Structured Beliefs in Fund Managers' Own Words: Fundamentals, Policy, and Sentiment *

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January 2026

Abstract

Using mandatory Outlook reports from Chinese mutual funds, we extract each fund's beliefs about the equity market and decompose them into three components: beliefs about macroeconomic fundamentals, beliefs about government policy, and a residual that captures fund sentiment. We find that policy beliefs—not macro fundamental—significantly predict subsequent market returns, helping explain the positive alphas observed in the Chinese mutual fund industry. At the same time, funds strategically incorporate a sentiment component that exerts the strongest influence on equity allocations. Fund sentiment predicts future fund flows, but not market returns, consistent with an incentive to attract flows.

* We are grateful to Nick Barberis, John Campbell, Bing Han, Zhen Huo, Wenxi Jiang, Jiacui Li, Stefan Nagel, Wei Ning, Baolian Wang, Zhengyang Xu, Liyan Yang, and seminar participants at ABFER, AFA, CICF, CityU Fintech Conference, CFRC, Conference on FinTech Advances in Emerging Markets, USTC Frontier in Finance Conference, CUHK, University of Florida, and University of Southern California for helpful comments and suggestions.

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Why do some fund managers consistently beat the market while others don't? Modern asset pricing theory tells us the answer lies in the risk-return tradeoff, shaped by macroeconomic fundamentals, government policy, and market sentiment. Yet despite decades of research on these forces individually, we still lack a systematic way to peek inside investors' heads and understand how these different beliefs interact to drive actual investment decisions.

The problem is simple but fundamental: we don't have good measures of what investors actually think, much less measures detailed enough to capture the full structure of their beliefs. Researchers have traditionally relied on surveys, asking financial analysts, professional economists, or random households what they expect, e.g., Shiller (2000), Manski (2004), Greenwood and Shleifer (2014), Coibion and Gorodnichenko (2015), Giglio et al. (2021), and Nagel and Xu (2022). But these respondents often don't represent the investors who actually move markets. Even when we do survey the right people, keeping them engaged over the years needed to track how beliefs evolve has proven nearly impossible. Recent efforts like Giglio et al.'s (2021) large-scale survey of Vanguard investors have made important progress, but still can't capture beliefs across multiple dimensions over long time horizons.

This paper takes a different approach. Rather than asking investors what they think, we observe what they say they think in mandatory public disclosures. Since 2008, China's securities regulator has required all mutual funds to publish comprehensive outlooks on financial markets, the economy, and government policies in their semi-annual and annual reports. [1] These aren't optional surveys—they're systematic, structured reports from professional fund managers who manage real money over a 16-year period. The reports don't just tell us what managers think about stocks; they reveal their views on macroeconomic trends and policy actions, letting us decompose their market expectations into distinct dimensions. And because the reports also disclose portfolio positions and performance, we can directly test how different belief components translate into investment strategies and returns in the world's second-largest financial market.

Crucially, funds have strong incentives for truthful reporting. These disclosures help market strategies to investors, but more importantly, inconsistencies between stated views and actual investments could be scrutinized as reckless risk-taking. This accountability ensures that reported beliefs reflect genuine convictions rather than empty rhetoric.

What makes this setting particularly compelling is that Chinese mutual funds, on average, deliver positive pre-fee alphas, as reviewed by Jiang (2021)—a stark contrast to their U.S.

[1] Mutual funds in the U.S. are not required to include outlooks in their reports; however, they may choose to disclose their outlooks voluntarily. Despite the limited and incomplete data available for U.S. mutual funds, a recent study by Dahlquist and Ibert (2024) provides insightful findings, showing that asset managers' equity premium expectations are countercyclical and that their portfolios reflect their heterogeneous expectations.

counterparts who typically don't. This raises a natural question: how do Chinese fund managers generate alpha?

Of course, these reports come in textual form, which creates its own challenge: how do we extract and quantify different dimensions of beliefs from the same document? Traditional bag-of-words approaches, as seen in Tetlock (2007) and Loughran and McDonald (2011), work well for measuring overall sentiment but fall apart when trying to distinguish sentiment across topics. [2] A fund manager might be pessimistic about macro fundamentals while remaining bullish on stocks because she's optimistic about government intervention. When pessimistic and optimistic phrases about different topics appear in the same text, simple word-counting fails.

Unlike traditional methods, Large Language Models (LLMs) can reliably identify not just whether a text is positive or negative overall, but which parts are positive about which topics. This capability—unavailable just a few years ago—lets us uncover the multi-dimensional structure of beliefs within each report.

We analyze semi-annual and annual reports from all mutual funds between 2008 and 2023—growing from 1,188 reports in 2008 to 35,388 in 2023 as China's fund industry expanded. Using DeepSeek-R1, optimized for Chinese text, we extract each manager's expectations along five dimensions: the stock market, the macroeconomy, monetary policy, fiscal policy, and regulatory policy. We validate these LLM-extracted beliefs against human labels and confirm that monetary and fiscal expectations from fund reports actually predict subsequent policy developments.

Some might worry about look-ahead bias in pretrained models, as pointed out by Glasserman and Lin (2024) and Sarkar and Vafa (2024)—could the training data embed future information that contaminates our analysis? This concern doesn't apply here. We're using the model to summarize and classify sentiment, not predict the future. More importantly, our analysis focuses on cross-sectional differences across funds: even if some aggregate look-ahead component existed, it wouldn't drive the variation we study.

The data structure itself supports this: fund and time fixed effects explain only a modest share of variation in beliefs, indicating that funds respond idiosyncratically to evolving conditions rather than recycling identical outlooks or echoing uniform narratives.

[2] See Gentzkow, Kelly, and Taddy (2019) for a review of the broad economic literature of treating text as data. Recently, Bybee et al. (2020) adopted the Latent Dirichlet Allocation (LDA) topic modeling approach of Blei et al. (2003) to estimate a topic model that summarizes business news from the Wall Street Journal into easily interpretable topical themes. They quantified the proportion of news attention allocated to each theme at different points in time. While this approach effectively decomposes news articles into a structured set of themes, identifying the sentiment of a report on a specific theme remains challenging.

What do we find? First, we can decompose equity market expectations into three components: macro fundamentals, policy expectations, and a residual. While both macro and policy expectations strongly correlate with equity market beliefs, substantial variation remains unexplained. We interpret this residual as sentiment—likely reflecting behavioral influences or factors unrelated to observable economic conditions.

Second, when we test which beliefs actually predict market returns, a clear hierarchy emerges. Time-series regressions show that funds' average policy expectations strongly and significantly predict subsequent three-month market returns, indicating genuinely informed views. Macro beliefs and sentiment, by contrast, show little or no predictive power.

Third, these beliefs translate into action: equity allocations correlate positively with stated market beliefs, confirming that reports reflect actual investment decisions. More importantly, managers' market timing success comes specifically from their policy views. Stronger policy beliefs lead to equity adjustments that systematically align with subsequent market moves, while macro and sentiment-based beliefs show no such relationship.

That informed policy beliefs contribute to positive alphas in Chinese mutual funds is perhaps unsurprising—but what is surprising is the complete absence of a comparable role for macro fundamentals. In most markets, beliefs about economic growth, corporate earnings, and other fundamentals would be central to generating alpha. Here they're not. This striking contrast points to something deeper about how China's financial markets function. As Brunnermeier, Sockin, and Xiong's (2022) theoretical model suggests, heavy policy interventions may fundamentally reorient investors' attention away from macro fundamentals toward policy signals. If true, this shift carries important implications: it not only explains where alpha comes from, but also suggests that China's stock market may be undermined in its core function of price discovery for economic fundamentals.

Yet the portfolio allocation results reveal a puzzle. Despite policy beliefs having the strongest predictive power for returns, they don't dominate portfolio decisions. Instead, sentiment—which actually has little market timing power—exerts the strongest influence on equity allocations. Why would managers overweight noisy sentiment relative to their informed policy views?

Behavioral limitations offer one explanation, but we find evidence of a strategic motive. Fund sentiment positively correlates with subsequent fund flows, while policy and macro beliefs don't. During high-inflow periods, both fund sentiment and its flow sensitivity rise, suggesting managers strategically tilt their stated beliefs toward prevailing market sentiment to attract capital. This pattern supports Gennaioli, Shleifer, and Vishny's (2015) argument that returns aren't the sole driver of flows. By aligning their expressed views with investor sentiment—even when doing so means deviating from their more informed policy beliefs—

funds appear to successfully attract greater inflows.

Related Literature

Our paper contributes to the literature on the relationship between investors' beliefs and investment decisions. A series of studies have connected survey expectations with respondents' investment behaviors, including expectations of wealthy retail investors surveyed by Vanguard (Giglio et al., 2021), return expectations of public pension funds (Andonov and Rauh, 2022), and equity premium expectations of large asset managers (Dahlquist and Ibert, 2024). Andonov and Rauh (2022) show that asset managers' return expectations tend to be extrapolative, while Dahlquist and Ibert (2024) find that equity premium expectations are countercyclical.

A key advantage of our dataset is its scale and richness. We observe all mutual funds in the world's second-largest economy over 16 years. More importantly, the comprehensive outlooks included in these fund reports allow us to explore the structure of fund managers' beliefs about the economy, government policies, and financial markets. This adds fund managers' policy beliefs as a new factor for market dynamics. While Ammer et al. (2022, 2023) also analyze the same Chinese mutual fund reports, their focus is limited to fund managers' market expectations, without delving into other dimensions or the structured beliefs we explore.

We also contribute to the long-standing literature on mutual fund managerial skill and return predictability. One line of research demonstrates that managers' ability to collect and process information about the fundamental value of target firms can predict fund performance (e.g., Kacperczyk and Seru, 2007; Jiang and Zheng, 2018). Another line of research uses return-based or holdings-based measures to forecast fund performance (e.g., Grinblatt and Titman, 1993; Daniel et al., 1997; Jiang et al., 2007; Kacperczyk et al., 2014; Berk and Van Binsbergen, 2015). More recently, a strand of the literature employs machine learning methods to predict fund returns (e.g., Abis, 2020; Li and Rossi, 2020; Kaniel et al., 2023; DeMiguel et al., 2023; Cao, Yang, and Zhang, 2024 and 2025). Unlike prior studies, we infer managers' skills from their structured beliefs, as extracted from their outlook statements on the economy, government policies, and financial markets, rather than solely from their investment choices and characteristics.

