Working Paper

2025/22/FIN
(Revised version of 2024/17/FIN)

Earnings Optimism Heuristics and Long-Term Stock Returns

Allaudeen Hameed
National University of Singapore (NUS), allaudeen@u.nus.edu

Massimo Massa
INSEAD, massimo.massa@insead.edu

Zhenghui Ni
Renmin University of China, nizhenghui@rmbs.ruc.edu.cn

We introduce a simple a cognitive shortcut investors use to assess managerial ability based on theconsistency of segment-level earnings within conglomerates: the Earnings Optimism Heuristic (EOH). We document that EOH amplifies the negative relationship between long-term expected earnings growth (LTG) and future stock returns: high-LTG conglomerates with high EOH experience stronger underperformance, with an annual alpha of -10%. Difference-in-difference analyses show that while SFAS 131 improves analysts' LTG forecasts, they remain unaffected by EOH. In contrast, mutual funds rely on EOH, increasing their active holdings in high-EOH conglomerates and experience subsequent long-term underperformance.

Keywords: Long-term Earnings Growth; Return Predictability; Heuristics; Biased Expectations; Earnings Optimism; Analyst Forecasts; Conglomerates.
JEL Codes: G10, G14, G32, G39

The authors thank Ben Charoenwong, Zhi Da, Sulei Han, Johnathan Loudis, Lin Peng, Johan Sulaeman, Chelsea Yao, Shen Yao, and seminars participants at Baruch College, Stevens Institute of Technology, University at Buffalo SUNY, University of Illinois at Chicago, and conference participants at ABFER, CICF, FMA, FMA Global, MFA, and NUS RMI. We are grateful to Young Jun Cho for sharing data on the SFAS 131 regulation.

Introduction

A well-documented anomaly in the stock market is the inverse relationship between expected long-term earnings growth (LTG) and future stock returns: firms with high (low) expected LTG tend to earn lower (higher) future returns. This phenomenon is attributed to investor extrapolative errors, wherein investors over-extrapolate past earnings growth, leading to mispricing. As a result, high-growth firms experience inflated prices and predictable negative long-term returns, while low-growth firms are undervalued and subsequently yield positive long-term returns (La Porta (1996) and Bordalo, Gennaioli, La Porta, and Shleifer (2019, 2024)). While existing research highlights that extrapolation biases drive anomalies, little is known about the conditions under which these biases are amplified or mitigated.

In this paper, we propose that investor perceptions of managerial ability play a critical role in shaping extrapolation biases. We argue that, when evaluating earnings information—especially in complex firms like conglomerates—investors rely on simplified heuristics to assess managerial ability. We introduce the Earnings Optimism Heuristic (EOH)—a cognitive shortcut in which investors assess managerial ability based on the alignment of segment and firm-wide earnings. Specifically, when segment earnings exhibit less variation than expected (given the variation observed in comparable single-segment firms) and the firm is performing well, investors demonstrate high EOH, interpreting this consistency as a sign of strong managerial ability in managing diverse business units beyond what firm-wide earnings alone would suggest. Similarly, when firm-wide earnings are weak but segment earnings are dispersed, investors attribute poor performance to external factors rather than managerial incompetence—the dispersion implies that different business segments face varying external pressures, thereby reducing the likelihood that the CEO is chiefly responsible for the weak performance. In such cases, investors become more optimistic about managerial skills and future earnings than the low earnings level alone would justify, indicating high EOH.

Conversely, when firm performance is strong but segment earnings are highly dispersed, investors become uncertain as to whether the success is driven by the CEO's strategic decisions or by favorable conditions in select segments. Consequently, they are less optimistic about managerial skills and future earnings than the strong overall earnings would warrant, indicating low EOH. Finally, when firm-wide performance is weak and segment earnings are consistent, investors interpret the poor performance as broad-based and likely due to ineffective management, which reinforces negative expectations regarding the CEO's ability and diminishes optimism about future earnings—again suggesting low EOH.

EOH offers a framework for understanding how investor optimism in managerial ability shapes extrapolation biases and mispricing. Rooted in the representativeness heuristic (Tversky and Kahneman, 1974), high EOH suggests that when segment earnings bolster investor optimism about management, investors become more confident in the persistence of earnings growth. This overconfidence leads to greater mispricing—namely, overvaluation for high-growth firms and excessive pessimism for low-growth firms. In effect, this mechanism contributes to the long-term earnings growth anomaly: firms with high expected LTG receive inflated valuations and subsequently underperform, while firms with low expected LTG remain undervalued despite their potential for improvement.

This framework is particularly relevant for longer-horizon forecasts, where distinguishing persistent growth from short-term fluctuations is challenging. Investors relying on EOH are more inclined to assume that high-growth firms will sustain their momentum, while low-growth firms will remain stagnant. In reality, long-term earnings growth tends to lack persistence: high-growth firms rarely maintain their rapid growth, whereas low-growth firms often improve over time (Chan, Karceski, and Lakonishok, 2003). Despite this, investors frequently over-extrapolate growth trends, leading to overpricing in high-growth firms and underpricing in low-growth firms. This tendency is especially pronounced among investors with shorter decision horizons or a preference for simplified heuristics (Shleifer and Vishny, 1997), thereby amplifying mispricing. These observations suggest that the impact of EOH on stock mispricing depends on a firm's expected earnings growth. Specifically, high EOH exacerbates the overvaluation of high-growth firms—pushing prices further above intrinsic value and resulting in predictable negative returns—while for low-growth firms, high EOH mitigates negative expectations, reducing undervaluation and aligning prices more closely with their long-term value. This leads to our first testable hypothesis: *the negative relationship between expected long-term earnings growth and future stock returns is more pronounced in firms with high EOH, particularly among high-growth firms.*

Two key market participants shape these dynamics: financial analysts and mutual fund managers. Analysts, focused on maintaining their reputation for accurate long-term forecasts, are less influenced by EOH, as they are more likely to assess firm performance using fundamentals rather than heuristics. In contrast, mutual fund managers, driven by short-term performance pressures and investor-driven fund flows (Shleifer and Vishny, 1997), are more susceptible to heuristics such as EOH. Consequently, high EOH is likely to have a greater influence on mutual fund managers' decisions, exacerbating the overvaluation of high-growth firms. This forms our second testable hypothesis: *EOH has a more pronounced impact on mutual fund managers than on analysts, leading to heightened mispricing in high-growth firms.*

We argue that conglomerates provide an excellent setting to test these hypotheses for two reasons. First. conglomerates generate multiple managerial signals: the diverse range of business segments allows investors to observe multiple performance indicators under a single CEO, affecting their optimism in managerial skills and future earnings. Even if segment earnings do not necessarily affect long-term firm fundamentals, their consistency or dispersion influences investor perception, shaping extrapolation biases. Second. a clean identification strategy using pseudo-conglomerates allows us to isolate the price effects of EOH. Pseudo-conglomerates are constructed as portfolios of single-segment firms that operate in similar industries as the segments in the conglomerates. These pseudo-conglomerates share similar earnings uncertainty but lack a common CEO. By comparing pricing errors between conglomerates and pseudo-conglomerates, we can separate the effect of EOH from biases in analysts' long-term expectations regarding earnings growth. This approach highlights how the decentralized structure of conglomerates allows investors to form heuristics about CEO ability, a process less relevant in single-segment firms. Hence, the decentralized structure and complexity of conglomerates enable the creation of heuristics on the CEOs that do not exist in single-segment firms.[1]

We first document that the negative relationship between expected LTG and future stock performance is prevalent in conglomerates. High-growth conglomerates underperform by 0.65% per month (t-stat = -4.68), or 7.49% annually, in terms of Fama-French 6-factor alpha (including the momentum factor), while the alpha for low-growth conglomerates is not significantly different from zero. A long-short portfolio strategy—long in low-growth conglomerates and short in high-growth conglomerates—yields a significant annual alpha of 8.34%. These findings are robust across different factor model specifications and controls for firm characteristics.[2] Importantly, the mispricing effect is stronger in conglomerates than in a broader sample that includes single-segment firms, indicating the potential role of EOH in shaping investor expectations and return predictability.

Next, we examine how EOH influences the relationship between LTG and future stock returns, addressing our first hypothesis. To empirically test this idea, we construct a proxy for EOH using segment-level earnings information in conglomerates. Given that conglomerates operate across multiple business segments, investors can infer managerial ability based on how well segment earnings align with firm-wide performance. Our EOH proxy classifies firms as having high EOH when (a) firm-wide earnings are strong and segment earnings are consistent, reinforcing the perception of effective management and increasing optimism about future earnings, or (b) firm-wide earnings are weak and segment earnings are dispersed, suggesting that poor performance is driven by external factors rather than managerial incompetence,

---

[1] Conglomerates may also distort earnings by shifting earnings across segments. The internal capital market allocations insulate conglomerates from external capital market frictions and provide coinsurance across segments (Matvos and Seru (2014), Matvos, Seru, and Silva (2018) and Boguth, Duchin, and Simutin (2022)). While these distortions may impact financial reporting, our focus is on how investors interpret earnings signals rather than on managerial incentives to manipulate them.

[2] Specifically, the calendar time portfolio returns on the portfolio that takes a long position in high-growth decile of conglomerate and shorts low growth rate conglomerates delivers a significant monthly alphas of between -0.70% (t-stat=-4.79) and -0.78% (t-stat=-5.02) when we adjust the returns based on the q-factor model of Hou, Xue, and Zhang (2015) and Stambaugh-Yuan (2018)'s mispricing factor model. On the other hand, a similar long-short portfolio returns constructed using all stocks (including single-segment firms) do not survive adjustment for common factors.

sustaining optimism. Conversely, firms are classified as having low EOH when (a) firm-wide earnings are strong but segment earnings are highly dispersed, making it unclear whether success stems from the CEO's strategic decisions or isolated segment-level conditions, or (b) firm-wide earnings are weak but segment earnings are consistent, reinforcing the belief that poor performance is broad-based and reflective of poor management, reducing optimism.

By linking EOH to investor optimism, we argue that EOH strengthens extrapolation biases without necessarily affecting the accuracy of long-term firm-level earnings forecasts. Investors in high EOH firms become more confident in their interpretation of performance signals, leading to stronger over-extrapolation of high-growth firms and weaker correction of undervaluation in low-growth firms.

Using this EOH proxy, we document that the relationship between expected LTG and future stock returns is amplified by EOH. A portfolio that shorts high-growth conglomerates with high EOH and goes long on low-growth conglomerates with high EOH earns a significant annualized Fama-French 6-factor alpha of 9.09%. In contrast, there is no significant return predictability among conglomerates with low EOH or among pseudo-conglomerates. These findings support our first hypothesis that EOH strengthens the negative relationship between LTG and future stock returns, particularly in high-growth firms.

Next, we examine how different market participants—financial analysts and mutual fund managers—respond to EOH. If EOH serves as a heuristic that boosts investor optimism without necessarily improving the accuracy of long-term earnings forecasts, then its influence should vary across market participants. Consistent with this idea, we find that analysts' forecast accuracy of long-term earnings is unaffected by EOH. Although analysts exhibit overreaction to long-term growth forecasts, as documented by Coibion and Gorodnichenko (2015), this overreaction appears unrelated to our EOH proxy. This suggests that analysts do not rely on perceived information quality when forming long-term earnings forecasts, likely because their incentives prioritize fundamental analysis over heuristics.

To further validate this finding, we exploit an exogenous regulatory event: the introduction of SFAS 131, an accounting regulation enacted in 1997 that mandated improved disclosure of segment-level information. By requiring firms to present disaggregated data based on how management internally evaluates performance, SFAS 131 increased transparency about managerial actions. Following Cho (2015), we compare analysts' forecast accuracy for conglomerates with high EOH prior to SFAS 131 (treated firms) to those with low EOH before the regulation. Our difference-in-difference tests confirm that analysts' forecast accuracy improves after SFAS 131, particularly in firms with previously high EOH. This result highlights that analysts incorporate disaggregated information when available but do not rely on perceived information quality when transparency is low.

In contrast, mutual fund managers appear to be more susceptible to EOH, supporting the idea that short-term investors are more affected by heuristics than analysts making long-term forecasts. Specifically, when high-LTG conglomerates exhibit high EOH, mutual fund managers significantly increase their active holdings in these stocks, further exacerbating overvaluation. This behavioral response translates into predictable underperformance: funds with high active exposure to high-growth, high-EOH stocks significantly underperform low-exposure funds, with lower annualized alphas ranging from -2.01% to -3.31%. Moreover, unlike analysts, mutual funds do not adjust their behavior following the SFAS 131 regulation. Their persistent reliance on EOH, even when additional transparency is introduced, underscores their greater susceptibility to perceived information quality as a heuristic.

Our findings contribute to the stock market anomaly literature by linking the low future returns of high-LTG firms (e.g., La Porta, 1996; Bordalo, Gennaioli, La Porta, and Shleifer, 2019, 2024) to investor heuristics. Specifically, we introduce EOH as a mechanism that shapes extrapolation biases, explaining how perceived information quality influences investor expectations. By examining how investors interpret segment earnings consistency within multi-segment firms, we distinguish the effects of EOH from broader extrapolative expectations.

Our findings also contribute to the literature on perceived information quality and market mispricing. For instance, we complement Cohen and Lou (2012) and Chen, Cohen, and Lou (2016), who show that greater mispricing of conglomerates arises from the slow incorporation of market information and window dressing. In contrast to these studies, we focus on how investors interpret earnings consistency as a heuristic for managerial ability, which in turn amplifies extrapolation biases and mispricing.

Our idea that investors use consistency in segment-level earnings as a signal of firm quality relates to Harbaugh, Maxwell, and Shue (2017), who show that firms strategically smooth segment earnings to reinforce credibility in good times. However, while their focus is on managerial incentives for earnings distortion, we instead examine how investors interpret segment consistency, leading to predictable mispricing and return predictability. This distinction underscores our key insight: EOH amplifies extrapolation biases, contributing to the long-term earnings growth anomaly.

Finally, our work connects to Jiang, Lee, Martin, and Zhou (2019), who develop a proxy for managerial sentiment using textual tone in corporate disclosures. We complement their findings by showing that investor perceptions of information quality—rather than managerial disclosures alone—can drive short-term overvaluation and long-term predictable underperformance.

2. Data

Our data sources are CRSP, Compustat, and I/B/E/S. We identify conglomerates using the historical segment data from Compustat. We require that each firm report segment-level sales data and that the sales of all identified segments are larger than 80% of the firm's total sales. A firm with more than one segment (industry) is classified as a conglomerate, as opposed to firms operating in a single segment. We define segments using the Fama-French 48 industry classifications.[3]

---

[3] We obtain the industry definitions from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html).

Following Cohen and Lou (2012), for each conglomerate firm, we construct the corresponding pseudo-conglomerate as the segment-sales weighted average of the industry portfolios which are constructed using single segment firms.[4] For example, if conglomerate C has two segments, A and B, with 60% and 40% total sales, respectively. The industry portfolio corresponding to segment A (B) comprises all single segment firms in the industry. We construct the return of the corresponding pseudo-conglomerate as the (segment sales-) weighted average returns of the two industries. The return of the pseudo-conglomerate corresponding to conglomerate C is equal to the weighted average of the return on the two industry portfolios, with weights of 60% and 40% for industry A and B. Other firm characteristics for pseudo-conglomerates, such as annual sales and book-to-market ratios, are constructed in the same way.

We extract the data on annual firm earnings from I/B/E/S Unadjusted Detail Actual and use I/B/E/S Unadjusted Detail History for analysts' earnings forecasts. We collect the forecasted value of annual earnings per share (EPS) for all the firms for horizons of three to five years ahead.[5] Our sample includes all the common stocks listed in the three major exchanges NYSE, NASDAQ, and AMEX provided by CRSP over the period from 1982 to 2019.[6] There are 216,241 conglomerate-month observations with valid long-term growth forecasts. On average, there are 468 conglomerates (with corresponding pseudo-conglomerates) each year.

3. Long-Term Earnings Growth, Stock Return Predictability and Conglomerates

---

[4] We also report an alternate way used to construct pseudo-conglomerates in Internet Appendix B. In the alternative way, we first match a stand-alone firm for each segment of a conglomerate and then average across segments by segment sales. The matched firm is based on the following firm characteristics: segment sale, analyst coverage, and segment industry. Results using this alternative construction of pseudo-conglomerates is qualitatively similar and are reported in Internet Appendix B.

[5] We extract forecasts of EPS with Forecast Period Indicator 0, 3, 4, and 5: i.e. Long-Term Growth Rate and for Fiscal Years 3 to 5. Detailed description of variables constructed using I/B/E/S data are in Internet Appendix C.

[6] When a stock is delisted, we use the delisted return as the return on the day. If delisted return is not available, we set the return to be -0.3 if the delisted code is one of 500, 520, 551:573, 574, 580, and 584 and to be -1 if not (Bali, Engle, and Murray 2016).

