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Beliefs That Predict Returns and Beliefs That Attract Flows: Policy Insights and Sentiment Catering in Mutual Funds

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ABSTRACT

Using mandatory Outlook reports from Chinese mutual funds, we decompose each fund's equity-market beliefs into macro fundamentals, government policy, and residual sentiment. Policy beliefs, rather than macro beliefs, predict subsequent market returns and help explain the positive alphas observed in China's mutual fund industry. By contrast, residual sentiment strongly shapes equity allocations and attracts investor flows, even though it does not predict returns. Using maturing wealth management products as an instrument for future aggregate fund flows, we show that funds strategically position their stated beliefs to cater to investors. Overall, our analysis reveals a core tension in active asset management: skilled managers generate performance through policy insights while attracting flows through sentiment alignment.

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How do professional money managers invest? A standard view is that professional managers possess informational advantages over retail investors. They may be better at analyzing economic fundamentals, interpreting government policy, or assessing market conditions, allowing them to trade against less informed investors, as in Grossman and Stiglitz (1980), Kyle (1985), Barber and Odean (2013), and Hendershott, Livdan, and Schürhoff (2015). Yet this view sits uneasily with a central fact from the U.S. mutual fund industry: actively managed funds, on average, do not outperform passive benchmarks, as documented by Malkiel (1995) and Fama and French (2010).

An alternative view emphasizes the delegated nature of asset management. Fund managers must not only deliver returns but also attract and retain investor capital. In the "money doctors" view of Gennaioli, Shleifer, and Vishny (2015), investors value trust, reassurance, and narratives that resonate with their beliefs. Fund managers may therefore cater to investor sentiment even when doing so does not improve performance.

Despite extensive research on these forces, we still know relatively little about how professional investors use their beliefs in actual investment decisions. The main obstacle is measurement. Researchers typically rely on surveys of households, analysts, professional forecasters, or investors to elicit expectations, as in Shiller (2000), Manski (2004), Greenwood and Shleifer (2014), Coibion and Gorodnichenko (2015), Giglio et al. (2021), and Nagel and Xu (2022). These surveys have generated important insights, but they face two limitations for studying professional money managers. First, survey respondents are often not the investors who make portfolio decisions at scale. Second, even when surveys target relevant investors, it is difficult to track rich, multidimensional beliefs over long horizons. Beliefs about the equity market, macroeconomic fundamentals, government policy, and investor sentiment may evolve differently, and a single survey question rarely captures this structure.

This paper takes a different approach. Instead of asking fund managers what they believe, we observe what they say they believe in mandatory public disclosures. Since 2008, the China Securities Regulatory Commission has required mutual funds in China to include outlook statements in their semi-annual and annual reports. These Outlook sections provide managers' views on economic and financial market conditions for the coming period. They are not optional surveys. They are repeated, mandatory disclosures written by professional managers who allocate real capital.[1] They also appear alongside information on fund holdings, flows, and performance, allowing us to link

[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.

stated beliefs to actual investment decisions and outcomes.

This setting offers three advantages. First, the reports provide a long panel of fund-manager beliefs from 2008 to 2023, covering a period of rapid growth in China's mutual fund industry. Second, the statements are rich enough to distinguish among multiple dimensions of beliefs. A manager may be pessimistic about macroeconomic fundamentals but optimistic about the equity market because she expects supportive policy intervention. Third, China is a particularly useful setting for studying policy beliefs, as argued by Brunnermeier, Sockin, and Xiong (2022). Government policy plays a central role in China's financial markets, and Chinese mutual funds have been shown to generate positive alphas on average, as reviewed by Jiang (2020), in contrast to the typical evidence from U.S. mutual funds. This contrast raises several important questions: Do Chinese fund managers generate alpha by analyzing fundamentals, policy, or something else? Do they also cater to investors? If so, how?

The textual nature of the reports creates a measurement challenge. Traditional dictionary or bag-of-words methods, such as those used in Tetlock (2007) and Loughran and McDonald (2011), are useful for measuring aggregate tone but are less suited for separating tone across topics. The same Outlook may contain negative language about macro fundamentals, positive language about policy support, and optimistic language about equity-market valuations. Simple word counts cannot reliably distinguish these dimensions.[2] We therefore use DeepSeek-R1, a large language model well suited to Chinese-language financial text, to extract structured belief measures from each Outlook section.

We analyze semi-annual and annual reports from all mutual funds between 2008 and 2023, as China's fund industry expanded from 1,188 reports in 2008 to 35,388 in 2023. For each report, we classify managers' views about the domestic equity market, macroeconomic fundamentals, fiscal policy, monetary policy, and regulatory policy. We validate the LLM-generated labels against human annotations and show that the extracted beliefs are reliable.

We also address potential look-ahead concerns by emphasizing that the model is used for classification rather than prediction.[3] Moreover, our empirical analysis relies

[2] See Gentzkow, Kelly, and Taddy (2019) for a review of the broad economic literature on treating text as data. Recently, Bybee et al. (2024) adopted the Latent Dirichlet Allocation (LDA) topic modeling approach of Blei, Ng, and Jordan (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 tone of a report on a specific theme remains challenging.

[3] A growing literature notes that pretrained language models may contain information about future events relative to the historical texts being analyzed, potentially creating look-ahead bias in empirical applications; see Glasserman

primarily on cross-sectional differences across funds, including differences across belief dimensions within the same fund, rather than on aggregate time-series patterns.

We first characterize the structure of fund managers' beliefs by decomposing each fund's equity-market expectation into three components: macroeconomic fundamentals, government policy, and residual sentiment. The macroeconomic and policy components are extracted directly from the Outlook statements. Residual sentiment is then defined as the portion of equity-market expectations that cannot be explained by these two belief components. We interpret this residual as capturing sentiment-related views, including assessments of market conditions, capital flows, or investor sentiment that go beyond fundamentals and policy. While both macroeconomic and policy beliefs are positively related to equity-market expectations, a substantial residual component remains.

We link stated beliefs to portfolio choices and performance. Equity allocations are positively related to stated equity-market expectations, indicating that managers act on the views they report in their Outlook sections. This alignment between stated beliefs and actual investment choices is natural. A disconnect between the two could raise investor concerns about excessive risk-taking or even invite regulatory scrutiny. The consistency also makes the beliefs expressed in fund Outlook sections particularly useful for analyzing funds' investment strategies.

When these expectations are decomposed, allocations are correlated with macroeconomic beliefs, policy beliefs, and residual sentiment, with the strongest association appearing for residual sentiment.We then examine how these belief components contribute to fund performance through market timing. Specifically, we ask whether belief-based return predictability translates into subsequent fund performance. We find that it does, but only through policy beliefs. Funds whose policy expectations better predict market returns subsequently earn higher raw returns and risk-adjusted alphas. By contrast, predictability based on macroeconomic beliefs is unrelated to performance, while predictability based on residual sentiment is negatively related to performance. Moreover, funds with stronger policy-analysis capability tend to exhibit residual sentiment that is less predictive of future returns.

These results reveal a central tension: managers who appear skilled at analyzing policy also express sentiment-related views that are weakly, or even negatively, related to subsequent market returns. As a result, these funds benefit from trading on their policy beliefs but are held back by their residual sentiment.

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and Lin (2023) and Sarkar and Vafa (2024).

We resolve this tension through a catering hypothesis. Fund managers are rewarded not only for performance but also for assets under management, since fees scale with fund size. If investors respond to optimistic market narratives, managers may benefit from expressing sentiment that resonates with investor demand, even when that sentiment does not predict returns. This mechanism is consistent with the money-doctor view of Gennaioli, Shleifer, and Vishny (2015): managers may attract capital by making investors more comfortable with market participation. Because investor sentiment often negatively predicts future returns, catering to it can naturally produce residual sentiment with weak or negative return-predictive power.

We provide several pieces of evidence supporting this hypothesis. First, residual sentiment is not positively related to past fund performance or past market returns, as a simple extrapolation or overconfidence explanation would predict. Second, residual sentiment is strongly related to aggregate mutual fund flows, but not to a fund's own past flows. This suggests that managers respond to market-wide investor demand. Third, this relation remains after controlling for equity allocations, mitigating the concern that stated sentiment simply reflects motivated beliefs used to justify existing portfolio positions.

To address endogeneity, we use an instrumental variable based on the maturity structure of bank wealth management products. These products are fixed-maturity instruments widely held by Chinese households. When a large volume matures, households receive liquid funds that must be reinvested, some of which may flow into mutual funds. This maturity-induced liquidity is driven by maturity choices made before the current reporting period, rather than by contemporaneous stock-market conditions, thereby providing a strong instrument for aggregate mutual fund flows. The first stage is strong: WMP maturities significantly predict aggregate fund flows. In the second stage, instrumented aggregate flows significantly increase funds' residual sentiment. These results support the view that managers adjust their stated sentiment in response to flow-driven investor demand.

Finally, we show that residual sentiment helps attract fund-specific flows. Fund flows respond positively to residual sentiment even after controlling for past performance and past flows. By contrast, macroeconomic and policy beliefs do not significantly predict subsequent flows. The effect of residual sentiment is especially strong when aggregate fund inflows are high, indicating that catering is most effective when investor demand is already elevated.

Taken together, the results reveal a fundamental tension in active asset management. Fund managers can generate alpha by acting on superior policy analysis, but they can

also attract assets by expressing beliefs that resonate with investor sentiment. Many skilled managers appear to do both: they generate performance through policy insights while attracting flows through sentiment alignment.

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. (2023, 2025) 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, Yao, and Yu, 2007; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014; Berk and Van Binsbergen, 2015). More recently, a strand of the literature employs machine learning methods to predict fund returns (e.g., Abis, 2022; Li and Rossi, 2020; Kaniel et al., 2023; DeMiguel et al., 2023; Cao, Yang, and Zhang, 2025, 2026). 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 market 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, not only by aligning the beliefs expressed in Outlook statements but also through their investment holdings, 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 quickly growing literature on the use of LLMs in financial applications, including classification (Hansen and Kazinnik, 2024; Yang and Menczer, 2025; Bernard et al., 2026; Dasgupta, Li, and Wu, 2025), sentiment analysis for return prediction (Chen, Kelly, and Xiu, 2022; Lopez-Lira and Tang, 2023; Jha et al., 2024; Bybee, 2023), and belief formation of financial analysts (Ke, 2024). We advance this methodology by using DeepSeek-R1 not only to score sentiment, but also 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) required all mutual funds in China to include, in their semi-annual and annual reports, a review of recent economic and financial market conditions as well as an outlook for the coming period. These statements appear in the "Manager Report" section.

