Structured Beliefs and Fund Investment*

Zhenyu Gao, Wei Xiong, and Jian Yuan**

March 2025

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 (CCP) beliefs measure, capturing each fund's expectations about policies offsetting economic shocks. Managers' market beliefs positively predict market returns, while CCP beliefs enhance this predictive power, improving fund performance. Our study highlights the role of structured beliefs in shaping investment decisions and market outcomes.

* We are grateful to Nick Barberis, John Campbell, Bing Han, Zhen Huo, Wenxi Jiang, Stefan Nagel, Baolian Wang, Liyan Yang, and seminar participants at ABFER, CUHK, and University of Florida for helpful comments and suggestions.

** Zhenyu Gao: The Chinese University of Hong Kong; Wei Xiong: Princeton University and NBER; Jian Yuan: The Chinese University of Hong Kong.

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 (CCP) 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 CCP 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 CCP beliefs, the predictive power of their trading on future market returns becomes even stronger, further underscoring the role of CCP beliefs in enhancing fund performance.

We find compelling evidence that funds exhibiting CCP 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 CCP 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 CCP 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 CCP funds—those that frequently engage more deeply with countercyclical policy analysis. Our analysis reveals that CCP 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). 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. These eight topics analyzed encompass key aspects of economic and financial landscapes. We set the GPT model's temperature to 0 to minimize creativity and obtain the highest probability results, enhancing reproducibility. The output consistency rate exceeds 90% when running the model a thousand times for the same report.

While there may be concerns about 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.

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 x {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:

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

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

where:

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

We apply the CH3 and CH4 models to estimate 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

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

the 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, 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 (CCP) beliefs. We then define a subset of funds as CCP funds, characterized by a higher frequency of CCP 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 area:

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.[7]

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:

- *CCPn_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* $\geqslant$ 0) to support the economy.
- *CCPp_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* $\leqslant$ 0).
- *CCP_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 *CCPn_X* or *CCPp_X* equals 1.

We then consolidate *CCP_X* indicators across all policy dimensions into a general

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

countercyclical policy expectation measure:

- *CCP_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 policy beliefs.

Panel A of Table 2 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:

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

  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:

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

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:

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

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 2 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 CCP beliefs related to mutual fund characteristics? We separately examine CCPn (reflecting pessimistic macroeconomic views and expectations of easing policies) and CCPp (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, CCPn 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, CCPp 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 CCPp and CCPn, suggesting that funds experiencing outflows are more inclined to hold countercyclical policy expectations. Lastly, age of funds (*age*) exhibits a positive association across all CCP 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, CCPn 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, CCPp 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 CCPn is positively correlated with both equity and bond market volatilities, while CCPp 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" (CCP 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 2 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 "CCP_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 CCP 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 CCP 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 CCP 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 CCP 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 CCP funds, at 0.0124 compared to 0.0086 for other funds, but this difference is not statistically significant. Overall, these results suggest that CCP 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 (CCP) beliefs. By assessing the interaction between market expectations and CCP 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 (CCP) beliefs, we introduce interaction terms between market expectations and CCP beliefs:

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

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

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

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

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

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 CCP fund and hold CCP beliefs. Since the countercyclical policy label is time-invariant at the fund level, it is absorbed by fund fixed effects.

Table 3 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 CCP beliefs to assess whether funds' market expectations predict index returns more effectively when managers hold CCP 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 CCP beliefs is not significant, suggesting that CCP beliefs do not enhance bond market predictions.

Columns (5) and (6) introduce the triple interaction involving CCP beliefs, the CCP fund dummy, and market expectations. The coefficient for the triple interaction is significantly positive in column (5), confirming that CCP funds holding CCP 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 CCP funds when they hold CCP beliefs. This suggests a potential mechanism behind the outperformance of CCP 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:

$$equity_ratio_{i,t} = \alpha_i + \beta_t + \gamma expect_equity_market_{i,t} + \delta X_{i,t} + \varepsilon_{i,t,}$$

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

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 (CCP) beliefs influence how market expectations translate into asset allocation decisions, we introduce interaction terms involving CCP beliefs and CCP 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 CCP 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 CCP beliefs, as well as the triple interactions involving market expectations, CCP beliefs, and CCP fund status, are statistically insignificant. This suggests that fund managers' asset allocation decisions are primarily driven by their market expectations, rather than their CCP beliefs. Therefore, if CCP 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 CCP 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 CCP beliefs and CCP fund status by incorporating interaction terms,

as outlined in previous subsections.

Table 4 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 CCP 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 CCP funds when they exhibit CCP 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 CCP funds that anticipate countercyclical policies.

These findings provide strong evidence that CCP 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. CCP 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' CCP beliefs on fund performance.

A. Fund Performance

We begin by exploring the relationship between fund managers' CCP beliefs and fund performance. Given that fund managers who hold CCP beliefs—particularly those in CCP 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:

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

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, $\text{CCP_belief}_{i,t}$ is a dummy variable indicating whether fund *i* holds CCP 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 5. 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 alpha_ch3 and alpha_ch4, respectively. All return metrics, whether raw or risk adjusted, are presented as percentages.

The coefficients for the CCP belief variable are all statistically significant, indicating a robust relationship between CCP 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 CCP 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:

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

where the key independent variable CCP_fund_i, is a dummy indicating whether a fund is classified as a CCP 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 *CCP_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 CCP 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 CCP funds outperform other funds to a greater extent than the outperformance observed among funds that hold CCP 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 CCP beliefs and CCP funds to examine their outperformance. First, we sort funds by their managers' CCP beliefs and create three semi-annual portfolios: one containing funds with CCP 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 6 present the results for the CCP belief portfolio, the non-CCP belief portfolio, and the long-short portfolio, respectively.

Panel A of Table 6 shows that funds holding CCP beliefs generate significant CH3 and CH4 alphas across both equal-weighted and value-weighted portfolios. Panel B indicates that funds without CCP beliefs exhibit smaller alphas. Panel C highlights the strong outperformance of funds with CCP 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 CCP and non-CCP funds, defining CCP funds as those in the top quintile of countercyclical policy expectations and non-CCP funds as those in the bottom quintile. We construct three portfolios: one for all CCP funds, one for all non-CCP funds, and a long-short portfolio that goes long on CCP funds and short on non-CCP 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 7 report the results for the CCP fund portfolio, the non-CCP fund portfolio, and the long-short portfolio, respectively.