We start by replicating the results of Bordalo, Gennaioli, La Porta and Shleifer (2019) (BGLS, henceforth) that future returns on stocks with high long-term earnings growth (LTG, henceforth) underperform stocks with low LTG in the broader sample of all firms, including both single segment and conglomerate firms. Following BGLS, we sort stocks into deciles based on LTG as per the I/B/E/S Summary files. The *low* long-term earnings growth portfolio is made of the bottom decile of the stocks with the most pessimistic forecasts, and the *high* long-term earnings growth portfolio is made of the top decile of the stocks with the most optimistic forecasts. Figure 1A displays the geometric average of one-year returns on the ten deciles of (equal-weighted) stocks sorted by the analysts' forecasts. Consistently with the findings in BGLS, we document a large drop in the annual returns as we move from the low growth to high growth decile, with the difference between the extreme deciles corresponding to a significant 10.36% (t=2.18) annually. The arithmetic mean of the low growth minus high growth portfolio returns is smaller at 6.28% (t=1.36) annually.

Next, we focus on conglomerates and investigate if the predictability of stock returns for high and low growth firms holds for the sample of conglomerates. We sort conglomerates into deciles based on long-term earnings growth forecasts (LTG). Figure 1B confirms that conglomerates in the highest LTG decile underperform those in the lowest LTG decile. The geometric mean annual return of the portfolio that longs low-LTG conglomerates and shorts high-LTG conglomerates is 9.11% (t=3.64). The arithmetic mean difference of the long-short portfolio of conglomerates is also significant at 7.98% (t=3.11). This simple analysis of raw returns (as per BGLS) shows that the negative predictive effect of earnings growth on future stock returns holds in conglomerates. Importantly, the link between predictability of return and conglomerate status survives the adjustment for exposure to multiple factors as advocated in recent asset pricing models.[7]

[7] We obtain significant alphas for these conglomerates sorted on LTG, after adjusting for exposure to factors in Fama-French (2016), Hou, Xue and Zhang (2015) and Stambaugh and Yuan (2018). For example, we find the high-minus-low LTG conglomerates earn a significant Fama-French (plus momentum) six-factor alpha of -4.62% (t=-2.08) annually (see Appendix Table A1). On the other hand, the risk-adjusted returns on the full sample of all firms is not different from zero, similar to the findings reported in BGLS (see their Internet Appendix).

To examine the long-term stock performance, we follow Mitchell and Stafford (2000) and use a calendar-time portfolio approach. Our key ranking variable is the forecast of long-term earnings growth rate or LTG. The LTG variable is obtained from the I/B/E/S Unadjusted Detail History file advocated in Payne and Thomas (2003) and Zhang (2006).[8] We rank conglomerates into deciles based on LTG and rebalance the portfolio each month, adding (dropping) firms that have fallen into (out of) the decile. We report the returns of the high and low LTG portfolios as well as the high-minus-low LTG (HMLG) portfolio. Similarly, we also construct portfolio returns for the portfolio of pseudo-conglomerates sorted on LTG.[9] Following Cohen and Lou (2012), the LTG and portfolio returns for pseudo-conglomerates are the (sales-weighted) average value of the mean standalone firm within the segments of the corresponding conglomerate. The portfolio returns are adjusted using multi-factor models to obtain portfolio alphas. In addition to raw returns, we consider risk-adjusted returns using Fama-French six factors (Fama-French five factors of market, size, book-to-market factors, operating profitability, and investment plus the momentum factor), Stambaugh and Yuan mispricing factors (market, size, management, and performance factors), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). For example, the Fama-French six-factor-adjusted alpha of portfolios under calendar-time portfolio approach in month t+1, α_{t+1}, is the intercept from the following regression:

$$R_{t+1} - R_{ft+1} = \alpha_{t+1} + \beta_{1,t+1} R_{MKTt+1} + \beta_{2,t+1} R_{SMB_{t+1}} + \beta_{3,t+1} R_{HML_{t+1}} + \beta_{4,t+1} R_{RMW_{t+1}} + \beta_{5,t+1} R_{CMA_{t+1}} + \beta_{6,t+1} R_{MOM_{t+1}} + \varepsilon_{t+1}, (1)$$

[8] Given that LTG is not available for all firms, we expand the sample of firms by using growth rates implied by the forecasts. When LTG is missing, we use the forecast-implied growth rate based on the average of the implied growth rates from earnings forecasts for 3 to 5-year horizon. The annualized forecast-implied growth rate of earnings per share (EPF) is defined as $\sqrt[\frac{1}{FPI}]{\frac{Forecasted\ EPS_t^{FPI}}{Actual\ EPS_{t-1}}} - 1$ where FPI is the forecast horizon, and is defined when forecasted EPS in month t is positive and we set the growth rate to be missing when the actual EPS is negative. We calculate implied LTG and other related variables based on the I/B/E/S detailed forecast data. Details on the forecast-implied growth rate is provided in the Table of Variable Definition and in Appendix C. Our results are qualitatively similar if we do not fill missing growth rate forecasts with the corresponding forecast-implied growth rate.

[9] As displayed in Appendix Table A2, conglomerates and the matched pseudo-conglomerates share similar firm characteristics.

where R_{t+1} is the monthly (value-weighted) return of the calendar time portfolio on month t+1:

$$R_{t+1} = \frac{\sum_{i=1}^{s_{t+1}} r_{i,t+1} * m_{i,t}}{\sum_{i=1}^{s_{t+1}} m_{i,t}}, (2)$$

and $r_{i,t+1}$ is stock i's monthly return in month t+1; s_{t+1} is the number of stocks included in the portfolio in month t+1 and $m_{i,t}$ is the market cap of stock i in month t to obtain value-weighted portfolio returns. We use the Newey-West correction for the standard errors of these monthly portfolio returns.

Table 1 reports our findings on the calendar-time portfolio returns on conglomerates and pseudo-conglomerates. Panel A shows that the *unconditional* returns do *not* differ between the two groups of firms: both conglomerates and pseudo-conglomerates earn a raw return of around 0.6% per month, averaged over the 12-month period. Similarly, when we adjust the stock returns for risk factors, we find that the factor models explain the average return on both sets of firms and the risk-adjusted alpha is not different from zero. These results indicate that the unconditional expected returns on conglomerates and the matched pseudo-conglomerates are similar.

Next, we turn to the predicted returns for portfolios sorted on LTG and find the returns to vary drastically between the two groups. We sort conglomerates and pseudo-conglomerates into deciles based on LTG and report the monthly calendar-time portfolio returns over the next one year. Table 1, Panel B reports the returns on the portfolios in the high and low LTG deciles as well as the returns on the zero-investment portfolio that longs the high growth decile and shorts the low growth decile. Focusing on the conglomerate sample, we find that the long-short portfolio delivers a significant monthly raw return of -0.91% (annualized return is -10.39%) and is economically and statistically significant (t=-4.89). The underperformance of high growth conglomerates is robust to the various factor model specifications. The annualized alpha of the high minus low growth conglomerates is between -8.12% (t=-4.79) and -8.92% (t=-5.02), across the three factor models in Fama-French six-factor model (five-factor plus momentum), the mispricing model and the Q-factor model. The significant predicted alphas come from the high growth conglomerates while the low growth conglomerates earn close to zero alpha.

The predictable relation between LTG and future returns on conglomerates is robust when we estimate Fama-MacBeth regressions of annual stock returns, controlling for firm characteristics that predict returns, as well as when we extend the calendar-time portfolio returns to holding periods of two years. The results are presented in Models 1 and 3 of Table 2. The cross-sectional Fama-MacBeth regression results confirm the strong negative relationship between LTG and long-term future stock returns for conglomerates.

In contrast, Table 1 shows that there is no evidence of predictable returns for the pseudo conglomerates sorted on long-term earnings growth rates, both in raw returns as well as alphas across all the factor model specifications. As we argued, conglomerates differ from pseudo-conglomerates in one important dimension: EOH is feasible in conglomerates but not in pseudo-conglomerates. Hence, we interpret these findings as preliminary evidence of the role of EOH in the LTG-stock return relation.

3.2 Long-Term Earnings Growth, Conglomerate Returns and EOH

The results of the previous section confirm that the sample of conglomerates is indeed a good testing ground as it displays high-growth return predictability. We focus on conglomerates and investigate the first hypothesis, linking earnings growth and stock return predictability to the EOH.

As we argued, we focus on proxies on the EOH that link the mean value to the its distribution. Given that conglomerates display earning across different segments, a proxy of the EOH is based on how consistent the earnings of the different segments are given the overall signal. If the cross-sectional variation in segment earnings is abnormally high compared to what the segments would have as single segments, it is difficult for the market to assign to managerial skills the performance of the company. That is, good firm-level earnings – i.e., high firm performance – with *consistent earnings across segments* or bad firm-level earnings – i.e., low firm performance – with *inconsistent earnings across segments* both provide optimism in the signal. In contrast, good firm-level earnings – i.e., high firm performance – with *inconsistent earnings across segments* or bad firm-level earnings – i.e., low firm performance – with *consistent earnings across segments* reduce optimism on the managerial skills and the persistence of the level of earnings.

We operationalize this intuition as follows. We start with a measure of segment earnings scaled by average assets, *EARN*, to make earnings comparable across firms and segments of different sizes (i.e. return on asset). The firm-level earnings are defined as the segment asset weighted sum of segment *EARN*. To illustrate, consider a segment of firm j in year t in industry i. Segment $EARN_{i,j,t}$ is defined as $EARN_{i,j,t} = \frac{sales_{i,j,t} - costs_{i,j,t}}{assets_{i,j,t}}$ and total firm $EARN_{j,t}$ is defined as $EARN_{j,t} = \frac{\sum_i (sales_{i,j,t} - costs_{i,j,t})}{\sum_i assets_{i,j,t}}$.[10] Consequently, for each conglomerate j in year t, we have the vector of earnings $\mathrm{v}_{j,t} = (EARN_{1,j,t}, \dots, EARN_{m,j,t})$ with standard deviation of earnings $\mathrm{STD}_{j,t}$, where m is the number of segments of the conglomerate.

We use industry data to construct a benchmark for how the consistency of segment earnings would vary with overall firm earnings news in the absence of strategic cost allocations. The benchmark earnings consistency measure using industry averages is calculated from single-segment firms corresponding to the segments of the conglomerates and accounts for differences in costs relative to sales across segments. In particular, let $\delta_{i,t}$ equal the ratio of average costs to average sales among standalone firms in the Fama-French 48 industries corresponding to segment i in year t: $\delta_{i,t} = \frac{\sum_j (costs_{jt})}{\sum_j (sales_{jt})}$ and $EARN_{i,t}$ equal the ratio of average earnings to average assets among all standalone firms in the industry of segment i: $EARN_{i,t} = \frac{\sum_j (sales_{j,t} - costs_{j,t})}{\sum_j (assets_{j,t})}$. The predicted segment earnings are:

$$\widehat{EARN}_{i,j,t} = \frac{1}{assets_{i,j,t}} \left(sales_{i,j,t} - \frac{\delta_{i,t} \cdot sales_{i,j,t}}{\sum_i (\delta_{i,t} \cdot sales_{i,j,t})} costs_{j,t} \right). \quad (3)$$

---

[10] In computing segment level earnings using Compustat Segment data, we use OPS as the value for $sales_{i,j,t} - costs_{i,j,t}$. According to Compustat, OPS represents segment-level operating profits, which is sales of the industry segment minus its operating costs and expenses, such as cost of goods sold, selling, general, and administrative expenses, and depreciation, depletion, and amortization. We avoid using segment-level $costs_{i,j,t}$ in Compustat due to low coverage of observations.

Note that the mean (industry-adjusted) predicted earnings for conglomerate j in year t is equal to the mean earnings of the conglomerate because EOH only affects the consistency of the earnings news (proxied by STD_{jt}) and preserves the mean earnings. We estimate the predicted consistency $\widehat{STD_{Jt}}$ as the standard deviation of the predicted segment earnings. We refer to $STD_{jt} - \widehat{STD_{Jt}}$ as the abnormal standard deviation of segment earnings. We benchmark the expected earnings for conglomerate j as the industry average earnings, $EARN_{j,t}^{ind} = \frac{\sum_i (assets_{i,j,t} * EARN_{i,t})}{\sum_i (assets_{i,j,t})}$ and measure the abnormal earnings news for the conglomerate as $EARN_{j,t} - EARN_{j,t}^{ind}$ to decide if the overall firm earnings news exceeds or falls short of industry-based expectations.

We define EOH as a dummy equal to 1 if $STD_{jt} - \widehat{STD_{Jt}} < 0$ when $EARN_{j,t} - EARN_{j,t}^{ind} > 0$ or $STD_{jt} - \widehat{STD_{Jt}} > 0$ when $EARN_{j,t} - EARN_{j,t}^{ind} < 0$ and 0 otherwise.

We focus on the effect of EOH on predictability of conglomerate stock returns and report the portfolio sorting results in Table 3. In line with our expectations, the difference in performance between high and low LTG conglomerates *is confined to stocks with high EOH*. The average monthly risk-adjusted returns for high-minus-low growth conglomerates, as per the Fama-French six-factor model over a 12-month horizon, are -0.79% (t=-3.75), or -9.08% per annum, for those with high EOH. However, the corresponding monthly returns drop to an insignificant -0.13% (t=-0.55) for conglomerates with low EOH. We obtain similar findings using alternative factor models based on mispricing factor and the Q-factor models: the annualized alphas for portfolios of high-minus-low growth conglomerates with high EOH are negative at -0.71% (t=-3.51) and -1.03% (t=-4.66), respectively. These findings consistently indicate that the high-minus-low growth conglomerate portfolio yields significant negative risk-adjusted returns when the conglomerates display high EOH. Moreover, we do not find significant predictability in the returns on low growth conglomerates, irrespective of EOH, which implies that the discerned effects predominantly originate from the high-growth conglomerates.

For robustness, we also run annual Fama-MacBeth regressions using a subsample of conglomerates. Specifically, we regressed future alphas on a high-growth dummy and its interaction with EOH. The results, presented in Table 2, confirm that the predictable relationship between long-term growth (LTG), EOH, and future returns on conglomerates is robust. This holds true when we control for firm characteristics that predict returns and when we extend the analysis to calendar-time portfolio returns over two-year holding periods. In terms of economic magnitude, high-growth conglomerates generate a one-year alpha of -6.3% and a two-year alpha of -9.8% compared to other conglomerates. High-growth conglomerates with high EOH yield even more negative alphas, with -7.2% for one-year and -15.0% for two-year holding periods. Importantly, the Fama-MacBeth regressions are not confined to comparisons between high and low growth conglomerates, which reinforces the robustness of a linear relationship across the entire sample.

The underperformance of high-growth conglomerates with high EOH is robust. We present the performance of all deciles of conglomerates sorted on LTG in Figure 2. Figure 2A shows that, among conglomerates with high EOH, there is a near monotonic decline in raw returns when we transition from low to high growth conglomerates. We observe strong underperformance of high-growth conglomerates in deciles 9 and 10 relative to low-growth conglomerates in deciles 1 and 2, both in raw returns and risk-adjusted alphas.

On the contrary, Figure 2B shows that there is *no clear relation between earnings growth and returns among firms with low EOH*. Additionally, the main findings in Table 3 remain intact when we sort conglomerates into LTG quintiles and EOH (see Appendix Table A3). Collectively, our findings substantiate the existence of a relationship between EOH and LTG affecting stock return predictability within a comprehensive sample of conglomerates.

Given that conglomerates in which managers engage in manipulation tend to display high EOH, we supplement the investigation with a proxy of EOH based on Chen *et al.,* (2016), that exploits sales management by the managers of conglomerates.[11] Chen *et al.,* (2016) show that managers operating in multiple segments with similar proportion of sales can re-allocate segment sales so that the primary segment is seen to be the segment with more favorable valuation. They do this to benefit from overall firm valuation being driven by the primary segment. Hence, we expect sales management to act as another information heuristic and boost the overvaluation of high growth conglomerates.

The results are reported in Table 4. In Panel A, we show that return predictability concentrates in conglomerates with sales management. The annualized alphas for the portfolio of high-minus-low growth conglomerates with sales management using the Fama-French six-factor, mispricing factor, and Q factor models are -10.21% (t=-2.17), -10.35% (t=-2.14), and -10.29% (-1.94), respectively.

3.3 The Role of Managerial Incentives

We now examine the link between EOH and managerial incentives. We employ two alternative measures commonly used to capture how much managerial wealth exposed to stock price movements: delta and vega (Core and Guay (2002), Coles, Daniel, and Naveen (2006).[12] Delta measures the sensitivity of CEO wealth to stock prices, while vega measures the sensitivity of CEO wealth to stock return volatility. With respect to vega, we argue that when the sensitivity of CEO compensation to stock return volatility is large, managers have stronger incentives to boost current stock prices because they can benefit from the increased volatility resulting from the current temporary overvaluation. With respect to delta, we argue that in the presence of managerial short-termism, CEOs may have incentives to enhance the perceived EOH to boost firm performance. Hence, we expect return predictability to be stronger for firms with higher delta and vega.

The results are reported in Table 4, Panel B and Panel C. We find subsequently low future negative returns for high growth conglomerates with either high delta or high vega. For example, the annualized

[11] Detailed construction on the alternative measure based on sales management and results are in Appendix D.
[12] We are grateful to Lalitha Naveen for making the data on delta and vega available online at https://sites.temple.edu/lnaveen/data/.

alphas for a portfolio of high-minus-low growth conglomerates with high delta and high vega using the Fama-French six-factor model are -11.22% (t=-4.53) and -11.67% (-4.91). Alphas are mostly insignificant for the groups of high-growth conglomerates with low delta or low vega. Overall, we uncover a strong and robust link between EOH, managerial incentives and stock return predictability based on earnings growth.

