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Downside-driven abnormal performance asymmetry and its family-level persistence: evidence from Chinese mutual funds

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Abstract. Using data on Chinese mutual funds from 2005 to 2025, this study constructs delta alpha, defined as the difference between downside-period alpha and upside-period alpha, to measure asymmetry in abnormal performance across market states. By shifting abnormal performance from an unconditional perspective to a state-dependent cross-sectional object, delta alpha characterizes how alpha is distributed across market environments rather than averaged over them. This study finds that performance asymmetry exhibits a one-sided structure: cross-sectional variation is driven almost entirely by downside-period alpha, while upside-period alpha displays minimal variation. Benchmark fit (R^2) significantly dampens downside-period alpha but does not explain differences in max-drawdown, suggesting that delta alpha captures relative performance structure rather than absolute risk exposure. Further analysis incorporating fund-family fixed effects shows that performance asymmetry clusters significantly among defensive families, even after controlling for fund size, age, benchmark fit, and max-drawdown. This study finds that abnormal performance under stress is better characterized as an organizational feature rather than purely individual manager skill; performance evaluation should therefore incorporate fund-family investment styles and internal capital allocation mechanisms.

Keywords: delta alpha, state-dependent performance asymmetry, downside-period alpha, mutual fund families, benchmark dependence, Chinese mutual funds

1. Introduction

Behavioral finance suggests that investors tend to be loss-averse. They judge outcomes relative to a reference point and give more importance to losses than to gains of the same size [1, 2]. As a result, investment performance is naturally assessed differently across favorable and adverse market states. In practice, however, fund performance is predominantly summarized using unconditional measures such as average returns or unconditional alpha. Consequently, they cannot show whether funds preserve capital better in downturns or perform differently across market environments.

The Chinese mutual fund market provides a suitable setting for studying state-dependent abnormal performance (see Appendix A). The market is dominated by retail investors, making downside performance especially relevant for investor evaluation and fund flows [3]. Benchmark-based evaluation is also salient, as deviations from stated benchmarks are associated with relative underperformance and capital outflows [4]. Besides, funds from the same family may use the same research platforms, risk-management systems, or internal resources. This common setup may lead to differences in performance across fund families and make family-level heterogeneity economically relevant.

This study makes three related contributions to the literature on performance evaluation and mutual fund families. First, this study introduces delta alpha as a measure of state-dependent abnormal performance asymmetry. Existing studies either model conditional performance through time-varying exposures [5], show that fund manager skill varies across macroeconomic states [6], examine downside risk exposure [7], analyze performance within particular market states [8, 9], or emphasize incentive-related variation in fund risk-taking [10]. By contrast, this study treats the asymmetry itself as a cross-sectional dimension of fund heterogeneity.

Second, this study shows that cross-sectional variation in delta alpha is driven primarily by downside-period alpha rather than upside-period alpha. This result indicates that the relevant asymmetry across funds arises mainly in adverse market conditions, rather than reflecting symmetric variation across market states. In this sense, the evidence complements studies emphasizing downside-market liquidity pressure and fire-sale effects [11] as well as theories predicting that some funds may deliver greater value in bad times [12]. Relative to studies that focus on state-specific performance levels, this result shows that the relevant asymmetry across funds arises mainly in adverse market conditions.

Third, this study documents a nontrivial family-level component in performance asymmetry. While Guedj and Papastaikoudi [13], Massa [14], and Nanda [15] emphasize persistent differences in average performance, fund flows, and internal resource allocation across families, related studies also suggest that asymmetric outcomes may arise through investor reactions and managerial incentives. Patel [16] document asymmetric investor responses to performance through fund flows, and Chevalier [17] show that career concerns can shape managers' risk-taking behavior. Building on these insights, this study shows that state-dependent abnormal performance asymmetry also aggregates at the family level.

2. Data and methodology

2.1. Data descriptions and characteristics

The sample covers 1,382 funds registered on the Shanghai and Shenzhen Stock Exchanges between January 2005 and November 2025 and uses the 610 funds with a total trading month count greater than 120 as the research sample. These funds are categorized into equity funds and mixed funds, and strategically into ordinary equity funds, equity-biased mixed funds, and hybrid allocation funds. The detailed fund data obtained from the Shanghai and Shenzhen Stock Exchanges, including fund name, fund-owning company, fund inception date, monthly fund returns and quarterly net assets under management, measured in RMB billions. The detailed variable definitions are provided in Appendix B.

