Extrapolative expectations and asset returns: Evidence from Chinese mutual funds

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Abstract

We examine how mutual funds form stock market expectations and the implications of these beliefs for asset returns, using a novel text-based measure extracted from Chinese fund reports. Funds extrapolate from recent stock market and fund returns when forming expectations, with more recent returns receiving greater weight. This recency tendency is weaker among more experienced managers. At the aggregate level, consensus expectations positively predict short-term future market returns, both in and out of sample. At the fund level, expectations are positively related to subsequent fund performance in the time series. In the cross-section, however, superior performance arises only when funds accurately forecast market direction and adjust their portfolios accordingly. This effect is stronger for optimistic forecasts and among funds with greater exposure to liquid stocks. Our findings highlight the conditional nature of belief-driven performance, shaped jointly by forecasting skill and the ability to implement views in the presence of execution frictions such as short-selling and liquidity constraints.

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1. Introduction

In financial economics, how investors form expectations about asset returns and how these expectations affect investors' portfolio choices and investment performance are central questions. Recent empirical studies elicit expectations through survey data and document a robust pattern of return extrapolation–the higher an asset's recent past returns, the more optimistic investors become about its future returns–across various economic agents (Greenwood and Shleifer, 2014; Kuchler and Zafar, 2019; Giglio et al., 2021; Da et al., 2021). In theoretical models, assuming investors hold extrapolative beliefs helps understanding market dynamics such as excess volatility and time-series predictability in aggregate stock markets, and the formation and collapse of bubbles (Barberis et al., 2015, 2018; Jin and Sui, 2022).

Despite ample evidence of return extrapolation among households or retail investors, little is known about whether mutual funds–arguably a more financially sophisticated group–also exhibit these extrapolative beliefs and how their expectations relate to subsequent aggregate market returns, particularly in influencing the performance of their portfolios. In this paper, we test the asset pricing implications of professional investor beliefs using a unique dataset of mandatory expectation disclosures imposed on Chinese mutual funds. The China Securities Regulatory Commission (CSRC) requires mutual funds to periodically disclose their outlooks on future macroeconomic conditions and financial markets. To comply with this policy, funds include their market outlooks in a section titled "Management's Outlook on the Macroeconomy, Securities Market, and Industry Trends" (henceforth MO) in quarterly, semi-annual, and annual reports.[1] This feature allows us to quantify each fund's stock market expectations using natural language processing techniques.

We collect periodic reports of actively-managed equity mutual funds spanning 2005–2022. Using a pre-trained deep learning model (BERT, or Bidirectional Encoder Rep-

[1]While mutual funds are required to provide market outlooks in semi-annual and annual reports, such disclosures in quarterly reports are voluntary.

resentations from Transformers (Devlin et al., 2018)), we conduct a systematic textual analysis of the MO section in these reports to derive each fund's expectation score for the A-share market, scaled between -1 and 1. To validate our text-based measure of expectations, we perform three tests. First, we compare model classifications with human evaluations using 10 out-of-sample randomly selected sentences. The model correctly identifies all 10 sentences labeled as optimistic and 9 out of 10 labeled as pessimistic. Word frequency analysis further supports the prediction, with commonly occurring phrases consistent with positive and negative sentiment. Second, we examine the correlation between our text-based expectations and survey-based expectations, finding a significant Pearson correlation coefficient of 0.5. Third, we show that fund managers adjust their portfolios in accordance with their reported expectations: optimistic funds reduce cash holdings, increase equity positions, and engage in risk-shifting by investing in high-beta stocks.

Next, we examine how mutual funds form expectations about future stock market performance. In the time series, we find that fund expectations are significantly and positively correlated with past monthly market returns, indicating that their subjective expectations are procyclical. More importantly, the associated t-statistics of the estimated coefficients on past τ-month annualized cumulative market returns decline as τ increases, falling below 1.65 for $\tau \geq 24$. These results suggest that mutual funds extrapolate from past market returns when forming expectations about future performance, assigning greater weights to more recent returns and smaller weights to distant ones. We then estimate nonlinear least squares regressions of an exponential decay function, which captures the declining influence of past returns on fund expectations over time with a single parameter, λ (Greenwood and Shleifer, 2014; Cassella and Gulen, 2018; Da et al., 2021). Specifically, λ quantifies the extent to which funds overweight recent past returns when forming expectations. Across various model specifications, we consistently find that λ is significantly less than one, suggesting a strong recency tendency. For example, in a nonlinear specification that includes lagged excess market returns from month $t-6$ to month $t-1$, the estimated λ is 0.575, indicating that the return in month $t-1$ receives approximately 16 times the weight of the return in month $t-6$. In other words, the three most recent monthly market returns collectively account for 84% of the total weight, highlighting a strong reliance on recent information in forming expectations. In addition, we find that negative returns and tail returns exert a larger and more persistent effect on funds' belief updating, consistent with the notion that salient past experiences have a stronger influence on investors' behavior (Malmendier and Nagel, 2011; Luo et al., 2022; Da et al., 2021). We also confirm this extrapolative pattern at the fund level. We do so by estimating a linear regression of individual fund expectations on past market and fund returns, controlling for fund$\times$horizon fixed effect to remove time-invariant manager bias in market forecasts across different horizons (Cassella et al., 2023; de Silva and Thesmar, 2024). Consistent with the aggregate pattern, fund expectations of future stock market performance rise on the back of both good past market and fund returns, particularly in the most recent past 3-month returns.

To deepen our understanding of mutual funds' extrapolative beliefs, we examine heterogeneity in expectation formation across fund characteristics. The literature on experienced effects shows that early personal experiences exert a long-lasting influence on investors' expectations and portfolio choices (see Malmendier (2021) for a survey). Although individuals put more weight on recent outcomes than on more distant realizations, early-life experiences still have a nontrivial impact on current investment behavior (e.g., Malmendier and Nagel (2011)). Building on this insight, we conjecture that the extrapolative behavior varies with managerial experience, with funds run by more experienced managers exhibiting a less recency tendency. Guided by prior literature, we focus on three proxies for experience: bubble-crash experience (Luo et al., 2022), recession experience (Chen et al., 2021), and manager age (Greenwood and Nagel, 2009). Consistent with this hypothesis, we find that experienced fund managers exhibit higher estimates of λ than their less experienced counterparts.

Having examined how mutual funds form stock market expectations, we now investigate the impact of these extrapolative beliefs on prices. We find that fund expectations significantly predict market returns over the next one to three months with a positive sign. For example, a one-standard deviation increase in fund expectations is associated with a 1.5% increase in market returns over the next month. This predictability remains robust after controlling for several well-known economic fundamentals (Goyal and Welch, 2008), suggesting fund expectations contain unique information beyond macroeconomic fundamentals.

One potential concern is that Chinese mutual funds may refrain from issuing overtly negative forecasts due to implicit pressures from the government. Under this hypothesis, funds might issue optimistic outlooks precisely when market conditions are deteriorating. If such behavior were prevalent, we would expect a negative relation between the proportion of optimistic forecasts and subsequent market returns. However, we find that the bullish component of consensus expectations positively predicts ex post market returns, while the bearish component negatively predicts them. Moreover, we find that voluntary forecasts disclosed in quarterly reports, which are not mandated by regulators, also significantly predict one-quarter-ahead market returns in the expected direction. Similarly, expectations extracted from mandatory semi-annual and annual reports predict six-month-ahead returns. Taken together, these findings suggest that fund expectations are informative about market trends instead of propaganda, whether disclosed voluntarily or under regulatory obligation.

At first glance, our results appear to contrast with evidence from the U.S. stock market, where extrapolative beliefs negatively predict asset returns (Greenwood and Shleifer, 2014; Da et al., 2021). This discrepancy can be reconciled by differences in forecast horizons and return dynamics. U.S. investor surveys typically elicit one-year-ahead expectations, a horizon over which index return autocorrelations are negative (Fama and French, 1988), making extrapolative beliefs contrarian signals. In contrast, the expectations we extract from Chinese fund reports likely target shorter horizons, where we document strong return predictability and where index returns are positively autocorrelated (Lo and MacKinlay, 1988; Cutler et al., 1991; Moskowitz et al., 2012). In such an environment, it is natural for sophisticated investors to form extrapolative beliefs and speculate on short-term trend continuation (Brunnermeier and Nagel, 2004). Importantly, this does not imply that the predictive power of fund expectations merely reflects return autocorrelation. Even after controlling for lagged market returns at one-, three-, six-, and twelve-month horizons, the predictive coefficient on fund expectations remains statistically significant, with a U-shaped pattern in magnitude. This result suggests that fund expectations are partially extrapolative but also contain additional information not captured by past returns alone.

We further complement the in-sample analysis with the out-of-sample (OOS) predictability tests. We find that fund expectations generate large, positive, and statistically significant out-of-sample R^2_{OOS} at the one-month forecast horizon. The R^2_{OOS} values for fund expectations range from 5.76% to 8.38%, depending on the OOS test methods and evaluation periods. These OOS forecasts based on fund opinions also provide sizable economic values for a mean-variance investor who optimally allocates wealth between equities and risk-free assets. For example, using a rolling predictive regression with a fixed 36-month window, the annualized certainty equivalent return (CER) gain for fund expectations is 3.95%. Additionally, the monthly Sharpe ratio for fund expectations is 0.44, exceeding that of the market portfolio over the same evaluation period.

We then turn to the performance implications of fund expectations at the individual fund level. We find that more optimistic market expectations are associated with higher future fund returns for a given fund, consistent with the aggregate predictive pattern. However, this positive expectation-performance relation does not hold in the cross-section, suggesting that superior performance depends not only on accurate forecasts but also on corresponding portfolio adjustments. Consistent with this conjecture, we find that funds that correctly anticipate a bullish market and shift their portfolios toward high-beta stocks earn higher returns. Similarly, funds that correctly predict market downturns and adjust to low-beta stocks experience smaller losses. The impact of aligning portfolio beta with optimistic expectations is more pronounced than with pessimistic ones. This asymmetry reflects binding short-sale constraints faced by mutual funds, making it easier to increase risk exposure during bull markets but limit their ability to hedge or reduce exposure during downturns. To investigate deeper how constraints on portfolio adjustments affect the link between forecasting skill and fund performance, we divide fund-year observations based on the liquidity of their holdings, a proxy for the cost of implementing portfolio changes. We find that the performance gains from correct, bullish expectation–aligned beta tilts are significantly larger among high-liquidity funds. The performance gap between high- and low-liquidity funds remains sizable across various risk-adjusted alpha measures. Collectively, this evidence highlights the conditional nature of belief-driven performance: translating expectations into superior returns requires both forecasting ability and the flexibility to act on those views, which in turn depends on frictions such as short-sale constraints and market liquidity.

In the final part, we first discuss the pros and cons of using the BERT-wise model versus large language models (LLMs) such as ChatGPT and DeepSeek. To make sure our results are not model-specific, we also quantify fund expectations via DeepSeek-V3, an open-source LLM designed with computational efficiency and strong performance in Chinese language tasks (Liu et al., 2025; Guo et al., 2025). We find a strong positive correlation (0.86) between the BERT-based consensus expectation series and the DeepSeek-based one. Moreover, most of our results remain qualitatively similar when we employ the DeepSeek-based fund expectations.

We also examine how extrapolative belief formation differs between mutual funds and retail investors. If mutual funds form expectations by rationally aggregating past returns, can retail investors do the same? To address this question, we extract retail sentiment from posts on Eastmoney Guba, China's largest online stock forum. Using a nonlinear exponential decay model with 20 lagged daily returns, we estimate a decay parameter (λ) of 0.696. To compare this with mutual funds' extrapolative intensity, we raise 0.696 to the 22nd power (corresponding to 22 trading days in a month), which yields a value close to zero, suggesting that retail investors exhibit a much more myopic and aggressive extrapolative weighting than that of mutual funds. Not surprisingly, the retail sentiment negatively predicts future market returns over one- to twenty-day horizons, albeit with statistically insignificant slopes. This finding is largely consistent with Da et al. (2021), suggesting that retail investors systematically overproject recent return trends, leading to biased expectations and poor return forecasts. Overall, these results highlight that not all extrapolative beliefs are alike: some can be predictive, while others are biased. The informativeness of such beliefs depends critically on the intensity (e.g., the length of return history considered) and rationality (e.g., incorporation of additional forward-looking information) of extrapolation, both of which are linked back to investor sophistication.

Our paper contributes to several strands of the literature. First, it adds to the growing literature on investors' expectation formation, with a particular focus on institutional investors. Prior studies document that retail investors exhibit extrapolative beliefs, assigning greater weight to recent returns when forming expectations, both in the time series and the cross-section Amromin and Sharpe (2014); Greenwood and Shleifer (2014); Da et al. (2021). In contrast, evidence on institutional investors is mixed. Andonov and Rauh (2022) demonstrate that U.S. public pension funds rely on past asset performance in setting future return expectations and act on those beliefs. By contrast, Dahlquist and Ibert (2024) show that equity expectations of U.S. large asset managers (i.e., fund families) form countercyclical equity return expectations. By shifting the focus to trading behavior, Timmer (2018) shows that German banks and mutual funds trade procyclically in bond markets, while insurance companies and pension funds behave countercyclically. Similarly, Raddatz and Schmukler (2012) find that global mutual funds respond to recent country returns by trading procyclically. We extend this literature by examining the expectation formation of mutual funds in the Chinese market. A key advantage of our setting is that Chinese mutual funds are required to report market outlooks in periodic filings, providing a comprehensive and representative dataset for belief measurement. This feature allows us to extract expectations directly from forward-looking text rather than inferring them from trading behavior, and avoids the criticisms often directed at survey-based beliefs (see e.g., Cassella et al., 2025). We find that Chinese mutual funds form expectations in an extrapolative manner, placing more weight on recent market and fund returns. We show that this recency behavior is related to financial sophistication or experiences, with more experienced funds exhibiting less degree of extrapolative weighting.

Second, it contributes to the literature on the asset pricing implications of extrapolative beliefs (Barberis et al., 2015, 2018; Jin and Sui, 2022; Cassella and Gulen, 2018; Cassella et al., 2025). Prior studies suggest that such beliefs are systematically incorrect, as average investor expectations tend to be negatively correlated with subsequent returns. In contrast, we find that consensus expectations among mutual funds positively predict market returns over short horizons. We argue that this discrepancy could reflect differences in return autocorrelation–positive at short horizons and negative at longer horizons (Cutler et al., 1991)–as well as investor sophistication. We find that Chinese retail investors also exhibit extrapolative beliefs but do so more aggressively, placing excessive weight on recent daily returns and virtually ignoring information beyond a month. Consistent with Da et al. (2021), such overextrapolative beliefs negatively predict short-term returns.

Finally, our paper is closely related to the literature on fund skill in forecasting macroeconomic conditions and financial markets (Ammer et al., 2022; Fang et al., 2024; Ammer et al., 2024; Gao et al., 2024). For example, using the same Chinese mutual fund reports, Ammer et al. (2022) demonstrate that funds accurately predict shifts in monetary policy, and this forecasting skill translates into higher performance for money market and bond funds. Fang et al. (2024) find that disagreement among mutual funds regarding future stock market performance is a sign of market overpricing. Ammer et al. (2024) show that funds also possess skill in predicting aggregate economic growth. In the same vein, Gao et al. (2024) construct a measure of countercyclical policy beliefs and show that funds with frequent countercyclical beliefs significantly outperform other funds. We build on this literature by inferring fund skills from their stock market expectations, documenting a positive time-series relation between expectations and performance for a given fund unconditionally. An important distinction between our paper and prior literature is its unique focus on an expectation-performance relation across funds. To outperform their peers, funds must not only form correct expectations but also adjust their portfolios in line with these expectations, which in turn depends on execution frictions such as short-selling constraints and limited liquidity.

The remainder of the paper is organized as follows. Section 2 describes our data and methods. Section 3 explores whether funds have extrapolative beliefs. Section 4 performs return predictability tests of fund beliefs. Section 5 examines the expectation-performance relation in the cross-section. Section 6 discusses pros and cons of different large language models (LLMs) in quantifying fund expectations, extrapolative beliefs between mutual funds and retail investors, and the rationale behind extrapolative beliefs. Section 7 concludes.

2. Data and validation tests

2.1. Fund characteristics

The main data sources for this paper are the China Stock Market & Accounting Research Database (CSMAR) and the Wind Database (WIND). We obtain fund net-of-fee accumulative returns adjusted for historical fund payouts and splits, total net assets (TNA), different types of fees, and other fund characteristics from the CSMAR, and fund holdings from the WIND. Since mutual funds' stock market expectations are our primary focus, we restrict the analysis to actively managed Chinese domestic open-end equity, equity-oriented hybrid funds, and flexible funds from 2004 to 2022. To ensure that funds are primarily invested in equities, we include equity funds that, on average, hold more than 80% of their assets in A-share stocks, as well as equity-oriented hybrid and flexible funds with more than 60% of their assets in A-shares. Because mutual fund establishment requires a public filing with the CSRC and the CSMAR starts collecting funds characteristics from their first trading day (Chi et al., 2022), our mutual fund data are incubation-bias-free (Evans, 2010).

Mutual funds often offer multiple share classes of the same portfolio to cater to different client types. These share classes typically vary only in their fee structures. Therefore, we aggregate all share classes into a single fund. A fund's total net assets (TNA) are calculated as the sum of TNA across all share classes. For returns and expense ratios (which equal the sum of the management, custodian, and sales fee), we compute the TNA-weighted average across all share classes. Fund age is the number of months in which the oldest share class in the fund is traded. Turnover is the minimum of the fund's total purchases and sales divided by the fund's TNA. As for fund flows, we assume that new money is invested at the end of the month and compute net flows as the change in TNA excluding growth in TNA due to fund returns.

Table 1, Panel A presents the summary statistics for fund-level variables in June and December.[2] Chinese actively managed funds, on average, exhibit superior skill, with a mean net-of-fee return of 4.5% per semi-year, consistent with the findings in prior literature (Jiang, 2020). The 10th to 90th percentile range of net-of-fee returns spans from −15.2% to 27.8%, indicating substantial variation in fund performance. The average (median) fund in our sample has a size of approximately 1.72 billion CNY (0.57 billion CNY) and a continuous operation history of 58 months (44 months). Most funds charge fees at a 1.75% rate.

[Insert Table 1 here]

2.2. Quantifying mutual fund stock market expectations

Mutual fund periodic reports are downloaded from the CSRC's Electronic Information Disclosure (EID) (eid.csrc.gov.cn/fund) and the website of East Money (fund.eastmoney.com), a leading financial news platform and data provider in China. To translate the qualitative information on stock market outlooks embedded in mutual fund reports into quantitative measures, we follow Fang et al. (2024) and employ a deep learning model.

First, we extract the management outlook (MO) texts from funds' reports, supplementing missing data by manually collecting it from the CSRC's EID database. Panel B of Table 1 shows that the original dataset consists of 104,181 quarterly, semi-annual, and annual reports, of which 50,628 reports provide outlooks on stock market performance, covering the period from December 2004 to December 2022. This discrepancy arises because the CSRC does not require mutual funds to include outlooks in quarterly reports, whereas semi-annual and annual reports are mandated to provide this information.

[2]Chinese mutual funds are required to disclose their top ten holdings in quarterly reports, whereas a full picture of holdings is only available in semi-annual and annual reports.

Second, we split the MO text into sentences using punctuation marks (i.e., ".", "!", and "?") and filter for sentences containing words or phrases related to the A-share stock market (i.e., "market", "A-share", "equity", and "stock market"). While using the broad term "market" as a filter inevitably includes sentences describing other macroeconomic conditions or financial markets (e.g., market interest rate, currency market, and housing market), we mitigate this issue by creating a pre-determined exclusion list to remove irrelevant sentences. This process results in 131,788 A-share-specific sentences.[3]

Next, we randomly select 20,000 sentences and manually classify them into positive, neutral, or negative categories, reflecting optimism, neutrality, or pessimism about future market performance.[4] For the remaining unlabeled sentences, we employ a deep learning model, specifically BERT, to construct a text classification model for predicting each sentence's label. BERT and its consecutive variants have shattered records on various natural language processing (NLP) tasks, including sentiment analysis (Jha et al., 2020). Among these off-springs, we choose the base MacBERT model, optimized for Chinese NLP tasks, for our classification (Cui et al., 2020).

Then, each sentence is assigned a score of −1, 0, and 1 for negative, neutral, and positive categories, respectively. To obtain fund-level expectations, we average the sentiment scores across all sentences:

$$\text{EXPECTATION}_{i,t} = \frac{1}{\text{S}_{i,t}} \sum_{s=1}^{\text{S}_{i,t}} \text{SCORE}_{i,s,t}, \tag{1}$$

where $\text{EXPECTATION}_{i,t}$ is fund i's mean sentiment toward future stock market performance at reporting period t. $\text{S}_{i,t}$ is the number of A-share-market-mentioned sentences in a fund's MO. Panel B of Table 1 shows that the mean values of fund expectations are positive across all forecast horizons.

Finally, the consensus expectation is defined as the difference between the ratio of

[3]While this approach may not fully eliminate non-stock market sentences, we show in Section 6 that our main results remain qualitatively similar when using DeepSeek to quantify fund expectations.

[4]Internet Appendix A presents two detailed examples of MO text and illustrates the construction of training data for prediction.

optimistic funds and the ratio of pessimistic funds:

$$\text{EXPECTATION}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \mathbb{1}_{\{\text{EXPECTATION}_{i,t}>0\}} - \frac{1}{N_t}\sum_{i=1}^{N_t} \mathbb{1}_{\{\text{EXPECTATION}_{i,t}<0\}}. \tag{2}$$

where $\mathbb{1}$ is the indicator function for the presence of a fund with an expectation value greater or less than zero. N_t is the total number of funds at time t. This text-based consensus expectation serves as a qualitative measure, similar to the survey-based approach employed by Greenwood and Shleifer (2014). A higher value of EXPECTATION_t suggests a greater level of optimism among funds regarding future stock market returns.