4. Distinguishing EOH and Biased Long-Term Earnings Forecasts

Our argument relies on the premise that the consistency between segment-level and firm-level signals impacts the trust of the market in the quality of the information without altering the expectation of future firm-level earnings. In other words, our measures of EOH deal with the "optimism" around the mean and are "mean preserving" in that they are not expected to impact the bias in the long-term earnings forecast of the sum of the segments – i.e., the conglomerate. To assess whether this is the case, we analyze the accuracy of analysts' long-term earnings forecasts in conglomerates in the presence of inter-segment earnings shifting.

We begin by describing the quality of earnings forecasts of conglomerates. We employ two measures to assess forecast quality: the absolute error in analyst forecasted earnings and the dispersion in analysts' forecasts. The absolute forecast error, (AFE, henceforth), is defined as the absolute value of the difference between the actual earnings per share (EPS) and the median value of the EPS forecasts by all analysts, deflated by the stock price at the beginning of the announcement year of the actual earnings.[13] A higher AFE implies that the forecasted mean value of EPS deviates further from the actual earnings and indicates weaker forecast accuracy. Forecast Dispersion (FD, henceforth) is defined as the standard deviation of all forecasted EPS deflated by the stock price at the beginning of the announcement year of the actual earnings.[14] A higher FD implies that the analyst forecasts are more dispersed and indicates greater difficulty in forecasting earnings, either due to uncertainty about future earnings or disagreement among analysts.

[13] Our definition of AFE follows those in the literature including Thomas (2002), Zhang (2006), Gu and Hackbarth (2013), Guo and Mota (2021).

[14] Following Thomas (2002), we require at least three forecasts to construct the forecast dispersion for each observation in the sample.

The two measures of earnings forecast accuracy are based on long-term forecasts of 3 to 5 years. As shown in Appendix Table A4, the mean (median) AFE of long-term earnings for conglomerates is 4.32% (3.76%) and the average (median) dispersion in long-term forecasts by analysts (FD) is 1.55% (1.47%). To further understand the distribution of AFE and FD, we report the average accuracy of earnings forecasts for conglomerates grouped by their forecast-implied growth rate quintiles. As expected, Appendix Table A4 also shows that conglomerates in the high growth quintiles have higher values of AFE and FD. For example, the average AFE for high-growth conglomerates is 9.07% – significantly higher than the AFE of 3.39% (3.85%) for median-growth (low-growth) conglomerates. This is consistent with the findings in BGLS that analysts' overoptimism is the most relevant to high long-term growth firms, leading to worse forecast outcomes. In the subsequent tests, we aim to separate the effects of forecast bias from EOH within conglomerates.

We examine whether EOH affects the accuracy of analysts' earnings forecasts for the conglomerates. We estimate the following regression using only long-term forecasts:

$$Y_{i,t,f} = \beta High\ EOH_{i,t} + \gamma\ Control_{i,t} + Firm_i + Ind\_Year_{n,t} + \varepsilon_{i,t}, (4)$$

where $Y_{i,t,f}$ can be absolute forecast error (AFE) or forecast dispersion (FD) for firm i in year t, $High\ EOH_{i,t}$ is a dummy variable indicating high EOH for firm i in year t and all the other variables remain the same as in previous equations.

Table 5, Panel A presents the results. In Column 1 and 2, we examine if AFE and FD are affected by EOH. However, we find no significant difference in AFE and FD between conglomerates with high or low EOH.[15] The estimates indicate that EOH in conglomerates does not directly affect on the long-term growth expectations, suggesting that analysts' forecasts are unaffected by EOH in conglomerates, further distinguishing their biased expectations amplified by EOH.

[15] We find qualitatively similar results using sales management as an alternative measure of EOH. The results are in Appendix D.

4.1 Overreaction in Analyst Forecasts

La Porta (1996) and BGLS show that analysts use a firm's past earnings performance to revise their long-term earnings forecasts and tend to overreact. In line with their findings, we examine if analysts exhibit overreaction in their long-term earnings forecasts of conglomerates. More importantly, we ask if this overreaction is influenced by EOH. If analysts' forecast biases were affected by EOH, we would expect to observe stronger overreaction in conglomerates with high EOH. To quantify the magnitude of analyst overreaction in the presence of EOH, we employ the regression models proposed in Coibion and Gorodnichenko (2015) and BGLS.

Coibion-Gorodnichenko (2015) show that if analysts' forecasts are fully rational and incorporate all information available to them at time t, their forecast revisions between time t-1 and t should be uncorrelated with their subsequent forecast bias. On the other hand, if the revisions reflect an overreaction (underreaction) to information, then a negative (positive) relation between the analyst forecast revision and subsequent forecast bias is expected. We estimate the Coibion-Gorodnichenko regression for analyst long-term earnings forecast revision and subsequent realized earnings (e.g., BLGS):

$$\left(\frac{EPS_{i,t+n}}{EPS_{i,t}}\right)^{\frac{1}{n}} - LTG_{i,t} = \alpha + \beta_1 High\,EOH_{i,t} + \beta_2\left(LTG_{i,t} - LTG_{i,t-1}\right) +$$

$$\beta_3 High\,EOH_{i,t} * \left(LTG_{i,t} - LTG_{i,t-1}\right) + Year_t + \varepsilon_{i,t}, \text{(5)}$$

where $[(EPS_{i,t+n}/EPS_{i,t})^{1/n} - LTG_{i,t}]$ is the forecast bias for firm i in year t computed as the difference in the actual earnings growth rate $(EPS_{i,t+n}/EPS_{i,t})^{1/n}$ and LTG for firm i at time t, $LTG_{i,t}$. $LTG_{i,t} - LTG_{i,t-1}$ is the revision in long-term earnings growth forecasted between period t-1 and t. $LTG_{i,t}$ is obtained from I/B/E/S and *n* corresponds to the forecast period of 3, 4, or 5 years ahead. The coefficient of interest is β_3, which indicates if the overreaction in analysts forecast revisions are different for conglomerates with and without high-quality information.

The results in Panel B of Table 5 reveal that analysts do exhibit overreaction in their forecast revisions, consistent with BGLS. However, we find no evidence that analysts exhibit greater overreaction in response to higher EOH when revising their long-term earnings growth forecasts. Specifically, the estimated β_2 is significantly negative, indicating an overreaction in the analysts' forecast revisions. The magnitude of overreaction ranges from -0.29 to -0.47 for the forecast horizons of 3 to 5 years. More importantly, the magnitude of the overreaction coefficient (as indicated by the estimated β_3) remains the same for conglomerates regardless of whether EOH is high or low. These findings suggest that EOH is not associated with the biases in analysts' forecasted earnings for conglomerate earnings.

4.2 Analysts Forecast Accuracy and Segment Information Disclosure: An Experiment

Despite the presence of forecast bias, the evidence so far suggests that analysts' forecasts are not influenced by a conglomerate's EOH. One potential explanation for this finding is that analysts incorporate disclosed segment-level information when forming their forecasts and are therefore unaffected by the reported EOH. We test this hypothesis by exploiting a disclosure policy change stemming from the introduction of SFAS 131 ("Statement of Financial Accounting Standards No. 131, "Disclosures about Segments of an Enterprise and Related Information"). This rule supersedes SFAS 14 (Statement of Financial Accounting Standards No. 14, "Financial Reporting for Segments of a Business Enterprise"),[16] which provided segment-level disclosures in a highly aggregated fashion (e.g., Herrmann and Thomas, 2000). SFAS 131 requires firms to define their segments in a manner consistent with their internal organizational structures for financial reporting purposes. There is strong evidence that the adoption of SFAS 131 improves the quality of disclosed information.[17] Moreover, Berger and Hann (2003) show a reduction in market value for firms that

[16] SFAS 131 was issued by the FASB in June 1997 and is effective for fiscal years commencing after December 15, 1997. Under SFAS No. 14, firms were required to disclose segment information by both line-of-business and geographic area with no specific link to the internal organization of the company or the measurements that were used for internal decision-making.

[17] Street, Nichols, and Gray (2000) find that there is a greater number of line-of-business (LOB) segments reported and both the quantity and quality of the segment-level reporting improves under SFAS 131. Berger and Hann (2003)

were reported as single-segment firms under SFAS 14 but multiple-segment firms under SFAS 131. This inefficiency is often related to agency costs (e.g. CEO's tendency toward "empire building") or the rent-seeking behavior of divisional managers. Cho (2015) shows that SFAS 131 helps resolve agency conflicts in the internal capital markets of diversified firms.

We examine whether the increased granularity of segment-level disclosures under SFAS 131 affects analyst ability to identify and incorporate segment-level information in their firm-level earnings forecasts, particularly for high-growth conglomerates with high EOH. Because high EOH alters the optimism around the mean while changing the aggregation of segment-level earnings, we expect that SFAS 131 to provide analysts with greater details and enhances their ability to account for EOH in their firm-level forecasts.

We follow Cho (2015) to identify firms that were forced to adopt SFAS 131. A firm is a forced adopter of SFAS 131 only if (1) its segments reported under SFAS 14 in the previous year are different from those restated under SFAS 131 and (2) the restated segments under SFAS 131 reveal additional operations in industries that were not disclosed under SFAS 14. The segment data for the pre-SFAS 131 period, restated in accordance with SFAS 131, is manually collected by reading the firms' 10-Ks.[18] To apply this classification using Compustat data, we compare a firm's segment identifiers (SIDs) and segment SIC codes in the previous year under SFAS 14 with the same firm's SIDs and segment SIC codes in the year under SFAS 131 (i.e., the adoption year). If the restated segment data for a firm shows a difference of more than 1% in the sum of segment revenues and earnings compared to historical reports for the same period, the firm is eliminated from the sample. This is to ensure that the difference in the restated segment data is only due to the forced implementation of SFAS 131 and not to other structure changes (see Cho (2015)).

---

and Ettredge, Kwon, Smith, and Zarowin (2005) find that SFAS 131 increases the transparency of segment information. Enhanced transparency renders greater difficulty for managers to manipulate across segments to maximize value.

[18] Firms disclose their restated segment data in the 10-Ks filed with the SEC in the year that they first adopted SFAS 131. The segment data, restated as required by SFAS 131, is from EDGAR, provided by the SEC (www.sec.gov). For firms with 10-Ks not available in EDGAR, their 10-Ks or annual reports on their investor relations websites are used. We are grateful to YJ Cho for sharing the data used in Cho (2015).

We employ a difference-in-difference model to compare the impact of SFAS 131 on analyst forecasts in the four years before and after its adoption, spanning a total of nine years. Our sample includes conglomerates forced to adopt SFAS 131, where treated firms are those with high EOH before implementation, and control firms are those with low quality. We hypothesize that analysts make more precise forecasts for treated firms after SFAS 131 adoption, relative to the control group. We estimate the following two-way fixed effect (TWFE) model:

$$Y_{i,t} = \beta_1 Ex - Ante\ High\ EOH_{i,t} * Post_{i,t} + \beta_2 Post_{i,t} + \gamma\ Control_{i,t} + Firm_i + Year_{n,t} + \varepsilon_{i,t}, (6)$$

where $Y_{i,t}$ includes two outcomes, $AFE_{i,t}$ and $FD_{i,t}$. $AFE_{i,t}$ is the absolute forecast error of all long-term forecasts for firm i in year t and $Forecast\ Dispersion_{i,t}$ is the standard deviation of all forecasts for firm i in year t. $Ex - Ante\ High\ Quality\ of\ Informatio_{i,t}$ is set to one if the frequency of firm i displaying high EOH is above median frequency in the three-year period before the implementation of SFAS 131 and zero otherwise,[19] $Post_{i,t}$ is a dummy variable set to 1 for post-SFAS 131 period, and $Control_{i,t}$ is a vector of control variables as in equation (4). Standard errors are clustered at the firm level. Following Cho (2015), we exclude firms operating in financial service industries (industry codes 44, 45, and 47) and regulated utility industries (industry code 31).

We report the results in Table 6. The coefficients on the interaction term $Ex - Ante\ High\ EOH_{i,t} * Post_{i,t}$ are significantly negative, indicating that conglomerates exhibiting higher EOH experienced a significant decrease in AFE and FD after SFAS 131 adoption, relative to the control group. Specifically, the AFE and FD for forced adopter conglomerates that had displayed higher EOH before decreased by 72%

[19] SFAS 131 was effective for firms with fiscal years beginning after December 15, 1997. Hence, December year-end firms adopted SFAS 131 in 1998, whereas non-December year-end firms adopted this standard in 1999. As a result, for December year-end firms, the pre-SFAS 131 period covers 1995, 1996 and 1997, and the post-SFAS 131 period covers 1998 and afterwards. For non-December year-end firms, the pre-SFAS 131 period covers 1996, 1997 and 1998, and the post- SFAS 131 period covers 1999 and afterwards.

and 17% respectively, in relation to the sample mean before the adoption. This indicates that the implementation of SFAS 131 made it easier for analysts to adjust.

Additionally, we test for parallel trends, estimating a version of the two-way fixed effect model that includes indicators for each distance to/from the adoption of SFAS 131. This allows us to analyse the effects of the treatment at different points in the time leading up to and following the adoption of the standard. By including these indicators, we ensure that changes in our outcome variables are driven by the adoption of the SFAS 131 rather than pre-existing trends or other external factors. Specifically, we estimate the following specification:

$$Y_{i,t} = \beta_1 \sum_{s=-4,s\neq-1}^{4} Ex - Ante\ High\ EOH_i * D_{s(i,t)} + \beta_2 Control_{i,t} + Firm_i + Year_t + \varepsilon_{i,t}, \quad (7)$$

where $Y_{i,t}$ is $AFE_{i,t}$ or $FD_{i,t}$ and $D_{i,s}$ is a set of indicator variables that take value one if the adoption of SFAS 131 was s years away for firm i in year t, with the adoption year (s=-1) as the omitted period.

Figure 3 presents the event study results, which support the parallel trends assumption: the coefficients on the years leading up to the adoption of SFAS 131 for firms with ex-ante high EOH are near zero, showing no discernible pre-trends. Figure 3 also demonstrates the dynamics of treatment effects. While the treatment effects on AFE vary, they are significantly smaller during the post-periods. We observe a similar but less significant pattern for FD. Overall, our results suggest that analysts effectively use segment-level information, causing their firm-level earnings forecasts to remain unaffected by managers' reported EOH.

5. Do Mutual Funds React to EOH?

Finally, we investigate the investors who are most impacted by EOH: mutual funds. The literature documents that mutual funds do not exploit predictability in equity returns arising from stock market anomalies and, in aggregate, tend to buy the stocks belonging to the short-leg of anomalies, thereby amplifying cross-sectional mispricing (Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015, and Edelen, Ince and Kadlec, 2016). We build on these findings to examine whether active mutual funds are affected by their exposure to mispriced high growth conglomerates with high EOH and whether they subsequently underperform.

The mutual fund data come from several sources, including Thomson Reuters fund holding data and CRSP fund holding, summary, and return data and we focus on actively managed equity funds in the U.S., with assets larger than $15 million.[20] To minimize data quality problems, we use Thomson Reuters fund holding data up to the first quarter of 2010 and then use CRSP fund holding data from the second quarter of 2010 (Zhu (2020) and Dou, Kogan, and Wu (2022)).[21] Because data coverage on the monthly TNA and quarterly portfolio holding is limited prior to 1997, our sample is from January 1997 to December 2018 and contains 6,678 distinct mutual funds, with a quarterly average of 1,370 funds.

The exposure of an active mutual fund to conglomerates with high long-term earnings growth is measured as the fund's active investment weight in conglomerates in the top decile of long-term earnings growth ("HGC"). Similarly, exposure to conglomerates with high long-term earnings growth and EOH is measured as the fund's active investment weight in conglomerates in the top decile of long-term earnings growth that also have high EOH ("HGCHEOH"). The *active* investment weights in HGC and HGCHEOH are defined as the deviation of the fund's investment weights from the fund's benchmark weights. Funds with positive exposure (i.e. HGC > 0 or HGCHEOH > 0) are sorted into quintiles based on the value of their active investment weights.[22]

[20] Similar to prior studies (Kacperczyk et al., 2005; Huang et al., 2011), we identify actively managed United States equity mutual funds based on their objective codes and their disclosed asset compositions. Detailed identification is provided in Appendix C.

[21] Zhu (2020) reports that starting from 2008, some newly founded U.S. equity mutual fund share classes in the CRSP mutual fund database cannot be matched to the Thomson Reuters database. Hence, we use fund holdings data from Thomson Reuters until the first quarter of 2010, given that CRSP provides wider coverage from 2010.

[22] We use active investment weights to account for the concern that active mutual funds investment in stocks with EOH and high growth (high HGCHEOH) simply reflects their benchmark indices or investment mandates. Active investment weight is defined as the raw investment weight minus the corresponding investment weight in the benchmark index of a fund. Information on the benchmark indices of the mutual funds is obtained from Thomson Reuters Lipper Fund Database. If the benchmark index of a fund is missing, we use S&P 500 as the benchmark index. The results on fund performance hold if we use raw investment weights. We exclude funds with non-positive HGC/HGCHEOH from our sample to account for the concern that funds may avoid investing high growth conglomerates (with EOH) because of investment objectives or investment mandates rather than their investment skills allowing them to foresee the potential underperformance associated with these firms. If this is the case, then the

We construct calendar time portfolios of fund performance defined as raw returns as well as risk-adjusted returns using the Carhart four factors (market, size, book-to-market, and momentum), Fama-French five-factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Ferson-Schadt conditional model, and benchmark returns grouped by investment objectives. Table 7 presents the average monthly returns for the following year on funds sorted by HGC or HGCHEOH. We find that funds with high exposure to high long-term growth conglomerates featuring high EOH (HGCHEOH) significantly underperform the funds with low exposure, with the annualized difference in alphas of -2.01% to -3.31%.[23] Interestingly, we do not find a significant effect of exposure to high growth conglomerates on mutual fund performance when EOH is low, indicating that the EOH is crucial for fund performance predictability (Appendix Table A5).

