Structured Beliefs and Fund Performance: An LLM-Based Approach*

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Abstract

Leveraging the unprecedented capabilities of Large Language Models (LLMs) to assess sentiment across different topics within the same text, we extract the structured beliefs of all mutual fund managers in China based on their reports spanning 2008 to 2023, regarding the economy, government policies, and financial markets. Specifically, we construct a measure for countercyclical policy (CCP) beliefs, where managers anticipate that government policies will counteract economic shocks. We find that funds exhibiting frequent CCP beliefs (CCP funds) significantly outperform other funds. To explain this superior performance, we demonstrate that CCP funds' market beliefs have stronger predictive power for market returns, their asset allocations show a stronger correlation with their market beliefs, and their performance is directly linked to their time-varying CCP beliefs.

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Although beliefs about the economy and asset market dynamics are crucial for financial investments, directly analyzing how these investor beliefs influence their investments and asset prices is challenging due to the lack of a direct measure of beliefs. To address this gap, researchers have often relied on surveys, such as Shiller (2000), Manski (2004), Greenwood and Shleifer (2014), Coibion and Gorodnichenko (2015), Giglio et al. (2021), and Nagel and Xu (2022). However, survey data come with significant limitations, particularly in terms of respondent representativeness and continuity. Typically, survey respondents include financial analysts, professional economists, and random households, who may not accurately represent the typical investors making decisions in financial markets. Furthermore, it is also challenging to obtain repeated survey responses from the same investors for an extended period, which is essential for analyzing asset market dynamics over time.

Studying structured beliefs presents an even greater challenge. Structured beliefs refer to the way investors' expectations about asset returns are intricately linked to their beliefs regarding the interactions between various forces driving the economy and financial markets. For instance, financial markets might be influenced by investors' beliefs about how monetary policy will respond to an initial inflation shock. Similarly, the stock price of a firm could depend on investors' beliefs about how industry competition might react to a positive shock to the firm. Additionally, the stock market's response to an initial negative economic shock may hinge on investors' beliefs about how government policies will respond to stimulate the economy. Despite the critical importance of understanding these mechanisms, the existing literature has to rely on indirect inference to analyze the relevance of these structured beliefs.

This paper explores how investors' beliefs about government interventions influence their investment strategies, especially in the context of China's hybrid economic structure, which mixes market mechanisms with strong state interventions. As Brunnermeier, Sockin, and Xiong (2022) have shown, investors may shift their focus between economic fundamentals and government policies, sometimes ignoring fundamentals entirely to concentrate on policy actions. This focus on government interventions creates distinct dynamics in China's financial markets, unlike those in many other countries. Despite the frequent emphasis by market commentators and portfolio managers on the importance of understanding government policies in investment decisions, providing direct and systematic evidence on this issue remains

challenging.

A closely related issue is the performance of mutual funds in China, a rapidly growing segment of the financial system. Unlike their counterparts in the U.S., Chinese mutual funds tend to outperform market indices (before management fees), as reviewed by Jiang (2020). This makes it particularly relevant to understand their investment strategies and how their beliefs about government policies impact their performance.

In this paper, we tackle these challenges by using newly developed large language models (LLMs) to create structured beliefs about the economy, government policies, and financial markets from the reports of all mutual fund managers in China over a 16-year period. Since 2008, the China Securities Regulatory Commission (CSRC) has required all mutual fund managers to include comprehensive reviews of the economy and financial markets, along with detailed outlooks for the future, in their semi-annual and annual reports. These reports provide systematic insights into each manager's views on recent economic and market developments, as well as their beliefs about future trends. Because these reports are consistently produced by professional fund managers—a key group of participants in the financial markets— over a long period, they offer a more reliable and systematic dataset than typical survey data.

Since these fund reports are provided in textual form, a key challenge we face is dissecting different aspects and quantifying each one individually. The widely used bag-of-words approach, as seen in Tetlock (2007) and Loughran and McDonald (2011), is effective for quantifying the overall sentiment of an article or report, but it cannot distinguish the sentiment across distinct topics within the same text.[1] This limitation is particularly significant when analyzing investors' structured beliefs. For example, an investor might be pessimistic about recent economic shocks but remain optimistic about the stock market due to their belief in the government's countercyclical policy interventions. The mix of pessimistic and optimistic phrases for different topics in the same text makes it difficult to use word counting to dissect the investor's beliefs about different topics.[2]

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[1] See Gentzkow, Kelly, and Taddy (2019) for a review of the broad economic literature of treating text as data.

[2] Recently, Bybee et al. (2020) adopted the Latent Dirichlet Allocation (LDA) topic modeling approach of Blei et al. (2003) to estimate a topic model that summarizes business news from the Wall Street Journal into easily interpretable topical themes. They quantified the proportion of news attention allocated to each theme at different

The newly emerged large language models (LLMs) offer unprecedented capabilities for analyzing textual data. Trained on vast amounts of diverse text and built on sophisticated neural network architectures, LLMs can not only reliably determine the overall sentiment of a given text but, more importantly, discern the sentiment associated with different topics within the text. This enables researchers to uncover the multi-dimensional structure of the text, allowing for a more nuanced analysis of how sentiments vary across different aspects—such as economic conditions, government policies, and market outlooks—within the same document. This capability is particularly valuable for analyzing the structure of beliefs.

We used GPT-4.0 to process reviews and outlooks from all mutual fund reports between 2008 and 2023. Specifically, we extracted each fund manager's review of six key areas over the past 6 months: the macroeconomy, monetary policy, fiscal policy, regulatory policy, the stock market, and the bond market. We also captured their beliefs about these areas for the upcoming period. Each review and belief was quantified into one of five categories: 1 (positive), 0.5 (weakly positive), 0 (neutral), -0.5 (weakly negative), and -1 (negative). [3]

Using these quantified reviews and beliefs, we constructed a set of countercyclical policy (CCP) belief variables to determine whether a manager expects government policies to counteract current economic conditions in each period. Specifically, these variables identify whether a manager holds a negative view of the economy while believing the government will implement accommodating policies (monetary, fiscal, or regulatory) to stimulate the economy, or, conversely, whether the manager holds a positive view of the economy while expecting the government to tighten such policies.

We find that fund fixed effects and time fixed effects together account for only about 20% of the variation in fund managers' CCP beliefs, suggesting that these beliefs are largely

points in time. While this approach effectively decomposes news articles into a structured set of themes, identifying the sentiment of a report on a specific theme remains challenging.

[3] Recently, Glasserman and Lin (2024) and Sarkar and Vafa (2024) have raised concerns about lookahead bias in outputs from pretrained language models. This issue arises because a language model's pretraining data may contain future information, which can inadvertently influence analyses that should only rely on past data. This lookahead bias is not relevant to our analysis, as we use GPT solely to assess the sentiment of a text on a specific topic, rather than instructing it to predict future events. Additionally, we conducted robustness checks by altering the dates in the fund reports and still obtained highly correlated belief measures.

driven by each fund's idiosyncratic reactions to time-varying economic conditions. Since, on average, funds hold CCP beliefs 20.2% of the time, we define a fund as a CCP fund if its frequency of holding CCP beliefs exceeds 20%. This higher frequency indicates the presence of an intrinsic framework that the fund consistently uses to analyze the economy and form beliefs about financial markets.

Interestingly, we find compelling evidence that CCP funds significantly outperformed non-CCP funds in our sample. We examined not only raw monthly fund returns but also risk-adjusted alphas using the 3-factor (CH3) and 4-factor (CH4) models developed by Liu, Stambaugh, and Yuan (2019). Even after controlling for various fund characteristics, CCP funds outperformed non-CCP funds on a monthly basis by 6.6 basis points (raw return), 5.9 basis points (CH3 alpha), and 6.7 basis points (CH4 alpha). This outperformance is significant across all measures, highlighting the potential importance of CCP beliefs in shaping investment decisions and driving subsequent fund performance.

To understand how CCP funds capitalize on their ability to effectively anticipate countercyclical policies, we conducted a comprehensive analysis in four steps. First, we examined whether the expectations of all funds regarding equity and bond markets, as extracted from their reports, could predict future returns of equity and bond market indices. Our analysis confirmed that these expectations indeed possess significant predictive power. More importantly, this predictive power is particularly strong for CCP funds, affirming their superior capability in anticipating market movements.

