock price declines; thus, high-resilience portfolios generate significant excess returns relative to their low-resilience counterparts. In contrast, during easing phases, marginal relaxation of external constraints enables export-oriented vulnerable firms to recover. Market sentiment shifts toward distressed turnaround strategies, where low-resilience stocks exhibit higher price elasticity. Consequently, the performance gap between resilience groups narrows, and the cross-sectional resilience premium becomes statistically insignificant.

Given that US-China trade flows are substantial and highly scrutinized by investors, we employ the US-China Trade Tension Index (UCT) as a proxy for bilateral trade shocks to examine state-dependent resilience pricing in China's equity market. Following Rogers et al. (2024), who construct the UCT using major American newspaper reports to quantify bilateral tensions, and referencing Elkamhi et al. (2024), we partition the sample into three regimes based on quantile thresholds: the bottom 30% as easing periods, the middle 40% as stable periods, and the top 30% as escalation periods. The corresponding cross-regime portfolio returns are presented below:

[Insert Table 11 here]

During easing periods, returns across all ten deciles range from 4.23% to 5.36%, with statistical significance at the 1% level for each group. However, returns do not decline monotonically as resilience beta increases; the long-short spread (P1–P10) is 0.80% ($t = 1.34$), remaining statistically insignificant both in raw terms and after FF3/CAR4 risk adjustments. With trade-related adverse shocks fully priced in and external constraints easing, market-wide risk appetite rises uniformly. Broad-based equity rallies occur as capital flows into equities indiscriminately, without finely discriminating between firms' supply chain robustness or export-shock resistance. Consequently, returns of high- and low-resilience assets converge, making it difficult to generate a significant resilience premium.

In stable regimes, average returns across all deciles decline to the 0.76%–1.11% range, with neither individual groups nor long-short spreads achieving statistical significance. As tariff policies are gradually absorbed by the market, both flight-to-safety and distressed-turnaround sentiments weaken. Firm-level resilience ceases to be a core pricing determinant; decile returns flatten completely, erasing cross-sectional dispersion.

During escalation periods, portfolio returns decline monotonically from P1 (high-resilience) at 0.11% to P10 (low-resilience) at –0.95%. The long-short spread yields 1.06%, significant at the 5% level, and remains robust after FF3/CAR4 risk adjustments. Rising tariffs and contracting external demand severely impact export-oriented firms; resilient companies leverage diversified supply chains and stable cost structures to buffer shocks, exhibiting superior earnings and price stability. Conversely, highly trade-dependent firms face surging costs, earnings pressure, and weak stock performance. Investors actively overweight resilient assets, ultimately generating a significant resilience beta premium. In summary, firm-level resilience is priced only during periods of escalating trade friction and heightened external shocks, confirming that resilience beta possesses effective cross-sectional predictive power

6. Conclusion

To investigate the asset pricing implications of capital resilience, this study constructs a comprehensive financial resilience index using three primary dimensions—shock resistance, absorption/buffering capacity, and recovery speed—based on macro- and micro-level indicators.

We estimate firm-specific resilience beta via rolling-window regressions. Subsequently, we form decile portfolios sorted by resilience beta and employ time-series portfolio sorts alongside cross-sectional Fama-MacBeth regressions to test the robustness of the resilience premium. We further implement bivariate portfolio sorts incorporating traditional risk factors (valuation, size, momentum, volatility, liquidity) to identify cross-sectional drivers, and condition on macroeconomic regimes (sentiment, economic cycle, market volatility) as well as policy uncertainty states. The empirical analysis yields five key findings:

1. We document significant positive returns for long-short portfolios sorted by resilience beta, confirming that low-resilience-beta firms bear higher tail risk and demand greater risk compensation. This premium remains robust even after controlling for liquidity, valuation, size, and common market factors.
2. The resilience premium is pronounced among small-cap stocks (aligning with China's small-size effect) and high book-to-market groups. It is also stronger in low-momentum subsamples. While raw returns are elevated for low-liquidity stocks, only high-turnover portfolios generate statistically significant long-short spreads. Finally, the premium concentrates predominantly in high-idiosyncratic volatility environments, with low-volatility deciles exhibiting weaker and mostly insignificant premia.
3. The resilience beta premium exhibits clear regime dependence. Long-short spreads are insignificant during low-sentiment periods. Nevertheless, arbitrage portfolios become highly significant during high-sentiment regimes. Portfolio returns remain muted in recessionary states, whereas expansionary phases yield robust positive long-short premiums (1.41%, $t=3.38$). Additionally, elevated market volatility significantly amplifies the premium: while spreads are insignificant in low-volatility environments, they achieve statistical significance ($P1-P10=1.02\%$) during high-volatility periods, remaining robust after FF3/CAR4 adjustments.
4. Economic policy uncertainty substantially modulates resilience pricing. Long-short spreads are statistically significant only in high-EPU regimes (yielding 1.02% abnormal returns), indicating that tail-risk defense capabilities command a premium specifically when macro-policy trajectories become ambiguous.
5. The resilience beta premium is pronounced during escalation phases but disappears during easing or stable periods characterized by broad market rallies and undifferentiated capital allocation.

Collectively, our findings confirm that capital resilience commands significant tail-risk compensation, extending asset pricing theory by isolating a novel, incrementally priced risk dimension rooted in firms' capacity to withstand systemic shocks. The results offer actionable implications for investors seeking crash-hedging strategies and policymakers designing state-contingent market stabilization mechanisms.

