Long-term Earnings Forecasts, Managerial Distortion, and Stock Returns[1]

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Abstract

We explain stock mispricing linked to long-term expectations of earnings growth in terms of managerial manipulation in high-growth conglomerates. Manipulation does not affect analysts' forecasts of conglomerate earnings, which are more accurate relative to pseudo-conglomerates. The combined effects of higher return and earning forecastability make high-growth conglomerates with manipulation earn significant alpha of -11% per-annum when accompanied by pessimistic analysts forecast revisions or positive change in investor sentiment. Using SFAS 131 as an experiment, we show that while analysts exploit transparent segment-level information disclosures, mutual funds actively invest in high growth conglomerate with distorted earnings and underperform in the long-run.

Keywords: overreaction, analyst forecasts, return predictability, earnings predictability, managerial manipulation, conglomerates.

JEL Codes: G12, G22, G23, G32

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Introduction

A growing literature argues that systematic errors in expectations contribute to mispricing in asset prices (e.g., Barberis and Thaler (2003), Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) and Hirshleifer (2001)). This argument assumes that investors form their expectations on the basis of information at hand and does not allow for the information to be strategically manipulated by corporate management. In fact, managers of firms, aware that investors are subject to a battery of behavioral biases, may strategically take advantage of such biases. The impact of such managerial manipulation *on expectations, and investor tendency to extrapolate the future value of the company* has not drawn much attention from the asset pricing literature. This is the subject of this paper.

We focus on a particular type of expectation: expectation of long-term earnings growth. La Porta (1996) and Bordalo, Gennaioli, La Porta and Shleifer (2019) link predictability of future stock returns to expected long-term earnings growth and find that "high growth firms" experience negative long term returns.[1] The intuition is that in high growth firms, investors extrapolate future high growth leading prices up and therefore inducing negative long run returns, while for the low growth firms investors extrapolate future low growth leading prices down and therefore inducing positive long run returns. We argue that part of this link is artificially created by the strategic behavior of firms that engage in earnings distortion that boost stock prices as opposed to pure extrapolation biases of the financial market players.

We start from two stylized facts. The first stylized fact is that managers engage in manipulation of earnings to boost prices and that such manipulation temporarily increases the stock price (e.g., Bergstresser and Philippon (2006), Chen, Cohen and Lou (2016), and Harbaugh, Maxwell, and Shue (2017)). In conglomerates, the availability of cash flows from many segments makes it possible to transfer funds across different divisions (e.g., Duchin (2010), Matvos and Seru (2014)) and easier for the firm to engage in cash flow manipulation doing "targeted" cost allocation and transfer pricing (e.g., Givoly, Hayn and D'Souza (1999)).[2]

[1] Bordalo et al (2019) argue that investors subject to extrapolative bias tend to wrongly extrapolate high past earnings growth into the future, leading to stock overvaluation and diminishing future prices. They find firms in the top decile in terms of expected earnings growth underperform those in the bottom decile. In related work, Da and Warachka (2011) find that underperformance of firms with high long-term earnings growth (relative to their short-term growth forecasts) is related to slow incorporation of information into long-term expected earnings and limited investor attention (DellaVigna and Pollet (2009) and Peng and Xiong (2006)).

[2] For example, Chen, Cohen and Lou (2016) find that the behavior of analysts as well as investors are influenced by the choice of segment information disclosures and report that managers of conglomerates "window dress" their

The second stylized fact is that "while some firms have grown at high rates historically, they are relatively rare instances. There is no persistence in long-term earnings growth beyond chance" (Chan, Karceski and Lakonishok, (2003)). This implies that, unconditionally, high growth firms are more likely to reduce their growth and low growth ones to increase their growth. In other words, in the case of high growth firms, the probability of being even higher growth is lower than for the case of low growth firms.

This suggests that the effect of manipulation is different in high and low growth firms. Indeed, manipulation boosts the stock price. However, if high growth firms are on average less likely to be high growth in the future, manipulation should boost the price only temporarily as in the long run the price declines to an average lower growth level. In contrast, if low growth firms are less likely to stay low and to become high growth in the future, manipulation should boost the price to a level that is more consistent to an average higher growth level. Therefore, manipulation will induce negative long term returns for high growth firms and scarce, if any, long term return effect for low growth firms.[3]

This lays out our first testable restriction: the negative relation between expected earnings growth and future stock returns is concentrated in conglomerates that engage in manipulation. Of course, the overpricing of high growth conglomerates with manipulation requires that market frictions or limits to arbitrage restrict the ability of the arbitrageurs in the market to arbitrage away the temporary mispricing. This represents our second testable restriction.

Finally, for the managerial manipulation to successfully generate mispricing, it must cater to investors who are interested in riding the short-term wave of price increases due to manipulation. We argue that such investors are the mutual fund managers given their open-end structure that may induce short-term views (Shleifer and Vishny (1997)) and the fact that they cannot easily short overvalued stocks.[4] In contrast, financial players who are compensated as a function of the quality of their long-term forecast (e.g., analysts) are less subject to it. This is the spirit of the third hypothesis.

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reported primary industry classification by shifting sales to favored industries to achieve higher short-term firm valuations.

[3] Moreover, the extrapolation hypothesis predicts undervaluation of low growth firms, which may be offset when these firms are subject to managerial manipulation which aims to increase stock valuations.

[4] DellaVigna and Pollet (2007) show that investors do not fully digest the information in long-term earnings due to limited attention. As we argued, fund managers may react positively to earnings manipulation and gain from the short-term price increases, although they do this at the expense of long-term stock underperformance.

The fact that these restrictions focus on conglomerates provides an ideal testing ground for another important reason. Extrapolation bias and manipulation have different implications in terms of the predictability of long-term earnings. Indeed, conglomerate firms tend to have – as confirmed in the data – better long-term earning predictability than single segment firms. The reason is that the cash flows of the different business units average out idiosyncratic (segment) shocks and therefore in the long-term are easier to predict than single segment firms whose cash flows are subject to segment-specific shocks. Moreover, if the cash flows of different segments can be actively shifted across segments to provide coinsurance across segments, then the cash flows of the conglomerates should be even more stable and predictable relative to similarly constructed "pseudo-conglomerates" based on portfolios of single segments firms. The relatively better ability to forecast earnings for the conglomerates is expected to increase with the horizon, as internal reallocations are likely to average out segment-specific idiosyncratic shocks over longer periods.

These considerations suggest that if the negative relation between long term return predictability and expected earnings growth were due to extrapolation bias, it should be accompanied by lower long term earnings forecastability. Indeed, more extrapolation will imply higher forecast error and worse quality of long term forecasts. In contrast, if the link between long term return predictability and growth were due to manipulation, we would expect it to be accompanied by lower long-term earning forecastability, *only if analysts fall for it*. In other words, extrapolation bias requires that analysts forecasts are biased. In contrast, the manipulation hypothesis is agnostic about the behavior of analysts. This provides us with an important and seemingly counterintuitive corollary. If investors react to manipulation and induce predictable future stock returns, while analysts correctly interpret long-term data in making earnings forecasts, there will be a positive correlation between stock return predictability and long-term earning predictability.

We test these hypotheses focusing on US firms over the period 1982 to 2019. First, we investigate the link between decreasing future prices for stocks with high earnings growth and directly link it to earnings manipulation. Second, we look at the role played by two types of players in the market: analysts and mutual funds managers.

In line with our first hypothesis, we document that the negative relation between *expected earnings growth rate and future stock performance concentrates in conglomerate stocks*, while there is little return predictability associated with earnings growth rate for pseudo conglomerates constructed using single segment firms. Moreover, the *predictability is concentrated in high growth conglomerates* while there is no predictability among low growth conglomerates. For example, high growth conglomerates underperform by 0.65% per month (t-stat=-4.68) or 7.49% per annum, in terms of Fama-French 6-factor alpha (including the momentum factor), while the alpha for low growth conglomerates is not different from zero, across all factor models. [5] Similarly constructed portfolios based on single segment firms or pseudo-conglomerates do not yield predictable returns. We obtain similar predictability in returns measured annually and adjusted for differences in firm characteristics using Fama-MacBeth regressions.

Next, we examine the *link between earnings manipulation and the predictability of stock returns in the case of high growth conglomerates*. We use a measure of strategic manipulation of earnings by conglomerates proposed in Harbaugh, Maxwell and Shue (2017). In Harbaugh, *et al.*, (2017), managers of conglomerates shift the allocation of costs to generate consistent earnings across segments in good times (i.e. when profits are higher than industry average), to improve the perception of managerial skill and benefit from it (e.g. higher current valuation and potentially bigger managerial compensation). When firm news is bad (i.e. when profits are lower than industry average), on the other hand, managers will distort segment earnings to appear less consistent to decrease the attribution of bad firm performance to the manager. The Harbaugh *et al.* (2017) measure of earnings manipulation relies on the intuition that, while manipulation increases the confidence of the investors in the ability of the manager, it does not affect the average long-term value of the cash flows. This implies that it should not impact the quality of the long-term earnings forecasts, suggesting a positive correlation between earnings and return predictability for conglomerates predicted by our hypothesis.

We find that the predictability of stock returns concentrates in conglomerates that display high earnings manipulation across segments. For example, high growth conglomerates earn an annualised (Fama-French 6-factor) alpha of -8.13% (t-stat=-3.46) when managers strategically

[5] Specifically, we build decile portfolios based on the current long-term earnings forecasts into high and low growth firms. We use a calendar time portfolio approach to compute stock returns over the following year. Consistent with our hypothesis, a portfolio that takes a long position in conglomerates that belong to the decile of high forecast-implied growth and shorts low growth rate conglomerates delivers a significant monthly return of -0.72% (t-stat=-4.96) or -8.34% per annum, based on the Fama-French (2016) six factor model. These findings are robust to alternative return specifications. We obtain similar 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.

manage their earnings but there is no significant evidence of return predictability in the absence of earnings manipulation. In contrast, low growth conglomerates do not deliver sizable alpha.

We obtain similar results using an alternative measure of managerial manipulation based on window dressing actions in conglomerates in Chen, Cohen and Lou (2016). In the Chen, Cohen and Lou (2016) measure, managers manipulate segment sales to make the "favourable" industry as their primary industry and benefit from this opportunistic classification in terms of higher current firm valuation. We add to their findings and show that conglomerates with high earnings growth that engage in window dressing earn low long-term returns.

To strengthen our investigation on the role of managerial manipulation, we also explore if conglomerate managers who are more likely to benefit from manipulation also amplify the high growth-low future return relation (Bergstresser and Philippon (2006)). Core and Guay (2002) and Coles, Daniel, and Naveen (2006) propose two measures related to the sensitivity of CEO compensation to firm value: the sensitivity of CEO wealth to stock prices (delta) and the sensitivity of CEO wealth to stock return volatility (vega).[6] Consistent with our expectation, we find that the returns on conglomerates with high growth is predictably lower for conglomerates when managers' compensation has higher delta and vega. Overall, we find strong evidence linking managerial manipulation or incentive to manipulate and the low returns associated with high growth firms.

Next, in line with our second hypothesis, we document that the *mispricing is related to market frictions* that limit the role of arbitrage activities. In particular, the impact of manipulation is stronger in the presence of market frictions and limits of arbitrage as measured by high shorting costs.

Finally, we focus on two sets of players: financial analysts and mutual fund managers. In line with our last hypothesis, we find that analysts – interested in the quality of the forecast – are less affected by the manipulation. In general, analyst earnings forecasts for conglomerates have lower forecast errors and lower dispersion of forecasts across analysts. For example, when we sort firms on the basis of expected earnings growth rate, forecast errors and forecast dispersions are systematically smaller for conglomerates relative to pseudo conglomerates. Additionally, analyst revisions of forecasts of long-term earnings of conglomerates reflect

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[6] For example, when the sensitivity of CEO compensation to stock return volatility (vega) is larger, managers have stronger incentives to boost current stock prices and benefit from the temporary overvaluation, despite the long-term price reversals.

smaller overreaction (less biased forecasts) compared to pseudo-conglomerates based on the regressions in Coibion and Gorodnichenko (2015). When we focus on manipulation, we see that analyst earnings forecast accuracy and dispersion of forecasts are unaffected by the earnings manipulation.

One possible reason why analysts are unaffected by managerial manipulation is that analysts are good in interpreting the segment level data. To test this, we exploit a change in accounting regulation in 1997 (SFAS 131) that increases the disclosure of the firms at the segment level to better understand the analyst (lack of) reaction to earnings manipulation. SFAS 131 requires firms to disclose more disaggregated segment level information enabling analysts to provide more accurate earnings forecasts for conglomerates. Following Cho (2015), we identify firms that are forced to adopt SFAS 131 in disclosing segment level information. Among conglomerates that were forced adopters of SFAS 131, we compare the analyst forecast accuracy of conglomerates that distorted earnings prior to SFAS 131 (treated firms) relative to conglomerates that did not (control firms). The difference-in-difference tests reveal that analyst forecasts accuracy and forecast dispersion improves for conglomerates with earnings manipulation, supporting the view that the accuracy of analyst forecasts is unaffected by the manipulation and benefits from the disaggregated data.

