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Let the Good Times Roll: Subjective Expectations and Asset Management

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Keywords: subjective expectations, belief formation, extrapolation, mutual funds, asset allocation

JEL Classification: D84, G11, G23, G41

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1. Introduction

Investors worldwide delegate the investment of over $68 trillion to the mutual fund industry as of 2023.[1] The expansion of delegated investment is particularly evident in emerging economies, where the mutual fund industry plays a pivotal role in enabling retail investors to participate in financial markets while facilitating broader risk-sharing across the economy. For instance, in China, the central government has introduced multiple initiatives to promote mutual funds, particularly equity mutual funds, as part of its efforts to cultivate a more market-driven and efficient investment ecosystem.[2] These initiatives include novel and original regulatory approaches not paralleled in developed financial markets, which aim to enhance the transparency of mutual fund portfolio managers' decision-making processes.

Portfolio managers are crucial decision makers in the mutual fund industry because their investment decisions determine the financial returns earned by millions of investors and can affect the equilibrium of financial markets. Understanding the factors that drive portfolio managers' asset allocation decisions is therefore key not only to assess the determinants of investors' wealth accumulation but also to interpret broader market dynamics. Asset allocation decisions are inherently forward-looking and depend on the subjective expectations of portfolio managers regarding future macroeconomic conditions and asset-specific outcomes. These expectations are essential for understanding the aggregate investment decisions as well as any heterogeneity in the investment choices that different portfolio managers make at the same point in time and hence under the same macroeconomic conditions. Despite their importance, however, we know little about the drivers and consequences of portfolio managers' subjective expectations, likely due to the

[1] https://www.ici.org/system/files/2024-05/2024-factbook.pdf .

[2] For instance, the 2024 "Several Opinions on Strengthening Supervision, Preventing Risks and Promoting High-Quality Development of the Capital Market" (also known as the "new 'National Nine Articles'") includes specific initiatives aimed at boosting the mutual fund sector (https://www.gov.cn/gongbao/2024/issue_11306/202404/content_6947724.html). In 2022, the China Securities Regulatory Commission (CSRC) issued the "Opinions on Promoting the High-Quality Development of Public Funds", which outlined targeted strategies for enhancing the mutual fund industry (http://www.csrc.gov.cn/csrc/c100028/c2368241/content.shtml).

lack of data. A growing body of literature elicits subjective expectations directly through surveys (D'Acunto and Weber, 2024), but surveys of portfolio managers run at regular frequencies do not exist. Moreover, whereas recruiting samples of households and firms that are representative of the aggregate population can be done by targeting census-based population figures, statistics about the universe of portfolio managers do not exist either. In order to be representative, studying portfolio managers' subjective expectations and their impact on investment decisions requires a method that measures the subjective expectations of an entire population of portfolio managers.

This study aims to tackle these challenges. We do so by exploiting unique regulatory requirements that allow direct measure of a full population of portfolio managers' subjective expectations. Specifically, we exploit mandatory disclosures of portfolio managers' outlooks on macroeconomic and security-market conditions imposed on *all* Chinese mutual funds to enhance the transparency of mutual funds' asset allocation decisions. Fund managers have to provide these outlooks in a section titled Management's Outlook on the Macroeconomy, Securities Market, and Industry Trends (henceforth, Market Outlook) in their annual and semiannual reports to comply with regulatory requirements by the China Securities Regulatory Commission (CSRC).

In addition to measuring the subjective expectations of the full population of agents we study, our design has the advantage of eliciting beliefs in a highly incentivized setting: the expectations that portfolio managers report are public information and are not observable only to the econometrician like in surveys of households and firms. For this reason, portfolio managers have a strong incentive to report subjective expectations that align with their investment choices—an incentive that does not exist in anonymous survey-based elicitation of expectations and that reduces concerns about the reliability of elicited expectations and noise in measurement (Konchitchki and Xie, 2023).

We collect the Market Outlook sections from the reports of 1,551 actively managed equity funds spanning the years 2012 to 2022. Because beliefs are reported in narrative texts rather than numerical values, we employ both traditional dictionary-based textual analysis techniques and advanced large language models to quantify each manager's subjective expectations coherently and consistently across managers and over time.[3]

Our first contribution is to document, to the best of our knowledge, for the first time, a set of stylized facts about portfolio managers' subjective expectations. First, in the cross-section, all our measures reveal that portfolio managers' outlook is systematically more likely to be positive than negative. Second, when focusing on time-series variation, we find that portfolio managers' outlooks vary significantly over time. Third, we document substantial heterogeneity in portfolio managers' subjective expectations, including for expectations formed at the same point in time and hence under the same macroeconomic and market conditions.

The substantial dispersion and heterogeneity in portfolio managers' subjective expectations is a surprising fact. Although consistent with the dispersion of subjective expectations of households and firm managers documented in prior literature, contrary to those economic agents, portfolio managers possess extensive and largely homogeneous information sets about the macroeconomy and financial-market conditions. Moreover, this fact dismisses the potential concern that a strategic motive plagues the expectations we observe, whereby portfolio managers report outlooks that aim to attract fund flows from the investors who read them. If this were the case, managers would report similar subjective expectations at the same point in time, i.e. those that maximize fund flows. The substantial dispersion in expectations suggests that at least some portfolio managers deviate from the full-information rational expectations (FIRE) paradigm, which is often assumed in theoretical and empirical asset management analyses based on the homogeneous and comprehensive nature of portfolio managers' information sets relative to the information sets of other types of agents.

Motivated by these baseline facts, we propose a set of tests to further assess in what ways portfolio managers' expectations depart from FIRE. We start by examining the

[3] We propose both standard measures based on bag-of-word approach (e.g., Loughran and McDonald, 2011) and alternative measure of expectations using ChatGPT (version 4.0). These measures are significantly correlated (with a correlation of 0.435 and a p-value of less than 0.01), which reassures us about their validity.

correlation between the time-series aggregate market outlook and both concurrent and subsequent market returns. At the aggregate level, we find that average market outlook is highly positively correlated with concurrent market returns. In sharp contrast, the correlation with subsequent-year market returns is strongly negative. These findings represent suggestive evidence that, at the aggregate level, portfolio managers extrapolate market returns when forming their subjective expectations, which is inconsistent with standard forms of the FIRE paradigm. Because these subjective expectations are public knowledge, portfolio managers know that their previously reported outlooks will be available to investors at any point of time going forward and hence this extrapolation cannot be due to a strategic motive and the attempt to attract more flows - an attempt that portfolio managers know would be easily detected by market participants.

We then explore the role of individual managers' recent investment performance in the formation and updating of their subjective expectations about market returns. Under FIRE, fund managers' past performance should be unrelated to their expectations about future market returns. In contrast, our analysis reveals that the recent investment performance of fund managers significantly influences their market outlooks. Managers with stronger performance exhibit greater optimism regarding future macroeconomic conditions and security markets relative to other managers even if all managers form beliefs under the same macroeconomic and market conditions. Crucially, and even more inconsistent with standard forms of FIRE, this extrapolation of past performance is asymmetric: managers who outperform are more likely to have positive outlooks following strong performance, whereas underperforming managers do not necessarily provide more pessimistic forecasts. Not only the first moment but also the second moment of fund managers' subjective expectations evolves asymmetrically: managers with better recent performance tend to use fewer uncertain and weak modal words, as defined by Loughran and McDonald (2011), suggesting increased confidence in their predictions. And, these results survive when we only exploit variation in performance and beliefs within managers.

Because past performance only matters for expectations when positive, our baseline are consistent with various forms of cognitive dissonance. We perform a set of cross-sectional tests to further assess the channels that might explain this form of beliefs. First, we find that the positive relationship between investment performance and outlook positivity is particularly strong among inexperienced managers (Greenwood and Nagel, 2009). Additionally, this effect is more pronounced among managers who already held a positive outlook in the previous year. These results hint toward a confirmation bias in beliefs related to preserving one's self-image, or self-confirmation bias: outperforming managers become more optimistic about market conditions and their ability to keep outperforming others, which leads them to excessively optimistic beliefs and hence risk taking.

To further assess this potential explanation, we propose three tests. First, we study if and how beliefs formation varies based on whether female managers are present in a fund's team. We consider female presence because the literature finds that men are more likely than women to display self-image-related biases in beliefs and choice (for instance, se Barber and Odean, 2001 and D'Acunto, 2021 among many others). We find that, indeed, the extrapolation of beliefs from past performance is substantially muted when female managers are part of the management team. Incidentally, this result fleshes out an overlooked channel through which gender diversity in the finance industry can reduce suboptimal choices (e.g., Huang and Kisgen, 2013; Griffin, Li and Xu, 2021).

Our second test directly assesses whether the link between past fund performance and beliefs about future aggregate conditions is person-specific, that is, whether it arises only for managers that managed the same fund in the previous year, or whether it is fund-specific, which could be consistent with a fund-level information-based explanation. For this test, we consider cases of managerial turnover, whereby new fund managers replace old ones. New fund managers are fully aware of the fund's performance in the previous year as well as any fund-level and firm-level information or incentive structure. But, crucially, they did not personally contribute to past performance. We find that the asymmetric extrapolation in beliefs formation does not arise after a funds outperform when new managers take over, which is direct evidence that managers' personal contribution to previous positive performance is a fundamental ingredient for asymmetric beliefs extrapolation to arise.

Third, we exploit another unique feature of mutual fund disclosures in China, that is, the requirement that all fund managers provide a subjective assessment of their own performance in the previous year as part of the disclosure forms. This requirement allows us to disentangle objective measures of past performance from fund managers' own subjective assessment. We find that the extrapolation of positive recent performance to aggregate market beliefs is more pronounced among managers who assess their recent performance more positively, even when controlling directly for our objective measure of fund performance.

In the second part of the paper, we explore how fund managers' expectations influence their asset allocation decisions. This analysis is critical because if subjective expectations were unrelated to portfolio managers' choices—such as in cases where decisions are dictated by higher management rather than being independently made by managers—the observed heterogeneity in expectations, both cross-sectionally and over time, would have no significant impact on real outcomes.