References:

- [1] Alexander, B., Braun, J., Weigert, F., 2026. Extreme-weather risk and the cross-section of stock returns. *J. Risk Insur.* 93, 163–175.
- [2] Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *J. Financ. Mark.* 3, 31–56.
- [3] Antoniou, C., Doukas, J.A., Subrahmanyam, A., 2013. Cognitive dissonance, sentiment, and momentum. *J. Financ. Quant. Anal.* 48, 245–275.
- [4] Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. *J. Financ.* 68, 929–985.
- [5] Bailey, A., 2022. A resilient financial system. BIS Working Paper.
- [6] Bandarchuk, P., Hilscher, J., 2013. Sources of momentum profits: evidence on the irrelevance of characteristics. *Rev. Financ.* 17, 809–845.
- [7] Bhattacharya, U., Spiegel, M., 1998. Anatomy of a market failure: NYSE trading suspensions (1974–1988). *J. Bus. Econ. Statist.* 16, 216–226.
- [8] Boubaker, S., Li, B., Liu, Z., Zhang, Y., 2021. Decomposing anomalies. *Econ. Lett.* 202, 109835.
- [9] Broto, C., Lamas, M., 2020. Is market liquidity less resilient after the financial crisis? *Econ. Model.* 93, 217–229.
- [10] Cakici, N., Chan, K., Topyan, K., 2017. Cross-sectional stock return predictability in China. *Eur. J. Financ.* 23, 581–605.
- [11] Carhart, M.M., 1997. On persistence in mutual fund performance. *J. Financ.* 52, 57–82.
- [12] Cerqueti, R., Cinelli, M., Ferraro, G., Iovanella, A., 2022. Financial interbanking networks resilience. *Ann. Oper. Res.*
- [13] Chai, D., Mardy, C., Zhong, A., Li, B., 2022. Another look at sources of momentum profits. *Int. Rev. Econ. Financ.* 79, 310–323.
- [14] Chen, Y., Zhang, D., Li, X., et al., 2026. Multi-term momentum effect and driving mechanisms based on machine learning. *Pac.-Basin Financ. J.* 96, 103065.
- [15] Christian, L., Campbell, R.H., Michele, G., 2023. Momentum turning points. *J. Financ. Econ.* 149, 378–406.
- [16] Constantinides, G.M., Duffie, D., 1996. Asset pricing with heterogeneous consumers. *J. Polit. Econ.* 104, 219–240.
- [17] Degryse, H., Jong, F.D., Ravenswaaij, M.V., Wuyts, G., 2005. Aggressive orders and the resiliency of a limit order market. *Rev. Finance* 9, 201–242.
- [18] Du, H.F., Ping, S.T., 2005. The Positive Analysis of Using P/S Ratio in A Share Market (translated from mandarin). *J. CUFE.* 10, 35–38.
- [19] Elkamhi, R., Jo, C., Salerno, M., 2024. Measuring State-level Economic Policy Uncertainty. *J. Financ. Quant. Anal.* 59, 3230–3266.
- [20] Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *J. Financ. Econ.* 33, 3–56.
- [21] Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. *J. Financ. Econ.* 116, 1–22.
- [22] Galbusera, L., et al., 2014. Developing Stress Tests to Improve Critical Infrastructure Resilience. European Commission.
- [23] Gao, Y.C., Mo, D.Y., 2021. Construction framework and realization path of resilient capital market. *Local Financ. Res.* 1, 106–112.
- [24] Gong, Y., Wang, M., Dlugosch, D., 2019. Impacts of ambiguity aversion on momentum. *Pac.-Basin Financ. J.* 55, 1–28.
- [25] Hmaied, D.M., Grar, A., Sioud, O.B., 2006. Dynamics of Tunisian stock market resiliency. *Electron. Mark.* 16, 140–153.
- [26] Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies. *Rev. Financ. Stud.* 28, 650–705.
- [27] Hou, K., Loh, R.K., 2016. Have we solved the idiosyncratic volatility puzzle? *J. Financ. Econ.* 121, 167–194.
- [28] Hu, H.F., Song, X.X., Dou, B., 2021. Building a resilient Chinese capital market (translated from mandarin). *Theor. Explor.* 2, 74–83.
- [29] Hounyo, U., Li, Z., 2026. Forecasting economic time series in the presence of weak factors: Multiple supervised learning-based approach. *Int. J. Forecast.* 42, 414–433.
- [30] Hutchinson, M.C., O'Brien, J., 2020. Time series momentum and macro risk. *Int. Rev. Financ. Anal.* 69, 101469.
- [31] Jiang, G.H., Lee, C.M., Zhang, Y., 2005. Information uncertainty and expected returns. *Rev. Account. Stud.* 10, 185–221.
- [32] Li, H., Zhou, D., Hu, J., et al., 2023. Forecasting the realized volatility of Energy Stock Market: A multimodel comparison. *N. Am. J. Econ. Financ.* 66, 101895.
- [33] Liu, J., Stambaugh, R.F., Yu, Y., 2019. Size and value in China. *J. Financ. Econ.* 134, 48–69.
- [34] Markman, G.M., Venzin, M., 2014. Resilience: Lessons from crisis-surviving banks. *Int. Bus. Rev.* 23, 1096–1107.
- [35] Martin, R., Sunley, P., 2015. On regional economic resilience. *J. Econ. Geogr.* 15, 1–42.
- [36] Novy-Marx, R., 2013. The gross profitability premium. *J. Financ. Econ.* 108, 1–28.

- [37] Olbrys, J., Mursztyn, M., 2019. Measuring stock market resiliency with DFT. *Phys. A* 513, 248–256.
- [38] Pagano, M., Wagner, C., Zechner, J., 2023. Disaster resilience and asset prices. *J. Financ. Econ.* 150, 103712.
- [39] Rogers, J.H., Sun, B., Sun, T., 2024. U.S.-China Tension. *SSRN Electron. J.*
- [40] Ruza, C., et al., 2019. Banking system resilience. *J. Econ. Stud.* 46, 1241–1257.
- [41] Sagi, J.S., Seasholes, M.S., 2007. Firm attributes and momentum. *J. Financ. Econ.* 84, 389–434.
- [42] Shi, W.Y., Mena, C., 2021. Supply chain resilience assessment. *IEEE Trans. Eng. Manage.*
- [43] Stambaugh, R.F., Yuan, Y., 2017. Mispricing Factors. *Rev. Financ. Stud.* 30, 1300–1342.
- [44] Tao, R., Brooks, C., Adrian, R.B., 2020. When is a MAX not the MAX? *J. Empir. Financ.* 57, 33–51.
- [45] Tian, L.H., Wang, G.Y., Tang, D.K., 2014. The inversion effect and asset pricing: how historical yields affect the present (translated from mandarin). *J. Financ. Res.* 10, 177 – 192.
- [46] Wang, H.J., Jiao, S.P., Ge, C., Sun, G.L., 2024. Corporate ESG rating divergence. *Energy Econ.* 129.
- [47] Wang, L., Kang, X., 2025. Digital finance and capital market resilience (translated from mandarin). *Theor. Pract. Financ. Econ.* 5, 10–16.
- [48] Wójcik, D., Cojoianu, T.F., 2018. Resilience of US securities industry. *Geoforum* 91, 182–194.
- [49] Zhang, X., 2006. Information uncertainty and stock returns. *J. Financ.* 61, 105–137.
- [50] Zhang, X., Ding, Z., Hang, J., He, Q., 2022. Stock indices and COVID shocks. *N. Am. J. Econ. Financ.* 60, 101672.

