

Structured Beliefs and Fund Investment*

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Abstract

We analyze fund managers' perceptions of government policies in mitigating economic shocks using mandatory outlook reports from Chinese mutual funds. Leveraging Large Language Models (LLMs) to assess sentiment across key topics, we extract their beliefs about markets, the economy, and policies. We construct a countercyclical policy (CP) beliefs measure, capturing each fund's expectations about policies offsetting economic shocks. Managers' market beliefs positively predict market returns, while CP beliefs enhance this predictive power, improving fund performance. Our study highlights the role of structured beliefs in shaping investment decisions and market outcomes.

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In January 2025, the U.S. stock market experienced a notable decline following the release of robust employment data. On January 10, the Labor Department reported an addition of 256,000 jobs in December 2024, surpassing economists' expectations. This strong job growth led to concerns that the Federal Reserve might delay anticipated interest rate cuts or even consider rate hikes to prevent the economy from overheating. As a result, major stock indices fell sharply, with the S&P 500 erasing its gains for the year.¹

This phenomenon recurs across global stock markets, demonstrating that asset market dynamics are shaped not only by economic fundamentals but also by investors' expectations of government policy responses. In particular, investors continuously update their beliefs about how policymakers—such as the Federal Reserve—will react to economic shocks, leading to market movements that may sometimes seem counterintuitive relative to economic data. These structured beliefs about the interaction between economic shocks and government policies are central to understanding asset market dynamics.²

Analyzing the structure of investors' beliefs about economic fundamentals and government policies is inherently challenging due to the lack of direct measures of investor expectations. To address this challenge, researchers have frequently turned to survey data, as seen in studies 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 regarding respondent representativeness and continuity. Survey respondents typically include financial analysts, professional economists, and randomly selected households, who may not accurately represent the actual investors driving financial market movements. Moreover, obtaining repeated survey responses from the same investors over an extended period is particularly challenging. Yet, such longitudinal data is crucial for analyzing how investor beliefs evolve over time and their role in shaping asset market dynamics.

To confront these challenges, this paper leverages systematic beliefs about financial markets, the economy, and government policies, as consistently revealed through regular

¹ See <https://www.reuters.com/markets/us/futures-drop-caution-ahead-key-payrolls-data-2025-01-10/>.

² The monetary policy literature has highlighted the crucial interplay between beliefs about economic fundamentals and policy decisions. Nakamura and Steinsson (2018) demonstrate that unexpected interest rate hikes by the Fed lead to a one-for-one increase in both nominal and real interest rates across the term structure, while expected inflation remains unchanged. Surprisingly, output growth forecasts rise, contradicting standard models of monetary tightening. This increase in forecasts reflects the market's interpretation of the Fed's policy decision as a signal of its confidence in strong economic fundamentals.

reports from 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 outlooks on financial markets and the economy, along with reviews of recent market and economic developments, in their semi-annual and annual reports. These reports provide structured insights into each manager's views on past events and beliefs about future trends.³

Because these reports are produced regularly by professional fund managers—a key group of participants in financial markets—over a long-time horizon, they offer a more reliable and systematic dataset than traditional survey data. Moreover, these reports also include detailed information on investment positions and fund performance, allowing us to systematically analyze how structured beliefs influence investment strategies and performance across all mutual funds in the world's second-largest financial market.

Since these fund reports are provided in textual form, a key challenge we face is dissecting different aspects of beliefs from the reports 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 measuring overall sentiment in an article or report. However, it is not effective in distinguishing sentiment across distinct topics within the same text.⁴ This limitation is particularly significant when analyzing investors' structured beliefs. For example, a fund manager might express pessimism about recent economic shocks while remaining optimistic about the stock market, based on her belief in the government's countercyclical policy interventions. The coexistence of pessimistic and optimistic phrases related to different topics within the same text makes it difficult to use word-counting methods to accurately dissect and quantify the investor's beliefs across different dimensions.⁵

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

³ 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.

⁴ See Gentzkow, Kelly, and Taddy (2019) for a review of the broad economic literature of treating text as data.

⁵ Recently, Bybee et al. (2020) adopted the Latent Dirichlet Allocation (LDA) topic modeling approach of Blei et al. (2003) to estimate a topic model that summarizes business news from the Wall Street Journal into easily interpretable topical themes. They quantified the proportion of news attention allocated to each theme at different points in time. While this approach effectively decomposes news articles into a structured set of themes, identifying the sentiment of a report on a specific theme remains challenging.

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 compile reviews and outlooks from semi-annual and annual reports of all mutual funds between 2008 and 2023. The number of reports increased from 615 in 2008 to 8,370 in 2023, reflecting the rapid expansion of China's fund industry. Using GPT-4.0, we extract each fund manager's assessment of six key areas over the past six months: the macroeconomy, monetary policy, fiscal policy, regulatory policy, the stock market, and the bond market. We also capture their expectations of these areas for the upcoming period. Each review and belief is categorized on a five-point scale: 1 (positive), 0.5 (weakly positive), 0 (neutral), -0.5 (weakly negative), and -1 (negative).

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 could inadvertently influence analyses that should only rely on past data. However, 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. Furthermore, in our robustness analysis, altering dates in the fund reports does not affect the belief measures, further confirming that our approach remains unbiased and consistent.

The quantified reviews and beliefs enable us to uncover the structure of fund managers' views on the economy, policies, and markets, particularly how their economic and policy beliefs shape their expectations for the stock and bond markets. We construct a set of countercyclical policy (CP) belief variables to assess whether a manager expects government policies to counteract prevailing economic conditions. Specifically, these variables capture whether a manager holds a negative review of the economy while anticipating accommodative monetary, fiscal, or regulatory policies, or conversely, a positive economic review while expecting policy tightening.

We find that fund fixed effects and time fixed effects together explain only a small portion of the variation in fund managers' beliefs, indicating that these beliefs are largely shaped by

each fund's idiosyncratic responses to evolving economic conditions. This suggests that fund managers do not simply repeat similar outlooks in every report, nor do they uniformly follow the same public analyses.

By integrating these quantified beliefs with each fund's investment positions and performance data from fund reports, we examine how these beliefs influence investment decisions and outcomes. Notably, fund managers' beliefs about the stock and bond markets exhibit significant and positive predictive power for index returns over the subsequent three months. This finding not only validates the credibility of their market beliefs but also underscores that Chinese fund managers act as smart money. Indeed, a recent review by Jiang (2020) highlights that mutual funds in China tend to outperform the market, contrasting with the well-documented lack of outperformance among U.S. mutual funds. Given that the Chinese stock market is dominated by retail investors (e.g., Song and Xiong, 2018; Allen et al., 2024), the outperformance of mutual funds reflects the advantages of professional investment managers over retail investors in navigating the market.

Importantly, we find that CP beliefs enhance the positive predictive power of fund managers' market expectations. Specifically, when a fund exhibits countercyclical policy beliefs, its expectations about the stock and bond markets more reliably predict subsequent market returns. This suggests that managers' analyses of the economy and policies sharpen their market expectations.

We also find that fund managers' trading activity, measured by increases in stock positions, has significant positive predictive power for future stock market returns, consistent with the predictive strength of their market beliefs. Moreover, when fund managers hold CP beliefs, the predictive power of their trading on future market returns becomes even stronger, further underscoring the role of CP beliefs in enhancing fund performance.

We find compelling evidence that funds exhibiting CP beliefs significantly outperform other funds. We examine 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, funds with CP beliefs outperform others on a monthly basis by 6.6 basis points (raw return), 5.4 basis points (CH3 alpha), and 3.2 basis points (CH4 alpha). This outperformance is significant across all measures, highlighting the potential importance of CP beliefs in shaping investment decisions and driving subsequent fund performance.

Furthermore, we delve deeper into the relationship between policy expectations and fund performance by focusing on CP funds—those that frequently engage more deeply with countercyclical policy analysis. Our analysis reveals that CP funds significantly outperform their counterparts, and their countercyclical policy beliefs specifically contribute to their market predictability and overall performance through improved market timing and stock-picking skills.

These findings not only help explain the superior performance of mutual funds in China but also underscores fund managers' ability to analyze the interaction between the economy and policies as a key driver of investment success. More broadly, our study provides strong evidence that government policies play a crucial role in shaping financial market dynamics in China, as argued by Brunnermeier, Sockin, and Xiong (2022).

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.

A key 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; Cao, Yang, Zhang, 2024 and 2025). 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 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 are closely linked to economic fundamentals and play a critical role in shaping fund managers' investment decisions.

Our study also relates to the literature on countercyclical economic policies. Zhang (2021) finds that countercyclical monetary policy explains the negative correlation between real stock market returns and inflation. This relationship is strongest in advanced economies with countercyclical monetary policy but disappears in countries with procyclical policy.

Additionally, we contribute 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.

Finally, 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.

To ensure sufficient longitudinal data for each fund, we include only those with at least 10 reports over the full period. The final sample comprises 428,278 fund-month observations and 75,448 reports spanning from 2008 to 2023. Table 1A in the Internet 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.⁶ These eight topics analyzed encompass key aspects of economic and financial landscapes. We set the

⁶ We utilize a single ChatGPT prompt to analyze all eight topics simultaneously. This consolidated approach ensures distinct topic differentiation, as experimental trials with *separate prompts per topic* revealed that generalized sentiment from the overall context could unduly influence the assessment of individual dimensions.

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 lookahead 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 five years. As demonstrated in Table 2A of the Internet Appendix A, even with these alterations, the model maintained a high output consistency rate, exceeding 90% across a thousand randomly selected reports in almost all dimensions examined in our empirical analysis, including the expectations related to fiscal, monetary, and regulatory policies, as well as domestic macroeconomic fundamentals, the domestic equity market, and the domestic bond market. 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

Internet 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.

We validate managers’ expectations regarding two critical policy dimensions: fiscal and monetary policies, by investigating their predictability for future policy developments.⁷ First, we analyze two key fiscal policy indicators: the deficit ratio target, typically announced each March since 2010, and a measure of changes in fiscal policy tone. The latter is derived from the content of two major political conventions, where we extract fiscal-related themes and compare them to the previous year's discussions to identify any shifts in tone. As shown in Panel A of Table 2, fund managers' expectations effectively predict the deficit ratio target, including its level, changes, and direction. Additionally, their expectations align with shifts in fiscal policy tone during significant government meetings.

Next, we investigate the predictability of expectations regarding monetary policies. We focus on the average monthly year-on-year (YoY) growth rate of M2 from the publication month of the fund’s (semi-)annual report to that of the subsequent report, as well as the average monthly YoY growth rate of RMB loans over the same period. We also assess changes in monetary policy tone based on the aforementioned political conventions, comparing the monetary-related content to the previous year's to identify tone shifts. As illustrated in Panel B of Table 2, fund managers’ expectations align closely with future monetary policies, further

⁷ We choose to focus on fiscal and monetary policies to validate our expectation measures because, in contrast to regulatory policies, these policies yield clear, quantifiable outcomes. This allows us to directly assess how well managers' expectations align with actual policy changes, which is central to our study's objectives.

confirming the relevance of these expectation measures. To assess the reliability of GPT-generated annotations, we conduct a validation process against human annotations. We select 50 high-quality data points and evaluate them across key dimensions including the fund managers' expectations on macroeconomic fundamentals, the equity market, and the bond market, and we ask three humans to annotate each of the fields.