2.2. Empirical framework

To evaluate mutual fund performance and estimate abnormal returns, this study adopts a factor-model-based framework. For each fund, this study estimates monthly excess returns using benchmark factor returns. The alpha for each fund is defined as the intercept term in the time-series regressions reported in Equation (1):

$$R_{i,t} = \alpha_{i,t} + 0.5CSI300_t + 0.5CSI500_t + \varepsilon_{i,t} \tag{1}$$

The baseline specification follows a CAPM-style model, with extensions to alternative benchmark specifications to ensure robustness.

To separate systematic exposure from abnormal performance, this study estimates alpha from historical return data solely and then conducts portfolio construction and subsequent performance evaluation on a strictly out-of-sample basis. This operation ensures the estimated alphas capture persistent cross-sectional signals—rather than transient noise—in fund performance.

This study defines market states based on the sign of the benchmark market return. Periods with negative benchmark returns are classified as downside-periods, and those with non-negative benchmark returns are treated as upside-periods. The zero threshold provides the most transparent and model-free baseline classification because it uses all months without imposing arbitrary tail cutoffs. This study then estimates conditional alpha separately for each state, using only observations falling within the corresponding market state.

Besides, this study estimates fund-level regressions under multiple benchmark specifications to account for heterogeneity in benchmark dependence across funds. Each fund is assigned to the benchmark yielding the highest explanatory power, as measured by its regression R^2. This assignment serves as an empirical proxy for the fund's dominant systematic exposure, rather than a structural identification of its underlying investment style. All subsequent analyses are conducted within these benchmark-defined groups.

3. Baseline performance and conventional alpha

3.1. Portfolio stylized result

This study constructs an equal-weight investment portfolio covering all available funds within each trading month and analyzes its cumulative performance relative to the broad market benchmark, providing a description of the overall market environment faced by mutual funds. This portfolio-based comparison provides a basic description of the risk and return characteristics of diversified fund investments during the sample period.

The portfolio's cumulative returns fluctuate in high synchrony with the benchmark index during major stress events. This suggests that during periods of intensified volatility, the overall performance is primarily driven by systematic market factors rather than idiosyncratic, fund-level dynamics. Simultaneously, the portfolio frequently experiences smaller declines than the benchmark during downside periods. This pattern underscores the ability of diversified allocation to partially mitigate adverse market shocks.

However, these portfolio-level patterns do not reveal whether systematic differences in abnormal performance exist across different market states, nor do they clarify whether such differences stem from specific fund behaviors or broader organizational characteristics. This study therefore conducts a more granular analysis of fund performance across market conditions.

3.2. Benchmark-adjusted alpha

Restricting attention to funds with sufficiently long return histories, this study estimates fund-level alphas under four benchmark models and group funds by the specification with the highest R^2. This study shows in Table 1 that this classification is empirically meaningful: each group tends to have a positive mean alpha relative to its assigned benchmark and weaker performance relative to alternatives. However, the magnitudes are small, suggesting that unconditional alpha alone provides limited information about fund performance.

4. Main results

4.1. Delta alpha

This study defines market states using the CSI 300 + CSI 500 composite benchmark. For each fund, this study then estimates conditional CAPM-style alphas separately within downside and upside states by regressing monthly fund returns on the benchmark return using only observations from the corresponding regime. Downside-period alpha and upside-period alpha are estimated from Equation (2) and Equation (3), respectively. Delta alpha is defined as the difference between downside-period alpha and upside-period alpha. This measure differs from unconditional alpha, which averages abnormal performance across all months, and from downside beta, which captures risk exposure rather than abnormal performance. If a fund's abnormal performance does not vary systematically across market states, delta alpha should be close to zero:

$$R_{i,t} = \alpha_i^{down} + \beta_i^{down} R_{m,t} + \varepsilon_{i,t} \tag{2}$$

$$R_{i,t} = \alpha_i^{up} + \beta_i^{up} R_{m,t} + \varepsilon_{i,t} \tag{3}$$

Using delta alpha as the dependent variable, this study finds that ordinary equity funds exhibit significantly higher state-dependent abnormal performance asymmetry than equity-biased hybrid funds, whereas hybrid allocation funds do not differ systematically from the baseline category. Unlike the unconditional skill literature, these results show that part of cross-sectional fund heterogeneity emerges specifically through state-dependent asymmetry [7, 18, 19]. In addition, R^2 enters with a significantly negative coefficient, indicating that funds with tighter benchmark fit display a smaller gap between downside-period and upside-period alphas.