These results suggest that mutual funds' long-term performance is negatively impacted by the EOH of conglomerates. To confirm that this is due to active mutual funds being susceptible to EOH and increasing their holdings of those stocks, we focus on the change in fund holdings. In particular, we test whether mutual funds increase their holdings of conglomerates that move into the top LTG decile from a lower LTG group and, at the same time, enter the high-growth conglomerates with high-quality-information group. Hence, we estimate the following regression for the subsample of conglomerates only:

$$\Delta w_{i,t} = \beta_1 High\ EOH_{i,t} + \beta_2\, \Delta HighLTG_{i,t} + \beta_3 \Delta HighLTG_{i,t} * High\ EOH_{i,t} + \gamma\ Control_{i,t} + Firm_i + YearQuarter_t + \varepsilon_{i,t}, \quad (8)$$

where $\Delta w_{i,t}$ is the mutual funds' ownership level (in percent) in conglomerate i in quarter t minus the ownership in quarter t-1. We measure both the change in mutual funds' ownership level and the change in active mutual funds' ownership in excess of the benchmark. $High\ EOH_{i,t}$ is a dummy variable that is set to

---

relationship between HGC/HGCHEOH and fund performance can be spurious and hence, we exclude funds with non-positive HGC/HGCHEOH when we estimate Equations 8 and 9.

23 Although we fail to find the objective-adjusted fund returns for the High-Minus-Low HGCHEOH group to be statistically significant, we do show that the high HGCHEOH group earns an average annualized objective-adjusted return of -1.35% (t=-2.72).

1 if firm i is a conglomerate that displayed high EOH in year y-1 and 0 otherwise. $\Delta HighLTG_{i,t}$ is set to 1 only if stock *i* moves from the bottom 90% in quarter t-2 to the top LTG decile in quarter t-1. $Control_{i,t}$ is a vector of firm characteristics, including firm size, past stock returns, and book-to-market ratio.

The results in Column 1 and Column 3 of Table 8 show that when a conglomerate moves to the top LTG decile, the mutual fund ownership, and *active* ownership in the stock, increases significantly by 1.1%. This finding is consistent with Table 7 Panel A, which shows that some mutual funds actively invest in the conglomerates when the stock moves to the top LTG deciles and then underperforms. The evidence in Column 2 and Column 4 of Table 8 further suggests that when a conglomerate moves to the top 10% LTG and exhibits high EOH, active mutual fund ownership level increases by 5.6%. This implies that mutual funds actively respond to the increase in LTG and EOH by adding these stocks to their portfolios, contributing to the mispricing of these stocks.

Next, we examine whether mutual funds adapt and correct their mistakes over time when it comes to holding shares of conglomerates with an optimistic change in LTG with high EOH. Consistent with this expectation, we find that mutual funds reduce their holdings of these firms in subsequent quarters. Appendix Table A6 shows mutual fund adjust their holding downward by 0.33% and 2.38% in the subsequent quarter for conglomerates moving to the top quintile LTG group and with high EOH, respectively.

Finally, we evaluate mutual funds' reaction to the disclosure of segment earnings information with SFAS 131. Applying the filters from Table 6, Table 9 presents findings that mutual fund managers' reactions to high-growth conglomerates with high EOH remain unchanged after SFAS 131 takes effect. Moreover, the significantly low returns on high-growth conglomerates with high EOH remain pronounced post-SFAS 131 (see Appendix Table A7). Overall, the findings imply that mutual funds do not fully exploit the segment-level disclosure mandated by SFAS 131.

Overall, the cumulative evidence supports the view that mutual funds react to the EOH of high-growth conglomerates in a way that reinforces mispricing (i.e., buying overpriced conglomerates) and suffer long-term underperformance.

Conclusion

We study the link between stock return predictability and EOH, focusing on the underperformance of firms with high expected long-term earnings growth. We find that this underperformance is concentrated in conglomerates with high EOH. This long-term underperformance is both economically significant and robust to various factor-model benchmarks and regression specifications, while it is absent in pseudo-conglomerates constructed using single-segment firms.

We argue that the predictive relationship between long-term growth expectations and stock returns is exacerbated by a higher EOH in high-growth firms. Specifically, high EOH inflates the prices of high-growth stocks, leading them to become more overpriced. Our evidence shows that a portfolio of high-growth conglomerates with high EOH earns an annualized risk-adjusted return of about -8%, while a comparable portfolio with low EOH yields statistically insignificant abnormal returns.

The evidence that analyst forecasts of conglomerate-level earnings are not influenced by EOH supports our contention that EOH introduces incremental stock-price effects beyond investor-expectation errors. Such EOH interacts with investors' long-term growth expectations, contributing to stock mispricing.

Overall, our results highlight the crucial role EOH plays in the pricing of long-term earnings growth. EOH not only amplifies stock mispricing but also reveals important dynamics among managerial actions, investor behavior, and stock return predictability.

References

Akbas, Ferhat, Will J. Armstrong, Sorin Sorescu, and Avanidhar Subrahmanyam. 2015. "Smart Money, Dumb Money, and Capital Market Anomalies." *Journal of Financial Economics* 118(2):355–82.

Atmaz, Adem, and Suleyman Basak. 2019. "Option Prices and Costly Short-Selling." *Journal of Financial Economics* 134 (1): 1–28.

Bali, Turan G., Robert F. Engle, and Scott Murray. 2016. Empirical Asset Pricing: The Cross Section of Stock Returns. Wiley Press.

Barberis, Nicholas R., and Richard H. Thaler, 2003, A survey of behavioral finance (Chapter 18) in George M. Constantinides, Milton Harris, and Rene Stulz, eds.: *Handbook of the Economics of Finance* (Elsevier North Holland, Amsterdam, Netherlands).

Berger, Philip G., and Rebecca Hann. 2003. "The Impact of SFAS No. 131 on Information and Monitoring." *Journal of Accounting Research* 41(2):163–223.

Bergstresser, Daniel, and Thomas Philippon. 2006. "CEO Incentives and Earnings Management." *Journal of Financial Economics* 80(3):511–29.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer. 2019. "Diagnostic Expectations and Stock Returns." *Journal of Finance* 74(6):2839–74.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer. 2024. "Belief Overreaction and Stock Market Puzzles." *Journal of Political Economy* 132(5): 1450–84.

Chan, Louis, K.C, Jason Karceski and Josef Lakonishok. 2003, "The Level and Persistence of Growth," *Journal of Finance*.

Chen, Huaizhi, Lauren Cohen, and Dong Lou. 2016. "Industry Window Dressing." *Review of Financial Studies* 29(12):3354–93.

Cho, Young Jun. 2015. "Segment Disclosure Transparency and Internal Capital Market Efficiency: Evidence from SFAS No. 131." *Journal of Accounting Research* 53(4):669–723.

Cohen, Lauren and Dong Lou. 2012. "Complicated Firms." *Journal of Financial Economics* 104(2):383–400.

Coibion, Olivier, and Yuriy Gorodnichenko. 2015. "Information Rigidity and the Expectations Formation Process : A Simple Framework and New Facts." *The American Economic Review* 105 (8): 2644–78.

Coles, Jeffrey L., Naveen D. Daniel, and Lalitha Naveen. 2006. "Managerial Incentives and Risk-Taking." *Journal of Financial Economics* 79 (2): 431–68.

Core, John, and Wayne Guay. 2002. "Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility." *Journal of Accounting Research* 40 (3): 613–30.

Da, Zhi, and Mitch Warachka. 2011. "The Disparity between Long-Term and Short-Term Forecasted Earnings Growth." *Journal of Financial Economics* 100 (2): 424–42.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. "Investor Psychology and Security Market Under- and Overreactions." *Journal of Finance* 53(6):1839–85.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam. 2001. "Overconfidence, Arbitrage, and Equilibrium Asset Pricing." *Journal of Finance* 56(3):921–65.

Dechow, Patricia, Weili Ge, and Catherine Schrand. 2010. "Understanding Earnings Quality: A Review of the Proxies, Their Determinants and Their Consequences." *Journal of Accounting and Economics* 50(2–3): 344–401.

DellaVigna, Stefano, and Joshua M. Pollet. 2007. "Demographics and Industry Returns." *The American Economic Review* 97 (5): 1667–1702.

Dellavigna, Stefano, and Joshua M Pollet. 2009. "Investor Inattention and Friday Earnings Announcements." *The Journal of Finance* 64 (2): 709–49.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina. 2002. "Differences of Opinion and the Cross Section of Stock Returns." *Journal of Finance* 57(5):2113–41.

Dou, Winston, Leonid Kogan, and Wei Wu. 2020. "Common Fund Flows: Flow Hedging and Factor Pricing." *SSRN Electronic Journal*.

Drechsler, Itamar, and Qingyi Freda Drechsler. 2014. "The Shorting Premium and Asset Pricing Anomalies." *SSRN Electronic Journal*.

Duchin, RAN. 2010. "Cash Holdings and Corporate Diversification." *The Journal of Finance* 65(3):955–92.

Edelen, Roger M., Ozgur S. Ince, and Gregory B. Kadlec. 2016. "Institutional Investors and Stock Return Anomalies." *Journal of Financial Economics* 119(3):472–88.

Ettredge, Michael L., Soo Young Kwon, David B. Smith, and Paul A. Zarowin. 2005. "The Impact of SFAS No. 131 Business Segment Data on the Market's Ability to Anticipate Future Earnings." *Accounting Review* 80(3):773–804.

Fama, Eugene F., and Kenneth R. French. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116(1):1–22.

Ferson, Wayne E., and Rudi W. Schadt. 1996. "Measuring Fund Strategy and Performance in Changing Economic Conditions." *Journal of Finance* 51(2):425–61.

Gaspar, José Miguel, Massimo Massa, and Pedro Matos. 2005. "Shareholder Investment Horizons and the Market for Corporate Control." *Journal of Financial Economics* 76(1):135–65.

Givoly, Dan, Carla Hayn, and Julia D'Souza (1999). "Measurement errors and information content of segment reporting," *Review of Accounting Studies* 4, 15–43.

Gu, Lifeng, and Dirk Hackbarth. 2013. "Governance and Equity Prices: Does Transparency Matter?" *Review of Finance* 17 (6): 1989–2033.

Guo, Yifeng, and Lira Mota. 2021. "Should Information Be Sold Separately? Evidence from MiFID II." *Journal of Financial Economics* 142 (1): 97–126.

Harbaugh, Rick, John Maxwell, and Kelly Shue. 2017. "Consistent Good News and Inconsistent Bad News." *SSRN Electronic Journal*.

Herrmann, D., and W. Thomas. 2000. "An Analysis of Segment Disclosures under SFAS No. 131 and SFAS No. 14." *Accounting Horizons* 14: 287–302.

Hirshleifer, David. 2001. "Investor Psychology and Asset Pricing." *Journal of Finance* 56(4):1533–97.

Hou, Kewei, Chen Xue, and Lu Zhang. 2015. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies* 28(3):650–705.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang. 2011. "Risk Shifting and Mutual Fund Performance." *Review of Financial Studies* 24 (8): 2575–2616.

Iacus, S. M., King, G., & Porro, G. (2009). "CEM: Coarsened exact matching software". *Journal of Statistical Software*, *30*(9), 1–27

Jiang, Fuwei, Joshua Lee, Xiumin Martin, and Guofu Zhou. 2019. "Manager Sentiment and Stock Returns." *Journal of Financial Economics* 132(1): 126–49.

Jiang, Hao and Sun, Zheng. 2015. "News and Corporate Bond Liquidity." *SSRN Electronic Journal.*

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng. 2005. "On the Industry Concentration of Actively Managed Equity Mutual Funds." *Journal of Finance* 60 (4): 1983–2011.

Kent, Daniel, David Hirshleifer, and Avanidhar Subrahmanyam. 2019. "Investor Psychology and Security Market Under- and Overreactions." *The Journal of Finance* 53(6):1839–85.

La Porta, Rafael. 1996. "Expectations and the Cross-Section of Stock Returns." *Journal of Finance* 51(5):1715–42.

Matvos, Gregor and Amit Seru. 2014. "Resource Allocation within Firms and Financial Market Dislocation: Evidence from Diversified Conglomerates", *Review of Financial Studies* 27 (4) 1143-1189.

Mitchell, Mark L., and Erik Stafford. 2000. "Managerial Decisions and Long-Term Stock Price Performance." *Journal of Business* 73(3):287–329.

Peng, Lin, and Wei Xiong. 2006. "Investor Attention, Overconfidence and Category Learning." *Journal of Financial Economics* 80 (3): 563–602.

Thomas, Shawn. 2002. "Firm Diversification and Asymmetric Information: Evidence from Analysts' Forecasts and Earnings Announcements." *Journal of Financial Economics* 64 (3): 373–96.

Stambaugh, Robert F., and Yu Yuan. 2017. "Mispricing Factors." *Review of Financial Studies*. 30(4): 1270-1315.

Street, D., N. Nicholas., and S. Gray. 2000. "Segment Disclosures under SFAS No. 131: Has Business Segment Reporting Improved?" *Accounting Horizons* 14: 259–85.

Zhang, X. Frank. 2006. "Information Uncertainty and Stock Returns." *Journal of Finance* 61 (1): 105–37.

Zhu, Qifei. 2020. “The Missing New Funds.” *Management Science* 20 (5): 554–55.

Variable Definition

Variable Name	Definition
Forecast-related variables (From I/B/E/S)	
Absolute Forecast Error (AFE)	AFE is constructed as follows. For firm i, year t and forecast horizon f, firm-level analyst forecast error is defined as the absolute value of the difference between the actual earnings per share (EPS) and the forecasted EPS consensus, which is the median value of all forecasted EPS, deflated by the stock price at the beginning of the announcement year of the actual earnings. $$AFE_{i,t,f} = \sum_{n}^{N} \left\lvert \frac{Analyst\ Forecasted\ EPS_{i,t,f,n} - Real\ EPS_{i,t,f,n}}{P_{i,t}} \right\rvert$$ where N is the number of analysts announcing f-horizon forecasts for firm i in year t. We also try to use actual earnings per share as an alternative deflator and replace the forecasted EPS consensus with the mean value of forecasted EPS. The AFE for pseudo-conglomerates is the segment-sales-weighted value of AFEs of matched industry portfolios. Alternative measures also doesn't harm our main results. AFE is multiplied by 100 for ease of interpretation.
Forecast Dispersion (FD)	FD is constructed as follows. For each conglomerate-year and each forecast horizon, FD is defined as the standard deviation of all forecasted EPS deflated by the stock price at the beginning of the announcement year of the actual earnings. For pseudo-conglomerates, FD is the-segment-sales-weighted value of FD of matched industry portfolios. Following Thomas (2002), we require at least three forecasts to construct the forecast dispersion for each observation in the sample. FD is multiplied by 100 for ease of interpretation.
Long-Term Growth Rate (LTG)	LTG (meanest) is obtained from the I/B/E/S Unadjusted U.S. Detail file. When LTG is missing, we fill the missing LTG with the simple average forecast-implied growth rate with forecast horizons of 3-5 years. Forecast-implied growth rate is defined as $\sqrt[\frac{1}{Forecast\ Horizon}]{\frac{Forecasted\ EPS_t^{Forecast\ Horizon}}{Actual\ EPS_{t-1}}} - 1$ when the actual EPS in the last year and the current forecasted median value of EPS have the same sign. Sometimes, we don't have a valid value for the forecast-implied growth rate because forecasted EPS can be non-positive. To obtain reasonable value under such circumstances, we define a more detailed way to calculate growth rate. We set the forecast-implied growth rate to be missing if the actual EPS is not positive. $$\text{forecast} - \text{implied growth rate} = \begin{cases} \sqrt[\frac{1}{Forecast\ Horizon}]{\frac{Forecasted\ EPS_t^{Forecast\ Horizon}}{Actual\ EPS_{t-1}}} - 1 \\ when\ \ Forecasted\ EPS_t^{FPI} > 0 \\ -\left(\sqrt[\frac{1}{Forecast\ Horizon}]{\frac{\lvert Forecasted\ EPS_t^{Forecast\ Horizon}\rvert + \lvert Actual\ EPS_{t-1}\rvert}{\lvert Actual\ EPS_{t-1}\rvert}} + 1 - 1\right) \\ when\ \ Forecasted\ EPS_t^{Forecast\ Horizon} < 0 \\ -1\ \ when\ Forecasted\ EPS_{t-1} = 0 \end{cases}$$ For pseudo-conglomerate sample, we first aggregate LTG (fill missing with forecast-implied growth rate) of stand-alone firms by FF-48 industries and calculate industry-average LTG for each industry-year. We match industry-average LTG to the corresponding segments of conglomerates by FF-48 industries and calculate average of industry-average LTG weighted by segment sales as the "pseudo" LTG.
Forecast Revision	Forecast revision is defined as the current long-term growth rate minus the prior long-term growth rate.
Firm-Level Characteristics (From CRSP, Compustat, I/B/E/S, and Thomson Reuters)	

Size	Size is the log value of firm market capitalization in millions.
Analyst Coverage	Analyst coverage is the number of analysts covering the firm.
Age	Age is firm age.
BM	BM ratio is the log value of book value of equity divided by market value of equity.
Conglomerate	A firm with segments in two different FF-48 industries is defined as a conglomerate and stand-alone firm otherwise. We require the total sales of all segments within a firm to be larger than 80% of the firm-level sale.
Sales	Sales is the log value of the summation of the segment level sales revenue in millions.
Earnings Optimism Heuristic (EOH)	We set "EOH" dummy variable to be 1 if the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations or is positive when firm news is worse than expectations and 0 otherwise. We refer to $s_{jt} - \widehat{s_{jt}}$ as the abnormal standard deviation of segment earnings, where s_{jt} is the log of the weighted standard deviation of the actual segment earnings and $\widehat{s_{jt}}$ is the log of the weighted standard deviation of the predicted segment earnings. We also measure whether overall firm news exceeds expectations using the difference between total firm earnings and the industry mean.
Fund-Level Characteristics (From CRSP, Compustat, I/B/E/S, and Thomson Reuters)	
HGC	HGC is the aggregate investment weight in conglomerates with top 10% LTG. HGC is based on active investment weights. Active investment weight is defined as the raw investment weight minus the corresponding investment weight in the benchmark index of a fund. Information on benchmark indices of mutual funds is obtained from Refinitiv Lipper Fund Database. At fund holding level, HGC is constructed using fund holding data at every year-quarter cross-section for each fund. The fund holding level data is obtained from Thomson Reuters and CRSP. Following Zhu (2020), we use Thomson Reuters before 2010 Q1 and CRSP after 2010 Q2.
HGCHEOH	HGCHEOH is the aggregate investment weight in conglomerates with top 10% LTG and high EOH. HGCHEOH is based on active investment weights and constructed in the same way of HGC.