Panel C of Table 1 reports the summary statistics of the consensus expectation. Consistent with the pattern observed in the cross-section, mutual funds as a whole on average are optimistic about the future stock market in the time series. Fig. 1 further plots the time series of consensus forecasts along with the closing price of the Shanghai Stock Exchange Composite Index (SSE).[5] The graph shows considerable variation in consensus forecasts over time. Additionally, fund expectations appear to predict market returns with a positive sign in the short term. For example, mutual funds grew increasingly optimistic in the year leading up to the 2007 bubble and became increasingly pessimistic before the bubble burst in 2008. A similar pattern is observed during the 2014–2015 bubble-crash event. We explore the predictability of fund expectations in more detail in Section 4.

[Insert Fig. 1 here]

2.3. Validation tests

In this subsection, we conduct three validation tests of our text-based measure of expectations. First, we compare MacBERT predictions with human evaluations using out-of-sample data. Second, we examine the correlation between our measure and a survey-based proxy. Third, we investigate whether the expectation measure aligns with observed fund investment strategies.

[5] To construct a continuous monthly time series of fund expectations, we interpolate missing data using the most recently available observations.

2.3.1. Manual review and word frequency analysis

To evaluate classification performance, we manually assess a random sample of sentences and their corresponding MacBERT predictions using data not included in the training set. As shown in Tables IA.1 and IA.2 of the Internet Appendix A, the model correctly predicts all 10 human-identified positive sentences and 9 out of 10 negative sentences. These results indicate that the model consistently produces high-accuracy results that align closely with human evaluations.

We further apply the segment function from the jiebaR package in R to split all A-share-related sentences into phrases. Panels A and B of Table IA.3 report the 50 most frequently occurring phrases in the positive and negative categories, respectively. Some proper nouns, such as “market”, “economy”, and ”A-shares” appear frequently in both categories. However, the descriptive phrases associated with these terms differ substantially. Positive sentences commonly include terms such as “loose”, “recovery”, “rebound”, “optimism”, “improvement”, and “enhancement”, whereas negative sentences feature phrases like “pressure”, “downturn”, “inflation”, “cautious”, “rate hikes”, and “shocks”.

2.3.2. Comparison with survey-based expectations

Next, we validate our text-based expectation measure by comparing it with survey-based expectations. Since April 2008, the China Securities Investor Protection Fund Corporation Limited, regulated by the CSRC, has conducted monthly surveys of investors, including both individual and institutional investors. The survey covers various aspects of the A-share stock market, such as investors’ views on the likelihood of a market upturn (OPTIMISM), intentions to increase stock holdings (BUY), expectations regarding the market’s ability to bounce back quickly from declines (BOUNCE and RESILIENCE), the impact of domestic economic policies on stock markets (ECONOMICS), and other relevant topics over the next one, three or six months. For example, participants are asked to rate their outlook on the performance of the SSE over the next month as “very optimistic,” “optimistic,” “neutral,” “pessimistic,” or “very pessimistic.” These responses are used to compute the China Securities Investor Confidence Index (CSICI), a composite measure of investor sentiment. Higher values of the CSICI and its sub-indices reflect greater investor confidence in an expected upward movement of the stock market index in the subsequent period.

Fig. 2 plots the time series of mutual fund expectations, extracted from fund reports (shown as a red solid line on the left y-axis), alongside the CSICI, constructed from surveys (represented by a cyan dashed line on the right y-axis). We find that CSICI differs from mutual fund expectations, despite a positive correlation between the two measures. Table 2 shows that these expectation proxies have a Pearson correlation coefficient of 0.50 and a Spearman correlation coefficient of 0.57. Additionally, mutual fund expectations are positively correlated with the various sub-indexes of the CSICI, with Pearson coefficients ranging from 0.37 to 0.62. These positive correlations validate our fund expectation measure, while the moderate magnitude of the coefficients suggests that, although there is some overlap in expectation formation, the two groups may also incorporate distinct information when forming their views on market performance.

[Insert Fig. 2 here]

[Insert Table 2 here]

2.3.3. Reported expectations and portfolio adjustments

Another method to validate our text-based expectation measure is to examine whether funds align their actions with their reported expectations (Greenwood and Shleifer, 2014). Specifically, more optimistic funds are expected to reduce cash holdings, increase equity positions, and engage in risk-shifting through investments in high-beta stocks.

Table 3 shows the results. In Columns (1) and (2), we test the relation between fund expectations and portfolio adjustments from an asset allocation perspective. As expected, funds with optimistic stock market expectations shift their portfolios from cash holdings to equity shares. The estimated coefficients for expectations on equity and cash holdings are 0.986 and -0.545, respectively, both statistically significant at the 1% level. A one-standard-deviation increase in expectations is associated with a 0.53% increase in equity shares and a 0.29% decrease in cash holdings. Given that the average cash weight in our sample is 11.29%, this magnitude implies that funds only translate 2.59% (0.29/11.29) of their cash position towards equity investments. Therefore, the transmission channel from expectations to portfolio adjustments appears to be weak, consistent with the findings of Giglio et al. (2021).

We confirm this weak positive pass-through pattern in Column (3), where we investigate whether funds act on their expectations by adjusting the beta of their portfolio holdings. We find that the estimated coefficient for fund expectation is 0.015, with a t-statistic of 6.485. However, the economic magnitude of this effect is small: a one-standard-deviation increase in expectations corresponds to a 0.008 increase in holdings' beta, representing only 0.9% of the sample mean.

Taken together, given that portfolio adjustments are aligned with funds' stated expectations, we conclude that Chinese mutual funds honestly report their stock market expectations.

[Insert Table 3 here]

3. Extrapolative expectation formation

In the previous section, we introduced a novel measure to capture fund expectations through textual analysis and deep learning, demonstrating its effectiveness as a reliable indicator of their true expectations. In this section, we examine whether mutual funds extrapolate past stock market returns when forming their expectations.

3.1. Aggregate patterns

3.1.1. Linear model

To gain an intuition for how past stock market returns affect mutual funds' expectations of future market performance, Fig. 3 plots a scatterplot of expectations against past one-month excess market returns. A visibly positive relation emerges, which is further supported by the nonparametric estimates (depicted by the red solid line). Specifically, higher past market returns are associated with more optimistic expectations. This relation appears to be approximately linear, consistent with findings in previous literature (e.g., Greenwood and Shleifer, 2014). To formalize this relation, we estimate the following linear regression model:

$$\text{EXPECTATION}_t = a + b \cdot R^M_{t-\tau \to t-\tau+1} + u_t \tag{3}$$

where EXPECTATION_t is the difference between the ratio of bullish and bearish funds regarding future stock market performance. $R^M_{t-\tau \to t-\tau+1}$ is the excess market return from month $t-\tau$ to $t-\tau+1$. Standard errors are corrected based on Newey and West (1987) with 12 lags.

[Insert Fig. 3 here]

Fig. 4 plots the estimated coefficients on past monthly market returns as τ goes from 1 to 36. Three interesting patterns emerge. First, the slopes are positive for lags up to 10 months, suggesting that Chinese mutual funds tend to extrapolate recent past market returns when forming their expectations. Second, the slopes decline with increasing lag length, suggesting a strong recency tendency, consistent with evidence from survey-based expectations in the US (Greenwood and Shleifer, 2014). Third, the slope on the most recent return (i.e., $\tau = 1$) is smaller than that on the one-month-lagged return (i.e., $\tau = 2$). This likely reflects the timing of mutual funds' expectation formation, as they may establish stock market outlooks approximately one month or earlier before publicly releasing them.

[Insert Fig. 4 here]

3.1.2. Exponential decay model

Spurred by the evidence that funds place more weight on recent market returns and less on distant ones, we follow previous studies (Greenwood and Shleifer, 2014; Cassella and Gulen, 2018; Da et al., 2021) and capture this decay pattern using an exponential weighting scheme. Specifically, we estimate the following nonlinear least squares regressions:

$$\text{EXPECTATION}_t = a + b \cdot \sum_{\tau=0}^{n-1} w_\tau R^M_{t-2-\tau \to t-1-\tau} + u_t \tag{4}$$

where n is the number of lagged monthly market returns included in the estimation. We exclude the most recent monthly market return to reflect the fact that funds typically establish their market outlooks about a month or more before publicly releasing them. The weight function w_τ is defined as:

$$w_\tau = \frac{\lambda^\tau}{\sum_{j=0}^{n-1} \lambda^j}. \tag{5}$$

This weight function parsimoniously captures the decay pattern in the relation between manager expectations and past market returns. The parameter λ reflects the relative weight assigned to recent versus distant returns. A lower value of λ indicates that more recent returns have a stronger influence on the expectation formation. For example, $\lambda = 0.5$ implies that the return in month $t-1$ receives twice the weight of the return in month $t-2$ ($1/0.5 = 2$) and eight times the weight of the return in month $t-4$ ($1/0.5^3 = 8$). The coefficient b quantifies the overall impact of the past return series on funds' current expectations.

Table 4 reports estimates of b and λ when different numbers of lagged monthly market returns are included in the nonlinear specification given by Eq. (4). The first row shows that when lagged excess market returns from month $t-6$ to month $t-1$ are included in the right-hand side, both the estimates of b and λ are positive and statistically significant at the 1% level, yielding a large pseudo R^2 of 21.9%. This finding is consistent with our previous linear model, suggesting that Chinese mutual funds exhibit extrapolative beliefs. An estimate of 0.575 for λ indicates that the weight assigned to the most recent monthly market return is approximately $0.575^0/\sum_{j=0}^{5} 0.575^j \approx 44.1\%$, while the weight on the return six months earlier is $0.575^5/\sum_{j=0}^{5} 0.575^j \approx 2.8\%$. In other words, the return in month $t-1$ has approximately 16 times the weight of the return in month $t-6$, confirming that more recent market returns exert a stronger influence on managers' expectations than more distant ones. Given that the three most recent monthly market returns have a total weight of 84%, funds exhibit a strong degree of extrapolation. To put this magnitude in perspective, we compare it with the findings of Greenwood and Shleifer (2014). The authors estimate λ from Investor Intelligence's summary of professional investors' beliefs, using quarterly past returns, and report a value of 0.493. Taking the one-third power of this value yields approximately 0.79, suggesting that Chinese professional investors exhibit a stronger degree of extrapolative weighting compared to their US counterparts. The remaining three rows of Table 4 show that the estimate of λ slightly decreases and stabilizes at 0.566 when more distant returns are included.

Overall, our findings based on the text-based expectations of Chinese mutual funds align with existing evidence from US surveys, confirming that even professional investors are extrapolators and their memory of past market performance fades swiftly.

[Insert Table 4 here]

3.1.3. Asymmetric effects of market returns

To better characterize fund expectation formation, we further study whether the degree of extrapolation differs in different return characteristics.

Positive versus negative market returns. Several studies suggest that negative market shocks have a larger impact on fund managers' belief updates than positive shocks (Chen et al., 2021; Luo et al., 2022). More relevantly, in the time-series, Cassella and Gulen (2018) document that investors' degree of extrapolative weighting (measured by $1-\lambda$) increases following a recent period of good stock market returns, implying that λ is higher during bear markets than in bull markets. Similarly, in the cross-section, Da et al. (2021) find that negative stock returns have a stronger and more persistent influence on investor expectations than positive returns.

Building on these findings, we separate past monthly returns into positive and negative returns and estimate the following equation:

$$\text{EXPECTATION}_t = a + b^+ \cdot \sum_{\tau=0}^{n-1} w_\tau^+ R^+_{t-2-\tau \to t-1-\tau} + b^- \cdot \sum_{\tau=0}^{n-1} w_\tau^- R^-_{t-2-\tau \to t-1-\tau} + u_t \quad (6)$$

where $w_\tau^+ = \frac{(\lambda^+)^\tau}{\sum_{j=0}^{n-1}(\lambda^+)^j}$, $w_\tau^- = \frac{(\lambda^-)^\tau}{\sum_{j=0}^{n-1}(\lambda^-)^j}$, $R^+ = \max(R^M, 0)$, and $R^- = \min(R^M, 0)$.

Table 5, Panel A presents the results of the asymmetric tests using monthly market returns. When including 12 or more lagged monthly excess market returns, we find that the estimates of b^- (weight on negative returns) are consistently larger than those of b^+ (weight on positive returns). This suggests that funds place more weight on negative information than on positive information when forming their expectations. In particular, when including 24 lagged monthly excess market returns ($n = 24$), fund expectations respond approximately 1.6 times more to negative returns than to positive returns.

Regarding the estimates of λ^- (decay rate for negative returns) and λ^+ (decay rate for positive returns), we find that the former is consistently larger than the latter across all specifications. For instance, when $n = 24$, negative returns from three months earlier are approximately 86% as important as the most recent returns in shaping funds' expectations, while positive returns from the same period are only about 19% as important. In other words, past bad outcomes have a longer-lasting effect on funds' expectations than positive outcomes.

Moderate versus extreme market states. Given that tail returns are more salient and attention-grabbing to investors than returns within conventional intervals, we expect that funds respond more strongly to past returns in either the left or right tail, and the weight assigned to these extreme returns is likely to decay more slowly.

Table 5, Panel B formalizes this idea by allowing for varying weights (b) and decay rates (λ) across different market states. The current stock market state is classified as moderate if monthly returns in the most recent month fall within the 5th to 95th percentiles of the past 60 monthly observations. Conversely, the market is classified as extreme if the monthly returns in the most recent month fall outside this interval, based on the same 60-month window. Consistent with our hypothesis, we find that the estimated coefficient on moderate market returns, b^M, is smaller than that on extreme market returns, b^E, suggesting that extreme returns in the tails have a more pronounced effect on expectation formation. Additionally, this salience is associated with a higher decay rate ($\lambda^E > \lambda^M$), resulting in a more persistent impact on funds' expectations.

Collectively, these findings indicate an asymmetry in the weight and decay rate assigned to different return characteristics in funds' expectation formation. Funds assign more weight to, and exhibit a slower decay rate for, negative and salient information.

[Insert Table 5 here]

3.2. Fund-level evidence

Next, we test whether funds extrapolate past market returns at the fund level. The literature on subjective expectation formation typically focuses on correlation rather than causation (Greenwood and Shleifer, 2014; Da et al., 2021; Dahlquist and Ibert, 2024). The key question is how funds' market expectations vary with prior market returns. To this end, we estimate an exponential decay model of each fund's expectations on past market:[6]

$$\text{EXPECTATION}_{i,t\to t+h} = a_i + b_i \cdot \sum_{\tau=0}^{n-1} w_{i,\tau} R^M_{t-2-\tau\to t-1-\tau} + u_{i,t,h}, \quad (7)$$

where $\text{EXPECTATION}_{i,t\to t+h}$ is the fund i's subjective expectation of stock market performance, extracted from fund reports issued at the end of month t, with h indicating the forecasting horizon. Our data includes expectations from quarterly, semi-annual, and annual reports, corresponding to 3-, 6-, and 12-month forecast horizons, respectively. $R^M_{t-2-\tau\to t-1-\tau}$ is the monthly market return from month $t-2-\tau$ to month $t-1-\tau$. $w_{i,\tau}$ is fund i's weight function whose expression follows:

$$w_{i,\tau} = \frac{\lambda_i^\tau}{\sum_{j=0}^{n-1} \lambda_i^j}, \ 0 \le \lambda_i < 1. \quad (8)$$

Table 6 reports summary statistics for the estimated parameters a, b, and λ from the nonlinear least squares regression model specified in Eq. (7). In Panel A, we estimate the degree of extrapolation using 6 lagged monthly market returns. The average estimated λ coefficient is 0.57, which aligns closely with the estimate derived from aggregate data in Table 4. The interquartile range of λ spans from 0.27 to 0.92, indicating that the degree of extrapolation varies substantially across mutual funds. Panels B–D present summary

[6] Since we estimate nonlinear regressions for each fund, we limit the tests to funds with records for reported expectations at least 24 times.

statistics for the estimated coefficients when we include 12 or more of the past monthly returns in the estimation. The results are quantitatively similar to those in Panel A. For example, the median estimate of λ is 0.64 for $n = 24$, implying that the three most recent monthly market returns account for 74% of the weight in determining a typical fund's stock market expectations.

[Insert Table 6 here]

Table 6 shows that a typical fund in our sample exhibits a strong degree of extrapolation. Specifically, funds rely heavily on the past one-quarter return when forming expectations, while returns from more distant periods have little effect on expectations. To confirm this pattern, we pool all funds together and estimate the following panel regression:

$$\text{EXPECTATION}_{i,t\rightarrow t+h} = \alpha_{i,h} + \beta_1 R^M_{t-3\rightarrow t-1} + \beta_2 R^M_{t-6\rightarrow t-4} + \varepsilon_{i,t,h}, \tag{9}$$

where $R^M_{t-3\rightarrow t-1}$ is the cumulative past 3-month market return from the beginning of month $t-3$ to the end of month $t-1$. $R^M_{t-6\rightarrow t-4}$ is the lagged cumulative past 3-month market return from the beginning of month $t-6$ to the end of month $t-4$. This regression design allows us to control for fund-level characteristics that help explain expectation formation, as well as a set of fixed effects, particularly the fund$\times$horizon fixed effect, $\alpha_{i,h}$. The inclusion of $\alpha_{i,h}$ serves two purposes: (i) it helps identify the time-series variation in expectations in response to variation in past market returns for a given manager and forecast horizon, and (ii) it purges out time-invariant manager bias in market forecasts across different horizons.[7] Standard errors are clustered at the fund and filing year-month level to correct for potential cross-sectional and serial correlation in the error term $\varepsilon_{i,t,h}$. Table 7 reports the results. Column (1) shows that the estimated coefficient on the prior 3-month excess market return is 0.647 and statistically significant, while the estimate for the lagged 3-month excess market return is positive but insignificant. Column (2) shows

[7]Prior literature documents that analysts are more optimistic at longer horizons(Cassella et al., 2023) and bias in analyst forecasts increases with the forecast horizon (de Silva and Thesmar, 2024).

a positive correlation between fund expectations and the log price-to-earnings ratio (PE), with an estimated coefficient of 0.004. Since the log price level is essentially the sum of all past returns, this low and insignificant estimate suggests that more recent returns have a stronger influence on fund expectations, consistent with our earlier findings. Column (3) controls for both past market returns and the PE ratio simultaneously. The coefficient on the past 3-month excess market return remains quantitatively similar, while the coefficient on the log PE ratio turns negative. This evidence suggests that fund expectation formation exhibits a pattern of short-term momentum and long-term reversals: when recent returns are high, funds tend to be optimistic about future stock market performance, whereas when returns from more distant periods are high, funds tend to become pessimistic.

It is also possible that fund expectations of future stock market returns rise on the back of good fund performance. Column (4) shows that when cumulative fund returns over the past 3 months are high, funds expect higher market returns going forward. However, lagged 3-month fund returns have no significant effect on expectations, consistent with the idea that the most recent one-quarter returns play a key role in expectation formation. Column (5) controls for market returns, fund returns, and the log price-to-earnings ratio. The estimate of the past 3-month market returns remains statistically significant, though its magnitude declines by approximately 20% compared to the estimate in Column (1). In contrast, the magnitude of the past 3-month fund returns sharply shrinks to 0.279, a decrease of about 115% compared to Column (3), suggesting that the impact of past fund performance on expectations is largely driven out once past market returns over the same period are included in the model. To check the robustness of these results, Column (6) additionally controls for manager- and fund-level characteristics. The inclusion of these controls has little impact on funds' extrapolation behavior. We consistently find that funds place greater weight on the most recent one-quarter market returns when forming expectations, whereas the effect of past one-quarter fund returns remains only marginally significant.

[Insert Table 7 here]

3.3. Fund manager experiences and extrapolative expectations

A key advantage of our mutual fund setting is that it provides data on both expectations and fund characteristics, allowing for a systematic analysis of heterogeneity in belief formation across funds. This is important, as Giglio et al. (2021) document substantial and persistent individual heterogeneity in expectations among U.S. wealthy retail investors using a large survey panel from Vanguard. Among all fund characteristics, we focus on manager experience as a key determinant of extrapolative behavior. This choice is motivated by both theoretical considerations and empirical evidence suggesting that past experiences affect agents' belief formation, attitudes toward risk, and investment style (Malmendier and Nagel, 2011). Less experienced managers, having seen fewer market cycles, tend to rely more heavily on recent returns when forming expectations. In contrast, more seasoned managers, shaped by a broader set of market experiences, are more likely to incorporate distant but salient return episodes, resulting in more tempered extrapolation of recent trends.

Table 8 presents estimation results of Eq. (7) across fund experiences.[8] We start by estimating λ separately for funds run by managers with and without bubble-crash experiences. Following Luo et al. (2022), bubble-crash experience is defined as a dummy variable equal to one if the fund is run by managers who experienced the 2007–2008 or 2014–2015 A-share market bubble-crash episodes. As expected, Columns (1) and (2) show that managers with bubble-crash experience display significantly lower extrapolation slopes than their peers (0.651 versus 0.493). Notably, for these managers, the weight assigned to returns from one year ago is approximately 15 times greater than that of managers without such experience, suggesting that firsthand exposure to market crises tempers the tendency to project recent realizations forward.