We establish human-annotated ground truth through the following procedure: three human labelers well-versed in finance and macroeconomics independently annotate each data point, and we determine the human label based on the majority vote. Table 3A in the Internet Appendix A presents the validation results. The agreement rate between GPT annotations and the human majority vote on these three dimensions is 76% ($=38/50$) for expectations on macroeconomic fundamentals, 70% ($=35/50$) for equity markets, and 86% ($=43/50$) for bond markets. Given the complexity of the task, human annotators are also prone to errors. To better understand cases of disagreement—both among human annotators and between humans and GPT—we additionally consult two additional domain experts. These experts assign a final label without knowing the annotation source (GPT vs. human) of existing disagreeing label pairs.

Notably, for 43 out of 150 (50 datapoints \times {macro, equity, bond}) instances of the fund managers' expectations where there are discrepancies between first-round human labels and GPT labels, we find that the final expert judgment aligns more closely with GPT-generated labels (25 out of 42 cases).

The consistency rates between GPT and expert-calibrated scores are finally 90%, 94%, and 98% for three dimensions, respectively. These findings suggest that GPT provides a reliable and scalable method for extracting the labels of interest from complex textual data in our study, and that GPT response can be more accurate than humans with domain knowledge.

C. Fund Characteristics

At the end of 2023, our sample included 4,627 funds, comprising 621 (13.4%) equity funds, 1,488 (32.2%) bond funds, 2,089 (45.1%) hybrid funds, 365 (7.9%) money market funds, and 64 (1.4%) funds of other types (e.g., FOF, REITs). Of these, 4,345 (93.9%) funds were actively managed, while 282 (6.1%) were passively managed. The total assets under management for these funds amounted to 12.2 trillion yuan (approximately 1.71 trillion U.S. dollars).

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:

$$CH3: r_t = \alpha + \beta MKTRF_t + s SMB_t + v VMG_t + \varepsilon_t \quad (1)$$

$$CH4: r_t = \alpha + \beta MKTRF_t + s SMB_t + v VMG_t + p PMO_t + \varepsilon_t \quad (2)$$

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.⁸

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 (2020).

Many factors may have contributed to the substantial variations in reviews and expectations revealed by fund reports. Table 4A in the Internet Appendix A explores the relationship between fund characteristics and the funds' reviews and expectations. Specifically,

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

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 4A in the Internet 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 equity markets are positively correlated with recent fund performance. The patterns for the other three variables—*log_tna*, *flow*, and *age*—are less uniform, displaying varying degrees of influence across different dimensions of reviews and expectations.

II. Countercyclical Policy Expectations and Funds

The fund managers' multidimensional reviews and expectations of the economy, government policies, and financial markets provide a unique opportunity to analyze the structure of their beliefs and potentially uncover the investment strategies they employ. In this section, we first construct a measure of fund managers' beliefs regarding the interaction between government policies and economic fundamentals—countercyclical policy (CP) beliefs. We then define a subset of funds as CP funds, characterized by a higher frequency of CP beliefs.

A. Countercyclical Policy Beliefs

A defining characteristic of the Chinese economic landscape is the government's consistent use of countercyclical macro interventions. To manage economic cycles, the Chinese government employs a diverse set of policy tools, 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) leverages these tools to regulate money supply and credit availability, influencing economic activity.
2. Fiscal policies -- The government undertakes large-scale infrastructure projects and implements industrial policies to promote and develop specific sectors. These measures are often used to stimulate economic growth during downturns.
3. Regulatory policies -- These include interventions such as IPO quotas and adjustments

to stamp taxes on stock trading. Such policies directly impact capital markets and influence investor behavior.

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 may not only analyze economic indicators but also anticipate and interpret government actions.⁹

Against 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 three indicators:

- CPn_X : This indicator is set to 1 for a fund manager who believes that the economy is in a downturn ($review_national_macroeconomic = -1$) and expects the government to adopt an expansionary policy in X ($expect_policy \geq 0$) to support the economy.
- CPp_X : This indicator is set to 1 for a manager who believes that the economy is performing well ($review_national_macroeconomic = 1$) but anticipates a tightening policy in X ($expect_policy \leq 0$).
- CP_X : This indicator is set to 1 if a manager expects government policy in X to counteract current economic conditions in either direction, meaning either CPn_X or CPp_X equals 1.

We then consolidate CP_X indicators across all policy dimensions into a general countercyclical policy expectation measure:

- CP_belief : This indicator is set to 1 if a manager exhibits countercyclical policy expectations in any of the three policy areas (fiscal, monetary, or regulatory).

To construct countercyclical policy variables, we classify fund managers based on whether they hold 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 approach enables a sharper identification of managers' countercyclical

⁹ As noted by Kaminsky, Reinhart and Vegh (2004), economic policies tend to be countercyclical in advanced markets and procyclical in emerging economies.

policy beliefs.

Panel A of Table 3 presents the descriptive statistics for 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, indicating that 17.5%, 15.9%, and 18.3% of the reports, respectively, express countercyclical policy expectations in these areas.

When considering a broader 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, suggesting a high correlation among countercyclical expectations across different policy domains. This implies that fund managers tend to anticipate coordinated countercyclical measures spanning fiscal, monetary, and regulatory policies rather than isolated interventions in specific areas.

There are substantial variations in these countercyclical policy measures across funds and over time. To explore these variations, we employ three fixed-effect regression models:

- Fund fixed effects: To account for time-invariant characteristics of individual funds, We incorporate fund fixed effects:

$$CCP_belief_{i,t} = \alpha_i + \varepsilon_{i,t}. \quad (3)$$

This captures inherent fund-specific traits that may shape countercyclical policy expectations.

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

$$CP_belief_{i,t} = \beta_t + \varepsilon_{i,t}. \quad (4)$$

This identifies common time-dependent factors that simultaneously impact all funds' expectations.

- Two-way Fixed Effects: To explore the interplay between fund-specific characteristics and time-varying factors, we incorporate both fund and time fixed effects:

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

This approach accounts for both idiosyncratic fund traits and evolving economic or market conditions that jointly shape countercyclical policy expectations.

We apply these fixed-effect specifications to fiscal, monetary, regulatory, and general policy expectations. Panel B of Table 3 reports the *R*-squared values for each of the three model specifications. Column (1) shows that fund fixed effects explain approximately 10% of the variation in countercyclical policy measures, suggesting that fund heterogeneity plays a meaningful role in shaping policy expectations. Column (2) reports that time fixed effects also account for around 10% of the variation, indicating that market-wide factors significantly influence countercyclical policy beliefs across funds.

Column (3) combines both fund and time fixed effects, revealing that the two-way fixed-effects model explains about 20% of the variation. Importantly, this implies that even after accounting for both fund-specific and time-dependent factors, the majority of variations (about 80%) remain unexplained. This substantial unexplained variation likely stems from fund-time interactions and forms the basis for our subsequent analysis on how these residual policy expectations may contribute to fund performance.

Panel B also reports the variation decomposition for fund managers' expectations in the equity and bond markets. Column (1) shows that fund fixed effects explain 31.4% of equity market expectations and 24.3% of bond market expectations, suggesting that individual funds' characteristics and investment philosophies significantly shape their views on these asset classes.

In contrast, column (2) reveals that time fixed effects account for a smaller portion of the variations, explaining 5.7% and 3.8% of equity and bond market expectations, respectively. This indicates that while market-wide factors play a role, fund-specific factors are more dominant.

In column (3), two-way fixed effects explain 37.6% of equity market expectations and 27.9% of bond market expectation variables, underscoring the importance of considering both fund-level and time-dependent characteristics in understanding market expectations.

Notably, fund fixed effects explain a larger fraction of variations in market expectations, especially for the equity market, compared to countercyclical policy expectations. The relatively lower explanatory power of fund fixed effects for policy expectations implies greater flexibility in managers' policy views, suggesting that policy expectations may be more responsive to changing economic conditions or new information. This adaptability could

potentially influence fund performance in ways that more stable fund characteristics cannot, motivating further exploration of how these dynamic policy expectations impact fund performance.

How are CP beliefs related to mutual fund characteristics? We separately examine CPn (reflecting pessimistic macroeconomic views and expectations of easing policies) and CPp (reflecting optimistic macroeconomic views and expectations of tightening policies). Table 5A of the Internet Appendix A reports their relationships across fiscal, monetary, regulatory policy dimensions with various mutual fund characteristics, including past semi-year performance, total net assets (*tna*), flows, and age.

Across all policy dimensions, CPn coefficients are negative and statistically significant for semi-year returns (*semi_ret*), indicating that funds with weak past performances tend to expect stimulus policies due to their pessimistic economic views. Conversely, CPp coefficients are positive and significant, suggesting that better-performing funds anticipate tightening policies, aligning with their optimistic economic outlooks.

The log of total net assets (*log_tna*) shows a consistently negative relationships, indicating that smaller funds are more likely to hold countercyclical policy expectations. Fund flows (*flow*) is also negatively correlated with both CPp and CPn, suggesting that funds experiencing outflows are more inclined to hold countercyclical policy expectations. Lastly, age of funds (*age*) exhibits a positive association across all CP measures, suggesting that older funds tend to exhibit stronger countercyclical policy expectations.

In Table 6A of the Internet Appendix A, we further examine the relationship between countercyclical expectations and market conditions. Across all policy dimensions, CPn shows a consistent negative correlation with equity index returns and a positive correlation with bond index returns. This suggests that funds are more likely to anticipate stimulative countercyclical policies in adverse market conditions. Conversely, CPp is positively correlated with equity index returns and negatively correlated with bond index returns, indicating that funds expect tightening policies during favorable market conditions.

Additionally, when examining market volatilities, measured by the semi-annual standard deviation of the market index, we find that CPn is positively correlated with both equity and bond market volatilities, while CPp is negatively correlated with volatilities across all three policy dimensions. This suggests that fund managers are more likely to anticipate stimulative policies in response to heightened market volatility.

B. Countercyclical Policy Funds

To further explore the relationship between countercyclical policy expectations, fund investment decisions, and fund performance, we identify funds that frequently exhibit such expectations, which we term “countercyclical policy funds” (CP funds). The underlying premise is that a consistent display of countercyclical policy expectations reflects a systematic framework used by fund managers to analyze the economy and financial markets. We aim to determine whether this structured approach to policy analysis translates into distinct investment decisions and fund performance outcomes.

To quantify a fund’s engagement with countercyclical policy expectations, we construct a measure representing the fraction of countercyclical policy expectations within a fund’s series of reports. Panel C of Table 3 presents the summary statistics for this measure, showing a mean value of 20.2% and a median value of 20%. Based on this distribution, we classify a fund as a “countercyclical policy fund” if its fraction of countercyclical policy expectations exceeds the top quintile threshold of 0.3. We then construct a dummy variable “CP_fund”, to indicate funds that meet this criterion. This classification allows us to focus on funds that consistently engage in countercyclical policy analysis.

To examine whether fund managers in CP funds exhibit distinct characteristics, we compare their attributes with those of other funds. Table 7A of the Internet Appendix presents various manager characteristics across the two groups. The results indicate that CP funds have a significantly higher proportion of fund managers with graduate degrees, with a ratio of 0.9565 compared to 0.9412 for other funds, and a p-value of 0.0115. The proportion of fund managers with PhDs is also significantly higher in CP funds at 0.119, compared to 0.0986 in other funds, with a p-value of 0.0119, indicating statistical significance at the 5% level. The male ratio is notably higher for CP funds, at 0.7823 compared to 0.7335 for other funds. In contrast, the proportion of fund managers with a foreign background is slightly higher in CP funds, at 0.0124 compared to 0.0086 for other funds, but this difference is not statistically significant. Overall, these results suggest that CP funds tend to be managed by individuals with higher levels of education, including a greater proportion of PhDs, and a higher male representation compared to other funds.