We find that managers with more optimistic outlooks engage in significantly greater risk-taking behavior. A more positive outlook is associated with higher levels of both idiosyncratic and total risk in the portfolio, more concentrated positions, more equity holding and lower cash holdings. Unsurprisingly, this excessive risk-taking behavior results in subpar subsequent performance. This negative relationship between outlook positivity and subsequent performance rules out rational learning as a potential explanation of our baseline findings. Although some forms of learning could account for the extrapolative behavior observed in the first part of the paper, they can barely account for a systematic negative relationship between outlook positivity and subsequent performance.

Finally, the last part of the paper studies how investors react to portfolio managers' market outlooks. On the one hand, investors might be naïve about the biases in portfolio managers' subjective expectations and their influence on asset allocation decisions, or even share the same biases themselves, resulting in a lack of reaction when deciding where to allocate their funds. On the other hand, investors might be sophisticated enough to recognize these biases and adjust their behavior by limiting the capital they allocate to biased portfolio managers. In our setting, investors could easily tame the effects of expectations biases by reallocating funds away from outperforming managers. In the case of analyst forecasts, which provide beliefs but do not directly influence investors' outcomes, the literature has documented that different types of investors may respond in opposite directions (Malmendier and Shanthikumar, 2014). We therefore analyze the responses of institutional and retail investors separately.

We find that, on average, a conservative tone (i.e., a more negative outlook) significantly attracts institutional fund flows, while retail fund flows tend to favor a positive outlook, although this latter relationship is not statistically significant. The superior subsequent performance of funds with a conservative tone not only suggests that institutional fund flows represent "smart money" (they are sophisticated about biases in portfolio managers' beliefs) but also confirms that managers' positive forecasts are not a strategic scheme.

Our paper contributes to at least two strands of literature in economics and finance. First, we contribute to the growing body of research on the characteristics and consequences of economic agents' subjective expectations. Due to data limitations, early work in this area has attempted to back out average expectations from market outcomes and choices by imposing assumptions typical of representative-agent models of belief formation. More recently, the literature has moved forward to measure expectations directly using survey-based instruments and to link individual-level expectations to the choices made by the same individuals. This approach enables researchers to identify heterogeneity in subjective beliefs and assess its consequences for decision-making (see D'Acunto and Weber, 2024, for a recent review). In the context of investors, early research focusing on specific groups of retail investors found that their expectations tend to be extrapolative (see Adam and Nagel, 2023, for a review). More recent studies, which link individual-level beliefs to actual choices, have also focused on individual investors (e.g., Giglio et al., 2021; Schnorpfeil, Weber, and Hackethal, 2024). Due to the lack of viable data on beliefs, there is considerably less evidence concerning expert investment professionals, whose expectations are formed using different information sets, inputs, and sophistication relative to retail investors (Levy et al., 2023). Of particular relevance to our work are Dahlquist and Ibert (2024), who identify countercyclical subjective risk premia at a one-year horizon among a group of large asset management firms, suggesting that these firms' expectations are not subject to extrapolation. We contribute to this area in two ways. First, we describe the subjective expectations of professional asset managers in the cross-section and time series. We document that, despite their access to broader information sets and more sophisticated economic modeling relative to retail investors, professional asset managers form beliefs that display departures from the FIRE paradigm. Second, we use beliefs elicited homogeneously for the universe of the agents we aim to study and in a highly incentivized setting, none of which characteristics are present in modern survey-based studies of subjective expectations (Konchitchki and Xie, 2023). This approach does not face concerns related to noise in answers to non-incentivized questions or selection of agents who are willing to answer surveys, who might differ from others based on demographics that relate systematically to beliefs and choices. Given that the expectations of financial intermediaries significantly impact asset prices, our results motivate follow-up research on understanding how intermediary capital affects asset prices and how heterogeneous beliefs impact investors and inequality, especially in light of the different reaction of institutional and retail investors to managers' beliefs.

Our paper also contributes to the vast mutual fund literature by documenting directly, to the best of our knowledge for the first time, that portfolio managers' subjective expectations do not conform to the FIRE paradigm, display systematic biases based on past performance, and impact their risk-taking and investment performance. Since Jensen (1968), studies on mutual funds have consistently found that fund managers underperform relative to passive market indices. Even those who do outperform rarely maintain their success into the following year (e.g., Malkiel, 1995; Carhart, 1997; Bollen and Busse, 2001). One primary explanation offered by researchers for these findings is the potential agency problems stemming from the misalignment of incentives between mutual fund managers and investors (see Spatt, 2020, for a comprehensive survey on agency issues in the asset management industry). Most of these studies assume that managers' beliefs conform to the FIRE paradigm, without acknowledging the possibility of systematic biases. In contrast, our paper offers a non-agency-based explanation for the mean reversion in fund managers' performance, grounded in the belief formation processes of asset managers. Systematic biases in belief formation lead portfolio managers to take on excessive risks, which in turn negatively affect fund performance. Our alternative explanation for funds managers' underperformance has important policy implications. While agency problems can be addressed through contract design to align fund managers' incentives with investor interests, biased beliefs cannot be mitigated through contractual mechanisms. Managers with biased beliefs are, by nature, unable to recognize or correct these biases because they believe they are optimizing their decisions based on their subjective expectations. For instance, performance-sensitive compensation contracts would not change the behavior of managers with biased beliefs, as these managers would perceive their actions as optimizing their expected performance, even when acting on distorted beliefs. Interventions that aim to align fund managers' choices with investors' interests thus require managing their expectations and making managers aware of the biases in their belief formation process.

2. Institutional Background

The Chinese mutual fund industry was established in the late 1990s as part of financial reforms aimed at developing a more robust capital market in China. Over the years, the mutual fund industry has expanded rapidly due to improved regulatory frameworks and increased investor demand. According to the Asset Management Association of China (AMAC), by the end of December 2023, China's mutual fund assets exceeded ¥23 trillion (US$3.2 trillion), making it the largest retail investment sector in the country.[4] Statista reports that China is now the world's fourth-largest asset management market, following the United States, Luxembourg, and Ireland.[5] Despite its recent growth, China's mutual fund market displays substantial untapped growth potential: its assets represent approximately 17% of the country's GDP, significantly lower than the relative size of the U.S. mutual fund industry (120% of U.S. GDP). And yet, a recent survey conducted by the Shanghai Advanced Institute of Finance (SAIF) and Ant Group indicates that mutual fund products comprise 38% of the portfolios of all Chinese investors, ranking second only to bank deposits,[6] which underscores the growing significance of the mutual fund industry within China's capital markets.

[4] https://www.amac.org.cn/sjtj/tjbg/gmjj/202401/P020240125599282291079.pdf.

[5] https://www.statista.com/statistics/270289/amount-of-fund-assets-in-selected-countries-of-the-world/.

[6] https://www.saif.sjtu.edu.cn/research-report.

In China, the mutual fund industry is regulated by the China Securities Regulatory Commission (CSRC), whose aim is to guarantee that these investment vehicles operate within a framework of transparency and investor protection. As part of their regulatory obligations, mutual funds must publish annual reports that provide comprehensive information on financial performance, investment strategies, and portfolio holdings, among other features. Similar to the U.S. Securities and Exchange Commission (SEC) requirements, which mandate a management discussion of past performance in shareholder reports, Chinese fund managers are also required to discuss historical performance in a dedicated section titled 'Management Review of Fund Performance' (Section 4.4, henceforth Manager Review).

A notable difference in the Chinese regulatory framework, however, is the obligation for fund managers to provide forward-looking insights on macroeconomic conditions, securities markets, and industry trends (Section 4.5). This prospective outlook contrasts with the backward-looking analysis in Section 4.4, offering valuable insights into how professional managers anticipate future market developments.

The annual reports are publicly accessible via the CSRC's Electronic Information Disclosure Platform (http://eid.csrc.gov.cn/fund) or East Money (fund.eastmoney.com), a leading financial data provider in China. The CSRC does not mandate specific topics or a standardized format for the forward-looking sections of these reports and fund managers can address the issues they deem most relevant. However, they are prohibited from making forecasts about individual securities. In this study, we employ these mandatory disclosures to elicit and measure the subjective expectations of the Chinese universe of portfolio managers and the impact of such expectations on asset allocation decisions.

3. Data, Variables and Sample Overview

3.1 Data

Our main source for mutual fund data is the survivorship-bias free China Stock Market & Accounting Research Database (CSMAR), which covers a comprehensive list of Chinese open-end mutual funds and provides information on fund names, inception dates, fund returns, assets under management (AUM), expense ratios, turnover ratios, fund family affiliations, manager names, and other key fund characteristics.

Following the literature, we focus on actively managed Chinese domestic equity and equity-oriented hybrid funds (i.e., funds with more than 50% equity holdings). To mitigate incubation bias (see Evans, 2010), we exclude the first three years of return history for each fund and drop funds with AUM below 10 million yuan from the sample. For funds with multiple share classes, we aggregate fund-level variables across share classes, calculating fund size as the sum of assets and using value-weighted averages for other characteristics.

For each fund in our sample, we obtained mutual fund annual reports from either the CSRC's Electronic Information Disclosure Platform or the East Money platform for the ten-year period between 2012 and 2022. We extracted the texts from Sections 4.4 and 4.5 of each annual report using custom-built algorithms, which led to locate 94% of the annual reports for funds in our sample over our sample period. We drop cases in which multiple funds within the same family use a standardized template that may not accurately reflect the expectations of individual fund managers. Our final sample consists of 1,551 unique mutual funds from 122 fund families managed by 1,886 managers. These sample funds correspond to 6,371 fund-year observations distributed over the 2012--2022 sample period.

3.2 Variables Definition and Measurement

3.2.1 Portfolio Managers' Subjective Expectations

Since managers' market outlooks are conveyed through narrative text rather than numerical data, we employ both traditional textual analysis techniques and advanced large language models (LLMs) to quantify each manager's subjective expectations in a homogeneous and consistent manner across managers and over time. Our primary measure, *Outlook Positivity*, is defined as the fraction of positive words minus negative words in each text based on the Loughran and McDonald (2011) dictionary, relative to the total words in the Market Outlook section of the fund's annual report.