Second, we explored the relationship between fund managers' expectations about equity and bond markets and their asset allocations, comparing CCP and non-CCP funds. Our findings indicate that funds generally allocate a larger fraction of their investments to stocks or bonds when they hold more optimistic beliefs about the equity or bond markets, respectively. This relationship is notably stronger for CCP funds, highlighting their more responsive and informed asset allocation strategies.

Third, we analyzed whether the funds' investment decisions could predict future market returns. We found that changes in CCP funds' portfolio allocations have a stronger predictive power for future index returns, providing direct evidence of their outperformance relative to non-CCP funds.

Finally, we assessed the performance of CCP funds based on whether they held CCP beliefs at a given time. Our results show that CCP funds' time-varying CCP beliefs are significantly associated with higher monthly returns and risk-adjusted returns. This finding provides direct evidence linking their superior performance to their CCP beliefs.

In summary, our analysis demonstrates that mutual funds in China frequently exhibit countercyclical policy beliefs, which significantly contribute to their investment performance. Our study not only provides strong evidence that state interventions play a crucial role in driving financial market dynamics, as argued by Brunnermeier, Sockin, and Xiong (2022), but also highlights mutual fund managers' ability to anticipate government policies as a key factor in explaining the superior performance of Chinese mutual funds, a distinctive phenomenon highlighted by Jiang (2020). More broadly, our results highlight investors' beliefs about government policies, not just market returns, as a crucial factor in their investment decisions.

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; Giglio et al., 2023), 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.

An advantage of our dataset is its relatively large sample size, encompassing all mutual funds in China. More importantly, the comprehensive reviews and 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' countercyclical policy beliefs as a new factor for investors' investment decisions. While Ammer et al. (2022, 2023) also analyze the same Chinese mutual fund reports, their focus is limited to fund managers' market expectations, without delving into other dimensions or the structured beliefs we explore.

We also contribute to the long-standing literature on mutual fund managerial skill and

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

Our paper also contributes to the recent literature on the use of LLMs in financial applications, including classification (Hansen and Kazinnik, 2023; Yang and Menczer, 2023; Bernard et al., 2023; Dasgupta, Li, & Wu, 2023) and sentiment analysis for return prediction (Chen et al., 2022; Lu et al., 2023; Lopez-Lira and Tang, 2023; Jha et al., 2023; Bybee, 2023). Specifically, Hansen and Kazinnik (2023) demonstrate that LLMs, particularly GPT-4, excel in classifying policy stances and identifying macroeconomic shocks through a narrative approach. Beyond simple disclosure classification, researchers are finding innovative ways to use ChatGPT for evaluating firms' financial characteristics. For example, Bernard et al. (2023) train a GPT-based LLM to classify XBRL tags and construct a modular measure of business complexity. Chen et al. (2022), Lopez-Lira and Tang (2023) and Bybee (2023) show that LLM-based sentiment analysis of news can effectively forecast returns and generate profitable trading signals.

Additionally, we contribute to the literature employing machine learning and AI to extract targeted and standardized information. For instance, Hassan et al. (2019) develop a novel measure of firm-level political risk by analyzing earnings conference calls through computational linguistics. Sautner et al. (2023) and Li et al. (2023) create specific dictionaries to capture firms' climate change exposures. Kim et al. (2023) use GPT to summarize and assess companies' exposure to political, climate, and AI-related risks from earnings calls, while Kim et al. (2024) find that GPT can generate summaries with richer information content for MD&As in 10-Ks and conference calls.

I. Data Description

A. Mutual Fund Reports

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

In these reports, fund managers offer a comprehensive analysis of economic factors relevant to their portfolio investments. The reports typically consist of two main sections:

- Review Section: This part examines recent developments in both Chinese and global economies, assesses government policies, and analyzes financial market performance.
- Outlook Section: Here, managers present their projections for future economic trends, potential policy responses, and anticipated performance of equity and bond markets in the upcoming period.

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

We utilize the Wind database to access these reports, focusing specifically on the review and outlook sections. Our dataset comprises 201,605 reports with valid sections spanning from 2008 to 2023. To maintain a focus on the Chinese market, we have excluded Qualified Domestic Institutional Investor (QDII) funds from our analysis.

We obtain additional data on mutual fund returns, flows, holdings, and other relevant market and accounting information from the Wind database. We align these semi-annual and annual reports with fund data based on the month of public release. For annual reports, which are typically published in March or April, we use the following matching criteria:

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

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

Semi-annual reports are matched with monthly data starting in October, as third-quarter holding data generally becomes available in that month.

The final sample comprises 432,073 fund-month observations and 75,448 reports spanning from 2008 to 2023. To ensure sufficient longitudinal data for each fund, we include only those with at least 10 reports over the full period. Table 1A in Appendix A presents the number of annual and semi-annual reports in our sample from 2008 to 2023. The data reveals a consistent growth in the number of funds over the years, indicating rapid expansion of the mutual fund industry in China: Semi-annual reports increased from 282 in the first half of 2008 to 4,208 in the first half of 2023, while annual reports grew from 333 in 2008 to 4,162 in 2023.

B. Quantifying Reviews and Outlooks

The CSRC grants fund managers significant discretion in their commentary focus, without imposing strict guidelines on content. The review and expectation sections vary considerably in length, ranging from 30 to over 6,000 Chinese characters, depending on the depth and breadth of topics covered.

Managers typically address three main areas in their reports. First, they analyze macroeconomics, distinguishing between domestic and global factors. Second, they discuss policies, including fiscal, monetary, and regulatory aspects. Third, they examine financial markets, differentiating between equity and bond markets. This structure allows for a comprehensive analysis of the factors influencing future outlook and fund investments, while providing flexibility for managers to emphasize areas they deem most relevant to their specific portfolios and investment strategies.

To convert the qualitative information in mutual fund reports into quantitative measures, we employ ChatGPT-4, a state-of-the-art natural language processing (NLP) model. This advanced AI system, trained on an extensive corpus of text data, excels in comprehending the structure and semantic meaning of natural language. ChatGPT-4's architecture incorporates transformer blocks and self-attention mechanisms, key features that enable it to process lengthy

text sequences effectively. These components allow the model to focus on the most pertinent parts of the input, resulting in enhanced semantic understanding and more precise responses. By leveraging ChatGPT-4's sophisticated capabilities, we can systematically analyze the nuanced content of fund manager reports, translating complex qualitative assessments into structured, quantifiable data.

Crafting effective prompts is crucial for guiding the GPT model to understand commands and respond appropriately. This process involves more than a simple search; it requires additional context, domain knowledge, and an understanding of the model's operational nuances to generate meaningful, contextually relevant responses. Prompts must be tailored to perform specific tasks.

In our study, we use the following prompt to separately process the review and outlook sections of each fund report in our sample:

"*Forget all your previous instructions. Assume the role of a Chinese financial expert specializing in financial report analysis. Your task is to assess the* ***review*** *(or* ***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."

In this prompt, we instruct ChatGPT to analyze the sentiment of a review or outlook section across eight topics, adopting the perspective of a professional Chinese financial expert. These eight topics analyzed encompass key aspects of economic and financial landscapes. We set the GPT model's temperature to 0 to minimize creativity and obtain the highest probability results, enhancing reproducibility. The output consistency rate exceeds 90% when running the model a thousand times for the same report.

While there may be concerns about look-forward bias when applying ChatGPT, as its training data is available up to December 2023, we emphasize that our study primarily uses the

model for *summarization* rather than *prediction*. This approach mitigates the risk of incorporating future information into our analysis.

To further validate our methodology, we conduct robustness checks by modifying temporal information in the report content. These modifications included removing year references, shifting dates forward or backward by 5 or 10 years. Even with these alterations, the model maintained a high output consistency rate, exceeding 90% across a thousand iterations per modified report. This consistency demonstrates the model's ability to extract sentiment and key information independently of specific temporal anchors, reinforcing the reliability of our summarization approach for historical financial reports.