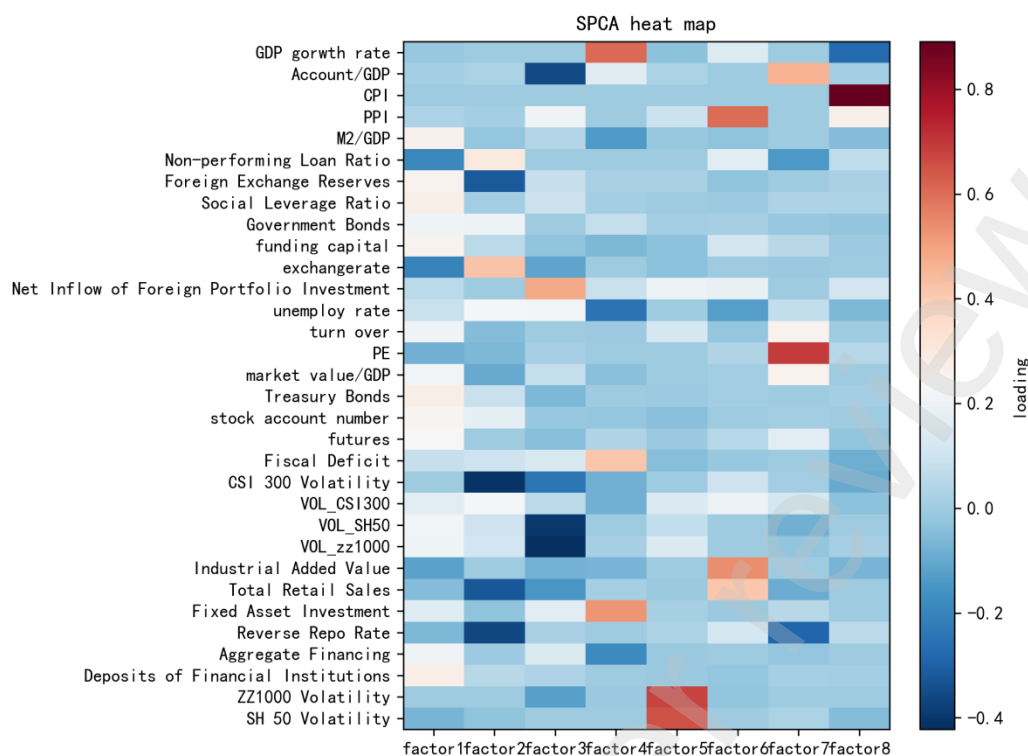


Figure 1. Contributions of Individual Factors. This figure displays the SPCA-derived factor loadings, illustrating each macro- and micro-indicator's relative weight in synthesizing the composite capital resilience index for China's equity market.

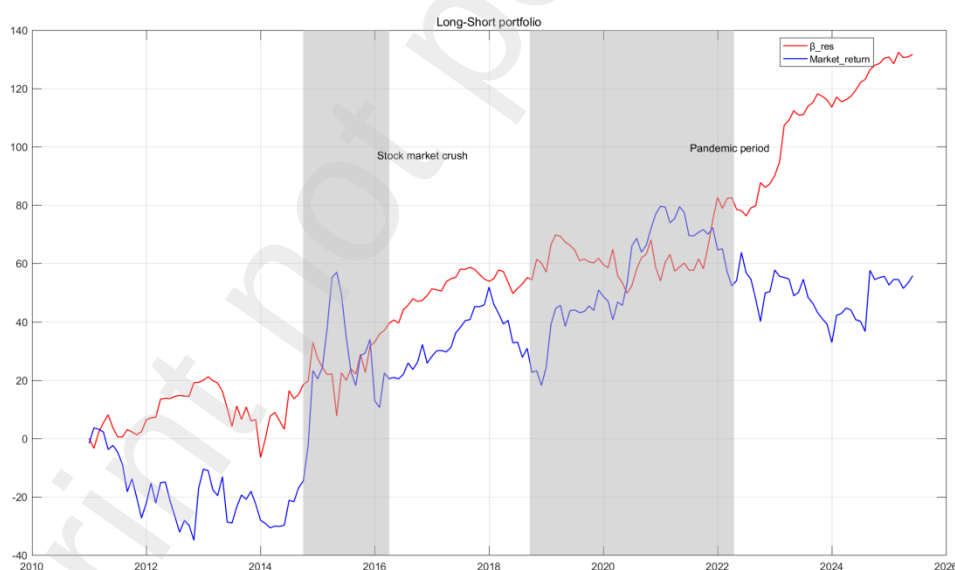


Figure 2. Resilience Beta Returns vs. Market Benchmark. Cumulative returns of the resilience beta arbitrage portfolio versus the CSI 300 index. Gray shaded areas denote the Chinese stock market crash (2015–2016) and global pandemic (2019–2022). While the strategy broadly outperforms the benchmark, temporary drawdowns during crises stem from liquidity squeezes, shock-induced pricing dislocation, and crowded trade unwinding. Subsequent recovery of excess returns reaffirms the factor's robust long-run pricing validity under normal market conditions.