Next, we estimate λ separately for recession managers and non-recession managers. Guided by Chen et al. (2021), a recession manager is defined as one who began their mutual fund management career during an economic recession. In Columns (3) and (4),

[8]For brevity, we report only the specification that includes 12 lagged monthly excess market returns.

we find that recession managers exhibit less extrapolative behavior, with an estimated λ of 0.600 compared to 0.512 for non-recession managers. This implies that recession managers assign roughly 5 times more weight to returns from one year ago than their counterparts, reinforcing the idea that early-career downturns attenuate the tendency to extrapolate recent returns.

Finally, Columns (5) and (6) split the sample by fund manager age.[9] In each reporting period, managers are classified as older if their age falls in the top tercile and younger if in the bottom tercile. Consistent with the prediction of the experience-based model (Malmendier and Nagel, 2011), recent returns account for less weight in expectation formation for the older than for the young, with estimated λ values of 0.637 and 0.528, respectively.

Taken together, these findings highlight the persistent influence of salient personal experiences on expectation formation. Managers with such experiences place greater weight on distant returns, resulting in a lower degree of recency bias compared to their less-experienced peers.

[Insert Table 8 here]

4. Return predictability tests

The previous section shows that Chinese mutual funds form their stock market expectations by extrapolating recent past market returns. Since expectations formed through extrapolation typically predict future asset returns with a negative sign, these beliefs are considered a behavioral bias (Greenwood and Shleifer, 2014; Da et al., 2021). However, in our context, Fig. 1 provides preliminary evidence of a positive relation between fund expectations and ex-post stock market returns. In this section, we examine whether the extrapolative beliefs of Chinese mutual funds are systematically biased by performing return predictability tests.

[9]Because most fund managers do not disclose their date of birth, the sample size decreases substantially.

4.1. Baseline regression results

To investigate whether the consensus forecasts of Chinese mutual funds are accurate or systematically biased, we estimate monthly predictive regressions for market returns of the form:

$$R^M_{t\to t+\tau} = \alpha + \beta \cdot X_t + \varepsilon_{t\to t+\tau}, \tag{10}$$

where $R^m_{t\to t+\tau}$ is the h-month ahead cumulative excess market return from month t to $t+\tau$, and X_t is a predictor (e.g., fund expectations) known at the end of month t. To ease economic interpretation, we standardize X_t to have zero mean and unit variance.

Of course, such time-series regressions are inherently fragile, and several econometric issues can distort statistical inferences. First, if both the left- and right-hand side variables exhibit high persistence, ordinary least squares (OLS) regression may produce spurious results. Second, because samples of long-horizon returns overlap, residuals in Eq. (10) are autocorrelated when $\tau > 1$. To account for the overlapping nature of the return variable, we use Hansen-Hodrick standard errors with τ lags (Hansen and Hodrick, 1980). Third, the well-known small sample bias (e.g., Stambaugh, 1999) arises in finite samples, and thus OLS estimates and associated t-statistics are unreliable. We mitigate this bias by computing p-values using a parametric bootstrap simulation. Our simulation process follows a similar approach to Ang and Bekaert (2007) and Yu (2011). Specifically, we estimate a restricted VAR for monthly excess returns and fund expectations under the null of no return predictability by fund expectations. We assume that the joint distribution of innovations in the VAR corresponds to their empirical distribution. Error terms are then drawn with replacement from the joint empirical distribution of the two residuals in the VAR equations. This process is repeated 5,000 times to generate a distribution of Hansen-Hodrick t-statistics. Based on this bootstrapped distribution, we compute the corresponding empirical p-value of the estimated t-statistic.

Table 9 reports the forecasting results, where the horizon τ ranges from one to twelve months. In Panel A, we test the predictive power of the consensus forecasts of funds. We find that fund expectations predict future stock market returns with a positive sign across various horizons. This predictive power is concentrated at shorter horizons, particularly within the first three months when bootstrapped p-values are used. For example, at the one-month horizon, the OLS regression slope on fund expectations is 0.015 and is statistically significant, with a Hansen-Hodrick t-statistic of 2.654 and a bootstrapped p-value of 0.01. In terms of economic significance, a one-standard-deviation increase in EXPECTATION corresponds to a 1.5% decrease in the expected excess market return for the next month. Given that the average monthly excess market return during our sample period is 1.2%, this estimate implies that the expected excess market return based on EXPECTATION is approximately 1.25 times larger in absolute magnitude than its average level, suggesting a large economic significance (Jiang, 2020). The forecasting model also produces a sizable in-sample R^2 of 3.2%. This level of predictability suggests considerable economic value, provided it persists in out-of-sample tests, which we explore in the next section.

4.2. Comparisons with macroeconomic predictors

Panel B examines whether the forecasting power of EXPECTATION is driven by economic fundamentals. To this end, we control for several well-known economic predictors one by one, including the analysts' consensus forecasts for earnings-per-share (EPS) growth (μ), where the growth is defined as the difference between the analysts' forecasts of EPS and the most recent realized EPS, scaled by the most recent realized EPS, the Baker and Wurgler (2006) investor sentiment index recalculated using data from the Chinese capital market (S), log dividend-price ratio (DP), log earnings-price ratio (EP), log book-to-market ratio (BM), stock market turnovers (TO), stock return variance (SVAR), inflation (INFL), net equity expansion (NTIS), 3-month government bond yield (STY), and 10-year government bond yield (LTY). We find that the estimates of the slope on fund expectations in a bivariate specification range from 0.011 to 0.016, all of which are negative and economically significant, consistent with the results from the earlier univariate predictive regression reported in Panel A. Moreover, Panel C shows that fund expectations still have incremental forecasting power after controlling for all economic indicators in one equation. These results demonstrate that fund expectations contain unique information beyond macroeconomic fundamentals, contributing independently to market return prediction.

[Insert Table 9 here]

4.3. Are Chinese mutual fund expectations politically biased or informative?

One potential concern is that mutual fund managers may be reluctant to issue strongly negative market forecasts due to political sensitivities or implicit pressures from government and media entities. As a result, consensus expectations may be systematically biased toward optimism. However, we provide several pieces of evidence that mitigate this concern. First, we show that mutual fund expectations are largely shaped by past stock market returns, with negative outcomes exerting a more persistent influence on belief formation. Second, prior research finds that forecasting accuracy is positively associated with fund flows (Ammer et al., 2022; Fang et al., 2024), suggesting that managers have clear incentives to form and report informed views. Third, Table 3 shows that portfolio adjustments are strongly aligned with stated expectations, indicating that the reported market outlook is not merely rhetorical, but reflects genuine investment beliefs.

Moreover, if this concern were valid, it would imply that the bullish component of our consensus expectation measure should exhibit little to no predictive power–or even a negative relation–with future market returns, as fund managers facing political pressures may be inclined to issue optimistic outlooks precisely when market conditions are deteriorating. However, Panel D of Table 9 shows that the proportion of optimistic funds, BULLISH, positively predicts ex post market returns, whereas Panel E shows that the proportion of negative funds, BEARISH, negatively predicts ex post market returns. Consistent with prior findings, the predictive power of both components is most pronounced at short horizons. These results suggest that fund expectations are informative about market dynamics and strongly counter the concern that they are merely noisy signals or politically biased statements.

4.4. Mandated expectations versus non-mandated expectations

So far, our results show that mutual fund expectations positively predict market returns over very short horizons. One possible explanation is the infrequent disclosure of fund expectations: they are updated only six times per fiscal year: four times in non-mandated quarterly reports and twice in mandated semi-annual and annual reports. To construct a monthly series for return prediction, we interpolate expectations using the last observation carried forward. This approach results in multiple consecutive months sharing the same expectation value, concentrating any predictive power in the initial month following a new disclosure. Beyond that, the interpolated expectation becomes "old news," offering limited informational value for forecasting future returns.

To better assess the forecasting power of fund expectations over longer horizons, it is preferable to construct separate consensus expectation series based on mandated (semi-annual and annual) and non-mandated (quarterly) disclosures, without applying interpolation. Although fund managers do not always explicitly state the forecast horizon, we conjecture that expectations expressed in quarterly reports pertain to the upcoming quarter, those in semi-annual reports to the next six months, and those in annual reports to the full year ahead.[10] This inference is supported by the typical wording found at the beginning of the management outlook section, where many funds specify the horizon explicitly–for example, "As for the outlook for the next quarter...," "As for the outlook for the second half of the year...," or "As for the outlook for the next year...," depending on the report type.

Table 10 presents results of predictive regressions. In Panel A, we construct the consensus expectation series based on quarterly non-mandated disclosures. We find that mutual funds' quarterly stock market expectations positively predict one-quarter-ahead market returns, with a slope coefficient of 0.178 and a Hansen and Hodrick (1980) t-

[10]In inferring Chinese mutual funds' monetary policy and economic forecasts, Ammer et al. (2022) and Ammer et al. (2024) also conjecture that the forecast horizon for quarterly reports is one quarter. Our treatment is consistent with theirs.

statistic of 1.999. Both the bullish and bearish components of these expectations exhibit predictive power in the expected directions: the estimated coefficient on the bullish component is 0.319 (t-stat $= 2.228$), while the coefficient on the bearish component is -0.277 (t-stat $= -1.455$). These results suggest that voluntary (non-mandated) expectations–despite not being required by regulators–still contain valuable information about future market performance, likely reflecting fund managers' genuine expectations rather than boilerplate language.

In Panel B, we construct the consensus expectation series using semi-annual and annual mandated disclosures. Because of the relatively short sample period (approximately 20 years), we pool the semi-annual and annual expectations together to improve estimation accuracy, despite their corresponding to different forecast horizons. As expected, expectations extracted from the mandatory disclosures also exhibit predictive power, and importantly, in both directions (bullish and bearish): bullish and bearish views are associated with subsequent positive and negative market returns, respectively, over the following six months. This evidence suggests that mandated expectations are not merely perfunctory compliance statements but instead reflect real-time belief updating and contain information relevant for market timing.

[Insert Table 10 here]

4.5. Market return autocorrelation and fund expectations

Autocorrelations in broader stock indices are predominantly positive due to the positive cross-autocorrelations among individual stocks (Campbell, 2018), particularly at short lags (Lo and MacKinlay, 1988; Cutler et al., 1991). Prior studies also document time series momentum (TSM), which reflects the positive predictability of an asset's own past returns (Moskowitz et al., 2012; Huang et al., 2020). Since mutual funds form expectations in part by extrapolating from recent market returns, it is essential to determine whether the observed return predictability of fund expectations simply reflects the continuation of stock price trends or contains additional information.

To disentangle these effects, we control for lagged past market returns over one-, three-, six-, and twelve-month horizons. Table 11 reports the results. Columns (1)–(4) show that lagged market returns positively predict next-month market returns, though only the past one-quarter return is statistically significant. In Columns (5)–(8), we include fund expectations in the predictive regressions. A notable U-shaped pattern emerges in the coefficients on expectations. In Column (5), which includes the past three-month return, the coefficient on expectations declines modestly to 0.013 from 0.015 in the baseline regression reported in Table 9. The decline is more pronounced in Column (6), where the magnitude drops by approximately 40% to 0.009 when controlling for the past six-month return. However, Columns (7) and (8) show that the coefficient rebounds at longer horizons; for instance, when controlling for the past twelve-month return, the coefficient on expectations rises to 0.014. These results suggest that part of the predictive power of fund expectations reflects their extrapolation of recent returns, particularly those over the past three to six months, consistent with our earlier evidence on the formation of fund expectations. However, fund expectations continue to exhibit marginal statistical significance even after controlling for lagged market returns, while the coefficients on past returns become uniformly insignificant across all horizons. This pattern indicates that mutual fund expectations not only reflect recent return dynamics but also contain incremental predictive information beyond what is captured by simple return extrapolation.

[Insert Table 11 here]

4.6. Out-of-sample predictability and economic value

In this section, we complement the in-sample analysis from the previous section with out-of-sample (OOS) tests. We examine the OOS performance of fund expectations using the widely used OOS R^2 statistic (Campbell and Thompson, 2008):

$$R^2_{OOS} = 1 - \frac{\sum_{t=r}^{T-1}(R^M_{t+1} - \hat{R}^M_{t+1})^2}{\sum_{t=r}^{T-1}(R^M_{t+1} - \bar{R}^M_{t+1})^2}, \tag{11}$$

where $\hat{R}^M_{t+1}$ is the one-step-ahead forecast value from a predictive regression using EXPECTATION as the predictor, estimated up to time t, and $\bar{R}^M_{t+1}$ is the historical average return. Therefore, R^2_{OOS} is a measure of the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average benchmark, ranging from negative infinity to 1 by construction. A positive value of R^2_{OOS} indicates that the MSFE of the predicted return using EXPECTATION is smaller than the historical average, suggesting better OOS performance of the "full" model with a predictor compared to the naïve one without the predictor. In addition, following Campbell and Thompson (2008), we impose an economic restriction on the estimated coefficients of the predictor and the corresponding forecast returns. Specifically, the predictive regression coefficient is set to zero if it has a sign opposite to the one estimated over the full sample. The forecast return is then set to zero whenever it is negative.

To test the statistical significance of R^2_{OOS}, we use two statistics. The first is the MSFE-adjusted statistic proposed by Clark and West (2007) (hereafter CW test). The rationale behind the CW test is that if the parsimonious model without predictors is true, it would be more efficient in predicting returns, resulting in a smaller MSFE than the "full" model with predictors. We test the null hypothesis that the historical average MSFE is less than or equal to the predictive regression forecast MSFE against the one-sided against the alternative hypothesis that The historical average MSFE is greater than the predictive regression forecast MSFE, corresponding to $H_0 : R^2_{OOS} \leq 0$ against $H_A : R^2_{OOS} > 0$.

We also perform the test proposed by Diebold and Mariano (1995) and later modified by McCracken (2007) (hereafter DM test). The DM test's null hypothesis is that the MSFE of one forecast equals the MSFE of another. We calculate the modified DM test statistic, which follows a nonstandard normal distribution for nested models, and use bootstrapped critical values for the nonstandard distribution.

To quantify the economic gains from incorporating mutual fund expectations in predicting market returns, we compute the certainty equivalent return (CER) gain for a mean-variance investor who optimally allocates between equities and the risk-free asset based on OOS predictive regression forecasts. We assume power utility with a coefficient of relative risk aversion (CRRA) of 3. At the end of month t, the investor optimally allocates

$$w_t = \frac{1}{3}\frac{\hat{R}^M_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{12}$$

of the portfolio to equities during month $t+1$, where $\hat{R}^M_{t+1}$ is the OOS forecast of excess market return and $\hat{\sigma}^2_{t+1}$ is the conditional excess-return variance. Following Campbell and Thompson (2008), we assume that the investor estimates the variance using a rolling five-year moving window of past monthly returns. The investor then allocates $1 - w_t$ of the portfolio to the risk-free asset, and the realized portfolio return for month $t+1$ is

$$R^P_{t+1} = w_t R^M_{t+1} + R^f_{t+1}, \tag{13}$$

where R^f_{t+1} is the one-year deposit interest rate. To make our scenario more realistic, we follow Campbell and Thompson (2008) and constrain w_t to lie between 0 and 1.5, excluding short sales and limiting leverage to 50%. Then, the investor's average ex post annualized CER is:

$$\text{CER}_P = \hat{\mu}_P - \frac{3}{2}\hat{\sigma}^2_P, \tag{14}$$

where $\hat{\mu}_P$ and $\hat{\sigma}^2_P$ are the sample mean and variance of the investor's portfolio over the OOS evaluation periods, respectively. Additionally, we calculate the OOS Sharpe ratio of the portfolio, defined as the mean excess portfolio return over the risk-free rate divided by the standard deviation of the excess return.

Since OOS statistics are sensitive to the relative length between the initial in-sample estimation period and the out-of-sample forecasting period, we prefer conducting out-of-sample predictive regressions using a rolling approach. We set the window sizes to 36, 48, and 60 months to balance estimation errors and forecast evaluation power while addressing concerns about size distortion in OOS forecasting performance.

Table 12 shows the results. In the first row, where we run predictive regressions using a 36-month rolling approach, fund expectations yield an R^2_{OOS} of 8.38%, with both the CW- and DM-test statistics statistically significant at the 1% level. This R^2_{OOS} corresponds to a large positive CER gain of 3.95%, suggesting that a mean-variance investor with power utility and a CRRA of 3 would be willing to pay up to 3.95% annually in portfolio management fees to access the predictive regression forecasts based on fund expectations, rather than using the historical average forecast. The OOS Sharpe ratio for fund expectations is approximately 0.44, much higher than the market Sharpe ratio of −0.14 for a buy-and-hold strategy over the same period. These results suggest that utilizing the beliefs of mutual funds generates sizable economic value for an investor from an asset allocation perspective. As shown in the second and third rows, the OOS predictability is robust to different lengths of the estimation window. Fund expectations consistently produce a positive and large R^2_{OOS} in longer rolling estimation periods of 48 and 60 months.

[Insert Table 12 here]

Given the strong OOS predictive power of fund expectations, a natural question is whether this predictability remains stable over time or is concentrated in specific subperiods. To this end, we follow the approach of Goyal and Welch (2008) and examine the time-varying in-sample (IS) and OOS performance of mutual fund consensus expectations. Specifically, we plot the cumulative difference in MSFE between the historical average benchmark and forecasts based on mutual fund consensus expectations. An upward trend in this series indicates that the fund-based forecasts outperform the historical average.

Fig. 5 shows the cumulative differences in MSFE for IS (red solid line) and OOS (cyan solid line) forecasts corresponding to the specification of the first row in Table 12. Along with the plot, we also shade in grey the two notorious bubble-crash episodes in China: the 2007–2008 market rise and collapse and the 2014–2015 market bubble crash, with vertical dashed black lines indicating the peak date of each bubble-crash cycle. Several noteworthy patterns emerge. First, both the IS and OOS series exhibit a generally upward trajectory and remain above the zero horizontal line throughout most of the sample period, indicating that expectation-based forecasts consistently outperform the historical average. The OOS performance is also statistically significant, as indicated by its position above the lower bound of the 95% confidence interval. Second, return predictability is especially pronounced during bubble-crash episodes. The IS performance increases sharply during market booms but tends to stabilize or decline during subsequent downturns. Between the two bubble-crash periods and in the post-2015 era, the IS performance is relatively stable with moderate fluctuations. In contrast, the curve associated with OOS predictions shows a more stable upward trend across both episodes. This performance difference could arise from the sign restrictions imposed on the slope coefficient of fund expectations, which ensure that only economically sensible (positive) relations are considered (Campbell and Thompson, 2008). Overall, these findings suggest that Chinese mutual funds possess stable stock market timing ability, particularly during periods of significant market movement. This aligns with prior evidence on their forecasting skills, such as monetary policy forecasts in Ammer et al. (2022), economic growth predictions in Ammer et al. (2024), and countercyclical policy forecasts in Gao et al. (2024).

[Insert Fig. 5 here]

5. Stock market expectations and fund performance

In this section, we examine the implications of fund expectations for performance. Since consensus forecasts of funds predict market returns with a positive sign, we expect that more optimistic stock market expectations predict higher future fund returns in the time series for a given fund. Specifically, we estimate the following regression:

$$\mathrm{PERF}_{i,t\to t+\tau} = a_i + b_1 \mathrm{EXPECTATION}_{i,t} + c'\mathrm{X}_{i,t} + \varepsilon_{i,t\to t+\tau}, \tag{15}$$

where $\mathrm{PERF}_{i,t\to t+\tau}$ is fund i's average monthly performance from the end of month t to $t+\tau$, annualized by multiplying by 12. $\mathrm{EXPECTATION}_{i,t}$ is the fund's stock market expectation. $\mathrm{X}_{i,t}$ is a set of standard fund-level controls. Standard errors are double-clustered at the fund and time level.

There are two additional caveats in estimating Eq. (15). (i) Chinese mutual funds are not legally required to disclose market outlooks in quarterly reports. To mitigate selection bias from discretionary disclosure, we conduct the regression using annual report data. (ii) A typical annual fund report, including expectations for the next calendar year, is publicly available to investors in March of the following year. Therefore, we measure fund performance from April to December of that year. For example, we use the EXPECTATION quantified from the 2010 annual report, released in March 2011, to forecast the remaining 9-month return from April to December 2011.

5.1. Expectations and performance: time series versus cross section

Table 13 reports the estimation results. In Column (1), we include fund fixed effects and use time-series variation to identify the effect of expectations on future fund performance. Consistent with the aggregate expectation-return relation, we find that the estimated coefficient on EXPECTATION is positive and statistically significant, with a t-statistic of 1.852. This relation is also economically significant. The average within-fund standard deviation of EXPECTATION is 0.465. Therefore, the estimated slope of 4.618 implies that a one-standard-deviation increase in a fund's expectation corresponds to a 2.15%(= 4.618×0.465) increase in its annualized expected return. This magnitude is substantial, in that it is about one-fifth of the fund's mean annualized return of 10.07%. In Column (2), we decompose fund expectations into two components: the positive part, EXPECTATION^{+}, and the negative part, EXPECTATION^{-}, where EXPECTATION$^{+} = \max\{\text{EXPECTATION}, 0\}$ and EXPECTATION$^{-} = \min\{\text{EXPECTATION}, 0\}$. This piecewise-linear specification allows for different expectation-performance sensitivities at different levels of expectations. We find that the effect of fund expectations on performance is primarily driven by the optimistic part. One potential explanation is that Chinese mutual funds face binding short-sale constraints. Optimistic funds can easily translate expectations into action by increasing exposure to high-beta stocks, boosting performance during market upturns. In contrast, pessimistic funds cannot fully adjust their portfolios via shorting risky stocks, limiting their ability to capitalize on market downturns.