4.2. Delta alpha and downside alpha

To identify the source of the asymmetric alpha performance, Equation (4) models downside-period alpha, while Equation (5) models upside-period alpha:

$$\alpha_i^{down} = Cons + +\beta_1^{Ordinary}(Ordinary_i = 1) + \beta_2^{Hybrid}(Hybrid_i = 1) + \beta_3 R_i^2 + \varepsilon_{i,t} \tag{4}$$

$$\alpha_i^{up} = Cons + \beta_1^{Ordinary}(Ordinary_i = 1) + \beta_2^{Hybrid}(Hybrid_i = 1) + \beta_3 R_i^2 + \varepsilon_{i,t} \tag{5}$$

This study shows in Table 2 that the cross-sectional pattern in delta alpha is driven primarily by downside-period alpha. Ordinary equity funds earn about 30 basis points higher downside-period alpha per month than equity-biased hybrid funds, whereas hybrid allocation funds do not differ significantly from the omitted category. A 0.1 increase in R^2 is associated with roughly 20 basis points lower downside-period alpha per month, indicating that the observed asymmetry is concentrated during downside market periods.

Importantly, the identification is limited to comparing funds with similar mandates and benchmark exposures. This interpretation is comparative rather than causal. When funds differ in mandate or investment universe, this study does not attempt to separate active managerial choices from ex-ante portfolio constraints.

4.3. R^2 matters for alpha, not risk

In terms of absolute downside risk, ordinary equity funds and hybrid allocation funds exhibit lower max-drawdown, by about 5 and 3 percentage points respectively. However, benchmark fit has no significant effect on max-drawdown (see Table 3), indicating that R^2 influences delta alpha but not absolute loss severity.

5. Family-level effects and organizational heterogeneity

5.1. Family fixed effects and heterogeneity

To examine whether delta alpha exhibits family-level clustering beyond observable fund characteristics, this study introduces the fund-family fixed-effects specification shown in Equation (6):

$$\Delta alpha_i = \beta_0 + \beta_1 Family\,effect_i + \beta_2 \log(fundsize_i) + \beta_3 \log(fundage_i) + \beta_4 MDD_i + \beta_5 R_i^2 \quad (6)$$

The inclusion of fund-family fixed effects reveals economically meaningful heterogeneity across fund families. The F-test strongly rejects the null that all family effects are jointly zero, and the adjusted R^2 rises to approximately 0.27. These results indicate that delta alpha is not distributed randomly across funds but exhibits substantial within-family correlation, even after controlling for fund size, fund age, max-drawdown, and benchmark fit.

A variance decomposition further shows that 12.73% of the total cross-sectional variation in delta alpha arises from between-family differences (see Table 4). Most heterogeneity remains at the fund level, but the family component is economically nontrivial and consistent with unobserved organizational factors shared within fund families. This evidence is descriptive rather than causal. It shows family-level clustering beyond observable fund characteristics, but does not identify the underlying mechanisms.

5.2. Family type classification

Building on the family-level heterogeneity documented above, this study classifies fund families using family-level averages of delta alpha and max-drawdown. This classification is descriptive rather than structural: delta alpha captures relative performance asymmetry across market states, whereas max-drawdown captures absolute loss severity, allowing the two dimensions to be distinguished explicitly (see Table 5). This framework explicitly distinguishes relative performance asymmetry from absolute loss severity—a distinction that traditional symmetric volatility measures fail to capture by conflating downside fluctuations with upside gains.

Selection may still matter. For example, conservative families may attract more risk-averse investors, which can affect portfolio risk characteristics. However, after this study includes standard fund-level controls (size, age, max-drawdown, benchmark dependence) when estimating the defensive family indicator, funds affiliated with defensive families continue to exhibit higher downside alpha.