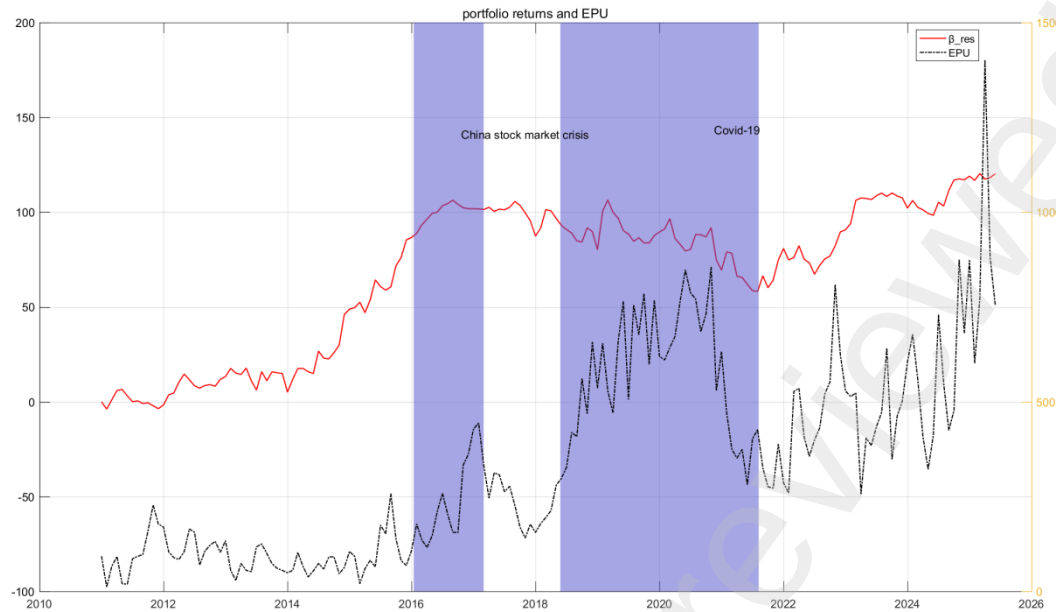


Figure 3. Cumulative returns of portfolios sorted by resilience beta under different economic policy uncertainty regimes. This figure compares the cumulative return trajectories of resilience beta-sorted portfolios in high-EPU shock periods (COVID-19 pandemic, 2015–2016 stock crash) and low-EPU stable periods (2010–2012), demonstrating that high economic policy uncertainty suppresses the returns of resilience beta strategies while low uncertainty facilitates positive cumulative returns.

Table 1. Construction of Capital Resilience Indicators. This table outlines a hierarchical evaluation framework comprising three primary dimensions—shock resistance, absorption/buffering capacity, and recovery speed—mapped to ex-ante, in-event, and ex-post perspectives. The system spans six secondary themes and 32 tertiary macro/micro metrics. A composite resilience score is synthesized via Sparse Principal Component Analysis (SPCA) using extracted common factor loadings.

Primary Indicator	Secondary Theme	Tertiary Metric(s)
Shock Resistance Dimension	Macro-capital Resilience	GDP Growth Rate;
		Current Account Balance/GDP;
		CPI
		PPI
		Fiscal Deficit
	Macro-financial System Stability	Government Bonds/GDP
		funding capital/market capital
		M2/GDP
		Non-performing Loan Ratio
		Social Leverage Ratio (Non-financial Corporations + Government + Households)/GDP
Absorption/Buffering Dimension	Price Volatility & Macro-stability	Foreign Exchange Reserves
		Net Inflow of Foreign Portfolio Investment
		exchange rate
		Market value/GDP (Capitalization Ratio)
		Turn over of stock markets
	Risk Hedging & Macro-diversification	CSI 300 Volatility
		7-day Reverse Repo Rate;
		Index Volatility (CSI 1000)
		Total Social Financing
		Index Volatility (SSE 50);
Recovery Dimension	Macroeconomic Recovery	Treasury Bonds
		Futures Trading Volume;
		Options Trading Volume
	Capital Market Functional Restoration Efficiency	Industrial Value Added
		unemployed rate
		Retail Sales of Consumer Goods
		Fixed Asset Investment
		PE
		Stock account number

Table 2. Variable Definitions and Construction Methods, This table details the measurement of control variables employed to investigate the capital resilience premium. Variables include firm size (Size), book-to-market ratio (BM), earnings-price ratio (EP), sales-price ratio (SP), market beta (Beta), idiosyncratic volatility (IVOL), momentum (MOM), reversal (Rev), realized volatility (VLT) and trading volume (VOL). The resilience rating is derived via principal component analysis of 32 macro- and micro-level indicators. All variables are constructed following established asset pricing conventions, with full specifications and references listed in the table.

Variable	Definition / Construction Method	References
Size	Free-float market capitalization, calculated as the product of tradable shares and stock price.	Zhang (2006); Wang et al. (2024)
BM	Shareholders' equity minus preferred stock book value, divided by free-float market cap.	Fama & French (2015); Chen (2026)
EP	Most recently reported net income divided by free-float market capitalization.	Liu et al. (2019)
SP	Operating revenue divided by free-float market capitalization.	Du et al. (2005)
Beta	Estimated via OLS regression of daily returns over the preceding month on the Fama-French three factors.	Hou et al. (2016); Chai et al. (2022)
IVOL	Standard deviation of residuals from regressing daily returns on the Fama-French (1993) three-factor model over the past month.	Zhang (2006); Gong et al. (2019); Tao et al. (2020); Chai et al. (2022)
MOM	Cumulative return from month $t-12$ to month $t-1$.	Carhart (1997)
Rev	Raw return over the past one month.	Tian et al. (2014)
VLT	Standard deviation of daily returns within a single calendar month.	Jiang et al. (2005); Zhang (2006); Sagi et al. (2007)
VOL	Total trading volume over the previous month.	Cheema et al. (2014)

Table3. Descriptive statistics and correlation coefficients. We report descriptive statistics and correlation coefficients for all variables to illustrate the fundamental structure of our variable set. Panel A reports summary statistics including averages, standard deviations, and distribution percentiles across the full sample period. Panel B presents the Pearson correlation matrix among risk factors, firm characteristics, and the resilience rating.