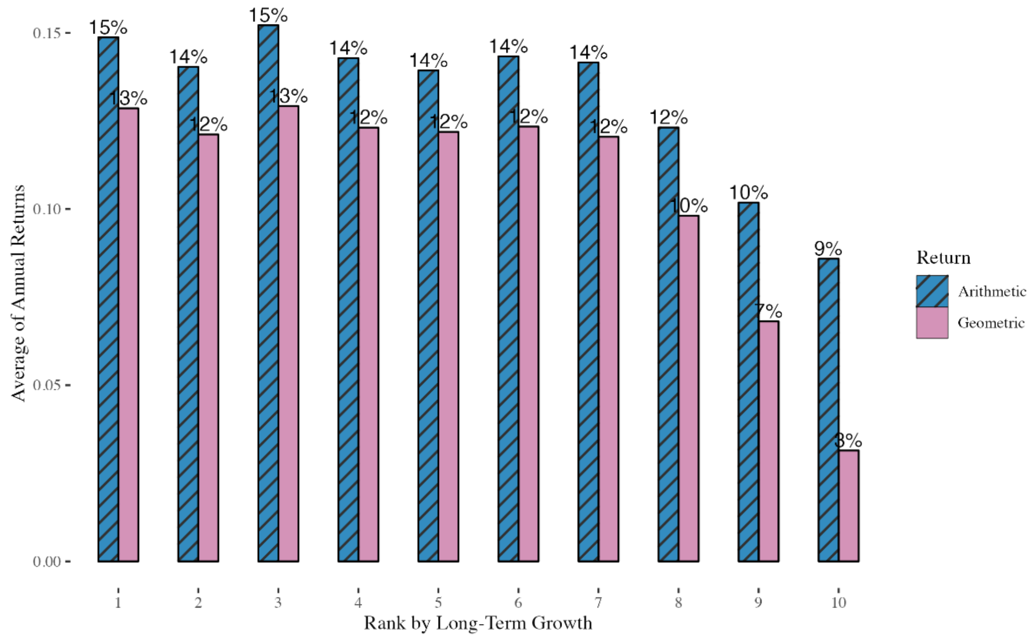


Figure 1A. Annual returns on stocks ranked on forecast of long-term earnings growth (LTG): decile portfolios of all firms. This figure is a replication of Figure 1 in Bordola, Gennaioli, La Porta and Shleifer (2019). In December of each year between 1981 and 2018, we form decile portfolios based on ranked analyst expected growth in long-term EPS and display the geometric and arithmetic average one-year returns over the subsequent calendar year for equally-weighted portfolios. A portfolio that is long low-LTG stocks and short high-LTG earns an average annual return of 10.36% (t=2.18) for geometric mean and 6.28% (t=1.36) for arithmetic mean.

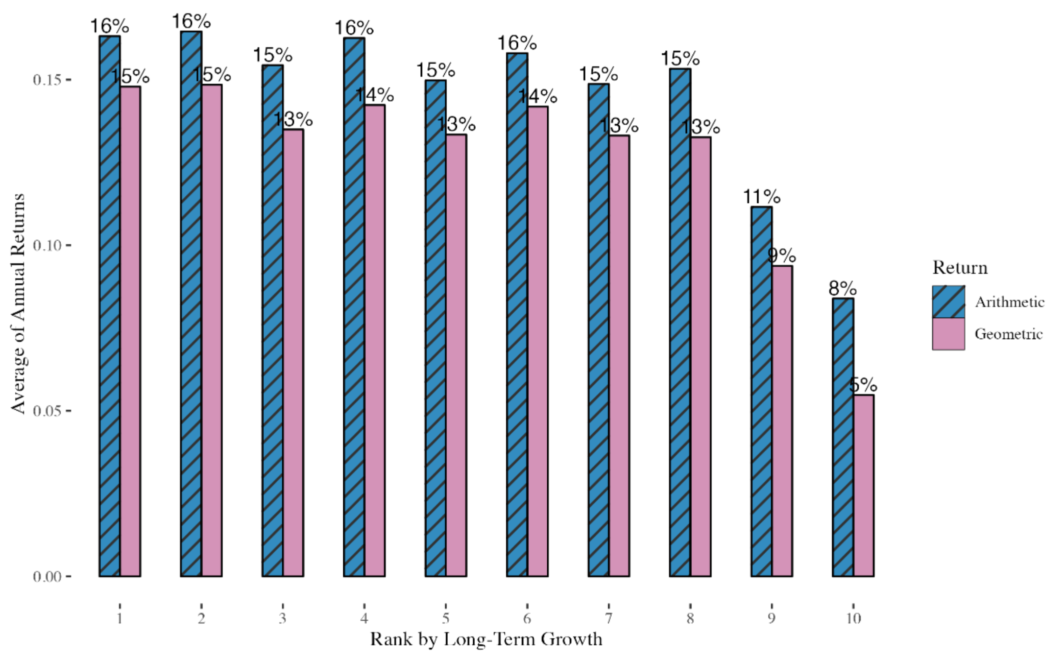


Figure 1B. Annual returns on stocks ranked on forecast of long-term earnings growth (LTG): decile portfolios of conglomerates. This figure is a replication of Figure 1 in Bordola, Gennaioli, La Porta and Shleifer (2019) using the sub-sample of conglomerates. In December of each year between 1981 and 2018, we form decile portfolios based on ranked analyst expected growth in long-term EPS and display the geometric and arithmetic average one-year returns over the subsequent calendar year for equally-weighted portfolios. A portfolio that is long low-LTG conglomerates and short high-LTG conglomerates earns an average annual return of 9.11% (t=3.64) for geometric mean and 7.982% (t=3.11) for arithmetic mean.

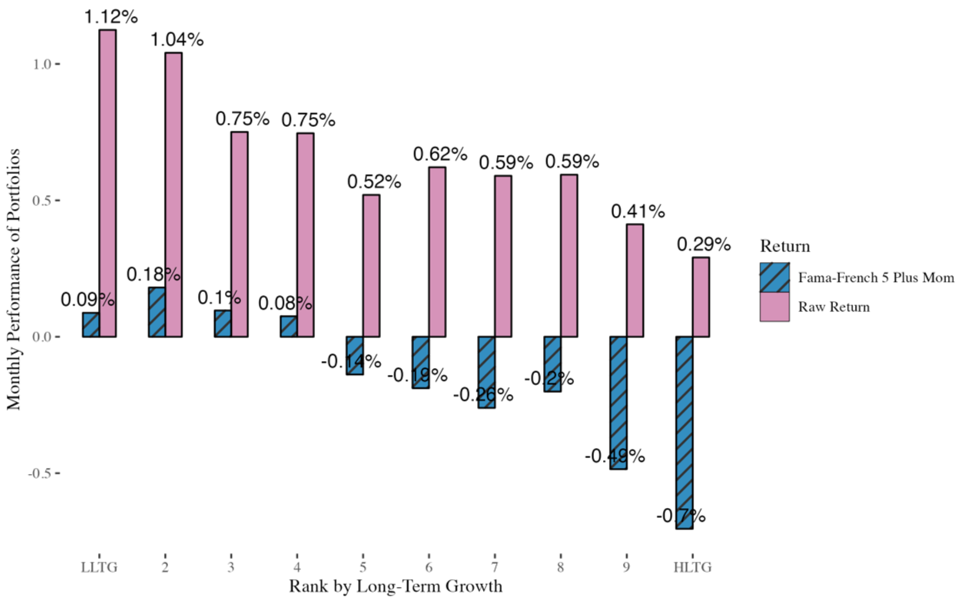


Figure 2A. Monthly performance of stocks ranked on forecast of long-term earnings growth (LTG): decile of conglomerates with high EOH. This figure show the monthly performance of calendar-time portfolios. In December of each year between 1981 and 2018, we construct 2*10 independent calendar-time portfolio sorted by EOH (high or low), and long-term growth forecasts (LTG, decile low to high) using the sample of only conglomerates.

We focus on the subsample consisting of conglomerates with high EOH and display the average monthly raw returns or alphas based on Fama-French 5 factors plus momentum factor over the subsequent calendar year for value-weighted portfolios. A portfolio that is long low-LTG conglomerates with high EOH and short high-LTG conglomerates with high EOH earns an average monthly outperformance of 0.83% (t=3.96) for raw return and 0.79% (t=3.75) for alpha.

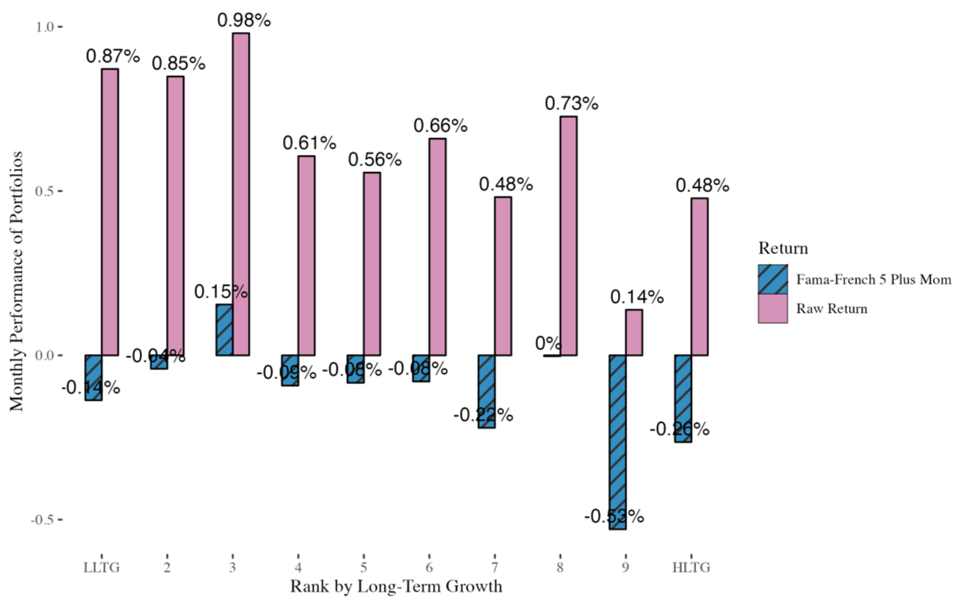
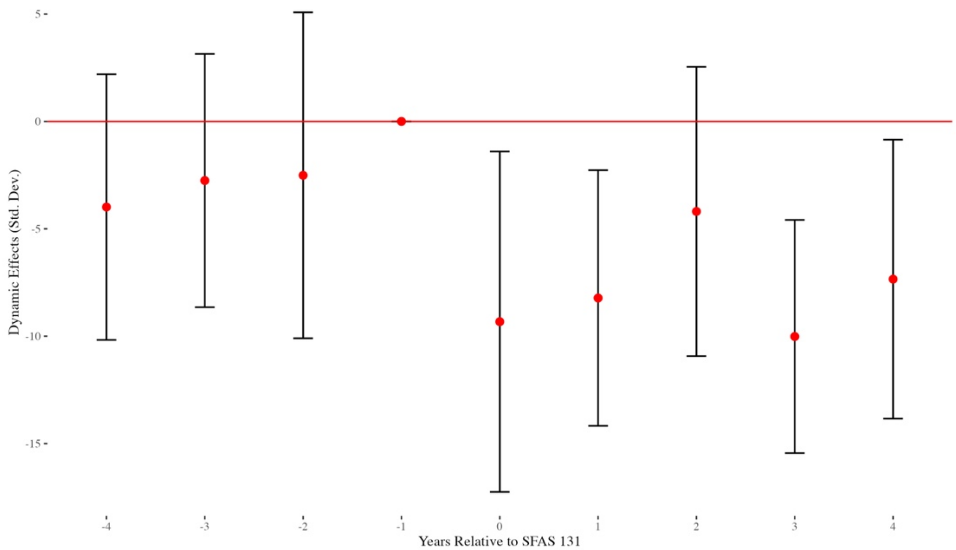
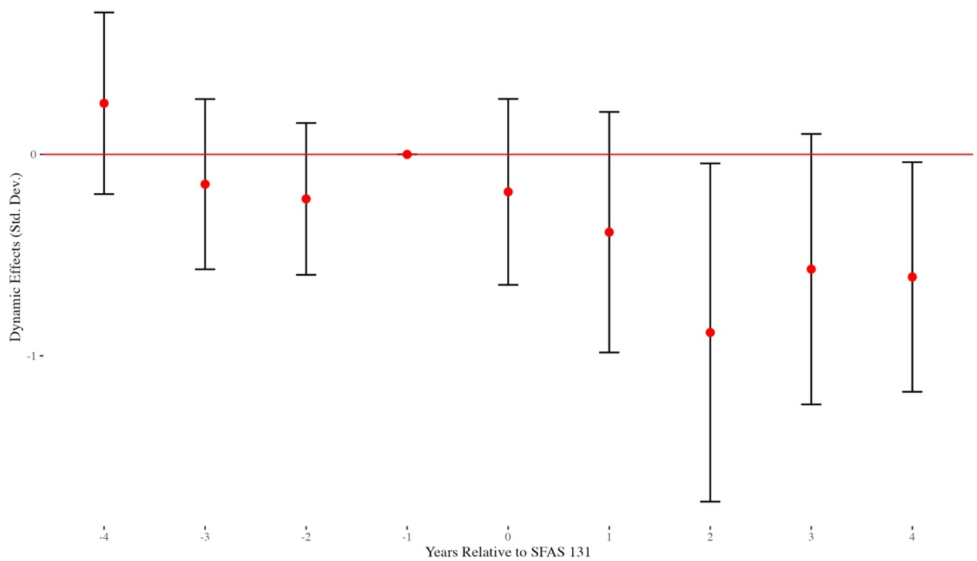


Figure 2B. Monthly performance of stocks ranked on forecast of long-term earnings growth (LTG): decile of conglomerates with low EOH
We focus on the subsample consisting of conglomerates with low EOH and display the average monthly raw returns or alphas based on Fama-French 5 factors plus momentum factor over the subsequent calendar year for value-weighted portfolios. A portfolio that is long low-LTG conglomerates with low EOH and short high-LTG conglomerates with low EOH earns an average monthly outperformance of 0.39% (t=1.43) for raw return and 0.13% (t=0.55) for alpha.



Panel A: The Effects of SFAS 131 on Absolute Forecast Errors



Panel B: The Effects of SFAS 131 on Forecast Dispersion

Figure 3 The Dynamic Effects of SFAS 131 on Absolute Forecast Errors and Forecast Dispersion of Conglomerates with Pre-SFAS 131 EOH. Here, we use the subset of only conglomerates and focus exclusively on long-term forecasts (3-5 years). Following Cho (2015), we restrict our sample to four years before and after the adoption year of SFAS 131 (9 years in total). Following Berger and Hann (2003), we eliminate change firms from the sample if the changes are contaminated by events (e.g., acquisition, divestiture, restructuring, or changes in accounting methods) other than pure reporting changes. In particular, we estimate:

$$Y_{i,t} = \beta_1 \sum_{s=-4, s\neq -1}^{4} Ex - Ante\ EOH_i * D_{s(i,t)} + \gamma\ Control_{i,t} + Firm_i + Year_t + \varepsilon_{i,t}$$

where the dependent variable $Y_{i,t}$ here is AFE in Panel A and forecast dispersion in Panel B and $D_{i,s}$ is a set of indicator variables that take value one if the adoption of SFAS 131 was s years away for firm i in year t. *Ex-Ante EOH* is a dummy variable set to 1 if EOH of the firm in pre-SFAS 131 period is high and 0 otherwise. Controls are the same as in the baseline specification. We include firm fixed effects and year fixed effects and standard errors are clustered by firm. The bars represent 95% confidence intervals.