To further account for observable selection-related characteristics, this study estimates the specification in Equation (7):

$$\Delta alpha_i = \beta_0 + \beta_1 Defensive\,family_i + \beta_2 log(fundsize_i) + \beta_3 log(fundage_i) + \beta_4 MDD_i + \beta_5 R_i^2 \quad (7)$$

This study shows in Table 6 that the defensive family indicator remains positive and significant after controlling for fund characteristics. Economically, the coefficient on defensive family implies that affiliated funds have about 1 percentage point higher monthly delta alpha than comparable funds in non-defensive families. Additionally, the negative coefficient on fund size is also consistent with the scale diseconomies in active management documented by Pástor [18].

6. Robustness checks and bias

6.1. Robustness check for portfolio ranking

To assess the robustness of alpha-based rankings, this study examines whether the relative ordering of high- and low-alpha portfolios remains stable across time and benchmark specifications. This study partitions the sample period from 2015 to 2025 into three sub-periods corresponding to different market environments and re-estimates alpha using four alternative benchmark models. For each benchmark and sub-period, this study constructs a portfolio that goes long in the highest-alpha portfolio and short in the lowest-alpha portfolio.

This study shows in Table 7 that the return spread between the highest and lowest-alpha portfolios remains of the same sign across all benchmark specifications and sub-periods. Importantly, this study focuses on ranking stability rather than on the economic magnitude of returns and this study finds that the consistent sign of the return spread indicates that alpha-based rankings are robust to alternative benchmark choices and market environments (see Appendix C for cumulative return dynamics).

6.2. Robustness check for market-state definition

To examine whether the results depend on the definition of market states, this study re-estimates conditional alphas using two alternative classifications. First, this study defines downside and upside periods by the 30th and 70th percentiles of benchmark returns and requires at least 24 monthly observations per regime (478 funds). Second, extreme adverse periods are defined using major financial stress episodes, including September–October 2008, June–July 2015, and February–March 2020, requiring at least three observations per crisis regime (531 funds). These two approaches allow testing whether the main results are sensitive to different market-state definitions.

This study shows in Table 8 that the baseline pattern remains intact under alternative market-state definitions. In both panels, ordinary equity funds continue to exhibit significantly higher downside-period alpha, whereas hybrid allocation funds remain insignificant. The coefficient on R^2 also remains negative and significant, indicating that the baseline result is not driven by how market downturns are defined.

6.3. Robustness check of family type classification

To assess the sensitivity of the baseline results to the construction of fund family types, this study conducts two alternative robustness checks using different classification schemes. First, families are classified into defensive, neutral, and pro-cyclical groups using a quantile-based approach on average max-drawdown and downside–upside alpha differentials. Second, a z-score-based classification is implemented using standardized delta alpha and max-drawdown measures.

This study shows in Table 9 and Table 10 that the main family-level ordering remains robust: neutral and pro-cyclical families continue to exhibit lower delta alpha than defensive families after controlling for fund characteristics, with economically meaningful differences of roughly 0.4–1 percentage point for neutral families and about 1 percentage point for pro-cyclical families. These results suggest that the baseline family-level pattern is not driven by a particular classification method or cutoff.

6.4. Survivorship bias

One concern in constructing the sample is survivorship bias: restricting to funds with at least 120 months of history necessarily excludes earlier liquidated or merged funds, potentially overstating downside-period performance. This study includes available return histories for defunct funds up to their exit points, but complete correction for survivorship and backfill biases is infeasible. Therefore, the estimated persistence of state-dependent abnormal performance should be interpreted with caution, and future research could use more comprehensive data tracking all exited funds.

7. Conclusion

Overall, unconditional average performance misses economically relevant differences in how funds perform in adverse markets, and part of these asymmetry clusters at the family level. These findings suggest that the evaluation of funds should incorporate both market-state dependence and organizational context rather than relying on unconditional alpha alone.

Future research could examine how investor flow responses, internal family incentives, and portfolio-level trading mechanisms affect state-dependent performance. Detailed study of compensation structures and portfolio holdings may further reveal the organizational channels driving persistent performance asymmetries.

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Appendix

1. Appendix A: the performance of equal-weighted investment portfolio and CSI 300 index from 2005 to 2025

Both the equal-weighted investment portfolio and the CSI 300 Index exhibited substantial drawdowns during the global financial crisis. Nevertheless, the max-drawdown of the equal-weighted portfolio was smaller than that of the index, suggesting that diversified investment has a stronger risk buffering ability under systemic shocks.