	Size	Beta	EP	BM	SP	VLT	IVOL	Rev	MOM	VOL	Res
Panel A Descriptive statistics											
mean	18.795	0.793	0.016	0.383	0.606	0.028	0.518	0.013	0.154	18.235	0.001
std	8.438	0.548	0.105	0.315	1.200	0.014	0.305	0.164	0.535	3.044	0.063
5th	1.26	0.000	-0.058	0.062	0.049	0.012	0.154	-0.190	-0.506	16.367	-0.073
25th	21.381	0.000	0.007	0.180	0.150	0.020	0.321	-0.069	-0.167	17.760	-0.021
50th	22.141	0.936	0.021	0.314	0.313	0.027	0.458	0.000	0.070	18.607	-0.001
75th	22.901	1.159	0.039	0.512	0.647	0.034	0.657	0.076	0.381	19.451	0.020
95th	24.341	1.525	0.091	0.963	1.973	0.050	1.089	0.253	1.085	20.706	0.080
Panel B Correlation coefficients											
Size	1.000	-0.187	0.000	-0.066	-0.069	0.009	-0.038	-0.001	-0.012	-0.032	0.045
Beta		1.000	-0.057	0.176	0.134	-0.042	0.076	-0.006	0.003	0.156	-0.092
EP			1.000	0.142	-0.002	-0.060	0.115	-0.012	0.007	0.018	0.012
BM				1.000	0.330	-0.189	0.348	-0.095	-0.296	0.189	-0.093
SP					1.000	-0.074	0.127	-0.036	-0.110	0.072	-0.051
VLT						1.000	-0.366	0.158	0.307	0.293	0.145
IVOL							1.000	-0.137	-0.278	0.193	-0.088
Rev								1.000	0.302	0.057	0.150
MOM									1.000	0.008	0.304
VOL										1.000	-0.016
Res											1.000

Table 4. Portfolio returns of resilience. Portfolio returns sorted by resilience beta. This table reports the average monthly returns for decile-sorted portfolios constructed by sorting stocks based on their estimated resilience beta, denoted as P1 through P10 (from lowest to highest). Panel A presents equal-weighted portfolio averages, while Panel B displays value-weighted averages. For each weighting scheme, we report the raw mean return (AVG) alongside risk-adjusted abnormal returns derived from time-series regressions of portfolio returns on three canonical pricing models: the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (1993) (FF3), and the Carhart four-factor model (1997) (Car4). The final column reports the monthly returns of a zero-cost long-short arbitrage strategy that goes long on P1 and shorts P10. All portfolios are rebalanced monthly at the end of each month.

EW	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10
Panel A. Equal-weighted returns											
AVG	1.26** (2.07)	1.23** (2.09)	1.06* (1.84)	1.14* (1.95)	1.07* (1.83)	1.06* (1.83)	1.09* (1.86)	1.08* (1.79)	0.81 (1.34)	0.5 (0.78)	0.76** (2.4)
CAPM	0.8 (1.66)	0.75* (1.7)	0.59 (1.36)	0.67 (1.51)	0.6 (1.35)	0.58 (1.35)	0.6 (1.4)	0.57 (1.31)	0.3 (0.68)	-0.02 (-0.03)	0.81*** (2.59)
FF3	1.15** (2.45)	1.06** (2.42)	0.87** (2.04)	0.92** (2.08)	0.87** (1.98)	0.85** (1.99)	0.9** (2.12)	0.91** (2.14)	0.69 (1.65)	0.49 (1.1)	0.66** (2.27)
Car4	0.51*** (3.77)	0.46*** (4.29)	0.3*** (3.11)	0.32*** (2.89)	0.25** (2.44)	0.23** (2.17)	0.26** (2.43)	0.22** (2.07)	-0.05 (-0.41)	-0.32* (-1.89)	0.83*** (3.38)
Panel B. Value-weighted returns											
AVG	0.6 (1.06)	0.66 (1.26)	0.74 (1.46)	0.64 (1.26)	0.6 (1.28)	0.67 (1.39)	0.63 (1.43)	0.59 (1.28)	0.43 (0.94)	-0.09 (-0.17)	0.69* (1.81)
CAPM	0.35 (0.65)	0.4 (0.83)	0.49 (1.06)	0.43 (0.9)	0.43 (0.96)	0.53 (1.13)	0.51 (1.18)	0.43 (0.97)	0.25 (0.59)	-0.28 (-0.57)	0.63* (1.697)
FF3	0.77 (1.51)	0.7 (1.48)	0.75 (1.62)	0.72 (1.53)	0.69 (1.56)	0.74 (1.58)	0.75* (1.74)	0.69 (1.57)	0.61 (1.46)	0.28 (0.62)	0.5* (1.681)
Csr4	0.09 (0.52)	0.11 (0.8)	0.17 (1.09)	0.05 (0.37)	0.08 (0.59)	0.13 (0.86)	0.14 (1)	-0.04 (-0.29)	-0.2 (-1.35)	-0.76*** (-4.26)	0.84*** (3.36)

Table 5. Time-series regressions of resilience beta-sorted portfolio returns on asset pricing models. This table reports intercepts (alpha) and factor loadings for seven asset pricing models: Daniel-Hirshleifer-Sun (2018), Hou-Xue-Zhang q-factor (2015), Novy-Marx (2013), Stambaugh-Yuan (2017), Fama-French five-factor (FF5, 2015), Carhart four-factor (Car4, 1997), and Fama-French three-factor (FF3, 1993). t-statistics are reported in parentheses below each loading. R-squared values appear at the bottom row. All portfolios are rebalanced monthly.