Furthermore, we contribute to the extensive literature on the drivers of mutual fund flows. The foundational view in this literature is that flows chase past performance. Seminal works

by Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998) document a convex relationship where top-performing funds attract disproportionate inflows, while poor performers do not suffer equal outflows. Berk and Green (2004) provide a rational equilibrium framework for this phenomenon, suggesting that investors chase past returns to identify skilled managers until inflows erode alpha.

However, a growing body of evidence suggests that flows are also driven by non-performance factors, including marketing, attention, and sentiment. Barber, Odean, and Zheng (2005) find that investors buy funds that attract their attention through marketing or media, regardless of economic fundamentals. Similarly, Ben-David et al. (2022) challenge the assumption that investors allocate capital based on sophisticated risk-adjusted performance measures, showing instead that flows are driven primarily by simple, salient signals such as Morningstar ratings and recent raw returns. Cooper, Gulen, and Rau (2005) provide evidence of "catering," showing that funds changing their names to reflect hot investment styles (e.g., "dotcom") attract significant inflows. Beyond attention and catering, aggregate flows often serve as a barometer for investor sentiment. Ben-Rephael, Kandel, and Wohl (2012) explicitly propose that mutual fund flows measure sentiment, finding that net exchanges into equity funds reflect noise trader demand and negatively predict future market returns. This corresponds to the "dumb money" effect documented by Frazzini and Lamont (2008), who show that retail flows tend to move into funds with high sentiment, subsequently predicting lower future returns.

Our findings bridge these two perspectives. We show that while past performance drives flows, a fund's stated sentiment—specifically the residual belief component unrelated to fundamentals—is also a strong predictor of inflows. This aligns with the view of Gennaioli, Shleifer, and Vishny (2015) that money managers compete for trust and sentiment rather than just returns. Our results suggest that managers may implicitly or explicitly cater to investor sentiment in their reports to attract capital, even when that sentiment negatively predicts future market returns.

Additionally, our study contributes to the literature on policy uncertainty and expectations in asset markets. Pastor and Veronesi (2012) develop a general equilibrium model showing that government policy uncertainty raises risk premiums, increases market volatility, and can drive stock price declines upon policy announcements. Bond and Goldstein (2015) highlight how policymakers' reliance on market prices influences traders' incentives and the informativeness of prices. Brunnermeier, Sockin, and Xiong (2022) emphasize that strong policy interventions

can shift investors' focus from economic fundamentals to policy noise, undermining the market's information discovery. Building on these insights, our analysis provides direct empirical evidence that policy expectations play a critical role in shaping fund managers' investment decisions.

Finally, we contribute to the recent literature on the use of LLMs in financial applications, including classification (Hansen and Kazinnik, 2024; Yang and Menczer, 2023; Bernard et al., 2023; Dasgupta, Li, and Wu, 2023), sentiment analysis for return prediction (Chen et al., 2022; Lopez-Lira and Tang, 2023; Jha et al., 2023; Bybee, 2023), and belief formation of financial analysts (Ke, 2025). We advance this methodology by using DeepSeek-R1 not just for sentiment scoring, but to decompose complex narratives into structured economic and policy beliefs. This approach allows us to disentangle the multidimensional nature of investor beliefs in a way that traditional NLP methods cannot.

I. Data Description

A. Mutual Fund Reports

Starting in 2008, the China Securities Regulatory Commission (CSRC) mandated that all mutual funds in China include comprehensive economic and financial market reviews for the recent period, along with detailed outlooks for the upcoming period, in their semi-annual and annual reports. These statements are required within the "Manager Report" section.

In these reports, fund managers present comprehensive outlooks on economic factors relevant to their portfolio investments, including projections for future economic trends, potential policy responses, and anticipated performance of equity and bond markets.

These detailed statements provide a holistic view of fund managers' perspectives on the evolving economy, government policies, and financial markets, offering valuable insights into the decision-making processes and market outlooks of key financial players in China.

We utilize the Wind database to access these reports, focusing specifically on the outlook sections. Our dataset comprises 201,605 reports with valid sections spanning from 2008 to 2023. To maintain focus on the Chinese stock market, we exclude bond funds or money market funds, and include only equity and hybrid funds.

We obtain additional data on mutual fund returns, flows, holdings, and other relevant market and accounting information from the Wind database. We align these semi-annual and

annual reports with fund data based on the month of public release. For annual reports, typically published in March or April, we use the following matching criteria:

- Reports published in March: Matched with monthly data from April of year t+1 to September of year t+1.
- Reports published in April: Matched with monthly data from May of year t+1 to September of year t+1.

These annual reports are also paired with first-quarter-end holding data. Semi-annual reports are matched with monthly data starting in October, when third-quarter-end holding data generally becomes available in that month.

To ensure sufficient time-series coverage for each fund, we include only those with at least 10 reports over our sample period. The final sample comprises 297,210 fund-month observations and 52,205 reports spanning from 2008 to 2023. Table 1A in the Internet Appendix reports the number of annual and semi-annual reports included in our sample from 2008 to 2023. These data reveal consistent growth in the number of funds over time, reflecting the rapid expansion of China's mutual fund industry. Semi-annual reports increase from 221 in the first half of 2008 to 2,774 in the first half of 2023, while annual reports increase from 266 in 2008 to 2,730 in 2023. Because our requirement of at least 10 reports (i.e., 5 years of history) excludes younger funds, the overall universe of stock and hybrid funds in China in 2023 is substantially larger than the funds in our sample.

B. Quantifying Outlooks

The CSRC grants fund managers substantial discretion over their outlooks, without imposing strict content guidelines. As a result, Outlook sections vary widely in length—from about 30 to over 6,000 Chinese characters—depending on the depth and breadth of topics covered.

Managers typically address three main areas. First, they analyze macroeconomic conditions, distinguishing between domestic and global factors. Second, they discuss policy developments, including fiscal, monetary, and regulatory measures. Third, they examine financial markets, typically separating equity and bond markets. This structure supports comprehensive discussion of the forces shaping future market conditions while giving managers flexibility to emphasize issues most relevant to their strategies.

Why should we trust these reports? They provide a useful channel for managers to

communicate strategies and demonstrate capabilities. As short-term performance is subject to considerable luck, it is particularly valuable for managers to align strong performance with previously articulated outlooks. Such consistency helps demonstrate that superior returns reflect skill rather than luck, whereas clear contradictions between realized performance and stated views could raise suspicions of gambling with investor capital. Consequently, managers have strong incentives to report their outlooks truthfully. As we show below, the market expectations and belief components revealed in these reports closely align with observed trading behaviors.

To be clear, fund statements are unlikely the only, or even most important, channel for marketing strategies to investors. What matters for our analysis is that funds consistently report their views and strategies in these mandatory disclosures.

To convert the qualitative information in mutual fund reports into quantitative measures, we employ the DeepSeek reasoning model (DeepSeek-R1, hereafter DeepSeek), a state-of-the-art natural language processing (NLP) system. DeepSeek is trained on an extensive corpus of text and excels at understanding the structure and semantics of Chinese-language content. Its architecture builds on transformer blocks and self-attention mechanisms—key features shared with other large language models such as ChatGPT—enabling it to process long text sequences and focus on the most relevant passages. Leveraging these capabilities, we systematically analyze fund manager reports and translate complex qualitative assessments into structured, quantifiable measures. [3]

Crafting effective prompts is crucial for guiding DeepSeek to interpret commands and respond appropriately. This requires providing relevant context, incorporating domain knowledge, and understanding the model's operational nuances to elicit accurate outputs. Prompts must therefore be carefully tailored to each specific task.

In our study, we use the following prompt to separately process the Outlook section of each fund report in our sample:

"*Forget all your previous instructions. Assume the role of a Chinese financial expert specializing in financial report analysis. Your task is to assess the outlook section of a mutual fund's periodic report. Evaluate each of the following dimensions: (1) domestic fiscal policy;*

3 We primarily use DeepSeek for its superior performance on Chinese-language text, though results using GPT-4 in an earlier draft were very similar.

(2) domestic monetary policy; (3) domestic regulatory policy; (4) domestic macroeconomic fundamentals; (5) global macroeconomic fundamentals; (6) domestic equity market; (7) domestic bond market; (8) overall assessment for fund investors.

Respond with 'Positive', 'Weakly Positive', 'Neutral', 'Weakly Negative', 'Negative', or 'Not Mentioned' (not applicable for the overall assessment). Follow each response with a concise, one-sentence elaboration in Chinese."

In this prompt, we instruct DeepSeek to analyze the sentiment of each Outlook section across different topics from the perspective of a professional Chinese financial expert. [4] We set the model's temperature to 0 to minimize creativity and obtain the highest-probability responses, enhancing reproducibility. The output consistency rate exceeds 90% when running the model 1,000 times on the same report.

One might worry about look-ahead bias Given that DeepSeek's training data extend to July 2024. However, we use the model primarily for *summarization* rather than *prediction*, which substantially mitigates the risk that future information contaminates our analysis.

To validate this approach, we conduct robustness checks by modifying temporal information in the reports. Specifically, we remove year references and shift dates forward or backward by five years. As shown in Table 2A of the Internet Appendix, the model maintains high output stability under these alterations: consistency rates exceed 90% across 1,000 randomly selected reports for almost all dimensions in our empirical analysis, including expectations about fiscal, monetary, and regulatory policies, domestic macroeconomic fundamentals, and the domestic equity market. This demonstrates that the model extracts sentiment and key information largely independently of specific temporal anchors, reinforcing the reliability of our summarization approach.