From 2014 to 2019, the equal-weighted portfolio basically rode the wave of the 2015 boom-and-bust cycle—going up early on, then settling into a steadier range of 6% to 8% (Figure 1). Between January 2015 and January 2017, returns were high but volatile, averaging 1.51% per month with a standard deviation of 10.41%, and it consistently outperformed the CSI 300 Index during that stretch.

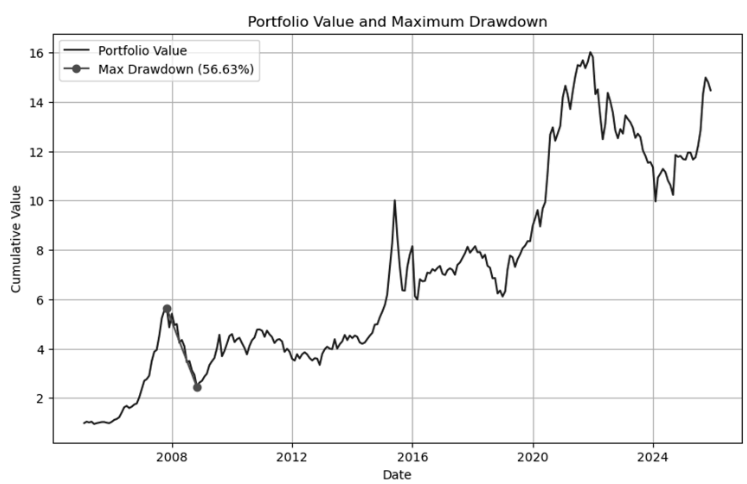

Figure 1. The performance of equal-weight portfolio

After 2019, the pandemic and subsequent liquidity expansion resulted in renewed market volatility. The equal-weighted portfolio rose to 16.01 in December 2021, then declined before gradually recovering and stabilizing around 14 by August 2025. However, the CSI 300 Index underperformed consistently during this period and did not exceed its 2007 peak (Figure 2).

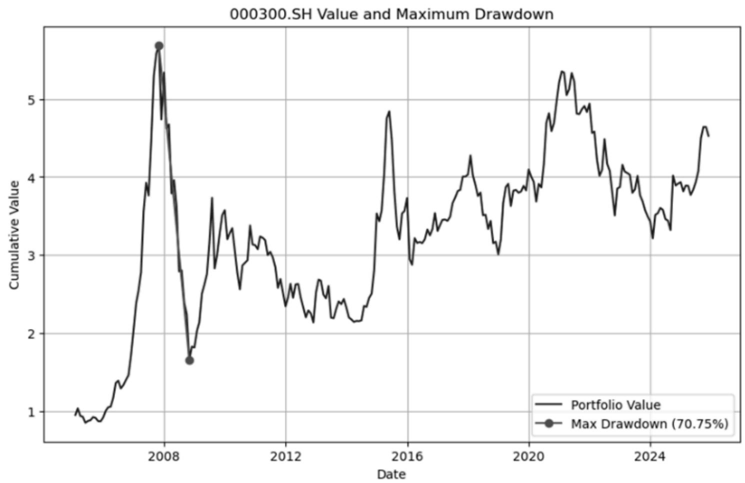

Figure 2. The performance of 000300.SH

In conclusion, while the long-term performance differs across portfolios, they tend to move in similar ways during major market stress. The equal-weighted portfolio had smaller losses and was more stable during market downturns, showing that spreading investments across assets helps manage risk, even without considering the skill or extra returns of individual funds.

2. Appendix B: Table B1. variable definitions

Table B1. variable definitions

Variables	Description
Main variables	
CSI 300 + CSI 500	The CSI 300 + CSI 500 benchmark is constructed as the simple average of the CSI 300 index return and the CSI 500 index return, which is a 50/50 combination of the two indices. It serves as the market benchmark factor in the baseline specification.
R^2	R^2 denotes the coefficient of determination from the time-series regression of a fund's returns on the CSI 300 + CSI 500 benchmark. It measures the explanatory power of this benchmark model for the fund's return variation.
Log (fund size)	Log (fund size) denotes the natural logarithm of average fund size. Fund size is computed as the weighted average of a fund's total net assets observed at quarter-end dates over 2020–2024, and the natural logarithm of this value is then taken.
Log (fund age)	Log (fund age) denotes the natural logarithm of fund age in years. Fund age is computed as the number of days between the fund's inception date and December 31, 2024, divided by 365.25, and the natural logarithm of this value is then taken.
MDD	MDD denotes maximum drawdown. Following Chekhlov [20], maximum drawdown is defined as the largest peak-to-trough decline in a fund's value over the sample period.