Panel A of Table 7 confirms that CCP funds generate strong CH3 and CH4 alphas for both equal-weighted and value-weighted portfolios. Panel B shows that non-CCP funds also have significant, though smaller, alphas in equal-weighted portfolios, while their value-weighted alphas are statistically insignificant. Panel C demonstrates that CCP funds significantly outperform non-CCP funds. The CH3-factor alphas of CCP funds exceed those of non-CCP funds by 0.264% (equal-weighted) and 0.318% (value-weighted) per month. For the CH4-factor model, CCP 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 CCP 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 CCP 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 CCP beliefs in driving fund returns, we examine the direct link between time-varying CCP beliefs and fund performance, conditional on the fund being classified as a CCP fund.

Table 8 presents regression results analyzing the relationship between time-varying CCP 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 CCP funds. This suggests that the superior performance of CCP 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 CCP 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 CCP beliefs, conditional on the fund being a CCP fund, using the following regression models:

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

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

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 9 presents the results linking CCP beliefs—including expectations of countercyclical fiscal, monetary, and regulatory policies, as well as the overall CCP measure—to investor skills in market timing and stock selection. Columns (1) through (4) show that fiscal, monetary, regulatory, and overall CCP beliefs significantly enhance market timing abilities for CCP 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 CCP 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' CCP 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 CCP funds' ability to anticipate and capitalize on policy-driven macroeconomic trends, which in turn contributes to their superior performance.

V. Robustness

In this section, we conduct a series of robustness tests by employing alternative methods to measure CCP beliefs and identify CCP funds, followed by re-examining the superior performance of CCP 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 CCP funds as those in the top 30% or top 50% of the most frequent CCP beliefs for robustness checks. We then construct three portfolios: one for all CCP funds, another for all non-CCP funds (those in the bottom 30% or bottom 50%), and a long-short portfolio that goes long on CCP funds and short on non-CCP 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 CCP fund classification, CCP 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 CCP 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 CCP funds as those in the top 20% of countercyclical policy beliefs across periods and non-CCP funds as those in the bottom 20%. Table 11A of the Internet Appendix demonstrates that CCP 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 CCP 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 CCP 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 CCP 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 CCP definitions consistently confirm that CCP funds outperform non-CCP 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 (CCP) in reaction to economic shocks.

Our analysis shows that mutual funds that frequently express CCP 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.

References

Abis, S. (2020). Man vs. machine: Quantitative and discretionary equity management. *Machine: Quantitative and Discretionary Equity Management (October 23, 2020)*.

Berk, J. B., & Van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics*, *118*(1), 1-20.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "Latent dirichlet allocation." *Journal of Machine Learning Research* 3, no. Jan (2003): 993-1022.

Bond, Philip, and Itay Goldstein. "Government intervention and information aggregation by prices." *The Journal of Finance* 70, no. 6 (2015): 2777-2812.

Brunnermeier, Markus K., Michael Sockin, and Wei Xiong. "China's model of managing the financial system." *The Review of Economic Studies* 89, no. 6 (2022): 3115-3153.

Bybee, Leland. "Surveying Generative AI's Economic Expectations." Working paper (2023).

Bybee, Leland, Bryan T. Kelly, Asaf Manela, and Dacheng Xiu. The structure of economic news. No. w26648. National Bureau of Economic Research, 2020.

Coibion, Olivier, and Yuriy Gorodnichenko. "Information rigidity and the expectations formation process: A simple framework and new facts." *American Economic Review* 105, no. 8 (2015): 2644-2678.

Dahlquist, Magnus, and Markus Ibert. "Equity return expectations and portfolios: Evidence from large asset managers." *Review of Financial Studies* 37, no. 6 (2024): 1887-1928.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, *52*(3), 1035-1058.

DeMiguel, V., Gil-Bazo, J., Nogales, F. J., & Santos, A. A. (2023). Machine learning and fund characteristics help to select mutual funds with positive alpha. *Journal of Financial Economics*, *150*(3), 103737.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy. "Text as data." *Journal of Economic Literature* 57, no. 3 (2019): 535-574.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus. "Five facts about beliefs and portfolios." *American Economic Review* 111, no. 5 (2021): 1481-1522.

Glasserman, Paul, and Caden Lin. "Assessing look-ahead bias in stock return predictions generated by gpt sentiment analysis." arXiv preprint arXiv:2309.17322 (2023).

Greenwood, Robin, and Andrei Shleifer. "Expectations of returns and expected returns." *The Review of Financial Studies* 27, no. 3 (2014): 714-746.

Grinblatt, M., & Titman, S. (1993). Performance measurement without benchmarks: An examination of mutual fund returns. *Journal of Business*, 47-68.

Jha, Manish, Jialin Qian, Michael Weber, and Baozhong Yang. ChatGPT and corporate policies. No. w32161. National Bureau of Economic Research, 2024.

Jiang, G. J., Yao, T., & Yu, T. (2007). Do mutual funds time the market? Evidence from

portfolio holdings. *Journal of Financial Economics*, *86*(3), 724-758.

Jiang, H., & Zheng, L. (2018). Active fundamental performance. *The Review of Financial Studies*, *31*(12), 4688-4719.

Jiang, Wenxi. "Investment funds in China." See Amstad, Sun & Xiong 2020 (2020): 359-82.

Kacperczyk, M., & Seru, A. (2007). Fund manager use of public information: New evidence on managerial skills. *The Journal of Finance*, *62*(2), 485-528.

Kacperczyk, M., Nieuwerburgh, S. V., & Veldkamp, L. (2014). Time-varying fund manager skill. *The Journal of Finance*, *69*(4), 1455-1484.

Kaminsky, Graciela, Carmen Reinhart, and Carlos Végh. "When it rains, it pours: Procyclical macropolicies and capital flows." NBER Macroeconomics Annual 2004 (2004): 11-53.

Kaniel, R., Lin, Z., Pelger, M., & Van Nieuwerburgh, S. (2023). Machine-learning the skill of mutual fund managers. *Journal of Financial Economics*, *150*(1), 94-138.