The effect of fund expectations on performance becomes even larger when considering the correctness of fund forecasts. In Column (3), we introduce a dummy variable, CORRECT, equal to one if the fund's annual forecast is in the same direction as the realized excess market return of the next year and zero otherwise. We find that the estimated coefficient on CORRECT is 19.089 ($t = 4.332$), suggesting that funds that correctly predict market direction are rewarded, consistent with earlier evidence on the predictive ability of Chinese mutual funds' monetary forecasts in the time series (Ammer et al., 2022). Column (4) further decomposes CORRECT into CORRECT$^+$ (i.e., funds are optimistic and the realized market return is positive) and CORRECT$^-$ (i.e., funds are pessimistic and the realized return is negative). The estimated coefficients on CORRECT+ and CORRECT− is 22.726 and −4.516, with t-statistics of 4.156 and −1.721, respectively. These findings align with the interpretation that short-sale constraints affect funds' ability to profit from pessimistic expectations. Despite accurately predicting market downturns, funds still underperform due to insufficient portfolio adjustments.

Our evidence so far suggests a positive relation between fund expectations and future fund performance. However, because of the weak (but positive) transmission of beliefs to actions (Giglio et al., 2021), directly regressing fund performance on its expectations may fail to yield a significant relation in the cross-section. Consider an extreme case: Suppose there are three funds–A, B, and C–with similar characteristics. At time t, fund A is optimistic about future stock market performance, fund B holds a neutral view, and fund C is pessimistic, yet none of these funds adjust their portfolios accordingly. If, from t to $t+1$, the stock market rises, all three funds would experience similar performance gains, despite having different expectations. One might then conclude that expectations have little to no effect on fund performance in the cross-section. Consistent with this idea, in Columns (5)–(8), where we identify the coefficients using cross-sectional variation by including year fixed effects, the magnitudes of the regression slopes for EXPECTATION and CORRECT shrink sharply and become statistically insignificant.

[Insert Table 13 here]

5.2. Forecasting skill, degree of pass-through, and fund performance

The cross-sectional results in Table 13 highlight that fund performance differs only if funds have correct expectations and adjust portfolios based on their expectations (e.g., optimistic funds tilt portfolios toward high-beta stocks). The stronger the pass-through, the greater the impact on performance. As such, we estimate the following regression:

$$\begin{aligned}\mathrm{PERF}_{i,t\rightarrow t+\tau} = a_i &+ b_1\mathrm{CORRECT}^{+}_{i,t} + b_2\mathrm{CORRECT}^{-}_{i,t} + b_3\mathrm{BETA}_{i,t} \\ &+ b_4\mathrm{CORRECT}^{+}_{i,t} \times \mathrm{BETA}_{i,t} + b_5\mathrm{CORRECT}^{-}_{i,t} \times \mathrm{BETA}_{i,t} \\ &+ c'\mathrm{X}_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t\rightarrow t+\tau}.\end{aligned} \tag{16}$$

We use three performance metrics for the funds: net-of-fee return, CAPM one-factor-adjusted alpha, and Carhart four-factor adjusted alpha. To compute the risk-adjusted alphas, we first estimate the fund's risk loadings based on the past 36 months of data. We then adjust the monthly fund returns using these estimated risk loadings. The average fund alphas are calculated from April to December and annualized by multiplying by 12. The superscript $+/-$ of CORRECT indicates the sign of the realized excess market return. BETA is the fund's holding-weighted beta, where a stock's beta is estimated using CAPM with daily returns over the past 12 months. μ_i and ν_t are fund and year fixed effects, respectively. The estimates of b_4 and b_5 are of primary interest, as they capture how the degree of pass-through from beliefs to actions affects fund performance.

To emphasize that the accuracy of expectations plays a crucial role in determining cross-sectional fund performance, we first replace CORRECT with EXPECTATION in Eq. (16) and present the estimation results in Panel A of Table 13. The estimated coefficients on EXPECTATION$^{+}\times$BETA and EXPECTATION$^{-}\times$BETA are statistically insignificant across all performance measures. However, in Panel B, where we report the estimation results of Eq. (16), the estimates of b_4 and b_5 become statistically significant. Column (1) shows that the estimated coefficient on the interaction term, CORRECT$^{+}\times$BETA, is 22.176, with a t-statistic of 3.295, suggesting that funds that correctly anticipate a bullish market in the next year and shift their portfolio toward high-beta stocks earn a higher return. The effect is also economically significant in two ways. First, for a fund with a correct prediction, a one-standard-deviation increase in portfolio beta is associated with a 2.25% increase in the fund's annualized expected return (calculated as $(22.176 - 10.480) \times 0.192$). Second, for a typical fund with a beta of one, the magnitude implies that the fund's skill in accurately predicting future stock market performance is rewarded with a $1.13\%(= 22.176 \times 1 - 21.051)$ net-of-fee return. Recall that the sample average annualized return is 10.07%, these magnitudes are sizable.

In contrast, the slope of the interaction term, CORRECT$^{-}\times$BETA is negative, indicating that funds that correctly anticipate a bearish market and adjust their portfolio to low-beta stocks experience smaller losses. However, this effect is statistically insignificant ($t = -1.271$). This differential effect of optimistic-versus-pessimistic pass-through transmission on future fund performance likely arises from mutual funds facing binding short-sale constraints, consistent with the results in Table 13. When funds are optimistic, they can easily increase exposure to high-beta stocks, boosting performance during market upturns. However, when funds are pessimistic, they cannot fully adjust their portfolios by shorting risky stocks, limiting their ability to profit from market downturns. Consequently, funds with correct optimistic forecasts and corresponding portfolio adjustments show stronger performance improvements, while those with pessimistic forecasts exhibit weaker and less significant performance improvements. Finally, we draw similar inferences from Columns (2) and (3), where the dependent variable is the CAPM one-factor-adjusted alpha and Carhart four-factor-adjusted alpha.

Taken together, while a fund's forecasting skill enhances its time-series performance unconditionally, its cross-sectional performance not only depends on market prediction skill but also on the degree of pass-through from beliefs to portfolio adjustments across funds. Correct optimistic expectations are more effectively passed through to portfolio choices and, in turn, to superior fund performance than pessimistic expectations. This asymmetry is broadly consistent with limits-to-arbitrage explanations, particularly given the short-sale constraints prevalent in China's mutual fund industry.

[Insert Table 14 here]

5.3. Liquidity and the execution of market expectations

In this section, we explore whether a fund's capacity to act on its market expectations depends on the liquidity of the stocks it holds. In frictional markets, liquidity plays a critical role in enabling timely and cost-efficient portfolio adjustments. If well-informed funds cannot rebalance into (or out of) riskier positions due to liquidity constraints, their forecasting skill may not fully translate into realized performance, as insufficient portfolio adjustments hinder the implementation of their views.

To test this hypothesis, we examine how liquidity affects the strength of the relation between expectation-aligned beta tilts and future fund performance. Specifically, we construct a fund-level liquidity proxy based on the allocation to liquid stocks, denoted as %LIQ, defined as the percentage of a fund's portfolio invested in liquid stocks. Liquid stocks are those in the bottom quintile of the Amihud (2002) illiquidity measure within each year. We then split the fund-year observations into low liquidity funds (below-median %LIQ) and high liquidity funds (above-median %LIQ) and estimate Eq. (16) separately for each subsample. This allows us to test whether the performance benefit of acting on correct bullish beliefs is more pronounced for funds with more liquid holdings.

Table 15 reports estimation results. We start by measuring fund performance using net-of-fee returns. Among low-liquidity funds (Column 1), the estimated coefficient on the interaction term, CORRECT^{+}×BETA, is 17.169 (t-stat = 2.680). Among high-liquidity funds (Column 2), the magnitude increases to 30.159 (t-stat = 3.267). This liquidity-dependent asymmetry is also economically meaningful. For funds with accurate optimistic expectations, a one-standard-deviation increase in beta (roughly 0.2) translates into a 2.24%$(= (17.169 - 5.992) \times 0.2)$ increase in future net-of-fee return for low-liquidity funds, compared to a 3.4%$(= (30.159 - 14.487) \times 0.2)$ increase for high-liquidity funds. The high-minus-low performance difference persists across various risk-adjusted alpha measures in Columns (3)–(6), ranging from 0.7% per year for the CAPM one-factor model to 0.8% per year for the four-factor model. These results suggest that even among funds with similar market expectations and beta tilts, liquidity amplifies the extent to which beliefs are translated into realized returns. In other words, liquidity serves as a transmission channel that allows skilled or correctly forecasting managers to more effectively implement their views.

Our findings complement those of Jiao et al. (2025), who show that global mutual funds with stronger preferences for trading cross-listed equities in more liquid venues tend to outperform. They interpret this "liquidity picking" behavior as a signature of informed trading: a manager's willingness to trade in thicker markets to exploit informational advantages while minimizing price impact. In our context, the superior performance of liquidity-tilted funds with accurate expectations similarly suggests that liquidity facilitates more effective execution of forecasts.

Overall, the evidence indicates that stock liquidity plays a pivotal role in conditioning the pass-through from expectations to performance. Liquidity shapes both the feasibility and effectiveness of portfolio adjustments.

[Insert Table 15 here]

6. Discussion

6.1. "Small" versus "large" LLMs

In the era of large language models (LLMs), a common question in text-based financial research is: why still use a "small" LLM (e.g., BERT) instead of using a "large" LLM (e.g., ChatGPT)? This section outlines our rationale for employing BERT instead of more recent LLMs to extract fund managers' beliefs from text. While models such as ChatGPT have made substantial progress in natural language understanding and generation, we highlight several reasons why BERT is a more appropriate tool for our study.

First, BERT models offer greater interpretability and verifiability than modern LLMs. BERT's architecture facilitates efficient task-specific fine-tuning, allowing us to tailor the model to the financial context of Chinese mutual fund reports. This customization also improves the interpretability and verifiability of our results, as each extracted belief can be directly traced back to specific textual evidence. In contrast, LLMs often rely on multi-step prompting, making it more difficult to trace outputs back to specific input features.

Second, reproducibility is a cornerstone of empirical research. BERT models yield deterministic outputs once trained, ensuring consistency across runs. In contrast, LLMs can produce variable results due to their probabilistic nature and sensitivity to prompt phrasing, which complicates reproducibility (Chen et al., 2025). This makes BERT a more stable and reproducible tool for our structured classification task.

Third, although LLMs exhibit superior semantic understanding, their application to domain-specific tasks such as belief extraction in financial texts often involves substantial computational costs (Barnett et al., 2024). For example, LLMs are generally more effective at resolving semantic ambiguity when terms like “market” may refer to equities, bonds, real estate, or currencies. With well-designed prompts, LLMs can often infer the correct referent from contextual cues (see, e.g., Gao et al. (2024)). However, this advantage comes at a cost: token-intensive prompts and elevated usage fees. OpenAI, for instance, recommends at least ten in-context examples per prompt to ensure reliable performance, which imposes serious scalability and cost challenges for large-scale belief extraction tasks. To strike a balance between performance and computational costs of our text-based belief extraction, we adopt a BERT-based framework. To address the ambiguity introduced by the term “market,” we develop a robust filtering procedure that incorporates a manually constructed exclusion list of terms unrelated to the A-share market. While we acknowledge that this approach may not entirely eliminate non-equity references, it substantially reduces noise and improves classification precision. This preprocessing step enables BERT to perform competitively in contexts where LLMs might otherwise exhibit a semantic advantage.

In sum, while LLMs offer strong capabilities for generative tasks, the interpretability, reproducibility, and cost-effectiveness of the BERT model make it better suited for our empirical analysis of mutual fund stock market expectations. Nevertheless, to ensure that our findings are not model-specific, we also quantify mutual funds’ expectations using DeepSeek-V3. Following Gao et al. (2024), the prompt is:

“*Forget all your previous instructions. Assume the role of a Chinese financial expert specializing in financial report analysis. Your task is to assess the outlook section of a mutual fund’s periodic report. Evaluate overall expectations for the A-share stock market and classify it as ['Positive', 'Weakly Positive', 'Neutral', 'Weakly Negative', 'Negative', 'Not Mentioned']. Assign a sentiment score between 0 and 100, with larger values being* *more optimistic. Give a concise, one-sentence elaboration in Chinese.* "

In this prompt, we instruct DeepSeek to evaluate expectations regarding the A-share stock market, providing both a qualitative classification and a quantitative sentiment score ranging from 0 to 100. Based on the model's outputs, we follow the methodology laid out in Eq. (2) and construct a measure of consensus expectations defined as the difference between the proportion of optimistic and pessimistic funds. Specifically, we classify responses labeled as "Positive" or "Weakly Positive" as optimistic, and those labeled as "Negative" or "Weakly Negative" as pessimistic. At the fund level, we standardize the sentiment score by subtracting 50 and dividing by 50, which transforms the DeepSeek-based expectation measure to lie within the interval $[-1, 1]$.

Fig. 6 compares the BERT-based (red solid line) and DeepSeek-based (dark blue dashed line) measures of mutual fund consensus expectations. The two series exhibit a closely aligned trend, with a Pearson correlation coefficient of 0.86, indicating strong agreement between the models' predictions. Internet Appendix B presents robustness checks using DeepSeek-based expectations: Table IB.1 replicates Table 4, Table IB.2 replicates Table 5, Table IB.3 replicates Table 8, and Table IB.4–IB.10 replicate Table 9–15. Our findings remain robust when expectations are extracted via DeepSeek-V3.

[Insert Fig. 6 here]

6.2. Extrapolative beliefs in retail investors

If mutual fund managers aggregate past returns rationally when forming expectations, a natural question arises: can retail investors do the same? We address this question in two steps. First, we examine whether retail investors also exhibit extrapolative beliefs. Second, we investigate the relationship between these beliefs and future market returns.

We proxy retail investors' stock market expectations (denoted as GUBA_EXPECTATION) using the aggregated Guba post tone, calculated as the difference between the number of positive and negative posts across all firms, scaled by their sum, on each trading day.[11]

[11]Because retail investors have a stronger degree of extrapolation than institutional investors and their

Table 16 reports the estimation results testing whether retail investors exhibit extrapolative beliefs. We find that the estimated λ stabilizes after incorporating five or more lagged daily excess market returns. For example, with 20 lagged returns included, a λ estimate of 0.696 implies that the return on day $t-1$ receives approximately 4 times the weight of the return on day $t-5$ ($0.696^0/0.696^4$), and about 26 times the weight of the return on day $t-10$ ($0.696^0/0.696^9$). This estimate is also comparable to that reported by Yang and Li (2025), who find a λ of 0.16 for Guba investors using firm-week data. Taking the fifth root of 0.16 yields approximately 0.693, which closely aligns with our estimate based on aggregated Guba tone. To further compare this with the extrapolative behavior of mutual funds, we raise 0.696 to the 22nd power–corresponding to 22 trading days in a month–which yields a value close to zero. This suggests that retail investors exhibit a substantially stronger degree of extrapolative weighting than mutual funds.

A natural follow-up question is whether retail investors' return expectations are accurate or systematically biased. Panel B provides preliminary evidence. We find that retail investors' expectations negatively predict short-term future market returns over horizons ranging from one to twenty trading days; however, the predictive coefficients are statistically insignificant based on the Hansen-Hodrick t-statistic. One possible explanation is that market crashes tend to occur in periods of elevated investor sentiment, yet the exact timing of such reversals within these high-sentiment windows is notoriously difficult to forecast (Baker and Wurgler, 2007).

These findings are consistent with the view that retail investors place excessive weight on recent returns (Da et al., 2021), forming overly optimistic (pessimistic) expectations following market rallies (downturns). Such overextrapolative behavior may lead to trend chasing behavior–buying at peaks and selling at troughs–which contributes to the observed negative return predictability. This interpretation also aligns with the so-called "dumb money" effect: Frazzini and Lamont (2008) show that mutual fund flows, often

memory of past outcomes decays more quickly (Greenwood and Shleifer, 2014; Da et al., 2021), we estimate the exponential decay model using daily market returns for this group.

used as a proxy for less sophisticated retail trading, negatively predict future individual stock returns. In contrast, while mutual funds also extrapolate from past market performance, they do so in a more moderate manner, incorporating additional forward-looking information that enhances return forecasting. Consequently, mutual fund expectations are better aligned with underlying return dynamics and appear to track time-series momentum more effectively, resulting in positive return predictability.

[Insert Table 16 here]

6.3. The rationale behind extrapolative beliefs of Chinese mutual funds

As noted earlier, evidence on institutional investors' expectation formation is mixed: some exhibit procyclical behavior, while others are countercyclical. Timmer (2018) suggest that these differences may stem from variation in financial constraints and investment horizons. In the case of Chinese mutual funds, the extrapolative beliefs and procyclical trading could be shaped jointly by the market structure, compensation design, and price dynamics. First, China's equity market is dominated by retail investors, who tend to chase short-term past performance. In this case, it is natural for more sophisticated investors (e.g., mutual funds) to speculate on price trends by riding bubbles and trading against retail investors (Brunnermeier and Nagel, 2004). Such speculative behavior can be further intensified in the presence of binding short-sale constraints. Second, Chinese fund managers' compensation is closely tied to short-term performance and assets under management. This structure encourages a short-term investment horizon and discourages contrarian, stabilizing investment philosophy. These incentives should be particularly strong for younger managers facing severe career concerns (Chevalier and Ellison, 1999), which is confirmed in Table 8. Third, autocorrelation of index returns is positive at short horizons but negative at longer horizons. This pattern makes extrapolation with a recency tendency appear rational. Consistent with this view, Table 11 shows that Chinese stock market returns are positively autocorrelated in short lags and the predictability of fund expectations can be partially explained by this short-term time-series momentum of market returns.

Beyond these reasons of extrapolation, fund expectations may also reflect genuine forecasting skill. As shown both in this paper (Table 1) and in prior studies (e.g., Jiang (2020)), Chinese actively managed funds earn high net-of-fee returns and outperform the market or other risk-adjusted benchmarks. Table 14 and Table 15 suggest that this superior performance is partly driven by accurate forecasts and the ability to act on them.

7. Conclusion

Chinese mutual funds are required to report their outlooks on macroeconomic conditions and financial markets in periodic fund reports. Using a state-of-the-art deep learning model, we construct a novel measure of funds' expectations for near-term stock market performance based on these disclosures. We document several key findings.

First, mutual funds extrapolate from past market and fund returns when forming expectations about future market performance. This tendency is less pronounced among more experienced managers. Second, consensus forecasts positively predict future market returns. Third, the relation between fund expectation and performance is statistically significant and positive in the time series, consistent with the aggregate pattern. However, the relation is statistically significant in the cross-section. For funds to outperform their peers, they must not only accurately predict future market movements but also act on these predictions. In other words, a fund's forecasting skill, coupled with the ability to adjust its portfolio in line with those forecasts, jointly explains superior performance. We further confirm this idea by showing that the effect of positive expectation-aligned beta tilts on future fund performance is stronger for funds with high liquidity holdings, a proxy for the cost of portfolio adjustment. Finally, we contrast the extrapolative behavior of mutual funds with that of retail investors. Using investor posts from Eastmoney Guba, we find that retail expectations are also extrapolative, but in a far more short-sighted and reactive manner. These expectations negatively predict short-term market returns, consistent with prior evidence of retail overreaction and biased belief formation. Taken together, our findings highlight how investor sophistication and institutional constraints shape the nature and consequences of extrapolative beliefs in financial markets.

While our expectation measure effectively captures the forward-looking statements embedded in fund reports, it has limitations. Most notably, it relies on sentiment scores derived from large language models, which are inherently qualitative and reflect tone rather than explicit return forecasts. Although these scores can be extracted from reports with varying forecast horizons, they offer limited insight into the term structure of mutual fund expectations. Future research could extend our framework by combining textual signals with structured forecast data, where available, to recover return magnitudes and examine the term structure of market expectations, as in recent studies (Cassella et al., 2023; van Binsbergen et al., 2023; de Silva and Thesmar, 2024)

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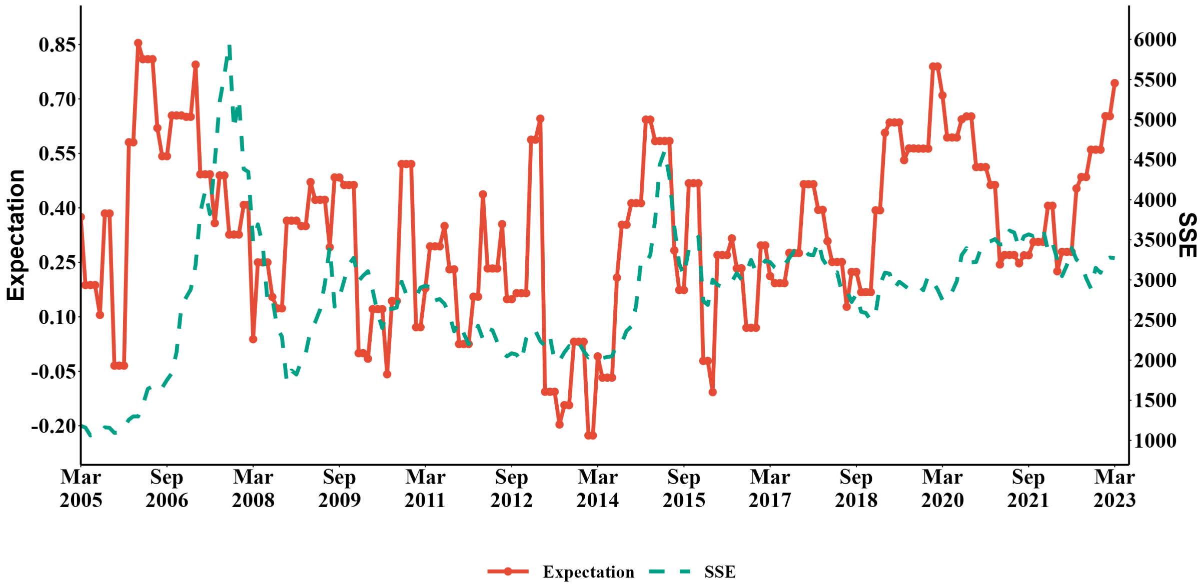

Fig. 1. Time series of fund expectations and the Shanghai Stock Exchange Composite Index (SSE), March 2005–March 2023. The consensus expectation of mutual funds is calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds (red solid line, left y-axis). Also plotted is the closing price of the SSE (green dashed line, right y-axis).