In these reports, fund managers discuss economic and market conditions relevant to their portfolio decisions, including expected macroeconomic trends, potential policy responses, and the prospective performance of equity and bond markets. These reports

therefore provide a systematic source for observing fund managers' stated views on the economy, government policies, and financial markets, offering direct insight into the beliefs that may shape their portfolio allocations.

We utilize the Wind database to compile these reports and focus specifically on the Outlook sections. Our initial dataset contains 201,605 reports with valid outlook sections from 2008 to 2023. To focus on the Chinese stock market, we exclude bond funds and money market funds and retain only equity and hybrid funds.

We obtain additional data on mutual fund returns, flows, holdings, and other relevant market and accounting information from Wind. We align semi-annual and annual reports with fund-level data based on the month in which each report is publicly released. For annual reports, which are typically released in March or April, we apply the following matching rule. Reports released in March are matched with monthly data from April to September of the same year, while reports released in April are matched with monthly data from May to September of the same year. These annual reports are also matched with first-quarter-end holding data. Semi-annual reports, typically published in September, are matched with monthly data starting in October, when third-quarter-end holding data generally become available.

The final sample of equity and hybrid funds includes 383,261 fund-month observations and 71,443 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 each year. The sample shows steady growth in the number of funds over time, reflecting the rapid expansion of China's mutual fund industry. The number of semi-annual reports rises from 221 in the first half of 2008 to 5,935 in the first half of 2023, while the number of annual reports increases from 266 in 2008 to 6,151 in 2023.

B. Quantifying Outlooks

The CSRC grants fund managers substantial discretion in preparing their outlooks and does not impose strict content guidelines. As a result, Outlook sections vary widely in length, ranging from about 30 to over 6,000 Chinese characters, depending on the depth of discussion and breadth of topics covered.

Appendix B provides two sample outlooks, each presented in the original Chinese and in English translation. These outlooks are typically written in compact language,

concisely summarizing the manager's broad views. The first example is an outlook for 2016. It conveys a mildly negative view of macroeconomic fundamentals, citing short-term economic adjustment and pressure on corporate earnings. It also expresses negative views on both monetary and regulatory policy. Together, these assessments lead the manager to adopt a cautious and mildly negative outlook on the equity market. The second example is an outlook for 2021. The manager is mildly negative about both macroeconomic fundamentals and policy. Nevertheless, the manager expresses a positive view of the equity market, pointing to continued inflows into the stock market. These examples highlight the richness of the Outlook statements and their value for distinguishing fund managers' views on macroeconomic fundamentals, government policy, and market conditions.

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 assess financial markets, typically separating equity and bond markets. This structure supports a comprehensive discussion of the forces shaping future market conditions while giving managers flexibility to emphasize issues most relevant to their investment strategies.

Why should we trust these reports? The outlook statements provide a useful channel for managers to communicate their investment strategies and demonstrate their capabilities. Because short-term performance is subject to considerable luck, managers benefit from showing that strong realized performance is consistent with previously stated outlooks and investment strategies. Such consistency helps investors attribute superior returns to skill rather than luck, whereas clear contradictions between realized performance and stated views could raise concerns that managers are gambling with investor capital, potentially inviting regulatory scrutiny and discipline. Managers therefore have strong incentives to report outlooks that are consistent with their investment strategies. As we show below, the market expectations and belief components extracted from these reports closely align with observed trading behavior.

To be clear, fund statements are unlikely the only, or even the most important, channel through which funds market their strategies to investors. Funds may also communicate their views and strategies through roadshows, investor meetings, and

other direct interactions. What matters for our analysis is that they consistently report their views and strategies in mandatory disclosures.

To convert the qualitative information in mutual fund reports into quantitative measures, we use the DeepSeek reasoning model (DeepSeek-R1, hereafter DeepSeek), a state-of-the-art natural language processing system. DeepSeek is trained on a large corpus of text and is well suited for interpreting the structure and semantics of Chinese-language content. Like other large language models, its architecture builds on transformer blocks and self-attention mechanisms, enabling it to process long text sequences and identify relevant passages. We use these capabilities to analyze fund reports systematically and translate qualitative assessments into structured, quantifiable measures.[4]

Effective prompting is crucial for guiding DeepSeek to interpret the task consistently and produce suitable outputs. Prompts must provide the relevant context, incorporate domain knowledge, and be tailored to the specific classification task. In our study, we use the following prompt to process the Outlook section of each fund report:

"*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; (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."

This prompt instructs DeepSeek to evaluate the tone of each Outlook section across multiple topics from the perspective of a professional Chinese financial expert.[5] We set the model temperature to zero to minimize randomness and obtain the highest-

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

5 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 tone could unduly spill over into the assessment of individual dimensions.

probability responses, thereby enhancing reproducibility. When running the model 1,000 times on the same report, the output consistency rate exceeds 90%.

One concern is potential look-ahead bias, since DeepSeek's training data extend to July 2024. This concern is mitigated by the fact that we use the model primarily for summarization and classification rather than prediction. To further validate this approach, we conduct robustness checks that modify 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. These results demonstrate that the model extracts tone and key information largely independently of specific temporal anchors, reinforcing the reliability of our classification approach.

More importantly, our analysis exploits cross-sectional heterogeneity in fund-level beliefs about aggregate conditions, rather than time-series movements in aggregate variables. Thus, even if the model were to contain some aggregate look-ahead information, such information would not mechanically generate the cross-sectional differences that underpin our main tests.

We instruct DeepSeek to generate a summary for each topic and convert the resulting assessment into a numerical score using the following mapping: "Positive"= 1, "Weakly Positive"=0.5, "Neutral"=0, "Weakly Negative"=-0.5, "Negative"=-1, and "Not Mentioned"= Missing.[6]

From each Outlook section, we extract five key variables: expectations about the domestic equity market, expectations about the national macroeconomy, and expectations about three dimensions of government policies: fiscal, monetary, and regulatory. The focus on policy reflects a distinctive feature of China's economy. As

[6] We treat "Not Mentioned" responses as missing because the belief variables are intended to capture explicit views on each topic. A potential concern is that non-mention may itself convey negative information, especially if fund managers are reluctant to disclose unfavorable views in reports for investors. Table 3A in the Internet Appendix addresses this concern by setting missing macroeconomic and policy beliefs to zero and adding two separate indicators for corresponding non-mentions in each category. Both indicators are positively associated with equity-market expectations, suggesting that omissions of macroeconomic or policy topics do not proxy for negative equity-market views. Moreover, our results remain robust when "Not Mentioned" responses are coded as zero.

argued by Xiong (2027), 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. Monetary policy includes interest-rate adjustments and control over aggregate bank lending, through which the People's Bank of China regulates money supply and credit conditions. Fiscal policy includes large-scale infrastructure investment and industrial policies aimed at promoting targeted sectors, especially as countercyclical tools during downturns. Regulatory policy includes measures such as IPO quotas and changes in stamp taxes on stock trading, which directly affect capital markets and investor behavior. We summarize overall policy expectations by taking the average of these three policy dimensions.

Panel A of Table 1 reports summary statistics of the expectations extracted from the Outlook sections. On average, fund managers' expectations are positive but exhibit substantial variation. Expectations about the national macroeconomy are slightly positive, with a mean of 0.107 and a standard deviation of 0.781. Average policy expectations have a mean of 0.529 and a standard deviation of 0.578, while equity-market expectations have a mean of 0.613 and a standard deviation of 0.502. Our analysis relies critically on both the time-series and cross-sectional variation in these expectations.

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

The correlations among expectations about the equity market, macroeconomy, and policy are also mostly positive, whether policy is measured by its individual dimensions or by the average policy measure. This pattern suggests that fund managers' equity-

market views are shaped jointly by their assessments of economic fundamentals and policy conditions.

The second Outlook example in Appendix B shows that fund managers pay close attention to capital flows. To systematically characterize this attention, we define a capital-flow mention indicator, which equals one when the Outlook text explicitly discusses expected inflows into the equity market. As reported in Table 1, this indicator has a mean of 0.062, indicating that roughly 6% of fund reports explicitly discuss capital flows into the equity market.

C. Validating LLM-Extracted Beliefs

For the two Outlook examples in Appendix B, DeepSeek's classifications appear reasonable. To assess the reliability of the DeepSeek-generated annotations more systematically, we validate them against human labels. We randomly select 500 observations that satisfy our data-quality filters and evaluate them along five key dimensions: fund managers' expectations about macroeconomic fundamentals, the equity market, fiscal policy, monetary policy, and regulatory policy. Three human annotators, all finance PhD students with training in finance and macroeconomics, independently label each field. We then construct a human-annotated benchmark using a majority-vote rule across the three annotators.

Table 4A in the Internet Appendix reports the validation results. The agreement rates between DeepSeek and the human majority vote are 77.4% (=387/500) for macroeconomic fundamentals, 76.4% (=382/500) for the equity market, 93.4% (=467/500) for fiscal policy, 90.0% (=450/500) for monetary policy, and 87.0% (=435/500) for regulatory policy. Overall, DeepSeek agrees with the human majority vote in 84.8% (=2,121/2,500) of belief instances.

Because the Outlook sections are structurally complex, human annotators are themselves prone to error. To better understand the sources of disagreement, we consult two additional domain experts, who assign final labels without knowing whether any given label comes from DeepSeek or from the initial human annotators. Among the 2,500 belief instances (500 outlooks across five dimensions), the first-round human majority label and the DeepSeek label differ in 379 cases. The experts' final judgment aligns with DeepSeek in 150 of these cases. As a result, the consistency rates between

DeepSeek and the expert-calibrated labels rise to 86.8%, 87.2%, 96.2%, 92.6%, and 91.4% for the five dimensions, respectively. The overall expert-calibrated consistency rate is 90.8% (=2,271/2,500). These findings indicate that DeepSeek provides a reliable and scalable method for extracting beliefs from complex textual data and, in many contested cases, can produce labels that are more consistent with expert judgment than the initial human majority vote.

D. Fund Characteristics

Over 2008-2023, our full sample comprises 7,169 unique funds, including 1,503 equity funds, or 20.97% of the sample, and 5,666 hybrid funds, or 79.03%. Among these funds, 6,475, or 90.32%, are actively managed, while 694, or 9.68%, are passively managed. At the end of 2023, total assets under management amount to RMB 4.96 trillion, approximately USD 0.73 trillion.