Table 1: Stock Return Predictability: LTG and Conglomerates

We construct 2 calendar-time portfolio sorted by conglomerate dummy in Panel A. We construct 2*10 dependent calendar-time portfolio sorted by first conglomerate dummy and then long-term growth forecasts(LTG, decile low(1) to high(10)) in Panel B. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries and we construct a pseudo-conglomerate for each conglomerate. LTG is from the I/B/E/S Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. LTG is lagged one month relative to the period during which the return is measured. To ensure that the conglomerate dummy used to sort portfolio is based on data that would have been publicly available by the time presumed in the analysis, the conglomerate dummy that is calculated using data from calendar year *y* is not assumed to be known until the end of June of year *y* + 1. Thus, the conglomerate dummy is based on data in year y-2 if we form portfolios in January to May of year y and based on data in year y-1 if we form portfolios the in June to December of year y. The future stock return is measured over a one-year horizon in Panel A and Panel B. Returns are value weighted. In addition to raw returns, we consider risk-adjusted returns using Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Stambaugh and Yuan mispricing factors (market, size, management, and performance), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). We report Newey-West t-stats in brackets.

Panel A: Unconditional Returns

	Raw Returns	FF5+Mom	Q-factor	Mispricing
Conglomerates	0.64***	-0.068	-0.071	-0.06
	(3.175)	(-1.566)	(-1.585)	(-1.156)
Pseudo-Conglomerates	0.676***	0.007	0.006	0.008
	(2.813)	(0.154)	(0.122)	(0.15)
Conglomerates Minus Pseudo-Conglomerates	-0.035	-0.075	-0.077	-0.068
	(-0.449)	(-1.549)	(-1.449)	(-1.312)

Panel B: One-Year Returns Conditional on LTG

Long-Term Growth Rate (LTG)		Raw Returns	FF5+Mom	Q-factor	Mispricing
High Growth Firms	Conglomerates	0.183	-0.647***	-0.611***	-0.583***
		(0.606)	(-4.682)	(-4.638)	(-4.126)
	Pseudo-Conglomerates	0.453	0.015	0.068	0.012
		(1.363)	(0.11)	(0.413)	(0.073)
	Conglomerates Minus Pseudo-Conglomerates	-0.27	-0.662***	-0.679***	-0.595***
		(-1.402)	(-3.603)	(-3.36)	(-2.747)
Low Growth	Conglomerates	1.093***	0.076	0.092	0.193
		(4.844)	(0.746)	(0.834)	(1.392)
	Pseudo-Conglomerates	0.87***	0.055	0.058	0.229
		(3.845)	(0.375)	(0.358)	(1.387)
	Conglomerates Minus Pseudo-Conglomerates	0.223	0.021	0.034	-0.036
		(1.401)	(0.133)	(0.22)	(-0.207)
High Growth Minus Low Growth	Conglomerates	-0.91***	-0.723***	-0.703***	-0.776***
		(-4.889)	(-4.961)	(-4.788)	(-5.024)
	Pseudo-Conglomerates	-0.417	-0.04	0.009	-0.217
		(-1.431)	(-0.195)	(0.036)	(-0.892)

Table 2: Return Predictability: Conglomerates, LTG, and EOH

We construct 2*10 independent calendar-time portfolio sorted by EOH (high or low), and long-term growth forecasts (LTG, decile low to high) using the sample of only conglomerates. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries and we construct a pseudo-conglomerate for each conglomerate. LTG is from the I/B/E/S Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We set "EOH" dummy variable to be 1 if the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise. LTG is lagged one month relative to the period during which the return is measured. To ensure that the conglomerate dummy and "EOH" dummy used to sort portfolio are based on data that would have been publicly available by the time presumed in the analysis, the conglomerate dummy and "EOH" dummy calculated using data from calendar year *y* are not assumed to be known until the end of June of year *y* + 1. Thus, the conglomerate dummy and "EOH" dummy are based on data in year y-2 if we form portfolios in January to May of year y and based on data in year y-1 if we form portfolios in June to Dec of year y. We only show the results of conglomerates with high and low LTG. The results on groups with low and median LTG are insignificant. The return horizon is one-year. Returns are value-weighted. In addition to raw returns, we consider risk-adjusted returns using Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Stambaugh and Yuan mispricing factors (market, size, management, and performance), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). We report Newey-West t-stats.

EOH	LTG	Raw Returns	FF5+Mom	Q-factor	Mispricing
High	High	0.291	-0.704***	-0.623***	-0.753***
		(0.918)	(-3.455)	(-3.177)	(-3.078)
	Low	1.125***	0.088	0.085	0.279
		(4.329)	(0.618)	(0.586)	(1.698)
	High Minus Low	-0.834***	-0.791***	-0.708***	-1.032***
		(-3.956)	(-3.754)	(-3.508)	(-4.656)
Low	High	0.478	-0.264	-0.158	-0.164
		(1.377)	(-1.463)	(-0.839)	(-0.759)
	Low	0.871***	-0.137	-0.096	0.025
		(3.388)	(-1.003)	(-0.577)	(0.137)
	High Minus Low	-0.393	-0.127	-0.062	-0.188
		(-1.428)	(-0.553)	(-0.239)	(-0.676)

Table 3: Fama-Macbeth Regressions for Return Predictability

This table shows annual Fama-Macbeth Regressions using the subsample of conglomerates. The dependent variable is the annual alpha, defined as the monthly six-factor alpha cumulated over the period of year t+1 or year t+1 and t+2. The monthly six-factor alpha is calculated as the difference between the realized return in excess of the risk-free rate and the expected return from a six-factor model that includes the market, size, value, profitability, investment, and momentum factors. The factor loadings are estimated from rolling- window time-series regressions of stock returns over the previous two years. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries in year t. High Growth is a dummy variable set to 1 if the forecast-implied growth rate for the firm is in top quintile in December of year t in the cross-section and 0 otherwise. High EOH dummy is set to 1 to be 1 if the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise. We report Newey-West adjusted t-stats.

Dependent Variable	One-year alpha		Two-year alpha	
	(1)	(2)	(3)	(4)
High Growth	-0.063***	0.001	-0.098**	0.001
	(0.021)	(0.022)	(0.038)	(0.063)
High EOH		-0.012		-0.012
		(0.013)		(0.022)
High Growth*High EOH		-0.072*		-0.150**
		(0.041)		(0.073)
Size	-0.022**	-0.022**	-0.045**	-0.049**
	(0.011)	(0.010)	(0.018)	(0.019)
Firm Age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Analyst Coverage	0.003	0.003	0.006*	0.007**
	(0.002)	(0.002)	(0.003)	(0.003)
BM	0.006	0.003	0.009	-0.000
	(0.014)	(0.015)	(0.025)	(0.028)
Constant	0.122	0.108	0.252**	0.266**
	(0.075)	(0.067)	(0.109)	(0.114)
Observations	11,761	7,243	11,180	6,988
R-squared	0.037	0.069	0.043	0.079
F	3.210	1.658	3.395	2.313

Table 4: Conglomerates, LTG, and EOH/Managerial Incentives

We construct 2*10 independent calendar-time portfolio sorted by alternative measures of EOH (yes or no/high or low), and long-term growth forecasts (LTG, decile low to high) using the sample of only conglomerates. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries and we construct a matched pseudo-conglomerate for each conglomerate. LTG is from the I/B/E/S Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We have results on three measures– sales management, delta, and vega - presented in Panel A, B, and C, respectively. We set sales management dummy variable to be 1 if a conglomerate is just above the 50% cut-off of sales from a favorable industry and 0 otherwise. Delta measures the sensitivity of CEO wealth to stock prices and vega measures the sensitivity of CEO wealth to stock volatility. To ensure that the conglomerate dummy and alternative measures of EOH used to sort portfolio are based on data that would have been publicly available by the time presumed in the analysis, the conglomerate dummy and alternative measures of EOH calculated using data from calendar year *y* are not assumed to be known until the end of June of year *y* + 1. Conglomerate dummy and alternative measures of EOH are based on data in year y-2 if we form portfolios in January to May of year y and based on data in year y-1 if we form portfolios in June to Dec of year y. We only show the results of conglomerates with high and low LTG. The results on groups with low and median LTG are insignificant. The return horizon is one-year. Returns are value-weighted. In addition to raw returns, returns are risk-adjusted returns using Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Stambaugh and Yuan mispricing factors (market, size, management, and performance), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). We report Newey-West t-stats.

Panel A: Sales Management and Stock Returns

Sales Management	LTG	Raw Returns	FF5+Mom	Q-factor	Mispricing
Yes	High	0.044	-0.767**	-0.795**	-0.748**
		(0.11)	(-2.236)	(-2.129)	(-2.272)
	Low	0.991***	0.126	0.111	0.153
		(2.629)	(0.472)	(0.378)	(0.512)
	High Minus Low	-0.947**	-0.893**	-0.906**	-0.901*
		(-2.492)	(-2.168)	(-2.138)	(-1.943)
No	High	0.714**	-0.028	0.05	0.212
		(2.05)	(-0.081)	(0.128)	(0.552)
	Low	0.909***	0.093	0.087	0.262
		(2.863)	(0.52)	(0.447)	(1.215)
	High Minus Low	-0.195	-0.121	-0.036	-0.05
		(-0.531)	(-0.281)	(-0.081)	(-0.103)

Panel B: Delta and Stock Returns

Delta	LTG	Raw Returns	FF5+Mom	Q-factor	Mispricing
High	High	0.13	-0.793***	-0.718***	-0.716***
		(0.357)	(-4.014)	(-3.804)	(-3.585)
	Low	1.168***	0.194	0.24	0.435**
		(4.091)	(1.257)	(1.393)	(2.122)
	High Minus Low	-1.038***	-0.987***	-0.958***	-1.151***
		(-4.039)	(-4.53)	(-4.112)	(-4.863)
Low	High	0.461	-0.296	-0.231	-0.083
		(1.277)	(-1.347)	(-0.988)	(-0.355)
	Low	1.008***	0.129	0.188	0.274
		(3.811)	(0.794)	(1.014)	(1.257)
	High Minus Low	-0.547**	-0.425	-0.419	-0.357
		(-2.009)	(-1.529)	(-1.495)	(-1.134)

Panel C: Vega and Stock Returns

Vega	LTG	Raw Returns	FF5+Mom	Q-factor	Mispricing
High	High	0.077	-0.852***	-0.773***	-0.734***
		(0.209)	(-4.188)	(-4.014)	(-3.655)
	Low	1.136***	0.178	0.228	0.37*
		(4.214)	(1.208)	(1.447)	(1.964)
	High Minus Low	-1.058***	-1.029***	-1.001***	-1.104***
		(-4.179)	(-4.908)	(-4.528)	(-4.896)
Low	High	0.621*	-0.415*	-0.286	-0.28
		(1.726)	(-1.73)	(-1.166)	(-1.029)
	Low	1.108***	0.245	0.302	0.434**
		(4.178)	(1.49)	(1.586)	(1.995)
	High Minus Low	-0.487*	-0.661***	-0.588**	-0.714***
		(-1.829)	(-2.671)	(-2.133)	(-2.732)

Table 5: Conglomerates' Earnings Predictability and EOH

Panel A: We focus on long-term forecasts (3-5years) and the subsample of only conglomerates. The dependent variable here is the absolute forecast error (AFE) and forecast dispersion. Firm-level absolute forecast error is defined as the absolute value of the difference between the actual earnings per share (EPS) and the forecasted EPS consensus, which is the median value of all forecasted EPS, deflated by the stock price at the beginning of the announcement year of the actual earnings: $Absolute\ Forecast\ Error_{i,t,f} = |\frac{Analyst\ Forecasted\ EPS_{i,t,f,m} - Real\ EPS_{i,t,f,m}}{P_{i,t}}|$. Forecast dispersion is the standard deviation of analyst forecasts scaled by the stock price at the beginning of the announcement year of the actual earnings. We set "High EOH" dummy variable to be 1 if the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise. Size is the log value of market capitalization in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Analyst Coverage is the number of unique analysts reporting the forecasts of corresponding forecast horizon for the firm in a year. Firm Age is just the number of years between the current year and the listing year of the firm. All variables are adjusted for stock splits and stock dividends. We include firm fixed effects and FF-48 industry times year fixed effects and standard errors are clustered by industry and year.

Dependent Variable:	AFE	FD
	(1)	(2)
High EOH	0.191	-0.024
	(0.279)	(0.052)
Size	-3.568***	-1.294***
	(0.670)	(0.177)
Firm Age	0.134***	0.052***
	(0.039)	(0.017)
Analyst Coverage	0.151**	0.070***
	(0.067)	(0.023)
BM	2.718***	0.506***
	(0.490)	(0.138)
Firm Fixed effects	Yes	Yes
Industry*Fiscal Year Fixed effects	Yes	Yes
Double Clustering by Industry and Fiscal Year	Yes	Yes
Observations	6,992	7,330
Adjusted R^2	0.659	0.628

Panel B: This panel runs Coibion-Gorodnichenko Regressions for analysts' forecasts of EPS using the subsample of conglomerates only. The dependent variables are the forecast errors $(EPS_{t+n}/EPS_t)^{1/n} - LTG_t$ for n = 3, 4, and 5. The variable of interest is the forecast revision LTG_t-LTG_{t-1}. Each entry in corresponds to the estimated coefficient of regressing the forecast errors on the forecast revision and its interaction with EOH dummy and year fixed effects. We set "High EOH" dummy variable to be 1 if the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise.

Dependent Variable:	$(EPS_{t+3}/EPS_t)^{1/3} - LTG_t$	$(EPS_{t+4}/EPS_t)^{1/4} - LTG_t$	$(EPS_{t+5}/EPS_t)^{1/5} - LTG_t$
	(1)	(2)	(3)
Revision	-0.286***	-0.455***	-0.474***
	(0.048)	(0.042)	(0.042)
High EOH	0.016	0.004	0.004
	(0.010)	(0.009)	(0.009)
Revision*High EOH	0.030	0.012	0.019
	(0.068)	(0.060)	(0.060)
Year Fixed Effects	Yes	Yes	Yes
Observations	7,195	6,473	5,873
Adjusted R2	0.038	0.059	0.055

Table 6: Earnings Predictability and EOH: Effect of SFAS 131

In this table, we use the subset of only conglomerates and focus exclusively on long-term forecasts(3-5 years). Following Cho (2015), we restrict our sample to four years before and after the adoption year of SFAS 131 (9 years in total). Following Berger and Hann (2003), we eliminate change firms from the sample if they are contaminated by events other than pure reporting changes (e.g., acquisition, divestiture, restructuring, or changes in accounting methods). The dependent variable here is absolute forecast error (AFE) and forecast dispersion. Firm-level AFE is defined as the absolute value of the difference between the actual earnings per share (EPS) and the forecasted EPS consensus, which is the median value of all forecasted EPS, deflated by the stock price at the beginning of the announcement year of the actual earnings: $Absolute\ Forecast\ Error_{i,t,f} = \left|\frac{Analyst\ Forecasted\ EPS_{i,t,f,m} - Real\ EPS_{i,t,f,m}}{P_{i,t}}\right|$. Forecast dispersion is the standard deviation of analyst forecasts scaled by the stock price at the beginning of the announcement year of the actual earnings. Ex-ante High EOH is a dummy variable set to 1 if EOH in pre-SFAS 131 period is high and 0 otherwise. Post is a dummy variable set to 1 if the year is in post-SFAS 131 and 0 otherwise. Pre is a dummy variable set to 1 if the year is in pre-SFAS 131 and 0 otherwise. Size is the log value of market capitalization in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Analyst Coverage is the number of unique analysts reporting the forecasts of corresponding forecast horizon for the firm in a year. Firm Age is just the number year between the current one and the listing year of the firm. All variables are adjusted for stock splits and stock dividends. We include firm fixed effects and year fixed effects and standard errors are clustered by firm.

Dependent Variable	AFE	FD
	(1)	(2)
Ex-Ante High EOH*Post	-5.469**	-1.143**
	(2.658)	(0.498)
Post	-2.479	-1.632*
	(5.069)	(0.833)
Size	-0.383	-0.044
	(0.715)	(0.234)
Firm Age	-0.065	-0.023
	(0.041)	(0.016)
Analyst Coverage	0.123	0.037
	(0.201)	(0.056)
BM	5.439***	1.415***
	(1.893)	(0.499)
Firm Fixed effects	Yes	Yes
Fiscal Year Fixed effects	Yes	Yes
Clustering by Firm	Yes	Yes
Observations	396	396
R^2	0.495	0.548
Adjusted R^2	0.339	0.409

Table 7: LTG, EOH and Mutual Fund Performance

In this table, we construct calendar-time fund portfolio sorting based on HGCHEOH (High-Growth Conglomerate with High EOH, quintile 1 (low) to 5 (high)) or HGC (High-Growth Conglomerates, quintile 1(low) to 5 (high)). HGC is the investment weight in conglomerates with top decile long-term growth rate (LTG). HGCHEOH is the investment weight in conglomerates with top decile LTG and high EOH. HGC and HGCHEOH are based on active investment weights. Active investment weight is defined as the raw investment weight minus the corresponding investment weight in the benchmark index of a fund. Information on benchmark indices of active mutual funds is obtain from Refinitiv and we set the benchmark index of a fund to be SP500 index if it's missing from the data. At fund holding level, HGCHEOH is constructed using fund holding data at every year-quarter cross-section for each fund. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries and we construct a pseudo-conglomerate for each conglomerate. LTG is from the I/B/E/S Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We define high EOH as the situation when the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise. Conglomerate dummy and EOH dummy are lagged one year. HGC and HGCHEOH are lagged one quarter. The return horizon is 1 year. Fund returns are after-expense and value-weighted. In addition to raw returns, we consider risk-adjusted returns using Carhart four factors (market, size, book-to-market, and momentum), Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Ferson-Schadt conditional model, and benchmark returns grouped by investment objectives. We obtain similar results for before-expense returns. Newey-West adjusted t-stats are reported.