We instruct DeepSeek to generate a summary for each topic and convert it into a numerical score using the following mapping:

- "Positive": 1
- "Weakly Positive": 0.5
- "Neutral": 0

4 We use a single DeepSeek prompt to analyze all topics simultaneously. This consolidated design preserves clear distinctions across topics: in experimental trials with *separate prompts per topic,* we found that overall contextual sentiment could unduly spill over into the assessment of individual dimensions.

- "Weakly Negative": -0.5
- "Negative": -1
- "Not Mentioned": Missing (NaN)

From the Outlook section, we extract five key variables: one capturing expectations about the domestic equity market, one focused on the national macroeconomy, and three related to government policies—fiscal, monetary, and regulatory. This focus on policy reflects a distinctive feature of China's economy. As argued by Xiong (2025), China operates under a "market-in-state hierarchy" in which market mechanisms are deeply integrated with centralized state control. A defining feature of this system is pervasive policy intervention through a systematic macro-management framework that jointly deploys monetary, fiscal, and regulatory tools to manage the real economy and the financial system.

To capture fund managers' policy expectations within this framework, we group policies into three broad categories:

1. Monetary policy – including adjustments to interest rates and control over total bank lending. The People's Bank of China (PBOC) uses these instruments to regulate money supply and credit conditions, thereby influencing economic activity.
2. Fiscal policy – encompassing large-scale infrastructure investment and industrial policies aimed at promoting and developing specific sectors, especially as countercyclical tools during economic downturns.
3. Regulatory policy – including measures such as IPO quotas and changes in stamp taxes on stock trading, which directly affect capital markets and investor behavior.

To summarize overall policy expectations, we construct an average policy variable by taking the mean of these three dimensions.

Panel A of Table 1 reports summary statistics for fund expectations extracted from the Outlook sections. On average, fund managers' expectations are generally positive but exhibit substantial variation. The expectation for the national macroeconomy is slightly positive, with a mean of 0.041 and a large standard deviation of 0.790. The average policy expectation has a mean of 0.490 and a standard deviation of 0.597, while the equity market expectation has a mean of 0.580 and a standard deviation of 0.519. Our analysis relies critically on both the time-series and cross-sectional variations in these expectations.

Panel B presents the correlation matrix for the five extracted beliefs and the average policy expectation. The three policy dimensions are highly correlated with one another, with pairwise correlations around 0.33. Consistent with China's coordinated macro-management framework, fund managers tend to anticipate broad-based policy packages spanning fiscal, monetary, and regulatory tools rather than isolated interventions.

Moreover, the correlations among expectations about the equity market, macroeconomy, and policy (whether individual dimensions or the average measure) are mostly positive. This suggests that policy conditions are closely tied to economic fundamentals and that, together, they shape fund managers' views about the equity market.

C. Validating LLM-Extracted Beliefs

To assess the reliability of DeepSeek-generated annotations, we validate them against human labels. We randomly select 50 observations that satisfy our data-quality filters and evaluate them along two key dimensions: fund managers' expectations about macroeconomic fundamentals and about the equity market. Three human annotators with training in finance and macroeconomics independently label each field. We construct a human-annotated ground truth using a majority-vote rule across the three annotators. Table 3A in the Internet Appendix reports the validation results. The agreement rate between DeepSeek and the human majority vote is 86% (=43/50) for macroeconomic fundamentals and 80% (=40/50) for the equity market.

Given the complexity of the task, human annotators are themselves prone to error. To better understand disagreement, we consult two additional domain experts who assign final labels without knowing whether any given label originated from DeepSeek or the initial human annotators. Among the 100 belief instances (50 data points × {equity, macro}) where the first-round human majority label and the DeepSeek label differ, the experts' final judgment aligns with DeepSeek in 12 out of 17 cases. The resulting consistency rates between DeepSeek and the expert-calibrated labels are 94% and 96% for the two dimensions, respectively. These findings indicate that DeepSeek provides a reliable and scalable method for extracting beliefs from complex textual data and that its responses can often be more accurate than those of human annotators with domain knowledge.

D. Fund Characteristics

At the end of 2023, our sample comprises 2,730 unique funds, including 541 equity funds

(19.82%), and 2,189 hybrid funds (80.18%). Among these, 2,548 funds (93.33%) are actively managed, while 182 (6.67%) are passively managed. [5] The average stock holding ratio is 61.07%, with a standard deviation of 34.05%. Total assets under management amount to 3.47 trillion yuan (approximately 0.49 trillion U.S. dollars).

Panel A of Table 1 reports statistics for various fund characteristics, with all variables winsorized at the 2.5% and 97.5% levels. The monthly fund return in our sample has a mean of 0.63% and a standard deviation of 5.90%, while the semi-annual fund return has a mean of 3.53% and a standard deviation of 14.89%.

Following Liu, Stambaugh, and Yuan (2019), we adjust fund performance using the three-factor (CH3) and four-factor (CH4) models constructed for the Chinese market. Fund performance is estimated as:

$$CH3: \quad r_t = \alpha + \beta MKTRF_t + s\,SMB_t + vVMG_t + \varepsilon_t \qquad (1)$$

$$CH4: \quad r_t = \alpha + \beta MKTRF_t + s\,SMB_t + vVMG_t + pPMO_t + \varepsilon_t \qquad (2)$$

where

- r_t is the return on a mutual fund in excess of the one-year deposit interest rate in China;
- $MKTRF_t$ is the excess return on the value-weighted portfolio of the top 70% of stocks (Liu, Stambaugh, and Yuan (2019) exclude the smallest 30% of stocks to avoid potential bias from reverse mergers);
- SMB_t is the size factor, also excluding the smallest 30% of stocks;
- VMG_t is the value factor based on the earnings-price ratio;
- PMO_t is a sentiment factor based on turnovers, introduced in the four-factor (CH4) model. [6]

We apply the CH3 and CH4 models to estimate alphas, defined as the constant term α in these time-series regressions. Newey-West standard errors with 11 lags are used to account for autocorrelation in the residuals.

Using each fund's daily returns, we compute its monthly alphas under both CH3 and CH4.

[5] The number of passive funds is small. We include them in our analysis for completeness. In the Internet Appendix, we also report robustness results that exclude these passive funds.

[6] Data for the three (CH3) and four factors (CH4) are obtained from Robert F. Stambaugh's homepage, https://finance.wharton.upenn.edu/~stambaug/.

The CH3 alpha has a mean of 0.29% and a standard deviation of 3.46%, while the CH4 alpha has a mean of 0.28% and a standard deviation of 3.40%. Simple t-tests confirm that these alpha measures are statistically significant. This positive average alpha contrasts with the negative alphas typically documented for U.S. mutual funds, but is consistent with the evidence on Chinese mutual fund performance reviewed by Jiang (2020).

Fund reports reveal substantial variation in expectations across managers. Table 4A in Internet Appendix examines how fund characteristics relate to these expectations by regressing each fund's expectation on past six-month performance (semi_ret), total net assets (log_tna), recent fund flow (flow), and fund age (age). Table 4A reports results using equity market expectations, as well as expectations about the macroeconomy and the average policy beliefs extracted from fund managers' Outlook sections. Recent fund performance is consistently and significantly positively related to policy expectations, but negatively related to market expectations. This suggests that stronger recent performance is associated with more optimistic views about government policies while inducing more cautious sentiment toward the equity market. By contrast, the relationships for log_tna, flow, and age are less uniform and exhibit varying influence across expectation dimensions.

II. Fund Expectations

Fund managers' multidimensional expectations of the stock market, economy, and government policies provide a unique opportunity to analyze their beliefs and uncover the investment strategies they employ. In this section, we examine variation in these expectations.

A. Variation in Fund Expectations

There is substantial variation in fund managers' expectations across funds and over time. To explore these patterns, we employ three fixed-effects regressions of the form Y_{it} (equity market expectations for fund i at time t) on different sets of fixed effects:

- Fund fixed effects: To account for time-invariant characteristics of individual funds, we include fund fixed effects: $Y_{i,t} = \alpha_i + \varepsilon_{i,t}$. This specification captures inherent fund-specific traits that may shape managers' expectations.

- Time fixed effects: To examine the influence of market-wide conditions, we include time fixed effects: $Y_{i,t} = \beta_t + \varepsilon_{i,t}$. This identifies common time-varying factors that

simultaneously impact all funds' expectations.

- Two-way fixed effects: To incorporate both fund-specific characteristics and time-varying factors, we estimate: $Y_{i,t} = \alpha_i + \beta_t + \varepsilon_{i,t}$. This specification accounts for idiosyncratic fund traits and evolving economic or market conditions that jointly shape expectations.

We apply these fixed-effect specifications to equity market expectations. Panel A of Table 2 reports the R^2 values for each model. Column (1) shows that fund fixed effects explain 13.6% of the variation in equity market expectations, suggesting that individual funds' characteristics and investment philosophies play an important role. Column (2) reveals that time fixed effects explain 13% of the variation, implying that market-wide factors also matter. In column (3), the two-way fixed-effects model explains 24.9% of the variation, underscoring the importance of considering both fund-level and time-dependent components. Even after accounting for both time and fund fixed effects, roughly three-quarters of the variation in fund managers' stock market expectations remains unexplained; this residual variation provides the key source of identifying variation for our subsequent analysis.

One potential concern is that funds within the same fund family might rely on a common in-house analyst when forming their market expectations or on the same administrative staff when drafting the Outlook section. If so, fund family fixed effects should explain a substantial fraction of the variation. Panel B of Table 3 reports the R^2 from regressions with fund family fixed effects, which account for only about 2% of the variation in equity market expectations. This low explanatory power suggests that common family-level research or reporting practices play only a minor role and that funds within the same family do not simply replicate a single analyst's views or a standardized Outlook.

A fund may change managers over time and a given manager may oversee multiple funds, Panel B also reports the R^2 from regressions with fund manager fixed effects, which account for approximately 28% of the variation in equity market expectations—substantially higher than when using fund fixed effects. This likely reflects substantial manager turnover within funds. When we include both fund manager and time fixed effects, the model explains 35.5% of the variation in equity market expectations, still leaving nearly two-thirds unexplained.