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

- "Positive": 1
- "Weakly Positive": 0.5
- "Neutral" and "Not Mentioned": 0
- "Weakly Negative": -0.5
- "Negative": -1

Appendix B contains an example of the review and outlook sections from our dataset, along with the sentiment analysis for each topic as conducted by the ChatGPT language model. This example illustrates our methodology and provides transparency into the sentiment extraction process.

Table 1 presents summary statistics for our sample of mutual funds, including those for GPT-generated variables. These variables are separated into those extracted from the review and outlook sections of fund reports, alongside fund accounting and characteristics.

From the review section, we extracted six key variables, three of which relate to government policies—fiscal policy, monetary policy, and regulatory policy. Additionally, we included one variable concerning the national macroeconomy and two focused on financial markets—equity and bond markets. On average, fund managers' reviews of these dimensions are generally positive but display substantial variation. For instance, the review of the national macroeconomy is slightly positive, with a mean of 0.012 and a large standard deviation of 0.593. The review of monetary policy has a higher mean of 0.383 and a standard deviation of

0.527, while the review of the equity market shows a mean of 0.087 and a standard deviation of 0.666.

From the outlook section, we extracted fund managers' expectations along the same six dimensions. Interestingly, their expectations tend to have higher means than their reviews, though with similarly high variation. For example, their expectation for the national macroeconomy has a mean of 0.187 and a standard deviation of 0.584, while their expectation for the equity market shows a mean of 0.38 and a standard deviation of 0.492.

C. Fund Characteristics

At the end of 2023, our sample included 4,627 funds, comprising 621 equity funds, 1,488 bond funds, 2,089 hybrid funds, 365 money market funds, and 64 funds of other types (e.g., FOF, REITs). Of these, 4,345 funds were actively managed, while 282 were passively managed. The total assets under management for these funds amounted to 12.2 trillion yuan (approximately 1.71 trillion U.S. dollars). Specifically, the assets were distributed as follows: 6.0% in equity funds, 31.4% in bond funds, 15.2% in hybrid funds, 47% in money market funds, and 0.4% in other types of funds. Additionally, 96.7% of the assets were managed by active funds, with the remaining 3.3% managed by passive funds.

Table 1 also reports statistics for various fund characteristics. The monthly fund return in our sample has a mean of 0.53% and a standard deviation of 4.55%, while the semi-annual fund return has a mean of 3.03% and a standard deviation of 12.77%.

Following Liu, Stambaugh, and Yuan (2019), we apply the three-factor (CH3) and four-factor (CH4) models, particularly constructed for the Chinese market, to adjust risks for fund performance. Specifically, fund performance based on CH3 or CH4 is estimated as follows:

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

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

where:

- r_t is the return on a mutual fund in excess of the one-year deposit interest rate in China.
- $MKTRF_t$ is the excess return on the value-weighted portfolio of the top 70% of stocks (Liu, Stambaugh, and Yuan (2019) exclude the smallest 30% of stocks to avoid potential

bias from reverse mergers).

- SMB_t is the size factor, also excluding the smallest 30% of stocks.
- VMG_t is the value factor based on the earnings-price ratio.
- PMO_t is a sentiment factor based on turnovers, introduced in the four-factor (CH4) model.[4]

We apply the CH3 and CH4 models to estimate the alphas, which are derived as the constant term in the regressions. In these time-series regressions, we calculate Newey-West standard errors with a lag of 11 months to control for autocorrelation of residuals.

We used each fund's daily returns to compute its monthly alpha by adopting both CH3 and CH4 models. The CH3 alpha has a mean of 0.21% and a standard deviation of 2.62%, while the CH4 alpha has a mean of 0.21% and a standard deviation of 2.57%. Interestingly, this positive fund alpha contrasts with the negative alphas typically observed for mutual funds in the U.S. However, it is consistent with the general findings of mutual fund performance in China, as reviewed by Jiang (2021).

Many factors may have contributed to the substantial variations in reviews and expectations revealed by fund reports. Table 2A in Appendix A explores the relationship between fund characteristics and the funds' reviews and expectations. Specifically, we regress each fund's review or expectation for each of the six dimensions on a set of fund characteristics, including the fund's performance over the past six months (*semi_ret)*, total net assets (*log_tna*), recent fund flow (*flow*), and fund age (*age*).

Panel A of Table 2A in Appendix A presents the results from using the six variables extracted from fund managers' reviews and Panel B shows the results for the six variables extracted from fund managers' outlooks. Interestingly, recent fund performance consistently exhibits a significantly positive relationship with almost all the extracted variables. This suggests that both fund managers' reviews and expectations regarding the economy, government policies, and financial markets are positively correlated with recent fund performance. The patterns for the other three variables—*log_tna*, *flow*, and *age*—are less

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

uniform, displaying varying degrees of influence across different dimensions of reviews and expectations.

II. Countercyclical Policy Expectations

The fund managers' multi-dimensional reviews and expectations of the economy, government policies, and financial markets provide a unique opportunity to explore the structure of their beliefs, potentially uncovering complex investment strategies employed by these professionals. This comprehensive approach allows us to gain insights into how fund managers integrate various factors into their decision-making processes.

A distinctive feature of the Chinese economic landscape is the government's regular adoption of countercyclical macro interventions. The Chinese government employs a wide range of policy tools to manage economic cycles, which can be broadly categorized into three main areas:

1. Monetary policies: These include adjustments to interest rates and control over total bank lending. The People's Bank of China (PBOC) uses these tools to influence money supply and credit availability in the economy.
2. Fiscal policies: The government implements large-scale infrastructure projects and industrial policies aimed at promoting and developing specific sectors. These measures are often used to stimulate economic growth during downturns.
3. Regulatory policies: These encompass measures such as IPO quotas and adjustments to stamp taxes for stock trading. Such policies directly impact the capital markets and can influence investor behavior.

Typically, the Chinese government provides more support during economic downturns to buffer against distress, while tightening policies during periods of economic boom. This approach aims to smooth out economic cycles and maintain stable growth. Brunnermeier, Sockin, and Xiong (2022) argue that these pervasive government interventions have become a key factor in investors' decision-making processes, alongside traditional economic fundamentals. This perspective suggests that successful fund managers in China must not only analyze economic indicators but also anticipate and interpret government actions.

Given this backdrop, we focus on fund managers' expectations of countercyclical policies. We define countercyclical policy variables using a combination of policy expectations and national macroeconomic reviews extracted from fund reports. For each policy dimension *X* (where X represents fiscal, monetary, or regulatory policy), we define four indicators:

- *CCPn_X*: This indicator is set for a fund manager who believes that the economy is currently in a downturn (*review_national_macroeconomic* = -1) while the government is likely to adopt an easy policy in X to support the economy (*expect_policy* $\geqslant$ 0).
- *CCPp_X*: This indicator is set for a manager who believes that the economy is performing well (*review_national_macroeconomic* = 1) but expects the government to implement a tightening policy (*expect_policy* $\leqslant$ 0).
- *CCP_X:* This indicator is set to 1 if a manager expects the government policy in *X* to counter the current economic conditions in either direction, i.e., either *CCPn_X* or *CCPp_X* equals 1.
- *CCP:* This indicator is set to 1 if a manager displays countercyclical policy expectations in any of the three policy areas (fiscal, monetary, or regulatory).

We construct countercyclical policy variables based on whether a fund manager holds a strongly negative or strongly positive view of the economy (i.e., *review_national_macroeconomic* = -1 or 1), as opposed to a *weakly* negative or weakly positive view (i.e., *review_national_macroeconomic* = -0.5 or 0.5). By focusing on more extreme economic views, this definition allows for a sharper identification of the manager's countercyclical policy beliefs.

Table 2, Panel A presents the descriptive statistics of our constructed countercyclical policy variables. The mean values of the three countercyclical policy dummy variables are 0.175 for fiscal policy, 0.159 for monetary policy, and 0.183 for regulatory policy. These figures indicate that 17.5%, 15.9%, and 18.3% of the reports, respectively, express countercyclical policy expectations in these areas.