Panel A: Returns on funds sorted by their Active Investment Weights in High-Growth Conglomerates (HGC)

High-Growth Conglomerates (HGC)	Raw Returns	Carhart	FF5+Mom	Ferson-Schadt	Objective Adjusted
Low	0.586*	-0.013	0.081	0.034	0.005
	(1.823)	(-0.233)	(1.204)	(0.55)	(0.098)
2	0.53*	-0.032	-0.021	-0.038	-0.027
	(1.745)	(-0.686)	(-0.478)	(-0.889)	(-0.987)
3	0.525*	-0.033	-0.075	-0.089	0.002
	(1.743)	(-0.497)	(-1.426)	(-1.68)	(0.042)
4	0.509*	-0.043	-0.073	-0.093	-0.009
	(1.652)	(-0.615)	(-1.195)	(-1.48)	(-0.256)
High	0.386	-0.166**	-0.184**	-0.211***	-0.089**
	(1.199)	(-2.48)	(-2.541)	(-3.39)	(-2.398)
High Minus Low	-0.2*	-0.152**	-0.265***	-0.246***	-0.094*
	(-1.84)	(-2.12)	(-3.058)	(-3.051)	(-1.653)

Panel B: Returns on funds sorted by their Active Investment Weights in High-Growth Conglomerates with High EOH(HGCHEOH)

High-Growth Conglomerates with High EOH(HGCHEOH)	Raw Returns	Carhart	FF5+Mom	Ferson-Schadt	Objective Adjusted
Low	0.553*	-0.017	0.001	-0.015	-0.014
	(1.854)	(-0.31)	(0.02)	(-0.299)	(-0.325)
2	0.567*	-0.03	-0.077	-0.082	-0.041
	(1.835)	(-0.426)	(-1.131)	(-1.187)	(-1.192)
3	0.525	-0.088	-0.09	-0.091	-0.03
	(1.619)	(-1.246)	(-1.276)	(-1.232)	(-0.678)
4	0.473	-0.095	-0.193**	-0.186**	-0.034
	(1.562)	(-1.085)	(-2.193)	(-2.287)	(-1.101)
High	0.362	-0.185	-0.279***	-0.27***	-0.113***
	(1.134)	(-2.086)	(-2.895)	(-2.807)	(-2.726)
High Minus Low	-0.191*	-0.169**	-0.28***	-0.255***	-0.099
	(-1.768)	(-2.203)	(-3.305)	(-2.732)	(-1.523)

Table 8: LTG, EOH and Mutual Fund Holdings

In this table, we regress the stock ownership level of mutual funds (in percentage) on the interaction between three dummy variables: ΔHighLTG and EOH and Conglomerate. The dependent variable here is change in mutual fund ownership level in Column 1&2 and change in active mutual fund ownership level in Column 3&4. Change in ownership level is defined as the percentage of a stock's total shares outstanding held by mutual funds in quarter t minus that in quarter t-1. Active mutual fund ownership level is defined as the percentage of a stock's total shares outstanding held by mutual funds in excess of the shares required by their benchmark indices. We look at the mutual fund ownership of all firms in Column 1&3 and within the group of conglomerates in Column 2&4. We only include mutual funds with positive HGC when we construct the ownership level in Column 1&3 and mutual funds with positive HGCHEOH when we construct the ownership measure in Column 2&4. ΔHighLTG dummy is set to 1 if a stock moves from the bottom 90% in quarter t-1 to the top decile of the long-term growth rates in quarter t and 0 otherwise. EOH dummy is set to 1 if a conglomerate shift earnings in year y-1 and 0 otherwise. Conglomerate dummy is set to 1 if a firm has segments in no less than two different FF-48 industries. Size is the log value of market capitalization in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Stock Return is the stock return from CRSP and adjusted for delisting. We include firm and year quarter fixed effects and standard errors are clustered by firm and year quarter.

Dependent Variable:	ΔMutual Fund Ownership Level (%)		ΔActive Mutual Fund Ownership Level (%)	
Sample Selection	All Firms	Only Conglomerates	All Firms	Only Conglomerates
	(1)	(2)	(3)	(4)
ΔHighLTG*Conglomerate	1.11***		1.10***	
	(0.153)		(0.148)	
ΔHighLTG*High EOH		5.68***		5.56***
		(0.380)		(0.377)
ΔHighLTG	0.031	0.032	0.045	0.056
	(0.063)	(0.107)	(0.061)	(0.103)
High EOH		0.024		0.021
		(0.023)		(0.021)
Conglomerate	-0.022***		-0.022***	
	(0.006)		(0.006)	
Stock Return	0.131**	0.308***	0.120**	0.315***
	(0.046)	(0.089)	(0.043)	(0.091)
Size	0.012	0.006	0.019	0.025
	(0.026)	(0.046)	(0.022)	(0.043)
BM	-0.030	0.004	-0.026	0.011
	(0.018)	(0.022)	(0.017)	(0.018)
Firm Fixed effects	Yes	Yes	Yes	Yes
Year Quarter Fixed effects	Yes	Yes	Yes	Yes
Clustering by Firm and Year Quarter	Yes	Yes	Yes	Yes
Observations	251,157	53,566	251,157	53,566
Adjusted R^2	0.104	0.130	0.084	0.106

Table 9: Mutual Fund Holdings and EOH: Effect of SFAS 131

In this table, we examine how the stock ownership level of mutual funds reacts to SFAS 131 regulation. Following Cho (2015), we restrict our sample to four years before and after the adoption year of SFAS 131 (9 years in total). Following Berger and Hann (2003), we eliminate change firms from the sample if they are contaminated by events other than pure reporting changes (e.g., acquisition, divestiture, restructuring, or changes in accounting methods). The dependent variable here is change in mutual fund ownership level in Column 1&2 and change in active mutual fund ownership level in Column 3&4. Change in ownership level is defined as the percentage of a stock's total shares outstanding held by mutual funds in quarter t minus that in quarter t-1. Active mutual fund ownership level is defined as the percentage of a stock's total shares outstanding held by mutual funds in excess of the shares required by their benchmark indices. We look at the mutual fund ownership of all firms in Column 1&3 and within the group of conglomerates in Column 2&4. We only include mutual funds with positive HGC when we construct the ownership level in Column 1&3 and mutual funds with positive HGCHEOH when we construct the ownership measure in Column 2&4. ΔHighLTG dummy is set to 1 if a stock moves from the bottom 90% in quarter t-1 to the top decile of the long-term growth rates in quarter t and 0 otherwise. EOH dummy is set to 1 if a conglomerate shift earnings in year y-1 and 0 otherwise. Ex-ante high EOH is a dummy variable set to 1 if EOH in pre-SFAS 131 period is high and 0 otherwise. Post is a dummy variable set to 1 if the year is in post-SFAS 131 and 0 otherwise. Conglomerate dummy is set to 1 if a firm has segments in no less than two different FF-48 industries. Size is the log value of market capitalization in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Stock Return is the stock return from CRSP and adjusted for delisting. We include firm and year quarter fixed effects and standard errors are clustered by firm and year quarter.

Dependent Variable:	ΔMutual Fund Ownership Level (%)		ΔActive Mutual Fund Ownership Level (%)	
Sample Selection	All Firms	Only Conglomerates	All Firms	Only Conglomerates
	(1)	(2)	(3)	(4)
ΔHighLTG*Conglomerate*Post	0.348		0.419	
	(0.370)		(0.349)	
ΔHighLTG* Ex-Ante High EOH*Post		0.891		0.841
		(1.53)		(1.47)
ΔHighLTG*Conglomerate	0.037		0.021	
	(0.043)		(0.044)	
ΔHighLTG*Post	0.229	0.358	0.175	0.404
	(0.242)	(0.832)	(0.211)	(0.858)
Conglomerate*Post	-0.004		-0.010	
	(0.086)		(0.086)	
ΔHighLTG* Ex-Ante High EOH		-0.135		-0.150
		(0.096)		(0.100)
ΔHighLTG*Post		0.033		0.030
		(0.060)		(0.060)
ΔHighLTG	-0.001	-0.049	0.001	-0.044
	(0.033)	(0.053)	(0.032)	(0.050)
Firm Fixed effects	Yes	Yes	Yes	Yes
Year Quarter Fixed effects	Yes	Yes	Yes	Yes
Clustering by Firm and Year Quarter	Yes	Yes	Yes	Yes
Observations	28,094	5,205	28,094	5,205
Adjusted R2	0.049	0.076	0.052	0.076

INTERNET APPENDIX

Internet Appendix A: Additional Results

Table A1: Robustness of Return Predictability: Conglomerates vs Single-Segment Firms

We construct 2*10 portfolios sorted by conglomerate dummy and long-term growth forecasts(decile low(1) to high(10)) in Panel A and Panel B. In December of each year between 1981 and 2018, we conduct dependent double sorting based on LTG and conglomerate dummy and display the arithmetic average one-year return over the subsequent calendar year for value-weighted portfolios with annual rebalancing. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries. LTG is directly obtained from I/B/E/S summary dataset for Panel A and is constructed based on raw detail forecast data and supplemented with forecast-implied growth rate for Panel B. To ensure that the conglomerate dummy used to sort portfolio is based on data that would have been publicly available by the time presumed in the analysis, the conglomerate dummy that is calculated using data from calendar year y is not assumed to be known until the end of June of year $y + 1$. Thus, the conglomerate dummy is based on data in year y-2 if we form portfolios in January to May of year y and based on data in year y-1 if we form portfolios the in June to December of year y. To alleviate the concern that industry sector effects drive our results, we use a matched sample in Panel B. In particular, we match each conglomerate to a single-segment firm in the same FF-48 industry with similar firm size, past year return, and analyst coverage. In addition to raw returns, we consider risk-adjusted returns using Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Stambaugh and Yuan mispricing factors (market, size, management, and performance), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). We report Newey-West t-stats in brackets.

Replicating BGLS with Factor Models					
Long-Term Growth Rate (LTG)		Raw Returns	FF5+Mom	Q-factor	Mispricing
High Growth Firms	Conglomerates	1.889	-5.43***	-5.633*	-10.207***
		(0.614)	(-2.89)	(-1.683)	(-3.121)
	Single-Segment Firms	12.293**	8.318*	-2.649	-3.864
		(2.138)	(1.693)	(-0.734)	(-0.828)
Low Growth Firms	Conglomerates	9.927***	-0.812	3.55**	2.004
		(6.308)	(-0.677)	(2.021)	(1.154)
	Single-Segment Firms	8.789***	0.982	3.862*	3.725**
		(4.375)	(1.021)	(1.936)	(2.043)
High Growth Minus Low Growth	Conglomerates	-8.038***	-4.618**	-9.183**	-12.211**
		(-3.599)	(-2.077)	(-2.484)	(-2.349)
	Single-Segment Firms	3.505	7.335	-6.511	-7.589
		(0.751)	(1.489)	(-1.308)	(-1.337)

Table A2: Summary Statistics: Conglomerates vs Pseudo-Conglomerates

In this table, we report summary statistics of firm characteristics for conglomerates and pseudo-conglomerates. Characteristics of each pseudo-conglomerate is sales-weighted average of the characteristics of all standalone firms within the industry of each of the conglomerate segment. We calculate the cross-sectional value-weighted average for each group of conglomerates and pseudo-conglomerates and then summarize the two time-series. Panel A reports mean, median, and standard deviation of six firm characteristics. Size is the log value of market capitalization in millions. Sales is the log value of summation of the segment level sales in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Analyst Coverage is the number of unique analysts reporting forecasts (1-5 years) for the firm in a year. Firm Age is just the number year between the current one and the listing year of the firm. We also report the differences between the means and t-stats. Variables are winsorized at 1% and 99%. All t-stats are Newey-West adjusted.

	Conglomerate (N= 2757)			Pseudo-Conglomerate (N= 2757)			Difference in Mean (a-b)	t-stat
Name	Mean (a)	Median	Standard Deviation	Mean (b)	Median	Standard Deviation		
Size	7.29	7.32	0.66	6.70	6.72	1.02	1.58	(1.05)
Sales	7.41	7.46	0.35	6.68	6.58	0.71	0.72	(0.43)
Book-to-Market	-0.58	-0.63	0.22	-0.19	-0.19	0.23	-0.39	(-4.06***)
Analyst Coverage	17.31	16.26	2.97	14.23	13.77	1.56	3.09	(1.60)
Firm Age	26.16	26.29	2.54	14.78	12.83	3.87	11.38	(1.78*)

Table A3: Robustness Check of Return Predictability: Conglomerates, LTG, and EOH

We construct 2*5 independent calendar-time portfolio sorted by EOH(yes or no), and long-term growth forecasts (LTG, decile low to high) using the sample of only conglomerates. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries and we construct a pseudo-conglomerate for each conglomerate. LTG is from the I/B/E/S Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We set "EOH" dummy variable to be 1 if the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise. LTG is lagged one month relative to the period during which the return is measured. To ensure that the conglomerate dummy and "EOH" dummy used to sort portfolio are based on data that would have been publicly available by the time presumed in the analysis, the conglomerate dummy and "EOH" dummy calculated using data from calendar year *y* are not assumed to be known until the end of June of year *y* + 1. Thus, the conglomerate dummy and "EOH" dummy are based on data in year y-2 if we form portfolios in January to May of year y and based on data in year y-1 if we form portfolios in June to Dec of year y. We only show the results of conglomerates with high and low LTG. The return horizon is one-year. Returns are value-weighted. In addition to raw returns, we consider risk-adjusted returns using Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Stambaugh and Yuan mispricing factors (market, size, management, and performance), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). We report Newey-West t-stats.

EOH	LTG	Raw Returns	FF5+Mom	Q-factor	Mispricing
High	High	0.285	-0.68***	-0.6***	-0.822***
		(0.839)	(-3.315)	(-3.003)	(-3.254)
	Low	0.942***	0.142	0.149*	0.151
		(3.696)	(1.669)	(1.716)	(1.524)
	High Minus Low	-0.656***	-0.822***	-0.748***	-0.972***
		(-3.68)	(-4.355)	(-4.047)	(-4.356)
Low	High	0.448	-0.311*	-0.169	-0.2
		(1.265)	(-1.685)	(-0.878)	(-0.925)
	Low	0.967***	0.116	0.162*	0.194*
		(4.082)	(1.374)	(1.868)	(1.982)
	High Minus Low	-0.519**	-0.427**	-0.331	-0.394
		(-2.305)	(-2.102)	(-1.546)	(-1.675)

Table A4: Summary Statistics of Analyst Forecasts of Conglomerates

In this table, we show the summary statistics of absolute forecast error (AFE) and forecast dispersion (FD). We first report the mean, median, and standard deviation of AFE and FD of the conglomerates. We then the mean value of AFE and FD grouped by corresponding forecast-implied growth rates. Absolute forecast error (AFE) is defined as the absolute value of the difference between the actual earnings per share (EPS) and the forecasted EPS consensus, which is the median value of all forecasted EPS, deflated by the stock price at the beginning of the announcement year of the actual earnings. Forecast dispersion (FD) is defined as the standard deviation of all forecasted EPS deflated by the stock price at the beginning of the announcement year of the actual earnings. AFE and FD are multiplied by 100 for ease of interpretation. A firm with segments in two different FF-48 industries is defined as a conglomerate. Forecast-implied growth rate, which is defined as $\sqrt[\frac{1}{Forecast\ Horizon}]{\frac{Forecasted\ EPS_t^{Forecast\ Horizon}}{Actual\ EPS_{t-1}}} - 1$, when the actual EPS in the last year and the current forecasted median value of EPS have the same sign. Variables are winsorized at 1% and 99%. All t-stats are Newey-West adjusted.

Absolute Forecast Error (AFE)			Forecast Dispersion (FD)		
Mean	Median	SD	Mean	Median	SD
4.32	3.76	1.88	1.55	1.47	0.47
Mean AFE Sorted by Forecast-Implied Growth Rate			Mean FD Sorted by Forecast-Implied Growth Rate		
High	Median	Low	High	Median	Low
9.07	3.39	3.85	2.94	1.33	1.20

Table A5: LTG, EOH and Mutual Fund Performance

In this table, we construct calendar-time fund portfolio sorting based on HGCLEOH (High-Growth Conglomerate with Low Earnings Optimism Heuristic, quarter 1 (low) to 5 (high)). HGCLEOH is the active investment weight in conglomerates with top 10% long-term growth rate (LTG) and low EOH. Active investment weight is defined as the raw investment weight minus the corresponding investment weight in the benchmark index of a fund. At fund holding level, HGCLEOH is constructed using fund holding data at every year-quarter cross-section for each fund. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries and we construct a pseudo-conglomerate for each conglomerate. LTG is from the I/B/E/S Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We define EOH as the situation when the abnormal standard deviation of segment earnings is negative when firm news exceeds expectations in year t or is positive when firm news is worse than expectations and 0 otherwise. Conglomerate dummy and EOH are lagged one year. HGCLEOH is lagged one quarter. The return horizon is 1 year. Fund returns are after-expense and value-weighted. In addition to raw returns, we consider risk-adjusted returns using Carhart four factors (market, size, book-to-market, and momentum), Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Ferson-Schadt conditional model, and benchmark returns grouped by investment objectives. We obtain similar results for before-expense returns. Newey-West adjusted t-stats are reported.