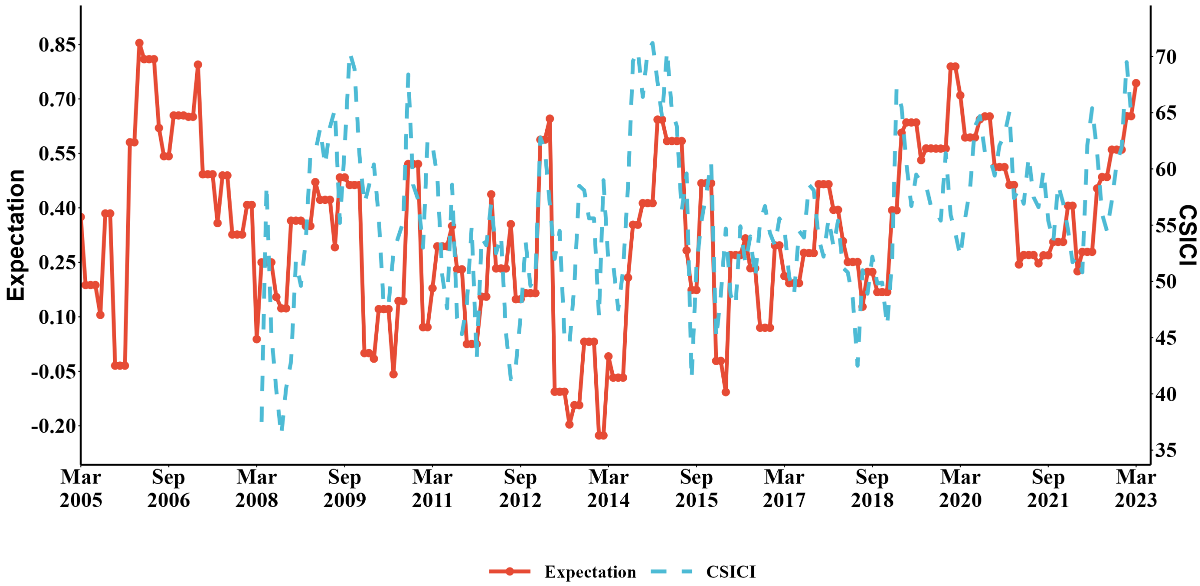

Fig. 2. Time series of fund expectations and the CSICI, March 2005–March 2023. The consensus expectation of mutual funds is calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds (red solid line, left y-axis). CSICI is the China Securities Investor Confidence Index, a survey-based expectation proxy (cyan dashed line, right y-axis).

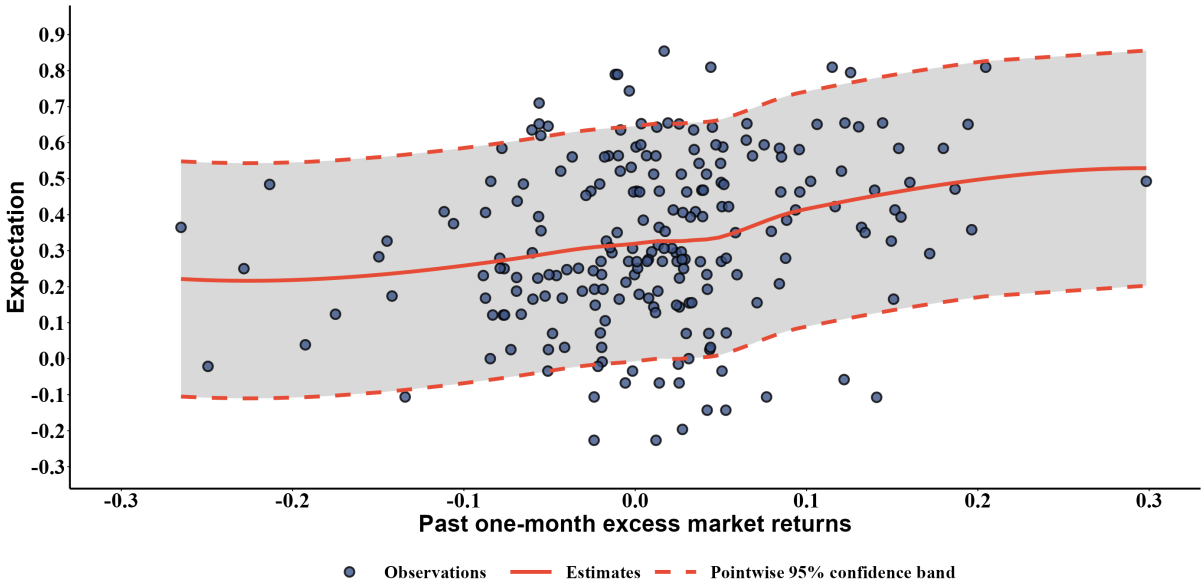

Fig. 3. Past one-month excess market returns and consensus expectations. This figure presents a scatterplot of funds' consensus stock market expectations against prior one-month excess market returns. The consensus expectation of mutual funds is calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds. A local polynomial nonparametric estimate of expectations conditional on past one-month excess market returns is also plotted. The 95% pointwise confidence band adjusts for the serial correlation using the Newey and West (1987) standard error. The sample consists of monthly observations from March 2005 to March 2023.

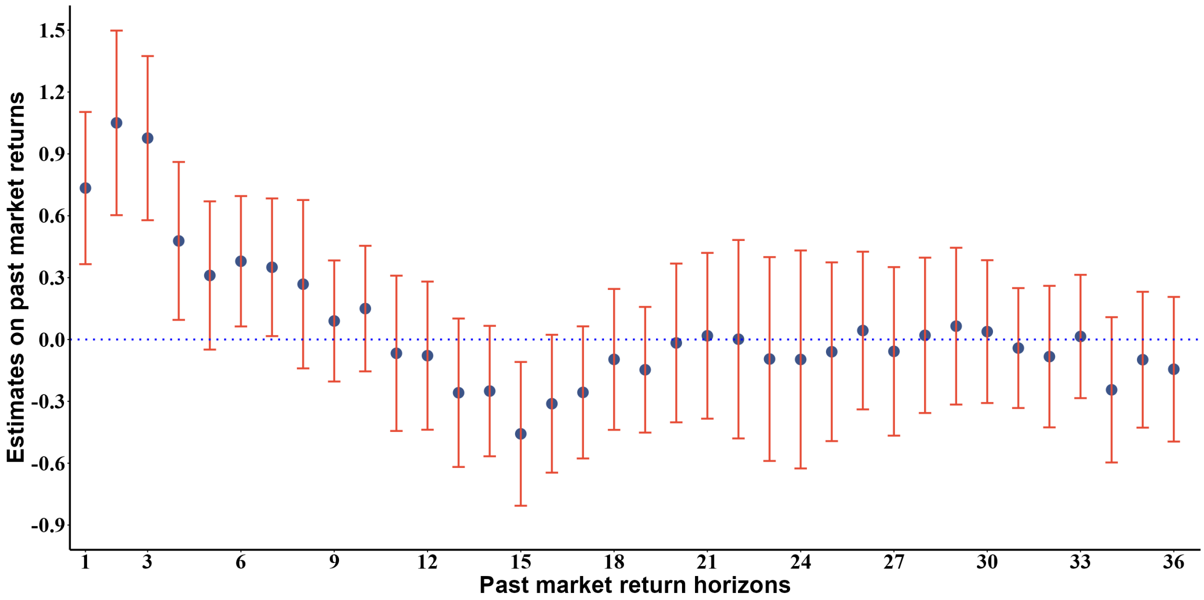

Fig. 4. Slopes on lagged monthly stock market returns. This figure plots the estimated coefficients from separate regressions of fund expectations on lagged monthly excess market returns, with lags ranging from 1 to 36 months. The error bar represents the 95% confidence intervals, computed using Newey–West adjusted standard errors with 12 lags.

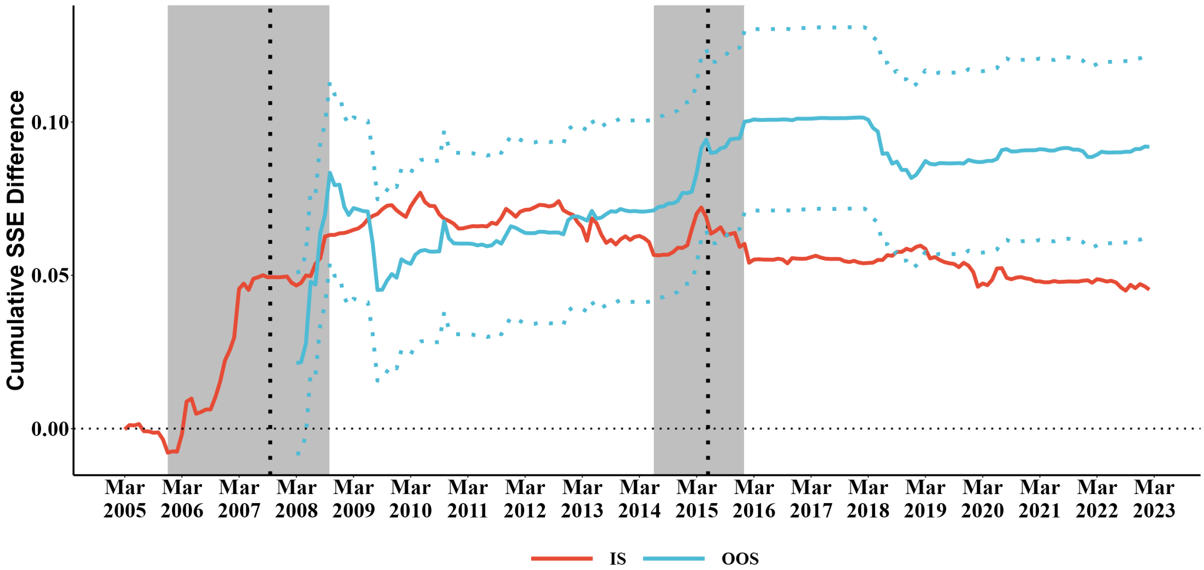

Fig. 5. Cumulative differences in mean squared forecast errors. This figure plots the in-sample (IS) and out-of-sample (OOS) performance of monthly predictive regressions. The time-varying performance is measured by the cumulative difference in mean squared forecast errors (MSFE) between the historical average benchmark and forecasts based on mutual fund consensus expectations. The consensus expectation of mutual funds is calculated as the difference between the proportion of optimistic funds and the proportion of pessimistic funds. The OOS period spans from March 2008 to March 2023. The cyan dashed line is the lower and upper 95% confidence bands based on MSFE-t critical values from McCracken (2007). Grey shaded areas mark two well-known bubble-crash episodes in China: the 2007–2008 market rise and collapse and the 2014–2015 market bubble crash. Vertical dashed black lines indicate the peak date of each bubble-crash cycle.

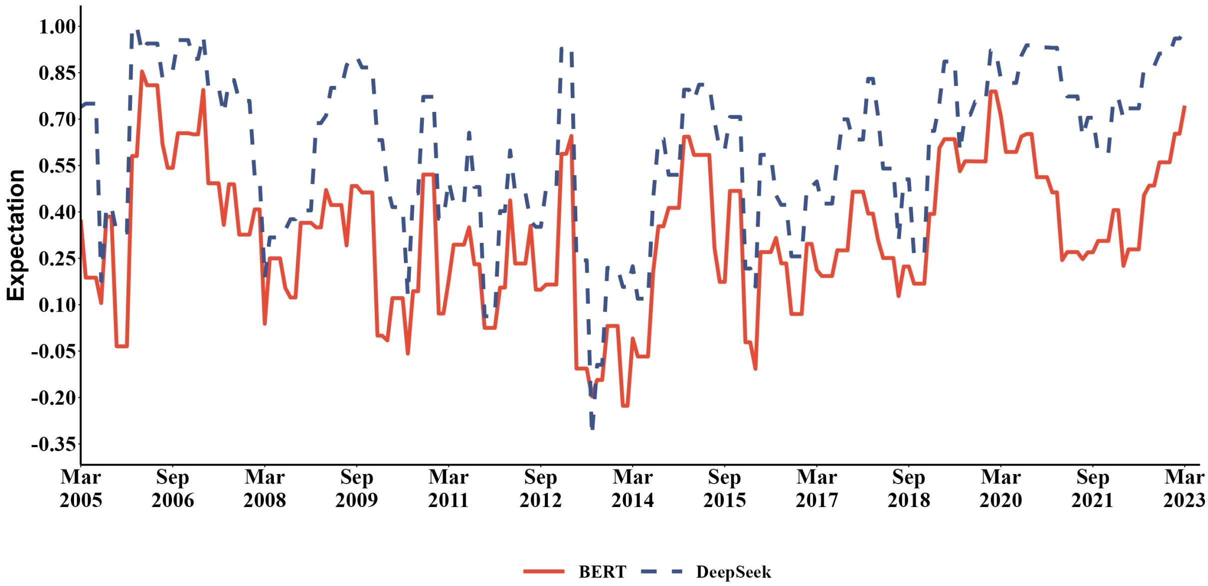

Fig. 6. Time Series of Fund Expectations, March 2005–March 2023. This figure compares the BERT-based (red solid line) and DeepSeek-based (dark blue dashed line) measures of mutual fund consensus expectations. Consensus expectation is defined as the difference between the proportion of optimistic funds and the proportion of pessimistic funds.

Table 1

Summary statstics

Panel A: Fund characteristics

Variable	# of observations	Mean	Std. dev.	P10	Median	P90
Net-of-fee return (percent)	32,551	0.045	0.178	−0.152	0.019	0.278
Expense ratio (percent)	35,889	1.722	0.211	1.750	1.750	1.820
Total net assets (billions of CNY)	35,889	1.720	3.342	0.059	0.572	4.473
Flow (percent)	32,582	28.215	473.477	−42.241	−7.081	47.129
Turnover	33,581	2.870	7.693	0.438	1.751	5.910
Fund age (Months)	35,889	57.635	48.453	8.000	44.000	131.000
Equity (percent)	35,889	0.808	0.144	0.647	0.854	0.924
Cash (percent)	35,861	0.155	0.126	0.055	0.119	0.293
Fund beta	35,114	0.889	0.227	0.612	0.916	1.139

Panel B: Fund expectations

Report	# of reports	# of forecasts	Mean	Std. dev.	P10	Median	P90
Q1	15,361	4,178	0.241	0.567	−0.500	0.000	1.000
Q2	17,117	4,943	0.235	0.576	−0.500	0.000	1.000
Q3	17,095	5,054	0.279	0.575	−0.500	0.250	1.000
Q4	18,721	5,730	0.323	0.563	−0.500	0.333	1.000
Semi-annual	17,119	14,451	0.265	0.536	−0.429	0.200	1.000
Annual	18,768	16,272	0.300	0.535	−0.333	0.286	1.000
Total	104,181	50,628	0.279	0.550	−0.500	0.250	1.000

Panel C: Consensus forecasts

Variable	# of observations	Mean	Std. dev.	P10	Median	P90
Optimism	109	0.517	0.152	0.307	0.500	0.711
Pessimism	109	0.183	0.101	0.064	0.170	0.320
Neutrality	109	0.300	0.095	0.180	0.291	0.406
Expectation	109	0.333	0.240	−0.002	0.316	0.644

This table presents the summary statistics for fund characteristics, fund-level expectations, and consensus expectations. Panel A reports the statistics for fund-level variables measured in June and December. The net-of-fee return is calculated over the past semi-year. The expense ratio is the sum of management, custodian, and sales fees. Total net assets (TNA) are the fund's assets under management. Flow is calculated as the change in TNA excluding growth in TNA due to fund returns. Turnover is defined as the minimum of the fund's total purchases and sales divided by the fund's TNA. Fund age is the number of months the oldest share class in the fund has been traded. Fund beta is the holding-weighted beta, where a stock's beta is estimated using CAPM with daily returns over the past 12 months. Panel B shows the statistics for fund-level expectations extracted from quarterly, semi-annual, and annual reports. Panel C shows the statistics for mutual funds' consensus forecasts. 'Optimism', 'Pessimism', and 'Neutrality' are the ratio of optimistic, pessimistic, and neutral funds, respectively. 'Expectation' is calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds.

Table 2

Correlations between text-based manager expectations and survey-based investor expectations

Methods	CSICI	OPTIMISM	BUY	BOUNCE	RESILIENCE	ECONOMICS
Pearson	0.504***	0.430***	0.368***	0.620***	0.370***	0.385***
Spearman	0.566***	0.473***	0.414***	0.658***	0.447***	0.438***

This table reports Pearson and Spearman correlation coefficients between text-based fund expectations and survey-based investor expectations. 'EXPECTATION' refers to the consensus expectation of mutual funds, calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds. 'CSICI' is the China Securities Investor Confidence Index. 'OPTIMISM', 'BUY', 'BOUNCE', 'RESILIENCE', and 'ECONOMICS' are the five sub-indexes of the CSICI. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3

Reported expectation and mutual funds' portfolio adjustments

	EQUITY	CASH	BETA
	(1)	(2)	(3)
EXPECTATION	0.986***	−0.545***	0.015***
	(6.723)	(−4.679)	(6.485)
NET-OF-FEE RETURN	0.027***	−0.025***	0.079***
	(3.432)	(−4.105)	(6.690)
EXPENSE	5.685	1.002	0.018
	(1.122)	(0.908)	(0.264)
FUND SIZE	0.216	−0.628***	0.004*
	(1.332)	(−5.666)	(1.701)
FLOW	−0.001	0.000	0.001
	(−0.560)	(0.495)	(0.673)
TURNOVER	−0.006	0.005	−0.0001
	(−0.385)	(0.352)	(−0.762)
FUND AGE	1.223***	−0.564**	0.013**
	(3.554)	(−2.221)	(2.485)
Controls	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	24,804	24,804	24,253
Adjusted R^2	0.394	0.287	0.493

This table reports the relation between funds' reported expectations and their portfolio adjustments. The dependent variables in Columns (1) and (2) are the percentage of equity holdings and the percentage of cash and its equivalent, respectively. The dependent variable in Column (3) is the fund's holding-weighted beta, calculated using stocks' betas estimated from daily return data over the past 12 months based on the fund's most recent portfolio holdings. 'NET-OF-FEE RETURN' is the fund's net-of-fee returns for the past semi-year. 'EXPENSE' is the sum of management, custodian, and sales fees. 'FUND SIZE' is the logarithm of total net assets (TNA). 'FLOW' is calculated as the change in TNA excluding growth in TNA due to fund returns. 'TURNOVER' is defined as the minimum of the fund's total purchases and sales divided by the fund's TNA. 'FUND AGE' is the logarithm of the number of months the oldest share class in the fund has been traded. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4

Past market returns and consensus expectations: Exponential decay model

n	a	t-stat	b	t-stat	λ	t-stat	Pseudo R^2 (%)	Obs.
6	0.306***	(8.478)	2.162***	(4.311)	0.575***	(10.036)	21.9	217
12	0.306***	(8.419)	2.214***	(4.116)	0.568***	(10.889)	22.0	217
18	0.306***	(8.416)	2.212***	(4.105)	0.566***	(10.847)	22.0	217
24	0.306***	(8.415)	2.213***	(4.105)	0.566***	(10.851)	22.0	217

This table reports the estimation results for a, b, λ, and pseudo R^2 statistics for the nonlinear least squares regression model:

$$\text{EXPECTATION}_t = a + b \cdot \sum_{\tau=0}^{n-1} w_\tau R^M_{t-2-\tau \to t-1-\tau} + u_t, \qquad \text{where } w_\tau = \frac{\lambda^\tau}{\sum_{j=0}^{n-1} \lambda^j},\ 0 \leq \lambda < 1.$$

The dependent variable is the consensus belief calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds. The explanatory variables include n lagged monthly excess market returns from month $t-n$ to month $t-1$. Newey-West t-statistics with twelve lags are in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Asymmetric effects of market returns on consensus expectations

n	a	t-stat	b^+	t-stat	b^-	t-stat	λ^+	t-stat	λ^-	t-stat	Pseudo R^2 (%)	Obs.
Panel A: Positive versus negative market returns												
6	0.298***	(4.386)	2.320***	(3.405)	2.035*	(1.903)	0.453***	(3.789)	0.803***	(4.908)	22.8	217
12	0.313***	(4.515)	2.341***	(3.296)	2.701*	(1.958)	0.433***	(4.075)	0.855***	(10.010)	23.7	217
18	0.322***	(4.631)	2.383***	(3.168)	3.106**	(2.093)	0.433***	(4.024)	0.869***	(13.320)	23.9	217
24	0.341***	(4.951)	2.464***	(2.976)	3.999**	(2.325)	0.433***	(3.541)	0.925***	(15.048)	24.5	217
Panel B: Moderate versus extreme market states												
n	a	t-stat	b^M	t-stat	b^E	t-stat	λ^M	t-stat	λ^E	t-stat	Pseudo R^2 (%)	Obs.
6	0.308***	(7.867)	1.930***	(2.811)	2.315***	(3.772)	0.503***	(3.467)	0.635***	(7.295)	21.9	214
12	0.313***	(7.454)	1.793**	(2.307)	2.535***	(3.358)	0.461***	(2.578)	0.657***	(7.457)	22.4	208
18	0.308***	(7.267)	1.716**	(2.232)	2.429***	(3.360)	0.463**	(2.442)	0.662***	(7.342)	21.8	202
24	0.302***	(7.057)	1.683**	(2.255)	2.149***	(3.423)	0.463**	(2.434)	0.626***	(6.189)	19.6	196