Li, B., & Rossi, A. G. (2020). Selecting mutual funds from the stocks they hold: A machine learning approach. *Available at SSRN 3737667*.

Liu, Jianan, Robert F. Stambaugh, and Yu Yuan. "Size and value in China." *Journal of Financial Economics* 134, no. 1 (2019): 48-69.

Loughran, Tim, and Bill McDonald. "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks." *The Journal of Finance* 66, no. 1 (2011): 35-65.

Nagel, Stefan, and Zhengyang Xu. "Asset pricing with fading memory." *The Review of Financial Studies* 35, no. 5 (2022): 2190-2245.

Nakamura, Emi, and Jón Steinsson. "High-frequency identification of monetary non-neutrality: the information effect." *The Quarterly Journal of Economics* 133, no. 3 (2018): 1283-1330.

Pastor, Lubos, and Pietro Veronesi. "Uncertainty about government policy and stock prices." *The journal of Finance* 67, no. 4 (2012): 1219-1264.

Sarkar, Suproteem K., and Keyon Vafa. "Lookahead bias in pretrained language models." Available at SSRN (2024).

Shiller, Robert J. "Measuring bubble expectations and investor confidence." *The Journal of Psychology and Financial Markets* 1, no. 1 (2000): 49-60.

Tetlock, Paul C. "Giving content to investor sentiment: The role of media in the stock market." *The Journal of Finance* 62, no. 3 (2007): 1139-1168.

Zhang, Zhongxia. “Stock returns and inflation redux: an explanation from monetary policy in advanced and emerging markets.” International Monetary Fund, 2021.

Tables

Table 1: Summary Statistics

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

	Mean	Sd	Min	P25	Med	P75	Max
Review:							
fiscal_policy	0.155	0.401	-1	0	0	0	1
monetary_policy	0.383	0.527	-1	0	0	1	1
regulatory_policy	0.012	0.43	-1	0	0	0	1
national_macroeconomy	0.012	0.593	-1	-0.5	0	0.5	1
equity_market	0.087	0.666	-1	-0.5	0	0.5	1
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_macroeconomy	0.187	0.584	-1	-0.5	0.5	0.5	1
equity_market	0.38	0.492	-1	0	0.5	1	1
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: 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 CCP fund.

Panel A: Countercyclical Policy Expect Summary

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

Panel B: Variation Decomposition

	(1) Fund FE	(2) Time FE	(3) Fund+Time FE
CCP_fiscal	0.087	0.103	0.182
CCP_monetary	0.087	0.094	0.175
CCP_regulatory	0.088	0.085	0.167
CCP_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_CCP_belief	0.202	0.123	0	0.091	0.167	0.226	0.300	0.8

Table 3: 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***		0.132***		0.117***	
	(6.62)		(4.02)		(3.16)	
expect_bond_market		0.00436		0.00514		0.000181
		(1.05)		(1.09)		(0.04)
expect_equity_market			0.300***		0.119	
X CCP_belief			(4.74)		(1.55)	
expect_bond_market				-0.00211		-0.0111
X CCP_belief				(-0.23)		(-1.04)
CCP_belief			-0.762***	0.00758**	-0.686***	0.00204
			(-19.38)	(2.02)	(-15.16)	(0.45)
expect_equity_market					0.0430	
X CCP_fund					(0.55)	
expect_bond_market						0.0327**
X CCP_fund						(2.14)
CCP_belief X CCP_fund					-0.211**	0.0182**
					(-2.33)	(2.28)
expect_equity_market					0.435***	
X CCP_belief X CCP_fund					(3.11)	
expect_bond_market						0.0173
X CCP_belief X CCP_fund						(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 4: 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
Δequity_ratio	0.00659***		0.00695***		0.00813***	
	(3.76)		(3.52)		(3.64)	
Δbond_ratio		0.00148***		0.00155***		0.00147***
		(7.83)		(7.10)		(6.26)
Δequity_ratio			-0.00135		-0.00644	
X CCP_belief			(-0.36)		(-1.37)	
Δbond_ratio				-0.000298		-0.00146***
X CCP_belief				(-0.66)		(-2.77)
CCP_belief			-0.641***	0.00750**	-0.638***	0.00132
			(-21.96)	(2.10)	(-18.27)	(0.31)
Δequity_ratio					-0.00529	
X CCP_fund					(-1.13)	
Δbond_ratio						0.000503
X CCP_fund						(0.81)
CCP_belief X CCP_fund					-0.0102	0.0197***
					(-0.16)	(2.59)
Δequity_ratio					0.0144*	
X CCP_belief X CCP_fund					(1.79)	
Δbond_ratio						0.00309***
X CCP_belief X CCP_fund						(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 5: CCP Belief, CCP 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 CCP belief. In Panel B, the key explanatory variable is the CCP 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: CCP Belief and Fund Performance						
Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)
		Ret		alpha_ch3		alpha_ch4
CCP_belief	0.0653***	0.0655***	0.0543***	0.0544***	0.0319***	0.0320***
	(4.62)	(4.63)	(4.60)	(4.61)	(2.82)	(2.83)
log_tna		-0.120***		-0.0732***		-0.0642***
		(-18.08)		(-14.65)		(-13.46)
flow		0.0344***		0.0431***		0.0503***
		(4.82)		(8.56)		(10.10)
age		0.00677***		0.00250		0.000798
		(2.60)		(1.20)		(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: CCP Fund and Fund Performance						
Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)
		Ret		alpha_ch3		alpha_ch4
CCP_fund	0.0830***	0.0691***	0.0674***	0.0644***	0.0708***	0.0687***
	(6.41)	(5.09)	(4.56)	(4.21)	(5.00)	(4.70)
log_tna		-0.0369***		-0.0130***		-0.00804***
		(-11.43)		(-4.21)		(-2.66)
flow		0.00506		0.0239***		0.0320***
		(0.73)		(4.75)		(6.38)
age		0.000619***		0.000151		0.000142
		(4.95)		(1.04)		(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 6: Performance of Funds with Countercyclical Policy Beliefs

