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# Visible Hands: Professional Asset Managers' Expectations and the Stock Market in China*

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**Abstract**

We study how professional fund managers' growth expectations affect the actions they take with respect to equity investment and in turn the effects on prices. Using novel data on China's mutual fund managers' growth expectations, we show that pessimistic managers decrease equity allocations and shift away from more-cyclical stocks. We identify a strong short-run causal effect of growth expectations on stock returns, despite statistically-significant delays in price discovery from short-sale constraints. Finally, we find that an earnings-based measure of price informativeness is increasing in fund investment.

**Keywords: Economic growth expectations; Mutual fund managers; Chinese financial markets; Price informativeness; Textual analysis**

**JEL Classification: G23, G12, D80, E66, G11**

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# 1 Introduction

In recent years, professional asset managers have played an increasing role in Chinese financial markets, mirroring a trend that began earlier in some other economies. An open question is the extent to which the more disciplined decision-making that professional analysis can bring to bear has a significant impact on market dynamics. In evaluating investment analysis, much of the previous empirical literature considers only issuer-level assessments, which often come from third parties, such as company earnings forecasts or credit ratings.[1] In this paper, we take a broader view of professional investors' portfolio decision-making by incorporating explicit consideration of the consequences of their macroeconomic outlook, which we infer through a systematic textual analysis. An advantage of our approach is that these opinions come from the investors themselves, so that they can be more directly linked to the investment decisions we observe for the asset managers in our data set. Through this, we document the links running from managers' macroeconomic growth expectations to their investment actions and through this to the price impact of those actions.

Expected macroeconomic growth, in particular, is likely to be an important factor in investment decisions, given the potential impact on companies' earnings growth trajectory and investors' ability to bear risks. This affects the risk premium, a critical component of expected returns. Chinese financial investors have further reason to be concerned about economic growth as state-owned enterprises (SOEs), which comprise about 38% of listed companies and 55% of stock market value in China, are crucial stabilizing tools that the government actively employs (Bai et al., 2006). These considerations again became prominent in the early 2020s, with pandemic-induced lockdowns in much of China.[2]

Despite the potential importance of these topics, there has been relatively little previous analysis about the extent to which investors change their investments according to those ex-

[1] Analyses of earnings forecasts are discussed in Bradshaw (2011), and Kothari et al. (2016). For credit ratings, see White (2013) and citations therein and Livingston et al. (2018) for an analysis in Chinese markets.

[2] See for example "Economists Cut China Growth Forecasts as Lockdowns Hit Economy," 19 May 2022 https://www.bloomberg.com/news/articles/2022-05-19/economists-cut-china-growth-forecasts-as-lockdowns-hit-economy.

pectations, or the consequences for asset pricing. In this paper, we provide evidence on these questions. We begin with a textual analysis of the qualitative discussion published in the quarterly reports of China's equity and mixed mutual fund managers. From this, we obtain an extensive panel of near-term expectations about China's GDP growth rate between 2008 Q3 and 2020 Q2 from a panel of fund managers that includes 7,579 funds.[3]

We use the constructed growth expectation measure to show that when expecting strong economic growth, fund managers increase the equity share and raise the stock market beta. These shifts in portfolio allocations are consistent with the fact that economic growth increases companies' earnings growth and improves investors' ability to bear risks, making it more lucrative to invest in risky stocks. Thus, we argue that variation in growth expectations reflects heterogeneous and time-varying beliefs among managers rather than measurement error. The close relationship between exposure to stock market risks and growth expectations has also been documented in recent work by Giglio et al. (2021a), who studied a confidential survey of U.S. retail investors with accounts at Vanguard. Their setting is quite different than the institutional investors we consider.

We also identify a significant reallocation of investment across industries based on managers' growth expectations. Fund managers who are optimistic about economic growth reallocate funds away from counter-cyclical industries like agriculture toward pro-cyclical industries such as transportation. This suggests that growth expectations may amplify cyclicalities at the sectoral level and is related to Kacperczyk et al. (2014), who document that U.S. fund managers actively adjust their allocations across industries over the business cycle. We also show that managers who are more optimistic about economic growth invest more in SOE stocks. This reallocation of investment between SOEs and non-SOEs can be due to the former's higher sensitivity of earnings to aggregate economic conditions. In particular, SOEs expand faster in macroeconomic booms due to implicit guarantees from the government and greater monopoly

[3]Fund managers have an incentive to report their true expectations, despite potential costs of reporting and positive externalities on competitors. Part of their responsibilities is to communicate with investors about expectations through presentations, newsletters, blogs, etc.. The marginal cost of discussing the same expectation in their fund reports is negligible. It is also almost impossible for mutual fund managers to hide their expectations from competitors since communications with investors are mostly public.

power (see, for example, Li et al. 2015). Meanwhile, SOEs suffer a more significant earnings loss during economic slowdowns because they are responsible for maintaining social stability, which prohibits them from firing workers and cutting procurement of intermediate goods (Lin et al. 1998 and Song et al. 2011).

Having described how managers' macroeconomic growth expectations affect their investment activity, we next study the impact of this on prices. We first document significant short-run asset pricing implications by showing that the stock return of a company is correlated with the growth expectations of fund managers who hold this company's stocks. Our identification strategy builds on the presumption that fund managers are unlikely to learn about economic growth from individual stocks' prices. We find that the optimism (pessimism) of fund managers about economic growth is associated with the high (low) return of the stocks they hold. The magnitude of the price impact is economically large. A one standard deviation rise (fall) in the average growth expectation of fund managers investing in a stock increases (decreases) the monthly stock return by 0.66%.

While the stock market is a powerful device for transmitting information and allocating resources, its efficiency can be impeded by various frictions such as short-sale constraints. Although short sales have become gradually available to many investors in the Chinese stock market, they are still strictly forbidden for mutual funds. This prevents bearish managers from selling stocks in which they hold a zero position. We show that pessimistic fund managers with a low position in stocks are associated with higher stock returns followed by a downward price adjustment. This is consistent with Hong and Stein (2003) who show that short-sale constraints mute negative beliefs in the short run. Similarly, the negative managerial consensus expectations have a lagged price impact on stocks held little by the fund managers. This is because fund managers' views cannot instantaneously pass through to these stocks' prices, while the other investors take time to learn from the negative consensus expectations.

After documenting the price impact of growth expectations, we then examine the role of Chinese mutual fund managers in driving the "price informativeness" of the stock market. In a well-functioning market, security prices provide accurate signals for resource allocation, as prices at any time fully reflect all available information (Fama, 1970). China's two stock exchanges, in Shanghai and Shenzhen, were established in the early 1990s and have grown to become the second largest in the world in terms of market capitalization, trailing only the United States. Foreign investors, traditionally restricted from trading in the domestic "A-share" market, have gradually but increasingly been granted access to these two exchanges (Ma et al., 2022). We follow the recent approach of Dávila and Parlatore (2018) to measure price informativeness of the Chinese stock market and present evidence that Chinese fund managers help to improve it (see also Bai et al. (2016) and Carpenter et al. (2021) for closely related work).

# 2 Data Description

## 2.1 Mutual fund reports

Our sample period runs from 2008Q3 to 2020Q4. During this time, all mutual fund managers in China were asked by the China Securities Regulatory Commission (CSRC) to discuss their expectations for near-term conditions in the real economy and financial markets. These commentaries were published in the Market Outlook subsections of the Quarterly, Semi-annual, and Annual Reports of the China Securities Journal. We obtain these reports from Wind.

The CSRC does not assign topics, so the managers are free to address what they find most relevant, though they are not allowed to mention any stock or company names. Managers provide qualitative forecasts of economic policies, economic conditions, and other subjects. The length of the Market Outlook subsection of each report ranges from 50 to 2000 Chinese characters, depending on the number of topics and the amount of detail. We posit that mutual fund managers have a reputational incentive to write the Market Outlook subsection carefully, as investors can evaluate managers' ability and credibility from the cohesiveness of their opinions.

While managers do not specify their forecast horizon in most cases, we conjecture that the horizon for the quarterly reports is one quarter. There are two reasons for this. First, we find that the consensus growth expectation constructed from the quarterly reports has the most predictive power as a one-quarter ahead forecast. Second, the expectations inferred from the quarterly report are different from—although positively correlated with—those communicated in the same funds' semi-annual and annual reports of the same vintage.

Since the first Chinese mutual fund launch in September 2001, the industry has experienced strong growth. At the end of 2020, the mutual fund industry had 7,403 funds, consisting of 1,277 equity funds, 2,370 bond funds, 3,202 mixed funds, 333 money market funds, 166 Qualified Domestic Institutional Investor (QDII) funds, and 54 funds of other types.[4] In this paper, we focus on active equity and mixed funds that invest in the stock market. The total assets under management were 20 trillion yuan (about 3.2 trillion US dollars) for the mutual fund industry. Of these, 9.3 and 24.2 percent were managed by equity and mixed funds, respectively.[5]

To map the qualitative information on expected GDP growth embedded in mutual fund reports to quantitative measures, we first construct a dictionary of words and phrases. This dictionary includes words and phrases related to China's GDP growth (e.g., "GDP growth" and "national income"), ones implying expected strength of GDP growth (e.g., "increase" and "stagnant"), ones reflecting the perceived probability or magnitude of GDP growth (e.g., "mildly" and "potentially"), and ones indicating negation (e.g., "no","not"). Each word and phrase is assigned a numerical score between -1 and 1.

Then we compute the *forecast score*, our growth expectation measure, of each report according to the combination of words and phrases from the dictionary. Section A of the Appendix provides details on the textual analysis algorithm, and Section B of the Appendix shows an explicit example of how we map from report text to a forecast score. The forecast score is denoted as $E_t^i(\Delta y_{t+1})$ for manager $i$ in period $t$, with $E_t^i(\Delta y_{t+1}) \in [-1, 1]$. The sign of $E_t^i(\Delta y_{t+1})$ indicates the expected strength of GDP growth in period $t+1$. It is positive if expects a strong economic growth, zero if expects a moderate growth, and negative if expects a weak growth.

The summary of the forecast score is reported in Panel A of Table 1. The data set has 73,506 quarterly reports. Of this total, 20,807 and 52,699 are reported by managers of equity

[4]QDII are domestic financial institutions that are allowed to invest in offshore markets. Funds of other types are specialized in commodity markets, REITs markets, and other markets.

[5]Due to the flexibility in investments, most active funds claim themselves as mixed funds than pure equity funds. This results in a small number of pure equity funds. Among the 9.3 percent of total assets managed by equity funds, 3.5 percent are managed by active equity funds.

and mixed funds, respectively. 32,661 of them have a valid GDP growth forecast score. A significant fraction of our sample is written by passive funds such as the index funds, which have 7,676 valid forecast scores. We will exclude them in all analyses. Panels B and C of Table 1 report the summary statistics for the main variables for funds and stocks, respectively.

## 2.2 Fund characteristics and investment data

A crucial detail of the mutual fund report for our purposes is that it identifies each fund and its manager. This enables us to match manager and fund characteristics, and investment history, to managers' expectations in a relatively long panel. The matched panel structure enables us to identify the effect of those expectations on investment behavior and returns.

We obtain reference information on the characteristics of both mutual funds and their managers from Wind and RESSET. We obtain monthly fund return, quarterly information on fund size (total net asset value under management), fund investments at the asset-type level, and stock investment at the industry level, and semi-annual detailed holdings in stocks.[6]

We observe fund expense ratios and their turnover ratio of equities semi-annually. At the fund level, we observe characteristics such as management fees, purchase and redemption fees, and geographic location.

We obtain stocks' characteristics from the China Stock Market & Accounting Research Database (CSMAR), including their monthly returns and quarterly market capitalization, prices, earnings and earnings per share, CAPM beta, and turnover and book-to-market ratios. We also obtain the monthly information on Fama-French factors and risk-free rates from CSMAR. We obtain the real GDP growth rate from CEIC.

Investor-level expectation datasets used in previous studies include the retail investors' survey at Vanguard (Giglio et al., 2021a,b), expectations of large fund families (Dahlquist and Ibert, 2021), and expectation of public pension funds (Andonov and Rauh, 2022). The advantage of our data set is the relatively large sample size and panel feature of the forecasts over a long period. This allows us to examine variation in the same investors' growth expectations

[6]Asset types include stocks, bonds, deposits, derivatives, and other financial assets.

over different phases of economic fluctuations.[7]

## 2.3 The incentive of forming accurate expectations

A natural concern in analyzing stated forecasts on fund reports is that fund managers do not have the incentive to form accurate expectations or to write the reports seriously. This subsection shows that fund managers' forecasting correctness is strongly associated with superior fund performance, which is consistent with the presumption that fund managers have the incentive to form accurate growth expectations and that the stated forecast reflects their true belief.

To measure the correctness of growth expectations, a methodological challenge is that our forecast measure is qualitative and the Chinese economy has seldom experienced a negative GDP growth rate in our sample period. The sharp and completely unanticipated 2020 Q1 downturn prompted by the onset of COVID-19 was the only reversal in the expansionary trend in aggregate activity. To map our qualitative growth expectation measure to a correctness measure, we need to make assumptions about the outcomes for which managers would consider economic growth to have been "strong" or "weak".

A plausible reference point for fund managers' growth expectations is the central government's growth targets set by the Central Economic Work Conference which is typically held in December of the previous year.[8] The Premier of the State Council will formally announce them to the annual assembly of the National People's Congress as part of the Annual Report on the Work of Government. The only exception was 2020, when the central government decided not to announce the growth target, possibly worrying that the growth target may divert pandemic-combating efforts. Figure 1 displays the growth target (the dashed curve) along with the real GDP growth rate (the solid curve). The shaded columns indicate the periods when economic growth (barely) fell short of the target.