Our analysis examines how variation in equity allocations relates to fund managers' stated beliefs about the equity market, macroeconomic fundamentals, and government policy. All funds in our sample invest in equities, but equity allocations differ across fund types. Hybrid funds hold an average of 58.15% of their assets in stocks and have a mean absolute semi-annual change in equity allocation of 6.73%. Among equity funds, active funds hold an average of 87.59% of their assets in stocks, while passive equity funds, excluding those that primarily invest through ETFs, hold an average of 90.16%. Their mean absolute semi-annual changes in equity allocation are 3.84% and 2.30%, respectively.[7]

Panel A of Table 1 reports statistics for fund characteristics, with all variables winsorized at the 2.5% and 97.5% levels. The average monthly fund return in our sample is 0.391%, with a standard deviation of 5.873%, while the average semi-annual fund return is 1.989%, with a standard deviation of 14.072%.

Following Liu, Stambaugh, and Yuan (2019), we adjust fund performance using the

[7] Although passively managed funds operate under more restrictive investment mandates, they retain some discretion in their allocation between cash and invested assets. Their reporting incentives may also remain relevant, since they continue to compete for investor capital and may use mandatory Outlook disclosures to communicate with investors. We therefore retain passively managed funds in the sample. In the allocation and flow analyses, fund fixed effects absorb time-invariant differences associated with fund type. Moreover, the performance results are robust to excluding these passively managed funds, as reported in the Internet Appendix.

three-factor (CH3) and four-factor (CH4) models constructed for the Chinese market. Specifically, we estimate fund performance using the CH3 and CH4 models:

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

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

where r_t is the return on a mutual fund in excess of China's one-year deposit interest rate; $MKTRF_t$ is the excess return on the value-weighted portfolio of the top 70% of stocks, following Liu, Stambaugh, and Yuan (2019), who exclude the smallest 30% of stocks to avoid potential bias from reverse mergers; SMB_t is the size factor, also constructed after excluding the smallest 30% of stocks; VMG_t is the value factor based on the earnings-price ratio; PMO_t is the turnover-based sentiment factor introduced in the CH4 model.[8]

We define fund alpha as the constant term, α, from 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 monthly alphas under both CH3 and CH4. The CH3 alpha has a mean of 0.184% and a standard deviation of 3.533%, while the CH4 alpha has a mean of 0.190% and a standard deviation of 3.483%. Simple t-tests confirm that both 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).

II. Fund Expectations

In this section, we examine variation in fund expectations.

A. Variation in Fund Expectations

There is substantial variation in fund managers' expectations across funds and over time. To characterize this variation, we estimate three fixed-effects specifications using any given type of expectations, Y_{it}, for fund i at time t.

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

First, we include fund fixed effects: $Y_{i,t} = \alpha_i + \varepsilon_{i,t}$. This specification captures time-invariant fund characteristics, such as investment style, mandate, or persistent differences in managerial philosophy, that may shape stated expectations.

Second, we include time fixed effects: $Y_{i,t} = \beta_t + \varepsilon_{i,t}$. This specification captures common time-varying forces, such as aggregate market conditions, macroeconomic developments, or policy cycles, that affect all funds' expectations.

Third, we estimate a two-way fixed-effects specification: $Y_{i,t} = \alpha_i + \beta_t + \varepsilon_{i,t}$. This specification accounts for both persistent fund-level heterogeneity and common time-varying conditions.

Panel A of Table 2 reports the R^2 values from these regressions for equity-market expectations. Column (1) shows that fund fixed effects explain 18.3% of the variation, suggesting that persistent fund-level characteristics and investment philosophies play an important role. Column (2) reveals that time fixed effects explain 14% of the variation, implying that market-wide conditions also matter. Column (3) shows that the two-way fixed-effects model explains 28.9% of the variation, underscoring the joint importance of fund-level and time-varying components. Even after accounting for both fund and time fixed effects, however, more than 70% of the variation in fund managers' equity-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 common in-house analysts when forming market expectations, or on the same administrative staff when drafting the Outlook sections. If so, fund-family fixed effects should explain a substantial fraction of the variation. Panel B of Table 2 reports the R^2 from regressions with fund-family fixed effects, which account for only about 2.5% 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. Funds within the same family do not appear simply to replicate a single analyst's views or a standardized Outlook.

Because 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. These fixed effects account for approximately 29.4% of the variation in equity-

market expectations, substantially higher than fund fixed effects. This pattern likely reflects substantial manager turnover within funds and the importance of manager-specific beliefs or styles. When both fund-manager and time fixed effects are included, the model explains 37.4% of the variation in equity-market expectations, still leaving nearly two-thirds of the variation unexplained.

Table 2 shows similar patterns for expectations about the macroeconomy and the three policy dimensions. Fund fixed effects, fund-manager fixed effects, and time fixed effects each explain part of the variation, but a substantial residual component remains. This remaining variation provides the key source of identifying variation for our analysis of how stated beliefs relate to funds' trading behavior.

Table 5A in the Internet Appendix relates fund expectations to past six-month performance (*semi_ret*), total net assets (*log_tna*), recent fund flow (*flow*), and fund age (*age*). Recent performance is positively and significantly associated with policy expectations but negatively associated with equity-market expectations: better-performing funds express more optimistic policy views but more cautious market views. By contrast, fund size, recent flows, and age show less consistent relationships across expectation dimensions.

Table 6A in the Internet Appendix examines how fund expectations vary with market conditions. Expectations across all dimensions are positively correlated with equity-index returns, indicating that funds express more favorable views about policy, fundamentals, and the equity market after strong market performance. By contrast, higher market volatility is associated with more optimistic policy expectations but more pessimistic macroeconomic and equity-market expectations, suggesting that managers anticipate policy support during volatile periods while expecting weaker fundamentals and market conditions.

B. Decomposing Market Expectations

For a fund's investment decisions, equity-market expectations are central because they directly shape portfolio strategy. To understand how managers form these expectations, we examine how each fund's equity-market outlook relates to two key factors emphasized in the finance literature: macroeconomic fundamentals and government policy.

Panel A of Table 3 reports panel regressions relating equity-market expectations to macroeconomic and policy expectations. Column (1) shows that macroeconomic expectations are positively associated with equity-market expectations. Columns (2) through (4) separately examine fiscal, monetary, and regulatory policy expectations. Each policy dimension has a highly significant positive coefficient, ranging from 0.168 to 0.180, indicating that more favorable policy views are associated with more optimistic equity-market outlooks. Column (5) aggregates these three policy dimensions into an average policy expectation, which remains significantly positive. Column (6) jointly includes macroeconomic expectations and average policy expectations; both remain significant, confirming their distinct and complementary roles.

Taken together, these results suggest that fund managers' equity-market expectations are shaped importantly by their views of macroeconomic fundamentals and government policy. Given that these panel regressions impose common coefficients across managers, a strong restriction, the high explanatory power reinforces the importance of macroeconomic and policy beliefs in shaping equity-market outlooks.

At the same time, macroeconomic and policy expectations leave substantial residual variation. We interpret this residual component as capturing the fund manager's beliefs about market sentiment, reflecting factors not directly captured by macro fundamentals or government policy. Guided by this interpretation, we decompose each fund's equity market expectation into three components: macro fundamentals, policy, and residual sentiment. The macro and policy components are directly extracted from the Outlook sections of fund reports. We construct the sentiment component as the residual from regressing equity-market expectations on domestic macroeconomic expectations and average policy expectations. The fitted values capture the fundamentals- and policy-driven components of the market outlook, while the residuals, by construction orthogonal to fundamentals and policy, serve as our proxy for managers' sentiment-related views.

We estimate each fund's residual sentiment component using fund-level time-series regressions, rather than imposing common coefficients in a panel specification. We require each fund to have at least 10 valid semi-annual or annual reports over the sample period. This restriction ensures sufficient within-fund time-series variation and reduces

measurement error from sparse observations. All subsequent analyses that use the residual component are therefore conducted on this restricted sample to maintain consistency and comparability across specifications.

The residual sentiment may reflect the managers' own sentiment or their assessments of market conditions beyond macroeconomic fundamentals and government policy. Because fund managers often discuss capital flows in their Outlook sections, Panel B of Table 3 relates the residual sentiment component to an indicator for whether the Outlook mentions capital flows, such as expected inflows into the equity market or the broader capital market. The coefficient is positive and statistically significant under both fund fixed effects and fund-manager fixed effects, suggesting that the sentiment component is closely related to fund managers' assessments of capital flows, an issue we examine further below.

III. 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' stated expectations translate into asset allocation decisions. Specifically, we estimate panel regressions of each fund's equity allocation, measured by its stock-holding ratio, on its equity-market expectation and the corresponding belief components. Table 4 reports the results. Columns (1) through (5) include time and fund fixed effects, while Columns (6) through (10) replace fund fixed effects by fund-manager fixed effects. The results are highly consistent across specifications.

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, indicating that fund managers act on the views stated in their Outlook sections.[9] Because these expectations are measured by

[9] Furthermore, fund managers' equity-market expectations may affect not only their overall stock-holding ratios but also their selection of individual stocks, such as tilting toward high- or low-beta stocks. These allocation and selection decisions jointly contribute to fund performance, which we examine in

applying an LLM to contextual statements, measurement noise is unavoidable and likely attenuates the estimated coefficient. Despite this downward bias, the magnitude remains economically meaningful and is consistent with related evidence in the literature, such as Giglio et al. (2021).

Columns (2) through (4) show that equity allocation is positively and significantly related to each of the three belief components: macro fundamentals, policy, and residual sentiment. Column (5) further shows that, when the three components are included jointly, funds respond positively to all three but most strongly to residual sentiment. A one-unit increase in beliefs about macro fundamentals, policy, and residual sentiment is associated with increases of 0.626, 0.630, and 1.359 percentage points in equity allocation, respectively.[10] This pattern suggests that fund managers place greater weight on residual sentiment than on macro fundamentals or policy when adjusting equity exposure.

These findings show that fund managers put their money where their mouth is. Their equity allocations are significantly correlated not only with their equity-market expectations but also with each of the three components: macro fundamentals, policy, and residual sentiment. In particular, allocations are most strongly correlated with residual sentiment.