Unlike analysts, mutual funds react differently to managerial manipulation. They, on average, underperform by increasing their holdings of conglomerates when the stock moves into the highest decile in terms of the forecast of long-term earnings growth and engage in earnings manipulation, supporting the notion that mutual funds are subject to the bias that drives the overvaluation of high growth conglomerates. Moreover, the introduction of SFAS 131 does not dampen the low stock return associated with high growth conglomerates, implying that investors, including mutual funds, do not fully benefit from the disaggregated segment information.

Overall, these results support our hypothesis on managerial manipulation and overvaluation of high growth conglomerates and suggest a new trading strategy based on exploiting the information contained in the joint use of predictability of earnings and predictability of returns. We construct 2x2 independent calendar-time portfolios sorted by analyst forecast revision (downward or upward) and earnings manipulation (conglomerates that distort or do not distort earnings) in the sub-sample of firms in the top decile in terms of forecasted long-term earnings growth rates. We find that the predictable long-term returns of high growth conglomerates with managerial manipulation of earnings is significant when analysts also revise their long-term earnings forecasts downward, which generates a large Fama-French 6-factor alpha of -10.55% (t-stat=-2.81) per annum. The mispricing is also amplified when earnings manipulation coincides with positive change in investor sentiment. Within the set of conglomerates with high forecasted long-term earnings growth rates, a positive change in sentiment accompanied by earnings management leads to an annualised Fama-French 6-factor alpha of -11.68% (t-stat=-2.74). There is no stock return predictability, on the other hand, when investor sentiment declines for the conglomerates with distorted earnings or when there is no earnings manipulation. The results support the dichotomy between analysts and investors.

Our findings provide a novel view of thinking stock return predictability providing a link between optimistic long-term earnings growth forecasts and low future returns on those stocks documented in La Porta (1996) and Bordalo, Gennaioli, La Porta and Shleifer (2019). In particular, we show that the long-term returns as well as earnings are *more* predictable for high growth stocks because of managerial manipulation of earnings among multi-segment firms.

We also contribute to the literature on manipulation. Cohen and Lou (2012) and Chen, Cohen and Lou (2016) show that greater mispricing of conglomerates is related slow incorporation of market information and window dressing. We complement their findings by documenting that managerial manipulation of earnings leads to short-term overvaluation and long-term predictable underperformance of high growth conglomerates. Additionally, we show that analyst earnings forecasts are more accurate for conglomerates and provide an additional signal of mispriced stocks when used in conjunction with earnings manipulation.

Our evidence is also related to the asset pricing work that argues that some of the stock market anomaly characteristics represent systematic mispricing that can be affected by firm management, such as equity issuance, accruals, asset growth and net operating assets. Stambaugh and Yuan (2017), for example, cluster the anomaly variables that reflect mispricing triggered by managerial action into a common mispricing factor. Daniel, Hirshleifer and Sun (2020) develop a long-horizon mispricing factor that captures the information in managers' decision related to equity issuance and repurchase. Our findings suggests that managerial manipulation is a source of mispricing and we find that this is not explained by the Stambaugh and Yuan (2017) mispricing factor model.

One important corollary of our results is the fact that managerial manipulation may make the *stocks with higher precision of information more mispriced*. This is contrary to the standard folk theorem that a higher predictability of earnings should translate into lower return predictability according to the efficient market hypothesis.

2. Data

Our analysis of predictability of stock returns and corporate earnings is built on the information obtained about conglomerates relative to that of pseudo-conglomerates. We identify conglomerates using the historical segment data from Compustat. We require that each firm reports segment sale data and that the sales of all identified segments is 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.[7] 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.[8] For example, if conglomerate C has two segments A and B, with 60% and 40% sales coming from each of the two segments, respectively. The industry portfolio corresponding to segment A (B) comprises all single segment firms in the industry. In constructing the return on the corresponding pseudo-conglomerate, we take 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, book-to-market ratio etc are constructed in a similar fashion.[9]

We extract the data on annual firm earnings from I/B/E/S Unadjusted Detail Actual and analysts forecast of the earnings from I/B/E/S Unadjusted Detail History. We collect the forecasted value of annual earnings per share (EPS) for all the firms for horizons of one to five

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

[8] 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 alternate pseudo-conglomerates is qualitatively similar and are reported in Internet Appendix B.

[9] We use value-weighted industry portfolio in computing industry portfolio returns but use equal-weighted average for all firm characteristics.

years ahead.[10] Our sample includes all common stocks listed in the three major exchanges NYSE, NASDAQ, and AMEX provided by CRSP during the period from 1982 to 2019.[11] There are 2757 unique conglomerates with valid long-term forecasts, with matching number of pseudo-conglomerates. On average, our sample contains 468 conglomerates (with corresponding pseudo-conglomerates) each year. We confirm that the sample of firms in the conglomerates and pseudo-conglomerates groups are reasonably well-matched in terms of fundamentals such as analyst coverage, annual sales, firm age and market capitalization (the summary statistics of the characteristics of conglomerates and pseudo-conglomerates are in Appendix Table A2).

3. Long-Term Earnings Growth and Stock Return Predictability

3.1 Evidence based on All Firms

Analyst forecasts of the long-term earnings growth (LTG, henceforth) have been documented to be a strong predictor of the companies' future stock returns. La Porta (1996) and Bordola, Gennaioli, La Porta and Shleifer (2019) (BGLS, henceforth) show that future returns on stocks with high LTG forecasts underperform stocks with low LTG. We replicate the main findings of BGLS using our extended sample in Figure 1A. Similar to BGLS, we sort stocks into deciles on the basis of analyst forecasts of LTG. LTG is directly obtained from the IBES Summary file. The *low* long-term earnings growth portfolio is the bottom decile of stocks with the most pessimistic forecasts, and the *high* long-term earnings growth portfolio is the top decile of stocks with the most optimistic forecasts. Figure 1A displays geometric averages of one-year returns on equal-weighted portfolio of stocks sorted by the analysts forecasts of long-term growth rate. Consistent with the findings in BGLS, there is large drop in the annual returns as we move from the low growth to high growth decile, with the difference between the extreme deciles is a significant 10.36% (t=2.18) per annum. The arithmetic mean of the low growth minus high growth portfolio returns is smaller in magnitude at 6.28% (t=1.36) annually.

3.2 Conglomerates vs Single Segment Firms

[10] We extract forecasts of EPS with Forecast Period Indicator 0 to 5: i.e. Long-Term Growth Rate and for Fiscal Years 1 to 5. Detailed description of variables constructed using I/B/E/S data are in Internet Appendix C.

[11] 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).

Our main thesis is that managerial manipulation affects stock return predictability associated with high/low earnings growth projections, beyond investor overreaction due to extrapolation bias. Given that manipulation is easier for conglomerate firms, we expect to find a stronger link between future stock performance and manipulation in conglomerates as opposed to single segment firms. We therefore examine if the predictability of stock returns for high and low growth firms differ between conglomerates and stand-alone firms. We sort firms into deciles on the basis of LTG conditioning on whether they are conglomerates or not. An interesting pattern is revealed in Figure 1B. Conglomerates and single-segment firms earn similar value-weighted average annual returns from lowest LTG to decile 8. However, as we move to higher LTG deciles, predicted returns decline at a faster rate for the portfolios of conglomerates than single-segment firms. For firms in the highest long-term earnings growth decile, conglomerates earn an arithmetic average annual return of 4% while the portfolio of single-segment firms earns a return of 12%. The high minus low growth ("HMLG") conglomerates earns a large, significant (value-weighted) annual return of -10.02% (t=-3.62). In contrast, the HMLG return based on the sample of standalone firms loses its statistical significance, with a return of -2.11% (t=-0.42). The simple analyses of raw returns show that the negative predictive effect of earnings growth on future stock returns concentrates in conglomerates.[12] We also consider expanding the sample of firms by using forecast implied growth rates since analysts forecast of earnings growth rate is not available for all firms. When analysts forecasted growth rate is missing, we use the forecast-implied growth rate by averaging the implied growth rates from earnings forecasts for 3 to 5 year horizon.[13]

Importantly, the predictable return in conglomerates we document survives the adjustment to exposure to multiple factors advocated in recent asset pricing models. We compute (risk-adjusted) portfolio returns and compare the performance of HMLG portfolios constructed using conglomerates versus pseudo-conglomerates, since these two sets of stocks are similar

[12] 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 HMLG conglomerates earn a significant Fama-French (plus momentum) six-factor alpha of -4.62% (t=-2.08) per annum (see Appendix Table A1 Panel A).

[13] 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. Details on the construction of forecast-implied growth rate is provided in the Table of Variable Definition. We calculate implied LTG and other related variables based on the I/B/E/S detailed forecast data. Details are provided in Appendix C. Our results are qualitatively similar if we do not fill missing growth rate forecasts with the corresponding forecast-implied growth rate (see Appendix Table A1).

in many characteristics as displayed in Appendix Table A2. Following Mitchell and Stafford (2000), we use a calendar time portfolio approach to compute long-term stock performance. In particular, each month we rank conglomerates into deciles based on our primary ranking variable, long-term expected growth in earnings or LTG. Similar to other firm characteristics, the LTG for pseudo-conglomerates is the (sales-weighted) average LTG of the mean standalone firm within the segments of the corresponding conglomerate. Then, we form portfolios of firms that fall into one of the ten deciles based on LTG and keep them in a portfolio for a pre-specified holding period. The portfolios are rebalanced monthly to drop all the firms that have just reached the end of their holding period and to add all firms whose LTG has just fallen into the group. We exclude repeated observations of the same firm that occur within the same holding period. We report holding periods of 1 to 12 months (one year) after the event month and note that the results are robust using 24 months (two years).

The calendar time portfolio returns are adjusted for exposure to multi-factor models. 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). To illustrate, 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:

$$R_{t+1} - R_{f\,t+1} = \alpha_{t+1} + \beta_{1,t+1}(R_{MKT\,t+1}) + \beta_{2,t+1}R_{SMB\,t+1} + \beta_{3,t+1}R_{HML\,t+1} + \beta_{4,t+1}R_{RMW\,t+1} + \beta_{5,t+1}R_{CMA\,t+1} + \beta_{6,t+1}R_{MOM\,t+1} + \varepsilon_{t+1}, (1)$$

where R_{t+1} is the monthly 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 on month t+1; s_{t+1} is the number of stocks included in the portfolio on month t+1 and $m_{i,t}$ is the market cap of stock i in month t for value-weighting and 1 for equal-weighting (value-weighted portfolio returns are reported in the main paper while equal-weighted results are available from authors). The standard errors of the portfolio returns use the Newey-West corrections.

Table 1 reports our findings on the predictability of returns on conglomerates and pseudo-conglomerates. Panel A shows that the *unconditional* returns do *not* differ between the two group of firms: both firms earn an average (raw) return of around 0.6% per month over one year. Similarly, when we adjust the stock returns for exposure to risk factors in recent pricing models, 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.

However, if we condition the predicted returns on the forecasted long-term growth rate in earnings, LTG, the results change drastically! In particular, we sort the 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. If we focus 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 annualised alpha of the high minus low growth conglomerates is between -8.12% (t=-4.79) and -8.92% (t=-5.02), across the three factors 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 short-leg of the strategy (i.e. shorting the high growth conglomerates) and the low growth conglomerates earns close to zero alpha. In contrast, there is no evidence of predictable returns for the pseudo conglomerates sorted on long-term growth rates, both in raw returns as well as alphas across all the factor model specifications.

These results are 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 multiple years. High growth conglomerates earn significantly lower six-factor adjusted returns, as shown in Models 1 and 4 in Appendix Table A4. On the contrary, we do not see significant predictability of returns for the pseudo-conglomerates in all holding periods. As shown in Appendix Table A1 Panel B, we also find that there is stronger return predictability for conglomerates relative to the sub-sample of stand-alone firms.

3.3 Effect of Managerial Manipulation

3.3.1 Main Measure of Managerial Manipulation

We now examine whether the higher predictability of long-term stock returns of conglomerates with high earnings growth is related to the greater ability of the managers of conglomerates to distort earnings. As we argued, unlike the case of pseudo-conglomerates, in conglomerates the managers have the freedom to allocate cash flows across segments to alter segment level earnings. We therefore postulate that the managers' strategic manipulation of earnings leads to higher current stock prices and low long-term returns. Our measure of strategic manipulation of earnings follows Harbaugh, Maxwell and Shue (2017), who show that managers of conglomerates re-allocate costs across segments to achieve *more consistent earnings across segments* when the firm is doing well (high profitability) to increase the probability that investors attribute the good performance to the manager's ability, hence, increase the value of the firm. This leads to stock price overvaluation of more profitable conglomerates. Similarly, for less profitable conglomerates, managers distort segment earnings to appear *less consistent across segments* (i.e. increase cross-segment variance in earnings) to decrease the attribution of firm performance to the managers.

The Harbaugh *et al.* (2017) measure of strategic manipulation of earnings in conglomerates starts 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 $EARN_{j,t} = \frac{\sum_i (sales_{i,j,t} - costs_{i,j,t})}{\sum_i assets_{i,j,t}}$. [14] Consequently, for each conglomerate j in year t, we have the vector of earnings $\mathrm{v}_{j,t} = (EARN_{1,j,t}, \ldots, EARN_{m,j,t})$ with standard deviation of earnings $\mathrm{STD}_{j,t}$, where m is the number of segments of the conglomerate. [15]

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[14] 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.