We find that when fund managers discuss details about the "weak" economic growth prospect

[7] Ammer et al. (2021) also use the CSRC-mandated reports to study the effect on Chinese bond and money market funds' fixed income investments of fund managers' monetary policy expectations. This paper focuses on equity and mixed funds' growth expectations and the implications for the stock market.

[8] The Central Economic Work Conference is jointly organized by the State Council and the Central Committee of the Communist Party of China.

**Table 1:** Summary Statistics

This table reports summary statistics for the main variables. Panels A-C report the summary statistics for the growth expectations, the main variables at the fund-quarter level, and the main variables at the stock-quarter level, respectively.

Panel A: Summary statistics of growth expectation

| Variable | #Reports | #Forecasts | Mean | Std. Dev. | Min | p25 | Median | p75 | Max |
|---|---|---|---|---|---|---|---|---|---|
| All | 73,506 | 32,661 | -0.02 | 0.79 | -1.00 | -1.00 | 0.00 | 0.92 | 1.00 |
| Mixed Funds | 52,699 | 23,429 | -0.04 | 0.78 | -1.00 | -1.00 | 0.00 | 0.92 | 1.00 |
| Equity Funds | 20,807 | 9,232 | 0.02 | 0.79 | -1.00 | -1.00 | 0.00 | 0.92 | 1.00 |

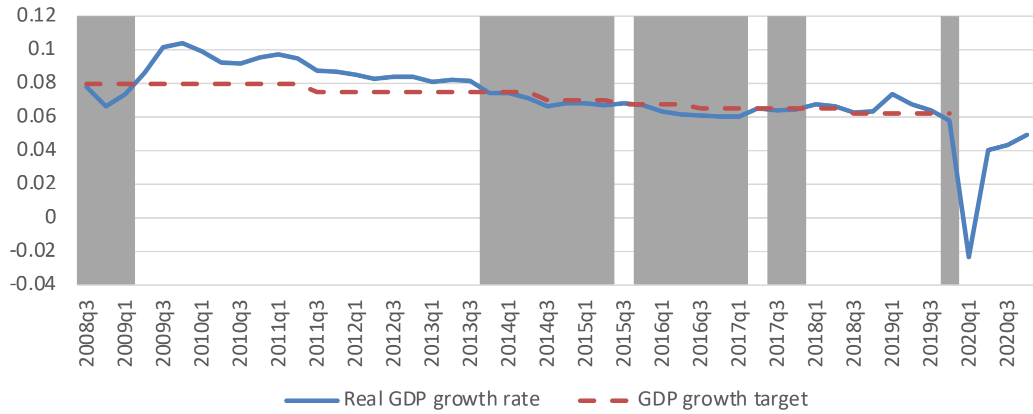
Panel B: Summary statistics of variables at the fund-quarter level

| Variable | #Observation | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| Abnormal Return | 47,180 | 9.41 | 26.57 | -4.57 | 6.19 | 21.47 |
| Abnormal Return(FF) | 47,181 | 2.30 | 14.60 | -4.75 | 1.73 | 9.36 |
| Participated | 47,404 | 0.42 | 0.49 | 0.00 | 0.00 | 1.00 |
| Correct(hist) | 19,770 | 0.50 | 0.50 | 0.00 | 1.00 | 1.00 |
| Correct(target) | 19,770 | 0.44 | 0.50 | 0.00 | 0.00 | 1.00 |
| Ln(TNA) | 47,404 | 6.24 | 1.63 | 5.07 | 6.30 | 7.48 |
| Ln(Age) (quarters) | 47,404 | 2.48 | 0.90 | 1.79 | 2.48 | 3.18 |
| Fund Inflow | 47,404 | 446.73 | 97,169.66 | -0.14 | -0.04 | 0.05 |
| Expense Ratios | 47,279 | 1.04 | 2.77 | 0.58 | 0.73 | 1.06 |
| Equity Proportion | 40,299 | 65.26 | 30.36 | 50.49 | 78.05 | 88.41 |
| Beta | 36,879 | 0.74 | 0.41 | 0.51 | 0.81 | 0.99 |
| Pro-Cycle (%) | 39,202 | 59.37 | 26.89 | 45.50 | 68.17 | 79.64 |
| Counter-Cycle (%) | 39,202 | 6.61 | 7.78 | 0.59 | 4.37 | 9.63 |
| Pro-Cycle over equity (%) | 39,174 | 90.73 | 10.03 | 86.65 | 93.25 | 98.27 |
| SOE (%) | 24,925 | 27.60 | 17.76 | 12.94 | 26.33 | 40.01 |
| POE (%) | 25,070 | 34.39 | 22.17 | 15.28 | 34.28 | 50.89 |
| SOE over equity (%) | 24,925 | 46.84 | 21.49 | 30.67 | 46.24 | 62.21 |

Panel C: Summary Statistics of variables at the stock-quarter level

| Variable | #Observation | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| FMH Consensus Growth Expectation | 39,233 | -0.03 | 0.52 | -0.39 | -0.05 | 0.35 |
| Stock Return in Report Month | 51,017 | 0.03 | 0.14 | -0.05 | 0.01 | 0.09 |
| Stock Return in Report Month | 49,760 | 0.01 | 0.13 | -0.07 | -0.01 | 0.07 |
| Forecasting manager holding | 51,017 | 0.25 | 0.43 | 0.00 | 0.00 | 0.00 |
| Consensus Growth Expectation | 51,017 | -0.10 | 0.28 | -0.32 | -0.14 | 0.10 |
| Market Capitalization | 51,017 | 8.71 | 1.08 | 7.96 | 8.58 | 9.29 |
| Turnover Ratio | 51,017 | 3.65 | 0.91 | 3.09 | 3.67 | 4.26 |
| EPS per share | 51,017 | 0.28 | 0.50 | 0.05 | 0.18 | 0.40 |
| Market-to-book ratio | 51,017 | 1.17 | 0.83 | 0.64 | 1.09 | 1.58 |
| CAPM beta | 46,155 | 1.15 | 0.80 | 0.76 | 1.15 | 1.52 |
| Price Informativeness | 47,392 | 0.05 | 0.08 | 0.00 | 0.02 | 0.07 |

**Figure 1:** GDP growth rate and growth target




The blue-solid line is the real GDP growth rate. The red-dashed line is the growth target rate. The shaded columns indicate the periods when GDP growth falls short of target.

in their reports, they usually mention that the growth rate might not reach the central government's growth target. Similarly, fund managers often discuss that the growth rate could surpass the growth target when they state optimism about economic growth. One possible reason the fund managers pay attention to the growth target is that the government is likely to implement policies to reach the target.[9]

Given the above observations, we postulate that the managers consider the economy to be strong (weak) if the real GDP growth rate is beyond (below) the growth target. Then we define correctness as:

$$\text{Correct}_t^i = \begin{cases} 1 & \text{if } sign\left[E_t^i\left(\Delta y_{t+1}\right)\right] = sign\left(\widehat{\Delta y}_{t+1}^{target}\right) \\ & or\ E_t^i\left(\Delta y_{t+1}\right) = 0\ \&\ |\widehat{\Delta y}_{t+1}^{target}| < \frac{std(\widehat{\Delta y}^{target})}{100}\ , \\ 0 & \text{if otherwise} \end{cases} \tag{1}$$

where $\widehat{\Delta y_{t+1}}^{target}$ is the gap between the real GDP growth rate and the target rate. In many cases, forecasts are zero, indicating that managers expect moderate economic growth. However, $\Delta y_{t+1}$ is never zero precisely, implying that all zero forecasts are automatically incorrect. To improve the evaluation of the zero forecasts, we consider them as correct if $\Delta y_{t+1}$ is sufficiently

[9] Lyu et al. (2018) provides evidence on the activities taken by governments (at the provincial level) to meet the growth target.

close to zero. We set $Correct_t^i = 1$ if $E_t^i(\Delta y_{t+1}) = 0$ and $|\widehat{\Delta y}_{t+1}^{target}| < 0.01 * std(\widehat{\Delta y}^{target})$.

Our benchmark fund performance measure is the abnormal return estimated from a CAPM model, reflecting the fund return that is not earned by being passively exposed to the stock market risk.[10] To examine whether GDP growth forecast skill (i.e., a high $\text{correct}_t^i$) contributes to a higher risk-adjusted fund performance, we estimate a panel regression model:

$$AR_{t+1}^i = a + c_1 Parti_t^i + c_2 Parti_t^i \times Correct_t^i + X_t^i + \chi^i + \epsilon_{t+1}^i, \tag{2}$$

The dependent variable is the fund's abnormal return in the next period, $\text{parti}_t^i$ is the participation dummy, which is equal to one if and only if a manager reports the growth expectation, and $\text{parti}_t^i \times \text{correct}_t^i$ is the indicator of a correct forecast (i.e., $Correct_t^i = 1$) *conditional* on reporting a growth expectation.[11] $X_t^i$ is the set of control variables. Importantly, we include fund fixed-effect $\chi^i$ as an independent variable, hence our estimates reflect whether correct growth expectation induces wise investments and rules out the effect of unobserved general managerial ability on fund performance. As the management fee is a fund fixed-effect, it is not included as a control variable.

As reported in Table 2, the new measure of GDP growth forecast correctness is positively related to the abnormal return. The result is statistically significant and economically large: the same fund manager obtains an additional yearly 1.17% risk-adjusted return when reporting a correct forecast than reporting an incorrect forecast.[12]

[10]For each quarter, we estimate the beta using monthly data in a rolling window of 12 months before the report submission date. Then we calculate the abnormal return as the difference between fund's excess return and the product of the market excess return and the estimated beta.

[11]Note that $parti_t^i \times correct_t^i$ is identical to $Correct_t^i$ because correct forecast must imply participation. We use the former term in equation (2) to emphasize that $c_2$ measures the effect of correct forecast on fund performance compared to incorrect forecast.

[12]In Table E.1 in Section E of the Appendix, we show that the result is similar if we use the Keqiang index as the measure of growth rates.

**Table 2:** GDP Growth Forecast Correctness and abnormal return, GDP target rate as the reference point: Panel

Data are quarterly between 2008 Q3 and 2020 Q2. *Participated* is a dummy variable that is equal to 1 if the manager has a valid forecast score in this quarter, and 0 otherwise. *Correct* is the dummy variable indicating the forecast accuracy. All standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Dependent Variable : | Abnormal return |
|---|---|
| Participated * Correct(target) | 1.171*** |
| | (3.09) |
| Participated | 1.165*** |
| | (3.66) |
| Lagged Log(TNA) | -1.823*** |
| | (-8.39) |
| Lagged Log(Age) | 1.140*** |
| | (4.47) |
| Lagged Fund flows | -0.000*** |
| | (-6.03) |
| Lagged Expense Ratio | 0.204*** |
| | (4.11) |
| Constant | 15.763*** |
| | (8.78) |
| Fund FE | Yes |
| Adj R-squared | 0.012 |
| Observation | 44,428 |

# 3 Actions: Managers' Expectations and Investment

We begin by relating growth expectations to investment decisions. Do managers' growth expectations comove with measures of portfolio choice in a way consistent with standard finance theory? We consider two dimensions of portfolio choice: exposure to stock market risks and reallocation of investment across industries and companies with various degrees of cyclicality.

**Exposure to stock market risks** We quantify exposure to stock market risks with two measures. The first is equity share, denoted as *Equity*, which is the proportion of fund value invested in equity rather than other types of assets such as bonds and cash. The second measure is the stock market beta, denoted as *Beta*, estimated from a CAPM model using daily data in the reporting period. For each measure of stock market risk exposure, we estimate:

$$S_t^i = \alpha + \eta E_t^i(\Delta y_{t+1}) + X_t + \chi^i + \gamma_t + \epsilon_t^i,\ S \in \{Equity, Beta\}, \tag{3}$$

where $S_t^i$ is equity share or stock market beta; $E_t^i(\Delta y_{t+1})$ is growth expectaton; $X_t$ is a vector of controls such as lagged fund size and fund flows; $\chi^i$ and $\gamma_t$ are fund and time fixed effects.

Column (1) of Table 3 shows that when expecting robust economic growth, fund managers increase investment in equity. Our result is consistent with the fact that, on average, listed companies' earnings growth is positively correlated with GDP growth. Moreover, robust economic growth enables investors to be more capable of bearing risks, inducing them to hold more risky assets such as stocks. Our finding is similar to Giglio et al. (2021a), who document a higher equity share for retail investors of Vanguard, those who are more optimistic about economic growth. Table C.1 in Section C of the Appendix verifies that the changes in equity share reflect fund managers' active and strategic portfolio choice rather than the valuation effect passively driven by changes in asset prices.

A possible explanation of the positive correlation between equity share and growth expectation is that stock market returns drive both simultaneously. As the stock market return is an aggregate variable, we can purge it from our estimation with time fixed-effects. Column (2) of Table 3 verifies that the positive and strongly statistically significant correlation between growth expectation and equity share is robust to including time fixed-effects. However, the magnitude of the estimate is about one-half its value in the regression without time-fixed effects, indicating that much of the comovement between managers' equity share and growth expectation is accounted for by comovement in the trends of the two variables.

The results for the stock market beta are displayed in Columns (3) and (4) of Table 3. Growth expectations are positively correlated with the stock market beta, which reinforces our findings in Columns (1) and (2) as beta is a complementary measurement of exposure to stock market risks. Moreover, there are many non-equity assets, such as convertible bonds, whose value is strongly tied to the stock market. The investment decision on these assets is not reflected in equity share but will be reflected by stock market beta.