When considering a general measure of countercyclical policy expectations across all policy types, 21.4% of the reports indicate this type of expectation. Notably, this overall

percentage is only slightly higher than the individual percentages for each policy area. This suggests a high correlation among countercyclical expectations across different policy domains, implying that fund managers tend to anticipate coordinated countercyclical measures across fiscal, monetary, and regulatory policies rather than isolated interventions in specific areas.

There are also substantial variations in these countercyclical policy measures. To explore these variations, we adopt three fixed-effect regression models:

- Fund fixed effects: We incorporate fund fixed effects to account for the unique, time-invariant features of individual funds:

$$CCP_{i,t} = \alpha_i + \varepsilon_{i,t}. \qquad (3)$$

  This captures the inherent characteristics of each fund that may shape its countercyclical policy expectations.

- Time Fixed Effects: To understand the influence of broader, market-wide conditions, we include time fixed effects:

$$CCP_{i,t} = \beta_t + \varepsilon_{i,t}. \qquad (4)$$

  This identifies common, time-dependent factors that simultaneously impact all funds and their expectations.

- Two-way Fixed Effects: We explore the interplay between fund-specific characteristics and time-varying factors by incorporating both fund and time fixed effects:

$$CCP_{i,t} = \alpha_i + \beta_t + \varepsilon_{i,t}. \qquad (5)$$

  This approach uncovers the interactions between idiosyncratic fund traits and evolving economic or market conditions that jointly influence countercyclical policy expectations.

We consider fiscal, monetary, regulatory, and general policy expectations for each fixed-effect specification. Panel B of Table 2 reports the R-squared values for each of the three model specifications. Column (1) shows that fund fixed effects explain around 10% of the variation in the countercyclical policy measures, suggesting that fund heterogeneity plays a significant role in shaping expectations about countercyclical policies. Column (2) reports that time fixed

effects also account for approximately 10% of the variation in countercyclical policy expectations. This implies that time-varying, market-wide factors influence funds' views on countercyclical policies across the mutual fund industry.

Column (3) combines both fund and time fixed effects, revealing that these two sets of factors collectively absorb around 20% of the variations in the countercyclical policy measures. Importantly, this highlights that even after accounting for both fund-specific and time-dependent characteristics, the majority of variations (about 80%) remain unexplained. This substantial unexplained variation is likely driven by factors specific to the interaction between individual funds and particular time periods. It forms a crucial basis for our subsequent analysis, where we explore how these residual countercyclical policy expectations may help explain fund performance.

Panel B also reports the variation decomposition for variables related to fund managers' expectations in the equity and bond markets. Column (1) shows that fund fixed effects explain 31.4% and 24.3% of the variation in equity and bond market expectation variables, respectively. This suggests that individual funds' inherent characteristics and investment philosophies significantly shape their outlooks on these asset classes' future performance.

In contrast, Column (2) reveals that time fixed effects account for a smaller portion of the variation, explaining 5.7% and 3.8% of the changes in equity and bond market expectations, respectively. This indicates that while common, market-wide factors influence all funds' views, fund-specific factors are more dominant in determining expectations about equity and bond markets. Column (3), considering the joint impact of both fund and time fixed effects, shows that two-way fixed effects collectively explain 37.6% and 27.9% of the variation in equity and bond market expectation variables. This underscores the importance of accounting for both fund-level and time-dependent characteristics when analyzing fund managers' market expectations.

Notably, fund fixed effects explain a larger fraction of variations in market expectations, especially for the equity market, compared to variations in countercyclical policy expectations. The relatively lower explanatory power of fund fixed effects for policy expectations implies greater flexibility in managers' policy views. This flexibility is intriguing and suggests that policy expectations may vary more in response to changing economic conditions or new

information. Such adaptability in policy expectations could potentially contribute to fund performance in ways that more stable fund characteristics cannot. This observation motivates a further exploration of how these dynamic policy expectations may help explain fund performance. We will examine this relationship in detail in the next section.

III. Countercyclical Policy Funds

To explore the relationship between countercyclical policy expectations and fund performance, we first identify funds that frequently display such expectations, which we term "countercyclical policy funds" (CCP funds). We then compare the performance of CCP funds with that of non-CCP funds. The premise underlying this analysis is that more frequent display of countercyclical policy expectations likely reflects a systematic framework used by the fund manager to analyze the economy and financial markets. By comparing these two groups, we aim to determine whether such a systematic approach to policy analysis translates into differential fund performance.

Specifically, we construct a measure representing the fraction of countercyclical policy expectations in a fund's series of reports. Panel A of Table 3 presents the summary statistics of this fraction measure. The mean value is 20.2%, and the median value is 20%. Based on this measure, we label a fund as a "countercyclical policy fund" if the fraction of their countercyclical policy expectations is greater than or equal to the median of 20%. We then construct a dummy variable "CCP_fund" to indicate this label. The summary statistics of this dummy variable are also reported in Panel A of Table 3. By construction, 50.5% of funds in our sample are labeled as CCP funds.[5]

We now compare the performance of CCP and non-CCP funds. We construct three portfolios: one for all CCP funds, one for all non-CCP funds, and a long-short portfolio that longs CCP funds and shorts non-CCP funds. We compute both equal- and value-weighted

[5] In the robustness tests, we also consider an alternative classification approach for identifying funds with an even more frequent display of countercyclical policy expectations. Specifically, we construct another dummy variable "CCP_fund_03" that indicates funds where the fraction of their countercyclical policy expectations is larger than or equal to the top quintile of the distribution, which is 30%. This alternative measure allows us to focus on funds that consistently demonstrate a higher level of engagement with countercyclical policy analysis, providing an additional perspective on the relationship between policy expectations and fund performance.

returns for these portfolios. We then run time-series regressions of the monthly returns of these fund portfolios on various risk factors, using both CH3 and CH4 models specified in equations (1) and (2). Panels B, C, and D of Table 3 report the regression results, covering the CCP portfolio, the non-CCP portfolio, and the long-short portfolio, respectively.

Panel B shows that CCP funds generate significant CH3 and CH4 alphas for both equal-weighted and value-weighted portfolios. In contrast, as shown in Panel C, non-CCP funds have significant but smaller alphas for equal-weighted portfolios, while their value-weighted alphas are statistically insignificant. Panel D demonstrates that CCP funds significantly outperform non-CCP funds. In terms of economic magnitude, the monthly CH3-factor alphas of CCP funds outperform non-CCP funds by 0.147% (equal-weighted) and 0.187% (value-weighted), while the monthly CH4-factor alphas of CCP funds outperform non-CCP funds by 0.127% (equal-weighted) and 0.166% (value-weighted).

To further examine the relationship between mutual fund performance and countercyclical policy beliefs, we conduct a series of panel regression analyses. The panel regression model takes the following form:

$$r_{i,t+1} = \alpha_t + \beta \text{CCP_fund}_i + \delta X_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t+1}$ represents the future monthly returns (before and after risk adjustment) of fund i, α_t captures time fixed effects, and CCP_fund_i is a dummy variable indicating a CCP fund. Control variables $X_{i,t}$ include the fund's total net assets (tna), fund flows, and fund age. This panel regression model accounts for unobserved fund-specific characteristics and market-wide factors that may influence the relationship between fund type and fund performance.

Table 4 reports the regression results. We examine raw monthly fund returns (*ret*), as well as the risk-adjusted monthly returns using the Chinese three-factor (CH3) and four-factor (CH4) models (*alpha_ch3* and *alpha_ch4*). All these raw or risk-adjusted returns are in percentage. As shown in Columns (1) to (3), the coefficients for the *CCP_fund* variable are 0.0662, 0.0590, and 0.0672, for funds' monthly raw returns, CH3-factor alphas, and CH4-factor alphas, respectively. All these coefficients are statistically significant. The results confirm that CCP funds have better performance, in terms of raw return, CH3-factor alpha, and CH4-factor alpha, after controlling for other fund characteristics.

In Table 3A of the Internet Appendix, we use an alternative dummy variable *CCP_fund_03* to identify countercyclical policy funds. This dummy is 1 for funds in the top quintile of countercyclical policy expectations (30% or higher). Results show similar outperformance of countercyclical policy funds, with even larger magnitudes compared to the main results. Coefficients on "*CCP_fund_03*" are 0.0740 for monthly raw returns, 0.0688 for CH3-factor alphas, and 0.0730 for CH4-factor alphas. These results indicate that funds with a higher fraction of countercyclical policy expectations perform even better than others. This stronger outperformance reinforces our main finding that CCP funds can generate superior returns.