[15] Similar to Harbaugh et al (2017), we exclude (i) business segments in the financial services or regulated utilities sectors (Fama-French Industry Code 31 and 47), as these industries face additional regulatory oversight over their

Harbaugh *et al*. (2017) suggest the 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. Similar to Harbaugh *et al.* (2017), 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. 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 is:

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

Note that the mean (industry-adjusted) predicted earnings for conglomerate j in year t is equal the mean earnings of the conglomerate because earnings manipulation 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.

Harbaugh *et al* (2017) predict that in the presence of strategic manipulation of earnings consistency, managers will increase consistency, $STD_{jt} < \widehat{STD_{Jt}}$, when firm earnings exceeds expectations - i.e. $EARN_{j,t} > EARN_{j,t}^{ind}$. Conversely, managers are expected to decrease earnings consistency, $STD_{jt} > \widehat{STD_{Jt}}$, when firm earning news is below expectations. Hence, we set "Strategic Manipulation" indicator variable to be 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.

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operations and accounting disclosure; (ii) very small segments, defined as segments with assets less than one-tenth of the total firm-level assets.

We focus on the effect of strategic manipulation on stock return predictability and report the results in Table 2. In line with our expectations, the difference in performance for the conglomerates with high LTG and the ones with low LTG concentrates in stocks with strategic manipulation of earnings. The monthly risk-adjusted returns based on the Fama-French six-factor model, averaged over a 12-month horizon, on high-growth conglomerates is -0.7% (t=-3.46) in the case of conglomerates with strategic manipulation of earnings but reduces to an insignificant -0.26% (t=-1.46) for conglomerates without strategic manipulation of earnings (annualised returns are -8.13% and -3.12% respectively). Moreover, we obtain similar annualised alphas for the portfolio of high growth conglomerates with strategic manipulation of earnings using the mispricing factor, and Q factor models at -7.23% (t=-3.18), and -8.67% (t=-3.08), respectively. We do not find predictable returns among low growth conglomerates, independent of manipulation. Hence, the return predictability is exclusive to high growth conglomerates with strategic manipulation of earnings.

In Figure 2, we plot the monthly Fama-French six-factor alpha of the portfolio of high LTG conglomerate with and without strategic manipulation of earnings. The negative performance of high LTG conglomerates with strategic manipulation of earnings shows up significantly from the first month after portfolio construction and the cumulative abnormal returns lasts for several years (see Figure 2A). In Figure 2B, we do not see significant predictability of returns for the group without strategic manipulation of earnings across all holding periods. In sum, the results suggest that the long-term return predictability associated with high earnings growth is stronger when the manager strategically distort the firm's earnings across segments.

3.3.2 Alternative Measures of Managerial Manipulation

Our previous discussion on the effects of manipulation focuses on the cost management, which arguably captures one important dimension of managerial manipulation. Here, we try to supplement the investigation with three alternative measures related to managerial manipulation, capturing sales management and managerial incentives to manipulate. The first alternative measure follows Chen *et al.,* (2016) and focuses on sales management by the managers of conglomerates[16]. 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

[16] Detailed construction on the alternative measure based on sales management and results are in Appendix D.

overall firm valuation being driven by the primary segment. Hence, we expect that sales management to boost the overvaluation of high growth conglomerates.

We also employ two alternative measures that have been used to capture the managerial wealth exposed to stock price movements: delta and vega (Core and Guay (2002), Coles, Daniel, and Naveen (2006).[17] Delta measures the sensitivity of CEO wealth to stock prices while vega means 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 larger, managers have stronger incentives to boost current stock prices because they can benefit from the increasing volatility resulted from the current temporary overvaluation and the long-term reversals. With respect to delta, we argue that in the presence of managerial short-termism, CEOs may have incentives to boost short-term stock prices at the cost of long-term losses. Hence, we expect that return predictability is stronger for firms with higher deltas and vegas arising from greater managerial incentive to manipulate.

The results are reported in Table 3. In Panel A, we show that return predictability concentrates in conglomerates with sales management. The annualised alphas for the portfolio of high growth conglomerates with sales management using the Fama-French six-factor, mispricing factor, and Q factor models are -8.83% (t=-2.24), -9.13% (t=-2.13), and -8.62% (-2.27), respectively. In Panel B and Panel C, we find stronger future negative returns for high growth conglomerates with high delta or high vega. For example, the annualised alphas for portfolio of high growth conglomerates with high delta and high vega using the Fama-French six-factor model are -9.11% (t=-4.01) and -9.76% (-4.19). Alphas are mostly insignificant for the groups of high growth conglomerates without sales management or with low deltas or low vegas. Overall, we uncover a strong and robust link between managerial manipulation and stock return predictability.

3.4 Role of Limits to Arbitrage

Next, we focus on the second hypothesis and consider the constraints on arbitrage of the mispricing documented in our paper, in the form of shorting constraints. Given that the profitability of the trading strategy is mostly based on shorting the overvalued, high-growth

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[17] We are grateful to Lalitha Naveen for making the data on delta and vega available online at https://sites.temple.edu/lnaveen/data/.

conglomerates (with managerial distortion), we ask whether high short selling costs are responsible for it.

We rely on the data on stock loan fees from Markit to capture short selling costs. Markit collects the equity lending data from a variety of contributing customers including beneficial owners, hedge funds, investment banks, lending agents, and prime brokers; the contributing participants account for the majority of all equity loans in the U.S. Following Drechsler and Drechsler (2014) and Atmaz and Basak (2019), we use the monthly value-weighted average loan fee as our measure of a stock's shorting fee.[18] A high shorting fee indicates that it is more costly for investors to hold short positions, making it difficult to arbitrage overvalued stocks.

Our working hypothesis posits that the mispricing – i.e., long-run return underperformance – related to the overvaluation concentrates on high growth conglomerates with managerial manipulation should be more pronounced in stocks with high shorting fees. The results are reported in Table 4. In line with our hypothesis, the underperformance of conglomerates with high forecasted growth and managerial manipulation concentrates in stocks with high shorting fees. The annualised alphas (adjusted using the Fama-French six factor model) for high LTG conglomerates with distortion is large at -10.98%(t=-2.63) in the case of high expected shorting fees and -8.64%(t=-2.28) for stocks with high actual shorting fees. These are economically significant returns. On the other hand, we do not find evidence of future abnormal returns when short selling is not costly and/or in the absence of managerial manipulation. The fact that the low future returns on high growth conglomerates subject to managerial distortion concentrates in stocks that experience high shorting costs is consistent with the view that arbitrage of overpricing in these cases is difficult. This supports our second hypothesis.

4. The Financial Players' Behavior

In this section, we evaluate the reaction of two sets of market players to managerial manipulation in conglomerates: financial analysts and mutual fund investors. We expect the reaction of players evaluated on the basis of long-term forecast accuracy (analysts) and players subject to short-term limits of arbitrage constraints (fund managers) to differ.

[18] From Markit database, we use simple average fee (SAF) to construct actual shorting fees and IndicativeFee to construct expected shorting fees. SAF measures the simple average fee for borrowing stocks while IndicativeFee captures the expected borrowing costs derived by Markit's proprietary analytics. Detailed description is provided in Variable Definition. Loan fee data only covers the period starting from 2008 because of data availability.

4.1 Analysts

4.1.1 Earnings Predictability of Conglomerates versus Pseudo-Conglomerates

We start by investigating whether analyst forecasts are affected by manipulation. Given the return predictability based on LTG and strategic manipulation of earnings, we ask whether analysts make more inaccurate forecasts for conglomerates relative to that for pseudo-conglomerates and overreact more when they forecast earnings of conglomerates, especially for the ones with distorted earnings, relative to pseudo-conglomerates.

In particular, we focus on the ability of analysts to predict future earnings of conglomerates versus pseudo-conglomerates and test if the difference in the predictability depends on forecast horizon. We consider forecasts of 1 to 5 years ahead.[19] Table 5, Panel A displays the summary statistics of analyst earnings forecasts of conglomerates versus pseudo-conglomerates. We employ two measures of the quality of forecastability of corporate earnings by analysts: (1) error in analyst forecasted earnings compared to actual earnings and (2) dispersion in the forecasts across analysts. 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. The AFE for pseudo-conglomerates is the segment-sales-weighted value of AFEs of matched industry portfolios. A high AFE implies that the forecasted mean value of EPS is further away from the corresponding actual earnings and indicates weaker forecastability.

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.[20] FD for pseudo-conglomerates is the-segment-sales-weighted value of FD of matched industry portfolios. A high FD implies that the analyst forecasts are more dispersed and indicates greater difficulty in forecasting earnings due to uncertainty about future earnings or disagreement among analysts.

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[19] The number of observations for three-to-five-year forecast horizons are fewer relatively to that for 1-year and 2-year forecast horizon. To achieve balance in the number of observations across different horizons, we combined the 3-5 years forecast horizon into one horizon, labelled as the “Long-term” horizon. The forecast horizon of this long-term forecasts also match the forecast horizon of LTG.

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

We find that the future earnings of conglomerates are more forecastable than the earnings of matched pseudo-conglomerates, particularly over the longer term. The mean and median absolute forecast error (AFE) and forecast dispersion (FD) are both significantly lower for conglomerates than the firms that make up the equivalent pseudo-conglomerate. As shown in Panel A of Table 5, the mean absolute forecast error (AFE) for conglomerates earnings in the long-term of 3 to 5 years is 4.32%. The corresponding AFE for pseudo-conglomerates is more than twice the magnitude and is significantly higher at 9.89%. As expected, long-term forecasts are less accurate relative to short-term forecasts, but conglomerate's forecast are always more accurate than single-segments. This holds in one and two year horizons as well. We obtain a similar interpretation of the ability to forecast earnings of conglomerates using the dispersion in the forecasted earnings. For example, the average dispersion in long-term forecasts by analysts is 1.55% for conglomerates, which is about half of the forecast dispersion of the pseudo-conglomerates at 2.95%, and the difference is statistically significant.

To further understand the distribution of AFE and FD, we also report the average accuracy of earnings forecasts for conglomerates relative to pseudo-conglomerates across firms grouped by their forecast-implied growth rate quintiles.[21] We first group all conglomerates from low earnings growth to high growth quintiles and compare the accuracy of earnings forecast between conglomerates and pseudo-conglomerates within each growth group. As shown in Panel B of Table 5, firms in high growth group tend to have higher unconditional mean value of AFE and FD relative to firms in low and median growth group. Importantly, the AFE and FD are generally lower for conglomerate relative to pseudo conglomerates. For example, the average long-term earnings forecast error (AFE) for high-growth conglomerates is 9.07 and is significantly lower than the AFE of 12.85 for high-growth pseudo-conglomerates. Hence, forecasts of earnings of high growth conglomerates are more accurate than similar pseudo-conglomerates (in the same industries), particularly over the long-term forecast horizon.

These results show that analysts do in fact predict earnings better for conglomerates than for pseudo-conglomerates. We confirm our findings in a regression setting that allows for control of omitted variables, including firm characteristics and firm and time fixed effects. The

[21] We show that conglomerates have significantly lower earnings volatility than pseudo-conglomerates based on matched stand-alone firms in the Appendix Table B3. Results are robust when we compare conglomerates with stand-alone firms directly or pseudo-conglomerates based on industry portfolios.

first set of panel regressions consider each of the one, two and long-term forecast horizons separately for our sample of conglomerates and pseudo-conglomerates:

$$Y_{i,t,f} = \beta_1 Conglomerate_{i,t} + \gamma Control_{i,t} + Firm_i + Ind\_Year_{n,t} + \varepsilon_{i,t}, \quad (4)$$

where $Y_{i,t,f}$ is the earnings forecastability measure (AFE or FD) of firm *i* in year *t* at forecast horizon *f*, $Conglomerate_{i,t}$ is set to one if the firm *i* in year *t* has multiple segments and zero for pseudo-conglomerates, and $Control_{i,t}$ is a vector of firm characteristics as control variables: *Size*, defined as the log value of firm market capitalization, *Analyst coverage*, defined as the number of analysts covering the firm, *Age*, defined as the age of the firm, and *BM*, log value of the book-to-market value of the firm. The firm characteristics for pseudo-conglomerates are the segment-sales-weighted values of the corresponding characteristics of the matched industry portfolios made up of single segment firms. All the independent variables are lagged by one year. The regressions include $Firm_i$, the firm fixed effects and $Ind\_Year_{n,t}$, FF-48 industry times year fixed effects. $Firm_i$ absorbs all firm-level time-invariant variation. $Ind\_Year_{n,t}$ takes care of time fixed effects and all time-variant and time-invariant industry effects. Standard errors are double-clustered by industry and year. We require a matched conglomerate and pseudo-conglomerate pair for each firm-year-horizon.

The second set of panel regressions considers all three forecast horizons and tests for differences in predictability of earnings of conglomerates in the short (1 or 2 years) and long-term (3 to 5 years):

$$Y_{i,t,f} = \beta_1 Conglomerate_{i,t} + \beta_2\, LT\_Dummy_{i,t} + \beta_3\, Conglomerate_{i,t} * LT\_Dummy_{i,t} + \gamma Control_{i,t} + Firm_i + Ind\_Year_{n,t} + \varepsilon_{i,t}, \quad (5)$$

where LT_Dummy is a dummy variable indicating 3 to 5 year forecast horizon, and everything else remains the same as equation (4).