	DHS	HXZ	NM	SY	FF5	Car4	FF3
Alpha	0.64** (1.96)	1.21*** (3.95)	0.72*** (2.98)	0.81*** (2.91)	0.58** (1.96)	0.83*** (3.38)	0.66** (2.27)
MKT	0.07 (1.13)	0.00 (0.08)	0.01 (0.22)	0.03 (0.6)	0.09* (1.69)	0.04 (0.82)	0.1* (1.92)
R_fin	0.16 (1.43)						
R_pead	0.02 (0.11)						
R_me		-0.37*** (-4.34)					
R_inv		0.37** (2.35)					
R_roe		-0.55*** (-4.34)					
HML			0.61*** (3.88)				
UMD			-1.24*** (-10.11)				
PMU			0.22 (1.15)				
R_mgmt				0.04 (0.36)			
R_perf				-0.47*** (-5.92)			
R_smb				0 (0.05)			
SMB					0.07 (0.69)	-0.01 (-0.16)	0.11 (1.44)
HML					0.51*** (4.17)	0.34*** (5)	0.48*** (6.2)
CMA					-0.14 (-0.68)		
RMW					-0.1 (-0.41)		
UMD						-0.31*** (-8.36)	
R ²	0.014	0.199	0.465	0.332	0.211	0.440	0.208

Table 6. Fama-MacBeth cross-sectional regressions of stock returns on resilience beta and control factors. This table reports time-series coefficients from monthly cross-sectional panels, where the dependent variable is month $t+1$ stock returns and the core explanatory variable is month t resilience beta (Res). Columns 1–10 present an incremental specification design: we first control for baseline risk (market beta and size), then sequentially add profitability (EP), valuation ratios (BM, SP), volatility measures (VLT, IVOL), trading volume/turnover, momentum (MOM), and reversal (Rev) effects. This framework tests whether conventional pricing factors subsume the cross-sectional predictive power of resilience beta. Coefficients are reported with t-statistics in parentheses below each estimate. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Return									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Alpha	0.02*** (2.634)	0.02*** (2.555)	0.01** (2.091)	0.02** (2.473)	0.03*** (4.642)	0.02* (1.928)	0.02** (2.516)	0.02*** (2.714)	0.13*** (5.946)	0.14*** (7.314)
Res	-0.06*** (-2.813)	-0.06*** (-2.713)	-0.05*** (-2.642)	-0.06*** (-2.756)	-0.03* (-1.787)	-0.05*** (-2.652)	-0.05** (-2.364)	-0.06*** (-3.52)	-0.05** (-2.28)	-0.04*** (-2.711)
Size	-0.007 (-1.628)	-0.007 (-1.648)	-0.004 (-1.110)	-0.006 (-1.482)	-0.004 (-1.065)	-0.006 (-1.584)	-0.007* (-1.808)	-0.007* (-1.761)	-0.009** (-2.295)	-0.005 (-1.576)
Beta	-0.001 (-0.580)	-0.001 (-0.645)	-0.002 (-1.013)	-0.001 (-0.780)	-0.001 (-0.810)	-0.001 (-0.711)	-0.001 (-0.568)	-0.001 (-0.600)	0.004*** (2.792)	0.002* (1.886)
EP		0.001 (0.076)								-0.002 (-0.161)
BM			0.009 (1.671)							0.015*** (4.013)
SP				0.002** (2.394)						0.001*** (2.572)
VLT					-0.380*** (-2.694)					-0.354*** (-2.580)
IVOL						0.002 (0.326)				-0.007** (-2.222)
Rev							-0.020*** (-3.007)			-0.012** (-2.098)
MOM								-0.002 (-0.662)		0.005*** (2.706)
VOL									-0.006*** (-5.752)	-0.007*** (-6.957)
R ²	0.021	0.028	0.035	0.025	0.040	0.031	0.029	0.030	0.038	0.081

Table 7. Capital resilience premium across extreme and normal market regimes. Panel A reports the time-series average monthly returns for decile portfolios sorted by resilience beta during extreme stress periods (2015–2016 Chinese equity crash and 2020–2022 global pandemic), while Panel B covers normal (stress-free) periods. Columns present raw excess returns alongside risk-adjusted alphas from the CAPM, Fama-French three-factor (FF3), and Carhart four-factor (CAR4) models for each decile (P1P1 to P10P10). The final columns report the long-short spread (P1–P10P1–P10). t-statistics are reported in parentheses below each estimate. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All portfolios are rebalanced monthly at the month of t+1.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10
Panel A. Extreme Market											
AVG	2.07*	1.88	2.08*	2.02*	2.14*	2.07*	1.84	1.82	1.64	1.18	0.89**
	(1.69)	(1.61)	(1.78)	(1.74)	(1.77)	(1.71)	(1.5)	(1.47)	(1.28)	(0.84)	(1.96)
CAPM	2.06	1.87	2.07*	2.01*	2.13*	2.06*	1.83	1.81	1.62	1.16	0.9*
	(1.67)	(1.59)	(1.76)	(1.72)	(1.75)	(1.69)	(1.48)	(1.46)	(1.26)	(0.83)	(1.89)
FF3	1.46	1.29	1.45	1.45	1.51	1.53	1.31	1.18	1.08	0.76	0.7
	(1.11)	(1.03)	(1.16)	(1.17)	(1.16)	(1.17)	(0.99)	(0.89)	(0.78)	(0.5)	(1.05)
CAR4	2.24*	2.09*	2.27**	2.26**	2.4**	2.34*	2.16*	2.16*	2.13*	1.79	0.46
	(1.84)	(1.8)	(1.97)	(1.97)	(2.01)	(1.94)	(1.78)	(1.76)	(1.69)	(1.29)	(0.78)
Panel B. Non-Extreme Market											
AVG	0.6	0.74	0.51	0.46	0.32	0.45	0.43	0.53	0.31	0.1	0.5
	(0.89)	(1.17)	(0.83)	(0.72)	(0.49)	(0.68)	(0.68)	(0.82)	(0.47)	(0.15)	(1.5)
CAPM	0.48	0.61	0.38	0.35	0.21	0.37	0.38	0.43	0.19	-0.01	0.49
	(0.69)	(0.94)	(0.6)	(0.53)	(0.33)	(0.54)	(0.59)	(0.65)	(0.28)	(-0.02)	(1.42)
FF3	1.14	1.26*	1.03	0.99	0.91	1.04	1	1.11	0.81	0.72	0.42
	(1.54)	(1.83)	(1.53)	(1.42)	(1.31)	(1.45)	(1.45)	(1.57)	(1.12)	(0.98)	(1.12)
CAR4	0.44	0.56	0.36	0.31	0.18	0.34	0.33	0.42	0.17	-0.02	0.46
	(0.64)	(0.86)	(0.56)	(0.48)	(0.28)	(0.5)	(0.51)	(0.62)	(0.25)	(-0.03)	(1.32)