**Industries with different cyclicalities** Next, we study how fund managers allocate investment across industries according to their growth expectations. We first calculate the correlation

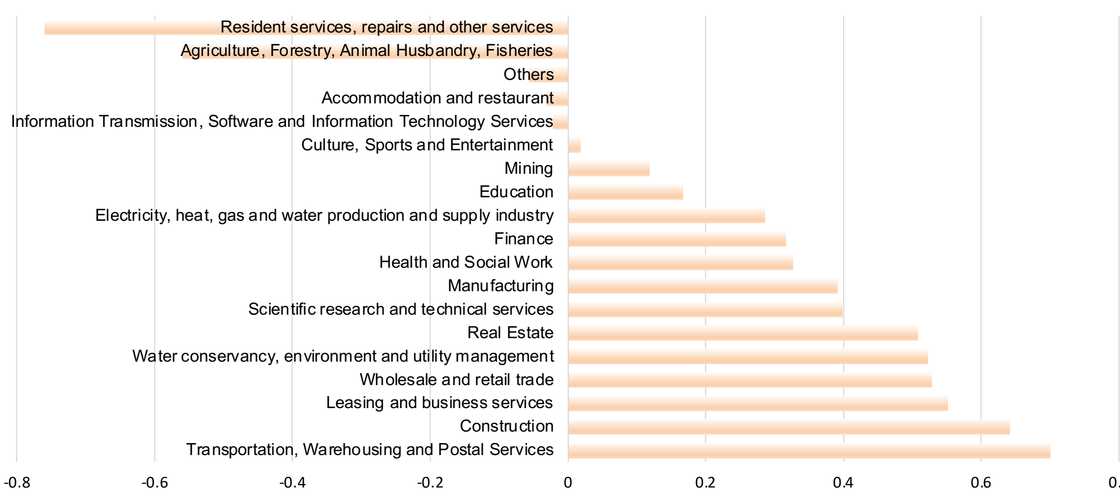
**Table 3:** Growth Expectation and Portfolio Adjustment: Panel

Data are quarterly between 2008 Q3 and 2020 Q2. *Equity* is the proportion of TNA in equity. *Beta* is the stock market beta estimated from a CAPM model. All standard errors are clustered at the fund and quarter levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable : | Equity (%) | | Beta | |
| Growth Expectation | 0.942*** | 0.400*** | 0.020*** | 0.007*** |
| | (4.57) | (3.86) | (3.13) | (3.54) |
| Lagged Equity | 0.497*** | 0.493*** | | |
| | (16.48) | (18.51) | | |
| Lagged Beta | | | 0.338*** | 0.349*** |
| | | | (7.15) | (6.50) |
| Lagged Log(TNA) | -0.561* | -0.512** | -0.005 | -0.004 |
| | (-1.76) | (-2.24) | (-1.03) | (-0.84) |
| Lagged Log(Age) | 0.892 | 0.277 | 0.041*** | 0.009 |
| | (1.54) | (0.89) | (5.82) | (1.58) |
| Lagged Fund flows | 0.006 | 0.006 | 0.000*** | 0.000*** |
| | (1.18) | (1.22) | (5.97) | (10.49) |
| Expense Ratio | -4.625* | -4.280 | -0.028 | -0.028 |
| | (-1.77) | (-1.56) | (-0.52) | (-0.54) |
| Constant | 31.919*** | 35.666*** | 0.412*** | 0.489*** |
| | (8.23) | (14.02) | (5.57) | (9.07) |
| Fund FE | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes |
| Adj R-squared | 0.883 | 0.893 | 0.726 | 0.749 |
| Observations | 20,271 | 20,271 | 18,372 | 18,372 |

coefficient between actual GDP growth and the earnings growth rate for 19 CSRC primary-level industries. This identifies pro-cyclical and counter-cyclical industries. Figure 2 displays the correlation coefficients for each industry from the most negative to the most positive. While most industries' earnings growth is pro-cyclical, a few are significantly counter-cyclical, such as Resident services/repairs/other services and Agriculture/forestry/animal husbandry/fisheries. Several papers have documented the counter-cyclicality of the Agricultural sector's value-added (e.g., Yao and Zhu (2021)), pointing out that the critical factor behind this is the reallocation of labor between agricultural and non-agricultural sectors. This intuition also applies to our context about companies' earnings: economic slowdown would induce the rural migrant workers to return from cities to the rural areas where they own farmland. The influx of labor supply would pull down the wage and improve the profitability of the agricultural sector. The counter-cyclicality of the Resident services/repairs/other services industry is less established in the literature. However, the pattern can be intuitively explained by the reallocation of time between home and work over the business cycle.

**Figure 2:** Correlation between GDP growth and industries' earnings growth




Data are quarterly between 2013 Q1 and 2020 Q4. Each column displays the correlation between industries' earnings growth and the GDP growth rate.

To study how fund managers reallocate their investment between pro- and counter-cyclical industries, we estimate the following regression:

$$\omega^i_{pro,t} = \alpha + \eta E^i_t(\Delta y_{t+1}) + X_t + \chi^i + \gamma_t + \epsilon^i_t, \tag{4}$$

where $\omega_{pro,t}$ is the fraction of fund value allocated to the pro-cyclical industries. $E^i_t(\Delta y_{t+1})$ is the growth expectation. $X_t$ is a vector of control variables such as lagged fund size and fund flows. $\chi^i$ and $\gamma_t$ are fund and time fixed effects.

Columns (1) and (2) of Table 4 report the results. Column (1) shows that expecting strong economic growth, fund managers increase their allocation of investment in pro-cyclical industries. Column (2) shows that this is robust to including time fixed effects. Columns (3) and (4) report results when the dependent variable is the fraction of fund value allocated to the counter-cyclical industries. Our findings indicate that fund managers who are optimistic about economic growth decrease their allocation of stocks in the counter-cyclical industries. Columns (5) and (6) show that our result holds when we measure exposure to pro-cyclical industries as the ratio of investment in these industries to the value of stock investment.[13]

Our results imply that growth expectations are a powerful mechanism that could amplify sectoral dispersion and volatility. In particular, in periods of robust economic growth prospects, companies in pro-cyclical industries receive more investment, propagating their development and making them even more pro-cyclical. Conversely, companies in counter-cyclical industries receive less investment, depressing their output and making them even more counter-cyclical.

**SOEs and non-SOEs** SOE stocks comprise a critical component of the Chinese stock market. As shown by the gray areas in Figure 3, SOE stocks account for 55% of the market cap and 38% of listed companies in China's stock market between 2008 Q2 and 2020 Q2. Meanwhile, SOEs serve as a critical stabilizing tool actively employed by the government (Bai et al., 2006). Next, we examine how growth expectations affect fund managers' investment decisions in SOEs.

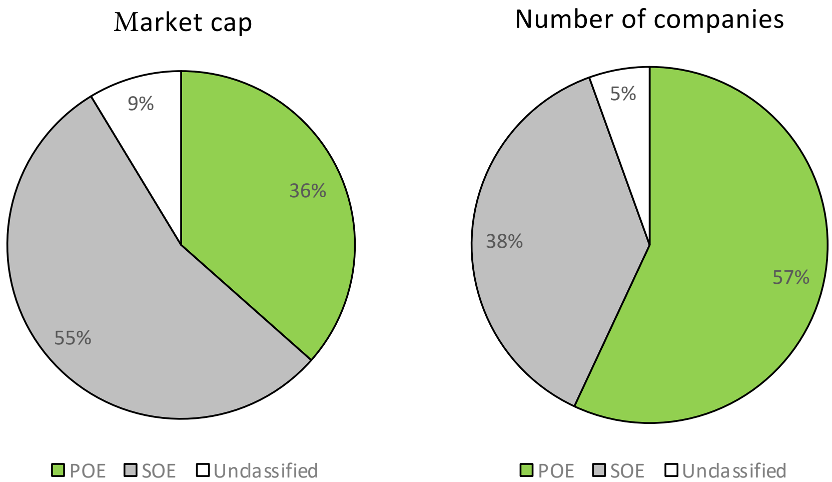
[13] Table C.1 in Section C of the Appendix further verifies that changes in exposure to pro-cyclical industries reflects fund managers' active and strategic portfolio choice rather than the valuation effect passively driven by changes in asset prices. Also, in results not reported, we find that lower growth expectations are associated with a net reduction in portfolio allocations to SOEs, which have more cyclical earnings on average than other listed firms.

**Table 4:** Growth Expectation and Portfolio Adjustment in Pro-Cyclical Industries: Panel

Data is semiannual between 2008 Q3 and 2020 Q2. In columns (1-4), the dependent variables, *Pro-Cycle* and *Counter-Cycle*, are the proportions of TNA in pro-cyclical and counter-cyclical industries. In columns (5-6), the dependent variable, *Pro-Cycle/Equity* is the proportion of equity market value in pro-cyclical industries. All standard errors are clustered at the fund and quarter levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable : | Pro-Cycle (%) | | Counter-Cycle (%) | | $\frac{Pro-Cycle}{Equity}$ (%) | |
| Growth Expectation | 1.263*** | 0.563*** | -0.392*** | -0.212*** | 0.684*** | 0.334*** |
| | (5.98) | (4.52) | (-3.40) | (-2.81) | (4.30) | (3.37) |
| Lagged Pro-Cyclical | 0.507*** | 0.502*** | | | | |
| | (20.52) | (22.49) | | | | |
| Lagged Counter-Cycle | | | 0.564*** | 0.555*** | | |
| | | | (16.97) | (18.82) | | |
| Lagged Pro-Cyclical/Equity | | | | | 0.471*** | 0.454*** |
| | | | | | (19.68) | (21.12) |
| Lagged Log(TNA) | -0.598* | -0.569*** | -0.076 | -0.023 | 0.125 | 0.073 |
| | (-1.99) | (-2.71) | (-0.83) | (-0.34) | (0.91) | (0.73) |
| Lagged Log(Age) | 0.718 | 0.431* | -0.171 | -0.191* | 0.304 | 0.255 |
| | (1.36) | (1.70) | (-1.22) | (-1.77) | (1.50) | (1.66) |
| Lagged Fund flows | 0.002 | 0.002 | -0.000 | -0.000 | 0.000 | 0.000 |
| | (0.69) | (0.84) | (-0.25) | (-0.84) | (0.05) | (0.49) |
| Expense Ratio | 15.281 | 15.138* | 1.711 | 0.493 | 0.194 | 2.192 |
| | (1.39) | (1.82) | (1.00) | (0.38) | (0.10) | (1.23) |
| Fund FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes | No | Yes |
| Adj R-squared | 0.855 | 0.868 | 0.590 | 0.618 | 0.473 | 0.504 |
| Observations | 19,678 | 19,678 | 19,678 | 19,678 | 19,648 | 19,648 |

**Figure 3:** The significant proportion of SOE stocks




The bar charts display the fractions of market cap and number of companies accounted for by the SOEs, POEs and unclassified stocks. For both measures, we compute the mean between 2008 Q2 and 2020 Q2.

We conjecture that SOE earnings are more pro-cyclical than non-SOEs, conditional on industry. In booms, SOEs expand faster due to cheaper financing costs from an implicit government guarantee (Song et al., 2011) and greater monopsony power that enables them to take advantage of the rising market demand (Fernández-Villaverde et al., 2021). However, SOEs suffer more significant earnings losses during economic slowdowns because they have a responsibility to maintain social stability (Bai et al., 2006), which prohibits them from firing workers and cutting procurement of intermediate goods.

To gauge the difference in earnings' cyclicality between SOEs and non-SOEs, we estimate:

$$\Delta Earnings_t^j = \eta_1 + \eta_2 \Delta y_t + \eta_3 SOE_t^j + \omega \Delta y_t \times SOE_t^j + indu^j + \epsilon_t^j,$$

where $\Delta Earnings_t^j$ is the earnings growth for company $j$, $\Delta y_t$ is the real GDP growth rate, $SOE_t^j$ is a dummy that equals one if a company is SOE (it has a time subscript because ownership can vary over time), and $indu^j$ is the industry fixed effect. By controlling for industry fixed effects, we rule out the potential effect of SOEs having a large weight in sectors with high or low cyclicality. The coefficient of interest is $\omega$, which is expected to be positive if SOE earnings are more cyclical than non-SOEs. Column (1) of Table 5 shows that the estimated interaction term is positive. In particular, our results indicate that SOE earnings are about 53%

**Table 5:** Cyclicality of SOEs' earnings: Panel

Data is semiannual between 2008 Q3 and 2020 Q2. The dependent variable is earnings growth. $\Delta y_t$ is the real GDP growth rate. $SOE_t^j$ is a dummy variable that equals one if a company is SOE. All standard errors are clustered at the indsutry and quarter levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) |
|---|---|---|
| Dependent Variable : | Earnings growth | |
| GDP Growth Rate | 2.07*** | 3.44*** |
| | (16.44) | (27.32) |
| SOE | -0.11*** | -0.11*** |
| | (-8.07) | (-5.56) |
| GDP Growth Rate*SOE | 1.09*** | 0.46** |
| | (5.97) | (2.50) |
| Constant | -0.19*** | -0.27*** |
| | (-20.65) | (-24.18) |
| Industry FE | Yes | No |
| Firm FE | No | Yes |
| R-squared | 0.01 | 0.16 |
| Observations | 114,754 | 114,960 |

(1.09/2.07) more sensitive to GDP growth than non-SOEs. The coefficient on $SOE$ is negative, showing that SOEs have lower average earnings growth than non-SOEs. Column (2) of Table 5 reports results when we replace industry with firm fixed effects. This shows that SOE earnings are more cyclical than non-SOEs under the alternative specification.

Greater cyclicality of SOE earnings suggests that fund managers will reallocate investment toward SOE stocks when expecting strong economic growth. We test this by estimating:

$$\omega^i_{SOE,t} = \alpha + \eta E^i_t(\Delta y_{t+1}) + X_t + \chi^i + \gamma_t + \epsilon^i_t,$$

where $\omega^i_{SOE,t}$ is the fraction of fund value allocated to the SOE stocks. $E^i_t(\Delta y_{t+1})$ is the growth expectation. $X_t$ is a vector of control variables such as lagged fund size and fund flows. $\chi^i$ and $\gamma_t$ are fund and time fixed effects.