The estimates of equations (4) and (5) are reported in Table 6 Panel A. We find that earnings forecasts of conglomerates display a smaller forecast error, especially over the longer term. In Models 1 to 3, we run the first set of panel regressions in equation (4). We observe significantly lower AFE of conglomerates relative to pseudo conglomerates over each forecast horizons while the difference increases as we move to the long-term horizon (-1.52 to -3.34). In Model 4, we estimate the specification in equation (5) that includes forecasts across all the horizons and estimates the marginal effect of the long-term forecasts. As shown by the coefficient on LT_Dummy, the forecast error (AFE) increases with horizon and is smaller for conglomerates.

More importantly, the long-term AFE is significantly smaller for conglomerates relative to pseudo-conglomerates as reflected by the negative estimate of β_3 in equation (5). *Figure 3A* is a graphical illustration of the differential effects of forecast horizon on AFE for conglomerates versus pseudo-conglomerates. The figure plots the AFE by the forecast horizon (one-year, two-year and long-term) for conglomerates and pseudo-conglomerates and shows that the forecast accuracy improves for conglomerates relative to pseudo-conglomerates over the longer horizon.

We document similar findings for earnings forecast dispersion (FD). In Models 5-7 of Table 6 Panel A, we observe significantly smaller dispersion in forecasted earnings of conglomerates relative to pseudo-conglomerates over each forecast horizon and the difference widens from -0.4% for one-year horizon to -0.84% for long-term forecasts. When we include the forecast dispersion measured at all horizons in the regression (Model 8), the long-term FD for conglomerates is smaller by 0.77 than that of pseudo-conglomerates compared to the shorter term (1 and 2 year) FD. *Figure 3B* is a graphical illustration of the differential effects of forecast horizon on FD for conglomerates versus pseudo-conglomerates. The figure plots the FD by the forecast horizon (one-year to long-term) for conglomerates and pseudo-conglomerates and shows that the FD is smaller for conglomerates relative to pseudo-conglomerates, particularly for the longer horizon.[22]

4.1.2 Overreaction in Analyst Forecasts

La Porta (1996) and BGLS show that analysts use a firm's past earnings performance to infer its future long-term earnings, but overreact. Following BGLS, we examine if the higher forecast accuracy in analysts predicting long-term conglomerate earnings is a reflection of a lower degree of overreaction in their forecasts. For instance, do analysts overreact less to past performance when making long-term forecasts for conglomerates as these firms are more diversified across sectors and have less volatile earnings (e.g. Duchin 2010)? To assess the magnitude of analyst overreaction, we employ the regressions in Coibion and Gorodnichenko (2015) and BGLS. Coibion-Gorodnichenko (2015) show that if analysts forecasts are fully

[22] The effect reported in Table 6 are economically sizable compared to the mean value of AFE (4.32) and the mean value of FD (1.55) over the 3-5 year forecast horizon. The long-run improved forecast accuracy for conglomerates also holds in the sub-periods before and after 2000. Our results are also unaffected by the potential concern that the firms with short and long-term forecasts may be different which in turn drives the variation in forecast accuracy. We address this concern by restricting our sample to firms with earnings forecasts across all three horizons (1 year, 2 years, and long-term). We report the regressions in Appendix Table A3 and our results remain qualitatively similar.

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 error. On the other hand, if analysts forecast revisions reflect an overreaction (underreaction) to information, we expect a negative (positive) relation between the analyst forecast revision between t-1 and t and the subsequent forecast error (i.e., difference between actual earnings at t+1 and the earnings forecasted at time t). BGLS. report that analysts overreact in their revision of long-term earnings growth forecasts: an upward (downward) revision in forecasted earnings growth at time t is associated with negative (positive) realized errors in the future period. We estimate the Coibion-Gorodnichenko regression for analysts long-term earnings forecast revision and subsequent realized earnings:

$$\left(\frac{EPS_{i,t+n}}{EPS_{i,t}}\right)^{\frac{1}{n}} - LTG_{i,t} = \alpha + \beta_1 Conglomerate_{i,t} + \beta_2\left(LTG_{i,t} - LTG_{i,t-1}\right) + \beta_3 Conglomerate_{i,t} * \left(LTG_{i,t} - LTG_{i,t-1}\right) + Year_{n,t} + \varepsilon_{i,t}, \quad (6)$$

where $[(EPS_{i,t+n}/EPS_{i,t})^{1/n} - LTG_{i,t}]$ is the forecast error 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 directly obtain from IBES and *n* corresponds to the forecast period of 3, 4, or 5 years. Similar to BGLS, we add year fixed effects $Year_{n,t}$. The coefficient of interest is β_3, which indicates if the overreaction in analysts forecast revisions are different for conglomerates.

The estimates of equation (6) are shown in Panel B of Table 6. Consistent with BGLS, an upward LTG revision predicts negative forecast errors and excessive optimism, indicating overreaction in the analysts forecast revisions. The estimated β_2 tends to be significantly negative, between -0.48 to -0.69 for the 3 to 5 year forecast horizons. More importantly, we find that the analyst overreaction is significantly smaller for conglomerates, as shown in the estimated β_3: the magnitude of the overreaction coefficient reduces between 0.20 to 0.28 for conglomerates relative to pseudo-conglomerates. Combining the effects of β_2 and β_3, it indicates that the same amount of forecast revision is associated with 40%-50% less forecast errors for conglomerates relative to pseudo-conglomerates. These findings point to smaller analyst overreaction (i.e. less bias) when they are forecasting earnings for conglomerates, consistent with our evidence that long-term earnings of conglomerates are easier to forecast.

4.1.3 Earnings Predictability and Managerial Manipulation

Next, we examine how analysts react to manipulation of segment earnings by managers. We are interested to know if strategic manipulation of earnings misleads analysts and makes earnings difficult to forecast relative to conglomerates without strategic manipulation earnings. We therefore estimate the following regression using only long-term forecasts for conglomerates:

$$Y_{i,t,f} = \beta Strategic\ Manipulation_{i,t} + \gamma\ Control_{i,t} + Firm_i + Ind\_Year_{n,t} + \varepsilon_{i,t}, (7)$$

where $Y_{i,t,f}$ can be absolute forecast error (AFE) or forecast dispersion (FD) for firm i in year t, $Strategic\ Manipulation_{i,t}$ is a dummy variable indicating strategic manipulation of earnings for firm i in year t and all other variables remain the same as in equation (4).

We report the results in Table 7. We regress AFE and FD on distortion dummy in Column 1 and 2, respectively. We find that on average AFE and FD for conglomerates with strategic manipulation of earnings are not statistically different from those for conglomerates without strategic manipulation of earnings.[23] The estimated β for AFE and FD are not significantly different from zero. Hence, the results are inconsistent with the expectation that strategic manipulation of earnings misleads analysts into overly extreme forecasts.

Overall, all our investigations of analyst earnings forecasts suggest that analysts are better able to forecasts the long-term earnings of conglomerates, and are unaffected by managerial manipulation.

4.2 Mutual Fund Managers

The second group of financial market players we investigate are mutual funds. The literature has document 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 and amplify cross-sectional mispricing (Akbas, Armstrong, Sorescu and Subrahmanyam, 2015, and Edelen, Ince and Kadlec, 2016). We build on these findings and test whether mutual funds are similarly exposed to mispriced high growth conglomerates with managerial manipulation and subsequently underperform.

[23] We find qualitatively similar results using sales management as an alternative measure of strategic manipulation of earnings. Results are in Appendix D.

4.2.1 Manipulation and Mutual Fund Performance

We start by examining whether the *long-term* performance of active mutual funds is affected by their exposure to high long-term growth conglomerates and to manipulation. We want to assess whether they are able to see it and therefore make money out of it or they fall for it and therefore underperform due to it. The mutual fund data come from the combination of several data sources: Thomson Reuters fund holding data and fund holding, summary, and return data from CRSP. We focus on the actively managed equity funds in the U.S., with fund size larger than 15 million.[24] To minimize data quality problems, we use Thomson Reuters fund holding data up to the first quarter of 2010 and use CRSP fund holding data from the second quarter of 2010 (Zhu (2020) and Dou, Kogan, and Wu (2022)).[25] Because data coverage on the monthly TNA and quarterly portfolio holding prior to 1997 is limited, our sample period spans from January 1997 to December 2018. The sample contains 6678 distinct mutual funds, with a quarterly average of 1370 funds.

We measure the exposure of an active mutual fund to conglomerates with high long-term earnings growth as the fund's investment weight in conglomerates in the top decile of long-term earnings growth (labelled as HGC). Likewise, the exposure of an active mutual fund to conglomerates with high long-term earnings growth and managerial manipulation is defined as the fund's investment weight in conglomerates in the top decile of long-term earnings growth *with* strategic manipulation of earnings (labelled as HGCD). We consider HGC and HGCD based on active investment weights defined as deviation of investment weights from benchmark weights. The funds with positive exposure (i.e. HGC >0 or HGCD > 0) are sorted into quintiles based on the value of HGC or HGCD.[26]

[24] 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.

[25] 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. We find that Thomson Reuters fund holding data provides better coverage from 2008 and we use this holding data up to the first quarter of 2010.

[26] We use active investment weights to account for the concern that active mutual funds investment in stocks with manipulation and high growth (high HGCD) 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/HGCD from our sample to account for the concern that funds may avoid investing high growth conglomerates (with distortion) because of investment objectives or investment mandates rather than their investment skills allowing them to foresee the potential underperformance associated with the firms. If this is the case, then the relationship between HGC/HGCD and fund performance can be spurious and hence, we exclude funds with non-positive HGC/HGCD when we estimate Equations 8 and 9.

We construct calendar time portfolios of fund performance defined as just raw returns as well as risk-adjusted returns using Carhart four factors (market, size, book-to-market, and momentum), Fama-French six-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 8 presents the monthly fund returns (averaged over a 12-month period). Performance is assessed over the next one year. We find that funds with high HGC (HGCD) significantly underperform the funds with low HGC (HGCD) over the next year. The underperformance of the High-Minus-Low HGC funds are robust to controlling for exposures to various factors, with annualised alphas ranging from -1.75% to -3.15%, all of which are statistically and economically significant. Moreover, the high HGCD funds also underperform the funds with low HGCD, with slightly larger magnitude. The annualised alphas for the High-Minus-Low HGCD group are statistically significant and range from -2.36% to -3.53%.[27] Interestingly, we do not find significant effect of exposure to high growth conglomerates on mutual fund performance when there is no managerial distortion in earnings, indicating that the managerial manipulation is crucial for fund performance predictability (the latter results are reported in Appendix Table A5).

These results suggest that mutual fund long-term performance is negatively impacted by manipulation in conglomerates. To confirm that this is due to the fact that they are influenced by the manipulation and as a result increase their holdings of these stocks, (and hence, contribute to the overpricing) we focus on the holdings. We design a panel specification which considers mutual funds' investment in high-growth conglomerates:

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

where $w_{i,t}$ is the percentage of stock *i* in quarter *t* owned by mutual funds relative to all shares of stock *i* outstanding. This is regressed on the dummy variables *Conglomerate*, which takes a value of 1 if and only if stock i is a conglomerate and $\Delta HighLTG_{i,t}$ which is set to 1 only if stock i moves from the bottom 90% in quarter t-2 to the top forecasted long-term earnings growth (LTG) decile in quarter t-1. $Control_{i,t}$ is a vector of stock characteristics as control

[27] Although we fail to find the objective-adjusted fund returns for the High-Minus-Low HGCD group to be statistically significant, we do show that the high HGCD group earns an average annualized objective-adjusted return of -1.64% (t=-2.87).

variables: firm size, past stock return, and book-to-market ratio. We include all mutual funds with positive investment in high-growth conglomerates (HGC) in our sample.

Next, we investigate if mutual funds are misled by the earnings manipulation of high growth conglomerates and contribute to the overpricing by increasing their holding of these stocks in their fund portfolio. In particular, we test whether mutual funds increase their holdings of conglomerates that move to the top LTG decile from a group of relatively lower LTG and, at the same time, move to the group of high-growth conglomerates with distorted earnings. Hence, we estimate the following regression for the subsample of conglomerates only:

$$w_{i,t} = \beta_1 \Delta Distortion_{i,t} + \beta_2 \Delta HighLTG_{i,t} + \beta_3 \Delta HighLTG_{i,t} * \Delta Distortion_{i,t} + \gamma\, Control_{i,t} + Firm_i + YearQuarter_t + \varepsilon_{i,t}, \quad (9)$$

where $w_{i,t}$ is the percentage of mutual funds' ownership level in conglomerate i in quarter t and we only include mutual funds with positive high-growth conglomerate with distortion (HGCD). $\Delta Distortion_{i,t}$ is a dummy variable set to 1 if conglomerate i did not strategically distort earnings in year y-2 but distorted earnings in year y-1 and 0 otherwise.

As shown in Column 1 of Table 9, we find that when the stock is a conglomerate and moves to the group of top LTG decile, the level of mutual fund ownership in the stock increases significantly by 1.59%. The evidence is consistent with our results in Table 8 Panel A, showing that some mutual funds are attracted to and actively invest in the conglomerates when they move to the top LTG deciles and deliver significant underperformance in the future. In Column 2 of Table 9, we further show that the mutual fund ownership level increases by 2.44% when a conglomerate moves to the group of conglomerates with top 10% LTG and exhibits strategic distortion of earnings. This suggests that mutual funds actively respond to the increase in LTG and manipulation of earnings by increasing the holdings of the conglomerates engaged in such practices. Overall, our evidence supports the argument that some mutual funds react to the manipulation of earnings of high growth conglomerates in the wrong direction of mispricing.

