Calm Stocks, Wild Hopes: Explaining the Low volatility Anomaly in China's A-share Market through Lottery Preferences

by

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Abstract

This paper investigates the persistence and underlying mechanisms of low-volatility anomalies in China's A-share market, focusing on two manifestations: the Beta anomaly and the Idiosyncratic Volatility (IVOL) anomaly. Grounded in asset pricing theory and behavioral finance, we hypothesize that investor preferences for lottery-like stocks—characterized by extreme upside potential—distort the traditional risk-return trade-off. Using univariate portfolio analysis from 1995 to 2024, we document a consistent low-volatility anomaly: the Beta anomaly appears contemporaneous, while the IVOL anomaly predicts future returns and has strengthened over time. Notably, equal-weighted portfolios exhibit more pronounced patterns, suggesting that small-cap stocks play a central role in anomaly formation due to their speculative appeal. To explain these patterns, we apply bivariate portfolio analysis to control for lottery-related characteristics such as maximum daily return (MAX), skewness, and kurtosis. Our results show that the anomalies remain statistically significant after controlling for these higher-moment variables. Furthermore, the anomalies become more prominent within high-MAX portfolios, indicating that investor lottery preference amplifies mispricing.

Keywords: low-volatility anomaly; beta anomaly; idiosyncratic volatility; lottery preference; China A-share market.

1. Introduction

The Capital Asset Pricing Model (CAPM) posits a positive relationship between systematic risk, measured by beta, and expected returns. Similarly, standard portfolio theory suggests that idiosyncratic volatility (IVOL) should be diversifiable and thus irrelevant in pricing. However, mounting empirical evidence challenges these assumptions, revealing a class of "low-volatility anomalies" in which low-risk stocks—measured by either beta or IVOL—consistently outperform their high-risk counterparts. While these anomalies have been documented extensively in developed markets, their presence and drivers in emerging markets, particularly China, remain less understood.

The Chinese A-share market offers a distinctive setting to examine these anomalies. Characterized by a high proportion of retail investors, constraints on arbitrage, and pronounced policy influences, it creates conditions conducive to behavioral mispricing. Existing literature on developed markets such as the U.S. and Europe has demonstrated that investor preferences for stocks with lottery-like features—proxied by measures such as maximum daily returns (MAX)—can help explain the idiosyncratic volatility (IVOL) anomaly. While some studies have applied similar approaches to China, they have predominantly focused on MAX and remain relatively fragmented. This study aims to provide a more comprehensive analysis by incorporating additional proxies for lottery preferences, including skewness and kurtosis, to systematically investigate their explanatory power for the low-volatility anomaly in China's A-share market over the past three decades. These speculative biases may lead to systematic overvaluation of high-risk stocks and persistent underperformance relative to their low-risk counterparts.

This study investigates the role of such behavioral forces in shaping the Beta and IVOL anomalies in China’s A-share market from 1995 to 2024. We hypothesize that stocks with high lottery-like characteristics attract disproportionate investor demand, leading to persistent mispricing. We employ univariate and bivariate portfolio analyses to test this hypothesis, conditioning traditional risk measures on higher-order moments, including maximum return (MAX), co-skewness, and kurtosis. Our methodology distinguishes between mechanical effects, such as the inflation of realized volatility by rare return spikes, and genuine pricing inefficiencies stemming from investor sentiment.

This paper makes four key contributions to the literature on low-volatility anomalies. First, we distinguish between contemporaneous and lead returns when assessing anomaly strength, revealing that the Beta anomaly tends to be contemporaneous while the IVOL anomaly possesses predictive power for future returns. Second, we jointly analyze Beta and IVOL rather than treating them as separate anomalies, allowing for a more integrated understanding of how different forms of volatility influence expected returns. Third, we explore the time-varying nature of these anomalies over a three-decade span (1995–2024), uncovering how their strength and patterns evolve across different market regimes. Finally, we systematically incorporate higher-moment proxies for lottery preference—namely, maximum daily return (MAX), skewness, and kurtosis—rather than focusing solely on MAX as in prior studies. This enables us to more rigorously evaluate the behavioral mechanisms underpinning the anomalies.

Our empirical analysis yields several important findings. First, we confirm the presence of a robust low-volatility anomaly in China's A-share market: low-beta stocks outperform high-beta ones in terms of contemporaneous returns, while low-IVOL stocks predict higher future returns. These patterns are particularly evident in equal-weighted portfolios, indicating that smaller firms, more susceptible to speculation, play a central role in anomaly formation. Second, we observe a strengthening trend in the IVOL anomaly over time, highlighting its growing relevance in the Chinese market. Third, we find that both the Beta and IVOL anomalies remain statistically significant even after controlling for lottery-like features. Interestingly, their magnitudes increase within high-MAX portfolios, suggesting that speculative demand amplifies pricing inefficiencies. These findings point to the persistent influence of behavioral biases and structural frictions in China's retail-dominated equity market and offer new insights into the mechanisms sustaining return anomalies in emerging markets.

2. Literature Review:

2.1 Beta Anomaly

The Capital Asset Pricing Model (CAPM), pioneered by Sharpe (1964), Lintner (1965), and Mossin (1966), establishes a fundamental relationship between an asset's systematic risk, measured by beta, and its expected return. In this framework, higher-beta assets are expected to yield higher returns as compensation for increased market risk exposure. However, subsequent empirical findings began to challenge this positive beta-return relationship. Black (1972) suggested that when investors face borrowing constraints and cannot leverage low-beta positions, the Security Market Line flattens, leading to an underpricing of low-beta assets and potential excess returns. Haugen and Heins (1975) provided some of the earliest empirical evidence that contradicted CAPM by showing that low-beta stocks actually outperform their high-beta counterparts on a risk-adjusted basis.

The literature has since evolved to explore both institutional and behavioral explanations. Frazzini and Pedersen (2014) developed the "Betting Against Beta" (BAB) model, which shows that leverage constraints can lead investors to tilt toward high-beta stocks, driving up their prices and lowering future returns. Baker et al. (2011) argue that institutional mandates and benchmarking practices discourage arbitrage activity that could correct such mispricing.

More recently, behavioral explanations have emerged. Bali et al. (2017) propose that the beta anomaly aligns with investors' lottery preferences—tendencies to favor assets with the potential for large, albeit rare, gains. High-beta stocks often exhibit such payoff structures and may become overvalued due to speculative demand. Empirical evidence from Hong and Sraer (2016) further supports this view, showing that high-beta stocks are particularly prone to speculative overpricing.

Early empirical research found no significant relationship between beta and expected returns in the Chinese market. For instance, studies using data from 1994 to 2002 and 1994 to 2005 observed that beta had little explanatory power relative to the market premium. Zhao and Lin (2021) provide evidence that the beta anomaly in China is largely behavior-driven, specifically by lottery demand and investors' overreaction to idiosyncratic risk. Han et al. (2019) demonstrate that overconfidence among Chinese retail investors flattens the Security Market Line (SML), making high-beta stocks overpriced relative to low-beta ones. Research also indicates that the anomaly fluctuates with market liquidity and anchoring behaviors tied to 52-week highs (Chen et al., 2025; Wang et al., 2023).