Recent studies, (e.g., see Lopez-Lira and Tang (2023) and Jha et al. (2024)) have documented the effectiveness of LLMs in extracting relevant information from financial texts. Building on these findings, our second group of measures is obtained using ChatGPT (version 4.0) to analyze the tone of managers' expectations in the Market Outlook section. The success of this approach relies significantly on the design of carefully crafted prompts, which direct the model's responses toward specific tasks and queries. For our analysis, we employ the following prompt:

"You are a Chinese financial expert with experience in fund recommendations. Answer 'POS' if the tone is positive, 'NEG' if the tone is negative, or 'NEU' if the tone is neutral. Then elaborate with one short and concise sentence on the next line. What is the tone of this fund manager's outlook?"

We set the temperature parameter to 0 to maximize the reproducibility of the results. The output from ChatGPT is then mapped into a variable labeled *Outlook Positivity GPT*, which can obtain one of three values:

$$Outlook\ Positivity\ GPT = \begin{cases} 1, & POS \\ 0\,, & NEU \\ -1, & NEG \end{cases}$$

In addition to different measurement procedures, *Outlook Positivity* and *Outlook Positivity GPT* thus have different distributional properties: our primary measure of managers' subjective expectations is a continuous variable, whereas our secondary measure is a multinomial variable. These two measures are significantly correlated (with a correlation of 0.435 and a p-value of less than 0.01), which reassures us about their validity.

3.2.2 Fund Performance

We measure fund performance using the classical Carhart (1997) four-factor model. Specifically, using 36-month rolling windows, we estimate the following regression to get the risk exposures to the market, size, book-to-market, and momentum factors:

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k,t} f_{k,t} + \varepsilon_{i,t} \qquad (1)$$

Here, $R_{i,t} - R_{f,t}$ is the net return of fund i in month t minus the risk-free rate, $f_{k,t}$ refers to the four factors in Carhart (1997). We then compute four-factor alpha for each fund-month observation as follows:

$$Alpha_{i,t} = R_{i,t} - R_{f,t} - \sum_{k=1}^{4} \beta_{i,k,t-1} f_{k,t} \qquad (2)$$

To ensure the robustness of our fund performance measures, we also calculate alphas using a variety of alternative asset pricing models, including the China Four-Factor Model, Fama-

French Three-Factor and Five-Factor Models, as well as the Capital Asset Pricing Model (CAPM). As shown in the Internet Appendix, our results are robust to employing these alternative measures of performance.

3.2.3 Fund Flows

Following the majority of the previous literature, we calculate Fund Flows as the net growth rate in fund assets beyond that due to capital gains and reinvested dividends (Sirri and Tufano, 1998). Specifically, for each fund i in time t in our sample, we construct Fund Flows by the following formula:

$$Fund\ Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times \left(1 + R_{i,t}\right)}{TNA_{i,t-1}} \qquad (3)$$

3.2.4 Other Variables

We define *Outlook Uncertainty* as the fraction of uncertain and weak modal words, as specified by the Loughran and McDonald (2011) dictionary, relative to the total word count in the Market Outlook section (Section 4.5) of the fund's annual report. *Performance Positivity* is defined as the fraction of positive words minus negative words, according to the Loughran and McDonald (2011) dictionary, relative to the total word count in the Manager Review section (Section 4.4) of the fund's annual report. To capture the risk-taking behavior of fund managers, we measure *Volatility* as the semi-annual standard deviation of excess net returns. We also construct the semi-annual standard deviation of the residuals from the Carhart Four-Factor Model (Carhart, 1997) as *Idiosyncratic Volatility* measure. *Industry Concentration* is calculated as the sum of the squared weights of each of the 85 industries, as defined by the CSRC, held by each fund. Finally, we define *Cash Holdings* and *Equity Holdings* as the percentages of total AUM invested in cash and equities, respectively.

Our analysis also includes a set of additional variables to control for fund- and family-specific characteristics. *Fund Age* is defined as the natural logarithm of the number of months since the fund's oldest share class began trading. *Fund Size* is the natural logarithm of the sum of assets under management across all share classes. *Expense Ratio* is calculated by dividing the fund's operating expenses by the average dollar value of its assets under management. *Turnover Ratio* is defined as the minimum of sales or purchases divided by the TNA of the fund. We aggregate the individual fund's AUM in the family and take the logarithm of it to obtain *Fund Family Size*.

3.3 Descriptive Statistics

Our working sample comprises 1,551 distinct mutual funds from 122 fund families, managed by 1,886 individual portfolio managers. These funds account for 6,371 fund-year observations. As shown in Table 1, the number of actively managed domestic equity funds in the market has exhibited a substantial upward trajectory, rising from 213 funds in 2012 to 1,188 in 2022. This growth is mirrored by a similar trend in total AUM over the same period.

[Insert Table 1 here]

Table 2, Panel A, presents descriptive statistics for all key variables used in our analyses. The magnitude of these variables is consistent with prior studies on Chinese mutual funds (e.g., Jiang, 2020). In comparison to the U.S. mutual fund industry, several distinct patterns emerge: on average, actively managed Chinese equity funds are significantly smaller in size than their U.S. counterparts. While U.S. mutual funds typically underperform market benchmarks, Chinese mutual funds exhibit the opposite trend, outperforming these benchmarks as indicated by the positive means of performance measures. Specifically, a typical fund in our sample manages approximately ¥1.524 billion in AUM and achieves an average four-factor alpha of 0.227%. Additionally, Chinese mutual funds tend to charge higher fees—the average expense ratio is 1.714%—and engage in more active trading, reflected in a turnover rate of 1.657.

[Insert Table 2 here]

The main novel variable of interest in our analysis is *Outlook Positivity*, about which the data reveal several stylized facts. First, portfolio managers' market outlooks are systematically more positive than negative, as illustrated in Figure 1. The average (median) measure of *Outlook Positivity* is 3.2% (3.1%), indicating a higher frequency of positive words compared to negative ones in the outlook. Similarly, *Outlook Positivity* as measured by ChatGPT shows that positive outlooks occur nearly four times more frequently than negative ones—40% versus 12%, with the remaining outlooks classified as neutral. Second, portfolio managers exhibit considerable time-series variation in their outlooks, indicating that managers regularly update their beliefs over time. The average time-series standard deviation of *Outlook Positivity* is 1.81. Relative to the mean value of 3.20, this implies that a one-standard-deviation increase (or decrease) in *Outlook Positivity* corresponds to a 57% shift in optimism (or pessimism). Third is the most striking and novel fact, that is, despite the prevailing assumption that portfolio managers operate with extensive and relatively homogeneous information sets, their expectations exhibit substantial heterogeneity. Specifically, the average cross-sectional standard deviation of *Outlook Positivity* is 2.15. Relative to the mean of 3.20, this indicates that a one-standard-deviation variation across managers corresponds to a 67% change in the level of optimism or pessimism in their outlooks. This heterogeneity in fund managers' subjective expectations motivates our empirical analyses.

[Insert Figure 1 here]

4. Baseline Results

4.1 Recent Performance and Subjective Expectations: Time-Series Evidence

We begin by analyzing the correlation between the time-series aggregate market outlook and both concurrent and subsequent market returns. Monthly value-weighted returns for all A-share stocks are calculated and averaged annually. Similarly, we compute the average market outlook across all managers for each year. The resulting correlations are presented in Figure 2.

[Insert Figure 2 here]

As shown in Figure 2, a clear positive correlation exists between the average *Outlook*

Positivity of portfolio managers and contemporaneous market returns for the year. However, this relationship turns negative when examining the correlation with market returns in the subsequent year. These results provide initial evidence that managers, on average, may overly project current market performance into the future, leading to misaligned expectations regarding future market performance.

4.2 Recent Performance and Cross-Sectional Dispersion of Subjective Expectations

We move on to our main analysis, which is run at the individual manager level, and assess whether managers' recent investment performance helps explain at least in part the striking cross-sectional variation in subjective expectations and their updating by managers at the same point in time and facing the same aggregate information sets. Our main linear specification is as follows:

$$Outlook\ Positivity_{i,t} = \beta_1 Performance_{i,t-1} + \gamma' X_{i,t-1} + \pi_i + \mu_t + \varepsilon_{i,t}\,, \qquad (4)$$

and is estimated at the level of fund i, and year *t*; $\boldsymbol{\pi_i}$ is a full set of fund fixed effects, and μ_t a full set of year fixed effects. The dependent variable, *Outlook Positivity*, captures subjective expectations and is defined in Section 2.2.1. The main covariate of interest in this analysis is *Performance*, which is defined as the average monthly Carhart four-factor alpha in the year prior to the formulation of subjective expectations. The coefficient β_1 captures the relationship between a manager's recent performance and her expectations about future market condition. Under FIRE, fund managers' past performance should be irrelevant to the formation of beliefs about future aggregate market conditions, i.e., β_1 should equal 0. Alternatively, if portfolio managers extrapolated signals about their own past performance when forming beliefs about future macroeconomic and aggregate market conditions, we would expect β_1 to be positive. Our set of control variables includes the logarithm of fund size, family size and fund age, fund flows, expense ratio and turnover ratio, all measured as of the previous month/year-end. The inclusion of fund and time fixed effects ensures that the estimates are not driven by systematic time-invariant fund-level characteristics or macroeconomic and market conditions. We cluster the standard errors at the fund level.