Table 2 shows similar patterns in the explanatory power of fund fixed effects, fund manager fixed effects, and time fixed effects for variation in expectations about the macroeconomy and the three policy dimensions. Even after accounting for these fixed effects,

a substantial share of variation remains unexplained, providing the key source of identifying variation for our analysis of funds' trading behavior.

We further examine how fund expectations fluctuate with market conditions in Table 5A of the Internet Appendix. Across all dimensions, fund expectations are consistently positively correlated with equity index returns. This suggests that funds are more likely to anticipate favorable policies and stronger fundamentals during periods of robust market performance and that they expect policy to help sustain these favorable fundamentals.

When we turn to market volatility—measured by the semi-annual standard deviation of the market index—we find that policy expectations are positively correlated with equity market volatility, whereas macroeconomic and equity market expectations are negatively correlated. This suggests that fund managers are also more likely to anticipate stimulative policy responses when volatility rises while simultaneously expecting weaker economic fundamentals during such periods.

B. Decomposing Market Expectations

For a fund's investment decisions, expectations about the equity market are central, as they directly shape the manager's strategy. To better understand how fund managers form these beliefs, we examine how each fund's equity market expectation relates to different factors. The finance literature highlights two broad determinants: macroeconomic fundamentals and government policy.

Table 3 reports panel regressions relating equity market expectations to these factors, including macroeconomic expectations and policy beliefs. First, fund managers' macroeconomic expectations are positively associated with their equity market expectations, as shown in Column (1). Second, Columns (2) through (4) isolate fiscal, monetary, and regulatory policy expectations, respectively. Each yields a highly significant positive coefficient (ranging from 0.179 to 0.188), indicating that equity market expectations are positively related to beliefs about individual policy dimensions. Column (5) aggregates these beliefs into average policy expectation, which remains significantly positive. Finally, Column (6) jointly includes macroeconomic fundamentals and average government policy and confirms their complementary roles, with both variables remaining significant.

Taken together, these findings suggest that macroeconomic and policy expectations are

important and distinct determinants of fund managers' equity market outlooks. The R^2 values from the single-variable regressions in Columns (1)–(5) all exceed 30%, and the R^2 from the joint regression in Column (6) is 36%. Because these panel regressions impose common coefficients across managers—a restriction unlikely to hold in practice—such high explanatory power, despite the restrictive specification, reinforces the view that fund managers' equity market expectations are shaped importantly by their views of macro fundamentals and policy.

While beliefs about macro fundamentals and policy explain a meaningful share of the variation in funds' equity market expectations, substantial variation remains. We interpret this residual component as capturing the fund manager's sentiment. This residual may reflect influences not directly captured by macro fundamentals or government policy, including the manager's own subjective views about future market movements and perceived beliefs of other market participants. Fully disentangling these channels is challenging. Nevertheless, this residual provides a broad, empirically tractable proxy for fund managers' sentiment.

With this interpretation in mind, we decompose each fund's equity market expectation into three components: macro fundamentals, policy, and sentiment. The macro and policy components are directly extracted from the Outlook sections of fund reports. We then construct the sentiment component as the residual from regressing equity market expectations on average policy expectations and domestic macroeconomic expectations. The fitted values capture the fundamentals- and policy-driven component of the market outlook, while the residuals—by construction orthogonal to fundamentals and policy—serve as our proxy for the fund's sentiment.

In what follows, we examine how a fund manager's views of these three dimensions relate to fund investment decisions and performance.

III. Predictability of Average Fund Beliefs

Do fund managers' expectations actually predict future market returns, macroeconomic fluctuations and policy developments? We explore this question by examining the predictive power of fund managers' average beliefs for the corresponding variables.

We begin with market returns. Running time-series regressions of subsequent three-month equity market index returns (RI_equity) on the cross-sectional averages of funds' expectations, our baseline specification is:

$$RI_equity_{t+1} = \alpha_i + \beta\overline{expectations_t} + \varepsilon_{t+1}. \qquad (3)$$

For the equity market benchmark, we use the Shanghai Shenzhen 300 Index (*hs300_index*), one of the most representative indices in China. The key independent variables are the cross-sectional averages of funds' expectations about the equity market and the three components related to macro fundamentals, policy, and fund sentiment ($expect_equity_market$, $expect_macro$, $expect_avg_policy$, and $equity_resid$) at time *t*.

Table 4 presents the regression results. Columns (1) to (5) are based on the simple average of funds' expectations, while Columns (6) to (10) employ the AUM-weighted average. To ensure statistical robustness, we apply Newey-West standard errors with three lags. The results under both approaches are highly consistent.

The findings reveal a striking pattern. Column (3) shows that the average policy expectations significantly and positively predict future equity index returns. Specifically, a one-unit increase in $expect_avg_policy$ corresponds to a 16.8% increase in the subsequent three-month equity index returns. In contrast, Columns (1), (2), and (4) show that average market expectations and the other belief components—including macroeconomic expectations and sentiment—exhibit no significant predicative power for future returns.

When we include macroeconomic expectations, policy expectations, and the sentiment proxy jointly in Column (5), the coefficient on policy expectations remains significantly positive and stable in magnitude, while the coefficients on other independent variables fall to insignificance.

What emerges from Table 4 is a clear picture: funds in our sample, on average, hold informed views about subsequent equity market returns. But here's what makes these results particularly noteworthy—this predictability is driven primarily by policy expectations rather than by overall views about the equity market or views about macro fundamentals. That funds possess informed policy views is perhaps unsurprising. What is striking, however, is that their macro-fundamental views contain little, if any, predictive content for subsequent market returns. This sharp contrast underscores the central role of government policy in shaping market dynamics in China, as argued by Brunnermeier, Sockin, and Xiong (2022).

The strong predictive power of fund managers' policy beliefs raises a natural follow-up question: can their expectations regarding specific policy dimensions—fiscal and monetary

policy—actually predict subsequent policy developments? [7] For fiscal policy, we focus on the government's deficit-to-GDP ratio target, announced in the central government work report typically released each March since 2010, which sets the target for the year. For monetary policy, we examine the average monthly year-on-year (YoY) growth rate of M2 from the publication month of a fund's semi-annual or annual report to that of the subsequent report. This focus reflects China's quantity-based monetary policy framework, which places greater emphasis on M2 growth than on a specific policy interest rate. We also investigate whether funds' expectations about macro fundamentals predict subsequent GDP growth.

We conduct time-series regressions of subsequent policy developments and macroeconomic outcomes on the corresponding cross-sectional averages of funds' expectations:

$$Policy/Macro_{t+1} = \alpha_i + \beta\overline{expectations}_t + \varepsilon_{t+1}. \qquad (3)$$

Table 5 presents the regression results. Columns (1)–(3) are based on the simple average of funds' expectations, while Columns (4)–(6) use the AUM-weighted average. We compute Newey–West standard errors with three lags. The results are remarkably consistent across specifications.

The evidence is compelling. Fiscal policy expectations significantly predict the subsequent deficit-ratio target in both the simple-average and AUM-weighted specifications (Columns (1) and (4)). Monetary policy expectations are likewise statistically significant predictors of future changes in M2 growth (Columns (2) and (5)). Macroeconomic fundamentals expectations also exhibit significant predictive power for subsequent GDP growth (Columns (3) and (6)). Across the board, managers' expectations map systematically into realized outcomes in both policy and macro domains.

Here's where the story gets interesting. While both macro beliefs and policy beliefs contain genuine forward-looking information, only policy beliefs predict subsequent market returns. This asymmetry suggests that fund managers' policy beliefs capture information beyond what is already incorporated in current market prices, while their beliefs about macro fundamentals are not so distinctive. The pattern is consistent with fund managers devoting greater effort to analyzing policy rather than fundamentals, as suggested by Brunnermeier, Sockin, and Xiong

[7] We focus on fiscal and monetary policies because, unlike regulatory policies, they generate clear, quantifiable outcomes, allowing us to directly assess how closely managers' expectations track realized policy changes.

(2022).

IV. Equity Allocations and Market Timing

In this section, we explore cross-fund variation to examine whether funds trade on their stated expectations and whether their expectations help them successfully time the equity market.

A. Expectations and Equity Allocations

Do funds put their money where their mouth is? We first examine whether funds' expectations translate into asset allocation decisions. We adopt a panel regression of each fund's equity allocation, measured as the stock holding ratio, on its expectation about the equity market or its belief component. Table 6 reports the results. We include time fixed effects and fund fixed effects in Columns (1)-(5). In Columns (6)-(1), we replace fund fixed effects by fund manager fixed effects. The results are highly consistent.

Column (1) shows that funds' equity allocations align with their equity market expectations. A one-unit increase in $expect_equity_market$ is associated with a 1.69 percentage-point increase in equity allocation. This confirms that fund managers act on what they say in their outlooks.

Columns (2)-(4) further show that equity allocation is positively and significantly correlated with each of the three belief components—macro fundamentals, policy, and sentiment. More interestingly, Column (5) reveals that while funds respond significantly and positively to each component, they respond most strongly to sentiment. A one-unit increase in beliefs about macro fundamentals, policy, and fund sentiment is associated with increases of 0.749, 0.762, and 1.271 percentage points in equity allocation, respectively. This pattern suggests that fund managers place greater weight on their own sentiment than on their beliefs about macro fundamentals or policy when adjusting equity exposure.

These findings reveal a striking disconnect. Although funds' policy beliefs exhibit the strongest predictive power for subsequent market returns, managers do not appear to fully capitalize this advantage in their equity allocation choices. Instead, equity allocations are driven most strongly by sentiment rather than by policy expectations. To the extent that their sentiment has little predictive power for subsequent market returns, this emphasis does not help improve fund performance.

B. Market Timing

We now turn to how managers' beliefs relate to their market timing ability. We measure market timing by interacting the change in a fund's equity share—the manager's active adjustment of market exposure—with the subsequent market return. This metric is positive when managers increase equity exposure ahead of rising markets or reduce exposure ahead of falling markets, and negative when the manager does the opposite.