2.2 IVOL Anomaly

Another challenge to traditional asset pricing theory stems from the relationship between idiosyncratic volatility (IVOL) and expected returns. Merton (1987) postulated that under market segmentation and incomplete information, investors may accept undiversified portfolios, possibly giving rise to a positive IVOL-return relationship. Barberis and Huang (2001) also predicted that high-IVOL stocks may offer higher expected returns due to behavioral reasons, including mental accounting and loss aversion. However, Ang et al. (2006) documented the opposite—a negative and significant relationship between IVOL and future returns in U.S. markets, a phenomenon now known as the IVOL anomaly. Bali et al.

(2011) further investigated this anomaly and found that the MAX effect, defined as the maximum daily return in a month, captures speculative behavior and subsumes the IVOL anomaly in the U.S. context.

Yet, global evidence on the substitutability of MAX and IVOL is mixed. Annaert et al. (2013) and Walkshäusl (2014) confirm the MAX-IVOL relationship in European markets, though the strength varies across countries. In contrast, Chinese markets show a more complex dynamic. Studies spanning 1994–2014 indicate that both MAX and IVOL effects persist independently. Research by Gou and Bie (2016) and Bi et al. (2022) reveals that Chinese investors exhibit strong preferences for lottery-like stocks, resulting in a pronounced MAX effect. However, this effect does not diminish the IVOL anomaly. Instead, Yao et al. (2019) and Cui et al. (2020) suggest that the IVOL effect remains significant even after controlling for MAX, pointing to deeper structural causes such as limits to arbitrage.

Indeed, several studies emphasize institutional constraints in China as crucial to the persistence of the IVOL anomaly. From 2002–2012, empirical work using limit-of-arbitrage indices (based on price limits, short-sale constraints, liquidity, and analyst coverage) shows that stocks with higher IVOL tend to have lower returns, and this effect strengthens when arbitrage activity is more restricted. Other studies find that the anomaly is amplified in low-turnover and low-liquidity environments, characteristic of China's retail-heavy equity markets. Moreover, some researchers argue that the IVOL anomaly in China may be more than just behavior-driven, reflecting structural frictions unique to emerging markets.

2.3 Chinese Literature

Collectively, the Chinese literature offers nuanced insights into the dynamics of beta, IVOL, and lottery preferences in an emerging market setting. The beta anomaly appears inconsistently over time, with strong effects during periods of elevated speculative activity.

Studies from 2000–2019 highlight that this anomaly is often rooted in behavioral biases like overconfidence and gambling preference. Recent works also show that beta anomaly strength is modulated by anchoring effects (e.g., proximity to 52-week highs), investor sentiment, and institutional changes.

The IVOL anomaly is more robust and stable across time. Studies from 1994–2014 confirm a strong negative correlation between idiosyncratic volatility and future returns. Unlike in the U.S., where the MAX effect can subsume IVOL, in China, the two effects coexist independently. Researchers emphasize the critical role of arbitrage constraints and institutional frictions in sustaining this pricing inefficiency. Notably, IVOL remains a significant predictor of future returns even after adjusting for turnover, analyst coverage, and liquidity proxies.

Finally, research on skewness (particularly idiosyncratic skewness or ISKEW) adds further behavioral dimensions to the Chinese context. Empirical results from 1997–2016 reveal a significant negative correlation between ISKEW and expected returns, reinforcing the hypothesis that investors systematically overvalue stocks with the potential for extreme positive payoffs. These findings underscore the persistent influence of speculative behavior in China’s retail-driven equity market and point to deep-seated behavioral and structural sources for the persistence of low-volatility anomalies.

3. Hypothesis: Lottery Preferences and the Mispricing of Risk

Building on the literature reviewed above, this study posits that the low-volatility anomaly, both in its Beta and IVOL manifestations, can be partially explained by the mispricing of stocks with lottery-like characteristics. The core hypothesis is that investor preferences for stocks with extreme but rare positive outcomes (i.e., lottery features) lead to persistent deviations from risk-return tradeoffs predicted by traditional asset pricing models.

Specifically, stocks exhibiting characteristics such as high MAX (maximum daily return in a month), high idiosyncratic volatility, extreme skewness (positive or negative), and high kurtosis tend to be overvalued due to speculative investor demand. These preferences are particularly pronounced in markets like China, where retail investor dominance and limited institutional arbitrage mechanisms create fertile ground for behavioral biases. Investors attracted to such stocks often neglect fundamental risk considerations in favor of potential windfall gains, leading to overpricing in the short term and underperformance in the long run.

In the context of the Beta anomaly, this hypothesis suggests that high-beta stocks—often more volatile and news-sensitive—also tend to exhibit lottery-like payoffs. These stocks may be disproportionately favored by investors seeking thrill or outsized returns, resulting in demand-driven overpricing. Conversely, low-beta stocks are typically more stable and offer modest but consistent returns, making them less attractive to speculative investors but potentially undervalued from a fundamental perspective.

Regarding the IVOL anomaly, the hypothesis implies a more direct link between mispricing and speculative demand. High-IVOL stocks inherently exhibit greater price dispersion and thus present more opportunities for extreme daily returns. When investors overestimate the likelihood or repeatability of such spikes, they bid up the prices of these stocks beyond what is justified by their fundamentals. The resulting disconnect leads to a negative relationship between idiosyncratic risk and expected returns.

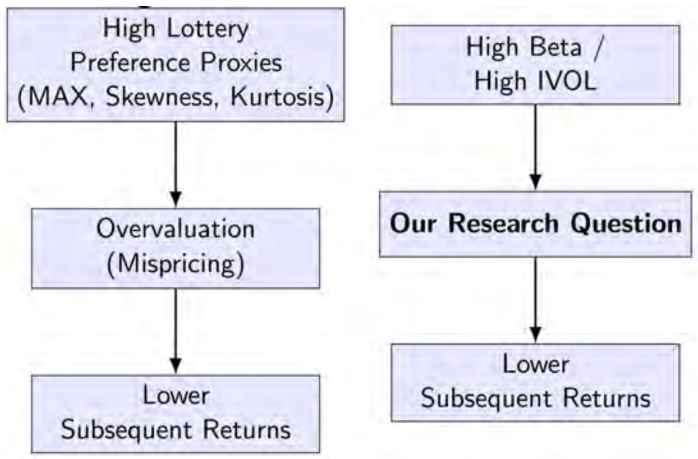

Figure 1. Lottery Preference Argument and Low Vol Anomaly

This hypothesis guides the empirical design that follows, where we analyze the pricing of risk under different levels of lottery preferences and examine how controlling for these features affects the strength and persistence of Beta and IVOL anomalies.

4. Methodology and Data:

4.1 Methodology

The empirical methodology builds on widely accepted practices in asset pricing research as outlined in *Empirical Asset Pricing: The Cross Section of Stock Returns*.

This study aims to empirically investigate two central research questions:

(1) What is the empirical pattern of the low-volatility anomaly in China's A-share market (1995–2024)?

(2) What explains the anomaly? Can it be attributed to lottery preferences?

To address the first question, we employ univariate portfolio analysis. Our dataset, sourced from the WIND Financial Terminal, includes monthly observations of key variables such as volatility measures, return variables, and lottery preference proxies. For each volatility metric

(Beta and Idiosyncratic Volatility, IVOL), we follow a standard portfolio construction process.