4.3 Segment-Level Disclosure

4.3.1 Do Analysts Interpret Segment Level Data Better?

In the above sub-sections, we show that analysts are not misled by the strategic manipulation of earnings. One possible reason is that they are incentivised to generate accurate earnings forecasts and are able to disaggregate the information at the segment level, nullifying the effect of internal cash flow manipulation. We test this hypothesis by exploiting a policy experiment: 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"),[28] that 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.

In addition, the accounting items disclosed for each segment are defined in a way that is consistent with internal segment information used to assess segment performance. This represents a salient divergence from the accounting items reported under SFAS 14. Indeed, it has been shown that the information environment improves upon the implementation of SFAS 131. For example, Street, Nichols, and Gray (2000) find that there is a greater number of line-of-business (LOB) segments reported and both of the quantity and quality of the segment-level reporting improves under SFAS 131. Berger and Hann (2003) argue that SFAS 131 implementation gives analysts access to more granular segment-level information which is hidden under SFAS 14 and provide evidence that SFAS 131 leads to significant drop in analyst forecast errors. Ettredge, Kwon, Smith, and Zarowin (2005) find that SFAS 131 increased the stock price informativeness, which indicates the ability of past stock returns to predict a firm's future earnings. All of these findings point to an increase in the transparency of segment information after the implementation of SFAS 131. Enhanced transparency renders greater difficulty for managers to manipulate across segments to maximize value. For instance, Berger and Hann (2003) show a reduction in market value for firms that were reported as single-segment firms under SFAS 14 but as multiple-segment firms after the implementation of SFAS 131. This inefficiency is often related to agency costs (e.g. CEO's tendency to "empire building") or rent-seeking behaviors among divisional managers. Cho (2015) shows that SFAS 131 help resolve agency conflicts in the internal capital markets of diversified firms.

Hence, we expect SFAS 131 to improve the transparency of cashflow allocations across segments, thereby reducing managers' discretion in aggregating segments and hence

[28] 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.

ameliorating the ability of the financial intermediaries to monitor managers. In particular, we expect that the implementation of SFAS 131 will make it easier for analysts to detect manipulation of earnings. Indeed, strategic manipulation of earnings alters the variance of segment-level earnings without altering the aggregation of segment-level earnings. To do so, managers need to shift reported earnings across segments by adjusting the allocation of the costs (e.g. costs of goods sold; selling, general and administrative expenses; and depreciation, depletion, and amortization). Under SFAS 131, the discretion over cost allocation is more visible to the analysts because SFAS 131 requires managers to disclose more disaggregated segment-level information and the analysts have the expertise to process the information. As a result, if analysts are less distracted by the strategic manipulation of earnings because they rely on segment level data, we expect the implementation of SFAS131 to improve their ability to forecast earnings and to be less affected by manipulation.

We follow Cho (2015) to identify firms that were forced to adopt SFAS 131. A firm is defined as a forced adopter of SFAS 131 if (1) its segments reported in the last year under SFAS 14 are different from those restated under SFAS 131 and (2) the restated segments under SFAS 131 reveal any additional operations in industries that were not disclosed under SFAS 14. Otherwise, a firm is not a forced adopter. The segment data for the pre-SFAS 131 period, restated in accordance with SFAS 131, is manually collected by reading the firms' 10-Ks.[29] To implement this classification using Compustat data, we compare a firm's segment identifiers (SIDs) and segment SIC codes in the last year under SFAS 14 (i.e., the lag adoption year) with the same firm's SIDs and segment SIC codes in the first year under SFAS 131 (i.e., the adoption year).

To make sure that our restated segment data capture only reporting changes related to the forced implementation of SFAS 131, we eliminate all contaminated firms if their restated data partially reflect other structural changes in the lag adoption year (e.g., restructuring, acquisitions, divestitures, or changes in accounting methods). Following Berger and Hann's (2003) and Cho (2015), we eliminate change firms from the sample if they are contaminated by the events above other than pure reporting changes. The algorithm compares the sums of segment revenues (and earnings) for the lag adoption year between the restated data and

[29] 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 in their investor relations websites is used. We are grateful to YJ Cho for sharing the data used in Cho (2015).

historical reports and considers firms as contaminated if the difference between the two sums exceeds 1% of the restated sum (see Cho (2015)).

We estimate a difference-in-difference model in the four years before and after the adoption of SFAS 131 (9 years in total). The treated firms are the conglomerates that are forced adopters and strategically distorted their earnings before the implementation of SFAS 131, and the control firms are the conglomerates that are forced adopters but did not distort. We expect that analysts make more precise forecasts for treated firms after the adoption of SFAS 131 than before the adoption of SFAS 131 relative to the control firms because SFAS 131 makes it easier to detect the strategic manipulation of earnings. We estimate the following two-way fixed effect (TWFE) model:

$$Y_{i,t} = \beta_1 Ex - Ante\ Distortion_{i,t} * Post_{i,t} + \beta_2 Post_{i,t} + \gamma\ Control_{i,t} + Firm_i + Year_{n,t} + \varepsilon_{i,t}, \quad (10)$$

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 (3-5 years) for firm i in year t and $Forecast\ Dispersion_{i,t}$ is the standard deviation of all forecasts (3-5 years) for firm i in year t. $Ex - Ante\ Distortion_{i,t}$ is set to one if the frequency of firm i strategically distorting earnings is above median frequency in the three-years period before the implementation of SFAS 131 and zero otherwise,[30] $Post_{i,t}$ is a dummy variable set to 1 for post-SFAS 131 period,and $Control_{i,t}$ is a vector of control variables. The control variables remain the same as in equation (4): Size, Analyst coverage, Age, and BM. The regressions include $Firm_i$, the firm fixed effects and $Year_{n,t}$, year fixed effects. 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 10. The coefficients on the interaction term $Ex - Ante\ Distortion_{i,t} * Post_{i,t}$ are negative and both economically and statistically significant. It indicates that after the implementation of SFAS 131, AFE and FD for conglomerates that are forced adopters with ex-ante manipulation of earnings decreased by 72% and 52% (relative to

[30] 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.

the ex-ante sample mean), respectively, more than conglomerates that are forced adopters without ex-ante manipulation.

In order to test for parallel trends and study the dynamics of treatment effects, we estimate an event study-version of the TWFE model with indicators for distance to/from the adoption of SFAS 131. Specifically, we estimate the following specification:

$$Y_{i,t} = \beta_1 \sum_{s=-4,s\neq-1}^{4} Ex - Ante\ Distortion_i * D_{s(i,t)} \ + \beta_2 Control_{i,t} + Firm_i + Year_t + \varepsilon_{i,t}, \ (11)$$

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. $Ex - Ante\ Distortion_{i,t}$ is a dummy variable set to 1 if the frequency of strategic manipulation of earnings of the firm in pre-SFAS 131 period is above the median frequency and 0 otherwise. Controls are the same as in the baseline specification.

Figure 4 presents the event study figures and shows that the estimates are consistent with the parallel trends assumption: the coefficients on the years prior to the adoption of SFAS 131 for a firm with ex-ante distortion are all close to zero and exhibit no discernible pre-trends. Figure 4 also sheds light on the dynamics of treatment effects. The treatment effects on AFE vary but is significant in the post-periods while the treatment effects on FD become significant from the third year after the event and increase over time. In general, SFAS 131 leads to sizable reduction in AFE and FD in the long run. Overall, our results support the conclusion that analysts make good use of segment level information and their earnings forecasts are not worsen by the strategic manipulation of earnings by managers.

4.3.2 Do Fund Managers Interpret Segment Level Data Better?

Finally, we use the previously described SFAS 131 experiment to see whether mutual funds react in the same way as analysts. That is, we want to see whether the implementation of SFAS131 improve the ability of the mutual fund managers to invest in conglomerates.

Earlier results reported in this paper show that the market overreacts to high LTG conglomerates with strategic manipulation of earnings, leading to negative abnormal returns in the future. We find that return predictability is robust even after the implementation of SFAS 131. As reported in Appendix Table A6, the annualised Fama-French six-factor alpha for high LTG conglomerates with strategic manipulation of earnings in future one year is -3.02% (t=-

1.02) before SFAS 131 and -9.46% (t=-3.14) after SFAS 131. That is, return predictability with respect to strategic manipulation of earnings does not decrease as the information environment improves due to SFAS 131. This suggests that investors tend to behave differently from analysts when managers distort earnings while analysts better utilize the segment-level information. Moreover, in unreported results, we also document that mutual fund managers do not react to the event either in terms of portfolio rebalancing or in terms of performance as a function of manipulation. This indicates that the fund managers do not exploit fully segment level information.

5. Discussion

In this final section, we connect the dots in terms of our findings on stock return and earnings predictability. In particular, if analyst forecasts are unaffected by managers' manipulation of earnings, forecast revisions that are inconsistent with an optimistic earnings expectation in high growth conglomerates with manipulation should serve as a negative signal on future stock returns. In other words, a downward revision of analysts forecast for high LTG conglomerates with managers' manipulation may indicate overvaluation of current stock prices. In this case, we expect stronger underperformance of the stocks when analysts make downward forecast revision in the face of strategic manipulation of high LTG conglomerates. Following this argument, we postulate that return predictability related to strategic manipulation of earnings is stronger (weaker) when analysts revise their earnings forecasts downward (upward).

Among stocks with high LTG conglomerates, we independently sort firms into 4 (2x2) groups based on the analyst forecast revisions (upward or downward) and the presence or absence of strategic manipulation of earnings. Table 11 shows the monthly returns averaged over a 12-month period. High LTG conglomerates with earnings manipulation earn a large negative annualised Fama-French six-factor alpha of -10.55% (t=-2.81) when accompanied by a downward revision in analyst forecasts. However, the risk-adjusted return become insignificant when analysts are also optimistic as indicated by an upward forecast revision. We also do not find evidence of predictable returns when the high LTG conglomerates are not subject to managerial manipulation. These findings are unchanged when we employ the mispricing factor or the q-factor models.

Also, we find that analysts utilize the segment-level information and are not swayed into extreme optimism by managerial manipulation of high LTG conglomerates while investors (mutual funds) fail to disaggregate the segment level information and are misled by managers. Moreover, investor sentiment turns more bullish with managerial manipulation of high growth conglomerates. This suggests that high LTG conglomerates are more likely to be overpriced when investor sentiment becomes more bullish.

Table 11 Panel B reports the predicted stock returns when high LTG conglomerates are sorted based on the presence or absence of strategic manipulation of earnings as well as changes in investor sentiment. Our measure of investor sentiment comes from Ravenpack and details are provided in the Variable Definition section at the end of the paper. The returns on the portfolio of these stocks with a positive change in sentiment and strategic manipulation of earnings is indeed strongly negative: the annualized Fama-French six-factor alphas on this portfolio is large -11.68% (t=-2.74). We obtain similarly large negative returns using the mispricing and q-factor models, ranging from -9.62% (t=-2.23), and -11.65% (t=-2.32), for the portfolio with strategic manipulation of earnings and positive change in investor sentiment. On the other hand, we do not find significant predictable returns on all the other subset of portfolios; i.e. when change in sentiment is negative or when strategic manipulation of earnings is absent.[31] Overall, these results indicate that investors and analysts react to the strategic manipulation of earnings differently and stocks are most mispriced when investors react positively (driven by sentiment) but analysts react negatively to the high LTG conglomerates with strategic manipulation of earnings. In general, these results reinforce our contention that low returns for high LTG firms are related to managerial manipulation of earnings and high investor optimism about future performance. At the same time, the underperformance of high growth conglomerates is not explained by extrapolation of high growth in earnings.

Conclusion

We study the link between long-term forecasts of earnings growth and future stock returns. We find that the underperformance of firms with high growth concentrates in conglomerates that manipulate earnings. This underperformance is economically significant and is robust to various benchmarks of factor models and is absent in pseudo-conglomerates similarly constructed using single segment firms. At the same time, we find analysts forecasts of earnings

[31] We further show, in Appendix Table A7, that conglomerates with high LTG experience significantly negative future returns with both positive and negative change in sentiment. This indicates that sentiment by itself is not sufficient to generate significant stock return predictability in the absence of earnings manipulation.

of conglomerates are more accurate, have smaller forecast dispersion and display weaker overreaction in the forecast revisions, relative to pseudo-conglomerates. These results are inconsistent with the pure extrapolation story which implies a negative link between earnings predictability and return predictability.

As an alternative explanation, we argue that the predictive relation stems from managerial manipulation that makes the high growth stocks more overpriced. In the presence of the incentives to take advantage of bullish expectations, managerial manipulation done in order to induce a temporary price increase induces stock longer term underperformance. There is supporting evidence that the portfolio of high growth conglomerates with distorted earnings earn an annualised risk-adjusted return of -6% while an otherwise same portfolio without distorted earnings generates statistically insignificant abnormal returns. The overpricing of high growth conglomerates with distorted earnings is higher when shorting is difficult. On the other hand, we find that analyst forecast accuracy of these high growth conglomerates is not affected by managerial manipulation. In fact, we find that the degree of overpricing of these conglomerates subject to manipulation is higher when analysts forecasts turns less optimistic, in disagreement with the optimistic growth expectations. Overall, our results points to the crucial role of managerial manipulation in pricing earnings growth.