Panels A and B report alpha and factor loadings of returns for funds making CCP beliefs and funds not making CCP 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 CCP beliefs and shorts funds that do not exhibit CCP 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: CCP Belief						
	Equal weighted			Value weighted		
Alpha	0.573***	0.528***	0.496***	0.430***	0.354***	0.404***
	(3.58)	(3.19)	(2.66)	(2.79)	(2.83)	(2.64)
MKTRF	0.503***	0.512***	0.514***	0.451***	0.466***	0.463***
	(12.08)	(14.44)	(13.66)	(7.32)	(8.27)	(8.07)
Smb	-0.0228	-0.0347	-0.0356	-0.0269	-0.0469	-0.0455
	(-0.64)	(-0.97)	(-1.01)	(-0.59)	(-1.02)	(-1.01)
Vmg	-0.201***	-0.198***	-0.197***	-0.145***	-0.140***	-0.142***
	(-5.14)	(-4.84)	(-4.80)	(-3.21)	(-3.27)	(-3.20)
Pmo		0.0638	0.0638		0.107*	0.107*
		(1.62)	(1.62)		(1.89)	(1.88)
Bond			0.0859			-0.136
			(0.46)			(-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-CCP Belief						
	Equal weighted			Value weighted		
Alpha	0.366***	0.363***	0.212	0.204*	0.171*	0.148
	(2.85)	(2.78)	(1.61)	(1.86)	(1.70)	(1.45)
MKTRF	0.439***	0.439***	0.448***	0.356***	0.362***	0.364***
	(19.86)	(19.26)	(23.43)	(8.39)	(9.01)	(8.98)
SMB	0.0392	0.0385	0.0343	0.0252	0.0167	0.0161
	(1.01)	(1.02)	(0.93)	(0.87)	(0.58)	(0.55)
VMG	-0.140***	-0.140***	-0.135***	-0.0883**	-0.0863**	-0.0855**
	(-3.23)	(-3.21)	(-3.29)	(-2.22)	(-2.21)	(-2.20)
PMO		0.00394	0.00416		0.0452	0.0452
		(0.14)	(0.15)		(1.05)	(1.05)
Bond			0.412***			0.0628
			(2.63)			(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**	0.164**	0.284***	0.227***	0.183***	0.255***
	(2.36)	(2.14)	(2.81)	(2.81)	(2.68)	(2.71)
MKTRF	0.0644	0.0729*	0.0659*	0.0949***	0.104***	0.0993***
	(1.58)	(1.94)	(1.82)	(3.36)	(4.16)	(4.01)
SMB	-0.0620*	-0.0732**	-0.0698**	-0.0521**	-0.0636**	-0.0616**
	(-1.93)	(-2.15)	(-2.09)	(-1.99)	(-2.42)	(-2.40)
VMG	-0.0601**	-0.0574**	-0.0614***	-0.0566***	-0.0538***	-0.0562***
	(-2.59)	(-2.46)	(-2.68)	(-3.03)	(-2.92)	(-2.98)
PMO		0.0598**	0.0596**		0.0616***	0.0615***
		(2.04)	(2.07)		(2.75)	(2.81)
Bond			-0.326***			-0.198*
			(-2.90)			(-1.74)
N	186	186	186	186	186	186
R-sq	0.249	0.289	0.324	0.410	0.448	0.460

Table 7: Performance of Countercyclical Policy Funds

Panels A and B report alpha and factor loadings of returns for CCP funds (proportion of periods characterized by countercyclical policy beliefs falls within the top 20%) and Non-CCP 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 CCP funds and shorts non-CCP 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: CCP Funds						
	Equal weighted			Value weighted		
Alpha	0.526***	0.494***	0.404**	0.434***	0.366**	0.349**
	(3.01)	(2.64)	(2.10)	(2.79)	(2.37)	(2.19)
MKTRF	0.576***	0.583***	0.588***	0.555***	0.568***	0.569***
	(23.24)	(26.80)	(27.50)	(15.80)	(18.94)	(18.72)
Smb	0.00782	-0.000684	-0.00318	-0.0106	-0.0284	-0.0289
	(0.16)	(-0.01)	(-0.07)	(-0.21)	(-0.60)	(-0.61)
Vmg	-0.203***	-0.200***	-0.198***	-0.177***	-0.172***	-0.172***
	(-3.61)	(-3.53)	(-3.55)	(-2.85)	(-2.87)	(-2.85)
Pmo		0.0455	0.0456		0.0954**	0.0955**
		(1.29)	(1.31)		(2.20)	(2.19)
Bond			0.243			0.0461
			(1.31)			(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-CCP Funds						
	Equal weighted			Value weighted		
Alpha	0.263**	0.290***	0.0465	0.116	0.104	0.0190
	(2.40)	(2.98)	(0.47)	(1.47)	(1.37)	(0.23)
MKTRF	0.371***	0.365***	0.380***	0.234***	0.236***	0.241***
	(8.49)	(8.01)	(9.49)	(6.61)	(7.32)	(7.25)
SMB	0.0390	0.0461	0.0393	-0.0183	-0.0216	-0.0240
	(1.03)	(1.24)	(1.06)	(-1.06)	(-1.34)	(-1.43)
VMG	-0.0787**	-0.0804**	-0.0724**	-0.0433	-0.0425	-0.0398
	(-2.21)	(-2.32)	(-2.35)	(-1.39)	(-1.40)	(-1.34)
PMO		-0.0377	-0.0374		0.0178	0.0179
		(-1.09)	(-1.15)		(0.58)	(0.60)
Bond			0.662***			0.230**
			(3.65)			(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**	0.204	0.358***	0.318**	0.262**	0.330**
	(2.12)	(1.58)	(2.66)	(2.54)	(2.05)	(2.49)
MKTRF	0.205***	0.217***	0.208***	0.321***	0.332***	0.328***
	(4.30)	(4.77)	(4.80)	(13.00)	(14.79)	(14.32)
SMB	-0.0312	-0.0468	-0.0425	0.00769	-0.00682	-0.00493
	(-0.87)	(-1.36)	(-1.17)	(0.19)	(-0.19)	(-0.13)
VMG	-0.124***	-0.120***	-0.125***	-0.133***	-0.130***	-0.132***
	(-3.68)	(-3.60)	(-3.48)	(-2.89)	(-2.81)	(-2.76)
PMO		0.0832**	0.0830***		0.0776**	0.0775**
		(2.58)	(2.62)		(2.39)	(2.41)
Bond			-0.419***			-0.184
			(-4.14)			(-1.38)
N	186	186	186	186	186	186
R-sq	0.603	0.623	0.639	0.789	0.799	0.801