Taken together, our analysis shows that CCP funds significantly outperform non-CCP funds, highlighting the importance of fund managers' countercyclical policy beliefs in potentially impacting their investment decisions and subsequent fund performance.

IV. Mechanisms

How do CCP funds outperform non-CCP funds? Their ability to anticipate countercyclical policies may enable them to better predict the returns of equity and bond market indices. This foresight might also help them select individual stocks or bonds that are more aligned with the prevailing policy environment. In this section, we focus on CCP funds' performance in timing the returns of equity and bond markets, while acknowledging that CCP funds may also excel in selecting individual stocks.

Specifically, we undertake a four-step analysis:

1. Prediction of Future Returns: We begin by examining CCP funds' ability to predict the future returns of equity and bond market indices, relative to non-CCP funds.
2. Relationship Between Expectations and Asset Allocations: Next, we investigate the relationship between fund managers' expectations about equity and bond markets and their corresponding asset allocations, comparing CCP and non-CCP funds.
3. Reliability of Investment Decisions: We then analyze whether the investment decisions of CCP funds more reliably predict future market returns than those of non-CCP funds.
4. Impact of Countercyclical Policy Expectations: Finally, we assess whether the countercyclical policy expectations of CCP funds can specifically predict market index

returns and consequently enhance their subsequent fund performance.

This comprehensive approach aims to provide insights into the mechanisms through which CCP funds potentially leverage their policy expectations to achieve superior performance.

A. Predictability of Market Expectations

We demonstrate that CCP funds can time equity or bond market movements by showing their market expectations can predict index returns. We run panel regressions of equity or bond market index returns (RI_equity and RI_bond, respectively) on funds' equity or market expectations:

$$RI_equity_{i,t} = \alpha_i + \beta_t + \beta expect_equity_market_{i,t} \times CCP_fund_i + \gamma expect_equity_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$$

$$RI_bond_{i,t} = \alpha_i + \beta_t + \beta expect_bond_market_{i,t} \times CCP_fund_i + \gamma expect_equity_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$$

Key independent variables are fund managers' expectations about equity and bond markets ($expect_equity_market$ and $expect_bond_market$, respectively), with interaction terms between these and the CCP dummy.

Table 5 results show that a one-unit increase in $expect_equity_market$ associates with a 0.131% increase in the next three-month HS300 stock index performance. The interaction term is positive and significant, indicating a stronger relationship for CCP funds. For bonds, the direct relationship between $expect_bonds_market$ and next three-month bond index performance is insignificant. However, the interaction term is positive and significant, suggesting a stronger relationship for CCP funds.

These results indicate that fund managers' equity market expectations positively relate to subsequent HS300 stock index performance, amplified for CCP funds. Similarly, the bond market expectations-performance relationship is positive for CCP funds. This provides evidence for a potential mechanism driving CCP funds' outperformance: their enhanced ability to anticipate and capitalize on equity and bond market movements.

B. Market Expectations and Asset Allocations

Next, we examine the relationship between fund managers' market expectations and portfolio allocations, focusing on CCP funds. We conduct panel regressions with fund and time fixed effects:

$$stock_ratio_{i,t} = \alpha_i + \beta_t + \gamma expect_equity_market_{i,t} + \theta expect_equity_market_{i,t} \times CCP_fund_i + \delta X_{i,t} + \varepsilon_{i,t}$$

$$bond_ratio_{i,t} = \alpha_i + \beta_t + \gamma expect_bond_market_{i,t} + \theta expect_bond_market_{i,t} \times CCP_fund_i + \delta X_{i,t} + \varepsilon_{i,t}$$

Here, *stock_ratio* and *bond_ratio* represent portfolio allocations to stocks and bonds, respectively. Independent variables *expect_equity_market* and *expect_bonds_market* measure fund managers' market expectations. We control for total net assets, fund flows, and fund age in $X_{i,t}$.

Table 6 presents the regression results. Column (1) shows that a one-unit increase in *expect_equity_market* is associated with a 1.944% increase in stock allocation. Column (2) shows that a one-unit increase in *expect_bonds_market* is associated with a 1.852% increase in bond allocation. Column (3) shows that the interaction term between equity market expectations and equity ratio is positive. Moreover, in Column (4), the relationship between bond market expectations and bond allocation is significantly stronger for CCP funds compared to non-CCP funds.

These findings indicate that fund managers' market expectations strongly correlate with corresponding portfolio allocations. This alignment appears more pronounced for CCP funds, as evidenced by the positive interaction effects. These results suggest that CCP funds may be more adept at translating their market expectations into portfolio decisions, potentially contributing to their outperformance.

C. Predictability of Asset Allocations

If CCP funds have a stronger ability to predict market returns, their holding changes may also predict market returns. To test this, we run the following regressions:

$$RI_equity_{t+1} = \alpha_i + \beta \Delta stock_{ratio_{i,t}} \times CCP_fund_i + \gamma \Delta stock_{ratio_{i,t}} + \delta X_{i,t} + \varepsilon_{i,t}$$

$$RI_bond_{t+1} = \alpha_i + \beta \Delta bond_{ratio_{i,t}} \times CCP_fund_i + \gamma \Delta bond_{ratio_{i,t}} + \delta X_{i,t} + \varepsilon_{i,t}$$

Here, the dependent variables are the returns of the equity market index and the bond market index, respectively. We focus on interaction terms between the countercyclical policy label and holding changes in the report release quarter. The countercyclical policy label dummy is absorbed by the fund fixed effect.

Table 7 shows that the interaction term between the countercyclical policy label and equity holding change is positive and statistically significant, indicating a stronger relationship between stock allocation changes and the subsequent HS300 index performance for CCP funds. Similarly, the interaction term for bond holding changes is positive and significant, suggesting a stronger relationship between bond allocation changes and bond index performance for CCP funds.

Notably, the direct effects of equity and bond holding changes on respective index performances are not statistically significant, implying that holding changes of non-CCP funds cannot predict subsequent market index movements.

These findings provide evidence that CCP funds have a greater ability to anticipate and capitalize on market movements, as reflected in the stronger predictive power of their portfolio allocation changes on future index returns. This could be a key driver of their outperformance compared to other fund types.

D. The Role of Countercyclical Policy Beliefs

The superior performance of CCP funds may reflect the overall abilities of CCP fund managers, who, in addition to having countercyclical policy expectations, may also possess other performance-enhancing attributes. To determine whether countercyclical policy beliefs specifically contribute to their market predictability and fund performance—rather than merely acting as a selection mechanism—we analyze the market predictions and performance of CCP funds, conditional on whether or not they hold countercyclical policy beliefs.

Panel A of Table 8 first presents the results concerning the predictability of returns for equity and bond market indices. As shown in Columns (1) and (2), for CCP funds, their

expectations regarding equity (bond) markets significantly predict the performance of the equity (bond) index over the next three months. This finding aligns with our results in Table 5.

More importantly, in Columns (3) and (4), we include interaction terms between market expectations and time-varying fund countercyclical policy expectations (represented by the CCP variable). We find that for CCP funds, the interaction between equity market expectations and CCP beliefs is significantly positive, suggesting that when CCP funds anticipate a countercyclical policy (CCP = 1), their equity market expectations can predict the performance of the equity market index even more accurately than during periods when they do not hold CCP beliefs. Interestingly, although the bond market expectations of CCP funds can, on average, positively predict the returns of the bond market index, the difference between periods with and without CCP beliefs is statistically insignificant, as indicated by the interaction term in Column (4).

Panel B then presents regression results analyzing the relationship between time-varying CCP beliefs and various fund performance measures, conditional on the fund being a CCP fund. We report results for raw return, CH3 alpha, and CH4 alpha in Columns (1) through (3), respectively. The positive coefficients and their statistical significance consistently indicate that expectations regarding different types of countercyclical policies can predict higher monthly returns and risk-adjusted returns for CCP funds. This suggests that the superior performance of CCP funds is directly related to their countercyclical policy beliefs.