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Variable Definition

Variable Name	Definition
Forecast-related variables (From IBES)	
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. $$AFE_{i,t,f} = \sum_{n}^{N} \lvert \frac{Analyst\ Forecasted\ EPS_{i,t,f,n} - Real\ EPS_{i,t,f,n}}{P_{i,t}} \rvert$$ 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 directly obtained from the IBES 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, IBES, 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.
SD of EPS	SD of EPS is the standard deviation of all historical EPS for each firm.
SD of EPS/PRC	SD of EPS/PRC is the standard deviation of all historical EPS divided by stock price in the same year.
Sale	Sale is the log value of the summation of the segment level sales revenue in millions.
Cash	Cash is defined as cash plus short-term investment divided by total book assets.
Strategic Manipulation of Earnings (Distortion)	We set "Strategic Manipulation" 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.
Short Selling Cost	Short selling cost is the monthly average fee of the daily stock borrow cost in the securities lending market for each stock. Loan fee data is from Markit. We use SAF to construct actual short selling costs and IndicativeFee to construct expected short selling costs. SAF is the simple average fee of stock borrow transactions from hedge funds in a security. The indicative fee captures the expected borrow cost for a hedge fund on a given day based on latest day trades. This is derived by Markit's proprietary analytics and data set and serves as an indication of the current market rate. Due to the availability of the Markit data, the short selling cost only covers the period after 2008.
Sentiment-related measure (From RavenPack)	
Firm-level Sentiment	The RavenPack news database provides a comprehensive sample of firm-specific news (see recent studies using this data set, e.g., Jiang and Sun, 2015; Kelley and Tetlock, 2017). To capture a news story specifically about a given firm,

	we use the “relevance score" that RavenPack provides, which ranges from 0 to 100, capturing how closely the underlying news applies to a particular company, with a score of 0 (100) meaning that the entity is passively (predominantly) mentioned. We require news stories in our sample to have a relevance score of 100. To include news only related to sentiment, we require the “FACT LEVEL” of news to be “forecast” or “opinion” instead of “fact”. To construct firm-level sentiment measure, we directly use the event sentiment score provided by RavenPack. At each firm-month, the sentiment score is the average of event sentiment scores for a firm in a particular month.
Fund-Level Characteristics (From CRSP, Compustat, IBES, 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(inclusive) and CRSP after 2010 Q2(inclusive).
HGCD	HGCD is the aggregate investment weight in conglomerates with top 10% LTG and strategic manipulation of earnings. HGCD is based on active investment weights and constructed in the same way of HGC.
HGCND	HGCND is the aggregate investment weight in conglomerates with top 10% LTG and without strategic manipulation of earnings. HGCND is based on active investment weights and constructed in the similar way of HGC.
Fund Return	Fund Return is the value-weight average of share-class level returns from CRSP.
Expense Ratio	Expense Ratio is directly obtained from CRSP.
Fund Size	Fund Size is the summation of share-class level total net assets from CRSP.

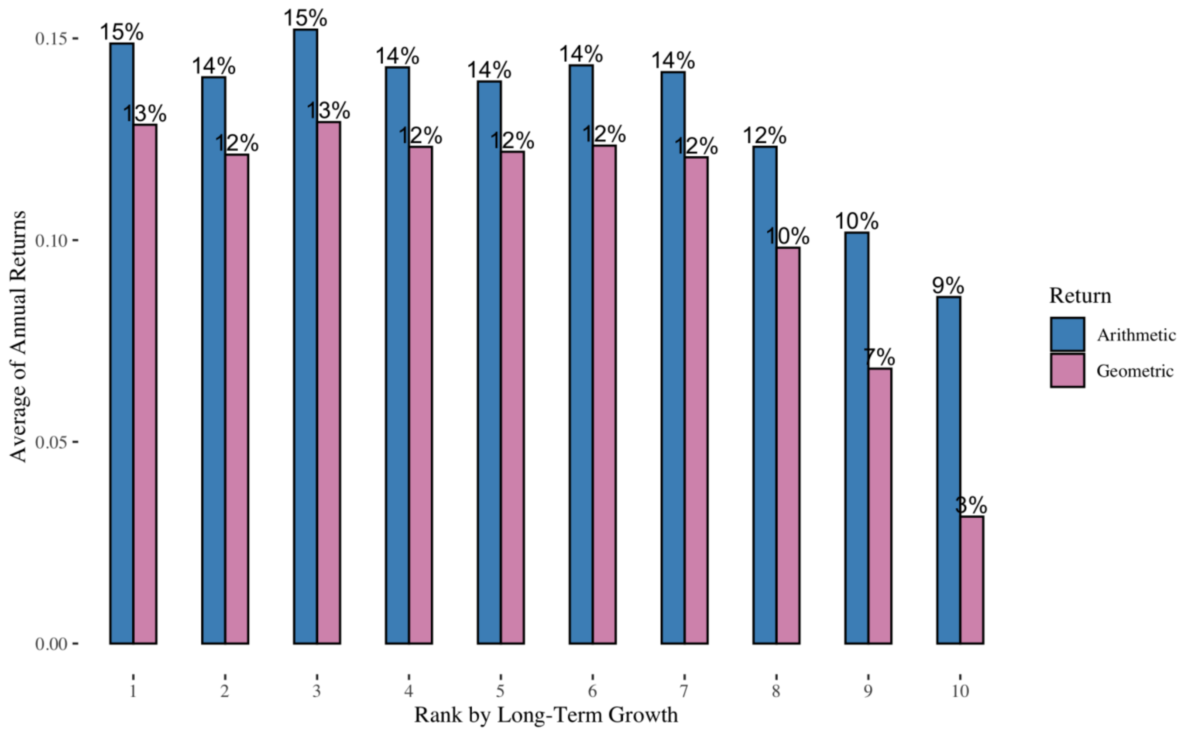


Figure 1A. Annual returns for portfolios formed on LTG. This figure is a replication of Figure 1in Bordola, Gennaioli, La Porta and Shleifer (2019). In December of each year between 1981 and 2018, we form decile portfolios based on ranked analyst expected growth in long-term EPS and display the geometric 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.

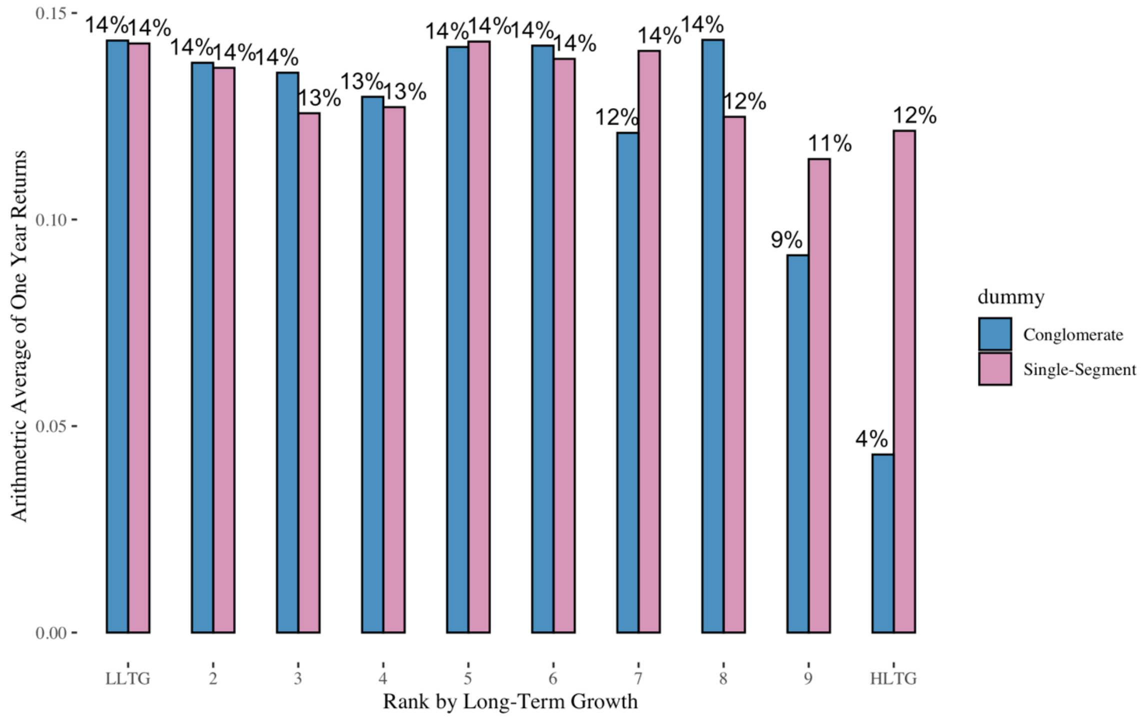


Figure 1B. Annual returns for portfolios of conglomerates and single-segment firms formed on LTG. This figure is a decomposition of Figure 1 in Bordola, Gennaioli, La Porta and Shleifer (2019) into portfolios of only conglomerates or only single-segment firms. In December of each year between 1981 and 2018, we conduct dependent double sorting based on ranked analyst expected growth in long-term EPS and conglomerate dummy and display the geometric average one-year return over the subsequent calendar year for value-weighted portfolios. A portfolio that is long low-LTG single-segment firms and short high-LTG earns an average annual return of 10.02% (t=3.62) for conglomerates and 2.11% (t=0.42) for single-segment firms. Results are similar if we report geometric mean of one year returns or if we sort portfolios independently.

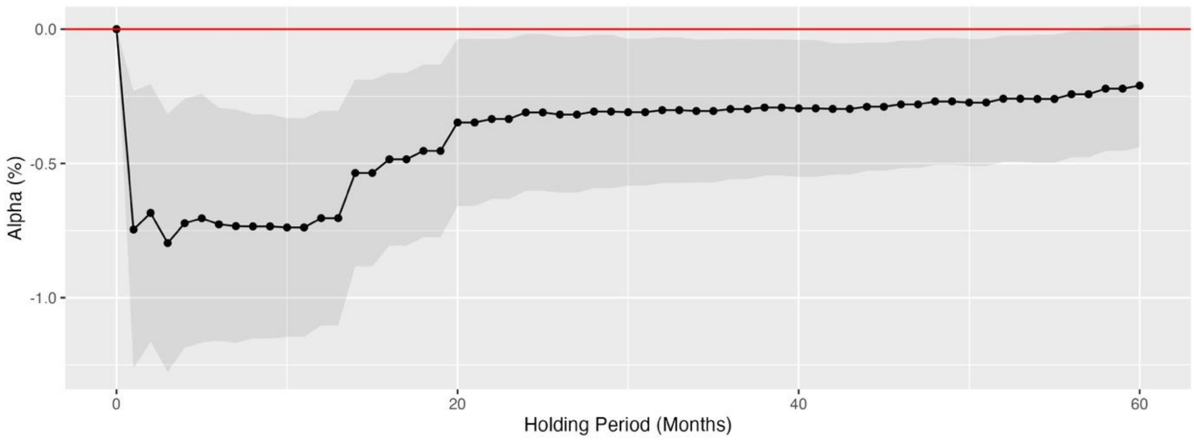


Figure 2A: Monthly Alpha of the Calendar-Time Portfolio for Conglomerates with Strategic Manipulation of Earnings
This figure shows the monthly alphas of portfolios for high LTG conglomerates with strategic manipulation of earnings. To obtain the alphas, we construct 2 calendar-time portfolios sorted by the dummy strategic manipulation of earnings using the subsample with only high LTG conglomerates. X-axies refers to the holding period for each stocks in the portfolio. Alphas are intercepts from the regressions of stock returns on Fama-French five factors and momentum factor (Mkt-RF, SMB, HML, RMW, CMA, and Mom). The shadowed area is the two-sided confidence interval at 95% level. We use Newey-West adjusted standard errors.

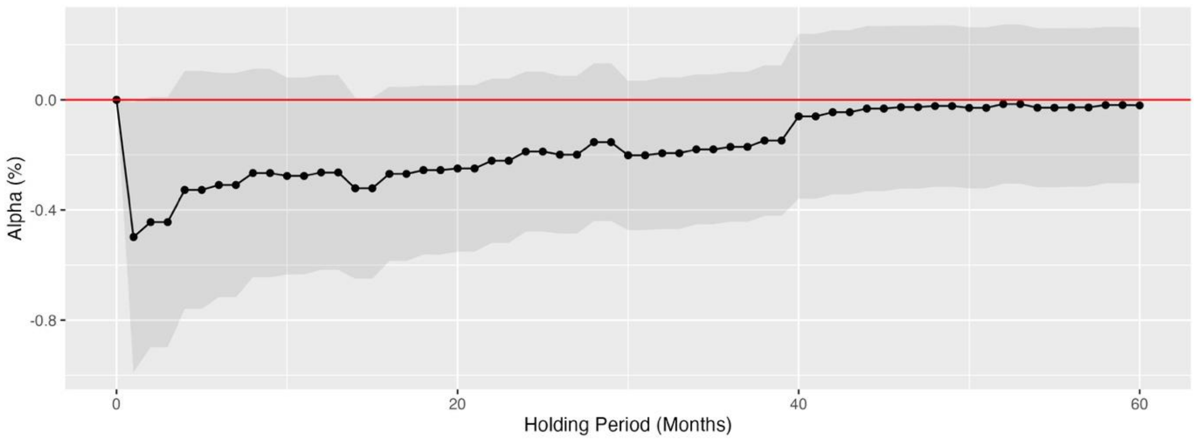


Figure 2B: Monthly Alpha of the Calendar-Time Portfolio for Conglomerates without Strategic Manipulation of Earnings
This figure shows the monthly alphas of portfolios for high LTG conglomerates without strategic manipulation of earnings. To obtain the alphas, we construct 2 calendar-time portfolios sorted by the dummy strategic manipulation of earnings using the subsample with only high LTG conglomerates. X-axies refers to the holding period for each stocks in the portfolio. Alphas are intercepts from the regressions of stock returns on Fama-French five factors and momentum factor (Mkt-RF, SMB, HML, RMW, CMA, and Mom). The shadowed area is the two-sided confidence interval at 95% level. We use Newey-West adjusted standard errors.