III. Fund Manager Expectations and Asset Allocations

In this section, we examine whether fund managers' ability to anticipate countercyclical policies enhances their ability to predict market returns and align their asset allocations with their expectations. Our analysis follows a three-step approach. First, we assess funds' ability to predict future returns of equity and bond market indices. Second, we examine the relationship between fund managers' expectations about equity and bond markets and their corresponding asset allocations to determine whether expectations translate into actual investment decisions. Third, we evaluate the reliability of these investment decisions by analyzing whether funds' asset allocations serve as effective predictors of future market returns.

A key focus is on whether fund managers' market expectations have a stronger predictive accuracy when they hold countercyclical policy (CP) beliefs. By assessing the interaction between market expectations and CP beliefs, we aim to understand whether fund managers who actively consider countercyclical policies exhibit a more systematic approach to market forecasting and investment positioning.

A. Predicting Market Returns

To examine whether fund managers' market expectations can predict index returns, we run panel regressions of future three-month equity and bond market index returns (*RI_equity* and *RI_bond*, respectively) on fund managers' market expectations. The baseline regressions take the form:

$$RI_equity_{t+1} = \alpha_i + \beta expect_equity_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},$$

$$RI_bond_{t+1} = \alpha_i + \beta expect_bond_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}.$$

The key independent variables are fund managers' expectations about equity and bond markets (*expect_equity_market* and *expect_bond_market*, respectively). We control for fund characteristics, including total net assets, fund flows, and fund age, captured in $X_{i,t}$. Time-invariant fund characteristics are absorbed by fund fixed effects α_i . For market indices, we use the most representative benchmarks in China: the Shanghai Shenzhen 300 Index (*hs300_index*) for equity and the ChinaBond Aggregate Index (*bond_index*) for bonds.

To assess whether fund managers' ability to predict market returns improves when they hold countercyclical policy (CP) beliefs, we introduce interaction terms between market expectations and CP beliefs:

$$\begin{aligned}
RI_equity_{t+1} = & \alpha_i + \beta expect_equity_market_{i,t} \times CP_belief_{i,t} \\
& + \gamma_1 expect_equity_market_{i,t} + \gamma_2 CP_belief_{i,t} + \delta X_{i,t} \\
& + \varepsilon_{i,t+1},
\end{aligned}$$

$$\begin{aligned}
RI_bond_{t+1} = & \alpha_i + \beta expect_bond_market_{i,t} \times CP_belief_{i,t} \\
& + \gamma_1 expect_bond_market_{i,t} + \gamma_2 CP_belief_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}.
\end{aligned}$$

Furthermore, we hypothesize that funds with the most frequent CP beliefs (CP funds) may exhibit stronger predictive power when they hold CP beliefs. To test this, we introduce a triple interaction term involving market expectations, CP beliefs, and the CP fund dummy:

$$\begin{aligned}
RI_equity_{t+1} = & \alpha_i + \beta expect_equity_market_{i,t} \times CP_belief_{i,t} \times CP_fund_i \\
& + \gamma_1 expect_equity_market_{i,t} \times CP_belief_{i,t} + \gamma_2 CP_belief_{i,t} \\
& \times CP_fund_i + \gamma_3 expect_equity_market_{i,t} \times CP_fund_i \\
& + \theta_1 CP_belief_{i,t} + \theta_2 expect_equity_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},
\end{aligned}$$

$$\begin{aligned}
RI_bond_{t+1} = & \alpha_i + \beta expect_bond_market_{i,t} \times CP_belief_{i,t} \times CP_fund_i \\
& + \gamma_1 expect_bond_market_{i,t} \times CP_belief_{i,t} + \gamma_2 CP_belief_{i,t} \\
& \times CP_fund_i + \gamma_3 expect_bond_market_{i,t} \times CP_fund_i \\
& + \theta_1 CP_belief_{i,t} + \theta_2 expect_bond_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}.
\end{aligned}$$

Here the focus is on the triple interaction term, which captures whether fund managers' market expectations become more predictive of index returns when they are part of a CP fund and hold CP beliefs. Since the countercyclical policy label is time-invariant at the fund level, it is absorbed by fund fixed effects.

Table 4 presents the regression results. Columns (1) and (2) show that a one-unit increase in *expect_equity_market* associates with a 0.199% increase in the next three-month equity index performance. For bonds, the direct relationship between *expect_bonds_market* and future bond index returns is positive but statistically insignificant.

In column (3), we introduce the interaction between market expectations and CP beliefs to assess whether funds' market expectations predict index returns more effectively when managers hold CP beliefs. The interaction term is positive and significant, indicating that equity market expectations are more predictive when fund managers exhibit countercyclical policy expectations. However, in column (4), the interaction between bond market expectations and

CP beliefs is not significant, suggesting that CP beliefs do not enhance bond market predictions.

Columns (5) and (6) introduce the triple interaction involving CP beliefs, the CP fund dummy, and market expectations. The coefficient for the triple interaction is significantly positive in column (5), confirming that CP funds holding CP beliefs demonstrate greater predictability of future equity index returns. In contrast, the coefficient for the triple interaction term in column (6) remains insignificant for the bond market.

These results indicate that fund managers' equity market expectations align positively with subsequent stock index performance, with this predictive power being stronger for CP funds when they hold CP beliefs. This suggests a potential mechanism behind the outperformance of CP funds: their enhanced ability to anticipate and capitalize on equity market movements.

B. Market Expectations and Asset Allocations

Next, we examine the relationship between fund managers' market expectations and their portfolio allocations. To do so, we conduct panel regressions with fund and time fixed effects:

$$\begin{aligned} equity_ratio_{i,t} &= \alpha_i + \beta_t + \gamma expect_equity_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}, \\ bond_ratio_{i,t} &= \alpha_i + \beta_t + \gamma expect_bond_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}. \end{aligned}$$

Here, $equity_ratio_{i,t}$ and $bond_ratio_{i,t}$ represent portfolio allocations to stocks and bonds, respectively, in the quarter when the fund report is released. The key independent variables, $expect_equity_market$ or $expect_bond_market$, measure fund managers' expectations for the equity and bond markets. We control for fund characteristics, including total net assets, fund flows, and fund age, captured in $X_{i,t}$. Fund and time fixed effects are included to account for time-invariant fund characteristics and common market-wide fluctuations.

To further examine whether countercyclical policy (CP) beliefs influence how market expectations translate into asset allocation decisions, we introduce interaction terms involving CP beliefs and CP fund status, as discussed in previous subsections. This allows us to explore whether the relationship between market expectations and portfolio allocations differs depending on the presence of CP beliefs.

Table 8A of the Internet Appendix A 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. Similarly, column (2) shows that a one-unit increase in $expect_bond_market$ is

associated with a 1.852% increase in bond allocation. These findings confirm that fund managers adjust their portfolio allocations in response to their market expectations.

However, as shown in columns (4) to (6), the interaction terms between market expectations and CP beliefs, as well as the triple interactions involving market expectations, CP beliefs, and CP fund status, are statistically insignificant. This suggests that fund managers' asset allocation decisions are primarily driven by their market expectations, rather than their CP beliefs. Therefore, if CP beliefs influence fund performance, their effect likely operates through the predictability of fund managers' market expectations rather than through a direct impact on asset allocation decisions.

C. Predictability of Asset Allocations

If CP funds possess a stronger ability to predict market returns, their holding changes may also serve as a predictor of market returns. To test this, we estimate the following regressions:

$$RI_equity_{t+1} = \alpha_i + \beta \Delta equity_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},$$

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

Here, the dependent variables represent the returns of the equity and bond market indices, respectively. The key independent variables, $\Delta equity_{i,t}$ and $\Delta bond_{ratio_{i,t}}$, capture changes in portfolio allocations to stocks and bonds during the report release quarter. We control for total net assets, fund flows, and fund age in $X_{i,t}$ as well as fund fixed effects. Additionally, we account for the influence of CP beliefs and CP fund status by incorporating interaction terms, as outlined in previous subsections.

Table 5 presents the regression results. The direct effects of equity and bond holding changes on their respective index performances are statistically significant, suggesting that changes in fund allocations can predict subsequent market movements. Specifically, columns (5) and (6) reveal that the coefficient for the interaction term involving CP beliefs, the countercyclical policy label, and equity holding changes is positive and statistically significant, indicating a stronger relationship between stock allocation adjustments and subsequent equity index performance for CP funds when they exhibit CP beliefs. Similarly, the interaction term for bond holding changes is also positive and significant, suggesting a stronger link between

bond allocation changes and bond index performance for CP funds that anticipate countercyclical policies.

These findings provide strong evidence that CP funds are more adept at anticipating and capitalizing on market movements, as reflected in the greater predictive power of their portfolio allocation changes on future index returns. This ability to adjust holdings in alignment with expected market conditions could be a key driver of their outperformance compared to other fund types.

IV. CP Beliefs and Fund Performances

Fund managers' beliefs influence not only their asset allocations but also their selection of individual stocks and bonds, as well as the dynamic trading of these securities. These effects ultimately shape overall fund performance. In this section, we investigate the impact of fund managers' CP beliefs on fund performance.

A. Fund Performance

We begin by exploring the relationship between fund managers' CP beliefs and fund performance. Given that fund managers who hold CP beliefs—particularly those in CP funds that consistently do so—demonstrate a superior ability to predict market returns, we hypothesize that these funds will outperform their counterparts.

To test this hypothesis, we conduct a series of panel regression analyses using the following model:

$$r_{i,t+1} = \alpha_i + \beta_t + \gamma \text{CP_belief}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t+1}$ represents the future monthly returns of fund i , both before and after risk adjustment. Fund fixed effects α_i account for time-invariant fund-specific characteristics, while time fixed effects β_t control for market-wide factors that may influence fund performance. The key independent variable, $\text{CP_belief}_{i,t}$ is a dummy variable indicating whether fund i holds CP beliefs in month t . Control variables, denoted as $X_{i,t}$, include the fund's total net assets (tna), fund flows, and fund age.

The regression results are presented in Panel A of Table 6. We examine both raw monthly fund returns (ret) and risk-adjusted returns, using the Chinese three-factor (CH3) and four-

factor (CH4) models, denoted as α_ch3 and α_ch4 , respectively. All return metrics, whether raw or risk adjusted, are presented as percentages.

The coefficients for the CP belief variable are all statistically significant, indicating a robust relationship between CP beliefs and fund performance. As shown in Columns (1) to (3), the estimated coefficients are 0.065 for monthly raw returns, 0.054 for CH3-factor alpha, and 0.032 for CH4-factor alpha. These results confirm that funds holding CP beliefs consistently exhibit superior performance, whether measured by raw returns or risk-adjusted alphas, even after accounting for other fund characteristics.

To further assess the performance of mutual funds that frequently hold countercyclical policy beliefs, we estimate the following panel regression model:

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

where the key independent variable CP_fund_i , is a dummy indicating whether a fund is classified as a CP fund. We control for time fixed effects and other fund-level characteristics, as described in previous analyses.

Panel B reports the regression results. As reported in Columns (1) to (3), the estimated coefficients for the CP_fund variable are 0.069, 0.064, and 0.069 for monthly raw returns, CH3-factor alpha, and CH4-factor alpha, respectively. All coefficients are statistically significant, confirming that CP funds consistently outperform their peers in terms of both raw and risk-adjusted returns, even after accounting for other fund characteristics.

A side-by-side comparison of Panels A and B shows that CP funds outperform other funds to a greater extent than the outperformance observed among funds that hold CP beliefs versus those that do not. These results emphasize that consistently incorporating countercyclical policy analysis into investment strategies leads to stronger and more persistent performance advantages.