Within a selected analysis period, we sort all eligible stocks each month into quintiles (five groups) based on the volatility variable under investigation. This sorting is done cross-sectionally at a monthly frequency. For each quintile group, we calculate the monthly portfolio returns using both equal-weighted and value-weighted methods, allowing us to assess whether firm size affects the presence or magnitude of the low-volatility anomaly. We then compute the average return of each quintile over the full time window and evaluate its statistical significance using Newey-West adjusted t-statistics to account for autocorrelation and heteroskedasticity.

To test the anomaly more directly, we construct a Low Minus High (LMH) portfolio by subtracting the return of the highest-risk quintile (Quintile 5) from that of the lowest-risk quintile (Quintile 1) in each month. This yields a time series of LMH returns, whose average and t-statistics we use to determine the anomaly's existence and strength. Importantly, we compute returns using both contemporaneous monthly returns and lead 1-month returns to differentiate whether the anomaly is more reflective of current mispricing or predictive power.

We further examine the robustness of the anomaly across different time periods. In addition to the full sample from January 1995 to September 2024, we replicate our analysis over sub-periods used in prior studies (e.g., 1994–2002, 1996–2016, and 2000–2019), confirming the stability of our findings. Finally, to capture the evolution of the anomaly over time, we adopt a rolling five-year window approach. By shifting the analysis window forward one month at a time, we obtain a time series of rolling LMH returns, which allows us to assess temporal trends in the low-volatility effect.

To address the second research question—whether lottery preferences can explain the anomaly—we conduct a bivariate portfolio analysis. Here, we double-sort stocks first by lottery preference proxies—MAX (maximum daily return), skewness, and kurtosis—into five groups. Within each lottery quintile, we further sort stocks by volatility measures (Beta or IVOL), again into quintiles, yielding a total of 25 portfolios per double sort. Portfolio returns are calculated in the same manner as in the univariate analysis.

By examining LMH returns within each lottery-sorted group, we can assess whether the low-volatility anomaly persists after controlling for speculative characteristics. This approach allows us to separate pricing effects due to volatility from those due to investor preference for lottery-like payoffs. If the anomaly weakens or disappears in low-lottery groups but strengthens in high-lottery groups, it would support the behavioral explanation rooted in investor sentiment and preference distortions.

All bivariate analyses are conducted over the full 30-year sample period (1995–2024/09), given the increased complexity and reduced cross-sectional sample size of double sorting.

4.2 Data and Summary of Statistics

This study utilizes stock-level data for the Chinese A-share market from January 1, 1995, to September 30, 2024, sourced from the Wind Financial Terminal. The dataset covers 5,365 stocks listed on the Shanghai and Shenzhen Stock Exchanges. To ensure data reliability and relevance, stocks from the financial and banking sectors were excluded due to their unique capital structures and regulatory constraints. Additionally, stocks listed for less than one year as of 2024 were removed to avoid distortions caused by IPO anomalies. For the remaining stocks, daily closing prices were obtained, and daily simple returns were calculated as the percentage change in prices, providing the foundational dataset for further analysis.

The study focuses on calculating beta, idiosyncratic volatility (IVOL), and higher-order moments such as skewness and kurtosis. Beta is estimated using the CAPM framework, employing rolling windows of one year and one month to compute betas over different horizons. Alternative beta calculations, such as the method proposed by Frazzini and Pedersen (2014), which integrates correlation and the ratio of individual to market standard deviations, will be incorporated for robustness later. Residuals from both the CAPM and Fama-French three-factor models are extracted to estimate IVOL and higher-order moments. The three factors—market return, size, and value—are constructed following standard Fama-French methodologies and are sourced from established databases such as factorwar.com. These residuals form the basis for measuring idiosyncratic risks and distributional characteristics of stock returns, including skewness, kurtosis, and co-skewness.

The figure below presents a Pearson correlation heatmap for the key variables used in this study, including Total Skewness, Co-skewness, Idiosyncratic Skewness, Total Volatility, Beta, IVOL, and higher-moment lottery proxies such as MAX and Kurtosis.

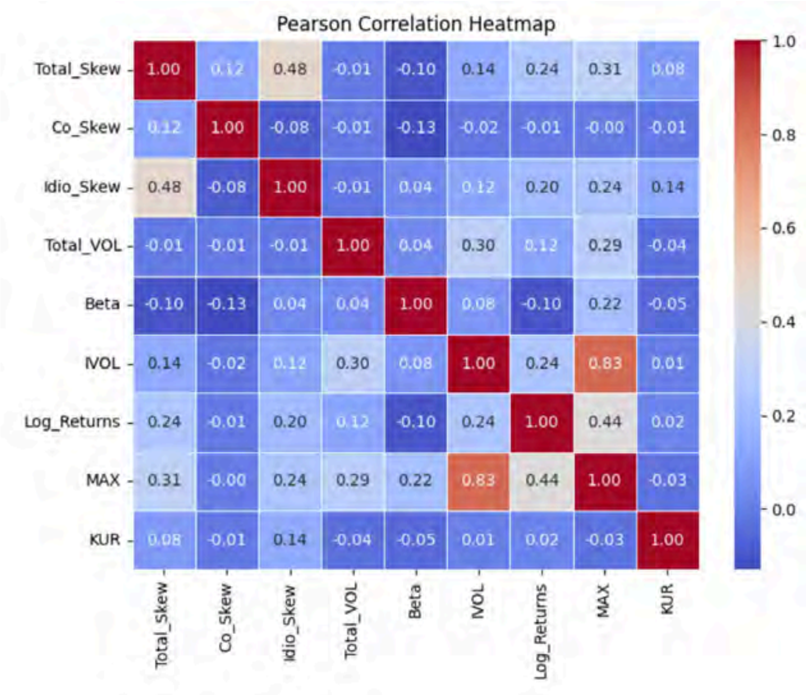

Figure 2. Pearson Correlation Heatmap for Core Variables

The correlation matrix reveals several important insights that guide our subsequent empirical analysis. First, IVOL is highly correlated with MAX (0.83), indicating that stocks with higher idiosyncratic volatility tend to experience more extreme daily returns. This supports the idea that IVOL and MAX may capture overlapping dimensions of speculative behavior, though they are conceptually distinct. Interestingly, both variables also show moderate correlations with log returns (0.24 and 0.44, respectively), suggesting that investors may indeed reward such characteristics in the short term, albeit inconsistently.

Idiosyncratic skewness (ISKEW) shows a moderately positive correlation with MAX (0.24). In contrast, total skewness is even more strongly correlated (0.31), which implies that stocks with more positively skewed returns also tend to experience large single-day price jumps. These interrelations further substantiate the importance of lottery-like characteristics in shaping investor behavior.

5. Results

5.1 Low Vol Examination

5.1.1 Full-Sample Evidence: 1995–2024

We begin our empirical analysis by examining the low-volatility anomaly over the full sample period from January 1995 to September 2024. Figure 3 reports the results of univariate portfolio sorts based on idiosyncratic volatility (IVOL) and beta, using both contemporaneous (same-period) and 1-month lead returns. We present both equal-weighted and value-weighted returns, with statistical significance assessed using Newey-West adjusted t-statistics.