In Appendix C, we further examine whether fund managers' expectations predict future market returns, macroeconomic fluctuations, and policy developments. Because each outcome variable has only one aggregate time series, we focus on the predictive power of the cross-sectional average of fund managers' beliefs. Although the sample is relatively small, with 32 semi-annual observations, both macroeconomic and policy beliefs contain forward-looking information about GDP growth and policy developments. This finding helps to further validate these belief measures. However, only policy beliefs predict subsequent market returns; neither macroeconomic beliefs nor residual sentiment has significant return-predictive power. This creates a curious disconnect: although policy beliefs best predict future market returns, managers do not appear to fully capitalize on this advantage in their equity allocations.

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the next section.

[10] Each belief component is subject to measurement error. The macroeconomic and policy beliefs are extracted from contextual statements using an LLM, while the residual sentiment component is further estimated from a regression. Such measurement error likely attenuates the estimated coefficients. To the extent that measurement error is larger for residual sentiment, its larger coefficient is even more notable.

B. Market Timing

We now directly examine how these beliefs contribute to funds' market timing. 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 before rising markets or reduce exposure before falling markets, and negative when they move in the opposite direction.

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 $\Delta stock_ratio_{i,t}$ is the change in the fund's equity share measured in percentage, RI_equity_{t+1} is the next-period market-index return, and $|expectations_{i,t}|$ is the absolute value of the relevant belief measure. The control vector $X_{i,t}$ includes total net assets, fund flows, and fund age. We include time fixed effects and either fund or fund-manager fixed effects. We use the absolute value of beliefs because both optimistic and pessimistic views can contribute to market timing if they lead managers to adjust exposure in the correct direction.

Table 5 reports the regression results. Market timing is related to the intensity of policy beliefs, but not to macro-fundamental beliefs or residual sentiment. Across specifications with fund fixed effects in Columns (1) to (5) and fund-manager fixed effects in 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 adjust equity exposure in ways that align with subsequent market movements.

By contrast, the absolute values of overall equity-market expectations, macroeconomic expectations, and residual sentiment are not significantly related to market timing. Their coefficients are small, statistically insignificant, and stable across specifications.

Two insights emerge. First, effective market timing in this setting is policy-driven: managers' dynamic exposure decisions are most successful when guided by strong policy views. Second, timing performance is not driven by views about macro

fundamentals or residual sentiment. This contrast confirms the importance of government policy in shaping market dynamics, as emphasized by Brunnermeier, Sockin, and Xiong (2022).

C. Fund Performance

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

To examine this issue, we construct fund-level measures of belief-based return predictability for overall market expectations and for each belief component: macro fundamentals, policy, and residual sentiment. For each fund, we estimate rolling-window regressions over five reporting periods:

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

We require at least three valid observations within each window, since some belief dimensions may be missing when a topic is not mentioned. The estimated coefficient b_i captures the recent predictive content of a fund's stated belief in a given dimension. To facilitate comparisons across funds, we normalize these coefficients within each period and convert them into cross-sectional rankings from 0 to 1.

We then relate these predictability measures to subsequent fund performance:

$$r_{i,t+1} = \lambda_t + \gamma Coef_expectation_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where $r_{i,t+1}$ is fund i's monthly return, measured both before and after risk adjustment. The key independent variable, $Coef_expectation_{i,t}$, is the coefficient estimated from the rolling-window regression above using data up to month t. The control variables $X_{i,t}$ include total net assets, fund flows, and fund age, and time fixed effects absorb market-wide shocks.

Table 6 reports the results. Panel A uses raw monthly returns, while Panels B and C

use risk-adjusted alphas from the CH3 and CH4 models. All return metrics, whether raw or risk adjusted, are reported in percentage terms.

Across all three panels, return predictability based on overall market expectations is positive but generally insignificant. When beliefs are decomposed, predictability based on macroeconomic expectations is negative and insignificant, whereas predictability based on policy expectations is consistently positive and statistically significant. In Column (3), the estimated coefficients are 0.228 for monthly raw returns, 0.0957 for CH3 alpha, and 0.0933 for CH4 alpha. These results suggest that funds with stronger policy-based return predictions deliver superior performance, even after controlling for fund characteristics. Column (4) presents a puzzling pattern: return predictability based on residual sentiment is significantly negative. This implies that funds whose residual sentiment is less predictive of future market returns tend to perform better.

To understand this tension, Panel D of Table 6 examines the relationship between a fund's policy-prediction ability and the predictive content of its residual sentiment. The two are strongly negatively related. Even after including fund fixed effects or fund-manager fixed effects, the coefficients remain negative, with t-statistics consistently exceeding 5. This pattern indicates that funds with stronger policy-analysis capability, the main source of fund alpha, tend to have residual sentiment with weaker predictive power for future market returns.

Taken together, these findings reveal a nuanced interaction among different components of fund beliefs. Funds' ability to analyze policy developments, rather than macro fundamentals, is the primary belief-based driver of performance. Yet the same funds that excel in policy analysis also express residual sentiment with weaker predictive content. These offsetting forces help explain why the overall relation between market-timing capability and performance is positive but relatively weak. This negative correlation between policy-analysis strength and residual-sentiment predictability is central to our interpretation and warrants closer examination. We turn to this issue in the next section.

We conduct several additional robustness tests. First, we exclude passively managed funds from the sample; the results are reported in Table 7A of the Internet Appendix. Second, to reduce measurement error in belief-based return predictability

arising from the short five-period rolling estimation window, we construct two alternative measures: an expanding-window approach that uses all past observations, and a ten-period rolling-window measure. The results are reported in Tables 8A and 9A, respectively.

Across both exercises, the findings remain unchanged: policy-based predictability consistently predicts future fund performance, whereas predictability based on macroeconomic expectations or residual sentiment does not. The robustness of these results across the five-period rolling window, the 10-period rolling window, and the expanding-window specification is important for interpretation. A purely luck-based measure would likely be highly sensitive to the estimation window. By contrast, the policy-predictability measure remains positively associated with subsequent raw returns and risk-adjusted alphas across specifications that place very different weights on recent versus longer-run information. This persistence suggests that the measure captures a stable fund-level ability to interpret policy signals, rather than an accidental correlation generated by a small number of forecasts.

IV. Catering to Fund Flows

Our analysis uncovers a puzzling contrast between funds' policy beliefs and residual sentiment. Policy beliefs strongly predict subsequent market returns, yet they are not the main driver of equity allocations. Instead, residual sentiment has the largest influence on equity holdings, despite having little return-predictive power. Moreover, funds with stronger policy-analysis capability tend to exhibit residual sentiment with weaker predictive power for future returns. How can we reconcile these patterns?

A. The Catering Hypothesis

One possibility is that some managers do not fully recognize the influence of their own sentiment. Behavioral forces, such as overconfidence and extrapolation, could lead them to overweight noisy signals at the expense of more informed policy views. Although this noise-trading channel may be part of the story, it is unlikely the whole explanation. After all, these funds generate positive alphas on average, and the funds with superior policy-analysis capabilities are precisely those whose residual sentiment is less predictive of market returns.

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. Superior performance attracts inflows, but it is not the only channel. 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 catering hypothesis suggests that funds may strategically adopt sentiment that aligns with investor sentiment to attract flows. This interpretation is consistent with the evidence in Panel B of Table 3, where residual sentiment is positively related to fund managers' discussion of capital flows in the Outlook sections. Since investor sentiment tends to negatively predict future returns (Baker and Wurgler, 2006), catering to investor sentiment would naturally lead fund managers to express a sentiment component with weak or negative return-predictive power. At the same time, because managers need to align their portfolio allocations with their stated beliefs, this motive can also make residual sentiment an important determinant of fund allocations despite its poor market-timing content.

To formally test the catering hypothesis, we proceed in three steps. First, we use descriptive analysis to examine whether funds' residual sentiment is more consistent with behavioral biases or with aggregate inflows into mutual funds. Second, to address potential endogeneity in the descriptive analysis, we use an instrumental variable for aggregate fund flows and show that funds' residual sentiment responds to instrumented fund flows. Finally, we show that residual sentiment helps funds attract fund flows.

B. Descriptive Analysis

To distinguish between these explanations, we first examine what drives funds' residual sentiment. The catering hypothesis predicts that residual sentiment responds to fund flows. When aggregate inflows into mutual funds are high, likely reflecting retail investors' exuberance about the equity market, fund managers may express more optimistic sentiment to cater to these investors. An alternative explanation is that managers' residual sentiment reflects their own behavioral biases.

We consider two types of biases. The first is backward-looking beliefs, such as extrapolation or path-dependent overconfidence, as in Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998). If residual sentiment were primarily bias-driven in this way, we would expect it to be positively correlated with past fund performance and past market returns. This implication can be tested directly.

The second is motivated beliefs, as reviewed by Bénabou (2015). Fund managers may adopt optimistic beliefs to justify their portfolio choices; that is, they may express more favorable market views after taking larger equity positions. This interpretation is consistent with Table 4, which shows that stock-holding ratios are positively associated with residual sentiment. However, this correlation does not distinguish whether optimistic beliefs drive portfolio positions or whether portfolio positions motivate optimistic beliefs. We therefore control for equity allocations to examine whether residual sentiment remains related to fund-flow incentives even after accounting for this channel.

Motivated by these considerations, we examine how residual sentiment relates to a fund's three-month alpha, three-month market return, aggregate fund flows, the fund's own flows, and its stock-holding ratio over the corresponding period. Table 7 reports the results. Across specifications, residual sentiment is negatively, though not significantly, correlated with both fund alpha and market returns. Rather than becoming more exuberant after strong performance, funds appear to express more optimistic market sentiment following weaker performance. This pattern runs counter to a simple bias-based explanation.

Residual sentiment is also unrelated to a fund's own flows but strongly and significantly positively correlated with aggregate fund flows. This pattern suggests that funds respond to market-wide flow conditions by aligning their expressed sentiment with investor demand, consistent with the catering hypothesis.

Importantly, this relationship remains after controlling for funds' equity allocations, and therefore for the possibility that stated sentiment merely reflects motivated beliefs tied to existing portfolio positions. Fund managers thus appear to adjust their stated sentiment in response to flow-related incentives beyond what is implied by their holdings. Taken together, the evidence points to strategic communication: funds cater their expressed market sentiment to attract investor flows.

C. Instrumental Variable

A key endogeneity concern is that aggregate fund inflows and individual fund managers' stated beliefs may both respond to a common underlying aggregate shock, making it difficult to cleanly identify whether managers are strategically catering to investor demand versus simply reflecting a shared information environment.