Table 6 reports the results. Column (1) shows that fund managers allocate more value to SOE stocks when expecting strong economic growth, consistent with the strong cyclicality of SOEs' earnings documented earlier. Column (2) shows that this is robust to including time fixed effects, so the positive correlation between SOE investment and growth expectations is not driven by the two variables' correlation with aggregate variables such as real GDP growth.

**Table 6:** Growth Expectation and Portfolio Adjustment in SOEs: Panel

Data is quarterly between 2008 Q3 and 2020 Q2. In columns (1-2), the dependent variables, *SOE* is the proportions of TNA in SOE stocks. In columns (3-4), the dependent variable, *SOE/Equity* is the proportion of equity market value in SOE stocks. All standard errors are clustered at the fund and quarter levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable : | SOE (%) | | $\frac{SOE}{Equity}$ (%) | |
| Growth Expectation | 1.011** | 0.283* | 0.791* | 0.200 |
| | (2.73) | (1.95) | (1.72) | (0.88) |
| Lagged SOE/TNA | 0.373*** | 0.344*** | | |
| | (7.19) | (12.77) | | |
| Lagged SOE/Equity | | | 0.367*** | 0.293*** |
| | | | (6.32) | (10.08) |
| Lagged Log(TNA) | -0.430 | -0.467** | -0.185 | -0.227 |
| | (-1.27) | (-2.32) | (-0.37) | (-0.52) |
| Lagged Log(Age) | -0.738 | -0.444 | -1.599 | -0.081 |
| | (-0.67) | (-1.38) | (-0.96) | (-0.15) |
| Lagged Fund flows | -0.004 | -0.002 | 0.008 | 0.010 |
| | (-0.52) | (-0.47) | (1.37) | (1.26) |
| Expense Ratio | 6.551 | 4.885 | -18.323** | -17.300* |
| | (0.43) | (0.53) | (-2.29) | (-1.80) |
| Constant | 1.870 | 23.004*** | 13.615 | 35.222*** |
| | (0.24) | (14.11) | (1.13) | (9.98) |
| Fund FE | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes |
| R-squared | 0.702 | 0.756 | 0.569 | 0.639 |
| Observations | 12,967 | 12,967 | 12,815 | 12,815 |

Lastly, Columns (3) and (4) show that fund managers who are optimistic about economic growth increase investment in SOE stocks as a fraction of equity investment. The results verify that the positive correlation between growth expectations and SOE investment (Columns (1) and (2)) is not simply due to the positive correlation between equity investment and growth expectations (note that equity investment itself is positively correlated with growth expectations), which reinforces our previous findings. Table C.1 in Section C of the Appendix verifies that the changes in SOE shares reflect fund managers' strategic portfolio choice rather than the valuation effect of changes in asset prices.

# 4 Effects on Prices

Given that growth expectations influence fund managers' portfolio choices, changes in optimism about economic growth should affect asset prices through shifts in demand. Greater (lower) optimism about economic growth encourages fund managers to take on more (less) stock market risk, pushing up (pulling down) stock prices. In this section we examine the price impact of managers' growth expectations. We also investigate longer-term asset pricing implications of these expectations by examining how expectations and investments shape how stock prices are related to companies' future earnings growth, following the literature on "price informativeness" (Bai et al. (2016), Dávila and Parlatore (2018), Carpenter et al. (2021)). We find evidence that fund managers' macroeconomic analysis improves price informativeness.

Beginning with aggregate data, Figure 4 displays a positive relationship between the consensus growth expectations (blue solid curve) and the log market price-dividend ratio in the last month of each quarter (black dashed curve). The consensus expectation (i.e., the average expectation across managers) is defined here as:

$$E_t^{cons}\left(\Delta y_{t+1}\right) = \frac{\sum_{i=1}^{N_t} E_t^i\left(\Delta y_{t+1}\right)}{N_t},$$

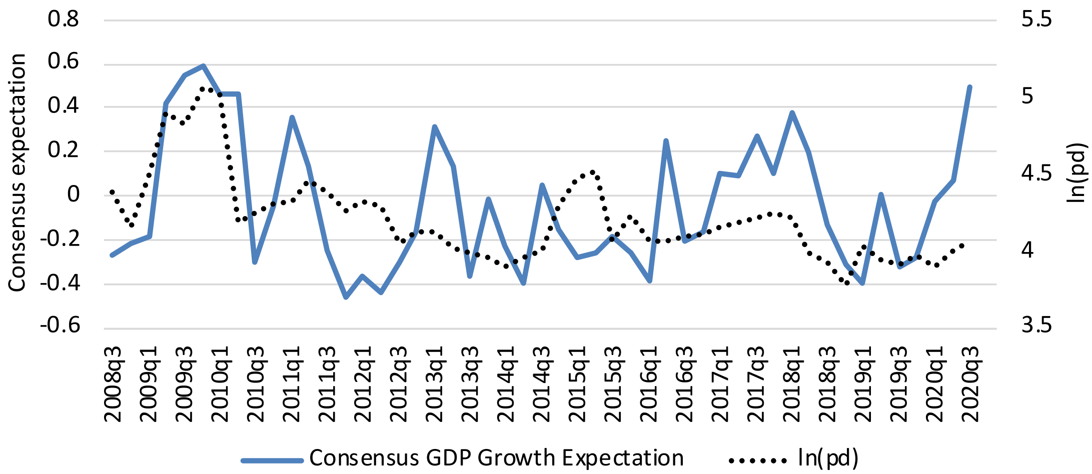
where $N_t$ is the number of reports with a usable GDP growth forecast score in period $t$. Pessimism about economic growth in 2018 Q3, for example, possibly due to weakness in growth and a series of announcements on trade restrictions between the United States and China was associated with a decline in the p-d ratio. This may have been driven by pessimistic investors' decreasing their stock market risk exposure.

We examine the relationship between consensus growth expectations and stock prices by estimating:

$$pd_t = \alpha + \eta E_t^{cons}(\Delta y_{t+1}) + \mu \Delta y_t + \epsilon_t, \tag{5}$$

where $pd_t$ is the log p-d ratio of the stock market index in the last month of each quarter. $E_t^{cons}(\Delta y_{t+1})$ is the consensus expectation.

**Figure 4:** Comovement of the consensus growth expectation and the p-d ratio




The blue solid curve is the consensus growth expectation, the black dashed curve is the log p-d ratio of the stock market.

**Table 7:** Growth Expectation and Stock Price: Time Series

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variables are the log p/d ratio and the monthly stock market return. *Consensus Growth Expectation* is the consensus expectation of the GDP growth rate. GDP Growth is the year-on-year GDP growth rate. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) |
|---|---|---|
| Dependent Variable : | log p-d ratio | |
| Consensus Growth Expectation | 0.43*** | 0.40*** |
| | (3.36) | (3.85) |
| GDP growth rate | | 7.78*** |
| | | (4.90) |
| Constant | 4.25*** | 3.66*** |
| | (113.61) | (30.32) |
| Adj R-squared | 0.18 | 0.45 |
| Observations | 49 | 49 |

Column (1) of Table 7 shows that the consensus growth expectation is positively correlated with the log p-d ratio, consistent with our hypothesis that greater allocation of equity and more risk-taking induced by optimism about economic growth boosts stock prices. Column (2) shows that the positive correlation between the aggregate stock market valuation and the consensus growth expectation is robust to including actual GDP growth. Appendix Section D shows that the consensus expectation predicts both real GDP growth and an alternative measure of macroeconomic growth.

While the above findings are suggestive of the price impact of growth expectations, causality could go the other way, i.e., fund managers learn from the stock market index when forming growth expectations. To clarify the causal effect of growth expectations, we test whether the stock return of a company is affected by the growth expectations of fund managers who held that stock at the end of the previous period. This exercise avoids the above-mentioned reverse causality, as fund managers are unlikely to learn about macroeconomic growth from individual stock prices. We estimate:

$$r_t^j = \alpha + \eta E_t^j(\Delta y_{t+1}) + \mu \Delta y_t + Z_{t-1}^j + \chi^j + \epsilon_t^j, \tag{6}$$

where $r_t^j$ is the end-of-month stock return in period $t$. $E_t^j(\Delta y_{t+1})$ is the average growth expectations of fund managers who held stock $j$ in the *previous* quarter. $Z_{t-1}^j$ is a vector of stock-level controls, including CAPM beta, market value, turnover rate, market-to-book ratio, and earnings-per-share, which are valued in the previous period. $\chi^j$ is the stock fixed-effect. The coefficient of interest is $\eta$. As detailed stock holding information is disclosed in mid-year and end-of-year reports, the estimation of equation (6) uses two observations per year.[14]

Benchmark results are in Column (1) of Table 8. The coefficient on $E_t^j(\Delta y_{t+1})$ is positive and statistically significant. Given that the standard deviation of $E_t^j(\Delta y_{t+1})$ is 0.51, a one standard deviation increase (decrease) in the average growth expectation of fund managers investing in a stock increases (decreases) the monthly return by 0.66% (1.3%*0.51), which is economically large. Column (2) shows that the result is robust to including common stock controls.

As shown in Section 3, fund managers tilt their investment to SOE stocks and cyclical industries when expecting robust economic growth. Hence it is natural to conjecture that SOE stocks and cyclical industries respond more strongly to changes in growth expectations. Columns (3-4) display the results when we include an interaction term between growth expectation and the SOE dummy variable. The interaction term is positive and statistically significant, implying that SOE stock prices are more sensitive to growth expectations.

Columns (5-6) display the results with an interaction term between growth expectation

[14]By construction, estimation of equation (6) is restricted to the sample of stocks that are held by forecasting managers.

**Table 8:** Growth Expectation and Return of Stocks with Various Manager Holdings: Panel

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variable is the stock returns in the last month of each quarter. *Forecasting Manager Holding* is the proportion of shares held by the managers that give growth forecasts. *Holders' Growth Expectation* is the consensus expectation of GDP growth rate of managers that hold the stock. *SOE* is a dummy that is equal to 1 if the firm is an SOE, and 0 otherwise. *Cycle* is a dummy that is equal to 1 if the firm is in a cyclical industry, and 0 otherwise. In columns (2), (4), and (6), stock controls include CAPM beta, market value, turnover rate, market-to-book ratio, earnings-per-share, and SOE. The standard errors are clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable : | Stock return in Month of Fund Report | | | | | |
| Holders' Growth Expectation | 0.014*** | 0.013*** | 0.007*** | 0.006*** | 0.010* | 0.011* |
| | (9.76) | (8.63) | (3.42) | (2.93) | (1.67) | (1.93) |
| Holders' Growth Expectation * SOE | | | 0.015*** | 0.014*** | | |
| | | | (5.64) | (4.74) | | |
| Holders' Growth Expectation * Cycle | | | | | 0.005 | 0.002 |
| | | | | | (0.80) | (0.32) |
| Forecasting Manager Holding | -0.237*** | -0.155*** | -0.240*** | -0.159*** | -0.238*** | -0.156*** |
| | (-7.22) | (-4.35) | (-7.33) | (-4.45) | (-7.24) | (-4.36) |
| GDP Growth Rate | 0.362*** | 0.371*** | 0.359*** | 0.370*** | 0.362*** | 0.371*** |
| | (12.36) | (11.29) | (12.29) | (11.27) | (12.36) | (11.29) |
| Constant | 0.004** | 0.091*** | 0.004** | 0.089*** | 0.004** | 0.090*** |
| | (2.24) | (5.76) | (2.36) | (5.64) | (2.24) | (5.75) |
| Stock Controls | No | Yes | No | Yes | No | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-squared | -0.013 | 0.001 | -0.012 | 0.002 | -0.013 | 0.001 |
| Observation | 39,129 | 35,408 | 39,129 | 35,408 | 39,129 | 35,408 |

and the cyclical industries dummy variable. Although the interaction term is positive, it is not statistically significant. A possible explanation is that the majority of stocks belong to cyclical industries (i.e., with a positive correlation between earnings growth and GDP growth), hence a large part of the reallocation occurs between industries that are strongly cyclical (such as construction) and mildly cyclical (such as mining). Indeed, Table F.1 in Section F of the Appendix shows that the industries whose cyclicality is above the median among the cyclical industries are more responsive to changes in growth expectations.

## 4.1 Short-sale constraints and growth expectations

While our previous findings imply a critical informational role of the stock market, pass-through of information can be incomplete and lead to allocative inefficiency due to frictions such as short-

**Table 9:** Short-sale Constraint and overpricing of stocks

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variable is the stock returns in the last month of each quarter. *Low Holdings of Negative Forecasters* is a dummy that is equal to 1 if the proportion of shares held by the managers with negative growth forecasts is in the bottom half. In column (2), stock controls include CAPM beta, market value, turnover rate, market-to-book ratio, earnings-per-share, and SOE. The standard errors are clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) |
|---|---|---|
| Dependent Variable : | Stock return in Month of Fund Report | |
| Low Holdings of Negative Forecasters | 0.010*** | 0.007*** |
| | (5.93) | (3.79) |
| Holders' Growth Expectation | 0.011*** | 0.011*** |
| | (7.80) | (7.15) |
| GDP Growth Rate | 0.338*** | 0.368*** |
| | (12.01) | (11.25) |
| Constant | -0.002 | 0.070*** |
| | (-1.02) | (4.64) |
| Stock Controls | No | Yes |
| Stock FE | Yes | Yes |
| Adj R-squared | -0.013 | 0.001 |
| Observation | 39,129 | 35,408 |

sale constraints. Although short sales have become gradually available to many investors in the Chinese stock market, they are still strictly forbidden for mutual funds, preventing bearish managers from selling stocks in which they hold a zero position.[15] As shown by Hong and Stein (2003) theoretically, this leads to the over-pricing of stocks followed by a downward adjustment.