The same-period IVOL sort yields a striking result: portfolio returns increase monotonically with IVOL. In the equal-weighted case, IVOL1 (the lowest-IVOL group) delivers −26.19% ($t = -6.43$) annually, while IVOL5 earns +67.20% ($t = 7.23$). The Low Minus High (LMH) portfolio produces a significantly negative return of −93.39% ($t = -14.18$). This pattern is also observed in value-weighted portfolios, though slightly weaker in magnitude, with LMH return of −86.49% ($t = -11.19$).

At first glance, this upward-sloping IVOL-return relationship appears to contradict the widely documented negative IVOL anomaly, which posits that higher idiosyncratic volatility predicts lower returns. However, this apparent contradiction can be explained by a mechanical statistical effect rather than true mispricing. As shown in our correlation heatmap (Figure 2), IVOL and MAX (maximum daily return) are highly correlated ($\rho = 0.83$). Since MAX itself is positively related to returns ($\rho = 0.44$), the observed positive association between IVOL and same-period returns is likely driven by the fact that IVOL proxies for rare return spikes captured by MAX.

This suggests that the contemporaneous IVOL-return relation is spurious—not a genuine anomaly but an artifact of return calculation mechanics. High-IVOL portfolios tend to contain more stocks that experience extreme daily gains (i.e., high MAX), inflating their realized returns. Therefore, we hypothesize that once MAX is controlled for, this reversed IVOL pattern should disappear or flatten, supporting the view that IVOL should theoretically be diversifiable and hence unpriced.

When we shift to the 1-month lead return sort, the relationship reverses: IVOL1 portfolios significantly outperform IVOL5, with LMH equal-weighted return of +21.62% (t = 8.47). The value-weighted LMH portfolio also earns +15.79% (t = 4.89). These results indicate a true IVOL anomaly, whereby stocks with higher past idiosyncratic volatility underperform in subsequent periods.

The beta-based portfolios reveal a complementary but distinct pattern. In the same-period sort, low-beta stocks outperform high-beta ones. Equal-weighted returns decline from +31.99% (Beta1, t = 5.81) to +3.63% (Beta5, t = 0.47), yielding an LMH return of +28.36% (t = 6.98). The value-weighted LMH return is +16.09% (t = 2.96). However, in the lead-return sort, the beta anomaly weakens considerably. LMH returns become insignificant, suggesting that the beta anomaly is primarily contemporaneous and lacks predictive power.

The full-sample evidence affirms the existence of low-volatility anomalies in China's A-share market, though their nature differs by measure. The IVOL anomaly is largely predictive, showing strong performance in lead returns, while its contemporaneous reversal is driven by MAX-induced mechanical effects. The beta anomaly, by contrast, appears contemporaneous and more muted in predictive contexts. These results underscore the importance of separating true pricing inefficiencies from statistical artifacts, and they motivate our further bivariate analysis in Section 5.3, where we control for MAX and other lottery proxies.

Same Period Sorted by **IVOL**(1995-2024)

Portfolio	Return	t
Equal-weighted		
IVOL1	-26.19%***	-6.43
IVOL2	-20.55%***	-3.84
IVOL3	-6.27%	-1.06
IVOL4	14.01%*	2.04
IVOL5	67.20%***	7.23
LMH	-93.39%***	-14.18
Value-weighted		
IVOL1	-18.50%***	-4.56
IVOL2	-8.60%*	-1.72
IVOL3	6.77%	1.16
IVOL4	25.09%***	3.67
IVOL5	68.00%***	6.97
LMH	-86.49%***	-11.19

1 Month Lead Sorted by **IVOL**(1995-2024)

Portfolio	Return	t
Equal-weighted		
IVOL1	13.74%*	2.46
IVOL2	12.60%*	2.10
IVOL3	9.03%	1.46
IVOL4	4.06%	0.65
IVOL5	-7.88%	-1.25
LMH	21.62%***	8.47
Value-weighted		
IVOL1	7.00%	1.35
IVOL2	7.66%	1.34
IVOL3	4.63%	0.79
IVOL4	1.67%	0.27
IVOL5	-8.80%	-1.41
LMH	15.79%***	4.89

Same Period Sorted by **Beta**(1995-2024)

Portfolio	Return	t
Equal-weighted		
Beta1	31.99%***	5.81
Beta2	6.52%	1.16
Beta3	-4.82%	-0.82
Beta4	-9.02%	-1.42
Beta5	3.63%	0.47
LMH	28.36%***	6.98
Value-weighted		
Beta1	26.51%***	4.43
Beta2	4.48%	0.90
Beta3	-3.35%	-0.57
Beta4	-6.46%	-1.01
Beta5	10.42%	1.26
LMH	16.09%**	2.96

1 Month Lead Sorted by **Beta**(1995-2024)

Portfolio	Return	t
Equal-weighted		
Beta1	2.91%	0.50
Beta2	6.48%	1.10
Beta3	7.74%	1.29
Beta4	8.42%	1.36
Beta5	6.14%	0.95
LMH	-3.24%	-1.36
Value-weighted		
Beta1	1.69%	0.31
Beta2	5.07%	0.94
Beta3	5.56%	0.97
Beta4	4.15%	0.70
Beta5	4.74%	0.76
LMH	-3.05%	-0.93

Figure 3. Univariate Portfolio Analysis 1995 - 2024

5.1.2 Sub-Sample Evidence: Robustness Test

To assess the robustness of the low-volatility anomalies documented in the full-sample analysis, we conduct univariate portfolio sorts over five subsample periods frequently adopted in prior literature: 1994–2002, 1994–2005, 1994–2011, 1996–2016, and 2002–2012. These periods are aligned with studies such as Wang and Di Iorio (2007), Han et al. (2019), Nartea et al. (2013), Gu et al. (2018), and others. This section serves two purposes: (1) to test whether the anomaly patterns hold across different market regimes, and (2) to compare our results with the empirical conclusions of prior research.

A. Idiosyncratic Volatility (IVOL) Anomaly: Consistent Predictive Power

Figures 4 and 5 present equal-weighted and value-weighted portfolio returns sorted by IVOL quintiles, using 1-month lead returns. Across all three subsample periods—1994–2011, 1994–2005, and 2002–2012—we observe clear, monotonic patterns: average returns decline as IVOL increases. The LMH (Low Minus High) portfolio yields economically large and statistically significant positive returns in all cases:

Equal-weighted LMH:

-1994–2011: 18.94% (t = 5.66)

-1994–2005: 26.77% (t = 7.96)

-2002–2012: 26.77% (t = 7.96)

Value-weighted LMH:

-1994–2011: 11.99% (t = 3.01)

-1994–2005: 8.65% (t = 1.98)

-2002–2012: 17.71% (t = 3.83)

These results strongly confirm the predictive nature of the IVOL anomaly across different decades and weighting schemes. The magnitude and persistence of the LMH returns suggest that high-IVOL stocks are systematically overvalued and underperform in subsequent months, consistent with the notion that speculative demand inflates their prices.