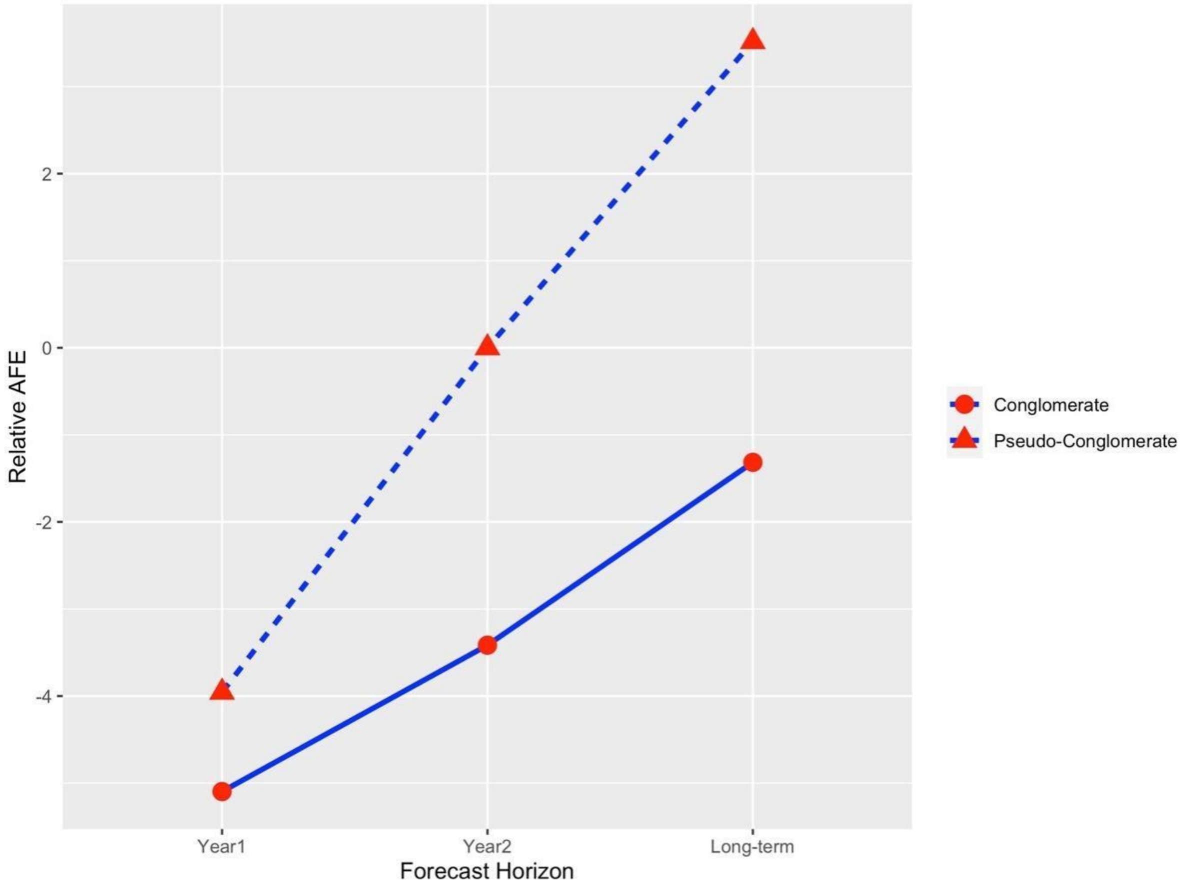


Figure 3A Absolute Forecast Errors (AFE) for Conglomerates and Pseudo-Conglomerates across Forecast Horizons. This figure is a graphic illustration of differential effects of forecast horizon on absolute forecast errors for conglomerates versus pseudo-conglomerates. We use the matched sample with all horizon available to estimate the relative AFE in the figure. In particular, we run the following regression:

$$AFE_{i,t,f} = \beta_1 Conglomerate_{i,t} * 1Year + \beta_2 Conglomerate_{i,t} * \text{LT\_Dummy} + \beta_3 Z_{i,t} + X_i + Y_{n,t} + \varepsilon_{i,t}$$

where $Conglomerate_{i,t}$ is a dummy set to 1 for conglomerates and 0 for pseudo-conglomerates, $Year1$ dummy is set to 1 if the forecast horizon f is 1 year and 0 otherwise, and LT_Dummy is set to 1 if the forecast horizon is 3-5 years and 0 otherwise. $Z_{i,t}$ is a set of control variables, including firm size, firm age, book-to-market ratio, and analyst coverage. We include firm fixed effects and FF-48 industry times year fixed effects and standard errors are clustered by industry and year.

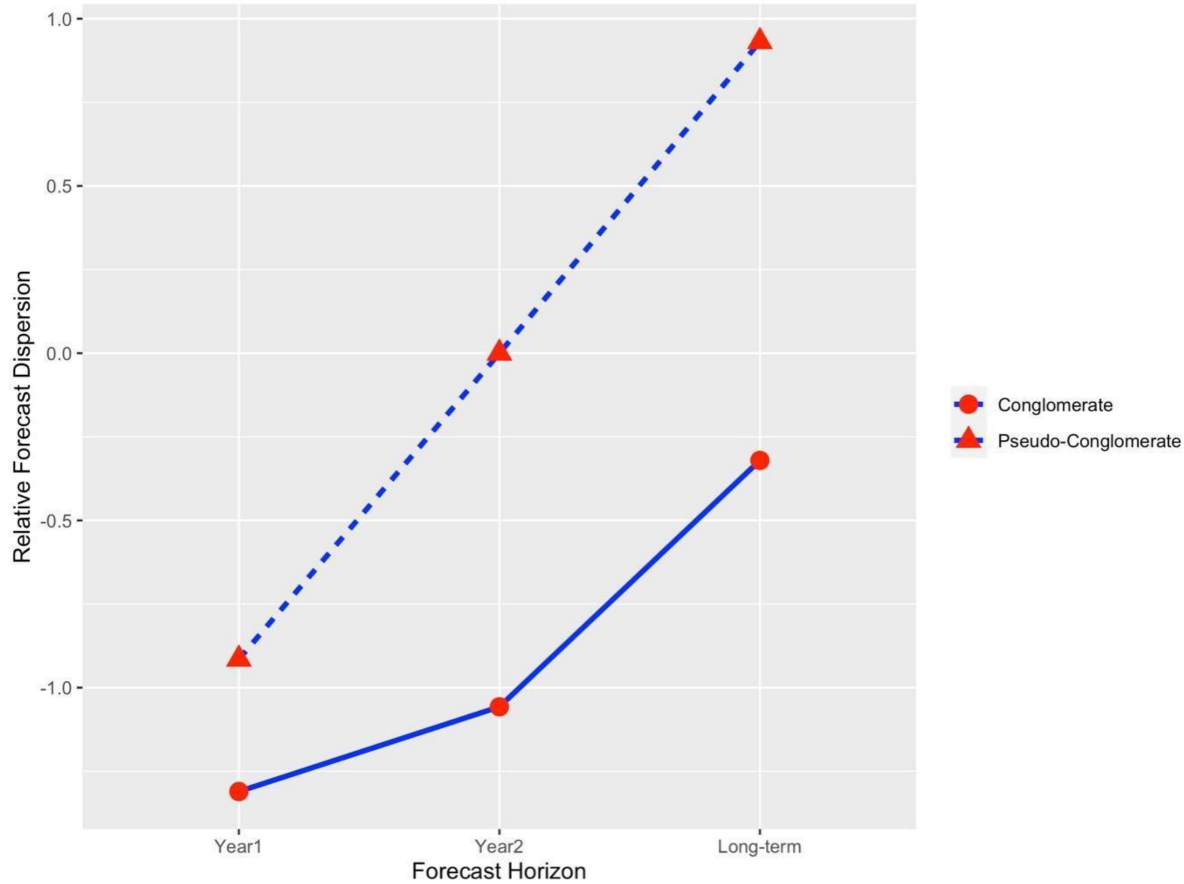
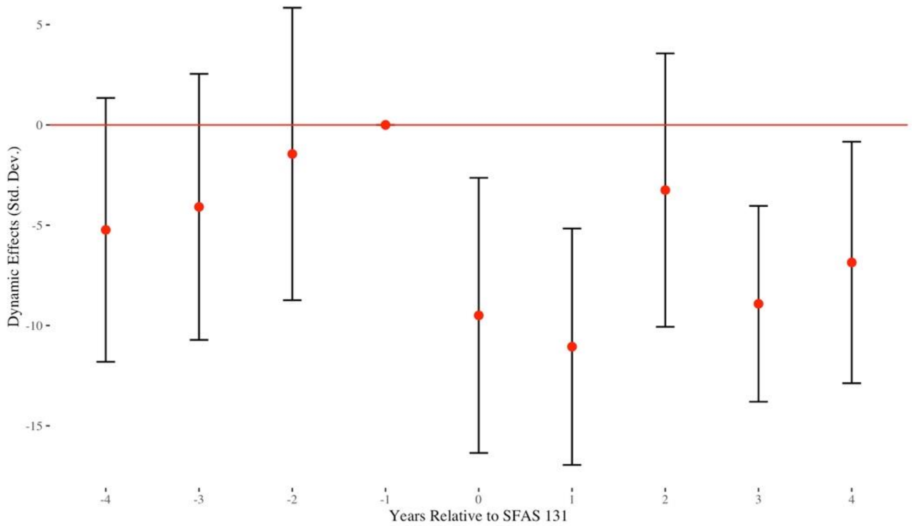


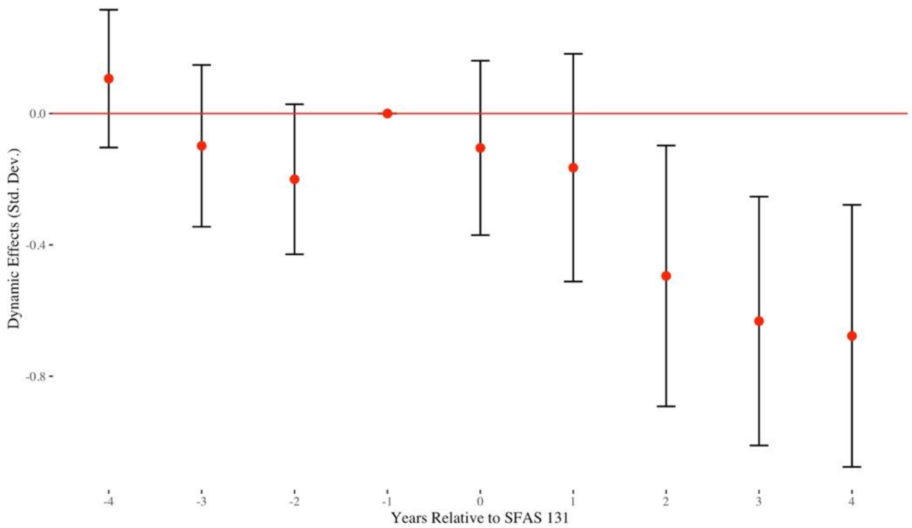
Figure 3B Forecast Dispersion for Conglomerates and Pseudo-Conglomerates across Forecast Horizons. This figure is a graphic illustration of differential effects of forecast horizon on forecast dispersion for conglomerates versus pseudo-conglomerates. We use the matched sample with all horizon available to estimate the relative forecast dispersion in the figure. In particular, we run the following regression:

$$Dispersion_{i,t,f} = \beta_1 Conglomerate_{i,t} * 1Year + \beta_2 Conglomerate_{i,t} * \text{LT\_Dummy} + \beta_3 Z_{i,t} + X_i + Y_{n,t} + \varepsilon_{i,t}$$

where $Conglomerate_{i,t}$ is a dummy set to 1 for conglomerates and 0 for pseudo-conglomerates, $1Year$ is a dummy set to 1 if the forecast horizon f is 1 year and 0 otherwise, and LT_Dummy is set to 1 if the forecast horizon is 3-5 years and 0 otherwise. $Z_{i,t}$ is a set of control variables, including firm size, firm age, book-to-market ratio, and analyst coverage. 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.