To study the effects of short-sale constraints on stock prices, we estimate:

$$r_t^j = \alpha + \eta \text{LowFMH}_{-,t}^j + \rho E_t^j(\Delta y_{t+1}) + \mu \Delta y_t + Z_{t-1}^j + \chi^j + \epsilon_t^j, \tag{7}$$

where $\text{LowFMH}_{-,t}^j$ is a dummy variable that equals one if stock $j$'s proportion of shares held by fund managers with negative (labeled by the subscript "-") growth expectation is below the median, which indicates a low position of pessimistic fund managers. Table 9 displays the results. Low holding of pessimistic fund managers induces a higher stock return. This is consistent with the fact that short-sale constraints impede the trading of pessimistic fund managers with low positions, hence the stock price is dominated by the positive view.

[15]The literature studying the implication of short-sale constraints is vast; see, for instance, Jones and Lamont (2002) and Saffi and Sigurdsson (2011).

**Table 10:** Short-sale Constraint and Lagged Price

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variable is the stock returns in the last month of each quarter. *Low Holdings of Negative Forecasters* is a dummy that is equal to 1 if the proportion of shares held by the managers with negative growth forecasts is in the bottom half. In column (2), stock controls include CAPM beta, market value, turnover rate, market-to-book ratio, earnings-per-share, and SOE. The standard errors are clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) |
|---|---|---|
| Dependent Variable : | Stock return in he Following Month | |
| Low Holding of Negative Forecasters | -0.006*** | -0.009*** |
| | (-3.56) | (-5.12) |
| Holders' Growth Expectation | 0.016*** | 0.015*** |
| | (11.31) | (9.67) |
| GDP Growth Rate | -0.058** | -0.346*** |
| | (-2.29) | (-10.51) |
| Constant | 0.016*** | 0.375*** |
| | (7.86) | (24.66) |
| Stock Controls | No | Yes |
| Stock FE | Yes | Yes |
| Adj R-squared | -0.010 | 0.044 |
| Observation | 38,188 | 34,576 |

Table 10 reports the result when the dependent variable in equation (7) is the stock return in the following month. Low holding of pessimistic fund managers predicts a downward adjustment of stock prices. A possible explanation is that investors observe the negative growth expectations of some fund managers who could not sell much due to the short-sale constraints. The investors would realize that the actual view of fund managers is more pessimistic than previously reflected in the stock price and sell accordingly. Section G in the Appendix shows similar results for the consensus growth expectations: short-sale constraints induce a muted and lagged response to negative consensus expectations for stocks held little by fund managers, because bearish fund managers are restrained from selling these stocks. While retail holders can sell, it takes time for them to learn from the consensus expectations.

## 4.2 Price informativeness

Given the above evidence that mutual fund managers and their growth expectations play a material role in price discovery, a natural extension is to assess more directly the extent to which the funds' investment choices contribute to equity valuations reflecting underlying fundamentals, which should depend mainly on companies' prospects for future payoffs. We follow Dávila and Parlatore (2018) in measuring price informativeness by estimating the extent to which a stock price reflects the future earnings of the firm. More specifically, we compare the fit of two alternative regression specifications for each stock $j$ in quarter $t$ in our sample, using its prices and earnings in a 32-quarter rolling window:

$$\Delta p_{\tau}^{j} = \overline{\beta}_{t}^{j} + \beta_{0,t}^{j}\Delta x_{\tau}^{j} + \beta_{1,t}^{j}\Delta x_{\tau+1}^{j} + d_{\tau}^{j,q} + \varepsilon_{\tau}^{j},\ \tau \in \{t-31, t-30, .., t\} \tag{8}$$

and

$$\Delta p_{\tau}^{j} = \overline{\zeta}_{t}^{j} + \zeta_{0,t}^{j}\Delta x_{\tau}^{j} + d_{\tau}^{j,q} + \epsilon_{\tau}^{j}, \tag{9}$$

where $\Delta p_{\tau}^{j}$ denotes the change in log stock price, $\Delta x_{\tau}^{j}$ is the earnings growth rate. Here, $d_{t}^{j,q}$ are the stock-specific quarterly dummies that control for potential seasonality. We denote the R-squared for regressions (8) and (9) as $R_{t,t+1}^{2,j}$ and $R_{t}^{2,j}$, respectively. Price informativeness for stock $j$ in quarter $t$ is then computed as:

$$PI_{t}^{j} = \frac{R_{t,t+1}^{2,j} - R_{t}^{2,j}}{1 - R_{t}^{2,j}}.$$

As shown by Dávila and Parlatore (2018), $PI_{t}^{j}$ is a number between 0 and 1 that measures the reduction in uncertainty about the future earnings growth ($\Delta x_{\tau+1}^{j}$) induced by the knowledge of price ($p_{\tau}^{j}$). Specifically, finding that $PI_{t}^{j} = x\%$ indicates that the uncertainty faced by an external observer about earnings growth is reduced by x% after observing the price.[16]

In this way, we obtain a panel of price informativeness for the stocks in the Chinese market. Similar to the distribution of price informativeness for U.S. stocks estimated by Dávila and Parlatore (2018), we find that the distribution of Chinese stock price informativeness is right-skewed with a median and mean of 2.1% and 5.4%, respectively. The average degree of price informativeness of Chinese stocks is slightly higher in our sample than the corresponding

[16] As shown by Dávila and Parlatore (2018), in a Gaussian environment, an alternative interpretation of $PI_{t}^{j} = x\%$ is that an external observer puts a weight of x% on the price signal, and a weight of 1-x% on the prior, when forming a posterior belief over future earnings growth.

statistics reported for U.S. stocks from 1980 to 2017 by Dávila and Parlatore (2018) (median 1.8% and mean 4.3%). This echoes the findings of Carpenter et al. (2021), who estimate the Chinese stock market's price informativeness using the alternative method of Bai et al. (2016).[17]

To gauge the role of Chinese fund managers in stock price informativeness, we split informativeness in each quarter into twenty bins (again following Dávila and Parlatore (2018)) and calculate average informativeness by bin in the quarter. Then we estimate:

$$\overline{PI}_t^b = a_0 + a_1 \overline{FMH}_{t-1}^b + Z_{t-1}^b + \gamma_t + \epsilon_t^j,\ b \in \{1, 2, \cdots, 20\} \tag{10}$$

where $\overline{PI}_t^b$ is the average price informativeness per ventile in period $t$. $\overline{FMH}_{t-1}^b$ is the average forecasting fund managers' holdings per ventile in the previous period. $Z_{t-1}^b$ is a vector of control variables, including market cap, book-to-market ratio, and turnover ratio in the previous period. $\gamma_t$ is the year fixed effect.

The results are reported in the first column of Table 11. Higher forecasting fund manager holdings are associated with higher price informativeness. The positive relationship could be driven by information about companies' future payoffs that is discovered by the fund managers, or perhaps fund managers pick stocks with high price informativeness. While we cannot rule out the latter channel, our previous findings about the price impact of forecasting fund managers' growth expectations support the former channel that forecasting fund managers improve price informativeness. Dávila and Parlatore (2018) similarly find that institutional ownership is positively associated with the price informativeness of U.S. stocks. The coefficient on market cap is estimated as positive, indicating that stocks with higher price informativeness are typically for larger companies, also similar to the findings in the U.S. market (Dávila and Parlatore, 2018). In contrast, the book-to-market and turnover ratios are not significantly related to price informativeness conditional on forecasting manager holding and market cap. The insignificant result for the turnover ratio is unsurprising as the Chinese stock market's trading volume is

[17]Their informativeness measure focuses on the predictive power of stock price on companies' long-term earnings growth. In contrast, the price informativeness measure proposed by Dávila and Parlatore (2018) is more short-term oriented which is relevant to our quarterly growth expectations.

dominated by retail investors who are less efficient in producing valuable information in the stock market.[18] The second column of Table 11 shows that the results are similar though milder when we consider the holdings of all fund managers, including the ones who did not report their growth expectations. The third column shows the result when fund managers' holdings are dropped from the regression. The adjusted $R^2$ is lower than in the first two columns, indicating that fund managers' holdings are a key determinant of stocks' price informativeness.

**Table 11:** Price informativeness and firm characteristics: Panel

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variable is the average price informativeness in each ventile bin. The independent variables are the average value of stock characteristics in each bin. *Manager Holding* is the weight of stock value held by mutual fund managers, *Forecasting Manager Holding* is the weight of stock value held by mutual fund managers with growth expectations, *Size* is the logarithm value of the market capitalization, *Value* is the book-to-market ratio, and *Turnover* is the turnover ratios of the stock. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable : | Price Informativeness | | |
| Forecasting Manager Holding | 3.598*** | | |
| | (3.04) | | |
| Manager Holding | | 2.184*** | |
| | | (4.97) | |
| Size | 0.092*** | 0.064** | 0.119*** |
| | (3.53) | (2.42) | (4.87) |
| Value | -0.093 | -0.109 | -0.092 |
| | (-1.03) | (-1.22) | (-1.01) |
| Turnover | -0.000 | -0.000 | -0.001 |
| | (-0.62) | (-0.75) | (-1.05) |
| Year FE | Yes | Yes | Yes |
| Observation | 480 | 480 | 480 |
| Adj R-squared | 0.068 | 0.097 | 0.051 |

# 5 Conclusion

We construct a novel measure of Chinese mutual fund managers' macroeconomic growth expectations, analyze how they invest according to these expectations, the subsequent effect on stock returns, and whether these actions improve price informativeness. We do this using a novel systematic textual analysis of the discussion in the quarterly reports of China fund managers.

[18]The Annual Statistical Report of Shanghai Stock Exchange shows that the retail investors accounted for 85.2% of trading volume at the Shanghai Stock Exchange in 2014, the middle year of our sample periods.

We have three main findings. First, expectations of lower GDP growth robustly explain bearish portfolio shifts; fund managers adjust exposure to stock market risks and reallocate between industries and companies with different degrees of cyclicality, accordingly. Second, growth expectations have significant short-run asset pricing implications. The contemporaneous impact on prices is weaker for stocks under-weighted by fund managers, broadly consistent with short-sale constraints impeding price discovery after the outlook for growth has weakened. Finally, fund managers improve price informativeness in the Chinese stock market.

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# Online Appendix: Material not Included for Publication

# A Details on the computation of forecast score

## A.1 Textual analysis algorithm

In this subsection, we describe the algorithm of textual analysis for the construction of forecast scores. We consider the following five-step procedure. **Step 1**: drop the sentences that express mutual funds' compliance with the regulatory rules and commitment to the investors. We identify them using "We appreciate the trust of our investors", "We treasure the trust of our investors", "We will try to", etc.[19]

**Step 2**: divide each report in the Market Outlook sections into semantic units that are separated by punctuation marks (commas, periods, and semicolons) and other indications that signal a pause in the narrative flow.

**Step 3**: keep the semantic units that are related to China's economic growth. To do so, we compute the frequency of use of all content words and phrases in the reports.[20] From the most frequently used 2586 words and phrases, including 1000 nouns, 1000 verbs, and 586 adverbs and adjectives (the total number), we judgmentally select a dictionary of words and phrases related to China's GDP growth from them, including

- 16 words and phrases that indicate GDP (e.g., "GDP growth" and "national income"), which we refer to as *keywords*;
- 274 words and phrases that indicate the expected strength of GDP growth (e.g., "increase" "stagnant"), which we refer to as *directional words*;
- 6 words and phrases that indicate both GDP growth and the expected strength of GDP growth (e.g., "economic growth slowdown" "hard landing"), which we refer to as *composite*

[19] These sentences need to be dropped before the textual analysis as some of them contain keywords related to economic growth and could be mistakenly interpreted as growth expectations. For example, "We will try to find the potential opportunities according to GDP growth condition and form robust investment strategies."

[20] Non-content words, such as function words, are automatically removed in the previous step.

*words*;

- 228 words and phrases that indicate the probability or magnitude of GDP growth (e.g., "mildly" and "potentially") or negation (e.g., "no","not"), which we refer to as *scaly words*.

We next apply a rule that treats a semantic unit as potentially informative about future GDP growth if it has at least one keyword and at least one word that indicates the expected strength of GDP growth or at least one composite word from our list. In addition to the dictionary of selection words and phrases, we also construct a list of disqualifying words and phrases such as "U.S." and "emerging market" that in our judgment indicates that the semantic unit does not characterize the stance of Chinese economic growth. Any semantic unit that contains these words and phrases is dropped. We then assign scores to the words and phrases defined in step 2. The score value of keywords is 1.[21] The directional words take the score value from $\{-1, -0.5, 0, 0.5, 1\}$.[22] Some directional words take the score of -0.5 and 0.5 as they show a low probability or small magnitude.[23] We assign to composite words score values from $\{-1, 0, 1\}$.[24] The scaly words take the score value within the set $[-1, 1]$. The assignment of score to scaly words can be complicated in some cases (such as "higher probability") in which they are a combination of an auxiliary word ("probability") and a directional word ("higher"). Appendix A.2 provides details on the assignment of scores to the scaly words.

**Step 4**: assign each semantic unit a score within the set $[-1, 1]$ based on the combination of words and phrases in the semantic unit. The next subsections provides details and examples for the computation of scores for semantic units. The sign of a semantic unit's score depends on the combination of keywords, directional words, and scaly words about negation, which jointly

[21] For example, score("GDP") = 1

[22] For example, score("pessimistic") = $-1$, score("increase") = 1, score("unchanged") = 0.

[23] For example, score("mild increase") = 0.5. Note that mild increase is one word in Chinese rather than two words as in its English translation.