This table reports the estimation results of the nonlinear least squares regression model for past market return characteristics. The dependent variable is the consensus expectation calculated as the difference between the ratio of optimistic funds and pessimistic funds. In Panel A, the explanatory variables include both the positive and negative parts of the lagged monthly excess market returns from month $t-n$ to month $t-1$ and the regression is specified as

$$\text{EXPECTATION}_t = a + b^+ \cdot \sum_{\tau=0}^{n-1} w_\tau^+ R^+_{t-2-\tau \to t-1-\tau} + b^- \cdot \sum_{\tau=0}^{n-1} w_\tau^- R^-_{t-2-\tau \to t-1-\tau} + u_t,$$

where $w_\tau^+ = \frac{(\lambda^+)^\tau}{\sum_{j=0}^{n-1}(\lambda^+)^j}$, $w_\tau^- = \frac{(\lambda^-)^\tau}{\sum_{j=0}^{n-1}(\lambda^-)^j}$, $R^+ = \max(R^M, 0)$, and $R^- = \min(R^M, 0)$. Panel B allows the weight and decay rate to differ across different market states:

$$\text{EXPECTATION}_t = a + b^M \cdot \sum_{\tau=0}^{n-1} \mathbb{1}_{\{R^M_{t-2-\tau \to t-1-\tau} \in M\}} \cdot w_\tau^M R^m_{t-\tau} + b^E \cdot \sum_{\tau=0}^{n-1} \mathbb{1}_{\{R^M_{t-2-\tau \to t-1-\tau} \in E\}} \cdot w_\tau^E R^E_{t-\tau} + u_t,$$

where the superscripts M and E indicate the moderate and extreme market states, respectively. The current stock market state is classified as moderate if monthly returns in the most recent month fall within the 5th to 95th percentiles of the past 60 monthly observations. Conversely, the market is classified as extreme if the monthly returns in the most recent month fall outside this interval, based on the same 60-month window. Newey-West t-statistics with twelve lags are in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Summary statistics of the fund-level degree of extrapolation

	Obs	Mean	Std. dev.	P25	Median	P75
Panel A: $n = 6$						
λ	691	0.570	0.357	0.266	0.632	0.921
a	691	0.220	0.162	0.116	0.205	0.316
b	691	3.304	3.940	1.309	2.769	5.087
Panel B: $n = 12$						
λ	691	0.571	0.336	0.312	0.639	0.865
a	691	0.218	0.162	0.108	0.206	0.311
b	691	3.719	5.048	1.387	3.118	5.985
Panel C: $n = 18$						
λ	691	0.560	0.332	0.300	0.639	0.841
a	691	0.216	0.164	0.108	0.199	0.311
b	691	3.989	6.170	1.444	3.200	6.627
Panel D: $n = 24$						
λ	691	0.563	0.330	0.308	0.641	0.845
a	691	0.216	0.167	0.108	0.201	0.310
b	691	3.979	7.575	1.448	3.217	6.927

This table reports summary statistics for the estimated a, b, and λ for the nonlinear least squares regression model:

$$\text{EXPECTATION}_{i,t\to t+h} = a_i + b_i \cdot \sum_{\tau=0}^{n-1} w_{i,\tau} R^M_{t-2-\tau\to t-1-\tau} + u_{i,t,h}, \quad \text{where } w_{i,\tau} = \frac{\lambda_i^\tau}{\sum_{j=0}^{n-1} \lambda_i^j},\ 0 \leq \lambda < 1.$$

The dependent variable, $\text{EXPECTATION}_{i,t\to t+h}$, is the subjective expectations of fund i on month t over the period from t to $t+h$. The explanatory variables include n lagged monthly excess market returns from month $t-n$ to month $t-1$.

Table 7

Extrapolative expectations: Evidence at the fund level

	Dependent variable: EXPECTATION					
	(1)	(2)	(3)	(4)	(5)	(6)
PAST 3-MONTH MARKET RETURN	0.647***		0.732***		0.515***	0.500***
	(4.882)		(4.941)		(3.015)	(2.578)
LAGGED PAST 3-MONTH MARKET RETURN	0.116		0.205		0.308*	0.320*
	(0.985)		(1.525)		(1.851)	(1.880)
PE		0.004	−0.005		−0.005	−0.004
		(1.469)	(−1.437)		(−1.485)	(−1.015)
PAST 3-MONTH FUND RETURN				0.601***	0.279**	0.247*
				(5.449)	(2.194)	(1.755)
LAGGED PAST 3-MONTH FUND RETURN				0.038	−0.126	−0.088
				(0.304)	(−0.937)	(−0.746)
CRASH EXPERIENCE						−0.017
						(−0.514)
RECESSION MANAGER						−0.021
						(−1.154)
FEMALE						−0.001
						(−0.063)
TEAM						0.016
						(1.116)
TENURE						0.022
						(1.539)
FLOW						0.004
						(0.929)
EXPENSE						−0.083*
						(−1.837)
FUND AGE						0.053**
						(2.421)
EQUITY						0.003***
						(3.645)
Fund×Horizon fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,628	50,628	50,628	46,584	46,584	45,540
Adjusted R^2	0.061	0.040	0.062	0.057	0.064	0.073

This table reports the estimation results of the fund-level extrapolation. The dependent variable is Chinese mutual funds' A-share market expectations. 'PAST 3-MONTH MARKET RETURN' is the cumulative three-month market return over month $t-3$ to month $t-1$. 'LAGGED PAST 3-MONTH MARKET RETURN' is the cumulative three-month market return over month $t-6$ to month $t-4$. 'PE' is the log of the market price-to-earnings ratio. 'PAST 3-MONTH FUND RETURN' is the cumulative three-month fund net-of-fee return over month $t-3$ to month $t-1$. 'LAGGED PAST 3-MONTH FUND RETURN' is the cumulative three-month fund net-of-fee return over month $t-6$ to month $t-4$. 'CRASH EXPERIENCE' is a dummy variable indicating whether fund managers have experienced one of the market crashes in 2008 or 2015 (Luo et al., 2022). 'RECESSION MANAGER' is a dummy variable indicating whether one of the managers began their career during a recession year (Chen et al., 2021). 'FEMALE' is a dummy variable indicating whether one of the managers is a woman. 'TEAM' is a dummy variable indicating whether the fund is team-managed. Other controls are the same as those in Table 1. All specifications include a fund-times-horizon fixed effect. Standard errors are double clustered on the fund and time (i.e., filing month) dimensions. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8

Extrapolative beliefs and fund manager characteristics

	Crash experience	No crash experience	Recession	Non-recession	Older	Younger
	(1)	(2)	(3)	(4)	(5)	(6)
a	0.259***	0.283***	0.276***	0.222***	0.266***	0.239***
	(49.270)	(57.642)	(61.897)	(33.403)	(18.804)	(19.827)
b	3.009***	1.837***	2.538***	1.910***	2.150***	1.894***
	(14.279)	(13.889)	(14.757)	(12.498)	(5.862)	(6.774)
λ	0.651***	0.493***	0.600***	0.512***	0.637***	0.528***
	(25.535)	(13.502)	(22.711)	(12.383)	(9.284)	(6.811)
Pseudo R^2	0.025	0.019	0.019	0.022	0.021	0.020
Observations	23,976	26,652	34,122	14,761	3,285	4,491

This table reports the estimated a, b, and λ for the nonlinear least squares regression model across different fund manager characteristics:

$$\text{EXPECTATION}_{i,t\to t+h} = a_i + b_i \cdot \sum_{\tau=0}^{n-1} w_{i,\tau} R^M_{t-2-\tau\to t-1-\tau} + u_{i,t,h}, \quad \text{where } w_{i,\tau} = \frac{\lambda_i^\tau}{\sum_{j=0}^{n-1} \lambda_i^j},\ 0 \leq \lambda < 1.$$

The dependent variable, $\text{EXPECTATION}_{i,t\to t+h}$, is the subjective expectations of fund i on month t over the period from t to $t+h$. The explanatory variables include n lagged monthly excess market returns from month $t-n$ to month $t-1$. Columns (1) and (2) report results for fund managers with and without bubble-crash experience, respectively. Columns (3) and (4) present results for managers who began their careers during a recession versus those who did not. Columns (5) and (6) compare older and younger fund managers, respectively.

Table 9

Mutual fund expectation and aggregate market return: In-sample forecasting

τ	1	2	3	4	5	6	12
Panel A: Ex post excess market return on expectation							
EXPECTATION	0.015***	0.028**	0.040*	0.051*	0.060	0.068	0.104
	(2.654)	(2.050)	(1.888)	(1.721)	(1.445)	(1.226)	(0.692)
CONSTANT	0.013**	0.027**	0.042**	0.059*	0.077*	0.096*	0.225
	(2.322)	(2.137)	(2.064)	(1.921)	(1.834)	(1.773)	(1.634)
Bootstrapped p-value	0.010	0.065	0.090	0.220	0.351	0.442	0.689
Observations	216	215	214	213	212	211	205
R^2	0.032	0.047	0.055	0.060	0.054	0.049	0.032
Panel B: Estimated coefficients on EXPECTATION, controlling for other predictors one-by-one							
μ	0.012**	0.022*	0.028*	0.035	0.040	0.043	0.054
	(2.305)	(1.862)	(1.732)	(1.606)	(1.335)	(1.187)	(0.555)
S	0.016***	0.031**	0.046**	0.059**	0.070*	0.081*	0.140
	(3.025)	(2.471)	(2.333)	(2.131)	(1.855)	(1.672)	(1.308)
DP	0.016***	0.031**	0.046**	0.060**	0.072*	0.084	0.154
	(2.936)	(2.385)	(2.247)	(2.105)	(1.822)	(1.600)	(0.984)
EP	0.015***	0.029**	0.043**	0.057**	0.067*	0.078*	0.135
	(2.653)	(2.236)	(2.155)	(2.168)	(1.911)	(1.687)	(0.991)
BM	0.015***	0.030**	0.044**	0.057*	0.068*	0.079	0.137
	(2.826)	(2.257)	(2.104)	(1.949)	(1.664)	(1.440)	(0.863)
TO	0.014***	0.028**	0.040**	0.053*	0.063	0.072	0.121
	(2.644)	(2.125)	(1.998)	(1.898)	(1.630)	(1.402)	(0.789)
SVAR	0.015***	0.028**	0.040*	0.051*	0.060	0.068	0.104
	(2.657)	(2.051)	(1.887)	(1.721)	(1.446)	(1.226)	(0.692)
INFL	0.012**	0.023*	0.034*	0.044	0.051	0.058	0.090
	(2.291)	(1.810)	(1.698)	(1.551)	(1.302)	(1.108)	(0.640)
NTIS	0.015***	0.028**	0.039*	0.050*	0.058	0.065	0.101
	(2.665)	(2.089)	(1.955)	(1.867)	(1.606)	(1.366)	(0.706)
STY	0.012**	0.022	0.030	0.037	0.041	0.045	0.061
	(2.049)	(1.535)	(1.372)	(1.224)	(1.022)	(0.867)	(0.464)
LTY	0.011*	0.020	0.028	0.035	0.040	0.045	0.066
	(1.856)	(1.428)	(1.327)	(1.183)	(0.981)	(0.837)	(0.506)
Panel C: Ex post excess market return on expectation, controlling for all predictors							
EXPECTATION	0.014**	0.023**	0.033**	0.040*	0.044	0.048	0.072
	(2.426)	(2.031)	(1.996)	(1.867)	(1.589)	(1.586)	(1.346)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	213	212	211	210	209	203
R^2	0.185	0.304	0.393	0.454	0.509	0.557	0.702

Table 9

(Cont'd)

τ	1	2	3	4	5	6	12
Panel D: Ex post excess market return on the proportion of bullish funds, controlling for all predictors							
BULLISH	0.099**	0.148*	0.213*	0.260*	0.297	0.336	0.382
	(2.554)	(1.927)	(1.887)	(1.732)	(1.561)	(1.553)	(1.134)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	213	212	211	210	209	203
R^2	0.187	0.303	0.390	0.451	0.509	0.557	0.698
Panel E: Ex post excess market return on the proportion of bearish funds, controlling for all predictors							
BEARISH	−0.094*	−0.191*	−0.278**	−0.342*	−0.344	−0.366	−0.770*
	(−1.816)	(−1.956)	(−1.999)	(−1.943)	(−1.526)	(−1.475)	(−1.702)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	213	212	211	210	209	203
R^2	0.177	0.300	0.388	0.449	0.504	0.551	0.705

This table presents the predictive power of mutual fund stock market expectation over the prediction horizon τ, where $\tau = 1$, 2, 3, 4, 5, 6, and 12 months. Panel A reports the results of the univariate predictive regression analysis based on fund expectations (EXPECTATION), defined as the difference between the ratio of optimistic funds and the ratio of pessimistic funds. Panel B compares the predictability of fund expectations with other predictors. μ is the value-weighted analysts' consensus forecasts for earnings-per-share (EPS) growth, where growth is defined as the difference between the analysts' forecasts of EPS and the most recent realized EPS, scaled by the most recent realized EPS. S is the Baker and Wurgler (2006) investor sentiment index, recalculated using data from the Chinese capital market. DP is the log dividend-price ratio. EP is the log earnings-price ratio. BM is the log book-to-market ratio. TO is the stock market turnovers. SVAR is the stock return variance. INFL is the inflation index. NTIS is the net equity expansion. STY and LTY are 3-month and 10-year government bond yields, respectively. Panel C controls for all economic predictors mentioned in Panel B, except for the $R^M_{t-13,t-2}$. Panel D reports the results of the univariate predictive regression analysis based on degree of extrapolation among funds (DOX), defined as $1 - \lambda$, where λ is estimated recursively from Eq. (4) using nonlinear least squares with a fixed 120-month window and at least 18 months of data for regression fitting. Panel E controls for all economic predictors mentioned in Panel B, except for the $R^M_{t-13,t-2}$. Hansen and Hodrick (1980) t-statistics with τ lags are in parentheses. Bootstrapped p-values of fund expectations are reported for Panel A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10

Mutual fund expectations and aggregate market returns: mandated versus non-mandated disclosures

	Panel A: Quarterly non-mandated disclosures $R^M_{t+3} = \alpha + \beta \cdot X_t + \varepsilon_{t+3}$				Panel B: Semi-annual and annual mandated disclosures $R^M_{t+6} = \alpha + \beta \cdot X_t + \varepsilon_{t+6}$			
	β	t-stat	R^2	Obs.	β	t-stat	R^2	Obs.
EXPECTATION	0.178**	1.999	0.058	71	0.417**	2.325	0.172	39
BULLISH	0.319**	2.228	0.072	71	0.533*	1.897	0.126	39
BEARISH	−0.277	-1.455	0.028	71	−0.999***	−2.583	0.175	39

This table presents the predictive power of mutual fund stock market expectations, controlling for market return autocorrelation. Panel A constructs the consensus expectation series using quarterly non-mandated disclosures. Panel B constructs the consensus expectation series using semi-annual and annual mandated disclosures, denoted. Hansen and Hodrick (1980) t-statistics with one lag are used. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11

Mutual fund expectations and aggregate market returns: controlling for market return autocorrelation

	Dependent variable: $R^M_{t\to t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXPECTATION					0.013**	0.009*	0.011*	0.014***
					(2.352)	(1.695)	(1.897)	(2.732)
R^M_{t-1}	0.115				0.057			
	(1.327)				(0.638)			
$R^M_{t-3\to t-1}$		0.097**				0.073		
		(2.013)				(1.438)		
$R^M_{t-6\to t-1}$			0.046				0.032	
			(1.614)				(1.070)	
$R^M_{t-12\to t-1}$				0.007				0.001
				(0.517)				(0.059)
Observations	216	216	216	216	216	216	216	216
R^2	0.013	0.041	0.030	0.003	0.035	0.051	0.045	0.032

This table presents the predictive power of mutual fund stock market expectations over the one-month prediction horizon, controlling for market return autocorrelation. $R^M_{t-\tau,t-1}$ is the market returns over the past τ months, skipping the most recent month. Hansen and Hodrick (1980) t-statistics with τ lags are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12

Out-of-sample analysis

Window size (months)	Forecast begin	$R^2_{OOS}(\%)$	CW test	DM test	CER gain (%)	Sharp ratio
36	2008/03	8.375	2.499***	1.879***	3.950	0.437
48	2009/03	5.763	2.494***	1.713***	4.213	0.627
60	2010/03	6.558	2.856***	2.123***	3.682	0.459

This table reports the out-of-sample forecasting performance for predicting one-month-ahead stock market returns using EXPECTATION. EXPECTATION is the difference between the ratio of optimistic and pessimistic funds. We perform out-of-sample predictive regressions using a rolling approach with window sizes of 36, 48, and 60 months. R^2_{OOS} is the out-of-sample R-squared proposed by Campbell and Thompson (2008). CW test is the Clark and West (2007) MSFE-adjusted statistic for testing $R^2_{OOS} \leq 0$. DM test is the Diebold and Mariano (1995) statistic modified by McCracken (2007) for testing the equality of the MSFE of one forecast relative to other forecasts. Also reported are the annualized certainty equivalent return gains (in percentages) and monthly Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of 3. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13

Expectation-performance relation in the time-series and cross-section

	Dependent variable: R^{Net}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXPECTATION	4.618*				−0.357			
	(1.852)				(−1.322)			
EXPECTATION^{+}		7.196**				−0.062		
		(2.236)				(−0.107)		
EXPECTATION^{-}		−0.061				−0.883		
		(−0.032)				(−0.975)		
CORRECT			19.089***				−0.293	
			(4.332)				(−0.676)	
CORRECT^{+}				22.726***				−1.005
				(4.156)				(−1.576)
CORRECT^{-}				−4.516*				0.491
				(−1.721)				(0.826)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Time fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	6,537	6,537	6,537	6,537	6,537	6,537	6,537	6,537
Adjusted R^2	0.009	0.012	0.173	0.291	0.625	0.625	0.625	0.625

This table reports the relation between fund expectations and future performance in the time-series and cross-section. EXPECTATION is the fund's stock market forecast for the next year. EXPECTATION^{+} is defined as max(EXPECTATION,0) and EXPECTATION^{-} is defined as min(EXPECTATION,0). CORRECT is a dummy variable equal to one if the fund's annual forecast aligns with the realized excess market return for the following year, and zero otherwise. The superscript +/− on CORRECT indicates the direction of the realized excess return. BETA is the fund's holding-weighted beta, calculated using stock betas estimated from daily returns over the past 12 months based on the fund's most recent portfolio holdings. Columns (1)–(4) control for fund fixed effects to identify the time-series variation, while Columns (5)–(8) include time fixed effects to capture the cross-sectional variation. Standard errors are double clustered at the fund and time level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14

The degree of pass-through from beliefs to actions and future fund performance

Panel A: Expectations, portfolio adjustments, and future fund performance

	R^{Net}	α^{CAPM}	α^{FFC4}
	(1)	(2)	(3)
EXPECTATION^{+}	−0.761	0.895	1.437
	(−0.230)	(0.293)	(0.475)
EXPECTATION^{-}	−0.354	−3.508	0.232
	(−0.101)	(−1.223)	(0.078)
BETA	−1.179	1.671	2.249
	(−0.181)	(0.306)	(0.598)
EXPECTATION^{+}×BETA	1.225	−0.496	−0.935
	(0.328)	(−0.145)	(−0.267)
EXPECTATION^{-}×BETA	−1.860	1.463	−1.936
	(−0.490)	(0.460)	(−0.598)
Controls	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	6,537	6,537	6,537
Adjusted R^2	0.653	0.409	0.285

Panel B: Correct expectations, portfolio adjustments, and future fund performance

	R^{Net}	α^{CAPM}	α^{FFC4}
	(1)	(2)	(3)
CORRECT^{+}	−21.051***	−15.258***	−11.283**
	(−3.398)	(−2.886)	(−2.478)
CORRECT^{-}	6.701	5.670	4.341
	(1.376)	(1.423)	(1.498)
BETA	−10.480**	−5.608	−3.268
	(−2.021)	(−1.625)	(−1.383)
CORRECT^{+}×BETA	22.176***	15.778***	12.309**
	(3.295)	(2.744)	(2.493)
CORRECT^{-}×BETA	−6.318	−5.389	−3.952
	(−1.271)	(−1.313)	(−1.295)
Controls	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	6,537	6,537	6,537
Adjusted R^2	0.662	0.418	0.294

This table reports the relation between fund expectations and future performance. EXPECTATION is the fund's stock market forecast for the next year. EXPECTATION^{+} is defined as max(EXPECTATION,0) and EXPECTATION^{-} is defined as min(EXPECTATION,0). CORRECT is a dummy variable equal to one if the fund's annual forecast aligns with the realized excess market return for the following year, and zero otherwise. The superscript +/− on CORRECT indicates the direction of the realized excess return. BETA is the fund's holding-weighted beta, where a stock's beta is estimated using CAPM with daily returns over the past 12 months. Standard errors are double clustered at the fund and time level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 15