Taken together, Panels A and B of Table 8 suggest that these funds have the ability to time the market and effectively anticipate and capitalize on their foresight of upcoming shifts in government policies designed to counteract prevailing macroeconomic trends, leading to their superior fund performance.

V. Conclusion

In this study, we leverage advanced Large Language Models (LLMs) to systematically extract and analyze the beliefs of mutual fund managers in China from their regular fund reports regarding the economy, government policies, and financial markets. This approach allows us to examine how these structured beliefs influence their investment strategies, particularly in

relation to the interaction of various economic forces. Specifically, we construct a variable that captures their beliefs about the government's countercyclical policies (CCP) in response to economic shocks. Our analysis reveals that mutual funds frequently expressing CCP beliefs significantly outperform other funds, driven by their strong predictive capabilities regarding market dynamics and their responsive portfolio allocations based on these beliefs.

Our findings provide compelling evidence for the critical role of fund managers' beliefs in driving investment performance, and more importantly, underscore the significance of their structured beliefs about government policies in shaping investment strategies. Additionally, our study highlights the potential of LLMs to explore more complex and structural issues in textual analysis.

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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 exclude QDII funds and those with fewer than 10 valid semi-annual or annual reports from 2008 to 2023. Our final sample comprises 432,073 fund-month observations and 75,448 reports spanning 2008 to 2023. The table presents statistics for GPT-generated variables, distinguishing between those extracted from the review and outlook sections of fund reports, as well as fund accounting and characteristics. Daily alpha is calculated using the Chinese factor model (Liu et al., 2019) and converted to monthly alpha. The holding difference is the percentage change in holdings between reporting periods. Semi-annual and quarterly data are aligned to monthly data based on the latest available information.

	Mean	Sd	Min	P25	Med	P75	Max
Review:							
fiscal_policy	0.155	0.401	-1	0	0	0	1
monetary_policy	0.383	0.527	-1	0	0	1	1
regulatory_policy	0.012	0.43	-1	0	0	0	1
national_macroeconomy	0.012	0.593	-1	-0.5	0	0.5	1
equity_market	0.087	0.666	-1	-0.5	0	0.5	1
bonds_market	0.23	0.516	-1	0	0	1	1
Outlook:							
fiscal_policy	0.329	0.477	-1	0	0	1	1
monetary_policy	0.374	0.477	-1	0	0.5	1	1
regulatory_policy	0.135	0.437	-1	0	0	0	1
national_macroeconomy	0.187	0.584	-1	-0.5	0.5	0.5	1
equity_market	0.38	0.492	-1	0	0.5	1	1
bonds_market	0.181	0.42	-1	0	0	0.5	1
Key variables:							
ret_m	0.53	4.55	-14.03	-0.75	0.28	1.63	15.70
alpha_ch3	0.21	2.62	-8.32	-0.62	0.06	0.89	10.02
alpha_ch4	0.21	2.57	-8.10	-0.62	0.06	0.88	9.93
semi_ret	3.03	12.77	-24.63	-1.94	1.65	5.89	47.99
stock_diff	0.265	7	-26.66	-1.06	0	1	32
bond_diff	0.298	8	-34.5	-0.71	0	1	37
cash_diff	0.008	8	-33.96	-1.81	0	2	34
stock_ratio	42	40	0	0	28	86	94
bond_ratio	39	41	0	0	20	84	100
tna (in millions)	2462	5631	6	172	613	2033	37420
flow	0.097	0.808	-0.829	-0.116	-0.02	0.021	6
age (in months)	65	44	7	32	56	86	202

Table 2: Countercyclical Policy Expectations

Panel A reports summary statistics for variables constructed to capture fund managers' countercyclical policy expectations across fiscal, monetary, and regulatory domains. Panel B displays the *R*-squared values from panel regressions of countercyclical policy variables and expectations for equity and bond markets. These regressions are conducted using three specifications: (1) fund fixed effects, (2) time fixed effects, and (3) both fund and time fixed effects.

Panel A: Countercyclical Policy Expect Summary

	Mean	**Sd**	**Min**	**P25**	**Med**	**P75**	**Max**
CCP_fiscal	0.175	0.38	0	0	0	0	1
CCP_monetary	0.159	0.366	0	0	0	0	1
CCP_regulatory	0.183	0.387	0	0	0	0	1
CCP	0.214	0.41	0	0	0	0	1

Panel B: Variation Decomposition

	Fund FE	Time FE	Fund+Time FE
CCP_fiscal	0.087	0.103	0.182
CCP_monetary	0.087	0.094	0.175
CCP_regulatory	0.088	0.085	0.167
CCP	0.090	0.122	0.204
expectation_equity_market	0.314	0.057	0.376
expectation_bonds_market	0.243	0.038	0.279

Table 3: Performance of Countercyclical Policy Funds

Panel A reports summary statistics for the fraction of a fund's reports displaying countercyclical policy expectations and the dummy for CCP fund. Panels B and C report alpha and factor loadings of returns for CCP funds and non-CCP funds, respectively. Panel D reports alpha and factor loadings for a long-short portfolio that holds CCP funds and sells short non-CCP funds. The sample consists of 432,073 fund-month observations spanning 2008 to 2023. All funds are equally (value) weighted within a given portfolio. Alpha is the intercept from a regression of monthly excess returns on factor returns. *t*-statistics, reported in parentheses, are based on Newey-West standard errors with a lag of 11 months. Coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary Statistics

	Mean	Sd	Min	P25	Med	P75	Max
fra_CCP	0.202	0.123	0	0.105	0.2	0.286	0.8
CCP_fund	0.505	0.5	0	0	1	1	1

Panel B: CCP Funds				
	Equal weighted		Value weighted	
Alpha	0.495***	0.471***	0.350***	0.294**
	(3.37)	(3.03)	(2.62)	(2.51)
MKTRF	0.511***	0.516***	0.458***	0.469***
	(23.82)	(27.07)	(9.70)	(10.53)
Smb	0.0150	0.00873	0.00548	-0.00904
	(0.36)	(0.22)	(0.14)	(-0.24)
Vmg	-0.183***	-0.182***	-0.138***	-0.134***
	(-3.81)	(-3.74)	(-2.80)	(-2.85)
Pmo		0.0337		0.0777
		(1.04)		(1.56)
N	186	186	186	186
R-sq	0.915	0.916	0.836	0.842
Panel C: Non-CCP Funds				
	Equal weighted		Value weighted	
Alpha	0.348***	0.344***	0.163	0.129
	(3.33)	(3.27)	(1.51)	(1.39)
MKTRF	0.378***	0.379***	0.270***	0.277***
	(16.93)	(17.00)	(5.44)	(5.76)
SMB	0.00958	0.00852	-0.0157	-0.0246
	(0.39)	(0.36)	(-0.49)	(-0.72)
VMG	-0.128***	-0.128***	-0.0669**	-0.0648**
	(-4.42)	(-4.35)	(-2.02)	(-2.14)
PMO		0.00571		0.0479
		(0.26)		(1.08)
N	186	186	186	186
R-sq	0.907	0.907	0.699	0.704
Panel D: Difference				
	Equal weighted		Value weighted	
Alpha	0.147***	0.127**	0.187***	0.166***
	(2.64)	(2.09)	(2.95)	(2.65)
MKTRF	0.133***	0.137***	0.188***	0.192***
	(8.46)	(9.30)	(13.75)	(13.14)
SMB	0.00545	0.000216	0.0211	0.0156
	(0.29)	(0.01)	(0.86)	(0.65)
VMG	-0.0555***	-0.0542***	-0.0706**	-0.0693**
	(-2.64)	(-2.60)	(-2.39)	(-2.34)
PMO		0.0280**		0.0298
		(2.13)		(1.45)
N	186	186	186	186
R-sq	0.785	0.793	0.813	0.818