[24] For example, score("Pessimistic economic outlook") = $-1$, score("unchanged GDP growth") = 0, score("strong GDP growth") = 1.

determines the expected strength of economic growth:

$$\text{score(semantic unit k)} \begin{cases} > 0 & \text{if expects a strong economic growth} \\ = 0 & \text{if expects a moderate economic growth} \\ < 0 & \text{if expects a weak economics growth} \end{cases}$$

The absolute value of the score depends on the scaly words that reflect either the degree of certainty or the magnitude of the expected monetary policy change (e.g., possibly; mildly); higher certainty or magnitude is assigned a larger absolute score. Either type of scaly word signals certainty about a nonzero move in that direction, which is what we ultimately test.

**Step 5**: compute the mean score across the semantic units within each report, denoted as $E_t^i(\Delta y_{t+1})$ for manager $i$ in period $t$. By construction, $E_t^i(\Delta y_{t+1}) \in [-1, 1]$. The sign of $E_t^i(\Delta y_{t+1})$ indicates the expected strength of GDP growth in period $t+1$:

$$E_t^i(\Delta y_{t+1}) \begin{cases} > 0 & \text{if expects a strong economic growth} \\ = 0 & \text{if expects a moderate economic growth} \\ < 0 & \text{if expects a weak economic growth} \end{cases}$$

$E_t^i(\Delta y_{t+1})$ incorporates the adverbs (e.g. "possibly", "mildly") across these semantic units, and thus we expect its absolute value to reflect the level of certainty and expected magnitude of the changes in GDP growth.

## A.2 The assignment of score to scaly words

Scaly words are the words and phrases that indicate the probabilities or magnitude of monetary policy shifts or indicate negation. In most cases, scaly words are simple words and phrases, to which we assign them scores from $\{-1, -0.5, 0, 0.5, 1\}$. For example, score(will not) $= -0.5$, score(likely) $= 0.5$, score(substantially) $= 1$.

In other cases, scaly words, such as "higher probability", are combinations of an *auxiliary* word such as “probability” and a verb or adjective such as “higher” that can also serve as a directional word. We first assign scores to the auxiliary words with values from $\{-1, 1\}$. For example, score(difficulty) $= -1$, score(probability) $= 1$. Then we compute the score of scaly word as:

$$\text{score(scaly word)} = 0.75 + 0.25 * \text{score(auxiliary word)} * \text{score(directional word)}.$$

For example, score(higher probability) $= 0.75 + 0.25 * 1 * 1 = 1$, score(less difficulty) $= 0.75 + 0.25 * (-1) * (-1) = 1$.

## A.3 The assignment of score to semantic units

In this subsection, we describe the assignment of score to semantic units. A semantic unit can have multiple keywords or composite words. We use the five words before and five words after each keyword/composite word. Then we calculate the score around the keyword/composite word. We first focus on the case in which there is only one keywords or composite words.

Case 1. When there is only one keyword, the score of semantic unit is determined by:

$$\text{score(semantic units)} = \text{score(keyword)} * \text{score(directional word)} * \text{score(scaly word)}.$$

When there is no directional word, we drop the semantic unit. When there is no scaly word, we treat score(scaly word) $= 1$. When there are multiple directional words or scaly words, we compute the mean of them.

Example:

$$\begin{aligned} &\text{score(Economic growth will slowdown with a higher probability)} \\ = &\text{score(Economic growth)} * \text{score(slowdown)} * \text{score(higher probability)} = 1 * (-1) * 1 = -1 \end{aligned}$$

Case 2. When there is only one composite word, the score of semantic unit is determined by:

$$\text{score(semantic units)} = \text{score(composite word)} * \text{score(scaly word)}.$$

When there is no scaly word, we treat score(scaly word) = 1. When there are multiple scaly words, we compute the mean of them.

Example:

$$\begin{aligned} &\text{score(Hard-landing is possible)} \\ &= \text{score(hard-landing)} * \text{score(possible)} = -1 * 0.5 = -0.5 \end{aligned}$$

Lastly, when there are more than one keyword or composite word in the same semantic unit, we keep one keyword or composite word at a time and compute the score as in Case 1 and Case 2. In this way, we obtain multiple scores for the semantic unit, each score corresponds to one keyword or composite word. Then we take the mean of the scores.

# B Sample mutual fund quarterly report

In this section, we provide an example of the *Market Outlook* sections.

The example is taken from a 2008 Q3 report written by Huaizhi Gong, the manager of Huaxia Chengzhang Equity Investment Fund. In 2008 Q3, the fund had a TNA of 8,162,348,304.30 RMB. The fund is an open fund that belongs to the fund family, Huaxia Fund Management.

[1] A 股市场经历了恐慌性下跌后(After the A-share market experienced a panic decline), [2] 上市公司整体估值已趋于合理水平(the overall valuation of listed companies has tended to a reasonable level). [3] 展望2008 年4 季度(Looking ahead to the fourth quarter of 2008), [4] **经济形势**的演变趋势和政策导向将主导市场运行方向(the evolutionary trend of the **economic situation** and policy orientation will dominate the direction of market operation). [5] 各国政府的持续救市行为以及A 股大股东不断在二级市场上增持上市公司股票有助于改善市场信心严重缺失的状态(Continued bailouts by the governments of various nations and the continued increase in the holdings of listed companies in the secondary markets by the major shareholders of the A-share market will help to improve the serious lack of confidence in the market). [6] 随着**经济增速**进一步**放缓** (With the further **slowdown** of **economic growth**),

[7] 上市公司业绩分化将愈发明显(the performance differentiation of listed companies will become more and more obvious), [8] 股票市场走势将呈现出个股分化与宽幅震荡的特征(the trend of the stock market will show the characteristics of individual stock differentiation and wide range shocks).

The above report contains 8 semantic units. The sixth semantic unit is effective by containing at least one keyword and one directional word (or a composite word) in bold. While the fourth semantic unit contains a keyword, it has no words or phrases that indicate the direction of GDP growth.

For the sixth semantic unit:

Score(With the further **slowdown** of **economic growth**) = score(economic growth) * score(slowdown) = 1 * (-1)=-1.

It yields that the forecast score for the report is equal to -1, indicating that the manager expects the economic growth to slow down.

# C Measuring portfolio shifts net of valuation effects

Section 3 shows that fund managers' equity share and the shares of pro-cyclical industries positively comove with their growth expectations. However, such comovement could be driven by changes in stock prices rather than fund managers' strategic portfolio adjustment. To isolate fund manager's strategic portfolio adjustment from the valuation effect of stock price changes, we compute a fund manager's hypothetical holding of an asset $j$ as:

$$\widetilde{S}^i_{j,t} = S^i_{j,t} - n_{j,t-1}(p_{j,t} - p_{j,t-1}), \tag{C.1}$$

where $\widetilde{S}^i_{j,t}$ and $S^i_{j,t}$ are the hypothetical and the actual holding of asset $j$, with $S^i_{j,t} = n_{j,t} \times p_{j,t}$. The last term on the RHS of equation (C.1), $n_{j,t-1}(p_{j,t} - p_{j,t-1})$, is the "passive" holding changes due to changes in price. Therefore, $\widetilde{S}^i_{j,t}$ is immune from the valuation effect of price changes.

We calculate the equity share and the shares of pro-cyclical industries based on the newly constructed asset holding measure, $\widetilde{S}^i_{j,t}$. Table C.1 displays the estimation results, which verify that our previous findings of managers' trading behavior according to growth expectations indeed reflect their strategic portfolio choice.

**Table C.1:** Growth expectation and Portfolio Adjustment Adjusted for Valuation Effect: Panel

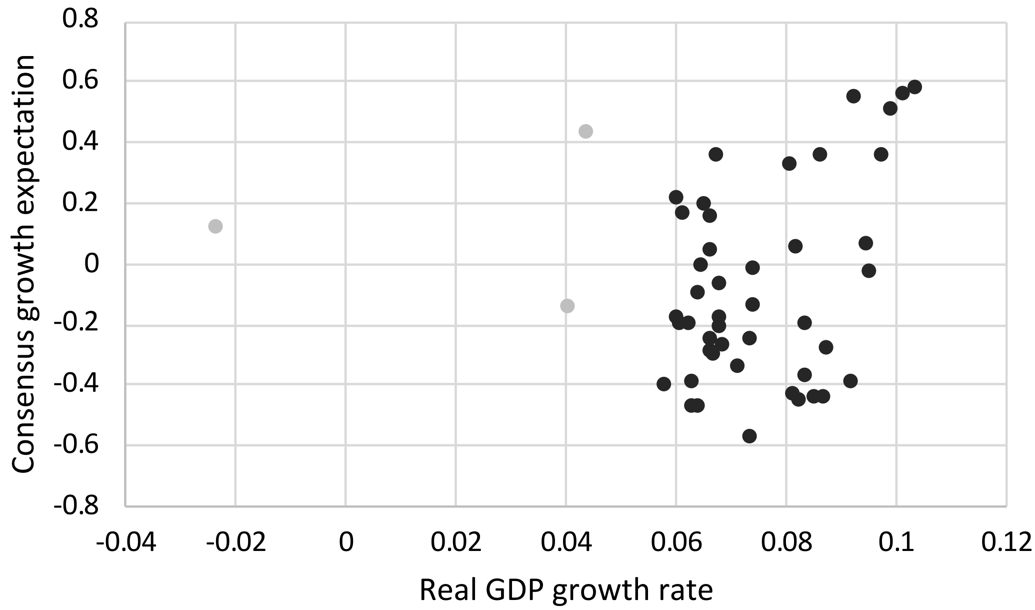
The table rules out the potential valuation effect in portfolio adjustments. Data are quarterly between 2008 Q3 and 2020 Q2. In columns (1-2), the dependent variable, *Equity/TNA* is the value proportion of equity over TNA where the value increase from price changes of stocks are removed. In columns (3-4), the dependent variable, *Pro-Cycle/Equity* is the value proportion of stocks in pro-cycle industries where the value increase from price changes of stocks are removed. All standard errors are clustered at the fund and quarter levels. In columns (5-6), the dependent variable, *SOE/Equity* is the value proportion of SOE stocks where the value increase from price changes of stocks are removed. All standard errors are clustered at the fund and quarter levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable : | $\frac{Equity}{TNA}$ (%) | | $\frac{Cycle}{Equity}$ (%) | | $\frac{SOE}{Equity}$ (%) | |
| Growth Expectation | 0.767*** | 0.397** | 0.897*** | 0.321** | 1.350** | 0.667 |
| | (2.99) | (2.33) | (3.91) | (2.42) | (2.16) | (1.50) |
| Lagged Equity/TNA | 0.234*** | 0.223*** | | | | |
| | (5.49) | (5.20) | | | | |
| Lagged Pro-Cyclical/Equity | | | 0.269*** | 0.219*** | | |
| | | | (7.10) | (7.05) | | |
| Lagged SOE/Equity | | | | | 0.229*** | 0.116** |
| | | | | | (3.18) | (2.17) |
| Lagged Log(TNA) | -1.050** | -1.523*** | 0.341* | 0.131 | 1.114* | -0.036 |
| | (-2.54) | (-3.81) | (1.78) | (0.88) | (1.86) | (-0.06) |
| Lagged Log(Age) | 0.646 | 0.777 | -0.590* | 0.177 | -6.503*** | 0.640 |
| | (0.80) | (1.29) | (-1.72) | (0.72) | (-3.85) | (0.40) |
| Lagged Fund flows | -0.014 | -0.013 | 0.002 | 0.003 | 0.009* | 0.013* |
| | (-1.00) | (-0.93) | (1.21) | (1.52) | (1.97) | (1.86) |
| Expense Ratio | 54.150*** | 42.909*** | -2.835 | -1.812 | -22.460 | -29.772 |
| | (2.89) | (3.33) | (-0.64) | (-0.45) | (-1.08) | (-1.08) |
| Constant | 54.893*** | 58.383*** | 66.694*** | 70.715*** | 44.609*** | 39.528*** |
| | (12.26) | (18.56) | (14.73) | (22.68) | (7.83) | (12.97) |
| Fund FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes | No | Yes |
| Adj R-squared | 0.837 | 0.844 | 0.311 | 0.363 | -0.077 | -0.071 |
| Observation | 13,195 | 13,195 | 13,187 | 13,187 | 12,762 | 12,762 |

# D Predictive power of the consensus growth expectation

To study how fund managers form expectations about economic growth, we first assess the predictive power of the consensus growth expectation (i.e., the average expectation across managers) to the realization of the real GDP growth rate in the subsequent quarter. The consensus

**Figure D.1:** Consensus growth expectation vs. Real GDP Growth




Data are quarterly between 2008 Q3 and 2020 Q3. The vertical axis is the consensus growth forecast, $E_{t-1}^{cons}(\Delta y_t)$. The horizontal axis is the real GDP growth rate, $\Delta y_t$.

growth expectation, denoted as $E_t(\Delta y_{t+1})$, is defined as:

$$E_t^{cons}(\Delta y_{t+1}) = \frac{\sum_{i=1}^{N_t} E_t^i(\Delta y_{t+1})}{N_t},$$

where $N_t$ is the number of reports with a GDP growth forecast score in period $t$.

By construction, the consensus growth expectation $E_t^{cons}(\Delta y_{t+1})$ takes a value between -1 and 1. A positive (negative) value indicates that, on average, managers expect strong (weak) economic growth. The consensus growth expectation is zero if, on average, managers expect moderate economic growth. The absolute value of the consensus growth expectation reflects the proportion of fund managers who expects the GDP growth to move in a certain direction.

Figure D.1 displays the scatter plot of the real GDP growth rate, $\Delta y_t$, and the consensus growth expectation made in the previous period, $E_{t-1}^{cons}(\Delta y_t)$. The correlation is positive, indicating generally good growth expectations. The three outliersïŒ 2020 Q1-Q3 (light gray dots), all occur during the outbreak of the Covid pandemic. This is unsurprising given that the pandemic was entirely unexpected and unprecedented.