Table 3 presents the regression results. Column (1) presents the baseline regression with no controls. In this specification, *Performance* is positively associated with *Outlook Positivity* ($\widehat{\beta_1}$ = 0.133). We can reject the null at any plausible level of significance (t-stat. =5.36). In terms of economic magnitude, a one-standard-deviation increase in past performance is associated with a 4.15% increase in *Outlook Positivity* relative to the mean. This finding suggests that fund managers do extrapolate signals from their own recent performance when forming expectations about future aggregate macroeconomic and security market conditions. Column (2) adds control variables, fund fixed effects and time fixed effects. The coefficient on *Performance* decreases only slightly in magnitude as we include the full set of fund-year-level controls in our specification and remains positive and statistically significant at all plausible levels. The results remain robust with the inclusion of manager fixed effects, as shown in Internet Appendix Table A3.[7]

Next, we assess whether fund managers extrapolate both positive and negative signals from their past performance when forming macroeconomic beliefs or whether this extrapolation is asymmetric. This test is important to inform which beliefs-formation mechanism alternative to FIRE is most consistent with our findings. For instance, in a basic naive reinforcement learning model, individuals should extrapolate equally in response to both positive and negative past performance. In contrast, models based on cognitive dissonance might suggest an asymmetric extrapolation: positive signals from past performance are readily reinforced because they align with cognitive dissonant individuals' positive perception of self, whereas the same agents might avoid to learn and extrapolate from negative signals, which would require managers to use information from a performance that would require them to acknowledge a negative perception of self.

We define *Performance (Positive)* as the absolute value of *Performance*, multiplied by a dummy that equals 1 if *Performance* is positive, and zero otherwise. Similarly, we define *Performance (Negative)* as the absolute value of *Performance* multiplied by a dummy that equals 1 if *Performance* is negative, and zero otherwise. Column (3) presents the results from adding these two variables to the right-hand side of the baseline

[7] As shown in Internet Appendix Table A2, our results remain robust when using semi-annual reports instead of annual reports.

specification. The results suggest that extrapolation of own past performance signals in the formation of aggregate macroeconomic beliefs is asymmetric: managers who outperformed the average fund in the previous year are systematically more likely to have positive aggregate outlooks, whereas underperforming managers do not provide more pessimistic forecasts.

[Insert Table 3 here]

4.3 Recent Performance and Subjective Expectations' Uncertainty

So far, we have focused on the first moment of aggregate macroeconomic expectations but the second moment (uncertainty of managers' aggregate economic outlook) is also an important outcome and one that might be affected by performance extrapolation. Indeed, if confirmation bias is an important ingredient in managers' beliefs-formation process, managers who face positive signals from past performance are likely not only to extrapolate those signals more when forming expectations but also to perceive those signals as more precise predictors of future aggregate economic conditions. In contrast, managers exposed to negative signal from own past performance not only would tend to not extrapolate those signals but they might also believe that those signals are a noisier predictor of future aggregate economic conditions.

To test this hypothesis, we re-estimate Equation (4), replacing the dependent variable with *Outlook Uncertainty*. We define the variable *Outlook Uncertainty* as the proportion of uncertain and weak modal words, following the classifications provided by Loughran and McDonald (2011), relative to the total word count in the Market Outlook section of fund annual reports. The uncertainty list comprises 285 words, including terms such as approximate, contingency, depend, fluctuate, indefinite, uncertain, and variability. Additionally, we incorporate 27 weak modal words—such as could, depending, might, and possibly—to further capture the level of uncertainty in the outlook.

[Insert Table 4 here]

The results, presented in Table 4, reveal that funds with stronger past performance tend to exhibit greater confidence in their market outlooks. The estimated coefficient attached to *Performance* is -0.667 with a t-stat. of 2.30. The relationship is asymmetric based on previous performance's sign: Managers who outperform the average are more likely to display heightened confidence following strong performance, whereas underperforming managers do not necessarily convey greater uncertainty in their forecasts.

5. Self-confirmation Bias in Fund Managers' Subjective Expectations?

The asymmetric reaction of the first and second moments of fund managers' subjective expectations to recent performance suggests that our findings might be explained by a form of self-confirmation bias in beliefs formation even for a highly sophisticated group of decision-makers and appear less easily explained by an information channel. To further assess this possibility, we conduct a set of heterogeneity analyses.

5.1 Experienced vs. Inexperienced Managers

Previous literature has shown that investment experience, which should enhance information-based learning as more information is accumulated over time, can instead help mitigate biases in learning (Gervais and Odean, 2001; Greenwood and Nagel, 2009; Kuchler and Zafar, 2019). If a self-confirmation bias in learning helps explain the asymmetric extrapolation of own investment performance to aggregate market expectations we document, we would expect experienced managers to be less prone to this form of belief-formation process.

Table 5 investigate this conjecture. We divide the sample into two groups: funds managed by managers with more than 10 years of industry experience, and those managed by less experienced managers. The reason we choose the threshold of 10 years is that in China, 10 years of experience is often considered the standard threshold for being classified as "experienced," particularly in industries like asset management where navigating multiple market cycles is seen as key to gaining expertise. We perform separate regressions of the baseline model from Equation (4) for these two subsamples. Column (1) shows that the estimated coefficient for recent-year performance is 0.236 for inexperienced managers, compared to 0.079 for experienced managers. This suggests that the impact of recent performance on inexperienced managers is almost three times as large as for their experienced counterparts. This result indicates that bias is significantly more pronounced among inexperienced managers, underscoring the role of experience in mitigating such biases.

[Insert Table 5 here]

5.2 Alignment vs. Misalignment with Previous Subjective Expectations

Confirmation bias operates on the principle that outcomes influence future behavior, with stronger extrapolation when initial expectations align with recent realizations. Specifically, if a manager starts with a positive outlook and performs well, the positive extrapolation is stronger, increasing the likelihood that the manager will make similar decisions in the future. Conversely, if the manager's outlook is negative, but the outcome turns out to be positive, the extrapolation effect is weaker. In this case, the manager may not fully adjust their behavior as the positive outcome is seen as an unexpected or less reliable deviation from their initial pessimistic view. In a standard form of confirmation bias, the same enhanced extrapolation would also arise in the negative domain, whereas in our baseline result extrapolation is asymmetric and only arises when managers perform well, which leads us to interpret the results as a self-comfirmation bias.

We investigate whether asymmetric extrapolation to beliefs varies depending on whether managers' previous expectations are confirmed in Table 6. We divide the sample into two subsamples based on the median value of *Outlook Positivity* in the previous year. For the subsample with an above-median positive tone in the previous outlook, the coefficient of *Performance* is twice as large as that for the negative tone subsample and is statistically significant with a t-stat. of 2.94. In contrast, the coefficient for the negative outlook subsample is not statistically significant. These findings suggest that the extrapolation effect is more pronounced when the previous outlook was positive, while a negative outlook in the prior year appears to diminish the impact of past performance on future outlooks.

[Insert Table 6 here]

5.3 Exposure to Unbiased Fund Managers: The Role of Gender

In this section, we examine whether the presence of women in a team may help to mitigate behavioral biases. Earlier work suggests that belief biases in financial decision-making are stronger for men than for women (Barber and Odean, 2001; D'Acunto, 2021), highlighting the potential for gender diversity to play a key role in improving decision-making processes within the finance industry. Research by Huang and Kisgen (2013) and Griffin, Li, and Xu (2021) points to the fact that men are more prone to certain cognitive biases, such as overconfidence, over-optimism, and risk-seeking behavior, which can distort investment decisions. In our case, managers who are exposed to other fund managers in their team that are less likely to display the same belief bias might be made aware and become sophisticated about the bias when forming their subjective expectations.

To test this conjecture, we divide the sample based on the gender composition of the management team, distinguishing between teams composed entirely of male managers and those with at least one female manager. Notably, all-male management teams are more prevalent in China, comprising 80.2% of our sample. Table 7 presents the results of this analysis. The findings indicate that the coefficient for performance is higher in magnitude for all-male management teams, and it is statistically significant only for these teams. This suggests that the extrapolation effect—where past performance influences future outlooks—is more pronounced in all-male management teams than in those with female representation.

[Insert Table 7 here]

5.4 Person-specific vs. Fund-Specific Bias: Evidence from Managerial Turnover

Our last test for whether a form of self-confirmation bias might explain our results examines whether the relationship between past fund performance and beliefs about future market conditions is person-specific or fund-specific. Under self-confirmation bias, asymmetric extrapolation of own past performance to aggregate expectations should only arise when the fund manager that forms beliefs and the one that is responsible for recent past performance are the same person. In contrast, if channels related to fund-level information processing or strategies in reporting aggregate beliefs explained our results, we should detect asymmetric extrapolation even when the two individuals are not the same.

For this test, we consider instances of managerial turnover, whereby new managers replace their predecessors. While new fund managers are fully informed about the fund's past performance and have access to relevant fund-level, firm-level, and incentive-related information, they did not personally contribute to the fund's previous outcomes.

[Insert Table 8 here]

Our analysis in Table 8 shows that asymmetric extrapolation of beliefs does not occur when new managers take over a fund that has outperformed in the recent past. This finding provides direct evidence that the personal involvement of managers in generating past performance is a critical factor driving asymmetric extrapolation of fund performance to aggregate market subjective expectations. In other words, managers tend to project overly optimistic future outcomes based on past performance only when they feel personally responsible for the fund's success, which highlights the importance of personal attribution in the beliefs formation process of mutual fund managers.

5.5 Self Attribution and Beliefs Formation: Managers' Review of Own Past Performance

In our earlier analyses, we rely on the realized performance of funds as a measure of past outcomes. However, portfolio managers are also required to provide a self-assessment of their performance for the prior year. This regulation requirements provides us with a unique possibility to test whether fund managers' subjective assessment of own past performance shapes their aggregate market expectations, which would be consistent with a role for self-attribution in the self-confirmation bias that the evidence hints as a plausible driver of our results.

Specifically, we estimate the following regression model:

$$Outlook\ Positivity_{i,t} = \beta_1 + \beta_2 Performance\ Positivity_{i,t} + X_{i,t-1}B_3 + \pi_i + \mu_t + \varepsilon_{i,t} \quad (5)$$

where i indexes a fund, t indexes a year, π_i represents fund fixed effects, μ_t denotes yea fixed effects, and $\varepsilon_{i,t}$ is the error term. *Outlook Positivity* and *Performance Positivity* are the degree of positivity in the Market Outlook and the Manager Review sections of the fund's annual report, respectively, as detailed in Section 2. The set of control variables remains consistent with those used in the baseline regression, all measured as of the previous month-end. We cluster the standard errors at the fund level.