To resolve this endogeneity concern, we adopt an instrumental variable for aggregate fund flows. The instrument builds on the popularity of wealth management products (WMPs) among Chinese households. Under China's financial repression regime, banks have historically offered artificially low deposit rates, which helped subsidize investment by lowering funding costs for borrowers. To partially liberalize household investment returns while preserving control over the formal banking system, regulators allow banks to intermediate WMPs, which are issued by borrowers and sold to savers, often existing bank depositors.[11]

Although these WMPs are not formally issued as bank deposits, investors have often perceived them as carrying implicit bank guarantees. As a result, WMPs became a cornerstone of China's shadow banking system, offering households returns above regulated deposit rates while allowing banks and borrowers to move credit intermediation partly off-balance sheet. The market is large: the outstanding balance of WMPs was about 26.8 trillion yuan at the end of 2023, equivalent to more than 20% of China's GDP.[12]

Our instrument is based on the maturity structure of bank WMPs, using data from Tonghuashun (THS), a widely used financial database. The data report maturity buckets ranging from seven days to one month, through intermediate maturities, and up to more than three years. We focus on WMPs with maturities of six months or longer and exclude shorter-maturity products, which are more likely to function as demand-like liquidity instruments and to respond to contemporaneous household cash-management needs, bank funding pressures, and short-term liquidity conditions.

Longer-maturity WMPs more closely resemble fixed-horizon investment products. Their maturity dates are determined by issuance decisions made before the current

[11] See Xiong (2027) for a review of China's financial policy and shadow banking system.

[12] See the announcement by China's State Council: https://english.www.gov.cn/archive/statistics/202501/17/content_WS678a376cc6d0868f4e8eee9d.html.

semi-annual reporting window and, therefore, before fund managers write their current Outlook statements. This timing feature is central to our identification strategy. Conditional on macroeconomic and liquidity controls, variation in the maturity of these longer-horizon products generates predetermined fluctuations in households' reinvestable wealth, rather than contemporaneous variation in market conditions or fund managers' sentiment.

We construct a monthly WMP maturity ratio, defined as the amount of bank WMPs in the relevant fixed-maturity buckets that mature in a given month, divided by the outstanding amount of WMPs in the same buckets that month. We then average this ratio over the three months, corresponding to the aggregate fund-flow window. The instrument exploits the fixed-maturity structure of WMPs: when a large volume of WMPs matures, households receive liquid funds that must be reinvested, some of which may flow into mutual funds. A higher maturity ratio therefore captures greater predetermined variation in households' reinvestable wealth and, hence, in aggregate mutual fund inflows.

The key identification assumption is that the maturity schedule of outstanding WMPs affects fund managers' residual sentiment only through aggregate mutual fund flows. This exclusion restriction is plausible for several reasons. First, the timing runs from past WMP issuance to current WMP maturities and then to household reinvestment. Because we use products with maturities of at least six months, maturity shocks around a report publication date are determined by issuance decisions made well before the current reporting cycle. Neither current market conditions nor fund managers writing an Outlook in the current period can affect the volume of WMPs issued six months or more earlier that mature today. This mitigates concerns that the instrument responds to current managerial beliefs or contemporaneous investor sentiment.

Second, we directly address the possibility that WMP maturities proxy for broader financial-system liquidity. WMP issuance and maturity patterns may be correlated with bank funding pressures, interbank rates, credit growth, or shadow-banking conditions, all of which fund managers may incorporate into their market views. We therefore control for year-on-year M2 growth, year-on-year RMB loan growth, the three-month SHIBOR rate, and the first principal component of WMP–deposit spreads across maturities. These variables capture aggregate money growth, formal credit conditions,

interbank liquidity pressure, and the relative attractiveness of WMPs versus bank deposits. The remaining identifying variation comes from the maturity schedule of longer-horizon WMPs after accounting for the main macro-financial and liquidity conditions that could directly shape managers' beliefs.

Third, excluding maturities below six months further strengthens the exclusion restriction. Very short-maturity WMPs may be rolled over frequently and may respond quickly to household liquidity demand, banks' short-term liability management, or contemporaneous money-market conditions. By focusing on maturity buckets of six months or longer, including 6 to 12 months, 1 to 3 years, and above 3 years, we isolate a slower-moving stock of household investment products whose maturity dates were fixed before the current reporting window. This makes the instrument closer to a predetermined reinvestment shock than to a contemporaneous measure of liquidity demand.

Finally, the second-stage dependent variable is a fund's residual sentiment, defined as the component of its equity-market outlook orthogonal to macroeconomic and policy beliefs. For the exclusion restriction to fail, maturities of longer-horizon WMPs would therefore have to affect this residual component through a channel other than aggregate mutual fund flows, even after controlling for macroeconomic growth, credit conditions, interbank liquidity, WMP–deposit spreads, fund characteristics, past market returns, past fund performance, equity allocations, and fixed effects. This is a demanding alternative explanation. A fund manager writing an Outlook statement has little reason to adjust residual sentiment in response to the aggregate volume of WMPs maturing in a given month, except insofar as those maturities release household investable funds and strengthen expected inflows into mutual funds.

To align the instrument with the timing of fund reports, we aggregate the monthly maturity ratio to the quarterly level by averaging it over the corresponding three-month calendar window. Although outstanding-amount data are available from mid-2016, coverage across maturity buckets is incomplete in the early part of the sample. We therefore begin the IV analysis in 2018H1, when most maturity buckets have consistent non-missing observations.

Table 8 reports the IV results, which corroborate the baseline findings in Table 7. In the first stage, the WMP maturity ratio strongly predicts aggregate fund flows,

consistent with maturity-induced variation in available investment capital. Across specifications, with either fund or fund-manager fixed effects and controls for either past CH3 or CH4 fund alpha, the t-statistic on the WMP maturity ratio consistently exceeds 3, and the weak-instrument F-statistic exceeds 10.

In the second stage, instrumented aggregate fund flows remain positive and highly significant across specifications. The coefficients are stable and, if anything, somewhat larger than the OLS estimates reported in Table 7. These results indicate that the flow–sentiment relation is not driven simply by reverse causality or by common contemporaneous shocks to fund flows and fund managers' narratives. Instead, residual sentiment rises when predetermined WMP maturities generate stronger aggregate mutual fund inflows, consistent with the catering hypothesis: fund managers adjust their stated sentiment in response to flow-driven investor demand.

D. Fund Flow Response to Residual Sentiment

We next examine whether fund flows respond to funds' residual sentiment or policy beliefs. Specifically, we use funds' overall equity-market beliefs and their three belief components to predict cumulative fund flows over the three months following the release of semi-annual or annual reports. The panel regressions control for fund performance over the prior three months.

Table 9 reports the results. Columns (1) through (6) include fund fixed effects, while Columns (7) through (12) include fund-manager fixed effects. Across all specifications, fund flows are positively and significantly related to past fund performance, confirming the central role of performance in shaping investor demand. Past fund flows are also positive and significant, indicating persistence in investor flows.

The key result is that fund flows respond positively to residual sentiment even after controlling for both past performance and past flows, independent of whether fund or fund-manager fixed effects are included. Column (1) shows that flows are positively and significantly associated with funds' overall equity-market beliefs. Column (4) shows that residual 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 do not significantly predict future flows. When all three components are included jointly in Column (5), residual sentiment

remains the only belief component significantly associated with future flows. These findings suggest that residual sentiment serves as an independent channel for attracting capital, distinct from demonstrated investment performance and the persistence of prior fund flows.

We further test whether residual sentiment is especially effective at attracting fund-specific inflows when aggregate fund inflows are strong. Specifically, we regress future fund flow on funds' beliefs about market sentiment, their interaction with aggregate fund flow, fund return, time fixed effects, and other controls. As shown in Column (6) of Table 9, the positive coefficient on the interaction term indicates that the relation between a fund's residual sentiment and its subsequent flows is stronger when aggregate flows are high. In other words, catering to investor sentiment is particularly effective during periods of market-wide exuberance.

Taken together, the results support the catering hypothesis. This evidence reveals a fundamental tension in asset management: fund managers face competing incentives. On the 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 and attract flows. The evidence suggests that many skilled managers pursue both objectives simultaneously, generating alpha through policy insights while attracting flows through sentiment alignment. Because managers need to align their investment choices with their stated beliefs, their catering incentives help explain why residual sentiment is the strongest driver of equity allocations despite its limited ability to predict subsequent market returns.

V. 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 sentiment component. This decomposition reveals a clear hierarchy of information content: the strength of managers' policy beliefs drives their market timing, with stronger policy views leading to equity exposure adjustments that systematically align

with subsequent market outcomes. By contrast, macroeconomic beliefs and residual sentiment do not generate similar timing ability. Consequently, funds with stronger policy-based forecasting ability deliver higher raw returns and risk-adjusted alphas.

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, residual sentiment, despite having little predictive power for subsequent market returns, exerts the strongest influence on equity allocations.

Our analysis resolves this tension by offering strong evidence for a catering incentive. Residual sentiment is closely related to aggregate fund flows, responds to instrumented flow shocks based on maturing wealth management products, and is the only belief component that robustly predicts subsequent fund-specific flows after controlling for past performance. The sentiment-flow link is especially 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. Fund managers face dual objectives: trading on informed views to generate alpha while also managing sentiment in their communications and portfolio allocations to sustain investor demand. This dual mandate helps explain why the most skilled policy analysts also act on residual sentiment that poorly predicts returns. Their stated market views are not pure forecasts; they partly reflect strategic communication designed to resonate with investors.

Although our analysis is based on Chinese mutual funds, the findings shed light on the broader puzzle of active fund underperformance. In the U.S., where active mutual funds typically fail to outperform passive benchmarks, the issue may not be simply that managers lack skill. Rather, managers may face incentives to combine investment decisions with investor-facing narratives that help attract and retain flows. When fee income depends on assets under management, catering to investor sentiment can distort both stated beliefs and portfolio choices. Our evidence from China shows this mechanism directly: policy analysis generates alpha, but sentiment alignment attracts assets. This distinction between return-generating beliefs and flow-attracting beliefs offers a new lens for understanding why professional money management may fall

short of its informational ideal.