We further construct portfolios based on CP beliefs and CP funds to examine their outperformance. First, we sort funds by their managers' CP beliefs and create three semi-annual portfolios: one containing funds with CP beliefs, another including the remaining funds, and a long-short portfolio that goes long on the first and short on the second. We calculate both equal-weighted and value-weighted returns and conduct time-series regressions on monthly portfolio returns using the CH3 and CH4 models. Panels A, B, and C of Table 7 present the results for

the CP belief portfolio, the non-CP belief portfolio, and the long-short portfolio, respectively.

Panel A of Table 7 shows that funds holding CP beliefs generate significant CH3 and CH4 alphas across both equal-weighted and value-weighted portfolios. Panel B indicates that funds without CP beliefs exhibit smaller alphas. Panel C highlights the strong outperformance of funds with CP beliefs. Economically, their CH3-factor alphas exceed those of other funds by 0.207% (equal-weighted) and 0.227% (value-weighted) per month. The CH4-factor alphas show a similar pattern, with outperformance of 0.164% (equal-weighted) and 0.183% (value-weighted). When incorporating the bond index factor, the magnitude of outperformance increases to 0.284% (equal-weighted) and 0.255% (value-weighted).

We then compare CP and non-CP funds, defining CP funds as those in the top quintile of countercyclical policy expectations and non-CP funds as those in the bottom quintile. We construct three portfolios: one for all CP funds, one for all non-CP funds, and a long-short portfolio that goes long on CP funds and short on non-CP funds. Using both CH3 and CH4 models, we regress the monthly returns of these portfolios on risk factors. Panels A, B, and C of Table 8 report the results for the CP fund portfolio, the non-CP fund portfolio, and the long-short portfolio, respectively.

Panel A of Table 8 confirms that CP funds generate strong CH3 and CH4 alphas for both equal-weighted and value-weighted portfolios. Panel B shows that non-CP funds also have significant, though smaller, alphas in equal-weighted portfolios, while their value-weighted alphas are statistically insignificant. Panel C demonstrates that CP funds significantly outperform non-CP funds. The CH3-factor alphas of CP funds exceed those of non-CP funds by 0.264% (equal-weighted) and 0.318% (value-weighted) per month. For the CH4-factor model, CP funds outperform by 0.204% (equal-weighted) and 0.262% (value-weighted). The outperformance remains significant when including the bond index factor, reaching 0.358% (equal-weighted) and 0.330% (value-weighted).

Overall, our analysis demonstrates that funds holding CP beliefs consistently outperform, underscoring the role of countercyclical policy beliefs in shaping investment decisions and fund performance. Notably, funds that systematically incorporate countercyclical policy expectations into their strategies achieve even higher returns than those that hold such beliefs sporadically.

B. The Role of Countercyclical Policy Beliefs

The superior performance of CP funds may reflect the broader abilities of their managers, who, in addition to forming countercyclical policy expectations, may possess other attributes that enhance performance. To further explore the role of CP beliefs in driving fund returns, we examine the direct link between time-varying CP beliefs and fund performance, conditional on the fund being classified as a CP fund.

Table 9 presents regression results analyzing the relationship between time-varying CP beliefs and various fund performance measures. Columns (1) through (3) report results for raw return, CH3 alpha, and CH4 alpha, respectively. The positive and statistically significant coefficients consistently indicate that expectations regarding different types of countercyclical policies predict higher monthly returns and risk-adjusted performance for CP funds. This suggests that the superior performance of CP funds is directly related to their countercyclical policy beliefs, rather than being solely attributed to other managerial attributes.

To further investigate the investment skills of CP fund managers, we analyze their market timing and stock selection abilities. Following the methodology of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), we construct two skill metrics: market timing, which measures a fund's ability to adjust market exposure based on prevailing conditions (increasing exposure during high-return periods and decreasing it during low-return periods), and stock selection, which reflects the extent to which managers allocate more capital to stocks that subsequently realize higher returns.

We examine how these skill measures relate to time-varying CP beliefs, conditional on the fund being a CP fund, using the following regression models:

$$Timing_{i,t} = \alpha_i + \beta_t + \gamma CP_{i,t} + \theta X_{i,t} + \varepsilon_{i,t},$$

$$Picking_{i,t} = \alpha_i + \beta_t + \gamma CP_{i,t} + \theta X_{i,t} + \varepsilon_{i,t},$$

where we follow equations (1) and (2) in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) to construct two measures: $Timing_{i,t}$ and $Picking_{i,t}$, for a fund's market-timing and stock-picking abilities, respectively. We control for fund size, fund flows, and fund age in $X_{i,t}$, as well as time fixed effects α_i and fund fixed effects β_t to account for unobserved heterogeneity.

Table 10 presents the results linking CP beliefs—including expectations of countercyclical

fiscal, monetary, and regulatory policies, as well as the overall CP measure—to investor skills in market timing and stock selection. Columns (1) through (4) show that fiscal, monetary, regulatory, and overall CP beliefs significantly enhance market timing abilities for CP funds, suggesting that these managers can dynamically adjust exposure in anticipation of macroeconomic shifts. Columns (5) through (8) show positive, though somewhat weaker, associations between CP beliefs and stock selection skills, indicating that countercyclical policy expectations may also play a role in security selection.

Overall, these findings suggest that fund managers' CP beliefs significantly influence their market timing and, to a lesser extent, stock selection abilities. This underscores the importance of countercyclical policy expectations in shaping investment strategies, highlighting CP funds' ability to anticipate and capitalize on policy-driven macroeconomic trends, which in turn contributes to their superior performance.

Fund managers' expectations may also influence their investors' decision making, particularly in the context of fund flows. Understanding these interactions is crucial for both fund managers and investors, as they can impact fund performance and market dynamics. Table 11 presents the results of fund flow forecasting regressions that examine the influence of CP beliefs on fund flows over a six-month period following the publication of (semi-)annual reports. We control for lagged fund performance from the preceding six months in all regressions. As shown in the table, the CP fiscal, monetary, regulatory, and belief variables all show significant positive coefficients, indicating a strong predictive relationship with fund flows. Additionally, the semi-annual return variable consistently demonstrates a robust positive association with fund flow across all specifications, underscoring the importance of past performance in predicting future inflows. Overall, our findings underscore the importance of understanding investor beliefs as a critical factor influencing fund flow dynamics.

V. Robustness

In this section, we conduct a series of robustness tests by employing alternative methods to measure CP beliefs and identify CP funds, followed by re-examining the superior performance of CP funds through portfolio sorting to validate the reliability of our findings.

First, we explore alternative classification methods for identifying funds that frequently exhibit countercyclical policy expectations. Specifically, we redefine CP funds as those in the

top 30% or top 50% of the most frequent CP beliefs for robustness checks. We then construct three portfolios: one for all CP funds, another for all non-CP funds (those in the bottom 30% or bottom 50%), and a long-short portfolio that goes long on CP funds and short on non-CP funds. Using both equal- and value-weighted returns, we conduct time-series regressions of their monthly returns against various risk factors, employing the CH3 and CH4 models along with the bond index factor. Tables 9A and 10A of the Internet Appendix show that regardless of the CP fund classification, CP funds consistently generate significant alphas across portfolio types. The long-short portfolios also yield statistically significant alphas across different configurations, reinforcing the relationship between countercyclical policy expectations and fund performance.

Second, we implement a rolling-based method to classify CP funds. For each period, we require funds to have at least one-third of the maximum possible number of semi-annual periods from 2008, the start of our sample, to the current year. For instance, in the 2013 semi-annual period, the total potential periods amount to 11, so we require at least 3 valid reports for inclusion. We define CP funds as those in the top 20% of countercyclical policy beliefs across periods and non-CP funds as those in the bottom 20%. Table 11A of the Internet Appendix demonstrates that CP funds identified through this method consistently exhibit significantly positive alphas, particularly in value-weighted portfolios, across various model specifications, further confirming their superior performance.

Third, we address potential biases arising from missing policy mentions in fund reports. Some fund managers may omit policy discussions in their outlook sections, which we interpret as a neutral stance. As a robustness check, we exclude these cases when constructing our policy expectation measures and repeat the portfolio sorting analysis. Table 12A of the Internet Appendix shows that CP funds continue to exhibit significantly positive alphas across different settings (equal-weighted, value-weighted, CH3, CH4, and bond index factors). However, the magnitude of performance differences decreases, likely due to the exclusion of missing observations.

Fourth, we apply a stricter definition of CP beliefs by excluding neutral policy expectations. Under this approach, we classify countercyclical policy expectations only when a fund manager's policy outlook fully contradicts their view on economic fundamentals. The portfolio sorting results in Table 13A of the Internet Appendix show that CP funds consistently produce significantly positive alphas across all weighting schemes and factor models, with even

stronger outperformance in value-weighted portfolios.

Overall, these robustness checks using alternative CP definitions consistently confirm that CP funds outperform non-CP funds across various settings, reinforcing the reliability of our core findings. These results affirm that countercyclical policy expectations play a significant role in mutual fund performance, underscoring the importance of structured policy beliefs in shaping investment strategies.

VI. 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, focusing on their views of the economy, government policies, and financial markets. This approach enables us to assess how these structured beliefs influence investment strategies, particularly in response to economic fluctuations and policy interventions. Specifically, we construct a variable that captures fund managers' expectations regarding the government's countercyclical policies (CP) in reaction to economic shocks.

Our analysis shows that mutual funds that frequently express CP beliefs significantly outperform other funds, a result driven by their superior ability to predict market dynamics and adjust portfolios accordingly. These findings provide strong evidence of the critical role that fund managers' beliefs play in driving investment performance. More importantly, they highlight the importance of structured beliefs about government policies in shaping investment strategies, reinforcing the notion that successful fund management extends beyond traditional market analysis to include anticipation of policy-driven macroeconomic shifts.

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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_macroecconomy	0.012	0.593	-1	-0.5	0	0.5	1
equity_market	0.087	0.666	-1	-0.5	0	0.5	1
bond_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_macroecconomy	0.187	0.584	-1	-0.5	0.5	0.5	1
equity_market	0.38	0.492	-1	0	0.5	1	1
bond_market	0.181	0.42	-1	0	0	0.5	1
Key variables:							
ret_m (in percent)	0.53	4.55	-14.03	-0.75	0.28	1.63	15.70
alpha_ch3 (in percent)	0.21	2.62	-8.32	-0.62	0.06	0.89	10.02
alpha_ch4 (in percent)	0.21	2.57	-8.10	-0.62	0.06	0.88	9.93
semi_ret (in percent)	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: Fund Beliefs Predicting Policies