Table 4: CCP Type and Fund Performance

This table presents the findings of panel regressions conducted at the monthly level, examining the relationship between fund performance and fund countercyclical type. Our sample comprises 432,073 fund-month observations, spanning from 2008 to 2023. The key explanatory variable is the countercyclical type dummy, assigned to funds where the proportion of periods characterized by countercyclical beliefs exceeds 0.2. Both returns and alphas are expressed in monthly percentage terms. All regressions incorporate time fixed effects and are estimated with constants (not reported here). We adjust standard errors for clustering at the fund level, and the reported *t*-statistics are derived using robust clustered standard errors. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)
	Ret		alpha_ch3		alpha_ch4	
CCP_fund	0.0807***	0.0662***	0.0619***	0.0590***	0.0688***	0.0672***
	(7.52)	(5.95)	(5.32)	(4.93)	(6.15)	(5.83)
log_tna		-0.0364***		-0.0126***		-0.00754**
		(-11.30)		(-4.07)		(-2.49)
flow		0.00483		0.0237***		0.0318***
		(0.69)		(4.71)		(6.34)
age		0.000559***		0.000102		0.0000786
		(4.48)		(0.71)		(0.57)
N	428284	428284	428286	428286	428286	428286
R-sq	0.415	0.415	0.097	0.097	0.072	0.072

Table 5: The Predictability of Market Expectations for Market Returns

This table reports results for monthly level panel regression of market index returns on fund market expectation. The sample period is the three months (a quarter) following the publication month of report. The sample consists of 214,562 fund-month observations spanning 2008 to 2023. The dependent variable in Column 1 is monthly return of CSI300 index, also known as the Shanghai Shenzhen 300 index. It consists of 300 largest and most liquid A-share stocks listed on the Shanghai and Shenzhen stock exchanges, and covers approximately 60% of the total market capitalization of both exchanges. The dependent variable in Column 2 is monthly return of CCBI or ChinaBond Aggregate Index. The explanatory variables are the expectations about the corresponding market. In Column 3 and 4, we also add interaction term between market expectation and countercyclical type dummy. Index returns are in monthly percent. All regressions include fund size, flow and age as controls. All regressions also include fund fixed effect and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. *t*-statistics calculated using the robust clustered standard errors are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1) hs300_index	(2) bond_index	(3) hs300_index	(4) bond_index
expect_equity_market	0.199***		0.131***	
	(6.63)		(2.93)	
expect_bonds_market		0.00435		-0.00425
		(1.05)		(-0.76)
expect_equity_market x CCP_fund			0.111*	
			(1.89)	
expect_bonds_market x CCP_fund				0.0177**
				(2.14)
N	214562	214562	214562	214562
R-sq	0.009	0.006	0.009	0.006

Table 6: Market Expectations and Fund Holdings

This table reports results for semi-annual level panel regression of fund market expectation on portfolio holding. The dependent variable is either the stock holding ratio (the first column), or the bond holding ratio (the second column). The explanatory variables are the expectations about the corresponding markets. In Column 3 and 4, we also add interaction term between market expectations and countercyclical type dummy. All regressions include fund size, flow and age as controls. All regressions also include fund and time fixed effect and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. *t*-statistics calculated using the robust clustered standard errors are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1) stock_ratio	(2) bond_ratio	(3) stock_ratio	(4) bond_ratio
expect_equity_market	1.944***		1.814***	
	(14.14)		(8.20)	
expect_bonds_market		1.852***		1.206***
		(10.38)		(5.55)
expect_equity_market x CCP_fund			0.214	
			(0.72)	
expect_bonds_market x CCP_fund				1.348***
				(3.79)
N	75129	75129	75129	75129
R-sq	0.928	0.928	0.928	0.928

Table 7: Holding Ratio Differences and Three-Month Market Index Predictions

This table reports results for monthly level panel regression of market real return on fund holding change. The sample period is the three months (a quarter) following the report's publication month. The sample consists of 214,562 fund-month observations spanning 2008 to 2023. The dependent variable is the monthly CSI300 index return (the first column), or the monthly CCBI index return (the second column). The explanatory variables are the percentage change in holdings from the report end month to the next quarter's holdings. In Column 3 and 4, we also add interaction term between holding change and countercyclical type dummy. For annual reports, the end month is typically December, with the publication month in March or April of the following year. For semi-annual reports, the end month is typically June, with the publication month in August of the same year. Index returns are in monthly percent. All regressions include fund size, flow and age as controls. All regressions also include fund fixed effect and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. *t*-statistics calculated using the robust clustered standard errors are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	hs300_index	bond_index	hs300_index	bond_index
Δstock_ratio	0.00659***		0.00117	
	(3.76)		(0.42)	
Δbond_ratio		0.00148***		0.000821***
		(7.83)		(3.07)
Δstock_ratio x CCP_fund			0.00859**	
			(2.42)	
Δbond_ratio x CCP_fund				0.00123***
				(3.26)
N	214524	214524	214524	214524
R-sq	0.009	0.006	0.009	0.006

Table 8: Market Prediction and Performance of CCP Funds' CCP Beliefs

This table reports results for monthly level panel regressions of CCP funds' market prediction and performance when making countercyclical expectations. Panel A reports results for three-month market index predictions. The dependent variable is the monthly CSI300 index return (the first and third columns), or the monthly CCBI index return (the second and fourth columns). The explanatory variables are the expectations about the corresponding markets. In Column 3 and 4, we also add interaction term of expectation and an overall variable indicating any countercyclical policy expectation (*CCP*). Panel B reports results for CCP fund performance conditional on whether they possess CCP beliefs. The dependent variable is raw return (the first column), the alpha of the Chinese three-factor model (the second column), or the alpha of the Chinese four-factor model (the third column). Returns and alphas are in monthly percent. All regressions include fund size, flow and age as controls. We include fund fixed effects in Panel A and fund and time fixed effect in Panel B. Standard errors are adjusted for clustering at fund level. *t*-statistics calculated using the robust clustered standard errors are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

Panel A: CCP belief and Market Index Prediction				
	(1)	(2)	(3)	(4)
	hs300_index	bond_index	hs300_index	bond_index
expect_equity_market	0.207***		0.102**	
	(5.23)		(2.24)	
expect_bonds_market		0.0128**		0.0145*
		(2.09)		(1.92)
expect_equity_market x CCP			0.353***	
			(4.56)	
expect_bonds_market x CCP				-0.00458
				(-0.39)
CCP			-0.767***	0.00700
			(-15.76)	(1.54)
N	118070	118070	118070	118070
R-sq	0.007	0.006	0.010	0.006

Panel B: CCP belief and Performance			
	(1)	(2)	(3)
	Ret	alpha_ch3	alpha_ch4
CCP	0.0704***	0.0538***	0.0330**
	(4.21)	(3.68)	(2.36)
N	235643	235643	235643
R-sq	0.485	0.139	0.108

Appendix A: Tables

Table 1A

Count of Fund Semi-Annual and Annual Reports

This table reports the valid observations of semi-annual and annual reports spanning 2008 to 2023. Qualified Domestic Institutional Investor (QDII) funds are excluded. Funds with less than 10 reports over the full period are excluded.