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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 our final sample comprises 383,261 fund-month observations and 71,443 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	0.613	0.502	-1.000	0.500	1.000	1.000	1.000
macro	0.107	0.781	-1.000	-0.500	0.500	1.000	1.000
fiscal_policy	0.764	0.471	-1.000	0.500	1.000	1.000	1.000
monetary_policy	0.473	0.613	-1.000	0.000	0.500	1.000	1.000
regulatory_policy	0.421	0.731	-1.000	0.000	1.000	1.000	1.000
avg_policy	0.529	0.578	-1.000	0.250	0.750	1.000	1.000
mention_capital_flow	0.062	0.241	0.000	0.000	0.000	0.000	1.000
Key variables:							
ret_m (in percent)	0.391	5.873	-38.585	-2.281	0.242	2.833	47.751
alpha_ch3 (in percent)	0.184	3.533	-39.508	-1.286	0.042	1.463	51.773
alpha_ch4 (in percent)	0.190	3.483	-43.369	-1.250	0.047	1.451	39.640
semi_ret (in percent)	1.989	14.072	-22.208	-7.588	0.706	8.242	40.454
stock_ratio (in percent)	60.298	34.770	0.000	19.290	78.890	89.450	93.930
stock_ratio_diff (in percent)	0.958	9.330	-22.770	-2.540	0.120	3.810	30.680
tna (in millions RMB)	1121.32	1744.85	12.82	117.81	396.47	1243.79	7942.99
flow	-0.016	0.313	-0.613	-0.126	-0.034	0.004	1.273
age (in months)	52.935	43.920	4	18	40	76	177

Panel B: Correlation Matrix

Expectation:	equity_market	macro	fiscal_policy	monetary_policy	regulatory_policy	avg_policy
equity_market	1.000					
macro	0.372	1.000				
fiscal_policy	0.230	0.189	1.000			
monetary_policy	0.285	-0.002	0.354	1.000		
regulatory_policy	0.366	0.302	0.327	0.334	1.000	
avg_policy	0.336	0.128	0.799	0.897	0.889	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 four specifications: Columns (1) and (2) 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 Effects			
	(1)	(2)	(3)
	Fund FE	Time FE	Fund+Time FE
Expectation:			
equity_market	0.183	0.140	0.289
macro	0.187	0.261	0.406
fiscal_policy	0.246	0.141	0.366
monetary_policy	0.166	0.416	0.518
regulatory_policy	0.316	0.192	0.419
avg_policy	0.164	0.306	0.416

Panel B: Variation Decomposition – Fund Family and Fund Manager Fixed Effects				
	(1)	(2)	(3)	(4)
	Fund Family		Fund Manager	
	FE	+ Time FE	FE	+ Time FE
Expectation:				
equity_market	0.025	0.159	0.294	0.374
macro	0.021	0.277	0.302	0.478
fiscal_policy	0.032	0.174	0.370	0.461
monetary_policy	0.021	0.427	0.288	0.575
regulatory_policy	0.038	0.219	0.444	0.518
avg_policy	0.020	0.320	0.283	0.487

Table 3: Decomposing Equity Market Expectations

This table reports regressions examining the relationship between fund managers' equity market expectations and their macroeconomic and policy expectations, as well as the role of capital-flow-related narratives. Panel A reports the baseline regressions relating equity market expectations to macroeconomic and policy expectations. Panel B reports regressions of equity market expectation residuals on an indicator for mentions of capital-flow keywords. Panel A includes fund and time fixed effects. In Panel B, column (1) includes fund and time fixed effects, and column (2) includes 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 the fund level. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Equity Market Expectations and Macro/Policy Expectations

	(1)	(2)	(3)	(4)	(5)	(6)
Expectation:	equity_market					
macro	0.190***					0.157***
	(57.05)					(42.35)
fiscal_policy		0.168***				
		(17.02)				
monetary_policy			0.170***			
			(25.80)			
regulatory_policy				0.180***		
				(25.12)		
avg_policy					0.214***	0.180***
					(37.41)	(31.25)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	58346	17654	34029	16427	45596	42563
R-sq	0.353	0.418	0.348	0.433	0.347	0.387

Panel B: Equity Market Residuals and Capital-Flow Mentions

	(1)	(2)
	expect_equity_resid	
mention_capital_flow	0.0329***	0.0246***
	(3.97)	(2.58)
Control	Yes	Yes
Fund FE	Yes	No
Manager FE	No	Yes
Time FE	Yes	Yes
N	32294	30048
R-sq	0.069	0.196

Table 4: 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 (10) 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 the 10%, 5%, and 1% levels, 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 5: Market Timing

This table reports results from semi-annual panel regressions of fund market timing on absolute levels of fund 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 publication 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 (10) 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 the 10%, 5%, and 1% levels, 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 6: 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, as well as the relation between policy belief prediction accuracy and equity market residual prediction accuracy. The sample period in Panels A to C 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), and the alpha of the Chinese four-factor model (Panel C). Both returns and alphas are expressed in monthly percentage terms. Panel D regresses policy belief prediction accuracy on equity market residual sentiment prediction accuracy. Panels A to C include time fixed effects. In Panel D, 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. We adjust standard errors for clustering at the fund level, and t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at the 10%, 5%, and 1% levels, 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

Panel D: Relationship of Belief Predictive Accuracy

	(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 7: Determinants of Funds' Residual Sentiment

This table reports panel regressions of funds' residual sentiment on fund performance and market conditions. Funds' residual sentiment is the residual component of funds' equity market expectations. All explanatory variables are constructed using the most recently available data prior to report publication. Specifically, for annual reports, we use data from October to December of the previous year, and for semi-annual reports, we use data from April to June of the same year. The explanatory variables include the fund's alpha based on the Chinese three-factor model in columns (1) and (3), the fund's alpha based on the Chinese four-factor model in columns (2) and (4), the CSI 300 index return (*mkt_3m_ret*), aggregate fund flow (*Avg_Flow*), and the fund's own flow (*fund_flow*) over the corresponding period. Columns (1) and (2) include fund fixed effects, and columns (3) and (4) include fund manager fixed effects. All regressions include fund size and age as controls and are estimated with constants, which are not reported. Standard errors are adjusted for two-way clustering at the fund and time levels. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	expect_equity_resid $_t$			
Avg_Flow	0.00363**	0.00353**	0.00361**	0.00354**
	(2.24)	(2.11)	(2.28)	(2.18)
fund_3m_alpha_ch3	-0.222		-0.197	
	(-1.67)		(-1.44)	
fund_3m_alpha_ch4		-0.224		-0.209
		(-1.48)		(-1.35)
mkt_3m_ret	-0.142	-0.137	-0.124	-0.119
	(-0.61)	(-0.59)	(-0.58)	(-0.55)
fund_flow	0.00130	0.00122	0.00114	0.00128
	(0.14)	(0.13)	(0.11)	(0.13)
stock_ratio	0.00153***	0.00155***	0.000679**	0.000687***
	(3.89)	(3.99)	(2.69)	(2.75)
Control	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	No
Manager FE	No	No	Yes	Yes
N	32200	32200	30010	30010
R-sq	0.016	0.016	0.151	0.151

Table 8: Instrumenting Aggregate Fund Flows with WMP Maturity Ratio

This table reports panel 2SLS regressions of funds' beliefs about market sentiment on aggregate fund flows. The dependent variable is funds' residual sentiment, measured by the residual component of funds' equity market expectations. The specification follows Table 7, except that aggregate fund flow (*Avg_Flow*) is instrumented with the WMP maturity ratio. The WMP maturity ratio is defined as the amount of bank wealth management products in fixed-maturity buckets that mature in a given month, divided by the outstanding amount in the same buckets. The fixed-maturity buckets include 6–12 months, 1–3 years, and above 3 years. To align the monthly maturity ratio with the reporting frequency of fund Outlooks, we average it over the corresponding pre-publication window. The table reports second-stage estimates in the upper part and first-stage estimates in the lower part. Columns (1) and (2) include fund fixed effects, and columns (3) and (4) include fund manager fixed effects. All regressions include the same controls as in Table 7, as well as additional unreported controls for M2 year-on-year growth, RMB loan year-on-year growth, the 3-month SHIBOR rate, and the first principal component of WMP-deposit spreads across different maturities. All regressions are estimated with constants, which are not reported. Standard errors are adjusted for two-way clustering at the fund and time levels. t-statistics are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Second Stage	expect_equity_resid $_t$			
Avg_Flow	0.00751***	0.00752***	0.00867***	0.00868***
	(4.21)	(4.19)	(4.65)	(4.64)
fund_3m_alpha_ch3	-0.0759		-0.0746	
	(-0.85)		(-0.83)	
fund_3m_alpha_ch4		-0.166		-0.180*
		(-1.75)		(-1.80)
mkt_3m_ret	-1.031***	-1.017***	-1.090***	-1.073***
	(-8.45)	(-8.44)	(-8.55)	(-8.60)
fund flow	0.00402	0.00494	-0.00164	-0.000429
	(0.35)	(0.45)	(-0.15)	(-0.04)
stock_ratio	0.00121***	0.00123***	0.000413	0.000425
	(3.61)	(3.62)	(1.74)	(1.79)
Control	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	No
Manager FE	No	No	Yes	Yes
N	20148	20148	18966	18966
First Stage	Avg_Flow			
WMP maturity ratio	727.1***	727.2***	624.5***	624.6***
	(3.75)	(3.75)	(3.17)	(3.17)
fund_3m_alpha_ch3	2.084		1.797	
	(0.85)		(0.61)	
fund_3m_alpha_ch4		3.206		3.060
		(1.24)		(1.03)
mkt_3m_ret	31.83**	31.64**	34.65*	34.43*

	(2.24)	(2.24)	(2.19)	(2.19)
fund flow	0.0374	0.0266	-0.0314	-0.0456
	(0.22)	(0.16)	(-0.17)	(-0.25)
stock_ratio	0.0112**	0.0109**	0.00567**	0.00552**
	(2.59)	(2.59)	(2.71)	(2.71)
Control	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	No
Manager FE	No	No	Yes	Yes
N	20148	20148	18966	18966
R-sq	0.754	0.754	0.756	0.756
F-Statistic	14.029	14.069	10.021	10.051