Specifically, for fund i at time t, we estimate:

$$\Delta stock_ratio_{i,t} \times RI_equity_{t+1} = \alpha_i + \lambda_t + \beta\,|expectations_{i,t}| + \delta X_{i,t} + \varepsilon_{i,t+1}$$

where *Δstock_ratio* is the change in the fund's equity share in percentage, RI_equity_{t+1} is the next-period market index return, and $|expectations_{i,t}|$ denotes the absolute value of the relevant belief measure. We control for total net assets, fund flows, and fund age in $X_{i,t}$, and include time fixed effects along with either fund or fund manager fixed effects. We use the absolute value of the manager's belief because trading induced by either optimistic or pessimistic beliefs may both contribute to market-timing performance.

Table 7 reports the regression results, which reveal a clear pattern: market timing is tightly linked to the absolute level of policy beliefs but is unrelated to fundamentals belief or fund sentiment. Across specifications with fund fixed effects (Columns (1) to (5)) and manager fixed effects (Columns (6) to (10)), the coefficient on |expect_avg_policy| is positive, economically meaningful, and highly significant. This indicates that when managers hold stronger policy views—regardless of direction—they scale their equity exposure in ways that align with subsequent market movements.

By contrast, neither the absolute value of overall equity market expectations nor macro expectations nor their sentiment component exhibit statistically significant relationships with market timing. Estimates for these variables are small in magnitude and accompanied by t-statistics close to zero. These results hold under both fund and manager fixed effects, with consistent controls and time fixed effects.

Two key insights emerge. First, effective market timing in this setting is policy-driven: managers condition their dynamic exposure decisions on the intensity of their policy views, and those policy-attuned adjustments pay off when markets subsequently move. Second, timing performance is not driven by views about contemporaneous macro fundamentals or by sentiment embedded in equity market beliefs.

V. Fund Performance

We have established that funds' market expectations—especially their policy beliefs—have strong predictive power for subsequent market returns. We have also shown that funds adjust their equity allocations in response to these expectations, and that successful market timing is driven by the absolute strength of policy beliefs rather than by macro beliefs or fund sentiment. This raises a natural question: does the return predictability embedded in managers' beliefs translate into fund performance?

Measuring Belief-Based Return Predictability. We construct a measure of each fund's belief-based return predictability not only for overall market expectations but also for each belief component, and then examine how these predictability measures relate to fund investment performance.

We begin by measuring each fund's expectation-based return predictability across four dimensions: equity market, macro fundamentals, policy, and sentiment. This measure captures how well a fund manager's expectations predict future equity market returns. Specifically, for each fund, we estimate a series of rolling-window regressions over five periods using:

$$RI_equity_{t+1} = a_i + b_i expectations_{i,t} + \varepsilon_{i,t+1}. \qquad (4)$$

We require at least three valid observations for estimation, since some periods within the five-period window may contain missing values for certain dimensions (e.g., "Not Mentioned"). For each fund i at time t, we estimate b_i and use it as a proxy for the recent predictive accuracy of that expectation. To facilitate comparisons across funds, we normalize these coefficients within each period and convert them into cross-sectional rankings ranging from 0 to 1.

Linking Predictability to Performance. To examine the relationship between fund performance and expectation-based return predictability, we estimate:

$$r_{i,t+1} = \lambda_t + \gamma \text{Coef_expectation}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}, \qquad (5)$$

where $r_{i,t+1}$ is the monthly return of fund i in month t+1, measured both before and after risk adjustment. The key independent variable, $\text{Coef_expectation}_{i,t}$, is the b_i coefficient estimated from equation (4) using data up to month t, and captures the fund's market-return predictability associated with a particular belief dimension. Time fixed effects λ_t account for

market-wide factors that may influence fund performance. The control variables $X_{i,t}$ include total net assets (tna), fund flows, and fund age.

Table 8 reports the regression results. We examine fund performance measured by raw monthly returns (ret) in Panel A, risk-adjusted alphas using the three-factor (CH3) in Panel B, and alphas from the four-factor (CH4) models in Panel C. All return metrics, whether raw or risk adjusted, are reported in percentage terms.

As shown in Columns (1) and (2) across Panels A to C, the coefficient on return predictability associated with overall market expectations is positive but generally insignificant, except in Panel C. When we decompose beliefs, the coefficients on return predictability linked to macro-fundamental expectations are negative and insignificant, whereas those associated with policy expectations are consistently statistically significant. This pattern indicates a robust relationship between funds' policy-analysis capability and their investment performance. In Column (3) of each panel, the estimated coefficients are 0.228 for monthly raw returns, 0.0957 for CH3 alpha, and 0.0933 for CH4 alpha, suggesting that funds with stronger policy-prediction ability deliver superior performance—whether measured using raw returns or risk-adjusted alphas—even after controlling for other fund characteristics.

The Sentiment Puzzle. Column (4) presents a puzzling finding: the coefficients on the return predictability associated with fund sentiment are significantly negative. This implies that funds whose residual beliefs are less effective at predicting market returns tend to perform better. At first glance, this seems counterintuitive—why would poorer market timing ability in residual beliefs enhance performance?

To better understand this tension, we examine the relationship between a fund's skill in predicting policy and the predictive content of its sentiment. Table 9 reports the results of regressing the predictive accuracy of a fund's policy beliefs on the predictive accuracy of its sentiment component. We find a statistically significant negative association between these two. Even after controlling for fund fixed effects or fund-manager fixed effects, the coefficients remain negative, with t-statistics consistently exceeding 5. This negative correlation reveals that funds with superior policy analysis capability—the main source of fund alpha—tend to have sentiment components that are less predictive of future market returns.

The Big Picture. Collectively, these findings reveal a nuanced interplay among different components of fund beliefs. Funds' ability to analyze policy developments, rather than macro

fundamentals, is the primary driver of their performance. Yet the same funds that excel in policy analysis also display sentiment with weaker predictive content for market returns. As a result of these offsetting forces, the overall relationship between funds' market-timing capability and performance is positive but relatively weak.

This negative correlation between policy-analysis strength and sentiment predictability is crucial and merits closer examination. We address this issue in the next section.

Robustness Checks. We conduct several additional validation tests. First, we exclude passive index funds from our sample; the results are reported in Table 6A of Internet Appendix. Second, we construct the expectation-based return predictability measures using an expanding-window approach rather than a rolling window; the results are reported in Table 7A of Internet Appendix. Across both exercises, the findings remain unchanged: policy-expectation-based predictability consistently predicts future fund performance, whereas predictability associated with macroeconomic expectations or fund sentiment does not.

VI. Fund Flows

Our analysis uncovers a puzzling contrast between funds' beliefs about policy and fund sentiment. Policy-related beliefs strongly predict subsequent market returns, yet they are not the primary determinant of equity allocations. In contrast, fund sentiment has little predictive power for market returns, yet it exerts the largest influence on equity holdings. Moreover, the funds that are most capable of analyzing policy also exhibit sentiment components that are worse at predicting future returns. How can we reconcile these patterns?

Two Possible Explanations. One possibility is that some managers may not fully recognize the influence of their own sentiment. Behavioral forces such as overconfidence could lead them to overweight noisy signals at the expense of their more informed views about policy. Although this noise-trading channel is likely part of the story, it cannot be the whole explanation. After all, these funds, on average, generate positive alphas, and the same funds with superior policy analysis capabilities also display weaker market-timing sentiment.

A second, more compelling explanation is that aligning stated beliefs with investor sentiment helps attract fund flows. Fund managers are rewarded not only for performance but also for assets under management, since management fees scale with fund size. Although superior performance attracts inflows, it is not the only mechanism. Resonance with investor

sentiment may also matter. Gennaioli, Shleifer, and Vishny (2015) argue that the relationship between fund managers and investors resembles that between doctors and patients: doctors may not always be able to cure patients, but what matters most is making them feel better.

This reasoning suggests that funds may strategically adopt sentiment that aligns with investor sentiment to attract fund flows. Since investor sentiment tends to negatively predict future returns (Baker and Wurgler, 2003), alignment with investor sentiment would require fund managers to adopt a sentiment component with weak or negative predictive power for market returns. This motive is consistent with our earlier finding that funds with superior policy insights tend to exhibit sentiment that is less effective at forecasting market movements.

Testing the Catering Hypothesis. Motivated by this idea, we hypothesize that fund sentiment is more strongly related to subsequent fund flows than policy beliefs. To test this hypothesis, we use funds' overall market beliefs and their three belief components to predict future flows in panel regressions. Table 10 reports the results for cumulative fund flows over the six months following the release of semi-annual or annual reports, with controls for lagged fund performance over the prior six months.

The results are striking. Column (1) shows that funds' overall equity-market beliefs are positively and significantly associated with subsequent flows. Column (4) shows that fund sentiment is also positively and significantly related to subsequent flows, with an even larger coefficient. By contrast, Columns (2) and (3) show that beliefs about macro fundamentals and policy are not significantly related to future flows. When all three components are included jointly in Column (5), sentiment remains the only component significantly associated with future flows, and the coefficient remains positive.

Across all specifications, past fund returns are positively and significantly related to subsequent flows, confirming the central role of performance in shaping investor demand. Critically, even after controlling for past performance, fund sentiment retains its positive association with future flows. This suggests that sentiment operates as an independent channel for attracting capital—one that is distinct from demonstrated investment skill.

Strategic Catering and Market Conditions. We next examine whether this catering to sentiment varies with aggregate market conditions. If funds align their stated beliefs with investor sentiment to attract flows, this strategy should be most effective when aggregate inflows are strong. Table 11 presents these results.

Panel A reveals that funds express more positive sentiment when the industry as a whole is experiencing large inflows. Specifically, we regress funds' sentiment (the residual component of their market expectations) on aggregate fund flows. The coefficient is positive and highly significant, indicating that funds, on average, express more bullish residual beliefs during periods of industry-wide enthusiasm. This pro-cyclicality suggests that funds tend to "ride the wave" of investor optimism.