Year	Semi	Annual	Total
2008	282	333	615
2009	389	448	837
2010	486	532	1018
2011	592	674	1266
2012	748	862	1610
2013	983	1130	2113
2014	1264	1413	2677
2015	1589	1968	3557
2016	2245	2596	4841
2017	2749	3408	6157
2018	3742	4017	7759
2019	4252	4402	8654
2020	4398	4367	8765
2021	4342	4308	8650
2022	4303	4256	8559
2023	4208	4162	8370
Total	36572	38876	75448

Table 2A

Fund Characteristics, Reviews and Expectations

This table reports results for semi-annual panel regressions of fund managers' beliefs on fund characteristics. Panel A presents the results for reviews, while Panel B presents results for expectations. 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 include time fixed effects and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at the fund level. t-statistics, calculated using robust clustered standard errors, are reported in parentheses. Coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Reviews Extracted from Fund Reports

	(1)	(2)	(3)	(4)	(5)	(6)
		Policy		**Macro**	**Market**	
	Fiscal	Monetary	regulatory	**Economy**	equity	bond
semi_ret	0.000325**	0.00176***	0.00199***	0.00286***	0.147***	0.000357**
	(2.07)	(9.54)	(12.83)	(13.95)	(56.98)	(2.24)
log_tna	0.000888	0.0406***	-0.00178*	-0.00360***	-0.0190***	0.0419***
	(0.80)	(22.59)	(-1.72)	(-2.81)	(-15.43)	(23.48)
flow	0.000627	0.00788***	0.000146	-0.00214	0.00309	0.0151***
	(0.40)	(4.09)	(0.09)	(-1.11)	(1.59)	(7.40)
age	0.0000399	-0.00111***	0.0000814*	0.000186***	0.000349***	-0.00160***
	(0.72)	(-12.31)	(1.81)	(3.12)	(5.98)	(-18.67)
N	73361	73361	73361	73361	73361	73361
R-sq	0.108	0.195	0.043	0.307	0.409	0.190

Panel B: Expectations Extracted from Fund Reports

	(1)	(2)	(3)	(4)	(5)	(6)
		Policy		**Macro**	**Market**	
	Fiscal	Monetary	regulatory	**Economy**	equity	bond
semi_ret	0.000300*	0.00000652	0.00148***	0.00161***	0.00302***	-0.00129***
	(1.66)	(0.04)	(9.01)	(8.28)	(16.65)	(-9.99)
log_tna	-0.00902***	0.00999***	-0.0118***	-0.0241***	-0.0503***	0.0267***
	(-6.49)	(8.10)	(-10.11)	(-15.87)	(-28.12)	(18.05)
flow	-0.00302*	0.00361**	-0.00385**	-0.00587***	-0.0124***	0.00995***
	(-1.67)	(2.08)	(-2.30)	(-2.94)	(-6.85)	(5.25)
age	0.000251***	-0.000455***	0.000375***	0.000952***	0.00135***	-0.00105***
	(3.85)	(-7.34)	(6.40)	(12.20)	(14.57)	(-14.95)
N	73361	73361	73361	73361	73361	73361
R-sq	0.097	0.161	0.021	0.216	0.100	0.059

Table 3A

CCP type fund performance (0.3 as cutoff)

This table reports result for monthly level panel regressions of fund performance on fund countercyclical type. The sample consists of 432,073 fund-month observations spanning 2008 to 2023. The explanatory variable is countercyclical type. Fund are labeled as countercyclical type if the fraction of countercyclical belief periods is greater than 0.3. Returns and alphas are in monthly percent. All regressions include fund and time fixed effect and are estimated with constants, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics calculated using the robust clustered standard errors are reported in parentheses. Coefficients marked with ∗, ∗∗, and ∗∗∗ are significant at 10%, 5%, and 1%, respectively.

Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)
	ret		alpha_ch3		alpha_ch4	
CCP_fund_03	0.0850***	0.0704***	0.0721***	0.0688***	0.0751***	0.0730***
	(6.63)	(5.25)	(4.95)	(4.57)	(5.36)	(5.06)
log_tna		-0.0367***		-0.0128***		-0.00781***
		(-11.37)		(-4.13)		(-2.59)
flow		0.00505		0.0239***		0.0320***
		(0.72)		(4.75)		(6.38)
age		0.000620***		0.000146		0.000138
		(4.98)		(1.01)		(0.99)
N	428284	428284	428286	428286	428286	428286
R-sq	0.415	0.415	0.097	0.097	0.072	0.072

Appendix B: Sample Report and ChatGPT Response

We use the review and expectation section from the 2015 annual report of 000031.OF, a mixed-type fund, as an example.

Review:

2015 年注定是载入史册的一年。这一年，宏观经济逐阶而下，GDP 增长率创下了十几年来的新低，企业盈利状况低迷。上半年，中央政府为了对冲经济增长下滑的势头，货币政策持续放水，流动性非常宽松。同时由于以银行为主渠道的间接融资体系受阻，中央政府对以股市为主渠道的直接融资体系大力扶持，股市出现了历史罕见的大幅上涨。从 6 月中旬开始，股市泡沫破灭，随后政府展开救市，市场逐步企稳，收复了部分失地。纵观全年，股市的波动幅度创下了多年以来的纪录，对投资者来说，2015 年成为难以忘怀的一年，盈亏得失自在心中。报告期内，本基金基本保持了较高仓位，但是在结构配置上跟市场热点出现了一定的偏差。全年的行业和风格配置基本保持均衡，对创业板的配置比例始终低于同业的平均水平，同时对于 2015 年最大的热点——“互联网+”的配置比例也不足，因此错失了上半年牛市最大的获利机会，全年业绩表现不够理想，但波动率低于同业平均水平。

The year 2015 is destined to be recorded in history. This year, the macroeconomic environment gradually declined, with GDP growth hitting a multi-year low, and corporate earnings remaining sluggish. In the first half of the year, the central government continuously eased monetary policy to counteract the downward trend in economic growth, resulting in very loose liquidity. Additionally, due to obstacles in the bank-dominated indirect financing system, the central government strongly supported the stock market as the main channel for direct financing, leading to an unprecedented surge in the market. Starting in mid-June, the stock market bubble burst, prompting the government to intervene and stabilize the market, recovering some of the lost ground. Over the entire year, market volatility reached record levels, making 2015 an unforgettable year for investors, with gains and losses keenly felt. During the reporting period, our fund maintained a relatively high position, but there were some deviations from market trends in structural allocation. Industry and style allocations remained generally balanced throughout the year, with our allocation to the Growth Enterprise Market lower than the industry average. Additionally, we under-allocated to the year's biggest hotspot, "Internet+", missing out on major profit opportunities in the bullish first half. Consequently, our annual performance was not ideal, though our volatility was below the industry average.

ChatGPT Response:

Expectation Response:

Review Response:

1. Fiscal Policy: Neutral

中央政府采取了一些措施，但未明确提及财政政策的具体内容。

The central government has taken measures, but specific details on fiscal policy were not mentioned.

2. Monetary Policy: Positive

货币政策持续放水，流动性非常宽松。

Monetary policy remains accommodative, with very loose liquidity.

3. Regulatory Policy: Positive

政府对股市的直接融资体系大力扶持，并在股市泡沫破灭后展开救市。

The government strongly supports the stock market's direct financing system and intervened to stabilize the market after the bubble burst.

4. National Macroeconomic Fundamental: Negative

GDP 增长率创下了十几年来的新低，企业盈利状况低迷。

GDP growth reached its lowest in over a decade, and corporate earnings are sluggish.

5. Global Macroeconomic Fundamental: Not Mentioned

报告中未提及全球宏观经济基本面。

The report does not address global macroeconomic fundamentals.

6. Equity Market: Weakly Positive

股市出现了大幅上涨，但随后泡沫破灭，尽管政府救市，市场仍有波动。

The stock market saw significant gains but then experienced a bubble burst. Despite government interventions, volatility persists.

7. Bonds Market: Not Mentioned

报告中未提及债券市场。

The report does not cover the bond market.

8. Overall Assessment of the Section for the Fund Investors: Weakly Negative

基金在结构配置上与市场热点出现偏差，错失获利机会，全年业绩不理想，但波动率低。

The fund's structural allocation diverged from market trends, missing profit opportunities. Annual performance was lackluster, though volatility remained low.

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: Positive

供给侧改革将推动经济向好转变。

Supply-side reforms are expected to drive economic improvement.

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: Neutral

注册制的实施会带来结构性变化，但长远影响尚不明确。

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

4. National Macroeconomic Fundamental: Positive

供给侧改革有望实现经济的“向死而生”。

Supply-side reforms are expected to achieve economic "rebirth through adversity."

5. Global Macroeconomic Fundamental: Weakly Negative

美元加息周期对人民币构成压力。

The US dollar interest rate hike cycle puts pressure on the RMB.

6. Equity Market: Neutral

股市将是休养生息的一年，但有结构性机会。

The stock market will be in a period of consolidation, but structural opportunities exist.

7. Bonds Market: Not Mentioned

未提及。

No mention in the report.

8. Overall Assessment of the Section for the Fund Investors: Weakly Positive

整体展望呈现出谨慎乐观态度，强调防御策略和结构性机会。

The overall outlook shows a cautiously optimistic attitude, emphasizing defensive strategies and structural opportunities.