Table 9: Fund Expectations Predicting Fund Flow

This table presents the results for fund flow forecasting regressions. Fund $flow_{t+1}$ is measured over the three months following the publication month of the (semi-)annual report. Columns (1) to (5) and columns (7) to (11) examine whether fund expectations predict future fund flows. Columns (6) and (12) evaluate how the impact of market residual sentiment on future fund flows varies with aggregate fund flow. The main explanatory variables in columns (6) and (12) are market residual sentiment and its interaction with aggregate fund flow. All regressions include lagged fund performance and lagged fund flow, calculated over the three months prior to the (semi-)annual report publication. Additional control variables include fund size, past flow, and age. Columns (1) to (6) include fund and time fixed effects, while columns (7) to (12) include fund manager and time fixed effects. All regressions are estimated with constants, which are not reported. Standard errors are adjusted for two-way clustering at the fund and time levels. 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)	(9)	(10)	(11)	(12)
Expectation:	Fund Flow$_{t+1}$											
equity_market	0.010***						0.009**					
	(2.829)						(2.198)					
macro		-0.001			-0.001			-0.003			-0.004	
		(-0.514)			(-0.550)			(-0.875)			(-1.113)	
avg_policy			-0.001		-0.001				0.000		0.001	
			(-0.392)		(-0.262)				(0.024)		(0.189)	
equity_resid				0.012***	0.012***	0.017***				0.012**	0.012**	0.016***
				(2.852)	(2.852)	(4.407)				(2.481)	(2.444)	(3.914)
equity_resid						0.208***						0.193***
× Avg Flow$_t$						(3.064)						(3.026)
fund flow$_t$	0.079***	0.077***	0.074***	0.075***	0.075***	0.075***	0.073***	0.072***	0.067***	0.069***	0.069***	0.069***
	(3.869)	(3.820)	(3.417)	(3.174)	(3.172)	(3.177)	(3.711)	(3.858)	(3.455)	(3.291)	(3.299)	(3.292)
quarterly_ret	0.300*	0.262	0.240	0.234	0.235	0.232	0.332**	0.289*	0.259	0.252	0.252	0.249
(Until publication)	(1.812)	(1.576)	(1.371)	(1.348)	(1.349)	(1.342)	(2.218)	(1.890)	(1.624)	(1.630)	(1.631)	(1.619)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Manager FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	47656	46545	37684	32226	32226	32226	45487	44353	35441	30024	30024	30024
R-sq	0.146	0.146	0.160	0.174	0.174	0.174	0.206	0.212	0.226	0.231	0.231	0.231

Internet Appendix

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

This table reports the valid semi-annual and annual reports spanning from 2008 to 2023. We include only equity and hybrid funds during this period.

Year	Semi	Annual	Total
2008	221	266	487
2009	309	360	669
2010	397	439	836
2011	491	565	1,056
2012	626	708	1,334
2013	751	829	1,580
2014	905	997	1,902
2015	1,143	1,558	2,701
2016	1,801	2,109	3,910
2017	2,263	2,757	5,020
2018	2,947	2,960	5,907
2019	3,012	3,247	6,259
2020	3,466	3,862	7,328
2021	4,339	4,899	9,238
2022	5,439	5,691	11,130
2023	5,935	6,151	12,086
Total	**34,045**	**37,398**	**71,443**

Table 2A: LLM Response Consistency

This table reports the verification results of our methodology to address concerns about lookahead bias when applying LLMs. 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 evaluate each specification.

	(1)	(2)	(3)
Expectation:	**no year**	**5y forward**	**5y backward**
equity_market	0.904	0.892	0.899
macro	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: Non-Mentioned Macro and Policy Beliefs

This table examines whether the baseline treatment of "Not Mentioned" responses as missing affects the decomposition of equity market expectations. The dependent variable is the equity market expectation. Macro and average policy expectations are set to zero when the corresponding topic is not mentioned, and separate indicators identify non-mentions of macro and policy beliefs. Column (1) includes fund and time fixed effects; Column (2) includes fund manager and time fixed effects. All regressions control for fund size, flow, and age. Standard errors are clustered 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)
	expect_equity_market	
avg_policy fill-0	0.179***	0.159***
	(34.35)	(25.47)
Policy non-mention	0.0942***	0.0945***
	(16.11)	(13.65)
Macro fill-0	0.176***	0.164***
	(54.88)	(43.22)
Macro non-mention	0.0586***	0.0563***
	(8.02)	(6.70)
Control	Yes	Yes
Fund FE	Yes	No
Manager FE	No	Yes
Time FE	Yes	Yes
N	64867	52392
R-sq	0.357	0.425

Table 4A: Validation of LLM Responses

This table reports the validation results of LLM-generated annotations against human annotations. We select 500 high-quality data points and evaluate them across five key expectation dimensions: macroeconomic fundamentals, the equity market, fiscal policy, monetary policy, and regulatory policy. 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**	**Fiscal Policy**	**Monetary Policy**	**Regulatory Policy**
First Round:					
Consistent Number	387	382	467	450	435
Inconsistent Number	113	118	33	50	65
1st Consistency Rate	0.77	0.76	0.93	0.90	0.87
Second Round:					
Agree with LLM Number	47	54	14	13	22
2nd Consistency Rate	0.87	0.87	0.96	0.93	0.91
Overall Consistency Rate			**0.91**		

Table 5A: Fund Expectations and Fund Characteristics

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 publication 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 6A: Market Conditions 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 publication month)	equity_market		macro		avg_policy		equity_resid	
semi_hs300_ret	0.347***		0.563***		0.0532***		0.237***	
	(23.04)		(25.82)		(3.11)		(15.47)	
semi_hs300_sd		-1.009		-10.36***		30.36***		-4.970***
		(-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 7A: Predictive Accuracy and Fund Performance (Excluding Passive Fund)

This table replicates Table 6 after excluding 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)	(2)	(3)	(4)
	alpha_ch3	alpha_ch3	alpha_ch3	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)	(2)	(3)	(4)
	alpha_ch4	alpha_ch4	alpha_ch4	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 8A: Predictive Accuracy and Fund Performance (Expanding Window Estimation)

This table constructs each fund's past predictive accuracy using an expanding window (starting after five periods) 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 6.

	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

Table 9A: Predictive Accuracy and Fund Performance (Alternative Rolling Window)

This table replicates Table 6 using rolling regressions over the past ten periods to construct each fund's past belief prediction accuracy, with at least six valid observations required for estimation.

Panel A: Raw Return				
	(1)	(2)	(3)	(4)
	ret_m	ret_m	ret_m	ret_m
Coef_equity_market	0.000219			
	(0.00)			
Coef_macro		-0.152***		
		(-2.98)		
Coef_policy			0.140**	
			(2.35)	
Coef_equity_resid				-0.100*
				(-1.68)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	84389	85233	68267	53670
R-sq	0.562	0.545	0.527	0.554
Panel B: Alpha (Three factors)				
	(1)	(2)	(3)	(4)
	alpha_ch3	alpha_ch3	alpha_ch3	alpha_ch3
Coef_equity_market	0.0272			
	(0.63)			
Coef_macro		-0.0609		
		(-1.47)		
Coef_policy			0.130**	
			(2.57)	
Coef_equity_resid				-0.0861*
				(-1.68)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	84389	85233	68267	53670
R-sq	0.124	0.120	0.112	0.121

Panel C: Alpha (Four factors)				
	(1)	(2)	(3)	(4)
	alpha_ch4	alpha_ch4	alpha_ch4	alpha_ch4
Coef_equity_market	0.0219			
	(0.51)			
Coef_macro		-0.0544		
		(-1.32)		
Coef_policy			0.0958*	
			(1.88)	
Coef_equity_resid				-0.110**
				(-2.09)
Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	84389	85233	68267	53670
R-sq	0.092	0.090	0.085	0.093

Appendix B: Sample Report and DeepSeek Response

Sample 1:

Outlook: (2015 annual report of 000031.OF)

Outlook:

展望 2016 年，宏观政策方面最大的看点就是供给侧改革，如果去产能、去库存、去杠杆、降成本、补短板的政策真的能够落地，那么 2016 年将是中国经济向死而生的一年。随着市场真正出清的完成，长期来看，中国经济前景充满光明。对应到股市上，2016 年需要降低预期收益率。首先，在经济出清的过程中，企业盈利短期会承受压力，局部的刚性兑付可能会被打破，这个过程中投资者的风险偏好会下降；其次，人民币汇率始终面临压力。在美国进入加息周期，美元持续走强的大背景下，人民币不贬值会面临资本外逃的压力，人民币贬值则牵制国内的货币政策无法放水，这个死结短期内很难解开；第三，注册制的实施会给市场带来长远的结构性变化，随着股票供给的增加，小盘股的壳资源价值会逐步消失，以创业板为代表的并购增长模式也会随着上市门槛的降低而变得越来越困难，因此中国股市长期存在的小盘股大幅溢价情况将会出现趋势性的变化。综上所述，2016 年股市整体上将是休养生息的一年，机会更多的体现在波段操作以及“自下而上”的结构性机会上。2016 年，本基金将采取积极防御的策略，重点把握以下几类投资机会：(1)积极进行波段操作，积小胜为大胜，努力谋求赚取市场波动的钱；(2)深入挖掘供给侧改革中蕴含的投资机会，如果国企改革政策能够破冰，可能会有较好盈利机会；(3)“自下而上”挖掘能够超越牛熊周期的真正经典成长股并长期持有，获取企业 EPS 增长的钱；(4)保留足够的现金，为下一轮牛市储备好充足的粮草。珍惜基金份额持有人的每一分投资和每一份信任，本基金将继续奉行华夏基金管理有限公司“为信任奉献回报”的经营理念，规范运作，审慎投资，勤勉尽责地为基金份额持有人谋求长期、稳定的回报。

Looking ahead to 2016, the biggest focus in macroeconomic policy is supply-side reform. If the policies of reducing overcapacity, destocking, deleveraging, lowering costs, and addressing weaknesses can be effectively implemented, then 2016 will be a year of revival for China's economy. Once the market fully clears, the long-term prospects for China's economy are bright.

In terms of the stock market, the expected return rate needs to be lowered in 2016. First, during the economic clearing process, corporate profits will face short-term pressure, and some rigid payments might be disrupted, leading to a decrease in investor risk appetite. Second, the RMB exchange rate is consistently under pressure. In the context of the U.S. entering a rate hike cycle and the continued strengthening of the dollar, if the RMB does not depreciate, it will face capital outflow pressure. If it does depreciate, it will constrain domestic monetary policy, making it difficult to ease in the short term. Third, the implementation of the registration system will bring long-term structural changes to the market. With the increase in stock supply, the value of small-cap shell resources will gradually disappear. The merger and acquisition growth model, represented by the ChiNext, will become increasingly challenging as listing thresholds are lowered. Therefore, the substantial premium on small-cap stocks, long present in the Chinese stock market, will

undergo a trend change.