Panel B tests whether the payoff to this sentiment—in the form of fund-specific inflows—depends on market conditions. We include an interaction between a fund's sentiment and aggregate flows. The positive coefficient on the interaction term indicates that the relationship between a fund's sentiment and its subsequent fund flows is stronger when aggregate flows are high. In other words, catering to investor sentiment is particularly effective in periods of market-wide exuberance. This finding supports the view that managers strategically adjust their stated beliefs when the marginal benefit of doing so is greatest.

Solving the Paradox. Taken together, the results support our hypothesis: fund sentiment is more strongly aligned with subsequent fund flows than policy beliefs. Moreover, during periods of high aggregate inflows, both fund sentiment and its flow sensitivity rise, suggesting that managers strategically adjust their stated beliefs to resonate with prevailing market sentiment and attract capital.

This logic also helps resolve the paradox we identified earlier. Skilled funds with strong alphas may deliberately tilt their overall market narratives toward prevailing sentiment to boost flows. Such strategic alignment can weaken the return predictability of the residual belief component (fund sentiment), helping explain why funds with stronger policy analysis ability tend to exhibit sentiment that is a poorer predictor of future returns. In essence, the best policy analysts are not bad at reading sentiment—rather, they strategically choose to express sentiment that attracts flows rather than predicts returns.

This evidence reveals a fundamental tension in asset management: fund managers face competing incentives. On one hand, they can maximize returns by acting on superior policy analysis. On the other hand, they can maximize fee income by expressing beliefs that resonate with investor sentiment. The evidence suggests that many skilled managers pursue both objectives simultaneously—generating alpha through policy insights while attracting assets through sentiment alignment. This dual strategy explains why fund sentiment is the most important driver of equity allocations despite its poor ability to predict subsequent market

returns.

VII. Conclusion

This paper provides new evidence on the structure and consequences of fund managers' beliefs in China by leveraging the mandatory Outlook sections in Chinese mutual fund semi-annual and annual reports. Using an LLM-based approach, we extract each fund's outlook for the domestic equity market and decompose it into beliefs about macroeconomic fundamentals, beliefs about government policy, and a residual component that we interpret as fund sentiment.

This decomposition yields a clear hierarchy of information content: funds' policy beliefs significantly predict subsequent market returns, while beliefs about macro fundamentals and sentiment offer little or no forecasting value. Furthermore, the strength of managers' policy beliefs drives their market timing: more pronounced views lead to equity exposure adjustments that systematically correspond to later market outcomes. Consequently, funds with stronger policy-based forecasting ability deliver higher raw returns and risk-adjusted alphas.

What makes this finding particularly striking is the contrast with macro fundamentals. Despite devoting substantial discussion to economic conditions in their reports, funds' beliefs about macro fundamentals contribute neither to their market timing nor to their performance. This pattern reveals where skilled managers direct their analytical efforts: they focus on interpreting government policies rather than forecasting economic fundamentals. Such prioritization is a rational response to China's market environment, where policy interventions exert outsized influence on asset prices.

At the same time, we document a striking tension between what predicts returns and what drives portfolio choice. Although policy beliefs contain the most valuable information for future market returns, they are not the dominant determinant of equity exposure. Instead, the residual sentiment component—despite having little predictive power for subsequent market returns—exerts the strongest influence on equity allocations and is the only belief component that robustly predicts subsequent fund flows after controlling for past performance. The sentiment–flow link is more pronounced during periods of high aggregate inflows, consistent with a catering motive in which funds align their narratives with prevailing investor sentiment to attract capital.

These patterns reveal a fundamental tension in asset management that extends beyond

China. Funds face dual objectives: trading on informed views to generate alpha while simultaneously managing sentiment in their communications and portfolio allocations to sustain investor demand. This dual mandate helps explain why the most skilled policy analysts also exhibit sentiment that poorly predicts returns—they are strategically catering to investor sentiment rather than expressing pure market views.

Beyond these substantive findings, our approach illustrates how modern language models can be used to recover multidimensional belief structures from textual disclosures, opening new avenues for studying how beliefs, incentives, and market dynamics interact.

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Tables

Table 1: Summary Statistics

This table presents summary statistics for key variables in our study, based on data from the Wind database. We include only equity and hybrid funds and exclude funds with fewer than 10 valid semi-annual or annual reports from 2008 to 2023. Our final sample comprises 297,210 fund-month observations and 52,205 reports spanning 2008 to 2023. Panel A presents summary statistics for LLM-generated variables, as well as fund accounting and characteristics. Daily alpha is calculated using the Chinese factor model (Liu, Stambaugh, and Yuan, 2019) and converted to monthly alpha. Semi-annual and quarterly data are aligned to monthly data based on the latest available information. Panel B displays the correlation matrix for expectations.

Panel A: Summary Statistics

	Mean	Sd	Min	P25	Med	P75	Max
Expectation:							
equity_market	0.580	0.519	-1	0.5	.5	1	1
macro	0.041	0.790	-1	-0.5	.5	1	1
fiscal_policy	0.752	0.485	-1	0.5	1	1	1
monetary_policy	0.434	0.631	-1	0	.5	1	1
regulatory_policy	0.375	0.749	-1	0	.5	1	1
avg_policy	0.490	0.597	-1	0	.75	1	1
Key variables:							
ret_m (in percent)	0.626	5.903	-48.435	-2.017	0.380	3.081	47.751
alpha_ch3 (in percent)	0.289	3.462	-39.508	-1.179	0.099	1.546	52.371
alpha_ch4 (in percent)	0.276	3.402	-39.891	-1.164	0.095	1.524	54.804
semi_ret (in percent)	3.529	14.894	-22.234	-6.368	1.756	10.716	43.692
stock_ratio (in percent)	61.069	34.042	0.000	21.410	78.520	89.120	93.910
stock_ratio_diff (in percent)	0.879	9.535	-23.470	-2.730	0.120	3.900	30.740
tna (in millions)	1195	1844	14.83	128	431.8	1333	8383
flow	-0.001	0.343	-0.592	-0.125	-0.033	0.010	1.464
age (in months)	65.613	45.671	5	30	57	90	187

Panel B: Correlation Matrix

Expectation:	equity_market	macro	fiscal_policy	monetary_policy	regulatory_policy	avg_policy
equity_market	1.000					
macro	0.357	1.000				
fiscal_policy	0.237	0.186	1.000			
monetary_policy	0.287	-0.025	0.346	1.000		
regulatory_policy	0.361	0.267	0.335	0.328	1.000	
avg_policy	0.338	0.102	0.794	0.897	0.886	1.000

Table 2: Equity Market, Macroeconomic, and Policy Expectations

Panel A displays the R-squared values from panel regressions of expectations for equity market, macroeconomic, and policy. These regressions are conducted using three specifications: (1) fund fixed effects, (2) time fixed effects, and (3) both fund and time fixed effects. Panel B displays the R-squared values from panel regressions estimated using six specifications: Columns (1) to (3) focus on fund family effects, sequentially including: (1) fund family fixed effects, and (2) fund family and time fixed effects. Columns (3) and (4) focus on fund manager effects, incorporating: (3) fund manager fixed effects, and (4) fund manager and time fixed effects.

Panel A: Variation Decomposition – Fund and Time Fixed Effect			
	(1)	(2)	(3)
	Fund FE	Time FE	Fund+Time FE
Expectation:			
equity_market	0.136	0.130	0.249
macro	0.125	0.264	0.375
fiscal_policy	0.214	0.146	0.342
monetary_policy	0.117	0.428	0.505
regulatory_policy	0.274	0.155	0.381
avg_policy	0.110	0.297	0.385

Panel B: Variation Decomposition – Fund Family and Fund Manager Fixed Effect				
	(1)	(2)	(3)	(4)
	Fund Family		Fund Manager	
	FE	+ Time FE	FE	+ Time FE
Expectation:				
equity_market	0.023	0.149	0.279	0.355
macro	0.018	0.280	0.278	0.463
fiscal_policy	0.030	0.177	0.354	0.450
monetary_policy	0.014	0.437	0.261	0.576
regulatory_policy	0.033	0.184	0.412	0.479
avg_policy	0.015	0.310	0.255	0.469

Table 3: Decomposing Equity Market Expectations

This table reports the results of regressions examining the relationship between fund managers' equity market expectations and their macroeconomic and policy expectations. All regressions include fund and time fixed effects. All regressions include fund size, flow and age as controls and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Expectation:				equity_market		
macro	0.197***					0.160***
	(51.27)					(38.26)
fiscal_policy		0.179***				
		(15.98)				
monetary_policy			0.185***			
			(25.26)			
regulatory_policy				0.188***		
				(24.92)		
avg_policy					0.228***	0.193***
					(36.31)	(30.45)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	43075	13518	26490	13541	34702	32406
R-sq	0.317	0.394	0.314	0.407	0.316	0.358

Table 4: The Predictability of Market Expectations for Market Returns

This table presents results from time-series regressions of market returns on fund expectations. The dependent variable is the quarterly return of the CSI 300 Index calculated over the three months following the report publish month. The index tracks the 300 largest, most liquid A-shares on the Shanghai and Shenzhen exchanges, representing about 60% of their total market capitalization. The independent variables of interest are the expectations for the equity market, expectations for the macroeconomy, the average expectation across three policy dimensions, and the residual obtained from regressing equity market expectations on macroeconomy and policy expectations. These variables are calculated as either an equal-weighted (columns 1 to 5) or value-weighted (columns 6 to 10) average across funds. In columns (5) and (10), we concurrently include policy and macroeconomy beliefs alongside the equity market belief residual to compare their relative explanatory power. Index returns are in monthly percent. Standard errors are Newey-West adjusted for serial correlation with a lag of three semi-annual periods. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					market_return					
Expectation:			Equal weighted					Value weighted		
equity_market	0.0798					0.0946				
	(0.65)					(0.74)				
macro		-0.0170			0.00226		-0.0229			-0.00819
		(-0.45)			(0.04)		(-0.59)			(-0.15)
avg_policy			0.168**		0.194**			0.176**		0.202***
			(2.53)		(2.68)			(2.62)		(2.77)
equity_resid				-0.130	-0.319				-0.00486	-0.210
				(-0.68)	(-1.61)				(-0.03)	(-1.26)
N	32	32	32	32	32	32	32	32	32	32
R-sq	0.015	0.003	0.207	0.010	0.264	0.022	0.005	0.218	0.000	0.253