Table 8: CCP Beliefs and Performance of CCP Funds

This table reports results for CCP fund performance conditional on whether they possess CCP beliefs. The dependent variable is raw return (the first column), the alpha of the Chinese three-factor model (the second column), 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)	(2)	(3)
	ret_m	alpha_ch3	alpha_ch4
CCP_belief	0.0589**	0.0590**	0.0407*
	(2.39)	(2.51)	(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 9: Countercyclical Policy Funds Skills

This table reports results for CCP fund skills conditional on whether they possess CCP 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
CCP_fiscal	0.00262**			
	(2.47)			
CCP_monetary		0.00208**		
		(2.05)		
CCP_regulatory			0.00209**	
			(2.04)	
CCP_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
CCP_fiscal	0.00253*			
	(1.70)			
CCP_monetary		0.00180		
		(1.20)		
CCP_regulatory			0.00239*	
			(1.68)	
CCP_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

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_macroeconomic	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**	0.00176***	0.00199***	0.00286***	0.147***	0.000357**
	(2.07)	(9.54)	(12.83)	(13.95)	(56.98)	(2.24)
log_tna	0.000888	0.0406***	-0.00178*	-0.00360***	-0.0190***	0.0419***
	(0.80)	(22.59)	(-1.72)	(-2.81)	(-15.43)	(23.48)
flow	0.000627	0.00788***	0.000146	-0.00214	0.00309	0.0151***
	(0.40)	(4.09)	(0.09)	(-1.11)	(1.59)	(7.40)
age	0.0000399	-0.00111***	0.0000814*	0.000186***	0.000349***	-0.00160***
	(0.72)	(-12.31)	(1.81)	(3.12)	(5.98)	(-18.67)
N	73361	73361	73361	73361	73361	73361
R-sq	0.108	0.195	0.043	0.307	0.409	0.190
Panel B: Expectations Extracted from Fund Reports						
	(1)	(2)	(3)	(4)	(5)	(6)
		Policy		**Macro**	**Market**	
	Fiscal	Monetary	regulatory	**Economy**	equity	bond
semi_ret	0.000300*	0.00000652	0.00148***	0.00161***	0.00302***	-0.00129***
	(1.66)	(0.04)	(9.01)	(8.28)	(16.65)	(-9.99)
log_tna	-0.00902***	0.00999***	-0.0118***	-0.0241***	-0.0503***	0.0267***
	(-6.49)	(8.10)	(-10.11)	(-15.87)	(-28.12)	(18.05)
flow	-0.00302*	0.00361**	-0.00385**	-0.00587***	-0.0124***	0.00995***
	(-1.67)	(2.08)	(-2.30)	(-2.94)	(-6.85)	(5.25)
age	0.000251***	-0.000455***	0.000375***	0.000952***	0.00135***	-0.00105***
	(3.85)	(-7.34)	(6.40)	(12.20)	(14.57)	(-14.95)
N	73361	73361	73361	73361	73361	73361
R-sq	0.097	0.161	0.021	0.216	0.100	0.059