We formally examine the predictive power of the consensus growth expectation by estimating the following regression model in the sample ending in 2019:

$$\Delta y_t = \alpha + \eta E^{cons}_{t-1}(\Delta y_t) + \epsilon_t, \tag{D.1}$$

where $\Delta y_t$ is the year-on-year real GDP growth rate. $E^{cons}_{t-1}(\Delta y_t)$ is the consensus growth expectation of fund managers. Column (1) of Table D.1 shows that the consensus growth expectation has significant predictive power. Furthermore, as demonstrated in Columns (2) and (3), the consensus growth expectation retains significance even with lagged GDP growth.

While the official GDP data serves as a critical reference for fund managers, they have good reason to pay attention to alternative indicators of economic activity such as electricity consumption, bank loans, and railway cargo volume. These indicators are considered to track actual economic conditions more closely than the official GDP data (Fernald et al., 2021) and are more timely. A popular index that parsimoniously summarizes these indicators is the "Keqiang Index," named after China's premier, Li Keqiang, who expressed his preference for these indicators over official GDP statistics.[25] It is a linear combination of the growth rate of the three previously mentioned indicators, initially constructed by The Economist and then updated by various data providers such as Wind.[26] This index has been shown to be a strong predictor of economic activity (Clark et al., 2020) and thus has been widely used by industry practitioners and academic researchers (Lyu et al., 2018).

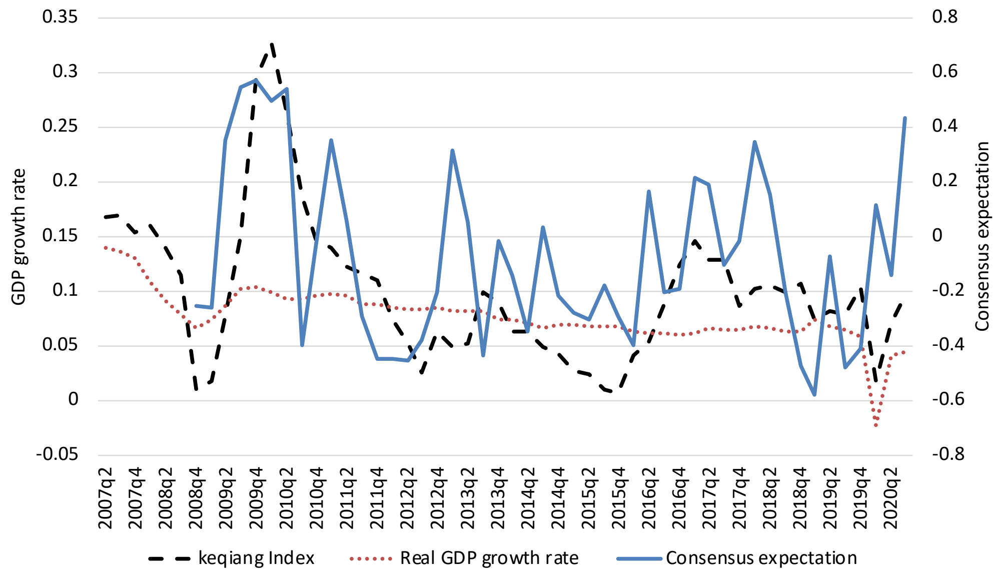
Figure D.2 plots the lagged consensus growth expectation (solid curve) with the real GDP growth rate (dotted curve) and the Keqiang Index (dashed curve). The Keqiang Index has a much stronger time-variation and higher correlation with the consensus growth expectation than the real GDP growth rate, implying that the former embodies vital information considered by fund managers when forming expectations about economic growth.

Columns (4)-(6) of Table D.1 display the results when the Keqiang Index is the dependent variable. Column (4) shows the significant predictive power of the consensus growth expectation

[25] See https://www.economist.com/asia/2010/12/09/keqiang-ker-ching for an introduction.

[26] The weights for electricity consumption, loans disbursed by banks, and the cargo volume on the railways are 0.4, 0.35, and 0.25, respectively.

**Figure D.2:** Consensus growth expectation, real GDP Growth, and Keqiang Index




Data are quarterly between 2007 Q2 and 2020 Q3. Keqiang Index a linear combination of the growth rate of electricity consumption (weight = 0.4), bank loans (weight = 0.35), and the railway cargo volume (weight = 0.25).

for the Keqiang Index. The adjusted R-squared (0.28) is much higher than in Column (1); this could either be due to the over-smoothing of the official GDP growth rate or fund managers' preference for the alternative indicators. Columns (5) and (6) show that the significant predictive power of the consensus growth expectation remains when the regression includes the lagged Keqiang Index. The adjusted R-squared in Columns (5) and (6) are lower than in Columns (2) and (3), suggesting that the Keqiang Index is less smooth than the official GDP growth rate.

**Table D.1:** The predictive power of the consensus growth expectation: Time series

Data are quarterly between 2008 Q4 and 2019 Q4. The dependent variable the year-on-year real GDP growth rate. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable : | Real GDP growth rate | | | Keqiang Index | | |
| Consensus Growth Expectation | 0.018*** | | 0.006** | 0.121*** | | 0.063*** |
| | (3.00) | | (2.27) | (4.32) | | (3.57) |
| Lagged GDP Growth rate | | 0.95*** | 0.881*** | | | |
| | | (16.13) | (14.48) | | | |
| Lagged Keqiang Index | | | | | 0.833*** | 0.727*** |
| | | | | | (10.80) | (9.17) |
| Constant | 0.077*** | 0.004 | 0.009* | 0.106*** | 0.016 | 0.031*** |
| | (42.67) | (0.80) | (1.85) | (11.98) | (1.66) | (3.17) |
| Adj R-squared | 0.15 | 0.87 | 0.85 | 0.28 | 0.70 | 0.75 |
| Observations | 46 | 46 | 46 | 46 | 46 | 46 |

# E Robustness of Correctness-Based Performance Result

An alternative candidate for fund managers' reference point in growth expectation is a moving average of the economic growth rate in the recent past. In particular, we assume that managers expect economic growth to be "strong" (i.e., $E_t^i\left(\Delta y_{t+1}\right) > 0$) if they anticipate $\Delta y_{t+1} > \overline{\Delta y}_{t-3,t}$, where $\overline{\Delta y}_{t-3,t}$ is the average economic growth rates in the past four quarters. Conversely, managers expect economic growth to be "weak" (i.e., $E_t^i\left(\Delta y_{t+1}\right) < 0$) if they anticipate $\Delta y_{t+1} < \overline{\Delta y}_{t-3,t}$.[27] Here we measure economic growth as the Keqiang Index since we have shown in Table D.1 that it embodies more information considered by the fund managers than the official GDP growth rate. Then we use a dummy variable $correct(hist)_t^i$, which is equal to one if the manager's forecast has the same sign as the gap between the economic growth rate and the recent year's economic growth rates, to measure the correctness of a forecast:

$$\text{Correct}_t^i = \begin{cases} 1 & \text{if } sign\left[E_t^i\left(\Delta y_{t+1}\right)\right] = sign\left(\widehat{\Delta y}_{t+1}\right) \\ & or\ E_t^i\left(\Delta y_{t+1}\right) = 0 \ \&\ |\widehat{\Delta y}_{t+1}| < \frac{std(\widehat{\Delta y})}{50}\ , \\ 0 & \text{if otherwise} \end{cases} \tag{E.1}$$

where $\widehat{\Delta y}_{t+1} = \Delta y_{t+1} - \overline{\Delta y}_{t-3,t}$, which is the gap between the economic growth rate and the economic growth rates in the recent year. In many cases, forecasts are zero, indicating that managers expect moderate economic growth. However, $\widehat{\Delta y_{t+1}}$ is never zero precisely, implying that all zero forecasts are automatically incorrect. To improve the evaluation of the zero forecasts, we consider them as correct if $\widehat{\Delta y_{t+1}}$ is sufficiently close to zero. In particular, we set $correct_t^i = 1$ if $E_t^i\left(\Delta y_{t+1}\right) = 0$ and $|\widehat{\Delta y}_{t+1}| < 0.02 * std(\widehat{\Delta y})$.

In Table E.1, we confirm here that correctness of fund managers' growth forecasts is associated with higher fund returns when forecast correctness is measured relative to the Keqiang index, instead of relative to GDP growth.

[27]Our results are robust to different time horizons.

**Table E.1:** GDP Growth Forecast Correctness and Fama-French alpha: Panel

This table shows that the result in Table 2 is similar if we use the Keqiang index to measure the GDP growth rate. Data are quarterly between 2008 Q3 and 2020 Q2. *Participated* is a dummy variable that is equal to 1 if the manager has a valid forecast score in this quarter, and 0 otherwise. *Correct* is the dummy variable indicating the forecast correctness which is equal to 1 if a manager's forecast has the same sign as the gap between the Keqiang index and the recent year's Keqiang index. All standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) |
|---|---|
| Dependent Variable : | Abnormal Return |
| Participated * Correct | 1.529*** |
| | (3.99) |
| Participated | 0.898*** |
| | (2.68) |
| Lagged Log(TNA) | -1.803*** |
| | (-8.29) |
| Lagged Log(Age) | 1.124*** |
| | (4.39) |
| Lagged Fund flows | -0.000*** |
| | (-5.61) |
| Lagged Expense Ratio | 0.204*** |
| | (4.10) |
| Constant | 15.680*** |
| | (8.72) |
| Fund FE | Yes |
| Adj R-squared | 0.012 |
| Observation | 44,428 |

# F Highly Cyclical Stocks' Response to Growth Expectation

We show here that the sensitivity of stock prices to growth expectations is higher for the most cyclical, defined as an above-median earnings sensitibity to GDP growth.

**Table F.1:** Growth Expectation and Return of Stocks with Various Manager Holdings: Panel

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variable is the stock returns in the last month of each quarter. *FMH* is the proportion of shares held by the managers that give growth forecasts. *FMH Consensus Growth Expectation* is the consensus expectation of GDP growth rate of managers that hold the stock. *High Cyclical* is a dummy that is equal to 1 if the firm is in a high-cyclical industry (correlation of the industry earning growth rate with the GDP growth rate is above the median among the cyclical industries), and 0 otherwise. In column (2), stock controls include CAPM beta, market value, turnover rate, market-to-book ratio, earnings-per-share, and SOE. The standard errors are clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) |
|---|---|---|
| Dependent Variable : | Stock return in Month of Fund Report | |
| FMH Consensus Growth Expectation * High Cyclical | 0.005 | 0.007** |
| | (1.62) | (2.20) |
| FMH Consensus Growth Expectation | 0.013*** | 0.011*** |
| | (7.94) | (6.66) |
| FMH | -0.237*** | -0.156*** |
| | (-7.22) | (-4.37) |
| GDP Growth Rate | 0.361*** | 0.370*** |
| | (12.34) | (11.25) |
| Constant | 0.004** | 0.091*** |
| | (2.27) | (5.79) |
| Stock Controls | No | Yes |
| Stock FE | Yes | Yes |
| Adj R-squared | -0.013 | 0.001 |
| Observation | 39,129 | 35,408 |

# G Short-sale constraints and the price impact of consensus expectations

We now consider how short-sale constraints affect the price impact of consensus expectations. Our hypothesis is that the sensitivity of stock returns to the consensus forecast is positively correlated with the proportion of shares held by the fund managers. We confirm a stronger contemporaneous relation between consensus growth expectation and stock returns through the sample split reported in the first two columns of Table G.1, which shows a larger coefficient when aggregate fund holdings are in the top quartile.

**Table G.1:** Growth Expectation and Return of Stocks with Various Manager Holdings: Panel

This table shows the responses to the consensus growth expectations for high- (top quartile) and low-holding stocks, respectively. Columns (1) and (2) use the subsamples when *HighFMH* is equal to 1, and 0, respectively. In column (3), the two subsamples are combined. Stock controls include CAPM beta, market value, turnover rate, market-to-book ratio, and earnings-per-share, their interactions with *Consensus Growth Expectation*, and SOE. The standard errors are clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable : | Stock return | | |
| Sample : | HighFMH | LowFMH | All |
| Consensus Growth Expectation | 0.313*** | 0.162*** | 0.161*** |
| | (29.29) | (34.20) | (34.62) |
| HighFMH * Consensus Growth Expectation | | | 0.156*** |
| | | | (14.76) |
| HighFMH | | | 0.035*** |
| | | | (9.82) |
| GDP Growth Rate | -0.041 | 0.615*** | 0.556*** |
| | (-0.26) | (20.31) | (19.20) |
| Constant | 0.298*** | 0.370*** | 0.341*** |
| | (5.32) | (17.37) | (17.87) |
| Stock Controls | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes |
| Adj R-squared | 0.156 | 0.060 | 0.073 |
| Observation | 7,548 | 24,004 | 31,965 |

An alternative story is that fund managers are likely to trade more intensively in firms that they have become familiar with from previous analysis, and familiarity can be proxied reasonably well by fund managers' holdings. We will show that this counter story is dominated by the short-sale constraint story. We next estimate:

$$r_t^j = \alpha + \eta \text{HighFMH}_{t-1}^j * E_t^{cons}(\Delta y_{t+1}) + \delta E_t^{cons}(\Delta y_{t+1}) + \kappa \text{HighFMH}_{t-1}^j + \mu \Delta y_t + Z_{t-1}^j + \chi^j + \epsilon_t^j, \tag{G.1}$$

where $r_t^j$ is the end-of-month stock return in period $t$. $\text{HighFMH}_{t-1}^j$ is a dummy variable that equals one if the fraction of market cap held in the previous quarter by the period $t$'s forecasting managers is in the top quartile among all stocks, and zero otherwise. $Z_{t-1}^j$ is a vector of stock-level controls, including CAPM beta, market value, turnover rate, market-to-book ratio, and earnings-per-share, which are valued in the previous period. $\chi^j$ is the stock fixed-effect. The coefficient of interest is $\eta$, which measures the marginal response of stock returns to the consensus growth expectation due to the holding by the forecasting managers.[28]

Columns (1) and (2) of Table G.2 report the results for our full-sample estimation. The coefficient on the interaction term is positive and significant, showing that stock returns for the top quartile of the distribution of holdings by the forecasting managers (i.e., $\text{HighFMH}_{t-1}^j = 1$) is more responsive to fluctuations in consensus growth expectations than low-weighted stocks (i.e., $\text{HighFMH}_{t-1}^j = 0$).[29] The stronger news-sensitivity of the prices of fund-held stocks result also implies that fund managers' growth forecasts entail more than just mechanical incorporation of public information that would be available to all investors.