Importantly, our findings align with and expand upon prior work. For example, Nartea et al. (2013) (1994–2011) also found a significant negative IVOL-return relationship in China. The 1994–2005 Chinese-language study echoed this conclusion and attributed it to excessive trading by retail investors and the absence of short-selling mechanisms. Gu et al. (2018) (2002–2012) further demonstrated that the IVOL anomaly strengthens under limits to arbitrage, such as price limits, low liquidity, and limited analyst coverage—all of which characterize the Chinese market.

Taken together, our results support the behavioral explanation of the IVOL anomaly and confirm its temporal robustness. In contrast to the beta anomaly, the IVOL anomaly is not only statistically significant but also consistent in direction and magnitude.

Portfolio	1994–2002	1996–2016
Beta1	10.16% (0.92)	8.73% (1.14)
Beta2	8.95% (0.86)	10.25% (1.29)
Beta3	10.25% (0.97)	12.08% (1.49)
Beta4	11.10% (1.08)	13.52% (1.65)
Beta5	11.30% (1.07)	11.30% (1.35)
LMH	-1.14% (-0.23)	-2.57% (-0.88)

Portfolio	1994–2011	1994–2005	2002–2012
IVOL1	15.43% (1.82)	16.34% (1.45)	16.34% (1.45)
IVOL2	13.73% (1.49)	11.53% (0.94)	11.53% (0.94)
IVOL3	10.34% (1.09)	7.18% (0.58)	7.18% (0.58)
IVOL4	6.38% (0.68)	2.66% (0.21)	2.66% (0.21)
IVOL5	-3.51% (-0.38)	-10.43% (-0.86)	-10.43% (-0.86)
LMH	18.94% (5.66)	26.77% (7.96)	26.77% (7.96)

Figure 4. Sub-Sample Univariate Portfolio Analysis, 1 Month Lead Sorted by **IVOL** and **Beta**, Equal Weighted Portfolio

Portfolio	1994–2002	1996–2016
Beta1	5.30% (0.45)	3.37% (0.45)
Beta2	6.02% (0.55)	8.02% (1.09)
Beta3	7.91% (0.73)	9.20% (1.17)
Beta4	7.92% (0.75)	8.02% (1.00)
Beta5	10.05% (0.89)	8.59% (1.04)
LMH	-4.75% (-0.91)	-5.22% (-1.36)

Portfolio	1994–2011	1994–2005	2002–2012
IVOL1	6.73% (0.81)	2.04% (0.25)	6.53% (0.62)
IVOL2	10.39% (1.16)	5.90% (0.69)	7.61% (0.66)
IVOL3	5.84% (0.63)	3.01% (0.34)	3.18% (0.27)
IVOL4	5.74% (0.61)	2.30% (0.24)	1.85% (0.16)
IVOL5	-5.27% (-0.57)	-6.61% (-0.72)	-11.17% (-0.95)
LMH	11.99% (3.01)	8.65% (1.98)	17.71% (3.83)

Figure 5. Sub-Sample Univariate Portfolio Analysis, 1 Month Lead Sorted by **IVOL** and **Beta**, Value Weighted Portfolio

B. Beta Anomaly: Episodic and Mostly Contemporaneous

The patterns for beta-sorted portfolios are less stable. In Figure 4 (equal-weighted lead returns) and Figure 5 (value-weighted lead returns), the LMH returns are small and statistically insignificant in all subsample periods:

Equal-weighted LMH (lead):

-1994–2002: −1.14% (t = −0.23)

-1996–2016: −2.57% (t = −0.88)

Value-weighted LMH (lead):

-1994–2002: −4.75% (t = −0.91)

-1996–2016: −5.22% (t = −1.36)

These results indicate that beta has limited predictive power for future returns, reaffirming our full-sample conclusion. The weak beta anomaly in lead returns corroborates early empirical findings in Wang and Di Iorio (2007) and Han et al. (2019), both of which observed that beta alone could not explain the cross-section of expected returns in China.

However, the picture changes when we consider same-period returns, as shown in Figure 6. In this setting, equal-weighted LMH portfolios show sizable returns:

Equal-weighted LMH (same-period):

-1994–2002: 12.65% (t = 1.35)

-1996–2016: 33.31% (t = 6.72)

Value-weighted LMH (same-period):

-1994–2002: 4.20% (t = 0.38)

-1996–2016: 22.70% (t = 3.29)

This suggests that the beta anomaly in China is primarily contemporaneous. These results echo Han et al. (2019), who found that overconfident investor behavior flattens the Security Market Line in China, leading to temporary mispricing of high-beta stocks.

Interestingly, the anomaly is far more pronounced under equal-weighting, indicating that smaller-cap stocks are more affected by speculative trading and retail flows.

2*Portfolio	Equal-weighted 1994–2002	Equal-weighted 1996–2016	Value-weighted 1994–2002	Value-weighted 1996–2016
Beta1	27.48% (2.78)	38.81% (5.39)	26.58% (2.55)	33.65% (4.15)
Beta2	4.30% (0.49)	13.85% (1.86)	3.90% (0.41)	8.74% (1.31)
Beta3	-1.32% (-0.14)	0.96% (0.12)	1.28% (0.12)	-0.75% (-0.09)
Beta4	0.20% (0.02)	-4.33% (-0.51)	0.02% (0.00)	-4.64% (-0.54)
Beta5	14.83% (0.97)	5.50% (0.54)	22.38% (1.28)	10.95% (0.99)
LMH	12.65% (1.35)	33.31% (6.72)	4.20% (0.38)	22.70% (3.29)

Figure 6. Sub-Sample Univariate Portfolio Analysis, Same Period Sorted by **Beta**, Equal and Value Weighted Portfolio

5.1.3 LMH Time Series and Low Vol Pattern over time

To explore how the low-volatility anomaly evolves over time, we implement a rolling-window approach to construct monthly LMH (Low Minus High) return series. Specifically, we use a 5-year rolling window that shifts forward by one month at a time, calculating LMH returns for each window based on univariate portfolio sorts by Beta and IVOL. This approach allows us to observe whether the anomaly identified in previous sections holds persistently across different market regimes or fluctuates over time. A significantly positive LMH return indicates the presence of a low-volatility anomaly during that subperiod.

Across Figures 7–14, we find that the previously documented low-volatility anomalies are broadly robust over time. Although the magnitude and statistical significance of LMH returns vary by weighting method and volatility measure, the general direction of the anomaly—low-risk portfolios outperforming high-risk portfolios—persists throughout most subperiods. This time-series validation complements our full-sample and sub-sample evidence, further reinforcing the anomaly's empirical relevance.

A. IVOL Anomaly: Strengthening and Consistent

Figures 9 and 10 depict the rolling LMH returns sorted by IVOL using 1-month lead returns. The equal-weighted LMH series (Figure 9) shows a clear upward trend over the past two decades, with consistently positive and mostly significant LMH values. This indicates that the

IVOL anomaly has not only persisted but has grown stronger over time. The anomaly appears particularly pronounced after 2004 and has maintained significance throughout the 2010s and early 2020s.

In the value-weighted series (Figure 10), while the IVOL anomaly remains positive, several subperiods exhibit insignificance (highlighted by red dots). This contrast suggests that the anomaly is more concentrated in smaller-cap stocks, consistent with the view that speculative demand and mispricing are more prevalent among less liquid and retail-dominated firms. These findings support our full-sample conclusion that IVOL anomaly is predictive and behaviorally driven. More importantly, the strengthening time trend observed in the equal-weighted LMH series highlights that investor mispricing based on idiosyncratic volatility has become increasingly salient in recent years.