Table 5: Fund Beliefs Predicting Policies & Macroeconomic Fundamentals

Table 2 presents results using semi-annual data from 2008 to 2023. The dependent variables represent either real policy targets or macroeconomic fundamentals. In columns (1) and (4), the dependent variable is the deficit ratio target, a proxy for fiscal policy typically announced in March of each year (since 2010) regarding the full ongoing year. In columns (2) and (5), the dependent variable is the average monthly year-on-year (YoY) growth rate of M2, serving as a proxy for monetary policy. In columns (3) and (6), the dependent variable is the average monthly YoY GDP growth rate, representing macroeconomic fundamentals. For both M2 and GDP, the growth rates are calculated over the period from the publication month of the fund's (semi-)annual report to the publication month of the subsequent report. All regressions control for the lagged value of the respective dependent variable, defined as the most recent value available prior to the current report's publication. The independent variable of interest is the belief measure (regarding fiscal policy, monetary policy, or macroeconomics), calculated as either an equal-weighted (columns 1 to 3) or value-weighted (columns 4 to 6) average across funds. Standard errors are Newey-West adjusted for serial correlation with a lag of three semi-annual periods. t-statistics are reported in parentheses. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Equal weighted			Value weighted		
	Deficit $\%_{t+1}$	$M2_YoY_{t+1}$	GDP_YoY_{t+1}	Deficit $\%_{t+1}$	$M2_YoY_{t+1}$	GDP_YoY_{t+1}
expect_fiscal_policy	0.720**			0.584*		
	(2.38)			(1.95)		
Deficit $\%_t$	0.609***			0.602***		
	(4.44)			(4.04)		
expect_monetary_policy		2.693**			2.679*	
		(2.09)			(1.99)	
$M2_YoY_t$		0.973***			0.968***	
		(9.44)			(9.41)	
expect_macro			1.803**			1.681*
			(2.20)			(2.03)
GDP_YoY_t			0.638***			0.638***
			(5.30)			(5.31)
N	29	32	32	29	32	32
R-sq	0.468	0.802	0.448	0.444	0.803	0.437

Table 6: Fund Expectations and Equity Allocations

This table reports results for semi-annual level panel regressions of fund portfolio holdings on fund expectations. The dependent variable is stock holding ratio in percentage. The explanatory variables are the expectations for the equity market, the expectations for the macroeconomy, the average expectation across the three policy dimensions, and the residual from regressing the equity market expectation on the macroeconomy and policy expectations. All regressions in columns (1) to (5) include fund and time fixed effects, while those in columns (6) to (12) include fund manager and time fixed effects. All regressions include fund size, flow and age as controls and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Expectation:						stock_ratio				
equity_market	1.691***					1.194***				
	(11.04)					(6.49)				
macro		0.749***			0.626***		0.571***			0.485***
		(6.87)			(4.79)		(3.87)			(2.82)
avg_policy			0.762***		0.630***			0.376*		0.118
			(5.25)		(4.05)			(1.91)		(0.57)
equity_resid				1.271***	1.359***				0.757***	0.806***
				(6.35)	(6.76)				(3.19)	(3.37)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Manager FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	47623	46509	37650	32200	32200	45467	44328	35422	30010	30010
R-sq	0.855	0.864	0.871	0.870	0.870	0.783	0.797	0.808	0.804	0.804

Table 7: Market Timing

This table reports results from semi-annual panel regressions of fund market timing on fund absolute beliefs. The dependent variable is fund market timing, measured as the interaction between the change in a fund's equity share and the subsequent quarterly equity market return following the report's publish month. The explanatory variables are the absolute values of expectations for the equity market, expectations for the macroeconomy, the average expectation across three policy dimensions, and the residual obtained from regressing equity market expectations on macroeconomy and policy expectations. All regressions in columns (1) to (5) include fund and time fixed effects, while those in columns (6) to (12) include fund manager and time fixed effects. All regressions include fund size, flow and age as controls and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Market_Timing					
|expect_equity_market|	-0.00512					-0.0210				
	(-0.32)					(-1.16)				
|expect_macro|		-0.00412			-0.0209		0.00274			-0.0222
		(-0.24)			(-0.96)		(0.14)			(-0.87)
|expect_avg_policy|			0.0596***		0.0715***			0.0607***		0.0820***
			(3.69)		(3.86)			(3.30)		(3.86)
|expect_equity_resid|				-0.0255	-0.0186				-0.0185	-0.0105
				(-0.93)	(-0.68)				(-0.61)	(-0.35)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Manager FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46802	45674	36939	31616	31616	44649	43491	34719	29442	29442
R-sq	0.177	0.176	0.192	0.204	0.204	0.258	0.257	0.272	0.286	0.287

Table 8: Predictive Accuracy and Fund Performance

This table presents the results of monthly panel regressions examining the relationship between fund performance and the past accuracy of fund beliefs in predicting equity market. The sample period is the three months (a quarter) following the current report's publication month. To construct each fund's past belief prediction accuracy at time t, we estimate the coefficient from a rolling regression over the past five periods, regressing the future three-month CSI300 index return following each (semi-)annual report's publication month on the corresponding report beliefs (equity market, macroeconomic, average policy, and equity market residual). At least three valid data points are required for this estimation. All coefficients are normalized and converted into rankings ranging from 0 to 1. The dependent variable is raw return (Panel A), the alpha of the Chinese three-factor model (Panel B), the alpha of the Chinese four-factor model (Panel C). Both returns and alphas are expressed in monthly percentage terms. All regressions include time fixed effects, and are estimated with constants (not reported here). We adjust standard errors for clustering at the fund level, and t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

Panel A: Raw Return				
	(1)	(2)	(3)	(4)
	ret_m	ret_m	ret_m	ret_m
Coef_equity_market	0.0361			
	(0.69)			
Coef_macro		-0.0823		
		(-1.64)		
Coef_policy			0.228***	
			(4.13)	
Coef_equity_resid				-0.132**
				(-2.39)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	101673	106914	89470	78017
R-sq	0.557	0.541	0.526	0.549
Panel B: Alpha (Three factors)				
	(1)	(2)	(3)	(4)
	alpha_ch3	alpha_ch3	alpha_ch3	alpha_ch3
Coef_equity_market	0.0555			
	(1.40)			
Coef_macro		-0.0340		
		(-0.87)		
Coef_policy			0.0957**	
			(2.22)	
Coef_equity_resid				-0.0932**
				(-2.16)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	101673	106914	89470	78017
R-sq	0.120	0.114	0.113	0.120

Panel C: Alpha (Four factors)				
	(1)	(2)	(3)	(4)
	alpha_ch4	alpha_ch4	alpha_ch4	alpha_ch4
Coef_equity_market	0.0916**			
	(2.24)			
Coef_macro		-0.00606		
		(-0.15)		
Coef_policy			0.0933**	
			(2.12)	
Coef_equity_resid				-0.0842*
				(-1.88)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	101673	106914	89470	78017
R-sq	0.090	0.086	0.084	0.091

Table 9: Relationship of Belief Predictive Accuracy

This table reports the regression results of the predictive accuracy of policy beliefs on the predictive accuracy of equity market residuals. All coefficients are normalized and converted into rankings ranging from 0 to 1. Column (1) includes fund and time fixed effects, and Column (2) includes fund manager and time fixed effects. All regressions include fund size, flow and age as controls and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with $*$, $**$, and $***$ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)
	Coef_policy	
Coef_equity_resid	-0.0608***	-0.0582***
	(-6.75)	(-5.97)
Control	Yes	Yes
Fund FE	Yes	No
Manager FE	No	Yes
Time FE	Yes	Yes
N	26389	24969
R-sq	0.368	0.442

Table 10: Fund Expectations Predicting Fund Flow

This table presents the results for fund flow forecasting regressions. Fund flow is measured over the three months following the publication month of the (semi-)annual report. All regressions include lagged fund performance, calculated over the three months prior to the (semi-)annual report publication. Additional control variables include fund size, past flow, and age. All regressions in columns (1) to (5) include fund and time fixed effects, while those in columns (6) to (10) include fund manager and time fixed effects. All regressions are estimated with constants (not reported here). Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Expectation:						**Fund Flow$_{t+1}$**				
equity_market	0.00988***					0.00874**				
	(3.29)					(2.57)				
macro		-0.00150			-0.00149		-0.00288			-0.00434
		(-0.68)			(-0.54)		(-1.14)			(-1.38)
avg_policy			-0.00145		-0.00110			0.0000934		0.000778
			(-0.47)		(-0.33)			(0.03)		(0.20)
equity_resid				0.0125***	0.0123***				0.0119**	0.0117**
				(2.85)	(2.80)				(2.38)	(2.33)
quarterly_ret	0.300***	0.262***	0.240***	0.234***	0.235***	0.332***	0.289***	0.259***	0.252***	0.252***
(Until publish month)	(10.42)	(8.88)	(7.31)	(6.50)	(6.49)	(10.46)	(8.98)	(7.19)	(6.32)	(6.31)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Manager FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	47656	46545	37684	32226	32226	45487	44353	35441	30024	30024
R-sq	0.146	0.146	0.160	0.174	0.174	0.206	0.212	0.226	0.231	0.231

Table 11: Market Expectation Residual and Aggregate Flow

Panel A presents regression results regarding the relationship between fund equity market expectation residuals and aggregate fund flows. The dependent variable is the equity market expectation residual, while the explanatory variable is aggregate fund flow (Avg $Flow_t$), defined as the value-weighted average of all sample funds' three-month flows prior to the fund report's publish month in each period. Column (1) includes fund fixed effects, and Column (2) includes fund manager fixed effects. Panel B reports the results of panel regressions designed to evaluate how the impact of equity market belief residuals on future fund flows varies with aggregate fund flow. Fund future flows (Fund $Flow_{t+1}$) are measured over the three months following the publish month of the (semi-)annual report. The main explanatory variable is the equity market expectation residual, and we also include interaction terms between the equity market expectation residual and aggregate fund flow. Column (1) includes fund and time fixed effects, and Column (2) includes fund manager and time fixed effects. All regressions in Panels A and B include fund size, flow, and age as controls and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

Panel A: Aggregate Flow and Market Expectation Residual		
	(1)	(2)
		$expect_equity_resid_t$
Avg $Flow_t$	0.281***	0.312***
	(5.66)	(5.34)
Control	Yes	Yes
Fund FE	Yes	No
Manager FE	No	Yes
N	32294	30048
R-sq	0.011	0.149
Panel B: Market Expectation Residual Predicting Fund Flow		
	(1)	(2)
		Fund $Flow_{t+1}$
$expect_equity_resid_t$	0.0172***	0.0158***
	(3.67)	(2.99)
$expect_equity_resid_t$	0.208***	0.193**
× Avg $Flow_t$	(2.67)	(2.21)
quarterly_ret	0.232***	0.249***
(Until publish month)	(6.41)	(6.24)
Control	Yes	Yes
Fund FE	Yes	No
Manager FE	No	Yes
Time FE	Yes	Yes
N	32226	30024
R-sq	0.174	0.231

Internet Appendix

Table 1A: Count of Fund Semi-Annual and Annual Reports

This table reports the valid observations of semi-annual and annual reports spanning from 2008 to 2023. We include only equity and hybrid funds, and we further exclude funds with fewer than 10 reports during this period.