Table 9 presents the results. In Column (1), the regression of *Outlook Positivity* on *Performance Positivity* shows a positive and statistically significant coefficient of 0.091 with a t-stat. of 5.38. The finding supports the notion that fund managers who view their past performance more favorably are more likely to have an optimistic outlook on future market conditions.

In Column (2), we introduce realized *Performance* as an additional control variable. This test is crucial to disentangle the manager's own subjective assessment of their performance from objective measures of fund performance, which are likely to be positively correlated. The results indicate that the effect of *Performance Positivity* remains significant, suggesting that managers' self-assessed performance positively influences their market outlook, independent of the actual realized performance. This finding underscores the incremental impact of perceived performance on managers' future expectations, consistent with a self-confirmation bias.

[Insert Table 9 here]

6. From Expectations to Choice: Outlook Positivity and Asset Allocation Choices

Having studied the properties of portfolio managers' subjective expectations, we now turn to examine their relationship with actual asset allocation decisions. Specifically, we investigate whether portfolio managers' subjective expectations have a tangible impact on real outcomes in terms of portfolio risk and returns. By understanding how these expectations shape the managers' investment choices, we can assess whether biases or misperceptions in their outlook lead to suboptimal allocation strategies, or if their subjective forecasts align with actual market performance. We begin by investigating whether fund managers with a positive outlook tend to take on more risk. To this end, we construct several proxies that captures the risk-taking activities including Volatility, Idiosyncratic Volatility, Industry Concentration, Equity and Cash Holding, and analyze their relationship with *Outlook Positivity*. Since mutual funds often adjust their strategies at mid-year (e.g., Schwarz, 2012) depending on the mid-year performance, the risk-taking measures are measured using six-month horizon.

[Insert Table 10 here]

Table 10 presents the results. Our findings reveal that managers translate their expectations into tangible actions—those with more optimistic outlooks engage in significantly greater risk-taking behavior. Specifically, a more positive outlook is associated with greater levels of both idiosyncratic and total portfolio risk, higher industry concentration, increased equity holding, and reduced cash holdings.

A natural question that arises is how a positive outlook which shown to induce greater risk-taking behavior ultimately affect fund performance. To investigate this potential relationship, we next explore the impact of *Outlook Positivity* on subsequent investment performance. Specifically, we run the following regressions:

$$Performance_{i,t+1} = \beta_1 + \beta_2 Outlook\ Positivity_{i,t} + X_{i,t}B_3 + \pi_i + \mu_{t+1} + \varepsilon_{i,t+1} \quad (6)$$

where i indexes a fund, t indexes a year, π_i represents fund fixed effects, μ_t denotes year fixed effects, and $\varepsilon_{i,t}$ is the error term. *Performance* is the average of monthly Carhart (1997) four-factor alpha over the subsequent six months. *Outlook Positivity* is defined in Section 3.2.1. Our set of control variables includes the logarithm of fund size, family size and fund age, expense ratio, turnover ratio and fund flows, all measured as of the previous month-end. Fund and time fixed effects are included in the regressions, and standard errors are clustered at the fund level.

Table 11 presents the results of the impact of *Outlook Positivity* on subsequent fund performance. In Column (1), we find that the coefficient of *Outlook Positivity* is -0.334 and statistically significant with a t-stat. of -2.89. One could argue that mutual fund performance exhibit a trend of mean-reversion. Thereby, since *Outlook Positivity* is positively correlated with fund past performance, the negative correlation between *Outlook Positivity* and subsequent fund performance is driven by the mean-reversion of fund performance. To address this concern, we include $Performance_{[t-11,t]}$ and the interaction of *Outlook Positivity* and $Performance_{[t-11,t]}$ in Equation (5), where $Performance_{[t-11,t]}$ is measured as the average of the monthly Carhart (1997) four-factor alpha from month t-11 to t. In Column (2) of Table 11, we find that the coefficient estimate of the interaction of *Outlook Positivity* and $Performance_{[t-11,t]}$ is -0.042 with a t-stats of -2.25. This finding suggests that taking into consideration of the mean-reversion in fund performance, *Outlook Positivity* still leads to reduced subsequent fund performance.

In sum, the negative relationship between outlook positivity and subsequent performance rules out forms of rational learning as potential explanations of our baseline findings. Although some forms of rational learning could account for the extrapolative behavior observed in the first part of the paper, it cannot account for a systematic negative relationship between outlook positivity and subsequent performance.

[Insert Table 11 here]

7. Investors' Reaction to Fund Managers' Beliefs: Outlook Positivity and Fund Flows

In this section, we study how investors react to portfolio managers' market outlooks. On the one hand, investors might be naïve about biases in portfolio managers' expectations and their influence on asset allocation decisions, or even share the same biases, and hence not react to them when considering where to invest their funds. On the other hand, investors might be sophisticated about these biases and react by limiting the flows they allocate to biased portfolio managers. Previous literature has suggested retail investors are less sophisticated than institutional investors (Baker and Wurgler, 2007; Malmendier and Shanthikumar, 2014). We therefore explore the heterogeneity among investor clienteles and investigate how different types of investors react portfolio managers' market outlooks.

We separate the sample into institutional funds and retail funds. We define institutional (retail) funds as those funds with more (less) than 80% fund's assets sold through institutional (retail) share classes.[8] This classification results in 2,336 institutional funds and 4,035 retail funds in our sample. We then estimate the following regression separately for institutional and retail funds:

$$Flows_{i,t+1} = \beta_1 + \beta_2 Outlook\ Positivity_{i,t} + X_{i,t}B_4 + \pi_i + \mu_t + \varepsilon_{i,t+1} \quad (7)$$

where *Flows* is the monthly flows constructed following Sirri and Tufano (1998), *Outlook Positivity* is defined in Section 3.2.1. We focus exclusively on the first month following the release of the annual report, as this period likely captures the funds' responses to the information disclosed in the report. We control for Fund Age, Fund Size, Expense Ratio, Turnover Ratio, Fund Family Size, past-year Performance and its square term in the regression. We also include the fund fixed effects and year fixed effects in the specification and we cluster the standard errors at the fund level.

[Insert Table 12 here]

Table 12 presents the results. We find that that a conservative tone—indicated by a more negative outlook—significantly attracts institutional fund flows, with a t-stat. of -2.42. This negative relationship is incremental to the effects of *Outlook Uncertainty*, where more confident outlooks are associated with increased institutional fund flows, along with other fund characteristics. For retail funds, flows tend to favor a more positive outlook, although this relationship is not statistically significant. Given that funds with more conservative outlooks demonstrate better subsequent performance, as shown in Table 10, it appears that institutional investors are exhibiting what is known as the "Smart Money Effect" in their allocation decisions. This effect suggests that institutional investors, by favoring funds with a more cautious tone, are able to anticipate better future performance and adjust their investments accordingly, reflecting a level of prudence and foresight in their behavior.

8. Robustness: Measuring Beliefs Using a Large Language Model

In our primary analyses, we measure portfolio managers' optimism using a dictionary-

[8] Our results are robust to using 70, 75, or 85% as the alternative cutoffs to define institutional vs. retail funds.

based bag-of-words textual analysis approach. However, recent advancements in textual analysis suggest that machine-learning-based methods, particularly those leveraging Large Language Models (LLMs), can outperform traditional dictionary-based techniques in certain contexts (Jha et al., 2024; Lopez-Lira and Tang, 2023). To ensure the robustness of our findings and mitigate concerns about methodological dependence, we incorporate ChatGPT into our analysis. First, we replace the dependent variable in our baseline regression with sentiment scores generated by ChatGPT. Second, we use ChatGPT to separately analyze sentiment tones related to macroeconomic conditions, securities markets, and industry trends, and then examine the relationship between each tone and the past performance of portfolio managers. This approach allows us to validate that our documented effects are not artifacts of the textual analysis method employed. Specifically, we estimate the following regression:

$$Outlook\ Positivity\ GPT_{i,t} = \beta_1 + \beta_2 Performance_{i,[t-1,t-12]} + X_{i,t-1}B_3 + \pi_i + \mu_t + \varepsilon_{i,t} \quad (8)$$

The setting is the same as in Section 4.2, where i indexes a fund, t indexes a year, π_i represents fund fixed effects, μ_t denotes year fixed effects, and $\varepsilon_{i,t}$ is the error term. The key dependent variable, *Outlook Positivity GPT*, captures the degree of positivity in the Market Outlook section as determined by ChatGPT, as detailed in Section 3.2.1. The independent variable of interest, *Performance,* is measured as the average of the monthly Carhart (1997) four-factor alpha over the previous year. Our set of control variables are the same with baseline regression, all measured as of the previous month-end. We cluster the standard errors at the fund level.

In Column (1) of Table 13, we present the regression results using *Outlook Positivity GPT* as the dependent variable with controls variables and fund- and year-fixed effects. The coefficient estimate of *Performance* is 0.029 with a t-stat. of 2.54. In terms of economic magnitude, a one-standard-deviation increase in past performance is associated with a 10.25% increase in Outlook Positivity GPT relative to the mean.

[Insert Table 13 here]

Moreover, Using ChatGPT for sentiment analysis allows us to disentangle and independently analyze the tone for distinct components of portfolio managers' market outlooks—namely, macroeconomy, securities market, and industry trends. This segmentation leverages ChatGPT's advanced text-categorization capabilities to assess the sentiment of each component individually.[9] Although most fund reports include outlooks on macroeconomic conditions and securities markets, not all address industry trends. To ensure the relevance of ChatGPT's analysis of industry trends, we first screen for industry-related content using a specialized word list (see Table 12, Column (4)). This list is derived from the industry classifications in the China Securities Regulatory Commission's Industry Classification (2012 Edition).

The results in Columns 2 through 4 of Table 13 indicate a positive correlation between the outlook positivity for each component—macroeconomy, securities market, and industry trends—and past performance. Notably, the positivity of the macroeconomic outlook shows a statistically significant positive relationship with past performance. This finding is particularly striking, as macroeconomic outlooks should theoretically be grounded in publicly available information rather than influenced by a portfolio manager's personal investment performance. This observation lends further support to the hypothesis that the positive relationship between past performance and outlook positivity may stem from a cognitive bias.