This table reports result for semi-annual level panel regressions of future fiscal policy (changes) on fund fiscal policy expectations (Panel A) and of future monetary policy (changes) on fund monetary policy expectations (Panel B). In Panel A, the dependent variable in column (1) is the deficit ratio target, typically announced in March each year since 2010, which sets the target for the full ongoing year. In column (2), the dependent variable is the change of this deficit ratio target. Column (3) uses a binary dependent variable indicating whether the change is positive. Column (4) uses a measure of fiscal policy tone change based on official Chinese government meetings. Specifically, we focus on the Two Sessions (全国两会) and the Central Economic Work Conference (中央经济工作会议), two of the most influential political conventions. We extract the fiscal-related content from these meetings and compare it to the previous year's content to determine the tone change. A value of 1 indicates a shift toward expansionary fiscal policy, -1 indicates a shift toward tightening, and 0 indicates no change. In Panel B, the dependent variable in column (1) is the average monthly year-on-year (YoY) growth rate of M2 during the period from the publication month of the fund's (semi-)annual report to the publication month of the subsequent report. Column (2) uses the average monthly YoY growth rate of RMB loans over the same period. Column (3) uses a measure of monetary policy tone change based on official Chinese government meetings. Specifically, we focus on the Two Sessions (全国两会) and the Central Economic Work Conference (中央经济工作会议), two of the most influential political conventions. We extract the monetary-related content from these meetings and compare it to the previous year's content to determine the tone change. A value of 1 indicates a shift toward expansionary monetary policy, -1 indicates a shift toward tightening, and 0 indicates no change. All regressions include the lagged value of each respective fiscal (monetary) policy measure, defined as the most recent available value prior to the current report's publication month. We also 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Fiscal Policy				
	(1)	(2)	(3)	(4)
	Deficit % _{t+1}	Δ Deficit % _{t+1}	Sign(Δ Deficit %) _{t+1}	Δ Fiscal_Tone _{t+1}
expect_fiscal_policy _t	0.0745*** (24.99)	0.103*** (27.08)	0.196*** (25.40)	0.0920*** (12.86)
Deficit % _t	0.138*** (68.92)			
Δ Deficit % _t		-0.0864*** (-44.19)		
Sign(Δ Deficit %) _t			-0.0706*** (-32.79)	
Δ Fiscal_Tone _t				-0.358*** (-103.58)
Fund FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	74435	73501	73501	75438
R-sq	0.442	0.032	0.036	0.234

Panel B: Monetary Policy

	(1)	(2)	(3)
	M2_YoY _{t+1}	RMB_Loan_YoY _{t+1}	ΔMonetary_Tone _{t+1}
expect_monetary_policy _t	0.744*** (55.07)	0.337*** (25.46)	0.296*** (45.77)
M2_YoY _t	0.709*** (451.16)		
RMB_Loan_YoY _t		0.561*** (215.35)	
ΔMonetary_Tone _t			-0.209*** (-100.54)
Fund FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	75438	75438	75438
R-sq	0.717	0.786	0.178

Table 3: 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 C reports summary statistics for the fraction of a fund's reports displaying countercyclical policy expectations and the dummy for CP fund.

Panel A: Countercyclical Policy Expect Summary								
	Mean	Sd	Min	P25	Med	P75	Max	
CP_fiscal	0.175	0.38	0	0	0	0	1	
CP_monetary	0.159	0.366	0	0	0	0	1	
CP_regulatory	0.183	0.387	0	0	0	0	1	
CP_belief	0.214	0.41	0	0	0	0	1	
Panel B: Variation Decomposition								
	(1)	(2)	(3)					
	Fund FE	Time FE	Fund+Time FE					
CP_fiscal	0.087	0.103	0.182					
CP_monetary	0.087	0.094	0.175					
CP_regulatory	0.088	0.085	0.167					
CP_belief	0.090	0.122	0.204					
expectation_equity_market	0.314	0.057	0.376					
expectation_bond_market	0.243	0.038	0.279					
Panel C: Frequency Summary								
	Mean	Sd	Min	P20	P40	P60	P80	Max
fra_CP_belief	0.202	0.123	0	0.091	0.167	0.226	0.300	0.8

Table 4: The Predictability of Market Expectations for Market Returns

This table reports result for monthly level panel regressions of market returns on fund market expectations. The sample period is the three months (a quarter) following the publish month of report. The dependent variable in column (1) is monthly returns 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 returns of CCBI or ChinaBond Aggregate Index. The explanatory variables are the market expectations for the corresponding market. In column (3) and (4), we add the interaction term of market expectations and the countercyclical policy type. In columns (5) and (6), we also include then triple interaction term involving market expectations, countercyclical policy beliefs, and the countercyclical policy type, along with all necessary double interaction terms. 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	hs300_index	bond_index	hs300_index	bond_index	hs300_index	bond_index
expect_equity_market	0.199*** (6.62)		0.132*** (4.02)		0.117*** (3.16)	
expect_bond_market		0.00436 (1.05)		0.00514 (1.09)		0.000181 (0.04)
expect_equity_market X CP_belief			0.300*** (4.74)		0.119 (1.55)	
expect_bond_market X CP_belief				-0.00211 (-0.23)		-0.0111 (-1.04)
CP_belief			-0.762*** (-19.38)	0.00758** (2.02)	-0.686*** (-15.16)	0.00204 (0.45)
expect_equity_market X CP_fund					0.0430 (0.55)	
expect_bond_market X CP_fund						0.0327** (2.14)
CP_belief X CP_fund					-0.211** (-2.33)	0.0182** (2.28)
expect_equity_market X CP_belief X CP_fund					0.435*** (3.11)	
expect_bond_market X CP_belief X CP_fund						0.0173 (0.77)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	214559	214559	214559	214559	214559	214559
R-sq	0.009	0.006	0.011	0.006	0.011	0.006

Table 5: Holding Ratio Differences and Three-Month Market Index Predictions

This table reports results for monthly level panel regressions of market returns on fund holding changes. The sample period is the three months (a quarter) following the report's publication month. 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 columns 3 and 4, we add the interaction term of holding changes and the countercyclical policy type. In columns 5 and 6, we also add the triple interaction term of holding changes, countercyclical policy beliefs, and the countercyclical policy type, together with all necessary double interaction term. 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	hs300_index	bond_index	hs300_index	bond_index	hs300_index	bond_index
Δ equity_ratio	0.00659*** (3.76)		0.00695*** (3.52)		0.00813*** (3.64)	
Δ bond_ratio		0.00148*** (7.83)		0.00155*** (7.10)		0.00147*** (6.26)
Δ equity_ratio X CP_belief			-0.00135 (-0.36)		-0.00644 (-1.37)	
Δ bond_ratio X CP_belief				-0.000298 (-0.66)		-0.00146*** (-2.77)
CP_belief			-0.641*** (-21.96)	0.00750** (2.10)	-0.638*** (-18.27)	0.00132 (0.31)
Δ equity_ratio X CP_fund					-0.00529 (-1.13)	
Δ bond_ratio X CP_fund						0.000503 (0.81)
CP_belief X CP_fund					-0.0102 (-0.16)	0.0197*** (2.59)
Δ equity_ratio X CP_belief X CP_fund					0.0144* (1.79)	
Δ bond_ratio X CP_belief X CP_fund						0.00309*** (2.89)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	214521	214521	214521	214521	214521	214521
R-sq	0.009	0.006	0.011	0.006	0.011	0.006

Table 6: CP Belief, CP Fund 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 policy expectations. The key explanatory variable in Panel A is CP belief. In Panel B, the key explanatory variable is the CP fund designation, which is assigned to funds where the proportion of periods characterized by countercyclical policy beliefs falls within the top 20% (i.e., greater than the 80th percentile). Both returns and alphas are expressed in monthly percentage terms. Importantly, we include fund and time fixed effects in Panel A and time fixed effects in Panel B, all regressions are estimated with constants (not reported here). We adjust standard errors for clustering at the fund level, and *t*-statistics are reported in parentheses. Significance levels are indicated as follows: * (10%), ** (5%), and *** (1%).

Panel A: CP Belief and Fund Performance						
Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)
		Ret		alpha_ch3		alpha_ch4
CP_belief	0.0653*** (4.62)	0.0655*** (4.63)	0.0543*** (4.60)	0.0544*** (4.61)	0.0319*** (2.82)	0.0320*** (2.83)
log_tna		-0.120*** (-18.08)		-0.0732*** (-14.65)		-0.0642*** (-13.46)
flow		0.0344*** (4.82)		0.0431*** (8.56)		0.0503*** (10.10)
age		0.00677*** (2.60)		0.00250 (1.20)		0.000798 (0.53)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	428278	428278	428278	428278	428278	428278
R-sq	0.420	0.421	0.119	0.120	0.094	0.094
Panel B: CP Fund and Fund Performance						
Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)
		Ret		alpha_ch3		alpha_ch4
CP_fund	0.0830*** (6.41)	0.0691*** (5.09)	0.0674*** (4.56)	0.0644*** (4.21)	0.0708*** (5.00)	0.0687*** (4.70)
log_tna		-0.0369*** (-11.43)		-0.0130*** (-4.21)		-0.00804*** (-2.66)
flow		0.00506 (0.73)		0.0239*** (4.75)		0.0320*** (6.38)
age		0.000619*** (4.95)		0.000151 (1.04)		0.000142 (1.02)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	428278	428278	428278	428278	428278	428278
R-sq	0.415	0.415	0.097	0.097	0.072	0.072

Table 7: Performance of Funds with Countercyclical Policy Beliefs

Panels A and B report alpha and factor loadings of returns for funds making CP beliefs and funds not making CP beliefs, respectively. The portfolios are rebalanced at the start of April or October, which are the latest months when (semi-)annual reports and holding data are available. Panel C reports the alpha and factor loadings for a long-short portfolio that longs funds exhibiting CP beliefs and shorts funds that do not exhibit CP beliefs. 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: CP Belief						
	Equal weighted				Value weighted	
Alpha	0.573*** (3.58)	0.528*** (3.19)	0.496*** (2.66)	0.430*** (2.79)	0.354*** (2.83)	0.404*** (2.64)
MKTRF	0.503*** (12.08)	0.512*** (14.44)	0.514*** (13.66)	0.451*** (7.32)	0.466*** (8.27)	0.463*** (8.07)
Smb	-0.0228 (-0.64)	-0.0347 (-0.97)	-0.0356 (-1.01)	-0.0269 (-0.59)	-0.0469 (-1.02)	-0.0455 (-1.01)
Vmg	-0.201*** (-5.14)	-0.198*** (-4.84)	-0.197*** (-4.80)	-0.145*** (-3.21)	-0.140*** (-3.27)	-0.142*** (-3.20)
Pmo		0.0638 (1.62)	0.0638 (1.62)		0.107* (1.89)	0.107* (1.88)
Bond			0.0859 (0.46)			-0.136 (-0.72)
N	186	186	186	186	186	186
R-sq	0.884	0.887	0.887	0.792	0.802	0.803
Panel B: Non-CP Belief						
	Equal weighted				Value weighted	
Alpha	0.366*** (2.85)	0.363*** (2.78)	0.212 (1.61)	0.204* (1.86)	0.171* (1.70)	0.148 (1.45)
MKTRF	0.439*** (19.86)	0.439*** (19.26)	0.448*** (23.43)	0.356*** (8.39)	0.362*** (9.01)	0.364*** (8.98)
SMB	0.0392 (1.01)	0.0385 (1.02)	0.0343 (0.93)	0.0252 (0.87)	0.0167 (0.58)	0.0161 (0.55)
VMG	-0.140*** (-3.23)	-0.140*** (-3.21)	-0.135*** (-3.29)	-0.0883** (-2.22)	-0.0863** (-2.21)	-0.0855** (-2.20)
PMO		0.00394 (0.14)	0.00416 (0.15)		0.0452 (1.05)	0.0452 (1.05)
Bond			0.412*** (2.63)			0.0628 (0.50)
N	186	186	186	186	186	186
R-sq	0.907	0.907	0.912	0.787	0.790	0.790