Year	Semi	Annual	Total
2008	221	266	487
2009	309	360	669
2010	397	439	836
2011	491	564	1,055
2012	625	707	1,332
2013	750	824	1,574
2014	896	985	1,881
2015	1,120	1,477	2,597
2016	1,682	1,911	3,593
2017	1,963	2,379	4,342
2018	2,609	2,760	5,369
2019	2,828	2,918	5,746
2020	2,912	2,893	5,805
2021	2,881	2,858	5,739
2022	2,857	2,819	5,676
2023	2,774	2,730	5,504
Total	25,315	26,890	52,205

Table 2A: LLM response consistency

This table reports the verification results of our methodology to avoid concerns about lookahead bias when applying LLM. We conduct robustness checks by modifying the temporal information in the report content. These verifications are performed using three specifications: (1) removing year references; (2) shifting dates forward by five years (e.g., replacing the year 2008 with 2013); and (3) shifting dates backward by five years. We randomly select one thousand samples and test for each specification.

	(1)	(2)	(3)
Expectation:	**no year**	**5y forward**	**5y backward**
equity_market	0.904	0.892	0.899
national_macroeconomic	0.901	0.905	0.904
fiscal_policy	0.907	0.904	0.905
monetary_policy	0.911	0.906	0.912
regulatory_policy	0.937	0.944	0.937

Table 3A: Validation of LLM Responses

This table reports the validation results of LLM-generated annotations against human annotations. We select 50 high-quality data points and evaluate them across three key expectation dimensions: macroeconomic fundamentals, the equity market, and the bond market. In the first round, three human labelers, well-versed in finance and macroeconomics, independently annotate each data point, and the human label is determined based on the majority vote. Given the complexity of the task, we require them to choose from three categories: positive, neutral, or negative. We also adjust LLM annotations from five categories to these three (e.g., weakly positive is mapped to positive). In the second round, we consult two additional domain experts. These experts assign a final label without knowing the source of the existing disagreeing label pairs (LLM vs. human).

	Macro	**Equity**
First Round:		
Consistent Number	43	40
Inconsistent Number	5	7
Human Label Conflict Number	2	3
1st Consistency Rate	0.86	0.80
Second Round:		
Agree with LLM Number	4	8
2nd Consistency Rate	0.94	0.96
Overall Consistency Rate	0.95	

Table 4A: Fund Expectations and Fund Characteristic

This table reports results for semi-annual panel regressions of fund managers' beliefs on fund characteristics. The explanatory variables include semi-annual return (semi_ret), fund size (tna), fund flow (flow), and fund age (age). All explanatory variables are based on the last non-missing available observation for the report's end month. All regressions in columns (1) to (4) include time fixed effects, while those in columns (5) to (8) include fund and time fixed effects. All regressions are estimated with constants, which are not reported. Standard errors are adjusted for clustering at the fund level. t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Expectation:			
	equity_market	macro	avg_policy	equity_resid	equity_market	macro	avg_policy	equity_resid
semi_ret	-0.0361	0.0918***	0.182***	-0.0856***	-0.0565**	-0.00726	0.185***	-0.0945***
(Until publish month)	(-1.46)	(2.59)	(6.36)	(-3.71)	(-2.30)	(-0.21)	(6.44)	(-3.73)
log_tna	-0.000310	0.000401	-0.00257	-0.000559	-0.000302	0.00171	0.00193	-0.000511
	(-0.16)	(0.14)	(-1.24)	(-0.60)	(-0.11)	(0.47)	(0.66)	(-0.21)
flow	-0.000574	0.00201	-0.0146**	0.00279	-0.00314	0.00159	-0.0191**	0.00303
	(-0.08)	(0.21)	(-1.99)	(0.45)	(-0.45)	(0.17)	(-2.49)	(0.44)
age	-0.0000923	0.000411***	0.000129	0.000442***	-0.000846	0.000307	-0.000146	-0.00108*
	(-1.16)	(3.50)	(1.62)	(12.00)	(-1.55)	(0.38)	(-0.24)	(-1.95)
Fund FE	No	No	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	47750	46642	37789	32279	47741	46635	37764	32279
R-sq	0.130	0.264	0.298	0.065	0.249	0.375	0.386	0.069

Table 5A: Market Condition and Fund Expectations

This table reports the results of semi-annual panel regressions of fund managers' expectations on market conditions. The explanatory variables include market performance data, represented by the semi-annual return of the Shanghai Shenzhen 300 Index (semi_hs300_ret), as well as market realized volatility data, measured by the semi-annual standard deviation of the daily returns of the Shanghai Shenzhen 300 Index (semi_hs300_sd). Both market return and realized volatility are measured up to the report's publication month. Additional control variables include fund size, past flow, and age. All explanatory variables are based on the last non-missing available observation for the report's end month. All regressions include fund fixed effects and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at the fund level. t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Expectation:			
(Until publish month)	equity_market		macro		avg_policy		equity_resid	
semi_hs300_ret	0.347***		0.563***		0.0532***		0.237***	
(Until publish month)	(23.04)		(25.82)		(3.11)		(15.47)	
semi_hs300_sd		-1.009		-10.36***		30.36***		-4.970***
(Until publish month)		(-1.58)		(-11.53)		(42.00)		(-7.85)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	47764	47764	46665	46665	37789	37789	32294	32294
R-sq	0.188	0.179	0.195	0.186	0.156	0.202	0.018	0.013

Table 6A: Predictive Accuracy and Fund Performance (excluding Passive Fund)

This table further excludes passive funds from our sample.

Panel A: Raw Return				
	(1)	(2)	(3)	(4)
	ret_m	ret_m	ret_m	ret_m
Coef_equity_market	0.0469			
	(0.85)			
Coef_macro		-0.0961*		
		(-1.82)		
Coef_policy			0.236***	
			(4.05)	
Coef_equity_resid				-0.137**
				(-2.34)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	95047	99243	83145	72268
R-sq	0.557	0.540	0.524	0.548

Panel B: Alpha (Three factors)				
	(1) alpha_ch3	(2) alpha_ch3	(3) alpha_ch3	(4) alpha_ch3
Coef_equity_market	0.0486			
	(1.19)			
Coef_macro		-0.0408		
		(-1.01)		
Coef_policy			0.0995**	
			(2.23)	
Coef_equity_resid				-0.0910**
				(-2.04)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	95047	99243	83145	72268
R-sq	0.132	0.128	0.128	0.135

Panel C: Alpha (Four factors)				
	(1) alpha_ch4	(2) alpha_ch4	(3) alpha_ch4	(4) alpha_ch4
Coef_equity_market	0.0870**			
	(2.07)			
Coef_macro		-0.0112		
		(-0.27)		
Coef_policy			0.0971**	
			(2.12)	
Coef_equity_resid				-0.0917**
				(-1.99)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	95047	99243	83145	72268
R-sq	0.100	0.097	0.096	0.102

Table 7A: Predictive Accuracy and Fund Performance (Expanding Window Estimation)

This table constructs each fund's past predictive accuracy using a 5-period expanding window regression, and still requires at least three valid data points for the estimation. We add the suffix "_e" to distinguish this method from the rolling-based estimation in Table 8.

Panel A: Raw Return				
	(1)	(2)	(3)	(4)
	ret_m	ret_m	ret_m	ret_m
Coef_equity_market_e	-0.0414			
	(-0.88)			
Coef_macro_e		-0.181***		
		(-3.86)		
Coef_policy_e			0.103*	
			(1.94)	
Coef_equity_resid_e				-0.109**
				(-2.26)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	111614	114708	107639	100689
R-sq	0.552	0.540	0.534	0.548

Panel B: Alpha (Three factors)				
	(1)	(2)	(3)	(4)
	alpha_ch3	alpha_ch3	alpha_ch3	alpha_ch3
Coef_equity_market_e	0.00316			
	(0.08)			
Coef_macro_e		-0.0387		
		(-1.02)		
Coef_policy_e			0.137***	
			(3.21)	
Coef_equity_resid_e				-0.0567
				(-1.46)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	111614	114708	107639	100689
R-sq	0.118	0.114	0.115	0.118

Panel C: Alpha (Four factors)				
	(1)	(2)	(3)	(4)
	alpha_ch4	alpha_ch4	alpha_ch4	alpha_ch4
Coef_equity_market_e	0.00330			
	(0.09)			
Coef_macro_e		-0.0347		
		(-0.92)		
Coef_policy_e			0.0901**	
			(2.09)	
Coef_equity_resid_e				-0.0781**
				(-1.99)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	111614	114708	107639	100689
R-sq	0.088	0.086	0.086	0.089