9. Conclusions

Using unique data from mandatory disclosures of Chinese mutual fund managers' beliefs, we provide a direct analysis of the subjective expectations of portfolio managers, which so far have been underexplored in asset management due to the lack of direct measurement. The analysis uncovers significant heterogeneity in managers' expectations

[9] The prompt provided to ChatGPT is as follows: "You are a Chinese financial expert with fund recommendation experience. You will be provided with the fund manager's outlook on macroeconomy, securities market and industry trends. First, do your best to separate the outlook on macroeconomy, securities market and industry trends. Second, answer 'POS' if the tone is positive, 'NEG' if the tone is negative, or 'NEU' if the tone is neutral. The reply on the first line only includes 'POS', 'NEG' or 'NEU'. Third, elaborate with one short and concise sentence on the next line. What is the tone of this fund manager's outlook on macroeconomy/ securities market/ industry trends? {text}"

despite their access to comprehensive and similar information sets. Expectations appear to deviate systematically from standard forms of FIRE, which are commonly assumed in theoretical and empirical research in this area. We find that, when forming subjective expectations of aggregate market conditions, fund managers extrapolate asymmetrically from their fund's past performance—only when they outperform. This asymmetric extrapolation holds within fund managers, only arises when the manager forming believes and making choices is the same person responsible for past performance, and is muted when female managers are part of a fund's team. Overall, these results are consistent with a confirmation bias arising from self-image concerns.

The biased beliefs formation process we document has critical implications for asset allocation decisions and fund performance. Specifically, portfolios managed by individuals with more optimistic outlooks exhibit greater levels of risk-taking, which, in turn, leads to subsequent underperformance. These findings suggest that managers' subjective beliefs may play a pivotal role in driving the well-documented phenomenon of mean reversion in mutual fund returns.

Our results contribute to the growing body of research on subjective expectations by examining the beliefs of professional asset managers. We demonstrate that these managers' expectations are neither rational nor homogeneous, even when they have access to shared information. This highlights the critical role of subjective beliefs in shaping individual investment decisions and influencing broader market dynamics. Furthermore, we provide robust evidence that biased expectations among portfolio managers materially affect their risk-taking behavior, leading to subsequent underperformance. In doing so, our findings introduce a non-agency-based perspective on fund underperformance, extending beyond traditional agency theory models that primarily attribute such outcomes to incentive misalignments. This distinction carries important policy implications: while agency issues in fund management can be mitigated through the accurate design of incentive contracts, biased subjective expectations cannot be addressed through incentive schemes alone. Instead, they necessitate direct forms of expectations management at the fund, firm, or regulatory level.

Appendix: Variable Definitions

Variable Name	Definition
Panel A: Market Outlook Variables	
Outlook Positivity (%)	The fraction of positive words minus negative words, as defined by the Loughran and McDonald (2011) dictionary, to the total word count in the Market Outlook section (i.e., Section 4.5) of the fund's annual report.
Outlook Positivity GPT	ChatGPT analyzes the sentiment in the Market Outlook section (i.e., Section 4.5) of fund annual reports and assign a score of 1 for positive, 0 for neutral, and -1 for negative tone.
Outlook Uncertainty (%)	The fraction of uncertain and weak modal words, as defined by the Loughran and McDonald (2011) dictionary, to the total word count in the Market Outlook section (i.e., Section 4.5) of the fund's annual report.
Panel B: Fund Characteristics	
Performance (%)	The average Carhart (1997) four-factor alpha over the past year. Factor loadings are estimated using a three-year window of monthly returns, and the last 12 months of realized fund and factor return data within this period are used to calculate alphas.
Performance(Positive)	The absolute value of *Performance* multiplied by a positivity indicator variable, which equals 1 if *Performance* is positive and zero otherwise.
Performance(Negative)	The absolute value of *Performance* multiplied by a negative indicator variable, which equals 1 if Performance is negative and zero otherwise.
Performance Positivity (%)	The fraction of positive words minus negative words, as defined by Loughran and McDonald (2011) dictionary, to total words in the Manager Review section (i.e., Section 4.4) of the fund's annual report.
Fund Flows (%)	Net growth rate in fund assets beyond that due to capital gains and reinvested dividends (Sirri and Tufano, 1998).
Fund Age (in months)	The number of months since the fund's oldest share class began trading.
Fund Size (in millions)	Sum of assets under management across all share classes of a fund.
Expense Ratio	Ratio of the fund's annual operating expenses to the average dollar value of its assets under management.
Turnover Ratio	The lesser of purchases or sales divided by average net assets.
Family Size (in millions)	Sum of assets under management across all funds in the family.
Volatility	The semi-annual standard deviation of excess net returns.
Idio. Volatility	The semi-annual standard deviation of the residuals of the Carhart Four-Factor Model (Carhart, 1997).
Industry Concentration	The sum of the squared weights of each of the 85 different industries, as defined by the CSRC, held by each fund.
Cash Holding (%)	Cash holdings divided by total assets under management.
Equity Holding (%)	Equity holdings divided by total assets under management.

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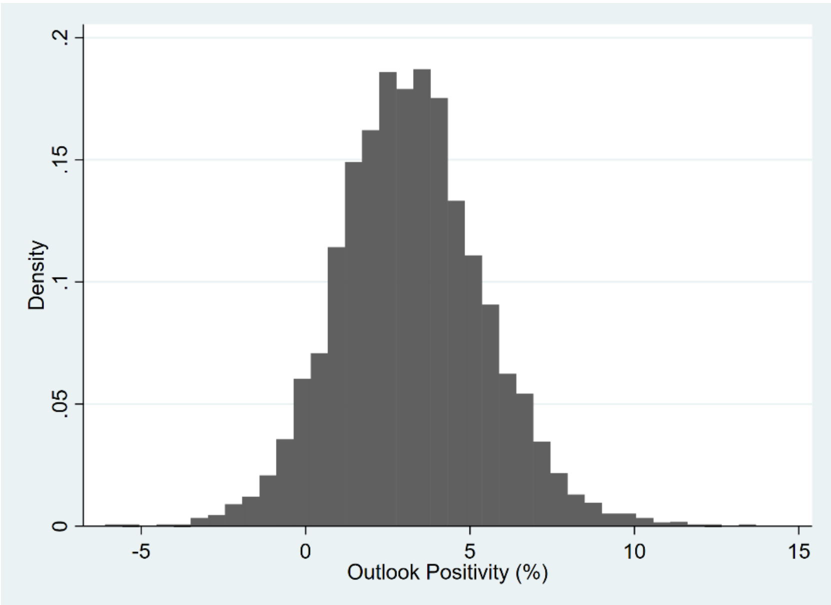
Figure 1. Distribution of Outlook Positivity

Figure 1 (a) presents the distribution of *Outlook Positivity*, which is the fraction of positive words minus negative words, as defined by the Loughran and McDonald (2011) dictionary, to the total word count in the Market Outlook section (i.e., Section 4.5) of the fund's annual report. Figure 1(b) displays the distribution of *Outlook Positivity GPT*. We use ChatGPT to analyze the sentiment in the Market Outlook section (i.e., Section 4.5) of fund annual reports and assign a score of 1 for positive, 0 for neutral, and -1 for negative tone, respectively.

(a) Distribution of *Outlook Positivity*



(b) Distribution of *Outlook Positivity GPT*

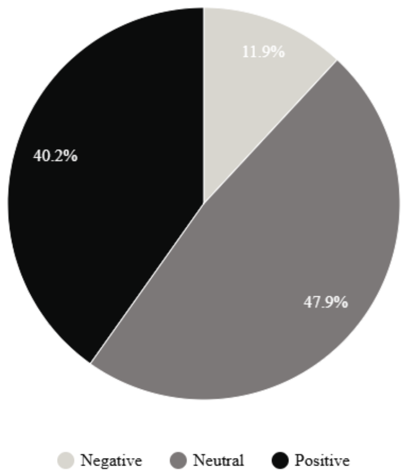
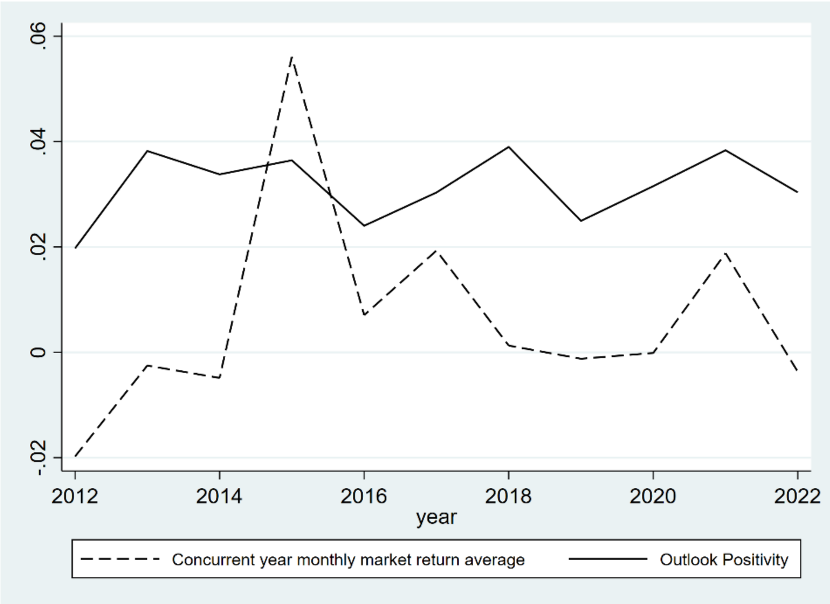


Figure 2. Market Returns and Aggregate Outlook Positivity

Figures 2 (a) and (b) display the time series of concurrent-year and subsequent-year market returns, along with the aggregate *Outlook Positivity* for the corresponding year. Market returns are defined as the annual average of monthly value-weighted returns of all stocks in the A-share market. Aggregate *Outlook Positivity* is calculated as the average of *Outlook Positivity* across all funds in our sample.