Panel C: Difference						
	Equal weighted			Value weighted		
Alpha	0.207** (2.36)	0.164** (2.14)	0.284*** (2.81)	0.227*** (2.81)	0.183*** (2.68)	0.255*** (2.71)
MKTRF	0.0644 (1.58)	0.0729* (1.94)	0.0659* (1.82)	0.0949*** (3.36)	0.104*** (4.16)	0.0993*** (4.01)
SMB	-0.0620* (-1.93)	-0.0732** (-2.15)	-0.0698** (-2.09)	-0.0521** (-1.99)	-0.0636** (-2.42)	-0.0616** (-2.40)
VMG	-0.0601** (-2.59)	-0.0574** (-2.46)	-0.0614*** (-2.68)	-0.0566*** (-3.03)	-0.0538*** (-2.92)	-0.0562*** (-2.98)
PMO		0.0598** (2.04)	0.0596** (2.07)		0.0616*** (2.75)	0.0615*** (2.81)
Bond			-0.326*** (-2.90)			-0.198* (-1.74)
N	186	186	186	186	186	186
R-sq	0.249	0.289	0.324	0.410	0.448	0.460

Table 8: Performance of Countercyclical Policy Funds

Panels A and B report alpha and factor loadings of returns for CP funds (proportion of periods characterized by countercyclical policy beliefs falls within the top 20%) and Non-CP funds (proportion of periods characterized by countercyclical policy beliefs falls within the bottom 20%), respectively. Panel C reports alpha and factor loadings for a long-short portfolio that longs CP funds and shorts non-CP funds. 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: CP Funds						
	Equal weighted				Value weighted	
Alpha	0.526*** (3.01)	0.494*** (2.64)	0.404** (2.10)	0.434*** (2.79)	0.366** (2.37)	0.349** (2.19)
MKTRF	0.576*** (23.24)	0.583*** (26.80)	0.588*** (27.50)	0.555*** (15.80)	0.568*** (18.94)	0.569*** (18.72)
Smb	0.00782 (0.16)	-0.000684 (-0.01)	-0.00318 (-0.07)	-0.0106 (-0.21)	-0.0284 (-0.60)	-0.0289 (-0.61)
Vmg	-0.203*** (-3.61)	-0.200*** (-3.53)	-0.198*** (-3.55)	-0.177*** (-2.85)	-0.172*** (-2.87)	-0.172*** (-2.85)
Pmo		0.0455 (1.29)	0.0456 (1.31)		0.0954** (2.20)	0.0955** (2.19)
Bond			0.243 (1.31)			0.0461 (0.28)
N	186	186	186	186	186	186
R-sq	0.913	0.914	0.915	0.881	0.887	0.888
Panel B: Non-CP Funds						
	Equal weighted				Value weighted	
Alpha	0.263** (2.40)	0.290*** (2.98)	0.0465 (0.47)	0.116 (1.47)	0.104 (1.37)	0.0190 (0.23)
MKTRF	0.371*** (8.49)	0.365*** (8.01)	0.380*** (9.49)	0.234*** (6.61)	0.236*** (7.32)	0.241*** (7.25)
SMB	0.0390 (1.03)	0.0461 (1.24)	0.0393 (1.06)	-0.0183 (-1.06)	-0.0216 (-1.34)	-0.0240 (-1.43)
VMG	-0.0787** (-2.21)	-0.0804** (-2.32)	-0.0724** (-2.35)	-0.0433 (-1.39)	-0.0425 (-1.40)	-0.0398 (-1.34)
PMO		-0.0377 (-1.09)	-0.0374 (-1.15)		0.0178 (0.58)	0.0179 (0.60)
Bond			0.662*** (3.65)			0.230** (2.17)
N	186	186	186	186	186	186
R-sq	0.837	0.839	0.858	0.736	0.737	0.742

Panel C: Difference						
		Equal weighted			Value weighted	
Alpha	0.264** (2.12)	0.204 (1.58)	0.358*** (2.66)	0.318** (2.54)	0.262** (2.05)	0.330** (2.49)
MKTRF	0.205*** (4.30)	0.217*** (4.77)	0.208*** (4.80)	0.321*** (13.00)	0.332*** (14.79)	0.328*** (14.32)
SMB	-0.0312 (-0.87)	-0.0468 (-1.36)	-0.0425 (-1.17)	0.00769 (0.19)	-0.00682 (-0.19)	-0.00493 (-0.13)
VMG	-0.124*** (-3.68)	-0.120*** (-3.60)	-0.125*** (-3.48)	-0.133*** (-2.89)	-0.130*** (-2.81)	-0.132*** (-2.76)
PMO		0.0832** (2.58)	0.0830*** (2.62)		0.0776** (2.39)	0.0775** (2.41)
Bond			-0.419*** (-4.14)			-0.184 (-1.38)
N	186	186	186	186	186	186
R-sq	0.603	0.623	0.639	0.789	0.799	0.801

Table 9: CP Beliefs and Performance of CP Funds

This table reports results for CP fund performance conditional on whether they possess CP beliefs. The dependent variable is raw return (the first column), the alpha of the Chinese three-factor model (the second column), 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. 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	(1) ret_m	(2) alpha_ch3	(3) alpha_ch4
CP_belief	0.0589** (2.39)	0.0590** (2.51)	0.0407* (1.87)
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	97438	97438	97438
R-sq	0.554	0.161	0.127

Table 10: Countercyclical Policy Funds Skills

This table reports results for CP fund skills conditional on whether they possess CP beliefs. The dependent variables are Timing (Panel A) and Picking (Panel B), defined following Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), where each stock's beta is measured over a 12-month rolling window. 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Timing Skills				
	(1)	(2)	(3)	(4)
	Timing	Timing	Timing	Timing
CP_fiscal	0.00262** (2.47)			
CP_monetary		0.00208** (2.05)		
CP_regulatory			0.00209** (2.04)	
CP_belief				0.00219** (2.18)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	14549	14549	14549	14549
R-sq	0.726	0.726	0.726	0.726
Panel B: Picking Skills				
	(1)	(2)	(3)	(4)
	Picking	Picking	Picking	Picking
CP_fiscal	0.00253* (1.70)			
CP_monetary		0.00180 (1.20)		
CP_regulatory			0.00239* (1.68)	
CP_belief				0.00272* (1.83)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	14549	14549	14549	14549
R-sq	0.265	0.265	0.265	0.265

Table 11: CP Belief Predicting Fund Flow

This table presents the results for fund flow forecasting regressions conditional on whether they possess CP beliefs. Fund flow is measured over the six months following the publication month of the (semi-)annual report. All regressions include lagged fund performance, calculated over the six months prior to the (semi-)annual report publication. Additional control variables include fund size, past flow, and age. The regressions also incorporate fund and time fixed effects and are estimated with intercepts, which are not reported. Standard errors are adjusted for clustering at fund level. t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	Fund Flow			
	(Semi-annual from publish month)			
CP_fiscal	0.0561*** (3.10)			
CP_monetary		0.0637*** (3.46)		
CP_regulatory			0.0601*** (3.32)	
CP_belief				0.0694*** (4.00)
semi_ret (Until publish month)	0.593*** (8.69)	0.592*** (8.68)	0.595*** (8.72)	0.593*** (8.69)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	70817	70817	70817	70817
R-sq	0.176	0.176	0.176	0.176

Internet Appendix

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 from 2008 to 2023. Qualified Domestic Institutional Investor (QDII) funds are excluded. We further exclude funds with fewer than 10 reports during this period.

Year	Semi	Annual	Total
2008	282	333	615
2009	389	448	837
2010	486	532	1018
2011	592	674	1,266
2012	748	862	1,610
2013	983	1,130	2,113
2014	1,264	1,413	2,677
2015	1,589	1,968	3,557
2016	2,245	2,596	4,841
2017	2,749	3,408	6,157
2018	3,742	4,017	7,759
2019	4,252	4,402	8,654
2020	4,398	4,367	8,765
2021	4,342	4,308	8,650
2022	4,303	4,256	8,559
2023	4,208	4,162	8,370
Total	36572	38876	75448

Table 2A: GPT response consistency

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

	(1)	(2)	(3)
	no year	5y forward	5y backward
fiscal_policy	0.907	0.904	0.905
monetary_policy	0.911	0.906	0.912
regulatory_policy	0.937	0.944	0.937
national_macro-economic	0.901	0.905	0.904
equity_market	0.904	0.892	0.899
bond_market	0.913	0.904	0.91

Table 3A: Validation of GPT Responses

This table reports the validation results of GPT-generated annotations against human annotations. We select 50 high-quality data points and evaluate them across three key expectation dimensions: macroeconomic fundamentals, the equity market, and the bond market. In the first round, three human labelers, well-versed in finance and macroeconomics, independently annotate each data point, and the human label is determined based on the majority vote. Given the complexity of the task, we require them to choose from three categories: positive, neutral, or negative. We also adjust GPT 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 (GPT vs. human).

	Macro	Equity	Bond
First Round:			
Consistent Number	38	35	43
Inconsistent Number	12	15	7
No majority vote	2	4	3
1st Consistency Rate	0.76	0.7	0.86
Second Round:			
Agree with GPT Number	7	12	6
2nd Consistency Rate	0.9	0.94	0.98
Overall Consistency Rate	0.94		

Table 4A: 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 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** (2.07)	0.00176*** (9.54)	0.00199*** (12.83)	0.00286*** (13.95)	0.147*** (56.98)	0.000357** (2.24)
log_tna	0.000888 (0.80)	0.0406*** (22.59)	-0.00178* (-1.72)	-0.00360*** (-2.81)	-0.0190*** (-15.43)	0.0419*** (23.48)
flow	0.000627 (0.40)	0.00788*** (4.09)	0.000146 (0.09)	-0.00214 (-1.11)	0.00309 (1.59)	0.0151*** (7.40)
age	0.0000399 (0.72)	-0.00111*** (-12.31)	0.0000814* (1.81)	0.000186*** (3.12)	0.000349*** (5.98)	-0.00160*** (-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* (1.66)	0.00000652 (0.04)	0.00148*** (9.01)	0.00161*** (8.28)	0.00302*** (16.65)	-0.00129*** (-9.99)
log_tna	-0.00902*** (-6.49)	0.00999*** (8.10)	-0.0118*** (-10.11)	-0.0241*** (-15.87)	-0.0503*** (-28.12)	0.0267*** (18.05)
flow	-0.00302* (-1.67)	0.00361** (2.08)	-0.00385** (-2.30)	-0.00587*** (-2.94)	-0.0124*** (-6.85)	0.00995*** (5.25)
age	0.000251*** (3.85)	-0.000455*** (-7.34)	0.000375*** (6.40)	0.000952*** (12.20)	0.00135*** (14.57)	-0.00105*** (-14.95)
N	73361	73361	73361	73361	73361	73361
R-sq	0.097	0.161	0.021	0.216	0.100	0.059

Table 5A: Fund Characteristics, Countercyclical Policy Expectations

This table reports the results of semi-annual panel regressions of fund managers' counter-cyclical policy beliefs on fund characteristics. We decompose CP into CPn (when the review of macroeconomic fundamentals is negative) and CPp (when the review of macroeconomic fundamentals is positive) and consider three policy dimensions—fiscal, monetary, regulatory policies. 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Fiscal		Monetary		Regulatory	
	CPn	CPp	CPn	CPp	CPn	CPp
semi_ret	-0.00172*** (-18.13)	0.00105*** (8.80)	-0.00174*** (-18.55)	0.00143*** (12.36)	-0.00164*** (-17.19)	0.00111*** (8.73)
log_tna	-0.00363*** (-6.67)	-0.00104* (-1.70)	-0.00324*** (-6.02)	-0.00246*** (-4.23)	-0.00314*** (-5.85)	-0.00182*** (-2.77)
flow	-0.00186** (-2.05)	-0.00140 (-1.38)	-0.00181** (-2.01)	-0.00132 (-1.39)	-0.00164* (-1.80)	-0.00209** (-1.99)
age	0.0000936*** (3.74)	0.000131*** (4.29)	0.0000893*** (3.60)	0.000162*** (5.37)	0.0000994*** (3.99)	0.000178*** (5.42)
Time FE	YES	YES	YES	YES	YES	YES
N	73361	73361	73361	73361	73361	73361
R-sq	0.145	0.186	0.143	0.168	0.147	0.154

Table 6A: Market Condition, Countercyclical Policy Expectations

This table reports the results of semi-annual panel regressions of fund managers' counter-cyclical policy beliefs on market conditions. The explanatory variables include market performance data, represented by the semi-annual return of the Shanghai Shenzhen 300 Index (*hs300_index*) and the ChinaBond Aggregate Index (*bond_index*), as well as market realized volatility data, measured by the semi-annual standard deviation of the daily returns of the Shanghai Shenzhen 300 Index (*hs300_semi_sd*) and the ChinaBond Aggregate Index (*bond_semi_sd*). We decompose CP into CP_n (when the review of macroeconomic fundamentals is negative) and CP_p (when the review of macroeconomic fundamentals is positive) and consider three policy dimensions—fiscal, monetary, regulatory policies. 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 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.