Figure 7. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Same Period** Sorted by **IVOL**, **Equal Weighted** Portfolio

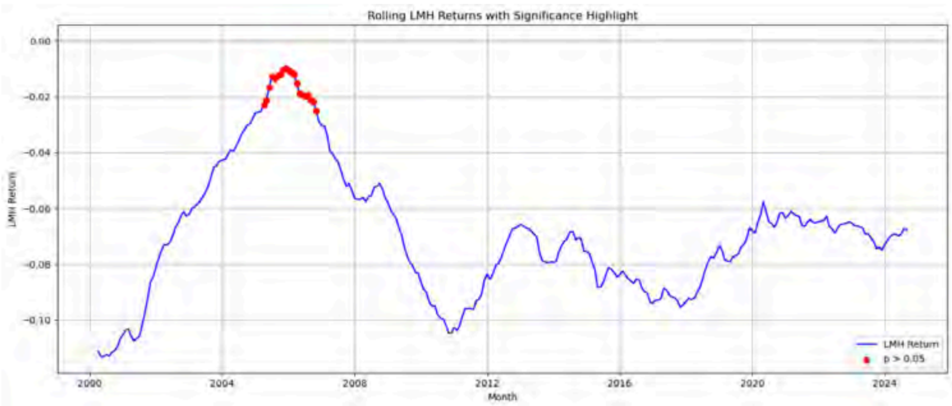

Figure 8. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Same Period** Sorted by **Beta**, **Value Weighted** Portfolio

Figure 9. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Lead 1 Month** Sorted by **IVOL**, **Equal Weighted** Portfolio

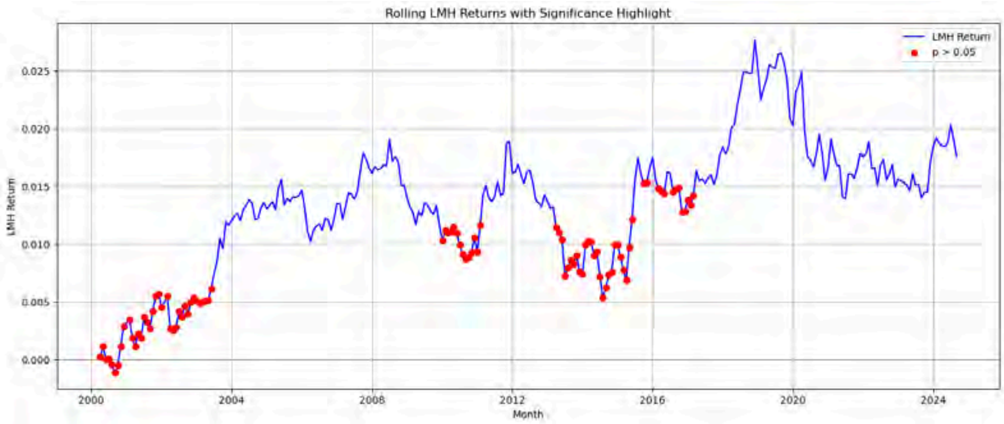

Figure 10. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Lead 1 Month** Sorted by **IVOL**, **Value Weighted** Portfolio

B. Beta Anomaly: Contemporaneous and Episodic

Figures 11 and 12 present rolling LMH returns based on same-period returns sorted by Beta. The equal-weighted LMH series (Figure 11) shows significant anomaly strength during the mid-2000s to early 2010s, peaking around 2011, after which the anomaly sharply declines. The value-weighted series (Figure 12) confirms this time pattern, though it displays greater volatility and more frequent insignificance in the later years.

These results reinforce our earlier interpretation that the beta anomaly is largely contemporaneous and sensitive to time-varying investor sentiment. Its significance peaks during periods of heightened market speculation and retail dominance, such as the mid-2000s, but fades in more institutionally stabilized market phases.

Figure 11. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Same Period** Sorted by **Beta**, **Equal Weighted** Portfolio

Figure 12. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Same Period** Sorted by **Beta**, **Value Weighted** Portfolio

Figure 13. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Lead 1 Month** Sorted by **Beta**, **Equal Weighted** Portfolio

Figure 14. LMH Monthly Time Series from Rolling 5-year Window Univariate Portfolio Analysis, **Lead 1 Month** Sorted by **Beta**, **Value Weighted** Portfolio

C. Size Effects and Weighting Sensitivity

A consistent theme across all rolling figures is the difference in anomaly strength between equal-weighted and value-weighted portfolios. For both Beta and IVOL sorts, the anomalies are more pronounced and statistically significant under equal weighting, whereas value-weighted results show more volatility and periods of insignificance. This divergence implies that small-cap stocks, which receive more weight under equal-weighting, are the primary drivers of low-volatility anomalies in China's A-share market.

5.2 Bivariate Portfolio Analysis, Controlling Lottery Preference Proxy Variables

To further investigate the behavioral underpinnings of the low-volatility anomaly, we implement bivariate portfolio analysis to control for investor preference for lottery-like stocks. Specifically, we use double sorting: in each month, stocks are first sorted into quintiles based on a lottery preference proxy, such as MAX (maximum daily return), kurtosis, total skewness, co-skewness, or idiosyncratic skewness. Within each lottery quintile, stocks are then sorted again into quintiles based on their volatility—either beta or idiosyncratic volatility (IVOL). This approach enables us to observe whether the low-volatility anomaly remains significant after controlling for speculative demand for lottery-like characteristics.

Among these lottery proxies, kurtosis—the fourth central moment of a return distribution—measures the extent of tail risk or the likelihood of extreme return realizations. Stocks with high kurtosis are more likely to deliver very large or very small returns, thus embodying the “lottery” payoff profile that attracts retail investors. Similarly, MAX, the maximum daily return within a month, is a widely used and intuitive proxy for extreme upside potential, capturing investors' attention toward unusually positive single-day spikes.

We begin with the same-period double sort by MAX and IVOL, shown in Figure 15. This table reveals a key pattern that supports the mechanical inflation hypothesis discussed in Section 5.1.1. In low-MAX groups (MAX1 to MAX4), the LMH portfolio yields significantly positive returns, especially in equal-weighted portfolios (e.g., LMH = 0.0762, t = 14.59 in MAX1). However, in the highest lottery group (MAX5), LMH becomes significantly negative (equal-weighted LMH = −0.0640, t = −12.48; value-weighted LMH = −0.0551, t = −9.97).

This stark reversal suggests that the positive same-period IVOL anomaly seen in the full sample is likely not a true pricing anomaly, but rather mechanically driven by extreme return spikes—i.e., MAX. Once MAX is held constant, the same-period IVOL anomaly reverts to its expected negative direction, affirming our earlier argument that this anomaly lacks economic substance and is likely inflated by the co-movement between IVOL and MAX.