Table 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 CCP into CCPn (when the review of macroeconomic fundamentals is negative) and CCPp (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	
	CCPn	CCPp	CCPn	CCPp	CCPn	CCPp
semi_ret	-0.00172***	0.00105***	-0.00174***	0.00143***	-0.00164***	0.00111***
	(-18.13)	(8.80)	(-18.55)	(12.36)	(-17.19)	(8.73)
log_tna	-0.00363***	-0.00104*	-0.00324***	-0.00246***	-0.00314***	-0.00182***
	(-6.67)	(-1.70)	(-6.02)	(-4.23)	(-5.85)	(-2.77)
flow	-0.00186**	-0.00140	-0.00181**	-0.00132	-0.00164*	-0.00209**
	(-2.05)	(-1.38)	(-2.01)	(-1.39)	(-1.80)	(-1.99)
age	0.0000936***	0.000131***	0.0000893***	0.000162***	0.0000994***	0.000178***
	(3.74)	(4.29)	(3.60)	(5.37)	(3.99)	(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 CCP into CCPn (when the review of macroeconomic fundamentals is negative) and CCPp (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: CCPn and CCPp Fiscal Policy								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CCPn_fiscal				**CCPp_fiscal**			
hs300_index	-0.264***				0.316***			
	(-36.02)				(50.65)			
bond_index		3.102***				-4.891***		
		(42.92)				(-59.01)		
hs300_semi_sd			6.707***				-11.20***	
			(27.57)				(-38.36)	
bond_semi_sd				34.11***				-57.99***
				(8.55)				(-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: CCPn and CCPp Monetary Policy								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CCPn_monetary				**CCPp_monetary**			
hs300_index	-0.250***				0.250***			
	(-34.27)				(43.41)			
bond_index		3.193***				-4.398***		
		(44.14)				(-54.59)		
hs300_semi_sd			6.565***				-11.42***	
			(27.48)				(-39.89)	
bond_semi_sd				38.02***				-40.11***
				(9.44)				(-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: CCPn and CCPp Regulatory Policy								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CCPn_regulatory				CCPp_regulatory			
hs300_index	-0.264***				0.348***			
	(-35.45)				(53.35)			
bond_index		3.123***				-4.454***		
		(42.84)				(-57.83)		
hs300_semi_sd			6.803***				-8.425***	
			(28.11)				(-30.21)	
bond_semi_sd				36.85***				-38.55***
				(9.09)				(-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 CCP 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	**CCP_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) stock_ratio	(2) bond_index	(3) stock_ratio	(4) bond_index	(5) stock_ratio	(6) bond_index
expect_equity_market	1.944***		2.006***		1.950***	
	(14.14)		(13.74)		(11.88)	
expect_bond_market		1.852***		1.927***		1.613***
		(10.38)		(10.57)		(8.59)
expect_equity_market X CCP_belief			-0.269		-0.525*	
			(-1.14)		(-1.84)	
expect_bond_market X CCP_belief				-0.390		-0.753*
				(-1.17)		(-1.95)
CCP_belief			-0.000187	-0.159	0.203	-0.199
			(-0.00)	(-1.32)	(1.36)	(-1.34)
expect_equity_market X CCP_fund					0.180	
					(0.46)	
expect_bond_market X CCP_fund						2.294***
						(3.69)
CCP_belief X CCP_fund					-0.583*	0.256
					(-1.90)	(1.01)
expect_equity_market X CCP_belief X CCP_fund					0.625	
					(1.24)	
expect_bond_market X CCP_belief X CCP_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 CCP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 30% (i.e., greater than the 70th percentile). Non-CCP 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: CCP Funds						
	Equal weighted			Value weighted		
Alpha	0.519***	0.489***	0.395**	0.403***	0.339**	0.316**
	(3.14)	(2.78)	(2.19)	(2.82)	(2.49)	(2.24)
MKTRF	0.555***	0.561***	0.567***	0.533***	0.546***	0.547***
	(24.14)	(28.12)	(28.49)	(14.38)	(16.29)	(16.12)
Smb	0.0156	0.00766	0.00503	0.00250	-0.0142	-0.0148
	(0.33)	(0.17)	(0.11)	(0.05)	(-0.33)	(-0.34)
Vmg	-0.198***	-0.196***	-0.193***	-0.162***	-0.158***	-0.157***
	(-3.64)	(-3.56)	(-3.59)	(-2.81)	(-2.84)	(-2.82)
Pmo		0.0423	0.0424		0.0893*	0.0894*
		(1.22)	(1.24)		(1.96)	(1.96)
Bond			0.256			0.0625
			(1.50)			(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-CCP Funds						
	Equal weighted			Value weighted		
Alpha	0.318***	0.326***	0.135	0.152	0.131	0.0762
	(3.05)	(3.24)	(1.35)	(1.58)	(1.53)	(0.83)
MKTRF	0.361***	0.360***	0.371***	0.260***	0.264***	0.267***
	(13.86)	(13.14)	(15.96)	(6.03)	(6.45)	(6.39)
SMB	0.0245	0.0264	0.0211	-0.0118	-0.0171	-0.0186
	(0.87)	(0.97)	(0.79)	(-0.51)	(-0.67)	(-0.72)
VMG	-0.114***	-0.115***	-0.108***	-0.0629**	-0.0616**	-0.0598**
	(-3.45)	(-3.49)	(-3.68)	(-2.05)	(-2.10)	(-2.05)
PMO		-0.0101	-0.00987		0.0281	0.0282
		(-0.40)	(-0.41)		(0.72)	(0.73)
Bond			0.520***			0.150
			(3.96)			(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**	0.163*	0.260***	0.252**	0.208**	0.240**
	(2.21)	(1.70)	(2.64)	(2.57)	(2.04)	(2.29)
MKTRF	0.194***	0.201***	0.195***	0.273***	0.282***	0.280***
	(6.99)	(7.74)	(7.87)	(14.00)	(14.54)	(14.04)
SMB	-0.00894	-0.0187	-0.0160	0.0143	0.00286	0.00377
	(-0.33)	(-0.73)	(-0.59)	(0.38)	(0.08)	(0.10)
VMG	-0.0837***	-0.0813***	-0.0845***	-0.0992**	-0.0965**	-0.0975**
	(-3.06)	(-3.04)	(-2.96)	(-2.41)	(-2.36)	(-2.33)
PMO		0.0524***	0.0523***		0.0612**	0.0611**
		(2.69)	(2.68)		(2.19)	(2.20)
Bond			-0.264***			-0.0880
			(-3.99)			(-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 CCP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 50% (i.e., greater than the 50th percentile). Non-CCP 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: CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.503***	0.479***	0.373**	0.356***	0.300**	0.284**
	(3.31)	(2.98)	(2.26)	(2.67)	(2.54)	(2.23)
MKTRF	0.519***	0.524***	0.530***	0.466***	0.477***	0.478***
	(24.41)	(27.49)	(28.36)	(10.27)	(11.16)	(11.05)
Smb	0.0157	0.00945	0.00648	0.00622	-0.00835	-0.00881
	(0.37)	(0.23)	(0.16)	(0.15)	(-0.22)	(-0.23)
Vmg	-0.188***	-0.186***	-0.183***	-0.140***	-0.136***	-0.136***
	(-3.80)	(-3.72)	(-3.77)	(-2.82)	(-2.86)	(-2.85)
Pmo		0.0334	0.0336		0.0780	0.0780
		(1.02)	(1.04)		(1.58)	(1.57)
Bond			0.289*			0.0448
			(1.82)			(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-CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.352***	0.346***	0.188*	0.166	0.130	0.110
	(3.38)	(3.28)	(1.77)	(1.56)	(1.42)	(1.11)
MKTRF	0.373***	0.374***	0.383***	0.268***	0.275***	0.276***
	(16.89)	(17.04)	(19.84)	(5.39)	(5.73)	(5.66)
SMB	0.00601	0.00443	0.0000331	-0.0177	-0.0271	-0.0276
	(0.25)	(0.19)	(0.00)	(-0.56)	(-0.79)	(-0.81)
VMG	-0.128***	-0.127***	-0.122***	-0.0687**	-0.0665**	-0.0658**
	(-4.47)	(-4.39)	(-4.68)	(-2.09)	(-2.22)	(-2.18)
PMO		0.00845	0.00868		0.0503	0.0503
		(0.38)	(0.41)		(1.15)	(1.15)
Bond			0.428***			0.0545
			(3.03)			(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**	0.133**	0.184***	0.189***	0.170***	0.173**
	(2.59)	(2.07)	(2.81)	(2.86)	(2.61)	(2.58)
MKTRF	0.146***	0.150***	0.147***	0.198***	0.202***	0.201***
	(10.32)	(11.22)	(11.61)	(13.35)	(12.18)	(11.91)
SMB	0.00968	0.00501	0.00644	0.0239	0.0187	0.0188
	(0.48)	(0.25)	(0.31)	(0.90)	(0.73)	(0.74)
VMG	-0.0602***	-0.0591***	-0.0608***	-0.0711**	-0.0699**	-0.0700**
	(-2.70)	(-2.66)	(-2.62)	(-2.33)	(-2.30)	(-2.28)
PMO		0.0250*	0.0249*		0.0277	0.0277
		(1.85)	(1.82)		(1.26)	(1.25)
Bond			-0.139***			-0.00969
			(-3.60)			(-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 CCP 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 5×2+1=11, meaning we require funds to have at least 11// 3=3 valid reports. We continue to define CCP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 20%, while non-CCP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 20%.