The weaker responsiveness of low-weight stocks can be either because forecasting managers are unfamiliar with them or because bearish fund managers are restrained from trading them. To gauge the relative importance of these, we estimate equation (G.1) for periods with negative and positive consensus expectations separately. If the short-sale constraint mechanism is more critical, one would expect a much stronger result for the subsample of negative consensus expectations when most fund managers aim to downscale stock market exposure.

Columns (3-4) and (5-6) in Panel (A) of Table G.2 display the estimation results for subsamples with negative and positive consensus growth expectations, respectively. The coefficient on

[28] As the detailed stock holding information that is used to construct $\text{HighFMH}^j$ is disclosed in the mutual funds' mid-year and end-of-year reports, the estimation of equation (G.1) uses two observations per year.

[29] Table G.1 in Appendix F shows that the returns of low-weight stocks have a positive and significant response to the consensus growth expectation, although weaker than the high-weighted stocks.

the interaction term is positive for the negative consensus subsample (Columns (3-4)) and much stronger than the full sample estimate, indicating that short-sale constraints are the dominant factor behind the different response of high- and low-weight stocks. The effect is economically large: consider a stock with $\text{HighFMH}^{j}_{t-1} = 1$; Noting that the standard deviation of the consensus expectation is 0.31, a one standard deviation increase (decrease) of the consensus growth expectation raises (reduces) the stock's return by 4.84% (0.156*0.31), according to the point estimate in Column (4) of Table G.2's Panel (A). In contrast, the effect is negative for the positive consensus subsample, contradicting the conjecture that fund managers trade their previously holding stocks more intensively. A natural explanation is that bullish fund managers have an incentive to diversify idiosyncratic risks by expanding their portfolios.

## G.1 Lagged response of stock price to the consensus expectation

Although fund managers are constrained from selling their low-weight stocks, retail holders can still learn from the negative consensus expectations and sell these stocks. However, learning takes time, particularly for unsophisticated retail investors. Thus, the price effect of expectations may have some persistence. We test the above conjecture by replacing the dependent variable of equation (G.1) with the stock return in the first month following the reporting period. Slower price discovery of low-weight stocks should induce a lagged decline in their prices, causing a lower response of high-weight stocks' *future* prices to the negative growth expectations.

Columns (3) and (4) in Panel (B) of Table G.2 display our central findings for the negative consensus subsample. The coefficient on the interaction term is indeed negative and statistically significant, implying a strong lagged response of low-weight stocks' returns to negative growth expectations. Intuitively, it takes longer for low-weight stocks to digest the negative growth expectations of fund managers as implied by the short-sale constraint. Columns (1-2) and (5-6) in Panel (B) of Table G.2 report the results for the full sample and positive consensus subsample, respectively. Interestingly, both cases entail a continued stronger response of the high-weight stocks. This could be driven by the herding behavior of other investors, likely the retail investors, who believe that the forecasting managers possess superior information and

**Table G.2:** Consensus Growth Expectation and Return of Stocks with Various Manager Holdings: Panel

Data are quarterly between 2008 Q3 and 2020 Q2. The dependent variables for Panels (A) and (B) are the stock returns in the last month of each quarter and the stock returns in the first month of the next quarter, respectively. *HighFMH* is a dummy that is equal to 1 if the proportion of shares held by the managers that give growth forecasts is in the top quartile. *Consensus Growth Expectation* is the consensus expectation of GDP growth rate. The sample includes periods with negative consensus in columns (3-4) and positive consensus in columns (5-6). In columns (2), (4), and (6), stock controls include CAPM beta, market value, turnover rate, market-to-book ratio, and earnings-per-share, their interactions with *Consensus Growth Expectation*, and SOE. The standard errors are clustered at the stock level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Panel (A) Dependent Variable : | Stock return in Month of Fund Report | | | | | |
| Sample period: | Full sample | | Negative consensus | | Positive consensus | |
| HighFMH * Consensus Growth Expectation | 0.022*** | 0.026*** | 0.128*** | 0.156*** | -0.024** | -0.039*** |
| | (5.12) | (5.40) | (12.61) | (14.76) | (-2.19) | (-2.97) |
| HighFMH | -0.005*** | -0.001 | 0.021*** | 0.035*** | 0.024*** | 0.026*** |
| | (-3.13) | (-0.60) | (6.17) | (9.82) | (5.90) | (5.58) |
| Consensus Growth Expectation | 0.098*** | 0.091*** | 0.161*** | 0.161*** | 0.296*** | 0.235*** |
| | (45.16) | (38.74) | (37.69) | (34.62) | (37.80) | (21.57) |
| GDP Growth Rate | -0.000 | 0.043 | 0.436*** | 0.556*** | -3.325*** | -4.427*** |
| | (-0.01) | (1.58) | (16.66) | (19.20) | (-47.34) | (-46.95) |
| Constant | 0.039*** | 0.181*** | 0.032*** | 0.341*** | 0.237*** | 0.704*** |
| | (23.74) | (14.91) | (17.91) | (17.87) | (51.66) | (24.98) |
| Stock Controls | No | Yes | No | Yes | No | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-squared | 0.027 | 0.047 | 0.022 | 0.073 | 0.096 | 0.181 |
| Observation | 50,935 | 46,070 | 35,005 | 31,965 | 15,615 | 13,863 |
| Panel (B) Dependent Variable : | Stock Return in the Following Month | | | | | |
| Sample period: | Full sample | | Negative consensus | | Positive consensus | |
| HighFMH * Consensus Growth Expectation | 0.009* | 0.023*** | -0.056*** | -0.076*** | 0.033*** | 0.072*** |
| | (1.94) | (4.59) | (-5.53) | (-7.12) | (2.87) | (5.58) |
| HighFMH | 0.025*** | 0.027*** | 0.014*** | 0.006* | 0.003 | -0.000 |
| | (14.82) | (15.29) | (3.90) | (1.69) | (0.82) | (-0.02) |
| Consensus Growth Expectation | -0.022*** | -0.038*** | -0.019*** | -0.024*** | 0.167*** | 0.078*** |
| | (-9.12) | (-13.87) | (-4.80) | (-5.02) | (22.64) | (8.32) |
| GDP Growth Rate | -0.108*** | -0.291*** | -0.178*** | -0.243*** | -0.168*** | -0.588*** |
| | (-5.11) | (-11.47) | (-7.52) | (-8.83) | (-2.73) | (-7.21) |
| Constant | 0.004*** | 0.336*** | 0.013*** | -0.026 | -0.042*** | 0.115*** |
| | (2.96) | (27.96) | (7.74) | (-1.37) | (-9.65) | (4.61) |
| Stock Controls | No | Yes | No | Yes | No | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-squared | -0.011 | 0.053 | -0.019 | 0.038 | 0.044 | 0.197 |
| Observation | 49,676 | 44,971 | 34,164 | 31,205 | 15,183 | 13,506 |

want to follow their steps.

To refine our reading of the dynamics of stock returns around the release of fund reports that convey managers' growth expectations, we increase the data frequency to semi-monthly returns. We estimate the following regression equations for high- and low-weight stocks, separately, for periods with negative consensus forecast:

$$r_{i,t+k-1/6,t+k} = \alpha + \tau E_t^{cons}(\Delta y_{t+1}) + X_t + \chi_i + Z_{i,t} + \epsilon_{i,t},\ k \in \{-1/6, 0, 1/6, 1/3\} \tag{G.2}$$

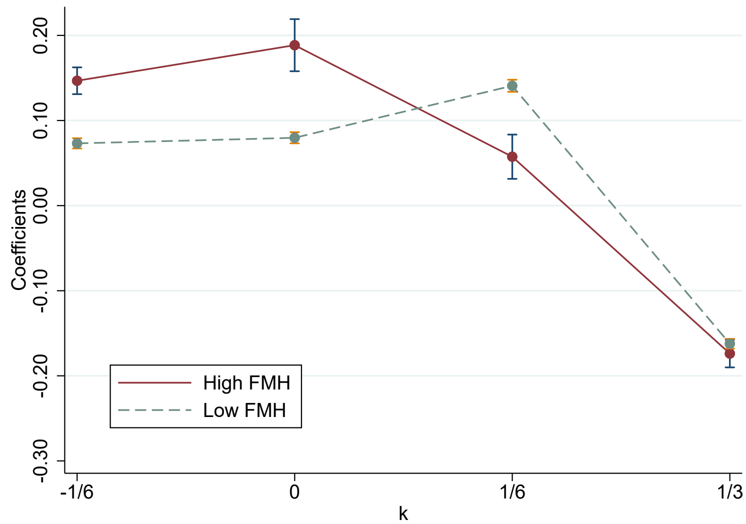
where $r_{i,t+k-1/6,t+k}$ is the stock $i$'s return over the 1/6 quarter (half month) interval of $[t+k-1/6, t+k]$. $X_t$ includes the consensus growth expectation and the actual GDP growth rate. $\chi_i$ is the stock fixed-effect. $Z_{i,t}$ is a vector of stock-level controls, including CAPM beta, market value, turnover rate, market-to-book ratio, and earnings-per-share. The coefficient of interest is $\tau$, which measures the sensitivity of stock return to the negative consensus growth expectation.

Note that the forecast scores capture managers' expectations at time $t$. The regressions are predictive for $k \geq 1/6$. Suppose the price discoveries were instantaneous and thorough. In that case, the consensus growth expectation is fully embodied in the current stock price and should have little predictive power for the stock returns.

The estimation results are presented in Figure G.1. The red and green dots plot the point estimates of $\tau$ for high- and low-weight stocks, respectively. The vertical lines around the dots display the 95% confidence intervals. For $k$ = -1/6 and 0, the coefficients of the consensus growth expectation are positive for both groups. However, the high-weight stocks' returns (red dots) are more sensitive to the consensus growth expectations than the low-weight stocks (green dots), which echoes our previous findings in Table G.2.

The result for $k = 1/6$ is substantially different than the previous cases. The coefficient of the low-weight stocks is higher than that of the high-weight stocks and its own in the earlier cases. This indicates a lagged price discovery for the low-weight stocks, which took longer to digest the negative growth expectations of the fund managers due to the short-sale constraint. In contrast, the high-weight stock's coefficient is lower than its previous estimates and close to zero.[30] Lastly, both groups display similar degrees of reversal when $k = 1/3$, which could be due to overreaction in stock prices in earlier periods and the subsequent corrections.

**Figure G.1:** Price discovery for high- and low-weight stocks with negative consensus

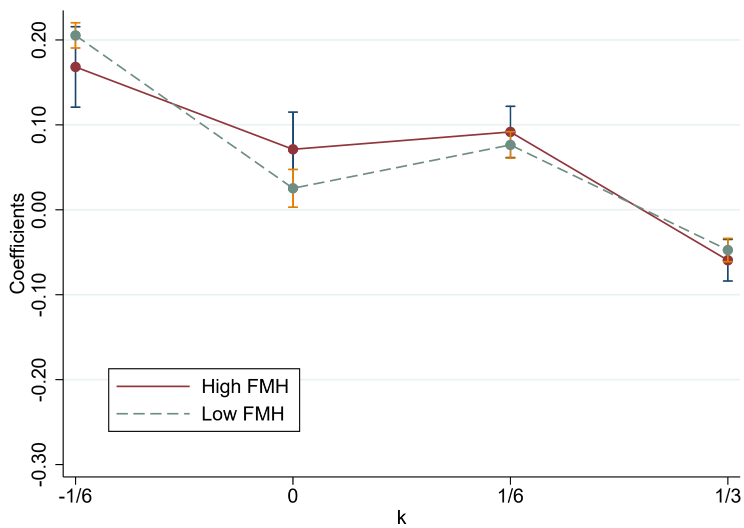



The y- and x-axes are $\tau$ and $k$ in equation (G.2), respectively. The red solid curve and the green dashed curve display the coefficient of the consensus growth expectation, $\tau$, for high- and low-weight stocks, respectively, when we focus on the sample periods with negative consensus growth expectation.

Figure G.2 displays the results for positive consensus growth expectations. These show that the high- and low-weight groups' stock returns respond to the positive consensus expectations symmetrically as the two curves are not significantly different from each other. This is in stark contrast to the case with negative consensus growth expectation shown in Figure G.1. Our findings suggest that the short-sale constraints impede the price impact of negative growth expectations.

[30]The positive and significant coefficient for the high-weight stocks implies that their price discovery is also not instantaneous and thorough, although much more than the low-weight stocks.

**Figure G.2:** Price discovery for high- and low-weight stocks with positive consensus




The y- and x-axes are $\tau$ and $k$ in equation (G.2), respectively. The red solid curve and the green dashed curve display the coefficient of the consensus growth expectation, $\tau$, for high- and low-weight stocks, respectively, when we focus on the sample periods with positive consensus growth expectation.