	MAX1	MAX2	MAX3	MAX4	MAX5
Panel A: Equal-weighted					
IVOL1	-0.0167 (-7.38)	-0.0168 (-3.77)	-0.0017 (-0.35)	0.0238 (4.24)	0.0720 (10.25)
IVOL2	-0.0303 (-8.86)	-0.0180 (-4.01)	-0.0005 (-0.11)	0.0276 (4.95)	0.0784 (11.21)
IVOL3	-0.0362 (-9.91)	-0.0196 (-4.32)	-0.0006 (-0.12)	0.0280 (4.89)	0.0833 (11.11)
IVOL4	-0.0469 (-11.34)	-0.0275 (-5.68)	-0.0108 (-2.15)	0.0202 (3.43)	0.0933 (11.89)
IVOL5	-0.0929 (-17.17)	-0.0662 (-10.93)	-0.0466 (-7.87)	-0.0143 (-2.11)	0.1360 (13.60)
LMH	**0.0762 (14.59)**	**0.0494 (13.27)**	**0.0449 (11.80)**	**0.0381 (9.28)**	**-0.0640 (-12.48)**
Panel B: Value-weighted					
IVOL1	-0.0202 (-6.66)	-0.0090 (-2.26)	0.0068 (1.52)	0.0369 (6.65)	0.0824 (11.64)
IVOL2	-0.0251 (-8.02)	-0.0114 (-2.79)	0.0078 (1.67)	0.0372 (6.87)	0.0876 (12.33)
IVOL3	-0.0334 (-10.62)	-0.0132 (-3.23)	0.0053 (1.16)	0.0339 (6.11)	0.0919 (12.31)
IVOL4	-0.0451 (-12.17)	-0.0261 (-5.70)	-0.0067 (-1.37)	0.0238 (4.06)	0.1008 (12.50)
IVOL5	-0.0914 (-18.24)	-0.0667 (-12.28)	-0.0455 (-8.11)	-0.0145 (-2.19)	0.1375 (13.52)
LMH	**0.0712 (10.97)**	**0.0577 (14.10)**	**0.0523 (12.22)**	**0.0514 (11.22)**	**-0.0551 (-9.97)**

Figure 15. Bivariate Portfolio Analysis, **Same Period** Double Sorted by **MAX** and **IVOL**

In contrast, when we examine lead 1-month returns sorted by IVOL within MAX groups (Figure 16), the IVOL anomaly remains not only significant but also becomes increasingly stronger across MAX quintiles. In the equal-weighted portfolio, LMH rises from 0.0045 (t = 1.62) in MAX1 to 0.0217 (t = 11.00) in MAX5. A similar pattern appears in the value-weighted case, where LMH increases from 0.0025 (t = 0.37) to 0.0227 (t = 7.82).

This monotonic increase in LMH across MAX quintiles suggests that the IVOL anomaly is amplified by investor preference for lottery-like stocks. High-IVOL stocks with strong upside potential attract excessive speculative demand, leading to subsequent underperformance. While we acknowledge that the precise behavioral mechanism remains difficult to quantify, the empirical pattern is robust and offers compelling support for the lottery-preference hypothesis.

	MAX1	MAX2	MAX3	MAX4	MAX5
Panel A: Equal-weighted					
IVOL1	0.0111 (2.48)	0.0137 (2.75)	0.0133 (2.63)	0.0104 (1.94)	0.0045 (0.83)
IVOL2	0.0113 (2.36)	0.0115 (2.29)	0.0106 (2.02)	0.0060 (1.15)	-0.0002 (-0.04)
IVOL3	0.0104 (2.18)	0.0096 (1.88)	0.0087 (1.65)	0.0049 (0.93)	-0.0044 (-0.85)
IVOL4	0.0079 (1.67)	0.0083 (1.63)	0.0067 (1.29)	0.0018 (0.33)	-0.0094 (-1.69)
IVOL5	0.0066 (1.27)	0.0054 (1.04)	0.0025 (0.51)	-0.0014 (-0.27)	-0.0172 (-3.05)
LMH	**0.0045 (1.62)**	**0.0083 (4.57)**	**0.0108 (6.27)**	**0.0118 (6.10)**	**0.0217 (11.00)**
Panel B: Value-weighted					
IVOL1	0.0036 (0.90)	0.0078 (1.76)	0.0093 (1.84)	0.0058 (1.13)	0.0042 (0.73)
IVOL2	0.0078 (1.70)	0.0064 (1.37)	0.0072 (1.37)	0.0031 (0.59)	-0.0019 (-0.35)
IVOL3	0.0057 (1.24)	0.0043 (0.87)	0.0053 (0.97)	0.0007 (0.14)	-0.0045 (-0.85)
IVOL4	0.0061 (1.26)	0.0035 (0.73)	0.0047 (0.92)	0.0010 (0.20)	-0.0075 (-1.34)
IVOL5	0.0011 (0.23)	0.0025 (0.49)	-0.0001 (-0.01)	-0.0037 (-0.69)	-0.0185 (-3.22)
LMH	**0.0025 (0.37)**	**0.0053 (2.02)**	**0.0094 (3.95)**	**0.0095 (3.64)**	**0.0227 (7.82)**

Figure 16. Bivariate Portfolio Analysis, **Lead 1 Month** Double Sorted by **MAX** and **IVOL**

We next turn to the same-period beta anomaly after controlling for MAX, shown in Figure 17. Surprisingly, we find that the beta anomaly—long considered weaker than IVOL, becomes highly significant after controlling for MAX. In equal-weighted portfolios, LMH increases steadily from 0.0539 (t = 12.75) in MAX1 to 0.0740 (t = 15.50) in MAX5. The value-weighted results display a similar pattern, with LMH rising from 0.0483 to 0.0763, all statistically significant.

These results indicate that the beta anomaly, like IVOL, is also stronger in stocks with higher lottery characteristics. This suggests that speculative demand inflates the prices of high-beta, high-MAX stocks, causing them to underperform their low-beta counterparts in the same period. Again, while we refrain from proposing a formal mechanism, these results highlight the behavioral channels through which the beta anomaly may operate in a retail-driven market like China.

	MAX1	MAX2	MAX3	MAX4	MAX5
Panel A: Equal-weighted					
BETA1	-0.0223 (-10.15)	-0.0006 (-0.11)	0.0210 (4.42)	0.0519 (9.28)	0.1391 (16.52)
BETA2	-0.0345 (-9.74)	-0.0136 (-2.98)	0.0037 (0.79)	0.0344 (6.08)	0.1033 (13.89)
BETA3	-0.0406 (-10.98)	-0.0265 (-5.70)	-0.0096 (-1.96)	0.0209 (3.66)	0.0853 (11.23)
BETA4	-0.0503 (-11.95)	-0.0393 (-8.11)	-0.0231 (-4.41)	0.0032 (0.56)	0.0698 (9.26)
BETA5	-0.0762 (-15.43)	-0.0682 (-12.70)	-0.0524 (-9.16)	-0.0254 (-3.93)	0.0651 (7.78)
LMH	**0.0539 (12.75)**	**0.0676 (21.05)**	**0.0734 (23.79)**	**0.0773 (25.17)**	**0.0740 (15.50)**
Panel B: Value-weighted					
BETA1	-0.0311 (-6.97)	0.0085 (1.98)	0.0304 (6.81)	0.0626 (11.91)	0.1438 (17.34)
BETA2	-0.0286 (-8.94)	-0.0100 (-2.31)	0.0103 (2.21)	0.0449 (8.14)	0.1121 (14.91)
BETA3	-0.0387 (-11.85)	-0.0268 (-5.98)	-0.0053 (-1.09)	0.0278 (4.81)	0.0930 (12.11)
BETA4	-0.0508 (-14.23)	-0.0399 (-8.22)	-0.0217 (-4.13)	0.0099 (1.69)	0.0787 (10.27)
BETA5	-0.0794 (-16.70)	-0.0710 (-13.13)	-0.0511 (-8.76)	-0.0201 (-3.01)	0.0675 (7.83)
LMH	**0.0483 (11.72)**	**0.0795 (20.53)**	**0.0815 (20.52)**	**0.0827 (20.24)**	**0.0763 (14.17)**