Table B1. Continued

Interaction variables	
Ordinary	Ordinary is an indicator equal to 1 if a fund's Type II classification at inception is ordinary equity, and 0 otherwise.
Hybrid	Hybrid is an indicator equal to 1 if a fund's Type II classification at inception is hybrid asset allocation, and 0 otherwise.
Defensive Family	A fund family is classified as defensive if (i) its family-level mean delta alpha (averaged across all funds within the family) is above the cross-family median of family-level mean delta alpha, and (ii) its family-level Mean Max-Drawdown (MDD) is below the cross-family median of family-level mean MDD, where delta alpha and MDD are computed over the same sample window as the main analysis.
Pro-cyclical family	A fund family is classified as pro-cyclical if (i) its family-level mean delta alpha (averaged across all funds within the family) is below the cross-family median of family-level mean delta alpha, and (ii) its family-level Mean Max-Drawdown (MDD) is above the cross-family median of family-level mean MDD, where delta alpha and MDD are computed over the same sample window as the main analysis.
Neutral family	A fund family is classified as Neutral if it is neither defensive nor pro-cyclical under the above criteria.

3. Appendix C: cumulative return performance of different investment portfolios under the benchmark

From the perspective of cumulative returns, there was a distinct stratification trend from 2016 to 2023. However, starting from 2024, the stratification of funds became significantly overlapping. This compression phenomenon occurred simultaneously with the intensification of the downward fluctuations in the entire market, which might have weakened the cross-sectional information value of the alpha signal. But again, there was a clear stratification starting from the upward market period in 2025. To assess whether alpha-sorted portfolios deliver performance beyond broad market movements, this study compares their cumulative returns with those of CSI 300 + CSI 500 benchmark. During the bull market in 2015, the cumulative returns of the index far exceeded any fund investment portfolio. However, during the subsequent decline, the cumulative returns of the index quickly dropped below 1.0 at the beginning and never exceeded the fund returns.

Comparing the investment portfolios, it is clear to see that the cumulative return gap between the portfolio with the highest alpha since 2016 and the one with the lowest alpha has been widening (Figure 3). This gap reached its peak in 2022 and then fluctuated and decreased between 2022 and 2024. In 2025, the cumulative return difference between the two portfolios stabilized at around 1.15. In fact, regardless of which index is used as the factor (CSI 300 + CSI 500, Shanghai 50, Shenzhen Composite Index, ChiNext Index), the cumulative return of the portfolio with the highest alpha is always greater than that of the portfolio with the lowest alpha.