Panel A: CP_n and CP_p Fiscal Policy								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CP_n_fiscal				CP_p_fiscal			
<i>hs300_index</i>	-0.264*** (-36.02)				0.316*** (50.65)			
<i>bond_index</i>		3.102*** (42.92)				-4.891*** (-59.01)		
<i>hs300_semi_sd</i>			6.707*** (27.57)				-11.20*** (-38.36)	
<i>bond_semi_sd</i>				34.11*** (8.55)				-57.99*** (-12.48)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	75439	75439	75439	75439	75439	75439	75439	75439
R-sq	0.114	0.118	0.096	0.086	0.108	0.140	0.101	0.079
Panel B: CP_n and CP_p Monetary Policy								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CP_n_monetary				CP_p_monetary			
<i>hs300_index</i>	-0.250*** (-34.27)				0.250*** (43.41)			
<i>bond_index</i>		3.193*** (44.14)				-4.398*** (-54.59)		
<i>hs300_semi_sd</i>			6.565*** (27.48)				-11.42*** (-39.89)	
<i>bond_semi_sd</i>				38.02*** (9.44)				-40.11*** (-8.95)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	75439	75439	75439	75439	75439	75439	75439	75439
R-sq	0.107	0.116	0.092	0.082	0.102	0.138	0.108	0.081

Panel C: CPn and Cpp Regulatory Policy								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CPn_regulatory				Cpp_regulatory			
hs300_index	-0.264*** (-35.45)				0.348*** (53.35)			
bond_index		3.123*** (42.84)				-4.454*** (-57.83)		
hs300_semi_sd			6.803*** (28.11)				-8.425*** (-30.21)	
bond_semi_sd				36.85*** (9.09)				-38.55*** (-7.59)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	75439	75439	75439	75439	75439	75439	75439	75439
R-sq	0.112	0.117	0.095	0.085	0.116	0.129	0.092	0.081

Table 7A: Fund Manager Characteristics across Countercyclical Policy Funds

This table reports a comparison of fund manager characteristics between CP funds and other funds. We calculate the ratios of fund managers with a PhD degree, a graduate degree (Master's or above), male fund managers, and foreign fund managers. For each fund, we take the time-series average of these ratios and then compare them at the cross-sectional level.

Manager Char	CP_funds	Other funds	p_value
Ph.D.	0.119	0.0986	0.0119 **
Graduate	0.9565	0.9412	0.0115 **
Male	0.7823	0.7335	0.0000 ***
Foreign	0.0124	0.0086	0.107

Table 8A: Market Expectations and Fund Holdings

This table reports results for semi-annual level panel regressions of fund portfolio holdings on market expectations. The dependent variable is either the stock holding ratio (the first column), or the bond holding ratio (the second column). The explanatory variables are market expectations for the corresponding markets. In columns 3 and 4, we add the interaction term of market expectations and the countercyclical policy type. In columns 5 and 6, we also include a triple interaction term involving market expectations, countercyclical beliefs, and the countercyclical policy type, along with all necessary double interaction terms. 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 are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	stock_ratio	bond_ratio	stock_ratio	bond_ratio	stock_ratio	bond_ratio
expect_equity_market	1.944*** (14.14)		2.006*** (13.74)		1.950*** (11.88)	
expect_bond_market		1.852*** (10.38)		1.927*** (10.57)		1.613*** (8.59)
expect_equity_market X CP_belief			-0.269 (-1.14)		-0.525* (-1.84)	
expect_bond_market X CP_belief				-0.390 (-1.17)		-0.753* (-1.95)
CP_belief			-0.000187 (-0.00)	-0.159 (-1.32)	0.203 (1.36)	-0.199 (-1.34)
expect_equity_market X CP_fund					0.180 (0.46)	
expect_bond_market X CP_fund						2.294*** (3.69)
CP_belief X CP_fund					-0.583* (-1.90)	0.256 (1.01)
expect_equity_market X CP_belief X CP_fund					0.625 (1.24)	
expect_bond_market X CP_belief X CP_fund						0.0673 (0.09)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	75129	75129	75129	75129	75129	75129
R-sq	0.928	0.928	0.928	0.928	0.928	0.928

Table 9A: Performance of Countercyclical Policy Funds (top 30th percentile as cutoff)

This table defines CP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 30% (i.e., greater than the 70th percentile). Non-CP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 30% (i.e., less than or equal to the 30th percentile).

Panel A: CP Funds						
		Equal weighted			Value weighted	
Alpha	0.519*** (3.14)	0.489*** (2.78)	0.395** (2.19)	0.403*** (2.82)	0.339** (2.49)	0.316** (2.24)
MKTRF	0.555*** (24.14)	0.561*** (28.12)	0.567*** (28.49)	0.533*** (14.38)	0.546*** (16.29)	0.547*** (16.12)
Smb	0.0156 (0.33)	0.00766 (0.17)	0.00503 (0.11)	0.00250 (0.05)	-0.0142 (-0.33)	-0.0148 (-0.34)
Vmg	-0.198*** (-3.64)	-0.196*** (-3.56)	-0.193*** (-3.59)	-0.162*** (-2.81)	-0.158*** (-2.84)	-0.157*** (-2.82)
Pmo		0.0423 (1.22)	0.0424 (1.24)		0.0893* (1.96)	0.0894* (1.96)
Bond			0.256 (1.50)			0.0625 (0.40)
N	186	186	186	186	186	186
R-sq	0.914	0.915	0.916	0.873	0.879	0.879
Panel B: Non-CP Funds						
		Equal weighted			Value weighted	
Alpha	0.318*** (3.05)	0.326*** (3.24)	0.135 (1.35)	0.152 (1.58)	0.131 (1.53)	0.0762 (0.83)
MKTRF	0.361*** (13.86)	0.360*** (13.14)	0.371*** (15.96)	0.260*** (6.03)	0.264*** (6.45)	0.267*** (6.39)
SMB	0.0245 (0.87)	0.0264 (0.97)	0.0211 (0.79)	-0.0118 (-0.51)	-0.0171 (-0.67)	-0.0186 (-0.72)
VMG	-0.114*** (-3.45)	-0.115*** (-3.49)	-0.108*** (-3.68)	-0.0629** (-2.05)	-0.0616** (-2.10)	-0.0598** (-2.05)
PMO		-0.0101 (-0.40)	-0.00987 (-0.41)		0.0281 (0.72)	0.0282 (0.73)
Bond			0.520*** (3.96)			0.150 (1.33)
N	186	186	186	186	186	186
R-sq	0.893	0.893	0.906	0.713	0.715	0.717

Panel C: Difference						
		Equal weighted			Value weighted	
Alpha	0.201** (2.21)	0.163* (1.70)	0.260*** (2.64)	0.252** (2.57)	0.208** (2.04)	0.240** (2.29)
MKTRF	0.194*** (6.99)	0.201*** (7.74)	0.195*** (7.87)	0.273*** (14.00)	0.282*** (14.54)	0.280*** (14.04)
SMB	-0.00894 (-0.33)	-0.0187 (-0.73)	-0.0160 (-0.59)	0.0143 (0.38)	0.00286 (0.08)	0.00377 (0.10)
VMG	-0.0837*** (-3.06)	-0.0813*** (-3.04)	-0.0845*** (-2.96)	-0.0992** (-2.41)	-0.0965** (-2.36)	-0.0975** (-2.33)
PMO		0.0524*** (2.69)	0.0523*** (2.68)		0.0612** (2.19)	0.0611** (2.20)
Bond			-0.264*** (-3.99)			-0.0880 (-0.82)
N	186	186	186	186	186	186
R-sq	0.755	0.768	0.777	0.804	0.812	0.813

Table 10A: Performance of Countercyclical Policy Funds (50th percentile as cutoff)

This table defines CP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 50% (i.e., greater than the 50th percentile). Non-CP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 50% (i.e., less than or equal to the 50th percentile).

Panel A: CP Funds						
		Equal weighted			Value weighted	
Alpha	0.503*** (3.31)	0.479*** (2.98)	0.373** (2.26)	0.356*** (2.67)	0.300** (2.54)	0.284** (2.23)
MKTRF	0.519*** (24.41)	0.524*** (27.49)	0.530*** (28.36)	0.466*** (10.27)	0.477*** (11.16)	0.478*** (11.05)
Smb	0.0157 (0.37)	0.00945 (0.23)	0.00648 (0.16)	0.00622 (0.15)	-0.00835 (-0.22)	-0.00881 (-0.23)
Vmg	-0.188*** (-3.80)	-0.186*** (-3.72)	-0.183*** (-3.77)	-0.140*** (-2.82)	-0.136*** (-2.86)	-0.136*** (-2.85)
Pmo		0.0334 (1.02)	0.0336 (1.04)		0.0780 (1.58)	0.0780 (1.57)
Bond			0.289* (1.82)			0.0448 (0.32)
N	186	186	186	186	186	186
R-sq	0.914	0.915	0.917	0.842	0.847	0.847
Panel B: Non-CP Funds						
		Equal weighted			Value weighted	
Alpha	0.352*** (3.38)	0.346*** (3.28)	0.188* (1.77)	0.166 (1.56)	0.130 (1.42)	0.110 (1.11)
MKTRF	0.373*** (16.89)	0.374*** (17.04)	0.383*** (19.84)	0.268*** (5.39)	0.275*** (5.73)	0.276*** (5.66)
SMB	0.00601 (0.25)	0.00443 (0.19)	0.0000331 (0.00)	-0.0177 (-0.56)	-0.0271 (-0.79)	-0.0276 (-0.81)
VMG	-0.128*** (-4.47)	-0.127*** (-4.39)	-0.122*** (-4.68)	-0.0687** (-2.09)	-0.0665** (-2.22)	-0.0658** (-2.18)
PMO		0.00845 (0.38)	0.00868 (0.41)		0.0503 (1.15)	0.0503 (1.15)
Bond			0.428*** (3.03)			0.0545 (0.46)
N	186	186	186	186	186	186
R-sq	0.907	0.907	0.915	0.699	0.705	0.706

Panel C: Difference						
		Equal weighted			Value weighted	
Alpha	0.151** (2.59)	0.133** (2.07)	0.184*** (2.81)	0.189*** (2.86)	0.170*** (2.61)	0.173** (2.58)
MKTRF	0.146*** (10.32)	0.150*** (11.22)	0.147*** (11.61)	0.198*** (13.35)	0.202*** (12.18)	0.201*** (11.91)
SMB	0.00968 (0.48)	0.00501 (0.25)	0.00644 (0.31)	0.0239 (0.90)	0.0187 (0.73)	0.0188 (0.74)
VMG	-0.0602*** (-2.70)	-0.0591*** (-2.66)	-0.0608*** (-2.62)	-0.0711** (-2.33)	-0.0699** (-2.30)	-0.0700** (-2.28)
PMO		0.0250* (1.85)	0.0249* (1.82)		0.0277 (1.26)	0.0277 (1.25)
Bond			-0.139*** (-3.60)			-0.00969 (-0.14)
N	186	186	186	186	186	186
R-sq	0.807	0.812	0.817	0.810	0.814	0.814

Table 11A: Performance of Countercyclical Policy Funds (Rolling based)

This table uses a rolling-based method to label CP funds. For each period, we require funds to have at least one-third of the potential periods with valid semi-annual or annual reports. The potential period is defined as the maximum possible semi-annual periods spanning from 2008 to the present. For example, in the 2013 semi-annual report period, the total potential periods amount to $5 \times 2 + 1 = 11$, meaning we require funds to have at least $11 // 3 = 3$ valid reports. We continue to define CP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 20%, while non-CP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 20%.