High-Growth Conglomerates Without Manipulated Earnings (HGCNM)	Raw Returns	Carhart	FF5+Mom	Ferson-Schadt	Objective Adjusted
Low	0.6*	0.009	0.059	0.049	0.016
	(1.868)	(0.143)	(0.888)	(0.683)	(0.271)
2	0.518*	-0.05	-0.025	-0.063	-0.031
	(1.686)	(-0.887)	(-0.422)	(-1.346)	(-0.906)
3	0.539*	-0.029	-0.044	-0.072	-0.017
	(1.792)	(-0.461)	(-0.925)	(-1.501)	(-0.403)
4	0.539*	-0.022	-0.047	-0.068	0.011
	(1.717)	(-0.291)	(-0.683)	(-0.959)	(0.304)
High	0.483	-0.058	-0.034	-0.055	-0.043
	(1.6)	(-1.403)	(-0.811)	(-1.472)	(-1.598)
High Minus	-0.117	-0.067	-0.093	-0.104	-0.059
Low	(-1.375)	(-1.214)	(-1.571)	(-1.615)	(-1.411)

Table A6: LTG, EOH and Future Mutual Fund Holdings

In this table, we regress the stock ownership level of mutual funds in the future (in percentage) on the interaction between three dummy variables: ΔHighLTG and EOH and Conglomerate. The dependent variable here is change in active mutual fund ownership level, defined as the percentage of a stock's total shares outstanding held by mutual funds in excess of the shares required by their benchmark indices in quarter t+1 (t+2) minus that in quarter t (t+1). We look at the mutual fund ownership of all firms in Column 1&3 and within the group of conglomerates in Column 2&4. We only include mutual funds with positive HGC when we construct the ownership level in Column 1&3 and mutual funds with positive HGCM when we construct the ownership measure in Column 2&4. ΔHighLTG dummy is set to 1 if a stock moves from the bottom 90% in quarter t-1 to the top decile of the long-term growth rates in quarter t and 0 otherwise. EOH dummy is set to 1 if a conglomerate manipulates earnings in year y-1 and 0 otherwise. Conglomerate dummy is set to 1 if a firm has segments in no less than two different FF-48 industries. Size is the log value of market capitalization in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Stock Return is the stock return from CRSP and adjusted for delisting. We include firm and year quarter fixed effects and standard errors are clustered by firm and year quarter.

Dependent Variable:	ΔMutual Fund Ownership Level (t+1 – t, in %)		ΔActive Mutual Fund Ownership Level (t+2 – t+1, in %)	
Sample Selection	All Firms	Only Conglomerates	All Firms	Only Conglomerates
	(1)	(2)	(3)	(4)
ΔHighLTG*Conglomerate	-0.330*		-0.184	
	(0.130)		(0.129)	
ΔHighLTG*High EOH		-2.38***		-1.71***
		(0.408)		(0.310)
ΔHighLTG	0.027	0.169	-0.024	0.146
	(0.060)	(0.116)	(0.057)	(0.136)
High EOH		-0.022		-0.061*
		(0.030)		(0.025)
Conglomerate	0.004		0.009	
	(0.007)		(0.007)	
Stock Return	0.094**	0.077	0.102**	0.152*
	(0.033)	(0.067)	(0.034)	(0.060)
Size	-0.011	-0.041	-0.046*	-0.059
	(0.024)	(0.043)	(0.022)	(0.037)
BM	-0.043*	-0.061*	-0.053**	-0.062*
	(0.017)	(0.024)	(0.018)	(0.029)
Firm Fixed effects	Yes	Yes	Yes	Yes
Year Quarter Fixed effects	Yes	Yes	Yes	Yes
Clustering by Firm and Year Quarter	Yes	Yes	Yes	Yes
Observations	251,157	53,566	251,157	53,566
Adjusted R^2	0.083	0.099	0.083	0.098

Table A7: Return Predictability and EOH: Pre & Post SFAS 131

This table shows future one-month returns pre and post SFAS 131 for the group of high LTG conglomerates with low EOH. Returns are value-weighted. In addition to raw returns, we consider risk-adjusted returns using Fama-French five factors (market, size, book-to-market factors, operating profitability, and investment) plus momentum factor, Stambaugh and Yuan mispricing factors (market, size, management, and performance), and Hou, Xue, and Zhang Q factors (market, size, investment, and profitability). We report Newey-West t-stats.

Period	Raw	FF5+Mom	Q-factor	Mispricing
Pre SFAS 131	0.534	-0.255	-0.341	-0.456**
	(1.439)	(-1.02)	(-1.585)	(-2.066)
Post SFAS 131	0.121	-0.825***	-0.656***	-0.853***
	(0.259)	(-3.136)	(-2.472)	(-2.561)

Internet Appendix B: Construction of Pseudo-Conglomerates

We have two ways to construct pseudo-conglomerates. The first way is to calculate industry portfolios and then average them by segment sales. Cohen and Lou (2012) uses this way to construct returns for pseudo-conglomerates. For each conglomerate firm, we construct the performance of each pseudo-conglomerate by aggregating the value-weighted average returns of the standalone firms within each of the conglomerate firm's industries. The definition is below:

$$R_t^{pseudo} = \frac{\sum_{i=1}^{s} r_{i,t} * sales_{i,t-1}}{\sum_{i=1}^{s} sales_{i,t-1}}$$

where $r_{i,t}$ is the value-weighted returns of the standalone firms within industry i of the segment of the conglomerate firm and $sales_{i,t-1}$ is the sales of the segment. Similarly, the forecast-implied growth rate for pseudo-conglomerates is constructed as below:

$$g_{t,f}^{pseudo} = \frac{\sum_{i=1}^{s} g_{i,t,f} * sales_{i,t-1}}{\sum_{i=1}^{s} sales_{i,t-1}}$$

where $g_{i,t,f}$ is the equal-weighted forecast-implied growth rates of the standalone firms within industry i of the segment of the conglomerate firm over horizon f. We construct AFE, forecast dispersion, size, and other characteristics in the same way. We call the pseudo-conglomerates based on industry portfolios "industry pseudo".

The second way is to find a matched stand-alone firm for each segment of a conglomerate and then average them by segment sales. The matching is based on segment sales, analyst coverage, and segment industry. First, we identify all the distinct industry segments of the multiple-segment firms and the stand-alone firms using the Fama French-48 industry classification. Then, in each year and within each Fama French-48 industry, we use a one-to-one coarsened exact matching (CEM)[24] to find a close match for each segment of conglomerates from the segments of stand-alone firms based on segment level sales and analyst coverage in the previous year. The segment level analyst coverage is just the firm level analyst coverage for segments from stand-alone firms and the sale-weighted analyst coverage for segments from conglomerates. For example, if one conglomerate is covered by 10 distinct analysts last year and consists of business segments from

[24] CEM is a monotonic imbalance bounding (MIB) matching method. Compared to PSM, CEM allows us to choose the maximum imbalance between the treated and control, rather than discovered through the usual laborious process of ex post checking and repeatedly re-estimating. Hence, CEM is a better choice when we have fewer observations and fewer variations in the treatment variable because of its non-parametric design.

two different industries, then the lagged analyst coverage is 5 for each segment. Table B1 shows the matching precision for conglomerates versus pseudo-conglomerates. we can find that the standardized mean difference (SMD) is below 0.2 for both analyst coverage and segment sales.

After we obtain the matched sample at the segment level, we aggregate segment level data into firm level weighted by the segment sales in the previous year or month. For example, the return of a pseudo-conglomerate is the average return of matched standalone firms of the corresponding conglomerate weighted by segment sales. The definition is below:

$$R_t^{pseudo} = \frac{\sum_{i=1}^{s} r_{i,t} * sales_{i,t-1}}{\sum_{i=1}^{s} sales_{i,t-1}}$$

where $r_{i,t}$ is the return of the matched standalone firm in industry i of the segment of the conglomerate firm and $sales_{i,t-1}$ is the sales of the segment. We call the pseudo-conglomerates based on matched stand-alone firms “stand-alone pseudo”.

Our main results are based on “industry pseudo” while our results are qualitatively similar if we uses the sample including “stand-alone pseudo”.

Table B1: Matching Accuracy

In this table, we report the matching accuracy of segment sale and analyst coverage for conglomerates and pseudo-conglomerates. Segment sales are the firm level sales for stand-alone firms and the segment level sales for the segments of conglomerates. Analyst coverage is the firm level analyst coverage for segments from stand-alone firms and the sale-weighted analyst coverage for segments from conglomerates. We report the mean value and standard deviation (in brackets) of segment sales and analyst coverage. SMD is the standardized mean difference between conglomerates and pseudo-conglomerates before and after matching.

	Matching Accuracy					
	Before Matching			After Matching		
	Conglomerates	Pseudo-Conglomerates	SMD	Conglomerates	Pseudo-Conglomerates	SMD
Number of firm	68750	57191		28971	28971	
Segment Sale	1781.16	2711.50	0.090	804.94	1089.28	0.092
	(8039.72)	(12194.98)		(2863.55)	(3285.30)	
Analyst Coverage	10.66	5.59	0.559	5.91	5.34	0.085
	(10.14)	(7.81)		(6.44)	(6.76)	

Internet Appendix C: Handling Data

C.1 Deal with I/B/E/S Data

Throughout the paper (except for Figure 1), we use data on forecasts of EPS provided in Unadjusted Detail History file rather than Adjusted Summary History file. The reason is that there are at least two problems with the standard-issue I/B/E/S summary data set. First, I/B/E/S uses all existing analyst forecasts to calculate summary statistics, and some of these forecasts are stale. Second, there is a rounding-error problem due to stock splits (Payne and Thomas 2003).

For I/B/E/S data prepared for analysis on earnings predictability, we use the cumulative factor to adjust shares (CFACSHR) in CRSP to adjust for stock splits or reverse splits. When one analyst makes multiple EPS forecasts for the same actual EPS for a firm, we use the most recent forecasted value.

For I/B/E/S data prepared for analysis on return predictability, we need to summarise individual forecasts to the monthly level. We closely follow the procedure in Diether et al. (2002) to summarise the forecasts by ourselves. We compute month-end medians from the individual estimates in the Unadjusted Detail History file by extending each forecast until its revision date. For example, if the forecast was made in May and was last confirmed as accurate in July, it will be used in our computation of medians for May, June, and July. If an analyst makes more than one forecast in a given month, only the last forecast is used in our calculations. In some records, a revision date precedes the actual forecast date, which constitutes an error on the part of I/B/E/S. In this case, the forecast will be assumed valid only for the month in which it was made. Our self-adjusted summary history file includes LTG and forecast concensus of FPI (forecast-horizon indicator) ranging from 3 year to 5 years at a monthly level.

C.2 Identify Active Equity Mutual Funds in U.S.

Similar to prior studies (e.g., Kacperczyk, Sialm and Zheng, 2008; Huang, Sialm and Zhang, 2011), we identify actively managed US equity mutual funds based on their objective codes and disclosed asset compositions. We first select funds with the following Lipper objectives: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT. If a fund does not have any of the above objectives, we select funds with the following strategic insight (SI) objectives: AGG, ENV, FIN,

GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, RLE. If a fund has neither the Lipper nor the SI objective, then we use the Wiesenberger fund type code to select funds with the following objectives: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, GPM. If none of these objectives is available and the fund holds more than 80% of its value in common shares, then the fund will be regarded as equity fund. After finishing the procedure described above, we further identify and exclude index funds based on their names and the index fund identifiers in the CRSP data. CRSP mutual fund data provide a variable "index fund flag" to identify index funds. We define a fund as an index fund if its index fund flag is B (index-based fund), D (pure index fund), or E (index fund enhanced). Similar to previous studies (e.g., Busse and Tong, 2012; Ferson and Lin, 2014; Busse, Jiang and Tang, 2021; Jones and Mo, 2021), we also define a fund as an index fund if its name contains any of the following text strings: Index, Ind, Idx, Indx, Mkt, Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000.

Internet Appendix D: Sales Management as an Alternative measure of EOH

Here, we follow Chen, *et al.,* (2016) to construct an alternative measure of EOH. This measure reduces our sample by nearly 80% because of the way it's constructed. Hence, we only use this measure to test the robustness of our results. The measure is based on a regulatory provision wherein a firm's primary industry is determined by the highest sales segment. And Chen, *et al.,* (2016) find that investors classify operationally nearly identical firms as starkly different depending on their placement around the sales cutoff. For short-term valuation purposes, managers may take advantage of this rule by sales management so that the highest sales segment is in the favorable industries.

As in Chen, *et al.,* (2016), we first identify industries which are more "favorable"—that is, have higher valuation or a lower cost of capital— than are others. Thus, it would be beneficial to be considered part of these "favorable" industries in certain periods. We construct industry FLOW, set industries with top 20 highest FLOW as "favorable industries", and the complement set "unfavorable industries". The detailed construction is listed as follow. At the end of each quarter, we compute a FLOW measure for each stock as the aggregate flow-induced trading across all mutual funds in the previous year. Stock level FLOW measure is introduced and shown to predict the price movements of stocks by Lou (2012). We then take the average FLOW across all stocks in Fama-French industry to compute industry FLOW.

We focus on a set of conglomerates whose top 2 largest segments (ranked by segment sales) are in "favorable industries" and "unfavorable industries", respectively. We also require each conglomerate in the sample has a sales weight in the favorable industry between 40% and 60% (scaled by the combined sales of the top two segments)[25]. Since the larger of the two segments determines the industry classification of the firm, the 50% sales cutoff is the relevant discontinuity point for industry status. When a conglomerate is just above the discontinuity cutoff of sales from a favorable industry (i.e., 50%), we expect that it truly manipulates operations opportunistically and can benefit from being classified as a member of these favorable industries. When a

[25] We follow Chen, *et al.*, (2016) to choose the range of sales weight (40% - 60%). The optimal range of sales weight is not clear ex anti. As it gets narrower, we are able to identify sales management more accurately but we will get a smaller sample.

conglomerate is just below the discontinuity cutoff, it's unlikely that it manipulates segment sales. By construction, this measure is highly selective and leads to a small sample.

We call the measure "Sales Management" in contrast with the measure in our main analysis, which relies on re-allocation of costs across segments. We first replicate Table 2 using Sales Management in Table 3 Panel A. To keep enough observations in each group, we sort stocks into only two LTG groups, high and low. We show that return predictability concentrates in high LTG conglomerates with sales management. We then proceed to replicate Table 5 Panel A in Table D1. Results indicate that sales management is not associated with larger absolute forecast errors and higher forecast dispersion. In conclusion, our alternative measure of EOH assures our previous finding that EOH of conglomerates is associated with stronger return predictability but has insignificant impacts on the accuracy of analyst forecasts.

Table D1: Conglomerates' Earnings Predictability and Sales Management

In this table, we focus on long-term forecasts (3-5years) and the subsample of only conglomerates. The dependent variable here is the absolute forecast error (AFE) and forecast dispersion. Firm-level absolute forecast error is defined as the absolute value of the difference between the actual earnings per share (EPS) and the forecasted EPS consensus, which is the median value of all forecasted EPS, deflated by the stock price at the beginning of the announcement year of the actual earnings: $Absolute\ Forecast\ Error_{i,t,f} = |\frac{Analyst\ Forecasted\ EPS_{i,t,f,m} - Real\ EPS_{i,t,f,m}}{P_{i,t}}|$. Forecast dispersion is the standard deviation of analyst forecasts scaled by the stock price at the beginning of the announcement year of the actual earnings. We set sales management dummy variable to be 1 if a conglomerate is just above the 50% cutoff of sales from a favorable industry and 0 otherwise. Size is the log value of market capitalization in millions. BM is the log value of the ratio of book value of equity divided by market value of equity. Analyst Coverage is the number of unique analysts reporting the forecasts of corresponding forecast horizon for the firm in a year. Firm Age is just the number of years between the current year and the listing year of the firm. All variables are adjusted for stock splits and stock dividends. We include firm fixed effects and year fixed effects and standard errors are clustered by industry and year.

Dependent Variable	AFE	Forecast Dispersion
	(1)	(2)
High EOH	-1.149	-0.242
	(1.312)	(0.317)
Size	-14.930***	-3.922***
	(1.815)	(0.763)
Firm Age	0.499	0.108
	(0.482)	(0.139)
Analyst Coverage	-0.281	-0.038
	(0.377)	(0.080)
BM	-2.428	-0.940
	(2.930)	(0.620)
Firm Fixed effects	Yes	Yes
Fiscal Year Fixed effects	Yes	Yes
Double Clustering by Industry and Fiscal Year	Yes	Yes
Observations	228	228
R2	0.751	0.688