Panel A: CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.462***	0.434***	0.332**	0.369**	0.313**	0.289**
	(3.18)	(2.86)	(2.13)	(2.60)	(2.55)	(2.18)
MKTRF	0.502***	0.508***	0.514***	0.483***	0.494***	0.495***
	(20.88)	(24.33)	(23.49)	(10.62)	(11.35)	(11.26)
Smb	0.0116	0.00437	0.00150	0.0109	-0.00378	-0.00444
	(0.30)	(0.12)	(0.04)	(0.25)	(-0.10)	(-0.11)
Vmg	-0.162***	-0.161***	-0.157***	-0.131**	-0.128***	-0.127***
	(-3.63)	(-3.53)	(-3.58)	(-2.59)	(-2.64)	(-2.63)
Pmo		0.0389	0.0390		0.0788	0.0788
		(1.20)	(1.22)		(1.54)	(1.53)
Bond			0.279*			0.0638
			(1.93)			(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-CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.331**	0.344**	0.101	0.149	0.126	0.0419
	(2.11)	(2.29)	(0.62)	(1.65)	(1.35)	(0.44)
MKTRF	0.408***	0.405***	0.419***	0.264***	0.268***	0.273***
	(8.69)	(8.14)	(9.79)	(8.91)	(10.28)	(10.17)
SMB	0.0246	0.0281	0.0213	-0.0226	-0.0286	-0.0310
	(0.53)	(0.61)	(0.47)	(-0.89)	(-1.18)	(-1.29)
VMG	-0.151***	-0.152***	-0.144***	-0.0896**	-0.0882**	-0.0854**
	(-3.39)	(-3.48)	(-3.60)	(-2.48)	(-2.51)	(-2.50)
PMO		-0.0187	-0.0183		0.0323	0.0324
		(-0.50)	(-0.52)		(1.20)	(1.25)
Bond			0.661***			0.230**
			(2.92)			(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	0.0905	0.231**	0.219**	0.186**	0.247**
	(1.15)	(0.98)	(2.01)	(2.02)	(2.02)	(2.39)
MKTRF	0.0946*	0.103*	0.0945*	0.219***	0.226***	0.222***
	(1.77)	(1.90)	(1.88)	(6.64)	(6.65)	(6.65)
SMB	-0.0130	-0.0237	-0.0198	0.0336	0.0249	0.0266
	(-0.36)	(-0.63)	(-0.52)	(1.06)	(0.86)	(0.93)
VMG	-0.0111	-0.00848	-0.0131	-0.0417	-0.0396	-0.0416
	(-0.40)	(-0.33)	(-0.50)	(-1.17)	(-1.14)	(-1.18)
PMO		0.0575	0.0573*		0.0465	0.0464
		(1.62)	(1.65)		(1.17)	(1.18)
Bond			-0.382**			-0.166
			(-2.55)			(-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 CCP Construction)

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

Panel A: CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.462***	0.434***	0.332**	0.369**	0.313**	0.289**
	(3.18)	(2.86)	(2.13)	(2.60)	(2.55)	(2.18)
MKTRF	0.502***	0.508***	0.514***	0.483***	0.494***	0.495***
	(20.88)	(24.33)	(23.49)	(10.62)	(11.35)	(11.26)
Smb	0.0116	0.00437	0.00150	0.0109	-0.00378	-0.00444
	(0.30)	(0.12)	(0.04)	(0.25)	(-0.10)	(-0.11)
Vmg	-0.162***	-0.161***	-0.157***	-0.131**	-0.128***	-0.127***
	(-3.63)	(-3.53)	(-3.58)	(-2.59)	(-2.64)	(-2.63)
Pmo		0.0389	0.0390		0.0788	0.0788
		(1.20)	(1.22)		(1.54)	(1.53)
Bond			0.279*			0.0638
			(1.93)			(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-CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.331**	0.344**	0.101	0.149	0.126	0.0419
	(2.11)	(2.29)	(0.62)	(1.65)	(1.35)	(0.44)
MKTRF	0.408***	0.405***	0.419***	0.264***	0.268***	0.273***
	(8.69)	(8.14)	(9.79)	(8.91)	(10.28)	(10.17)
SMB	0.0246	0.0281	0.0213	-0.0226	-0.0286	-0.0310
	(0.53)	(0.61)	(0.47)	(-0.89)	(-1.18)	(-1.29)
VMG	-0.151***	-0.152***	-0.144***	-0.0896**	-0.0882**	-0.0854**
	(-3.39)	(-3.48)	(-3.60)	(-2.48)	(-2.51)	(-2.50)
PMO		-0.0187	-0.0183		0.0323	0.0324
		(-0.50)	(-0.52)		(1.20)	(1.25)
Bond			0.661***			0.230**
			(2.92)			(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	0.0905	0.231**	0.219**	0.186**	0.247**
	(1.15)	(0.98)	(2.01)	(2.02)	(2.02)	(2.39)
MKTRF	0.0946*	0.103*	0.0945*	0.219***	0.226***	0.222***
	(1.77)	(1.90)	(1.88)	(6.64)	(6.65)	(6.65)
SMB	-0.0130	-0.0237	-0.0198	0.0336	0.0249	0.0266
	(-0.36)	(-0.63)	(-0.52)	(1.06)	(0.86)	(0.93)
VMG	-0.0111	-0.00848	-0.0131	-0.0417	-0.0396	-0.0416
	(-0.40)	(-0.33)	(-0.50)	(-1.17)	(-1.14)	(-1.18)
PMO		0.0575	0.0573*		0.0465	0.0464
		(1.62)	(1.65)		(1.17)	(1.18)
Bond			-0.382**			-0.166
			(-2.55)			(-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 CCP Construction)

This table uses an alternative method to construct CCP 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 CCP funds as those whose proportion of periods characterized by countercyclical beliefs falls within the top 20%, while non-CCP funds are defined as those whose proportion of periods characterized by countercyclical beliefs falls within the bottom 20%.