Panel A: CP Funds						
	Equal weighted			Value weighted		
Alpha	0.462*** (3.18)	0.434*** (2.86)	0.332** (2.13)	0.369** (2.60)	0.313** (2.55)	0.289** (2.18)
MKTRF	0.502*** (20.88)	0.508*** (24.33)	0.514*** (23.49)	0.483*** (10.62)	0.494*** (11.35)	0.495*** (11.26)
Smb	0.0116 (0.30)	0.00437 (0.12)	0.00150 (0.04)	0.0109 (0.25)	-0.00378 (-0.10)	-0.00444 (-0.11)
Vmg	-0.162*** (-3.63)	-0.161*** (-3.53)	-0.157*** (-3.58)	-0.131** (-2.59)	-0.128*** (-2.64)	-0.127*** (-2.63)
Pmo		0.0389 (1.20)	0.0390 (1.22)		0.0788 (1.54)	0.0788 (1.53)
Bond			0.279* (1.93)			0.0638 (0.43)
N	186	186	186	186	186	186
R-sq	0.911	0.913	0.914	0.838	0.843	0.843
Panel B: Non-CP Funds						
	Equal weighted			Value weighted		
Alpha	0.331** (2.11)	0.344** (2.29)	0.101 (0.62)	0.149 (1.65)	0.126 (1.35)	0.0419 (0.44)
MKTRF	0.408*** (8.69)	0.405*** (8.14)	0.419*** (9.79)	0.264*** (8.91)	0.268*** (10.28)	0.273*** (10.17)
SMB	0.0246 (0.53)	0.0281 (0.61)	0.0213 (0.47)	-0.0226 (-0.89)	-0.0286 (-1.18)	-0.0310 (-1.29)
VMG	-0.151*** (-3.39)	-0.152*** (-3.48)	-0.144*** (-3.60)	-0.0896** (-2.48)	-0.0882** (-2.51)	-0.0854** (-2.50)
PMO		-0.0187 (-0.50)	-0.0183 (-0.52)		0.0323 (1.20)	0.0324 (1.25)
Bond			0.661*** (2.92)			0.230** (2.06)
N	186	186	186	186	186	186
R-sq	0.853	0.853	0.868	0.829	0.832	0.836

Panel C: Difference						
		Equal weighted			Value weighted	
Alpha	0.132 (1.15)	0.0905 (0.98)	0.231** (2.01)	0.219** (2.02)	0.186** (2.02)	0.247** (2.39)
MKTRF	0.0946* (1.77)	0.103* (1.90)	0.0945* (1.88)	0.219*** (6.64)	0.226*** (6.65)	0.222*** (6.65)
SMB	-0.0130 (-0.36)	-0.0237 (-0.63)	-0.0198 (-0.52)	0.0336 (1.06)	0.0249 (0.86)	0.0266 (0.93)
VMG	-0.0111 (-0.40)	-0.00848 (-0.33)	-0.0131 (-0.50)	-0.0417 (-1.17)	-0.0396 (-1.14)	-0.0416 (-1.18)
PMO		0.0575 (1.62)	0.0573* (1.65)		0.0465 (1.17)	0.0464 (1.18)
Bond			-0.382** (-2.55)			-0.166 (-1.39)
N	186	186	186	186	186	186
R-sq	0.233	0.255	0.285	0.645	0.652	0.654

Table 12A: Performance of Countercyclical Policy Funds (Ignore “Not mentioned” in CP Construction)

This table uses an alternative method to construct CP beliefs. Rather than converting 'Not mentioned' to 0, we leave it unchanged in this specification. We continue to define CP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 20%, while non-CP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 20%.

Panel A: CP Funds						
		Equal weighted			Value weighted	
Alpha	0.462*** (3.18)	0.434*** (2.86)	0.332** (2.13)	0.369** (2.60)	0.313** (2.55)	0.289** (2.18)
MKTRF	0.502*** (20.88)	0.508*** (24.33)	0.514*** (23.49)	0.483*** (10.62)	0.494*** (11.35)	0.495*** (11.26)
Smb	0.0116 (0.30)	0.00437 (0.12)	0.00150 (0.04)	0.0109 (0.25)	-0.00378 (-0.10)	-0.00444 (-0.11)
Vmg	-0.162*** (-3.63)	-0.161*** (-3.53)	-0.157*** (-3.58)	-0.131** (-2.59)	-0.128*** (-2.64)	-0.127*** (-2.63)
Pmo		0.0389 (1.20)	0.0390 (1.22)		0.0788 (1.54)	0.0788 (1.53)
Bond			0.279* (1.93)			0.0638 (0.43)
N	186	186	186	186	186	186
R-sq	0.911	0.913	0.914	0.838	0.843	0.843
Panel B: Non-CP Funds						
		Equal weighted			Value weighted	
Alpha	0.331** (2.11)	0.344** (2.29)	0.101 (0.62)	0.149 (1.65)	0.126 (1.35)	0.0419 (0.44)
MKTRF	0.408*** (8.69)	0.405*** (8.14)	0.419*** (9.79)	0.264*** (8.91)	0.268*** (10.28)	0.273*** (10.17)
SMB	0.0246 (0.53)	0.0281 (0.61)	0.0213 (0.47)	-0.0226 (-0.89)	-0.0286 (-1.18)	-0.0310 (-1.29)
VMG	-0.151*** (-3.39)	-0.152*** (-3.48)	-0.144*** (-3.60)	-0.0896** (-2.48)	-0.0882** (-2.51)	-0.0854** (-2.50)
PMO		-0.0187 (-0.50)	-0.0183 (-0.52)		0.0323 (1.20)	0.0324 (1.25)
Bond			0.661*** (2.92)			0.230** (2.06)
N	186	186	186	186	186	186
R-sq	0.853	0.853	0.868	0.829	0.832	0.836

Panel C: Difference						
		Equal weighted			Value weighted	
Alpha	0.132 (1.15)	0.0905 (0.98)	0.231** (2.01)	0.219** (2.02)	0.186** (2.02)	0.247** (2.39)
MKTRF	0.0946* (1.77)	0.103* (1.90)	0.0945* (1.88)	0.219*** (6.64)	0.226*** (6.65)	0.222*** (6.65)
SMB	-0.0130 (-0.36)	-0.0237 (-0.63)	-0.0198 (-0.52)	0.0336 (1.06)	0.0249 (0.86)	0.0266 (0.93)
VMG	-0.0111 (-0.40)	-0.00848 (-0.33)	-0.0131 (-0.50)	-0.0417 (-1.17)	-0.0396 (-1.14)	-0.0416 (-1.18)
PMO		0.0575 (1.62)	0.0573* (1.65)		0.0465 (1.17)	0.0464 (1.18)
Bond			-0.382** (-2.55)			-0.166 (-1.39)
N	186	186	186	186	186	186
R-sq	0.233	0.255	0.285	0.645	0.652	0.654

Table 13A: Performance of Countercyclical Policy Funds (Policy Expectation Larger than 0 in CP Construction)

This table uses an alternative method to construct CP beliefs. In this specification, we require policy expectations to be strictly greater than 0 when the macroeconomic fundamental review is negative and strictly less than 0 when the macroeconomic fundamental review is positive. We continue to define CP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 20%, while non-CP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 20%.

Panel A: CP Funds						
		Equal weighted			Value weighted	
Alpha	0.448*** (3.19)	0.423*** (2.88)	0.311** (2.07)	0.355*** (2.61)	0.300** (2.57)	0.275** (2.21)
MKTRF	0.487*** (22.68)	0.492*** (26.33)	0.498*** (25.59)	0.454*** (10.04)	0.465*** (10.50)	0.467*** (10.52)
Smb	0.0123 (0.33)	0.00581 (0.16)	0.00267 (0.08)	0.0257 (0.60)	0.0113 (0.29)	0.0106 (0.27)
Vmg	-0.165*** (-3.86)	-0.164*** (-3.76)	-0.160*** (-3.83)	-0.141*** (-2.85)	-0.137*** (-2.94)	-0.136*** (-2.93)
Pmo		0.0349 (1.15)	0.0351 (1.18)		0.0767 (1.46)	0.0768 (1.46)
Bond			0.305** (2.18)			0.0681 (0.49)
N	186	186	186	186	186	186
R-sq	0.914	0.915	0.917	0.824	0.830	0.830
Panel B: Non-CP Funds						
		Equal weighted			Value weighted	
Alpha	0.351*** (2.82)	0.357*** (2.94)	0.169 (1.37)	0.145 (1.50)	0.116 (1.29)	0.0878 (0.91)
MKTRF	0.412*** (14.93)	0.411*** (13.97)	0.422*** (16.46)	0.286*** (6.55)	0.291*** (7.07)	0.293*** (6.99)
SMB	0.0320 (0.83)	0.0336 (0.89)	0.0283 (0.78)	-0.00992 (-0.39)	-0.0174 (-0.68)	-0.0182 (-0.71)
VMG	-0.130*** (-3.13)	-0.130*** (-3.17)	-0.124*** (-3.29)	-0.0669** (-1.98)	-0.0651** (-2.00)	-0.0642** (-1.99)
PMO		-0.00874 (-0.28)	-0.00847 (-0.29)		0.0400 (1.15)	0.0401 (1.16)
Bond			0.512*** (3.67)			0.0771 (0.78)
N	186	186	186	186	186	186
R-sq	0.906	0.906	0.915	0.771	0.775	0.775

Panel C: Difference						
		Equal weighted			Value weighted	
Alpha	0.0973 (1.23)	0.0660 (0.99)	0.142** (2.00)	0.210*** (2.77)	0.184*** (2.76)	0.187*** (2.65)
MKTRF	0.0748** (2.44)	0.0810*** (2.62)	0.0765** (2.59)	0.169*** (8.36)	0.174*** (7.87)	0.174*** (7.70)
SMB	-0.0196 (-0.83)	-0.0278 (-1.12)	-0.0257 (-1.03)	0.0356 (1.36)	0.0287 (1.34)	0.0288 (1.33)
VMG	-0.0356** (-2.09)	-0.0336** (-2.09)	-0.0361** (-2.19)	-0.0738** (-2.49)	-0.0722** (-2.53)	-0.0723** (-2.51)
PMO		0.0437* (1.83)	0.0436* (1.85)		0.0367 (1.24)	0.0367 (1.23)
Bond			-0.207*** (-3.12)			-0.00896 (-0.09)
N	186	186	186	186	186	186
R-sq	0.334	0.359	0.377	0.654	0.661	0.661

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.