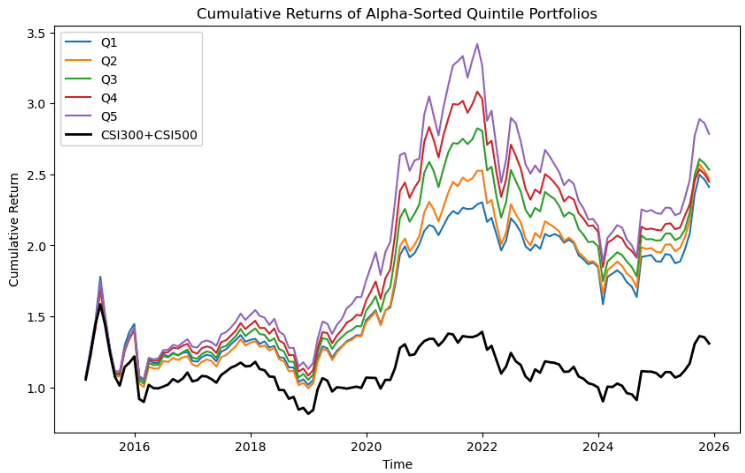

Figure 3. Cumulative returns of alpha-sorted quantile portfolios

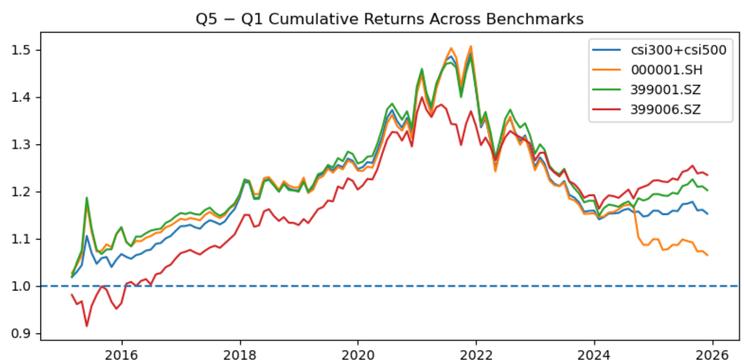

Figure 4. Cumulative return spread (Q5–Q1) across alternative benchmarks

Table 1 reports mean monthly alpha estimates by benchmark-defined fund group. Each fund is assigned to the benchmark specification with the highest fund-level R^2 among four alternatives: CSI 300 + CSI 500, 000001.SH, 399001.SZ, and 399006.SZ (Figure 4). The table then reports the cross-sectional mean alpha for each group under all four benchmark models. Variable definitions are described in Appendix B.

Table 1. benchmark-based fund classification yields sign-consistent monthly average alphas

Style/Alpha	CSI 300 + CSI 500	000001.SH	399001.SZ	399006.SZ
CSI 300 + CSI 500	-0.001	-0.003	-0.001	-0.001
000001.SH	0.002	0.001	0.003	0.003
399001.SZ	-0.002	-0.003	-0.001	-0.002
399006.SZ	-0.001	-0.002	-0.001	-0.001

Table 2 reports the regression results of fund-level downside-period alpha. The sample includes 610 fund observations. Variable definitions are provided in Appendix B. Heteroskedasticity-robust t-statistics (HC1) are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 2. The regression results of fund-level downside-period alpha

Variable	Coefficient
Constant	0.02***
	(7.29)
Ordinary	0.003***
	(4.85)
Hybrid	0.001
	(1.46)
R^2	-0.02***
	(-4.87)

Table 3 reports regression result of fund-level max-drawdown. The sample includes 610 fund observations. Variable definitions are provided in Appendix B. Heteroskedasticity-robust t-statistics (HC1) are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 3. Regression result of fund-level max-drawdown

Variable	Coefficient
Constant	0.53***
	(8.86)
Ordinary	-0.05***
	(-4.32)
Hybrid	-0.03**
	(-2.54)
R^2	< 0.001
	(0.01)

Table 4 reports the variance decomposition of fund-level delta alpha into between-family and within-family components. The sample includes 556 funds in the baseline sample. The table reports the variance and proportion of total cross-sectional variation attributable to each component.

Table 4. The variance decomposition of fund-level delta alpha into between-family and within-family components

Components	Variance	Share
Between family variance	$1.17 * 10^{-5}$	12.73%
Within family variance	$8.01 * 10^{-5}$	87.27%
Total variance	$9.18 * 10^{-5}$	100%

Table 5 reports the construction of the family-type classification and the composition of each group. The sample includes 610 funds, of which 556 belong to families managing at least five funds. Panel A reports the classification criteria based on family-level mean delta alpha and max-drawdown. Panel B reports the number of families and affiliated individual funds in each category. Panel C reports the average characteristics of defensive, neutral, and pro-cyclical families, including mean delta alpha, mean downside alpha, Mean Max-Drawdown (MDD), and mean R^2.

Table 5 A. Classification criterion

Dimension	Measure	Interpretation
Relative downside performance	Delta alpha	Difference between downside and upside alpha
Absolute loss severity	Max-drawdown	Peak-to-trough loss over sample period
Classification rule	Median split	Above/below median in both dimensions

Table 5 B. Group composition

Family type	Number of families/individual funds
Defensive	8/105
Neutral	36/376
Pro-cyclical	7/75

Table 5 C. Average characteristics across family groups

Variable	Defensive	Neutral	Pro-cyclical
Mean delta alpha	0.004	0.001	-0.001
Mean downside alpha	0.011	0.008	0.007
Mean MDD	0.489	0.523	0.547
Mean R^2	0.667	0.661	0.670