In summary, 2016 will be a year of recovery for the stock market, with opportunities primarily in short-term trading and bottom-up structural opportunities. In 2016, this fund will adopt an actively defensive strategy, focusing on several key areas. First, active short-term trading, accumulating small gains for larger profits. Second, exploring investment opportunities in supply-side reforms, particularly if state-owned enterprise reform policies break new ground. Third, bottom-up selection of true classic growth stocks that can transcend market cycles, aiming to benefit from EPS growth. Fourth, maintaining sufficient cash reserves for the next bull market.

The fund will continue to uphold the company's philosophy of "delivering returns for trust," operating compliantly, investing prudently, and diligently seeking long-term, stable returns for fund shareholders.

Expectation Response:

1. Fiscal Policy: Not Mentioned

文本未直接提及国内财政政策的具体内容或评价，仅讨论供给侧改革的结构性调整。

The text does not directly mention specific domestic fiscal policy content or evaluate it; it only discusses supply-side reform as a structural adjustment.

2. Monetary Policy: Weakly Negative

人民币面临贬值压力，限制了货币政策的灵活性。

The RMB faces depreciation pressure, limiting the flexibility of monetary policy.

3. Regulatory Policy: Negative

注册制实施将导致小盘股壳资源价值消失和并购增长模式困难，作者明确提及其对市场结构的长期负面影响。

The implementation of the registration system will bring structural changes, but long-term effects are negative.

4. National Macroeconomic Fundamental: Weakly Negative

短期经济出清过程中企业盈利承压，刚性兑付可能被打破，风险偏好下降，但长期前景被谨慎乐观提及。

During short-term economic clearing, corporate earnings will be under pressure, implicit guarantees may be broken, and risk appetite may fall, although the long-term outlook is mentioned with cautious optimism.

5. Global Macroeconomic Fundamental: Not Mentioned

文本仅提及美国加息周期和美元走强对人民币汇率的影响，未直接评价全球宏观经济基本面。

The text only mentions the impact of the US rate-hiking cycle and a stronger US dollar on the RMB exchange rate; it does not directly evaluate global macroeconomic fundamentals.

6. Equity Market: Weakly Negative

整体市场预期收益率需降低，机会仅存于波段操作和结构性机会，且小盘股溢价趋势将逆转

Overall equity-market return expectations need to be lowered; opportunities are limited to tactical trading and structural stock selection, and the small-cap premium is expected to reverse.

7. Bond Market: Not Mentioned

未提及。

No mention in the report.

Sample 2:

Outlook: (2020 annual report of 004807.OF)

Outlook:

由于 2020 年的低基数效应，2021 年国内经济增速料将前高后低，但短期内经济增速的走高料将不会构成影响债市的主要变量，经济环比增速、货币政策、通胀和疫苗接种进度将会是影响 2021 年债市的重要因素。财政刺激力度料将较去年趋缓，货币政策向常态化回归，资金利率中枢将较 2020 年明显抬升，警惕货币政策收紧下的信用收缩风险，债券市场有波段操作机会，但难有趋势性行情。我们分析，2021 年股市的行情推动力在盈利，大部分行业大部分股票的估值修复基本到位。资本市场的改革在持续推进，公募基金的赚钱效应在改变投资者的理财行为，预计增量资金还会持续流入股票市场，结构性的机会可能向中小市值与景气反转的传统行业蔓延。需要时刻警惕的是，国内货币政策的转弯、信用市场的收紧对高估值板块的冲击。为此，我们继续保持较高的股票仓位，行业配置要适度均衡，并根据市场的变化及时调整仓位，保住绝对收益。

Due to the low-base effect from 2020, domestic economic growth in 2021 is expected to be front-loaded and then slow later in the year. However, the near-term pickup in growth is unlikely to be the main variable driving the bond market. Sequential economic momentum, monetary policy, inflation, and vaccine rollout progress will be the important factors for bonds in 2021. Fiscal stimulus is expected to moderate relative to last year, monetary policy is returning to a more normal stance, and the funding-rate center is likely to rise materially from 2020 levels. Investors should watch for the risk that monetary tightening and credit-market

contraction may weigh on the market. The bond market may offer tactical trading opportunities, but it is unlikely to enter a sustained trend.

For equities, we believe the main driver in 2021 will be earnings. Valuation repair has largely been completed across most industries and stocks. Capital-market reform is continuing, and the wealth effect from public mutual funds is changing investors' wealth-management behavior. As a result, incremental funds are expected to continue flowing into the stock market, and structural opportunities may broaden toward small- and mid-cap stocks as well as traditional industries with cyclical recovery momentum. At the same time, investors should remain alert to the impact of a turn in domestic monetary policy and tighter credit conditions on high-valuation sectors. Therefore, we will continue to maintain a relatively high equity allocation, keep sector exposure moderately balanced, and adjust positions in response to market changes in order to preserve absolute returns.

Expectation Response:

1. Fiscal Policy: Weakly Negative

财政刺激力度较去年趋缓，显示政策支持力度减弱。

Fiscal stimulus is expected to slow relative to last year, indicating weaker policy support.

2. Monetary Policy: Negative

货币政策向常态化回归，资金利率中枢明显抬升，且需警惕收紧风险。

Monetary policy is returning to normal, the funding-rate center is rising materially, and tightening risk needs to be watched.

3. Regulatory Policy: Not Mentioned

4. National Macroeconomic Fundamental: Weakly Negative

经济增速呈现前高后低趋势，隐含对后续增长动能的担忧。

Economic growth is expected to be front-loaded and then slow, implying concern about later growth momentum.

5. Global Macroeconomic Fundamental: Not Mentioned

6. Equity Market: Weakly Positive

预计增量资金持续流入，结构性机会向中小市值及传统行业扩散。

The author expects incremental funds to keep flowing in and structural opportunities to broaden toward small- and mid-cap stocks and traditional industries.

7. Bond Market: Weakly Positive

存在波段操作机会，但趋势性行情受货币政策收紧制约。

The bond market offers tactical trading opportunities, but a sustained trend is constrained by monetary tightening.

Appendix C: Predictability of Average Fund Beliefs

This appendix examines whether fund managers' expectations predict future market returns, macroeconomic fluctuations, and policy developments. Because each macroeconomic and policy outcome has only one aggregate time series, we focus on the predictive power of the cross-sectional average of fund managers' beliefs for the corresponding variables.

We begin with market returns by running time-series regressions of subsequent three-month equity market index returns, RI_equity_{t+1}, on the cross-sectional averages of funds' expectations at time t:

$$RI_equity_{t+1} = \alpha + \beta \overline{expectations}_t + \varepsilon_{t+1}. \qquad (3)$$

For the equity-market benchmark, we use the CSI 300 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 belief components related to macro fundamentals, policy, and market sentiment: $expect_equity_market$, $expect_macro$, $expect_avg_policy$, and $equity_resid$.

Table C1 presents the regression results. Columns (1) through (5) use simple averages of funds' expectations, while Columns (6) through (10) use AUM-weighted averages. We compute Newey-West standard errors with three lags. The results are highly consistent across the two weighting schemes.

The table reveals a striking pattern. Column (3) shows that the average policy expectations significantly and positively predict future equity index returns. Despite the relatively short time series of 32 semi-annual observations, the coefficient is statistically significant, with a t-statistic above 2.5. A one-unit increase in $expect_avg_policy$ is associated with a 16.8 percentage-point increase in 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 residual sentiment, have no significant predictive power for future returns.[13]

When macroeconomic expectations, policy expectations, and residual sentiment are

[13] These results further suggest that look-ahead bias is unlikely to be a major concern in our setting. If future market information embedded in the LLM training data were contaminating our prediction exercise, we would expect average market expectations to systematically predict future market returns. We find no such evidence. This is because our approach uses the model to extract and classify the tone of fund managers' stated beliefs across different dimensions, rather than to forecast future outcomes.

included jointly in Column (5), the coefficient on policy expectations remains significantly positive and similar in magnitude, while the coefficients on the other variables are insignificant. Table C1 therefore shows that fund managers' average beliefs contain information about future equity-market returns, but this predictability comes primarily from policy expectations rather than from their overall equity-market views or macro-fundamental views. This contrast underscores the central role of government policy in shaping market dynamics in China, consistent with Brunnermeier, Sockin, and Xiong (2022).

The predictive power of policy beliefs raises a natural follow-up question: do fund managers' expectations about specific policy dimensions predict subsequent policy developments?[14] For fiscal policy, we focus on the government's deficit-to-GDP target, announced in the central government work report, which has typically been released each March since 2010 and sets the fiscal 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 measure reflects China's quantity-based monetary policy framework, which has historically placed greater emphasis on M2 growth than on a single policy interest rate. We also examine whether funds' macroeconomic expectations predict subsequent GDP growth.

We use the same time-series regression specified in (3), replacing the left-hand variable with the macro variable. Table C2 presents the results. Columns (1) through (3) use simple averages of funds' expectations, while Columns (4) through (6) use the AUM-weighted averages. We again compute Newey–West standard errors with three lags. The results are consistent across specifications. Fiscal policy expectations significantly predict the subsequent deficit-ratio target in both the simple-average and AUM-weighted specifications. Monetary policy expectations also significantly predict future M2 growth. Macroeconomic expectations also significantly predict subsequent GDP growth. Thus, managers' stated beliefs map systematically into realized outcomes in both policy and macroeconomic domains.

Taken together, Tables C1 and C2 reveal an important asymmetry. Both macroeconomic and policy beliefs contain genuine forward-looking information, but only policy beliefs predict subsequent market returns. This pattern suggests that fund managers' policy beliefs capture information not fully incorporated into current market prices, whereas their beliefs about macro fundamentals do not have comparable return-predictive content. The evidence is consistent

[14] 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.

with fund managers devoting particular attention to policy analysis in China's policy-sensitive financial markets.

Table C1: 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 publication 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 each 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 percentage. 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 the 10%, 5%, and 1% levels, 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 C2: Fund Beliefs Predicting Policies & Macroeconomic Fundamentals

This table presents results using semi-annual data from 2008 to 2023. 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 and the number of time-series observations is 29. 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 the 10%, 5%, and 1% levels, 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