Limited portfolio adjustments and fund performance: the role of liquidity

Dependent variable:	R^{Net}		α^{CAPM}		α^{FFC4}	
Sort variable: %LIQ	Low	High	Low	High	Low	Highh
	(1)	(2)	(3)	(4)	(5)	(6)
CORRECT^{+}	−14.509***	−30.184***	−10.620**	−22.834***	−6.536*	−17.594***
	(−2.705)	(−3.437)	(−2.024)	(−3.472)	(−1.654)	(−3.334)
CORRECT^{-}	6.243	3.087	6.304	0.427	5.306	−1.845
	(1.004)	(0.815)	(1.187)	(0.156)	(1.394)	(−0.651)
BETA	−5.992*	−14.487**	−2.455	−9.737**	0.184	−6.238*
	(−1.867)	(−2.137)	(−1.065)	(−2.124)	(0.073)	(−1.927)
CORRECT^{+}×BETA	17.169***	30.159***	12.068*	22.887***	8.043*	18.355***
	(2.680)	(3.267)	(1.896)	(3.320)	(1.714)	(3.428)
CORRECT^{-}×BETA	−5.795	−2.260	−5.585	−0.051	−3.927	2.449
	(−0.800)	(−0.621)	(−0.919)	(−0.017)	(−0.848)	(0.800)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,259	3,279	3,259	3,279	3,259	3,279
Adjusted R^2	0.672	0.687	0.467	0.446	0.330	0.324

This table examines how liquidity affects the strength of the relation between expectation-aligned beta tilts and future fund performance. CORRECT is a dummy variable equal to one if the fund's annual forecast aligns with the realized excess market return for the following year, and zero otherwise. The superscript +/− on CORRECT indicates the direction of the realized excess return. BETA is the fund's holding-weighted beta, where a stock's beta is estimated using CAPM with daily returns over the past 12 months. %LIQ is defined as the percentage of a fund's portfolio invested in liquid stocks. Liquid stocks are those in the bottom quintile of the Amihud (2002) illiquidity measure within each year. We then split the fund-year observations into low liquidity funds (below-median %LIQ) and high liquidity funds (above-median %LIQ) and estimate Eq. (16) separately for each subsample. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 16

Extrapolative beliefs in retail investors

Panel A: Exponential decay model for retail investors								
n	a	t-stat	b	t-stat	λ	t-stat	Pseudo R^2 (%)	Obs.
5	0.083***	(19.578)	1.970***	(4.243)	0.710***	(9.070)	3.332	3,649
10	0.083***	(19.603)	2.266***	(3.072)	0.698***	(7.277)	3.403	3,649
15	0.083***	(19.604)	2.308***	(2.820)	0.696***	(6.877)	3.404	3,649
20	0.083***	(19.604)	2.314***	(2.774)	0.696***	(6.832)	3.403	3,649

Panel B: Retail investors' expectations and future market returns					
τ	1	5	10	15	20
GUBA_EXPECTATION	−0.004	−0.007	−0.022	−0.049	−0.062
	(−1.298)	(−0.682)	(−1.081)	(−1.555)	(−1.491)
CONSTANT	0.0002	0.0003	0.001	0.003	0.004
	(0.438)	(0.247)	(0.274)	(0.753)	(0.759)
Observations	3,649	3,649	3,649	3,649	3,649
R^2	0.001	0.001	0.002	0.007	0.008

This table examines retail investors' expectation formation and its implications for future market returns. Panel A reports the estimation results for a, b, λ, and pseudo R^2 statistics for the nonlinear least squares regression model:

$$\text{GUBA\_EXPECTATION}_t = a + b \cdot \sum_{\tau=0}^{n-1} w_\tau R^M_{t-2-\tau \to t-1-\tau} + u_t, \qquad \text{where } w_\tau = \frac{\lambda^\tau}{\sum_{j=0}^{n-1} \lambda^j},\ 0 \leq \lambda < 1.$$

The dependent variable is the daily aggregated Guba post tone, which proxies for retail investors' stock market expectations. It is computed as the difference between the number of positive and negative posts across all firms, scaled by their sum, on each trading day. The explanatory variables include n lagged daily excess market returns from day $t-n$ to day $t-1$. Newey-West t-statistics with twelve lags are in the parentheses. Panel B presents the predictive power of retail investors' stock market expectation over the prediction horizon τ, where $\tau = 1$, 5, 10, 15, and 20 days. Hansen and Hodrick (1980) t-statistics with τ lags are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Extrapolative expectations and asset returns: Evidence from Chinese mutual funds
Online Appendix

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IA. Management Outlook example

In this appendix, we first provide two examples to illustrate how the training data for the MacBERT model is constructed. Then, we show some examples of the MacBERT predictions.

IA.1. Construct training data

We split the MO text into sentences using punctuation marks (i.e., "。", "!", and "?") and retain those containing words or phrases related to the A-share stock market (i.e., "market", "A-share", "equity", and "stock market"). The example below is taken from the 2007 fourth-quarter report of the ChinaAMC Large-Cap Hybrid Investment Fund (华夏大盘精选混合 A). We first present the original content in Simplified Chinese, followed by its English translation. Sentences regarding the A-share market are highlighted in red, with A-share-related keywords shown in bold.

2008 年中国经济面临央行紧缩性货币政策和外部经济体增长放缓的压力，强劲的增长动力将受到遏制，但仍有望保持较快的增长。【**股票市场**流动性过剩的局面将有所缓和，而上市公司的整体业绩增长难以大幅超出预期，**市场**估值水平将逐步向下回归。】本基金在投资策略上将回避股价透支未来业绩的高估值品种，选择风险释放充分、未来高成长而目前估值偏低以及内在价值对股价有支撑的品种。

*In 2008, China's economy is expected to face pressures from the central bank' s tightening monetary policy and a slowdown in external economic growth. While the strong growth may be restrained, the economy is still expected to maintain a relatively rapid pace of growth. [The excess liquidity in the **stock market** is likely to ease, the overall performance of listed companies is unlikely to significantly beat expectations, and* $\underbrace{\textit{\textbf{market} valuations are expected to decline.]}}_{\textit{Negative}}$ *The fund will avoid high-valuation stocks that have priced in overly optimistic future earnings and will instead select stocks with risks being fully released, high future growth potential, currently undervalued, and intrinsic value that aligns with the stock price.*

珍惜基金份额持有人的每一分投资和每一份信任，华夏大盘精选基金将继续奉行华夏基金管理有限公司”为信任奉献回报”的经营理念，规范运作，审慎投资，勤勉尽责地为基金份额持有人谋求长期、稳定的回报。

Cherishing every cent of investment and every bit of trust from fund shareholders, the ChinaAMC Large-Cap Fund will continue to uphold China Asset Management Co., Ltd.' s investment philosophy of "delivering returns for trust," operate in a standardized manner, invest prudently, and diligently strive to achieve long-term and stable returns for fund shareholders. □

The above outlook includes one sentence regarding the A-share market with a negative expectation; thus, the fund-level expectation score is assigned a value of -1.

The second example is drawn from the 2021 annual report of the China Securities Value-Growth Hybrid Investment Fund (中信建投价值增长 A). The fund's outlook is presented below.

【影响当前**市场**的因素是显而易见的。】【首先从宏观经济角度，当前国内经济本不乐观，2021 年 12 月中央经济工作会议定调稳增长，政策基调是托而不举，**市场**乐观预期并不强烈，叠加疫情影响，造成**市场**上涨动力不足。】美联储收水，未来加息预期较强，资金收紧政策将会影响全球资金流向。【从库存周期看，当前工业企业产成品库存较高，未来库存下降，根据历史经验，去库存时期**权益市场**一般表现欠佳。】【从**股市**牛熊周期转换来看，2019 至 2021 年**股市**投资收益较好，2022 年收益预期不高。】

*[The factors currently shaping the **market** are clear.]* Neutral *[Macroeconomic conditions remain subdued, with domestic growth prospects appearing pessimistic. At the December 2021 Central Economic Work Conference, policymakers emphasized growth stability. However, the policy stance, while supportive, lacks meaningful stimulus, and overall **market** sentiment remains weak. Combined with ongoing pandemic-related disruptions, upward **market** momentum is constrained.]* Negative *In addition, the U.S. Federal Reserve's tightening cycle, including anticipated interest rate hikes, is expected to redirect global capital*

flows. From an inventory cycle perspective, industrial firms are facing elevated levels of finished goods. [Historically, $\underbrace{\textbf{\textit{equity markets}}\ \textit{underperform}}_{\textit{Negative}}$ *during inventory destocking phases.] [From the* ***stock market****'s bull-bear cycle perspective, high* ***equity*** *returns from 2019 to 2021 suggest* $\underbrace{\textit{a low return for 2022.}}_{\textit{Negative}}$*]*

我们认为，降低预期肯定不会有太大错误。在过去的 *2021* 年，业绩实现高增长的公司表现突出，而业绩增速明显下滑的公司表现很差，盈利源于企业的业绩增长。*2022* 年，在整体经济放缓的情况下，企业盈利增速放缓概率大，继续因业绩高增长获益的机会可能变少，尤其那些预期满、估值高的公司，可能随着业绩增速放缓，证券表现变差。当然部分高景气行业和长期逻辑可能还会支持这类企业股价的优异表现，但从低估值、低预期的公司入手，寻找机会胜率会更高，这是我们未来努力挖掘标的的方向。当前持仓中的很多标的，从估值角度看并不贵，虽然业绩增速暂时不能达到高速增长要求，但业绩增长的确定性高。【**市场**是很难预测的，关注焦点变化很快，当前看稳经济主线相对清晰。】今年以结构化、重质而非重势行情概率大。

We believe that managing expectations conservatively is prudent. In 2021, firms with strong earnings growth outperformed, while those with declining growth lagged. Profitability was largely driven by earnings growth. In 2022, as the economy slows, corporate earnings growth is also likely to decelerate. Opportunities driven by high earnings growth will become less frequent, especially for highly valued firms with elevated expectations. These companies may underperform as growth slows. Nevertheless, select high-prosperity industries and long-term thematic sectors may continue to show strong performance. We believe focusing on low-valuation, low-expectation firms offers a higher probability of success and will guide our investment strategy. Many current portfolio holdings are attractively valued. Although their short-term earnings growth may not be high, it is relatively certain. $\underbrace{\textit{[Given the inherent unpredictability of the}\ \textbf{\textit{market}}}_{\textit{Neutral}}$ *and its rapidly shifting focus, we see economic stabilization as a dominant theme.] Consequently, this year is more likely to favor structural trends that emphasize quality over momentum.*

The above outlook contains five sentences related to the A-share market–two neutral and three negative. Accordingly, the fund-level expectation score is calculated as $\frac{1}{5}(2 \times 0 - 3 \times 1) = -0.6$.

IA.2. Predictions from the MacBERT model

Table IA.1 and Table IA.2 present 10 out-of-sample sentences related to the A-share stock market that the BERT model classifies as positive and negative, respectively. Each classification is accompanied by human evaluation to assess the model's accuracy. To further validate the BERT model's predictions, Table IA.3, Panels A and B report the 50 most frequently occurring phrases in the positive and negative categories, respectively.

[Insert Table IA.1 here]

[Insert Table IA.2 here]

[Insert Table IA.3 here]

IB. Empirical results for DeepSeek-based expectations

This section presents robustness checks using DeepSeek-based expectations: Table IB.1 replicates Table 4, Table IB.2 replicates Table 5, Table IB.3 replicates Table 8, and Table IB.4–IB.10 replicate Table 9–15.

[Insert Table IB.1 here]

[Insert Table IB.2 here]

[Insert Table IB.3 here]

[Insert Table IB.4 here]

[Insert Table IB.5 here]

[Insert Table IB.6 here]

[Insert Table IB.7 here]

[Insert Table IB.8 here]

[Insert Table IB.9 here]

[Insert Table IB.10 here]

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Table IA.1
Sentences classified as positive by MacBERT

Sentences (in Chinese)	**Sentences (in English)**	**Human evaluation**
各项经济指标在一季度大概率仍然会继续回暖，市场流动性持续改善	Various economic indicators are likely to continue recovering in the first quarter, and market liquidity is steadily improving.	Positive
随着市场整体风险偏好的提升和经济数据的逐步好转，券商、银行、地产、建材等顺周期板块也有望阶段性修复估值	With the overall improvement in market risk appetite and gradual recovery in economic data, procyclical sectors such as brokerages, banks, real estate, and building materials are expected to experience a phased valuation recovery.	Positive
另一方面，本届政府也展示出前所未有的维护资本市场稳定的信心	On the other hand, the current government has shown unprecedented confidence in maintaining capital market stability.	Positive
监管层非常呵护市场	Regulators are highly protective of the market.	Positive
低估值、高分红的大盘蓝筹股对市场有稳定作用，具有一定成长性的中盘蓝筹有望成为推动市场上行的主力板块	Large-cap blue-chip stocks with low valuations and high dividends provide market stability, while mid-cap blue chips with growth potential are expected to be key drivers of market gains.	Positive
随着宏观经济在改革中日渐趋稳，证券市场的未来表现相较于去年有望出现喘息	As the macroeconomy gradually stabilizes amid reforms, the securities market is expected to see a breather compared to last year.	Positive
市场方面，从整体估值角度看，截止 7 月 29 日，沪深 300 指数的估值水平处于近 5 年约 30% 分位数水平，估值水平较低	From a market valuation perspective, as of July 29, the valuation level of the CSI 300 Index is around the 30th percentile over the past five years, indicating relatively low valuation.	Positive
估计未来不会出台进一步的紧缩政策，保持 gdp 的适度增长，将成为政策的出发点，我们对下半年证券市场的投资机会持乐观态度	It is estimated that no further tightening policies will be introduced, and maintaining moderate GDP growth will be the policy focus. We are optimistic about investment opportunities in the securities market in the second half of the year.	Positive
展望 2023 年，国内方面，管理人判断经济将会保持温和复苏，流动性环境维持宽松，风险偏好逐步修复，相比 2022 年权益环境得到显著改善	Looking ahead to 2023, domestically, the manager expects a mild economic recovery, a continued loose liquidity environment, and a gradual restoration of risk appetite, with the equity environment significantly improved compared to 2022.	Positive
站在当前时点，我们对全年权益市场并不悲观，仍维持去年年底的降低收益预期 + 寻找结构性机会的市场观	At the current point in time, we are not pessimistic about the full-year equity market and continue to maintain the year-end view of lowering return expectations while seeking structural opportunities.	Positive

Table IA.2
Sentences classified as negative by MacBERT

Sentences (in Chinese)	Sentences (in English)	Human evaluation
三, 从风险偏好角度, 当前市场整体风险溢价率较低，情绪指标相对较热，特别是在部分新兴产业，需提防下半年紧信用强化对于估值的潜在压力	Third, from a risk appetite perspective, the current overall market risk premium is low, sentiment indicators are relatively heated, especially in some emerging industries. It is necessary to guard against the potential valuation pressure caused by tighter credit in the second half of the year.	Negative
当前 A 股市场面临着一些不利因素	The current A-share market is facing some unfavorable factors.	Negative
总的来说, 经过两年的牛市, 08 年的市场投资难度大幅增加, 我们将继续保持冷静的心态, 理性思考, 明辨风险, 克尽职守, 以优异的投资业绩回报广大投资者的信任	Overall, after a two-year bull market, investment in 2008 has become significantly more difficult. We will remain calm, think rationally, discern risks, fulfill our duties, and reward investors' trust with outstanding performance.	Negative
从我们的日常工作层面上，随着市场的持续上涨，我们的上述操作原则受到了极大的挑战	From our day-to-day operations, the sustained market uptrend has greatly challenged our operational principles.	Negative
但是, A 股市场自去年以来, 已经出现了较大幅度的调整，这些不利影响很大程度上应该已经反映在股价中	However, since last year, the A-share market has undergone substantial corrections, and these adverse effects should be largely reflected in stock prices.	Positive
2017 年一季度，一月份周期品表现较好，随着市场对复苏的持续性担忧加剧以及 PPI 进入冲高回落的阶段，周期板块表现开始偏弱	In the first quarter of 2017, cyclical products performed well in January. As concerns about the sustainability of the recovery grew and PPI entered a peak-to-decline phase, the performance of cyclical sectors began to weaken.	Negative
货币政策持续紧缩及通胀水平居高难下，是三季度市场的主要制约因素	Continued monetary tightening and persistently high inflation were the main constraints on the market in the third quarter.	Negative
与此同时，新股发行和再融资的资金需求也会制约市场反弹的空间	Meanwhile, capital demand from IPOs and refinancing will also limit the room for a market rebound.	Negative
预期短期内 A 股震荡将会加剧, 在进入第五个保本期后, 权益投资将会持谨慎态度, 以捕捉结构性行情，精选个股为主	The A-share market is expected to experience intensified short-term volatility. After entering the fifth capital preservation period, equity investment will adopt a cautious approach, focusing on structural opportunities and selective stock picking.	Negative
但本轮疫情的长尾效应以及疫情常态化防控下，市场主体活力不足, 居民消费意愿低迷, 融资需求仍然偏弱，经济修复动能不强	However, due to the long-tail effects of the pandemic and the normalization of pandemic controls, market vitality is insufficient, consumer willingness is low, financing demand remains weak, and economic recovery momentum is not strong.	Negative

Table IA.3
Most frequently occurring phrases in the positive and negative categories

中文	English	中文	English	中文	English	中文	English	中文	English
Panel A: Phrases from positive sentences									
市场	Market	经济	Economy	估值	Valuation	a 股	A-shares	机会	Opportunity
权益	Equity	政策	Policy	流动性	Liquidity	整体	Overall	预期	Expectation
有望	Expected to	国内	Domestic	投资	Investment	未来	Future	行业	Industry
持续	Continue to	处于	Be in	宽松	Loose	预计	Expect	资金	Capital
风险	Risk	配置	Allocation	股市	Stock market	股票市场	Stock market	资产	Asset
修复	Recovery	资本市场	Capital market	长期	Long term	复苏	Rebound	环境	Environment
盈利	Profitability	乐观	Optimism	增长	Growth	表现	Performance	因素	Factor
疫情	Pandemic	改善	Improvement	提升	Enhancement	结构性	Structural	货币政策	Monetary policy
风险偏好	Risk appetite	企业	Enterprise	改革	Reform	影响	Impact	调整	Adjustment
全球	Global	短期	Short term	中国	China	依然	Still	行情	Market trend
Panel B: Phrases from Negative sentences									
市场	Market	经济	Economy	估值	Valuation	预期	Expectation	压力	Pressure
流动性	Liquidity	风险	Risk	整体	Overall	影响	Impact	政策	Policy
a 股	A-shares	国内	Domestic	因素	Factor	调整	Adjustment	持续	Continue to
短期	Short-term	机会	Opportunity	下行	Downturn	行业	Industry	盈利	Profitability
较大	Considerable	面临	Face	权益	Equity	股市	Stock Market	通胀	Inflation
未来	Future	资金	Capital	全球	Global	预计	Expect	投资	Investment
杠杆	Leverage	风险偏好	Risk Appetite	增速	Growth Rate	带来	Bring	处于	Be in
疫情	Pandemic	货币政策	Monetary Policy	股票市场	Stock Market	对市场	Toward Market	导致	Lead to
复苏	Recovery	谨慎	Cautious	环境	Environment	加息	Rate Hike	进一步	Further
宽松	Loose	企业	Enterprise	美国	United States	股票	Stock	冲击	Shock

Table IB.1
Past market returns and consensus expectations: Exponential decay model

n	a	t-stat	b	t-stat	λ	t-stat	Pseudo R^2 (%)	Obs.
6	0.572***	(13.637)	2.789***	(6.017)	0.725***	(11.359)	23.830	217
12	0.570***	(13.467)	2.940***	(5.290)	0.683***	(11.954)	23.867	217
18	0.570***	(13.415)	2.931***	(5.098)	0.674***	(11.870)	23.770	217
24	0.570***	(13.405)	2.933***	(5.068)	0.673***	(11.860)	23.768	217

This table reports the estimation results for a, b, λ, and pseudo R^2 statistics for the nonlinear least squares regression model:

$$\text{EXPECTATION}_t^{\text{DeepSeek}} = a + b \cdot \sum_{\tau=0}^{n-1} w_\tau R^M_{t-2-\tau \to t-1-\tau} + u_t, \qquad \text{where } w_\tau = \frac{\lambda^\tau}{\sum_{j=0}^{n-1} \lambda^j},\ 0 \leq \lambda < 1.$$

The dependent variable is the DeepSeek-based consensus belief calculated as the difference between the ratio of optimistic funds and the ratio of pessimistic funds. The explanatory variables include n lagged monthly excess market returns from month $t-n$ to month $t-1$. Newey-West t-statistics with twelve lags are in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table IB.2