Figure 17. Bivariate Portfolio Analysis, **Same Period** Double Sorted by **MAX** and **IVOL**

Finally, Figure 18 presents the results of double sorting by kurtosis and IVOL using lead 1-month returns. The IVOL anomaly persists across all kurtosis quintiles, but we observe a declining trend in LMH as kurtosis increases. For example, in equal-weighted portfolios, LMH falls from 0.0218 ($t = 8.79$) in KURTOSIS1 to 0.0145 ($t = 6.60$) in KURTOSIS5. The value-weighted pattern is similar: LMH drops from 0.0202 to 0.0144, though still statistically significant.

This result is somewhat puzzling. Intuitively, one might expect higher kurtosis (greater lottery appeal) to enhance mispricing, and thus strengthen the anomaly. However, we observe the opposite. While we do not have a conclusive explanation for this pattern, we highlight it as an intriguing direction for future research. It is possible that kurtosis captures both upside and downside tail risk, which may dilute the net speculative effect observed with MAX.

	KURTOSIS1	KURTOSIS2	KURTOSIS3	KURTOSIS4	KURTOSIS5
Panel A: Equal-weighted					
IVOL1	0.0126 (2.47)	0.0118 (2.41)	0.0115 (2.36)	0.0105 (2.21)	0.0103 (2.16)
IVOL2	0.0093 (1.80)	0.0107 (2.14)	0.0110 (2.12)	0.0097 (1.92)	0.0092 (1.85)
IVOL3	0.0063 (1.15)	0.0067 (1.30)	0.0083 (1.56)	0.0074 (1.45)	0.0065 (1.27)
IVOL4	0.0027 (0.51)	0.0044 (0.84)	0.0036 (0.68)	0.0032 (0.62)	0.0024 (0.45)
IVOL5	-0.0092 (-1.71)	-0.0060 (-1.09)	-0.0061 (-1.15)	-0.0046 (-0.85)	-0.0042 (-0.79)
LMH	**0.0218 (8.79)**	**0.0178 (7.42)**	**0.0176 (8.15)**	**0.0151 (6.79)**	**0.0145 (6.60)**
Panel B: Value-weighted					
IVOL1	0.0090 (1.95)	0.0075 (1.58)	0.0068 (1.52)	0.0060 (1.37)	0.0083 (1.86)
IVOL2	0.0049 (1.01)	0.0095 (1.86)	0.0085 (1.68)	0.0046 (1.02)	0.0061 (1.18)
IVOL3	0.0018 (0.35)	0.0037 (0.74)	0.0048 (0.91)	0.0048 (0.94)	0.0024 (0.48)
IVOL4	-0.0001 (-0.01)	0.0028 (0.57)	0.0020 (0.37)	0.0010 (0.19)	-0.0002 (-0.04)
IVOL5	-0.0112 (-2.04)	-0.0047 (-0.85)	-0.0076 (-1.43)	-0.0032 (-0.58)	-0.0061 (-1.21)
LMH	**0.0202 (6.09)**	**0.0122 (3.79)**	**0.0144 (4.78)**	**0.0092 (2.84)**	**0.0144 (5.29)**

Figure 18. Bivariate Portfolio Analysis, **Lead 1 Month** Double Sorted by **Kurtosis** and **IVOL**

5.3 Discussion of the Empirical Results

The findings of this study shed new light on the behavioral mechanisms underlying the low-volatility anomaly in China's A-share market. By separating contemporaneous from predictive returns and controlling for lottery-like characteristics, we demonstrate that the observed anomalies are not merely statistical artifacts, but rather reflect persistent mispricing driven by investor sentiment.

Our results confirm the coexistence of two distinct but related anomalies: the contemporaneous Beta anomaly and the predictive IVOL anomaly. The former appears episodic, sensitive to investor mood and speculative cycles, while the latter exhibits temporal robustness and strengthens over time. This divergence implies that the two anomalies, while both challenging traditional risk-return paradigms, are shaped by different forces. The Beta anomaly aligns more with transient behavioral shifts, such as bursts of overconfidence, whereas the IVOL anomaly is more structural, reflecting persistent market inefficiencies and retail dominance.

Importantly, our bivariate analysis validates the explanatory power of lottery preference proxies. While earlier literature often emphasized MAX alone, our results show that skewness and kurtosis also meaningfully relate to investor behavior. High-MAX stocks amplify the mispricing associated with both beta and IVOL, indicating that speculative demand clusters around assets with extreme upside potential. However, the weakening of the IVOL anomaly in high-kurtosis portfolios suggests a more nuanced investor response to tail risk, possibly reflecting risk aversion to downside extremes or an inability to disentangle good and bad tails.

A key implication of our findings is that equal-weighted portfolios, where small-cap, illiquid, and speculative stocks receive greater influence, exhibit stronger anomalies. This underscores the role of microstructure and investor base in anomaly formation. It also suggests that portfolio managers and policymakers need to consider the unique features of emerging markets when applying asset pricing models derived from developed market data.

Furthermore, our study offers empirical support for the broader behavioral finance narrative: when frictions limit arbitrage and investors pursue non-traditional preferences, markets deviate from rational expectations. In China's A-share market, where retail investors dominate and constraints on leverage and short-selling persist, such deviations are especially durable.

6. Conclusion

This paper provides a comprehensive investigation of the low-volatility anomaly in China's A-share market from 1995 to 2024, focusing on both beta- and IVOL-based manifestations. Through a combination of univariate and bivariate portfolio analyses, we offer robust evidence that these anomalies persist over time and are amplified by investor preferences for lottery-like stocks.

Our key conclusions are as follows: The Beta anomaly is primarily contemporaneous and more pronounced during speculative market phases, especially in smaller stocks; The IVOL anomaly is predictive and robust, with low-IVOL stocks consistently outperforming high-IVOL ones in subsequent months; These patterns are not fully explained by MAX, skewness, or kurtosis alone, but the anomalies are significantly amplified within high-lottery preference groups, providing strong evidence for behavioral mispricing mechanisms; The IVOL anomaly has strengthened over time, especially in equal-weighted portfolios, reflecting the increasing influence of speculative behavior and possibly the growing participation of retail investors; The same-period IVOL anomaly, when uncontrolled, appears misleadingly positive due to mechanical return inflation by extreme events—a result clarified through double sorting.

Our study advances the understanding of low-volatility anomalies in emerging markets. It highlights the importance of accounting for higher-order moments when interpreting asset pricing patterns in markets dominated by speculative trading. Future research could explore additional behavioral proxies, such as media sentiment or retail trading flows, to better quantify investor attention.

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