(a) Concurrent Year Market Return and Outlook Positivity



(b) Subsequent Year Market Return and Outlook Positivity

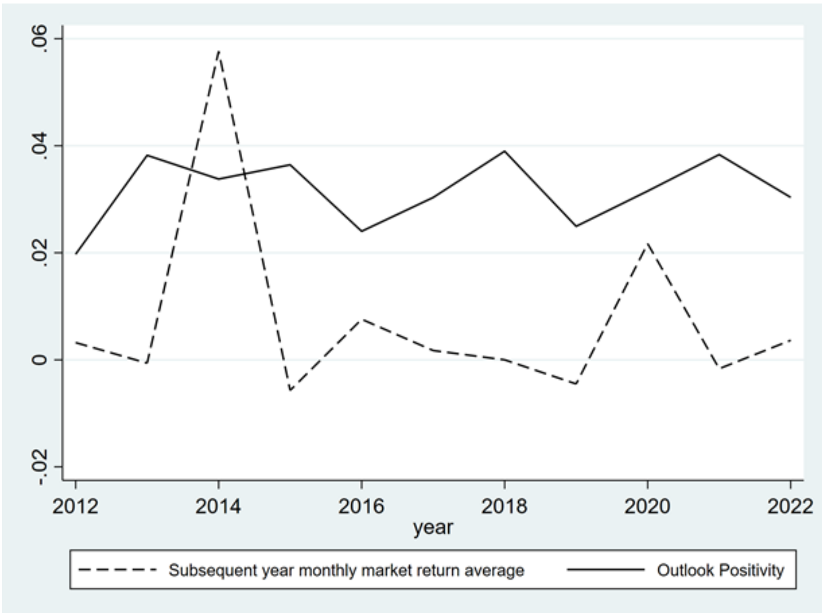


Table 1. Sample Distribution

This table presents the number of unique actively managed domestic equity funds and their total assets under management (AUM) in the Chinese mutual fund industry by year for the period of 2012 to 2022.

Year	Number of Funds	Total AUM (in ￥Millions)
2012	213	881,411
2013	262	877,416
2014	220	623,109
2015	312	933,564
2016	371	558,541
2017	441	686,995
2018	552	827,165
2019	749	990,500
2020	970	1,313,899
2021	1,093	2,162,210
2022	1,188	2,403,827

Table 2. Descriptive Statistics

This table presents the descriptive statistics for the main variables in Panel A, and the average standard deviations for outlook measures across time or fund in Panel B. All variables are defined in the Appendix. The sample period spans from 2012 to 2022. Panel A reports the number of observations (N), mean, standard deviation (SD), first percentile (P1), median (P50), and the 99th percentile (P99) for the main variables. Panel B shows the average standard deviations across one dimension (fund or time), while holding the other dimension fixed.

Panel A. Descriptive statistics

	N	Mean	SD	P1	P50	P99
Outlook Positivity (%)	6,371	3.203	2.223	-1.914	3.120	8.978
Outlook Positivity GPT (%)	6,330	0.283	0.664	-1.000	0.000	1.000
Outlook Uncertainty (%)	6,371	3.845	1.682	0.549	3.698	8.743
Performance (%)	5,183	0.227	1.000	-2.339	0.178	2.861
Performance Positivity (%)	6,367	2.093	2.689	-5.164	2.239	8.257
Fund Age(in months)	6,371	88	43	37	75	210
Fund Size(in billions)	6,371	1.524	2.709	0.016	0.574	12.578
Expense Ratio	6,371	1.714	0.185	0.765	1.750	2.065
Turnover Ratio	5,183	1.657	1.476	0.085	1.206	7.969
Fund Family Size(in billions)	6,371	27.115	32.845	0.104	15.444	145.490
Fund Flows (%)	5,179	-1.208	23.476	-44.329	-2.628	104.894
Volatility	5,181	4.747	2.473	0.733	4.461	11.730
Idio. Volatility	5,183	2.955	1.715	0.455	2.647	8.138
Industry Concentration	6,358	0.143	0.094	0.048	0.116	0.528
Equity Holding (%)	6,371	80.684	13.265	27.760	84.710	93.980
Cash Holding (%)	6,371	11.543	9.021	0.750	9.220	46.330

Panel B. Average standard deviations across fund/manager and time

	Standard Deviations across		
	Whole sample	Fund/Manager	Time
Outlook Positivity (%)	2.223	2.152	1.819
Outlook Positivity GPT	0.664	0.636	0.585
Macroeconomy Positivity GPT	0.830	0.790	0.768
Securities Market Positivity GPT	0.678	0.651	0.618
Industry Positivity GPT	0.718	0.695	0.606

Table 3. Past Performance and Outlook Positivity

This table presents the results of a panel regression analysis examining the relationship between *Outlook Positivity* and last year's *Performance*, along with various control variables, using fund-year observations from 2012 to 2022. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook Section of the fund's annual report. *Performance* is calculated as the average Carhart (1997) four-factor alpha for the previous year. *Performance (Positive)* and *Performance (Negative)* represent the absolute value of *Performance*, multiplied by a dummy variable indicating positivity or negativity, respectively. All other variables are defined in the Appendix. Regressions in Columns (2) and (3) include both fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$		
	(1)	(2)	(3)
Performance$_{[t-12,t-1]}$	0.133***	0.127***	
	(5.36)	(3.40)	
Performance(Positive)$_{[t-12,t-1]}$			0.167***
			(2.93)
Performance(Negative)$_{[t-12,t-1]}$			-0.065
			(-0.82)
Fund Age$_{t-1}$		0.469	0.316
		(1.11)	(0.83)
Fund Size$_{t-1}$		0.033	0.025
		(0.52)	(0.41)
Expense Ratio$_{t-1}$		0.570	0.625
		(1.00)	(1.06)
Turnover Ratio$_{t-1}$		0.081**	0.077**
		(2.56)	(2.51)
Fund Family Size$_{t-1}$		-0.029	-0.010
		(-0.28)	(-0.11)
Flows$_{[t-12,t-1]}$		-0.004	-0.005*
		(-1.51)	(-1.76)
Year FE	NO	YES	YES
Fund FE	NO	YES	YES
Nobs.	5,982	4,578	4,578
Adjusted R^2	0.005	0.266	0.266

Table 4. Past Performance and Outlook Uncertainty

This table presents the results of a panel regression analysis examining the relationship between *Outlook Uncertainty* and last year's *Performance*, along with various control variables, using fund-year observations from 2012 to 2022. *Outlook Uncertainty* is calculated as the fraction of uncertain and weak modal words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook section of the fund's annual report. *Performance* is measured as the average Carhart (1997) four-factor alpha from the previous year. Control variables are the same as those in Table 3. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Uncertainty$_t$	
	(1)	(2)
Performance$_{[t-12,t-1]}$	-0.667**	
	(-2.30)	
Performance(Positive)$_{[t-12,t-1]}$		-1.333***
		(-2.88)
Performance(Negative)$_{[t-12,t-1]}$		-0.378
		(-0.58)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	4,578	4,578
Adjusted R^2	0.180	0.181

Table 5. Past Performance and Outlook Positivity
– Inexperienced vs. Experienced Managers

This table presents the results of a subsample panel regression analysis examining the relationship between *Outlook Positivity* and last year's *Performance*, along with various control variables, using fund-year observations from 2012 to 2022. The regressions are conducted separately for two subsamples: inexperienced managers (industry experience <10 years) and experienced managers (industry experience >= 10 years). *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook section of the fund's annual report. Performance is calculated as the average Carhart (1997) four-factor alpha from the previous year. All regressions include fund- and year-fixed effects. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$	
	Inexperienced	Experienced
	(1)	(2)
Performance$_{[t-12,t-1]}$	0.236**	0.079
	(2.39)	(1.27)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	596	2,120
Adjusted R^2	0.255	0.272

Table 6. Past Performance and Outlook Positivity – Positive vs. Negative Last Outlook

This table presents the results of the subsample panel regression analysis of *Outlook Positivity* against last year's *Performance* and various control variables for fund-year observations over the period from 2012 to 2022. The regressions are conducted for subsamples of funds with above-average *Outlook Positivity* (positive last outlook) and those with below-average *Outlook Positivity* (negative last outlook) from the previous year. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined in Loughran and McDonald (2011), to total words in the Market Outlook section of the fund's annual report. *Performance* is calculated as the average of the Carhart (1997) four-factor alpha over the previous year. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$	
	Positive Last Outlook	Negative Last Outlook
	(1)	(2)
Performance$_{[t-12,t-1]}$	0.228***	0.138*
	(2.94)	(1.86)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	1,596	1,588
Adjusted R^2	0.198	0.172

Table 7. Past Performance and Outlook Positivity – All Male Managers vs. With Female Managers

This table presents the results of a subsample panel regression analysis examining the relationship between *Outlook Positivity* and last year's *Performance*, along with various control variables, using fund-year observations from 2012 to 2022. The regressions are conducted for two subsamples: funds with all male managers and funds with at least one female manager. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook section of the fund's annual report. *Performance* is calculated as the average Carhart (1997) four-factor alpha from the previous year. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$	
	All Male Managers	With Female Managers
	(1)	(2)
Performance$_{[t-12,t-1]}$	0.145***	0.097
	(3.56)	(0.95)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	3,655	806
Adjusted R^2	0.278	0.253

Table 8. Predecessors' Performance and Outlook Positivity

This table presents the results of a panel regression analysis examining the relationship between *Outlook Positivity* and last year's *Performance* for the subsample of new management team. New management team is defined as the team with all managers' tenure strictly less than one year. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook Section of the fund's annual report. *Performance* is calculated as the average Carhart (1997) four-factor alpha for the previous year. *Performance (Positive)* and *Performance (Negative)* represent the absolute value of *Performance*, multiplied by a dummy variable indicating positivity or negativity, respectively. All other variables are defined in the Appendix. Regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$	
	(1)	(2)
Performance$_{[t-12,t-1]}$	0.056	
	(0.41)	
Performance(Positive)$_{[t-12,t-1]}$		-0.089
		(-0.39)
Performance(Negative)$_{[t-12,t-1]}$		-0.294
		(-1.04)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	368	368
Adjusted R^2	0.288	0.287