Asymmetric effects of market returns on consensus expectations

n	a	t-stat	b^+	t-stat	b^-	t-stat	λ^+	t-stat	λ^-	t-stat	Pseudo R^2 (%)	Obs.
Panel A: Positive versus negative market returns												
6	0.570***	(7.473)	2.816***	(3.506)	2.744***	(2.836)	0.654***	(5.694)	0.823***	(5.216)	24.0	217
12	0.586***	(7.383)	2.818***	(3.268)	3.423***	(2.622)	0.591***	(5.564)	0.826***	(7.289)	24.6	217
18	0.591***	(7.076)	2.831***	(3.189)	3.647**	(2.262)	0.588***	(5.245)	0.819***	(7.334)	24.6	217
24	0.597***	(6.854)	2.846***	(3.120)	3.912**	(2.041)	0.584***	(5.282)	0.838***	(8.271)	24.7	217
Panel B: Moderate versus extreme market states												
n	a	t-stat	b^M	t-stat	b^E	t-stat	λ^M	t-stat	λ^E	t-stat	Pseudo R^2 (%)	Obs.
6	0.571***	(12.905)	2.846	(3.198)	2.757	(5.835)	0.656	(5.835)	0.778	(9.456)	24.0	217
12	0.570***	(12.651)	2.957	(2.853)	2.909	(4.790)	0.638	(6.166)	0.708	(7.492)	24.0	217
18	0.570***	(12.611)	2.948	(2.784)	2.910	(4.465)	0.631	(5.828)	0.699	(7.396)	23.9	217
24	0.570***	(12.608)	2.947	(2.774)	2.915	(4.428)	0.631	(5.810)	0.699	(7.462)	23.9	217

This table reports the estimation results of the nonlinear least squares regression model for past market return characteristics. The dependent variable is the DeepSeek-based consensus expectation calculated as the difference between the ratio of optimistic funds and pessimistic funds. In Panel A, the explanatory variables include both the positive and negative parts of the lagged monthly excess market returns from month $t-n$ to month $t-1$ and the regression is specified as

$$\text{EXPECTATION}_t^{\text{DeepSeek}} = a + b^+ \cdot \sum_{\tau=0}^{n-1} w_\tau^+ R_{t-2-\tau\to t-1-\tau}^+ + b^- \cdot \sum_{\tau=0}^{n-1} w_\tau^- R_{t-2-\tau\to t-1-\tau}^- + u_t,$$

where $w_\tau^+ = \frac{(\lambda^+)^\tau}{\sum_{j=0}^{n-1}(\lambda^+)^j}$, $w_\tau^- = \frac{(\lambda^-)^\tau}{\sum_{j=0}^{n-1}(\lambda^-)^j}$, $R^+ = \max(R^M, 0)$, and $R^- = \min(R^M, 0)$. Panel B allows the weight and decay rate to differ across different market states:

$$\text{EXPECTATION}_t^{\text{DeepSeek}} = a + b^M \cdot \sum_{\tau=0}^{n-1} \mathbb{1}_{\{R^M_{t-2-\tau\to t-1-\tau}\in M\}} \cdot w_\tau^M R_{t-\tau}^m + b^E \cdot \sum_{\tau=0}^{n-1} \mathbb{1}_{\{R^M_{t-2-\tau\to t-1-\tau}\in E\}} \cdot w_\tau^E R_{t-\tau}^E + u_t,$$

where the superscripts M and E indicate the moderate and extreme market states, respectively. The current stock market state is classified as moderate if monthly returns in the most recent month fall within the 5th to 95th percentiles of the past 60 monthly observations. Conversely, the market is classified as extreme if the monthly returns in the most recent month fall outside this interval, based on the same 60-month window. Newey-West t-statistics with twelve lags are in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table IB.3
Extrapolative beliefs and fund manager characteristics

	Crash experience	No crash experience	Recession	Non-recession	Older	Younger
	(1)	(2)	(3)	(4)	(45)	(6)
a	0.120***	0.127***	0.131***	0.109***	0.122***	0.112***
	(83.481)	(89.448)	(109.553)	(56.777)	(31.082)	(32.276)
b	1.121***	0.750***	0.934***	0.873***	0.868***	0.880***
	(20.805)	(17.581)	(17.718)	(19.907)	(8.675)	(10.387)
λ	0.721***	0.603***	0.691***	0.611***	0.692***	0.617***
	(51.631)	(27.794)	(41.468)	(29.035)	(19.409)	(17.352)
Pseudo R^2	0.035	0.027	0.023	0.043	0.038	4.433
Observations	30,508	34,615	42,781	19,859	4,304	5,917

This table reports the estimated a, b, and λ for the nonlinear least squares regression model across different fund manager characteristics:

$$\text{EXPECTATION}^{\text{DeepSeek}}_{i,t\to t+h} = a_i + b_i \cdot \sum_{\tau=0}^{n-1} w_{i,\tau} R^M_{t-2-\tau\to t-1-\tau} + u_{i,t,h}, \quad \text{where } w_{i,\tau} = \frac{\lambda_i^\tau}{\sum_{j=0}^{n-1} \lambda_i^j},\ 0 \leq \lambda < 1.$$

The dependent variable, $\text{EXPECTATION}^{\text{DeepSeek}}_{i,t\to t+h}$, is the subjective expectations of fund i on month t over the period from t to $t+h$ quantified via DeepSeek-V3. The explanatory variables include n lagged monthly excess market returns from month $t-n$ to month $t-1$. Columns (1) and (2) report results for fund managers with and without bubble-crash experience, respectively. Columns (3) and (4) present results for managers who began their careers during a recession versus those who did not. Columns (5) and (6) compare older and younger fund managers, respectively.

Table IB.4
Mutual fund expectation and aggregate market return: In-sample forecasting

τ	1	2	3	4	5	6	12
Panel A: Ex post excess market return on expectation							
EXPECTATION$^{\text{DeepSeek}}$	0.011**	0.022*	0.032	0.039	0.043	0.046	0.058
	(2.055)	(1.810)	(1.588)	(1.332)	(1.060)	(0.865)	(0.416)
CONSTANT	0.012**	0.027**	0.042**	0.058*	0.077*	0.096*	0.224
	(2.297)	(2.106)	(2.020)	(1.867)	(1.776)	(1.709)	(1.568)
Bootstrapped p-value	0.043	0.087	0.151	0.375	0.517	0.618	0.837
Observations	216	215	214	213	212	211	205
R^2	0.032	0.047	0.055	0.060	0.054	0.049	0.032
Panel B: Estimated coefficients on EXPECTATION$^{\text{DeepSeek}}$, controlling for other predictors one-by-one							
μ	0.011**	0.022*	0.029*	0.034	0.039	0.041	0.046
	(2.050)	(1.874)	(1.688)	(1.377)	(1.072)	(0.907)	(0.452)
S	0.013**	0.028**	0.042**	0.052*	0.060	0.068	0.117
	(2.525)	(2.320)	(2.132)	(1.827)	(1.537)	(1.349)	(1.056)
DP	0.012**	0.027**	0.039**	0.050*	0.059	0.067	0.125
	(2.420)	(2.289)	(2.098)	(1.869)	(1.584)	(1.382)	(0.834)
EP	0.011*	0.024*	0.037*	0.046	0.053	0.058	0.094
	(1.949)	(1.901)	(1.759)	(1.642)	(1.404)	(1.255)	(0.793)
BM	0.012**	0.026**	0.037*	0.047*	0.054	0.061	0.104
	(2.319)	(2.122)	(1.897)	(1.650)	(1.369)	(1.176)	(0.696)
TO	0.010**	0.023*	0.033*	0.041	0.047	0.052	0.081
	(1.977)	(1.846)	(1.653)	(1.470)	(1.230)	(1.049)	(0.569)
SVAR	0.011**	0.022*	0.032	0.039	0.043	0.046	0.058
	(2.058)	(1.810)	(1.586)	(1.329)	(1.057)	(0.863)	(0.415)
INFL	0.005	0.011	0.017	0.021	0.022	0.022	0.022
	(0.986)	(0.987)	(0.932)	(0.761)	(0.558)	(0.424)	(0.176)
NTIS	0.011**	0.022*	0.032	0.038	0.042	0.044	0.055
	(2.047)	(1.823)	(1.600)	(1.372)	(1.105)	(0.909)	(0.418)
STY	0.007	0.014	0.018	0.019	0.016	0.013	−0.006
	(1.226)	(1.105)	(0.902)	(0.657)	(0.426)	(0.266)	(−0.054)
LTY	0.007	0.014	0.020	0.022	0.022	0.021	0.018
	(1.215)	(1.153)	(1.025)	(0.805)	(0.579)	(0.434)	(0.152)
Panel C: Ex post excess market return on expectation, controlling for all predictors							
EXPECTATION$^{\text{DeepSeek}}$	0.004	0.011	0.018	0.017	0.012	0.011	0.024
	(0.811)	(1.026)	(1.109)	(0.809)	(0.484)	(0.402)	(0.473)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	213	212	211	210	209	203
R^2	0.169	0.289	0.375	0.433	0.492	0.541	0.693

Table IB.4
(Cont'd)

τ	1	2	3	4	5	6	12
Panel D: Ex post excess market return on the proportion of bullish funds, controlling for all predictors							
$\text{BULLISH}^{\text{DeepSeek}}$	0.029	0.074	0.120	0.109	0.073	0.059	0.150
	(0.743)	(0.953)	(1.035)	(0.738)	(0.407)	(0.309)	(0.388)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	213	212	211	210	209	203
R^2	0.169	0.288	0.374	0.432	0.492	0.541	0.693
Panel E: Ex post excess market return on the proportion of bearish funds, controlling for all predictors							
$\text{BEARISH}^{\text{DeepSeek}}$	−0.037	−0.095	−0.157	−0.151	−0.118	−0.112	−0.219
	(−0.870)	(−1.098)	(−1.181)	(−0.883)	(−0.566)	(−0.503)	(−0.587)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	213	212	211	210	209	203
R^2	0.169	0.289	0.376	0.434	0.493	0.542	0.694

This table presents the predictive power of mutual fund stock market expectation over the prediction horizon τ, where τ = 1, 2, 3, 4, 5, 6, and 12 months. Panel A reports the results of the univariate predictive regression analysis based on DeepSeek-based fund expectations ($\text{EXPECTATION}^{\text{DeepSeek}}$), defined as the difference between the ratio of optimistic funds and the ratio of pessimistic funds. Panel B compares the predictability of fund expectations with other predictors. $R^M_{t-13,t-2}$ is the market returns over the past 12 months skipping the most recent month. μ is the value-weighted analysts' consensus forecasts for earnings-per-share (EPS) growth, where growth is defined as the difference between the analysts' forecasts of EPS and the most recent realized EPS, scaled by the most recent realized EPS. S is the Baker and Wurgler (2006) investor sentiment index, recalculated using data from the Chinese capital market. DP is the log dividend-price ratio. EP is the log earnings-price ratio. BM is the log book-to-market ratio. TO is the stock market turnovers. SVAR is the stock return variance. INFL is the inflation index. NTIS is the net equity expansion. STY and LTY are 3-month and 10-year government bond yields, respectively. Panel C controls for all economic predictors mentioned in Panel B, except for the $R^M_{t-13,t-2}$. Hansen and Hodrick (1980) t-statistics with τ lags are in parentheses. Bootstrapped p-values of fund expectations are reported for Panel A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IB.5

Mutual fund expectations and aggregate market returns: controlling for market return autocorrelation

	Dependent variable: $R^M_{t\to t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXPECTATION$^{\text{DeepSeek}}$					0.008*	0.004	0.006	0.010**
					(1.689)	(0.865)	(1.155)	(2.081)
R^M_{t-1}	0.115				0.080			
	(1.327)				(0.913)			
$R^M_{t-3\to t-1}$		0.097**				0.086*		
		(2.013)				(1.702)		
$R^M_{t-6\to t-1}$			0.046				0.038	
			(1.614)				(1.250)	
$R^M_{t-12\to t-1}$				0.007				0.002
				(0.517)				(0.112)
Observations	216	216	216	216	216	216	216	216
R^2	0.013	0.041	0.030	0.003	0.023	0.043	0.034	0.018

This table presents the predictive power of mutual fund stock market expectations over the one-month prediction horizon, controlling for market return autocorrelation. $R^M_{t-\tau,t-1}$ is the market returns over the past τ months, skipping the most recent month. Hansen and Hodrick (1980) t-statistics with τ lags are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IB.6
Mutual fund expectations and aggregate market returns: mandated versus non-mandated disclosures

	Panel A: Quarterly non-mandated disclosures $R^M_{t+3} = \alpha + \beta \cdot X_t + \varepsilon_{t+3}$				Panel B: Semi-annual and annual mandated disclosures $R^M_{t+6} = \alpha + \beta \cdot X_t + \varepsilon_{t+6}$			
	β	t-stat	R^2	Obs.	β	t-stat	R^2	Obs.
EXPECTATION$^{\text{DeepSeek}}$	0.111	1.560	0.032	71	0.286	1.601	0.083	39
BULLISH$^{\text{DeepSeek}}$	0.220	1.614	0.035	71	0.555	1.583	0.085	39
BEARISH$^{\text{DeepSeek}}$	−0.220	-1.494	0.029	71	−0.556	−1.620	0.077	39

This table presents the predictive power of mutual fund stock market expectations, controlling for market return autocorrelation. Panel A constructs the consensus expectation series using quarterly non-mandated disclosures. Panel B constructs the consensus expectation series using semi-annual and annual mandated disclosures, denoted. Hansen and Hodrick (1980) t-statistics with one lag are used. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IB.7
Out-of-sample analysis for DeepSeek-based consensus expectations

Window size (months)	Forecast begin	$R^2_{OOS}(\%)$	CW test	DM test	CER gain (%)	Sharp ratio
36	2008-03-31	5.969	2.366***	1.045**	4.102	0.405
48	2009-03-31	2.506	1.979**	0.589*	4.315	0.537
60	2010-03-31	5.192	2.663***	1.730***	3.658	0.430

This table reports the out-of-sample forecasting performance for predicting one-month-ahead stock market returns using EXPECTATION$^{\text{DeepSeek}}$. EXPECTATION$^{\text{DeepSeek}}$ is the DeepSeek-based consensus expectations, defined as the difference between the ratio of optimistic and pessimistic funds. We perform out-of-sample predictive regressions using a rolling approach with window sizes of 36, 48, and 60. R^2_{OOS} is the out-of-sample R-squared proposed by Campbell and Thompson (2008). CW test is the Clark and West (2007) MSFE-adjusted statistic for testing $R^2_{OOS} \leq 0$. DM test is the Diebold and Mariano (1995) statistic modified by McCracken (2007) for testing the equality of the MSFE of one forecast relative to other forecasts. Also reported are the annualized certainty equivalent return gains (in percentages) and monthly Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of 3. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IB.8

Expectation-performance relation in the time-series and cross-section

	Dependent variable: NET-OF-FEE RETURN							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{EXPECTATION}^{\text{DeepSeek}}$	4.091				−0.011			
	(1.341)				(−0.023)			
$\text{EXPECTATION}^{\text{DeepSeek},+}$		8.290**				−0.316		
		(2.275)				(−0.337)		
$\text{EXPECTATION}^{\text{DeepSeek},-}$		−1.709				0.428		
		(−0.345)				(0.361)		
$\text{CORRECT}^{\text{DeepSeek}}$			20.882***				0.595	
			(4.455)				(1.409)	
$\text{CORRECT}^{\text{DeepSeek},+}$				23.686***				0.543*
				(4.397)				(1.831)
$\text{CORRECT}^{\text{DeepSeek},-}$				−3.848				0.655
				(−1.378)				(0.793)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Time fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	7,301	7,301	7,301	7,301	7,301	7,301	7,301	7,301
Adjusted R^2	-0.006	-0.005	0.202	0.297	0.629	0.629	0.629	0.629

This table reports the relation between fund expectations and future performance in the time-series and cross-section. $\text{EXPECTATION}^{\text{DeepSeek}}$ is the DeepSeek-based fund's stock market forecast for the next year. $\text{EXPECTATION}^{\text{DeepSeek},+}$ is defined as $\max(\text{EXPECTATION}^{\text{DeepSeek}}, 0)$ and EXPECTATION^{-} is defined as $\min(\text{EXPECTATION}^{\text{DeepSeek}}, 0)$. $\text{CORRECT}^{\text{DeepSeek}}$ is a dummy variable equal to one if the fund' s annual forecast aligns with the realized excess market return for the following year, and zero otherwise. The superscript $+/-$ on $\text{CORRECT}^{\text{DeepSeek}}$ indicates the direction of the realized excess return. BETA is the fund's holding-weighted beta, calculated using stock betas estimated from daily returns over the past 12 months based on the fund's most recent portfolio holdings. Columns (1)–(4) control for fund fixed effects to identify the time-series variation, while Columns (5)–(8) include time fixed effects to capture the cross-sectional variation. Standard errors are double clustered at the fund and time level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IB.9
The degree of pass-through from beliefs to actions and future fund performance

Panel A: Expectations, portfolio adjustments, and future fund performance

	Net-of-fee return	CAPM Alpha	FFC4 Alpha
	(1)	(2)	(3)
$\text{EXPECTATION}^{\text{DeepSeek},+}$	−18.949	−19.433*	−15.587
	(−1.513)	(−1.709)	(−1.521)
$\text{EXPECTATION}^{\text{DeepSeek},-}$	10.860	5.231	12.048*
	(1.510)	(0.791)	(1.895)
BETA	−6.169	−4.108	−2.379
	(−1.331)	(−1.082)	(−0.901)
$\text{EXPECTATION}^{\text{DeepSeek},+}\times\text{BETA}$	21.434	21.373*	16.791
	(1.570)	(1.708)	(1.477)
$\text{EXPECTATION}^{\text{DeepSeek},-}\times\text{BETA}$	−13.462	−5.970	−13.081*
	(−1.641)	(−0.785)	(−1.695)
Controls	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	7,301	7,301	7,301
Adjusted R^2	0.651	0.397	0.266

Panel B: Correct expectations, portfolio adjustments, and future fund performance

	Net-of-fee return	CAPM Alpha	FFC4 Alpha
	(1)	(2)	(3)
$\text{CORRECT}^{\text{DeepSeek},+}$	−27.660***	−21.768***	−16.680**
	(−3.065)	(−2.583)	(−2.349)
$\text{CORRECT}^{\text{DeepSeek},-}$	−3.495	−3.346	−4.582*
	(−0.938)	(−1.417)	(−1.834)
BETA	−14.446***	−9.524***	−6.355***
	(−3.447)	(−4.203)	(−4.066)
$\text{CORRECT}^{\text{DeepSeek},+}\times\text{BETA}$	31.668***	24.750***	19.452**
	(3.248)	(2.733)	(2.532)
$\text{CORRECT}^{\text{DeepSeek},-}\times\text{BETA}$	4.313	3.840	5.099
	(0.895)	(1.172)	(1.461)
Controls	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	7,301	7,301	7,301
Adjusted R^2	0.665	0.414	0.283

This table reports the relation between fund expectations and future performance. $\text{EXPECTATION}^{\text{DeepSeek}}$ is the fund's stock market forecast for the next year. $\text{EXPECTATION}^{\text{DeepSeek},+}$ is defined as $\max(\text{EXPECTATION}^{\text{DeepSeek}}, 0)$ and $\text{EXPECTATION}^{\text{DeepSeek},-}$ is defined as $\min(\text{EXPECTATION}^{\text{DeepSeek}}, 0)$. $\text{CORRECT}^{\text{DeepSeek}}$ is a dummy variable equal to one if the fund' s annual forecast aligns with the realized excess market return for the following year, and zero otherwise. The superscript +/− on $\text{CORRECT}^{\text{DeepSeek}}$ indicates the direction of the realized excess return. BETA is the fund's holding-weighted beta, where a stock's beta is estimated using CAPM with daily returns over the past 12 months. Standard errors are double clustered at the fund and time level. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IB.10
Limited portfolio adjustments and fund performance: the role of liquidity

Dependent variable:	R^{Net}		α^{CAPM}		α^{FFC4}	
Sort variable: %LIQ	Low	High	Low	High	Low	Highh
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{CORRECT}^{\text{DeepSeek},+}$	−24.628***	−35.966***	−19.436**	−29.394***	−12.951**	−24.044***
	(−2.915)	(−3.074)	(−2.272)	(−2.875)	(−1.994)	(−2.885)
$\text{CORRECT}^{\text{DeepSeek},-}$	−7.985*	7.561	−6.032*	4.562	−7.870***	3.345
	(−1.734)	(1.644)	(−1.873)	(1.120)	(−2.650)	(0.929)
BETA	−12.013***	−17.847***	−7.794***	−13.618***	−4.197*	−9.581***
	(−5.340)	(−2.709)	(−3.803)	(−3.103)	(−1.938)	(−3.310)
$\text{CORRECT}^{\text{DeepSeek},+}\times\text{BETA}$	30.342***	39.206***	23.377**	32.629***	16.665**	26.946***
	(3.197)	(3.059)	(2.426)	(2.923)	(2.298)	(3.006)
$\text{CORRECT}^{\text{DeepSeek},-}\times\text{BETA}$	9.015	−6.679	6.813	−4.180	8.970**	−2.971
	(1.548)	(−1.303)	(1.613)	(−0.931)	(2.193)	(−0.761)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,653	3,649	3,653	3,649	3,653	3,649
Adjusted R^2	0.689	0.687	0.478	0.445	0.334	0.326

This table examines how liquidity affects the strength of the relation between expectation-aligned beta tilts and future fund performance. $\text{CORRECT}^{\text{DeepSeek}}$ is a dummy variable equal to one if the fund’ s annual forecast aligns with the realized excess market return for the following year, and zero otherwise. The superscript +/− on $\text{CORRECT}^{\text{DeepSeek}}$ indicates the direction of the realized excess return. BETA is the fund’s holding-weighted beta, where a stock’s beta is estimated using CAPM with daily returns over the past 12 months. %LIQ is defined as the percentage of a fund’ s portfolio invested in liquid stocks. Liquid stocks are those in the bottom quintile of the **?** illiquidity measure within each year. We then split the fund-year observations into low liquidity funds (below-median %LIQ) and high liquidity funds (above-median %LIQ) and estimate Eq. (**??**) separately for each subsample. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.