Panel A: CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.448***	0.423***	0.311**	0.355***	0.300**	0.275**
	(3.19)	(2.88)	(2.07)	(2.61)	(2.57)	(2.21)
MKTRF	0.487***	0.492***	0.498***	0.454***	0.465***	0.467***
	(22.68)	(26.33)	(25.59)	(10.04)	(10.50)	(10.52)
Smb	0.0123	0.00581	0.00267	0.0257	0.0113	0.0106
	(0.33)	(0.16)	(0.08)	(0.60)	(0.29)	(0.27)
Vmg	-0.165***	-0.164***	-0.160***	-0.141***	-0.137***	-0.136***
	(-3.86)	(-3.76)	(-3.83)	(-2.85)	(-2.94)	(-2.93)
Pmo		0.0349	0.0351		0.0767	0.0768
		(1.15)	(1.18)		(1.46)	(1.46)
Bond			0.305**			0.0681
			(2.18)			(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-CCP Funds						
		Equal weighted			Value weighted	
Alpha	0.351***	0.357***	0.169	0.145	0.116	0.0878
	(2.82)	(2.94)	(1.37)	(1.50)	(1.29)	(0.91)
MKTRF	0.412***	0.411***	0.422***	0.286***	0.291***	0.293***
	(14.93)	(13.97)	(16.46)	(6.55)	(7.07)	(6.99)
SMB	0.0320	0.0336	0.0283	-0.00992	-0.0174	-0.0182
	(0.83)	(0.89)	(0.78)	(-0.39)	(-0.68)	(-0.71)
VMG	-0.130***	-0.130***	-0.124***	-0.0669**	-0.0651**	-0.0642**
	(-3.13)	(-3.17)	(-3.29)	(-1.98)	(-2.00)	(-1.99)
PMO		-0.00874	-0.00847		0.0400	0.0401
		(-0.28)	(-0.29)		(1.15)	(1.16)
Bond			0.512***			0.0771
			(3.67)			(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	0.0660	0.142**	0.210***	0.184***	0.187***
	(1.23)	(0.99)	(2.00)	(2.77)	(2.76)	(2.65)
MKTRF	0.0748**	0.0810***	0.0765**	0.169***	0.174***	0.174***
	(2.44)	(2.62)	(2.59)	(8.36)	(7.87)	(7.70)
SMB	-0.0196	-0.0278	-0.0257	0.0356	0.0287	0.0288
	(-0.83)	(-1.12)	(-1.03)	(1.36)	(1.34)	(1.33)
VMG	-0.0356**	-0.0336**	-0.0361**	-0.0738**	-0.0722**	-0.0723**
	(-2.09)	(-2.09)	(-2.19)	(-2.49)	(-2.53)	(-2.51)
PMO		0.0437*	0.0436*		0.0367	0.0367
		(1.83)	(1.85)		(1.24)	(1.23)
Bond			-0.207***			-0.00896
			(-3.12)			(-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的新低，企业盈利状况低迷。上半年，中央政府为了对冲经济增长下滑的势头，货币政策持续放水，流动性非常宽松。同时由于以银行为主渠道的间接融资体系受阻，中央政府对以股市为主渠道的直接融资体系大力扶持，股市出现了历史罕见的大幅上涨。从 6 月中旬开始，股市泡沫破灭，随后政府展开救市，市场逐步企稳，收复了部分失地。纵观全年，股市的波动幅度创下了多年以来的纪录，对投资者来说，2015 年成为难以忘怀的一年，盈亏得失自在心中。报告期内，本基金基本保持了较高仓位，但是在结构配置上跟市场热点出现了一定的偏差。全年的行业和风格配置基本保持均衡，对创业板的配置比例始终低于同业的平均水平，同时对于 2015 年最大的热点——“互联网+”的配置比例也不足，因此错失了上半年牛市最大的获利机会，全年业绩表现不够理想，但波动率低于同业平均水平。

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

ChatGPT Response:

Expectation Response:

Review Response:

1. Fiscal Policy: Neutral

中央政府采取了一些措施，但未明确提及财政政策的具体内容。

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

2. Monetary Policy: Positive

货币政策持续放水，流动性非常宽松。

Monetary policy remains accommodative, with very loose liquidity.

3. Regulatory Policy: Positive

政府对股市的直接融资体系大力扶持，并在股市泡沫破灭后展开救市。

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

4. National Macroeconomic Fundamental: Negative

GDP 增长率创下了十几年来的新低，企业盈利状况低迷。

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

5. Global Macroeconomic Fundamental: Not Mentioned

报告中未提及全球宏观经济基本面。

The report does not address global macroeconomic fundamentals.

6. Equity Market: Weakly Positive

股市出现了大幅上涨，但随后泡沫破灭，尽管政府救市，市场仍有波动。

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

7. Bonds Market: Not Mentioned

报告中未提及债券市场。

The report does not cover the bond market.

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

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

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

Outlook:

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

并长期持有，获取企业 EPS 增长的钱；(4)保留足够的现金，为下一轮牛市储备好充足的粮草。珍惜基金份额持有人的每一分投资和每一份信任，本基金将继续奉行华夏基金管理有限公司“为信任奉献回报”的经营理念，规范运作，审慎投资，勤勉尽责地为基金份额持有人谋求长期、稳定的回报。

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

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

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

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

Expectation Response:

1. Fiscal Policy: Positive

供给侧改革将推动经济向好转变。

Supply-side reforms are expected to drive economic improvement.

2. Monetary Policy: Weakly Negative

人民币面临贬值压力，限制了货币政策的灵活性。

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

3. Regulatory Policy: Neutral

注册制的实施会带来结构性变化，但长远影响尚不明确。

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

4. National Macroeconomic Fundamental: Positive

供给侧改革有望实现经济的“向死而生”。

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

5. Global Macroeconomic Fundamental: Weakly Negative

美元加息周期对人民币构成压力。

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

6. Equity Market: Neutral

股市将是休养生息的一年，但有结构性机会。

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

7. Bonds Market: Not Mentioned

未提及。

No mention in the report.

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

整体展望呈现出谨慎乐观态度，强调防御策略和结构性机会。

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