Table 8. Capital resilience premium across conditioning firm characteristics. This table reports the time-series average monthly returns from bivariate portfolio sorts of resilience beta, conditional on five characteristics: market capitalization (Size), book-to-market ratio (BM), momentum (MOM), trading volume (VOL), and idiosyncratic volatility (IVOL). For each characteristic, stocks are initially partitioned into three groups based on bottom 30%, middle 40%, top 30% of each characteristic. Within each group, firms are further sorted by resilience beta into ten deciles (P1 to P10). Columns report raw excess returns for each decile alongside the long-short spread (P1–P10), Fama-French three-factor alphas (FF3), and Carhart four-factor alphas (CAR4). t-statistics are reported in parentheses below each estimate. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All portfolios are rebalanced monthly.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	FF3	CAR4
Small-cap	3.03** *	2.83** *	3.37** *	2.63** *	2.66** *	2.6***	2.87** *	2.81** *	2.96** *	2.31** *	0.72**	0.79** *	0.81** *
	(4.29)	(4.22)	(4.36)	(3.73)	(3.61)	(3.56)	(3.87)	(4.03)	(3.71)	(3.06)	(2.43)	(2.64)	(2.74)
Big-cap	0.91 (1.35)	0.93 (1.48)	0.83 (1.32)	0.8 (1.3)	0.69 (1.17)	0.87 (1.42)	0.66 (1.16)	0.87 (1.38)	0.56 (0.89)	0.6 (0.87)	0.31 (0.85)	0.01 (0.03)	0.18 (0.62)
Low-BM	1.52**	1.58** *	1.53**	1.2*	1.06*	1.55**	1.33**	1.69**	0.99	1.26*	0.26	0.14	0.3
	(2.35)	(2.58)	(2.28)	(1.91)	(1.72)	(2.45)	(2.13)	(2.38)	(1.51)	(1.79)	(0.82)	(0.46)	(1.1)
High-BM	2.25** *	2.38** *	2.28** *	2.18** *	2.27** *	2.03** *	2.16** *	2.06** *	1.98** *	1.82** *	0.43*	0.35	0.45**
	(3.25)	(3.58)	(3.52)	(3.4)	(3.5)	(3.2)	(3.32)	(3.19)	(3.09)	(2.72)	(1.9)	(1.53)	(2.09)
Low-MOM	1.83** *	2.09** *	1.78** *	1.7***	1.74** *	1.5**	1.58**	1.59**	1.3*	1.21*	0.61**	0.45*	0.46*
	(2.55)	(2.82)	(2.64)	(2.59)	(2.65)	(2.31)	(2.44)	(2.36)	(1.96)	(1.79)	(2.31)	(1.77)	(1.82)
High-MOM	0.76 (0.95)	1.33* (1.81)	0.71 (1.01)	1.25* (1.72)	1.13 (1.63)	0.79 (1.13)	1.12 (1.54)	1.22 (1.67)	0.68 (0.92)	0.81 (1.11)	-0.05 (-0.12)	-0.3 (-0.69)	-0.26 (-0.61)
Low-Volume	2.44** *	2.33** *	2.09** *	1.97** *	2.27** *	2.17** *	2.16** *	2.08** *	2.08** *	1.88** *	0.56	0.23	0.32
	(3.51)	(3.52)	(3.14)	(3.03)	(3.32)	(3.15)	(3.17)	(3.1)	(3)	(2.72)	(1.66)	(0.8)	(1.17)
High-Volume	0.8	0.99	0.88	0.87	0.91	0.65	0.61	0.55	0.64	0.1	0.7**	0.63**	0.79** *
	(1.13)	(1.44)	(1.29)	(1.27)	(1.35)	(0.99)	(0.9)	(0.82)	(0.9)	(0.13)	(2.21)	(2)	(2.87)
Low-IVOL	1.08 (1.5)	1.46** (2.08)	1.08 (1.52)	1.41* (1.91)	1.06 (1.5)	1.19* (1.68)	1.36* (1.82)	1.11 (1.53)	1.05 (1.4)	0.96 (1.26)	0.12 (0.35)	-0.04 (-0.12)	0.07 (0.24)
High-IVOL	1.74** *	1.75** *	1.62** *	1.62** *	1.67** *	1.36**	1.58** *	1.68** *	1.46**	1.19*	0.55** *	0.36*	0.43**
	(2.58)	(2.72)	(2.54)	(2.62)	(2.75)	(2.22)	(2.57)	(2.74)	(2.39)	(1.95)	(2.54)	(1.73)	(2.18)