Table 6 reports the regression results of fund-level delta alpha. The sample includes 556 funds belonging to families managing at least five funds. Variable definitions are provided in Appendix B. Heteroskedasticity-robust t-statistics (HC1) are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 6. Tthe regression results of fund-level delta alpha

Variable	Coefficient
Constant	0.03***
	(4.56)
Defensive family	0.01***
	(4.27)
Log (fund size)	-0.001**
	(-2.51)
Log (fund age)	-0.01***
	(-5.30)

Table 6. Continued

MDD	0.02***
	(5.79)
R^2	-0.02***
	(-4.61)

Table 7 reports alpha-based portfolio performance across alternative benchmark specifications and sub-periods. For each benchmark and period, the table reports annualized mean return, annualized standard deviation, and Sharpe ratio for the alpha-sorted portfolio. Benchmark specifications include CSI 300 + CSI 500, 000001.SH, 399001.SZ, and 399006.SZ. The three sub-periods are 2015–2018, 2019–2021, and 2022–2025.

Table 7. Alpha-based portfolio performance across alternative benchmark specifications and sub-periods

Model	Period	Annual mean	Annual Std	Sharpe ratio
CSI 300 + CSI 500	2015-2018	0.048	0.052	0.933
000001.SH	2015-2018	0.051	0.073	0.696
399001.SZ	2015-2018	0.049	0.078	0.636
399006.SZ	2015-2018	0.033	0.059	0.549
CSI 300 + CSI 500	2019-2021	0.059	0.085	0.691
000001.SH	2019-2021	0.059	0.087	0.681
399001.SZ	2019-2021	0.059	0.080	0.733
399006.SZ	2019-2021S	0.059	0.065	0.916
CSI 300 + CSI 500	2022-2025	-0.051	0.061	-0.836
000001.SH	2022-2025	-0.072	0.070	-1.030
399001.SZ	2022-2025	-0.040	0.059	-0.679
399006.SZ	2022-2025	-0.020	0.044	-0.453

Table 8 A. Quantile-based market-state definition

Variable	Coefficient
Constant	0.02***
	(4.37)
Ordinary	0.01***
	(5.77)
Hybrid	0.001
	(1.08)
R^2	-0.02***
	(-3.23)

Table 8 B. Crisis-month market-state definition

Variable	Coefficient
Constant	0.07***
	(5.55)
Ordinary	0.01***
	(3.54)
Hybrid	0.004
	(0.98)
R^2	-0.09***
	(-4.62)

Table 8 reports robustness regressions of fund-level downside-period alpha under alternative market-state definitions. Panel A uses quantile-based definitions of downside and upside periods, while Panel B uses crisis-month definitions. The sample includes 478 funds in Panel A and 531 funds in Panel B. Regressions include fund-type indicators and benchmark dependence proxied by R^2. Variable definitions are provided in Appendix B. Heteroskedasticity-robust t-statistics (HC1) are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

5. Table 9. family-type ranking in delta alpha is robust to quantile-based classification

Table 9 reports the regression results of fund-level delta alpha using an alternative quantile-based family classification. The sample includes 556 funds belonging to families managing at least five funds. Variable definitions are provided in Appendix B. Heteroskedasticity-robust t-statistics (HC1) are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 9. Family-type ranking in delta alpha is robust to quantile-based classification

Variable	Coefficient
Constant	0.03***
	(5.36)
Neutral family	-0.004***
	(-4.48)
Pro-cyclical	-0.01***
	(-9.15)
Log (fund size)	-0.001**
	(-2.43)
Log (fund age)	-0.01***
	(-4.98)
MDD	0.02***
	(5.58)
R^2	-0.02***
	(-4.25)

Table 10 reports the regression results of fund-level delta alpha using an alternative z-score-based family classification. The sample includes 556 funds belonging to families managing at least five funds. Variable definitions are provided in Appendix B. Heteroskedasticity-robust t-statistics (HC1) are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 10. The regression results of fund-level delta alpha using an alternative z-score-based family classification

Variable	Coefficient
Constant	0.03***
	(5.59)
Neutral family	-0.01***
	(-7.29)
Pro-cyclical	-0.01***
	(-17.70)
Log (fund size)	-0.001**
	(-2.39)
Log (fund age)	-0.01***
	(-4.95)
MDD	0.02***
	(5.55)
R^2	-0.02***
	(-4.22)