Table 9. Self-Attribution: Managers' Subjective Review of Past Performance

This table presents the results of the panel regression analysis of *Outlook Positivity* against *Performance Positivity* and various control variables for fund-year observations from 2012 to 2022. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined in Loughran and McDonald (2011), to total words in the Market Outlook section of the fund's annual report. *Performance positivity* is the fraction of positive words minus negative words, as defined in Loughran and McDonald (2011), to total words in the Manager Review section of the fund's annual report. Control variables are the same as those in table 3. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$	
	(1)	(2)
Performance Positivity$_t$	0.091***	0.095***
	(5.38)	(5.49)
Performance$_{[t-12,t-1]}$		0.116***
		(3.13)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	4,796	4,575
Adjusted R^2	0.272	0.272

Table 10. Outlook Positivity and Future Risk Taking

This table presents the results of the panel regression analysis examining various future risk measures in relation to *Outlook Positivity* and a set of control variables for fund-year observations from 2012 to 2022. *Volatility* is the standard deviation of future six-month monthly net return. *Idio. Volatility* represents the standard deviation of the residuals from the Carhart (1997) four-factor model over the next six months. *Industry Concentration* is measured using the Herfindahl index, following Kacperczyk, Sialm, and Zheng (2005). *Equity and Cash Holding* is the ratio of current equity and cash assets to total assets under management, respectively. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined in Loughran and McDonald (2011), to total words in the Market Outlook section of the fund's annual report. Control variables are the same as those in Table 3. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Volatility $_{[t+1,\ t+6]}$	*Idio. Vol.* $_{[t+1,\ t+6]}$	*Industry Concent.* $_{t+6}$	*Equity Holding* $_t$	*Cash Holding* $_t$
	(1)	(2)	(3)	(4)	(5)
Outlook Positivity $_t$	2.590**	1.977**	1.064**	0.179**	-0.099*
	(2.06)	(1.99)	(2.25)	(2.11)	(-1.65)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES
Nobs.	4,890	4,893	4,888	4,799	4,799
Adjusted R^2	0.720	0.547	0.500	0.443	0.294

Table 11. Outlook Positivity and Future Performance

This table presents the results of the panel regression analysis examining future *Performance* in relation to *Outlook Positivity* and various control variables for fund-year observations from 2012 to 2022. Future *Performance* is measured as the average monthly Carhart (1997) four-factor alpha over the next six months. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined in Loughran and McDonald (2011), to total words in the Market Outlook section of the fund's annual report. Control variables are the same as those in Table 3. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	$Performance_{[t+1,\ t+6]}$	$Performance_{[t+1,\ t+6]}$
	(1)	(2)
$Outlook\ Positivity_t$	-0.033***	-0.011
	(-2.89)	(-0.82)
$Performance_{[t-11,t]}$		-0.130
		(-1.55)
$Outlook\ Positivity_t \times Performance_{[t-11,t]}$		-0.042**
		(-2.25)
Controls	YES	YES
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	4,893	3,117
Adjusted R^2	0.233	0.190

Table 12. Outlook Positivity and Fund Flows

This table presents the results of the panel regression analysis examining institutional and retail fund *Flows* in relation to *Outlook Positivity* and various control variables for fund-year observations from 2012 to 2022. *Flows* is the next month's fund flows calculated following Sirri and Tufano (1998) and is divided by 100. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined in Loughran and McDonald (2011), to total words in the Market Outlook section of the fund's annual report. Institutional Fund are the funds whose retail investor holdings account for 80% or less of the total. Retail funds are the funds with retail investor holdings exceeding 80%. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Net Flows$_{t+1}$	
	Institutional Fund	Retail Fund
	(1)	(2)
Outlook Positivity$_t$	-1.155**	0.038
	(-2.42)	(0.21)
Outlook Uncertainty$_t$	-0.001*	0.000
	(-1.81)	(0.65)
Fund Age$_t$	0.010	-0.135***
	(0.10)	(-2.97)
Fund Size$_t$	-0.132***	-0.070***
	(-7.48)	(-6.51)
Expense Ratio$_t$	0.152	0.086
	(1.21)	(0.78)
Turnover Ratio$_t$	-0.065***	-0.018***
	(-6.66)	(-4.90)
Fund Family Size$_t$	0.008	-0.018**
	(0.31)	(-2.07)
Performance$_{[t-11,t]}$	0.036***	0.022***
	(4.00)	(5.41)
Performance$_{[t-11,t]}^2$	-0.003*	-0.001
	(-1.89)	(-0.59)
Year FE	YES	YES
Fund FE	YES	YES
Nobs.	1,455	2,994
Adjusted R^2	0.108	0.220

Table 13. Robustness: Measuring Beliefs with ChatGPT

This table reports the results of panel regression analysis examining the relationship between ChatGPT's outlook positivity and the prior year's performance for fund-year observations from 2012 to 2022. The dependent variables include overall outlook positivity and segment-specific positivity for macroeconomy, securities markets, and industry trends. Outlook Positivity GPT is a categorical variable taking the value 1 if the ChatGPT's analysis of the tone of the Market Outlook section is positive, 0 if neutral and -1 if negative. Similarly, Macroeconomy Positivity GPT, Securities Market Positivity GPT, and Industry Positivity GPT are categorical variables reflecting ChatGPT's analysis of the tone of the corresponding segments of the outlook. Performance is the average of the monthly Carhart (1997) four-factor alpha from the previous year. We use the CSRC industry word list to screen for relevant mentions of the outlook on industry trends.Control variables are the same as those in Table 3. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Pos. GPT_t	*Macro. Pos.* GPT_t	*Sec. Mkt Pos.* GPT_t	*Industry Pos.* GPT_t
	(1)	(2)	(3)	(4)
$Performance_{[t-12,t-1]}$	0.029**	0.031**	0.045***	0.033**
	(2.54)	(2.22)	(2.85)	(2.50)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES
Nobs.	4,545	4,473	4,570	3,426
Adjusted R^2	0.147	0.114	0.136	0.140

Internet Appendix

Let the Good Times Roll:

Subjective Expectations and Asset Management

Francesco D'Acunto, Baixiao Liu, Linlin Ma, Yizou Wu

Table A1. Past Performance and Outlook Positivity: Alternative Performance Measures

This table presents the results of the panel regression analysis of *Outlook Positivity* against the last year's average alpha measured using alternative models. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook Section of the fund's annual report. *China Four* is the average China four-factor alpha (Liu et al. (2019)) ; *FF Five* is the average Fama-French five-factor alpha (Fama and French (2015)) ; *FF Three* is the average Fama-French three-factor alpha (Fama and French (1993)) ; *CAPM* is the average CAPM alpha (Jensen (1968)), all measured over the preceding year. Control variables are the same as those in Table 3. All regressions include fund- and year-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$			
	(1)	(2)	(3)	(4)
China Four$_{[t-12,t-1]}$	0.114***			
	(3.17)			
FF Five$_{[t-12,t-1]}$		0.118***		
		(3.19)		
FF Three$_{[t-12,t-1]}$			0.120***	
			(3.12)	
CAPM$_{[t-12,t-1]}$				0.107***
				(2.95)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES
Nobs.	4,578	4,578	4,578	4,578
Adjusted R^2	0.265	0.265	0.265	0.265

Table A2. Past Performance and Outlook Positivity: Semi-annual Frequency

This table presents the results of the baseline regression conducted at a semi-annual frequency, where we conduct panel regression analysis of *Outlook Positivity* against the average alpha over the past six months and various control variables for fund-semiannual observations from 2012 to 2022. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook Section of the fund's annual and semi-annual report. *Carhart Four* is the average Carhart four-factor alpha (Carhart, 1997); *China Four* is the average China four-factor alpha (Liu et al., 2019) ; *FF Five* is the average Fama-French five-factor alpha (Fama and French, 2015) ; *FF Three* is the average Fama-French three-factor alpha (Fama and French, 1993) ; *CAPM* is the average CAPM alpha (Jensen, 1968), all measured over the preceding six months. Control variables are the same as those in Table 3. All regressions include fund- and semi-annual-period-fixed effects. All standard errors are clustered at the fund level. The coefficients of the controls and the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$				
	(1)	(2)	(3)	(4)	(5)
Carhart Four$_{[t-6,t-1]}$	0.089***				
	(5.02)				
China Four$_{[t-6,t-1]}$		0.118***			
		(6.99)			
FF Five$_{[t-6,t-1]}$			0.097***		
			(5.21)		
FF Three$_{[t-6,t-1]}$				0.102***	
				(5.48)	
CAPM$_{[t-6,t-1]}$					0.071***
					(4.08)
Controls	YES	YES	YES	YES	YES
Semi-annual FE	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES
Observations	9,483	9,483	9,483	9,483	9,483
Adjusted R^2	0.232	0.235	0.232	0.233	0.231

Table A3. Past Performance and Outlook Positivity: Manager Fixed Effect

This table presents the results of a panel regression analysis examining the relationship between *Outlook Positivity* and last year's *Performance*, along with various control variables, using fund-year observations from 2012 to 2022. *Outlook Positivity* is measured as the fraction of positive words minus negative words, as defined by Loughran and McDonald (2011), relative to the total word count in the Market Outlook Section of the fund's annual report. *Performance* is calculated as the average Carhart (1997) four-factor alpha for the previous year. *Performance (Positive)* and *Performance (Negative)* represent the absolute value of *Performance*, multiplied by a dummy variable indicating positivity or negativity, respectively. All other variables are defined in the Appendix. Regressions include manager-, fund- and year-fixed effects. All standard errors are double clustered at the fund and manager level. The coefficients of the constant are omitted for brevity. The t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Outlook Positivity$_t$	
	(1)	(2)
Performance$_{[t-12,t-1]}$	0.114**	
	(2.58)	
Performance(Positive)$_{[t-12,t-1]}$		0.176***
		(2.74)
Performance(Negative)$_{[t-12,t-1]}$		-0.010
		(-0.10)
Controls	YES	YES
Year FE	YES	YES
Manager FE	YES	YES
Fund FE	YES	YES
Nobs.	3,613	3,613
Adjusted R^2	0.206	0.206