Table 9. Capital resilience premium across different market conditions. This table reports the time-series average monthly returns for decile portfolios sorted by resilience beta, conditional on three macro-financial regimes: investor sentiment (Panel A), business cycle measured by GDP growth (Panel B), and market volatility based on CSI 300 index standard deviation (Panel C). Each regime is partitioned into terciles using quantile thresholds: bottom 30% representing low/worst states, middle 40% representing neutral/median states, and top 30% representing high/best states. Columns report raw excess returns, Fama-French three-factor alphas (FF3), and Carhart four-factor alphas (CAR4) for each decile alongside the long-short spread (P1–P10). t-statistics are reported in parentheses below estimates. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All portfolios are rebalanced monthly.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	FF3	CAR4
Panel A. Market sentiment													
Low	2.85** (2.27)	2.84** (2.37)	2.73** (2.29)	2.77** (2.28)	2.68** (2.19)	2.95** (2.38)	3.01*** (2.54)	2.85** (2.36)	2.85** (2.31)	2.57** (2.01)	0.28 (0.51)	0.17 (0.3)	-0.06 (-0.16)
middle	1.71 (1.67)	1.9** (2)	1.97** (2.07)	1.79* (1.87)	1.73* (1.79)	1.66* (1.72)	1.52 (1.65)	1.63* (1.73)	1.57 (1.61)	1.26 (1.28)	0.45 (1.39)	0.41 (1.27)	0.41 (1.33)
High	1.26 (1.02)	1.58 (1.23)	1.1 (0.91)	1.21 (0.96)	0.94 (0.77)	1.22 (1.01)	0.9 (0.74)	0.78 (0.64)	0.72 (0.56)	0 (0)	1.26** (2.04)	1.28** (2.06)	1.32*** (3.02)
Panel B. Business cycle													
Low	1.08 (0.86)	1.15 (0.99)	1.24 (1.05)	0.88 (0.74)	1.25 (1.03)	1.19 (0.98)	1.3 (1.11)	1.24 (1.05)	1.63 (1.27)	1.46 (1.17)	-0.38 (-0.72)	-0.41 (-0.76)	0.32 (0.87)
middle	2.48** (2.4)	2.5 (2.52)	2.43** (2.45)	2.4** (2.45)	2.2** (2.2)	2.56*** (2.62)	2.24** (2.31)	2.27** (2.31)	1.98* (1.95)	1.69 (1.58)	0.79* (1.72)	0.79 (1.66)	0.63 (1.66)
High	2.01* (1.72)	2.49** (2.05)	1.98* (1.78)	2.31* (1.91)	1.73 (1.54)	1.78 (1.53)	1.62 (1.44)	1.53 (1.35)	1.37 (1.2)	0.6 (0.51)	1.41*** (3.38)	1.4*** (3.31)	1.23*** (3.64)
Panel C. Market volatility													
Low	1.31 (1.54)	1.26 (1.58)	1.28 (1.67)	1.08 (1.38)	1.17 (1.47)	1.2 (1.53)	1.06 (1.36)	1.35* (1.69)	1.19 (1.49)	0.82 (1)	0.49 (1.1)	0.38 (0.89)	0.95*** (2.77)
middle	1.03 (1.1)	1.22 (1.37)	1.17 (1.31)	1.27 (1.4)	1.01 (1.09)	1.14 (1.23)	1.04 (1.17)	0.98 (1.08)	1 (1.02)	0.61 (0.63)	0.43 (1)	0.04 (0.09)	0.37 (1.28)
High	3.69** (2.34)	4.07*** (2.6)	3.6** (2.37)	3.61** (2.3)	3.38** (2.22)	3.65** (2.39)	3.44** (2.3)	3.14** (2.09)	3.11** (2.01)	2.67 (1.66)	1.02* (1.79)	1.17** (2.16)	1.07** (2.05)

Table 10. Capital resilience premium across economic policy uncertainty (EPU) regimes. This table reports the time-series average monthly returns for decile portfolios sorted by resilience beta, conditional on EPU states. The sample is partitioned into three regimes: low EPU (bottom 30%), medium/neutral EPU (middle 40%), and high EPU (top 30%). Columns report raw excess returns, Fama-French three-factor alphas (FF3), and Carhart four-factor alphas (Car4) for each decile alongside the long-short spread (P1–P10). t-statistics are reported in parentheses below estimates. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All portfolios are rebalanced monthly.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	FF3	Car4
											0		
Low-EPU	3.96** * (2.61)	4.19** * (2.78)	3.81** * (2.58)	3.94** * (2.6)	3.7** (2.51)	3.95** * (2.67)	3.65** * (2.54)	3.48* * (2.4)	3.75* * (2.46)	3.38* * (2.25)	0.58 (0.96)	0.54 (0.85)	0.42 (0.89)
Median-EPU	1.07 (1.07)	1.42 (1.5)	1.3 (1.38)	1.22 (1.27)	1.02 (1.05)	1.34 (1.38)	1.26 (1.32)	1.22 (1.27)	1.1 (1.1)	0.71 (0.68)	0.36 (0.96)	0.34 (0.89)	0.27 (0.88)
High-EPU	0.99 (1.2)	0.87 (1.11)	0.9 (1.22)	0.82 (1.09)	0.83 (1.08)	0.64 (0.84)	0.57 (0.76)	0.68 (0.9)	0.42 (0.55)	-0.02 (-0.03)	1.02** (2.14)	1.07* (2.23)	1.42** (4.07)

Table 11. Capital resilience premium across UCT regimes. This table reports the time-series average monthly returns for decile portfolios sorted by resilience beta, conditional on US-China trade tension states. The sample is partitioned into three regimes based on quantiles of the US-China Tension Index (UCT): bottom 30% as easing periods, middle 40% as stable periods, and top 30% as escalation periods. Columns report raw excess returns, Fama-French three-factor alphas (FF3), and Carhart four-factor alphas (CAR4) for each decile alongside the long-short spread (P1–P10). t-statistics are reported in parentheses below estimates. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All portfolios are rebalanced monthly.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	FF3	Car4
Easing	5.03*** (3.95)	5.36*** (4.11)	4.91*** (3.88)	4.77*** (3.8)	4.47*** (3.55)	4.96*** (3.91)	4.72*** (3.85)	4.64*** (3.79)	5.02*** (3.76)	4.23*** (3.23)	0.8 (1.34)	0.34 (0.6)	0.49 (0.82)
Normal	0.93 (0.87)	1.11 (1.1)	1.01 (1)	1.11 (1.03)	1.11 (1.05)	1.14 (1.09)	1.11 (1.09)	1 (0.97)	0.88 (0.84)	0.76 (0.7)	0.17 (0.41)	0.13 (0.37)	0.21 (0.56)
Escalation	0.11 (0.11)	0.1 (0.11)	0.19 (0.22)	0.14 (0.15)	-0.04 (-0.05)	-0.11 (-0.12)	-0.31 (-0.36)	-0.19 (-0.21)	-0.56 (-0.63)	-0.95 (-0.97)	1.06** (2.42)	1.06** (2.48)	0.99** (2.38)