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



Panel B: The Effects of SFAS 131 on Forecast Dispersion

Figure 4 The Dynamic Effects of SFAS 131 on Absolute Forecast Errors and Forecast Dispersion of Conglomerates with Pre-SFAS 131 Manipulation. 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:

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

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 Distortion* is a dummy variable set to 1 if the frequency of strategic manipulation of earnings of the firm in pre-SFAS 131 period is above the median frequency 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: Return Predictability: Conglomerates and LTG

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 IBES 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 (93)	1.093***	0.076	0.092	0.193
		(4.844)	(0.746)	(0.834)	(1.392)
	Pseudo-Conglomerates (93)	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 Strategic Manipulation of Earnings

We construct 2*10 independent calendar-time portfolio sorted by strategic manipulation of earnings(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 IBES Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We set "Strategic Manipulation" 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 "Strategic Manipulation" 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 "Strategic Manipulation" 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 "Strategic Manipulation" 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.

Panel A: One-Year Returns for High & Low Growth Conglomerates					
LTG	Strategic Manipulation	Raw Returns	FF5+Mom	Q-factor	Mispricing
High	Distorted	0.291	-0.704***	-0.623***	-0.753***
		(0.918)	(-3.455)	(-3.177)	(-3.078)
	Not Distorted	0.478	-0.264	-0.158	-0.164
		(1.377)	(-1.463)	(-0.839)	(-0.759)
	Distorted Minus Not Distorted	-0.187	-0.44	-0.465*	-0.589**
		(-0.788)	(-1.586)	(-1.684)	(-1.812)
Low	Distorted	1.125***	0.088	0.085	0.279
		(4.329)	(0.618)	(0.586)	(1.698)
	Not Distorted	0.871***	-0.137	-0.096	0.025
		(3.388)	(-1.003)	(-0.577)	(0.137)
	Distorted Minus Not Distorted	0.253	0.224	0.182	0.255
		(1.524)	(1.326)	(1.053)	(1.33)

Table 3: Return Predictability: Conglomerates, LTG, and Alternative Measures of Manipulation

We construct 2*10 independent calendar-time portfolio sorted by alternative measures of manipulation (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 IBES Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We have results on three alternative measures of manipulation – 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 manipulation 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 manipulation 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 manipulation 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

LTG	Sales Manipulation	Raw Returns	FF5+Mom	Q-factor	Mispricing
High	Distorted	0.044	-0.767**	-0.795**	-0.748**
		(0.11)	(-2.236)	(-2.129)	(-2.272)
	Not Distorted	0.714	-0.028	0.05	0.212
		(2.05)	(-0.081)	(0.128)	(0.552)
	Distorted Minus Not Distorted	-0.702	-0.771	-0.889*	-1.016*
		(-1.554)	(-1.458)	(-1.672)	(-1.823)
Low	Distorted	0.991	0.126	0.111	0.153
		(2.629)	(0.472)	(0.378)	(0.512)
	Not Distorted	0.909	0.093	0.087	0.262
		(2.863)	(0.52)	(0.447)	(1.215)
	Distorted Minus Not Distorted	0.077	0.05	0.038	-0.094
		(0.228)	(0.155)	(0.114)	(-0.256)

Panel B: Delta and Stock Returns

LTG	Delta	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	0.461	-0.296	-0.231	-0.083
		(1.277)	(-1.347)	(-0.988)	(-0.355)
	High Minus Low	-0.331	-0.497***	-0.487*	-0.633**
		(-1.484)	(-2.187)	(-1.893)	(-2.318)
Low	High	1.168***	0.194	0.24	0.435**
		(4.091)	(1.257)	(1.393)	(2.122)
	Low	1.008***	0.129	0.188	0.274
		(3.811)	(0.794)	(1.014)	(1.257)
	High Minus Low	0.16	0.065	0.052	0.161
		(1.266)	(0.47)	(0.376)	(1.162)

Panel C: Vega and Stock Returns

LTG	Vega	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	0.621*	-0.415*	-0.286	-0.28
		(1.726)	(-1.73)	(-1.166)	(-1.029)
	High Minus Low	-0.543***	-0.436**	-0.486**	-0.454*
		(-2.582)	(-2.031)	(-2.169)	(-1.791)
Low	High	1.136***	0.178	0.228	0.37**
		(4.214)	(1.208)	(1.447)	(1.964)
	Low	1.108***	0.245	0.302	0.434**
		(4.178)	(1.49)	(1.586)	(1.995)
	High Minus Low	0.028	-0.068	-0.074	-0.064
		(0.224)	(-0.545)	(-0.596)	(-0.502)

Table 4: Return Predictability: Strategic Manipulation of Earnings and Limits of Arbitrage

We construct 2*2 independent calendar-time portfolio sorted by limits of arbitrage measures, strategic manipulation dummy (distorted or not distorted). We only use the subsample of conglomerates with top quintile LTG. 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 IBES Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. Limits of arbitrage measures are based on stock borrow costs for hedge funds. Expected shorting fee is the monthly average of daily expected stock borrow costs for hedge funds estimated by Markit and serves as the indication of the current market cost. Actual shorting fee is the monthly average fee of stock borrow transactions from hedge funds in the security. LTG and short selling measures are lagged one month relative to the period during which the return is measured. To ensure that the strategic manipulation dummy used to sort portfolio are based on data that would have been publicly available by the time presumed in the analysis, the strategic manipulation dummy calculated using data from calendar year *y is* not assumed to be known until the end of June of year $y + 1$. Thus, the strategic manipulation 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 in June to Dec of year y. We only show the results of conglomerates with high LTG. Results are insignificant for conglomerates with 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.

Panel A: One-Year Returns Based on Expected Shorting Fees for High Growth Conglomerates

Strategic Manipulation	Expected Shorting Fee	Raw Returns	FF5+Mom	Q-factor	Mispricing
Distorted	High	-0.101	-0.965***	-0.955***	-0.92***
		(-0.145)	(-2.637)	(-2.52)	(-2.601)
	Low	0.501	-0.533	-0.393	-0.405
		(0.723)	(-1.391)	(-1.095)	(-1.165)
	High Minus Low	-0.603***	-0.432*	-0.562**	-0.515*
		(-2.721)	(-1.71)	(-2.397)	(-1.849)
Not Distorted	High	0.69	-0.32	-0.283	-0.168
		(1.041)	(-0.844)	(-0.741)	(-0.465)
	Low	0.979	-0.255	0.029	0.178
		(1.394)	(-0.656)	(0.072)	(0.473)
	High Minus Low	-0.289	-0.064	-0.312	-0.346
		(-0.967)	(-0.228)	(-1.075)	(-1.223)

Panel B: One-Year Returns Based on Actual Shorting Fees for High Growth Conglomerates

Strategic Manipulation	Actual Shorting Fee	Raw Returns	FF5+Mom	Q-factor	Mispricing
Distorted	Low	0.414	-0.75**	-0.818**	-0.835**
		(0.818)	(-2.278)	(-2.432)	(-2.096)
	High	1.115**	-0.125	-0.124	-0.262
		(2.32)	(-0.439)	(-0.426)	(-0.828)
	Low Minus High	-0.701***	-0.625**	-0.694**	-0.573
		(-2.812)	(-1.978)	(-2.19)	(-1.313)
Not Distorted	Low	1.325***	-0.13	-0.126	-0.265
		(2.61)	(-0.448)	(-0.433)	(-0.927)
	High	1.344**	-0.446	-0.322	-0.332
		(2.458)	(-1.507)	(-1.035)	(-0.796)
	Low Minus High	-0.019	0.316	0.195	0.068
		(-0.059)	(0.846)	(0.482)	(0.147)

Table 5: Summary Statistics of Analyst Forecasts: Conglomerates vs Pseudo-Conglomerates

In this table, we show the summary statistics of absolute forecast error (AFE) and forecast dispersion (FD). In Panel A, AFE and FD are grouped by forecast horizon and conglomerate dummy. In Panel B, AFE and FD are grouped by corresponding forecast-implied growth rates and conglomerate dummy. 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.

Panel A: Analysts Forecasts

Forecast Horizon	Absolute Forecast Error (AFE)								Forecast Dispersion							
	Conglomerate			Pseudo-Conglomerate			Dif (a-b)	t-stat	Conglomerate			Pseudo-Conglomerate			Dif (a-b)	t-stat
	Mean (a)	Median	SD	Mean (b)	Median	SD			Mean (a)	Median	SD	Mean (b)	Median	SD		
1	1.11	0.94	0.50	3.41	3.01	1.46	-2.30	(-8.43***)	0.88	0.87	0.31	1.67	1.47	0.66	-0.79	(-8.84***)
2	2.79	2.47	1.18	7.42	6.95	2.92	-4.63	(-9.64***)	1.12	1.00	0.50	2.46	2.19	1.00	-1.34	(-11.13***)
3-5	4.32	3.76	1.88	9.89	9.34	4.76	-5.56	(-6.05***)	1.55	1.47	0.47	2.95	2.71	1.39	-1.40	(-3.13***)

Panel B: Analyst Forecasts by Growth Rate of Forecasts

		Absolute Forecast Error (AFE)				Forecast Dispersion			
Forecast Horizon	Growth Rate	Conglomerate	Pseudo-Conglomerate	Dif	t-stat	Conglomerate	Pseudo-Conglomerate	Dif	t-stat
	High	4.04	4.08	-0.04	(-0.07)	1.92	2.01	-0.09	(-0.44)
1	Median	1.18	3.21	-2.03	(-5.87***)	0.94	1.62	-0.68	(-10.44***)
	Low	0.70	2.87	-2.17	(-3***)	0.64	1.43	-0.79	(-2.86***)
	High	7.52	9.23	-1.71	(-2.29**)	2.26	2.91	-0.65	(-2.66***)
2	Median	2.82	7.14	-4.32	(-10.11***)	1.05	2.23	-1.19	(-6.31***)
	Low	2.08	6.18	-4.10	(-3.77***)	0.86	2.06	-1.19	(-4.67***)
	High	9.07	12.85	-3.79	(-3.13***)	2.94	3.66	-0.73	(-1.23)
3-5	Median	3.39	9.85	-6.45	(-5.85***)	1.33	3.05	-1.71	(-4.29***)
	Low	3.85	7.66	-3.81	(-4.86***)	1.20	2.18	-0.99	(-3.56***)

Table 6: Earnings Predictability and Forecast Horizon: Conglomerates vs Pseudo-Conglomerates

Panel A: In this Panel, we divide our sample based on the forecast horizons (1 year, 2 years, and Long-term(3-5 years)). The dependent variable here is the absolute forecast error (AFE) and forecast dispersion (FD). 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. Using actual earnings per share as an alternative deflator does not change our conclusions and replacing the forecasted EPS consensus with the mean value of forecasted EPS doesn't harm our main results, either. A firm with segments in two different FF-48 industries is defined as a conglomerate. We require the total sales of all segments within a firm to be larger than 80% of the firm-level sale. LT_Dummy is a dummy variable set to 1 if the forecast horizon is the 3-5 years forecast horizon 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 FF-48 industry times year fixed effects and errors are clustered by industry and year.

Dependent variable:	AFE				FD			
Sample	1Year	2Year	3-5Years	ALL	1Year	2Year	3-5Years	ALL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT_Dummy				5.533***				1.470***
				(0.742)				(0.275)
Conglomerate	-1.519***	-2.581***	-3.343***	-1.654***	-0.400**	-0.616***	-0.840**	-0.368**
	(0.486)	(0.654)	(1.056)	(0.492)	(0.161)	(0.204)	(0.376)	(0.159)
LT_Dummy*Conglomerate				-3.010***				-0.774***
				(0.588)				(0.258)
Size	-0.525***	-1.161***	-0.982***	-0.914***	-0.250***	-0.298***	-0.238***	-0.290***
	(0.164)	(0.166)	(0.222)	(0.147)	(0.045)	(0.037)	(0.060)	(0.039)
Firm Age	0.002	0.010	0.028	0.010	0.001	0.002	0.005	0.002
	(0.006)	(0.010)	(0.016)	(0.008)	(0.002)	(0.003)	(0.006)	(0.003)
Analyst Coverage	-0.003	0.021	0.100*	0.026**	0.006*	0.014***	0.044*	0.018***
	(0.011)	(0.016)	(0.055)	(0.011)	(0.003)	(0.005)	(0.023)	(0.003)
Book-Market	0.671**	2.050***	3.969***	1.928***	0.415***	0.773***	1.064***	0.697***
	(0.305)	(0.493)	(0.751)	(0.388)	(0.104)	(0.146)	(0.163)	(0.115)
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Fiscal Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Double Clustering by Industry and Fiscal Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,375	30,346	14,986	75,707	30,375	30,346	14,986	75,707
Adjusted R^2	0.442	0.514	0.533	0.440	0.442	0.535	0.550	0.445

Panel B: This panel runs Coibion-Gorodnichenko Regressions for EPS. 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 conglomerate dummy and year fixed effects. We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries.

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	-0.482***	-0.688***	-0.610***
	(0.109)	(0.075)	(0.071)
Conglomerate	0.118***	0.160***	0.167***
	(0.009)	(0.006)	(0.006)
Revision*Conglomerate	0.236**	0.283***	0.200***
	(0.118)	(0.080)	(0.076)
Year Fixed Effects	Yes	Yes	Yes
Observations	28,418	25,830	23,655
Adjusted R^2	0.095	0.219	0.274

Table 7: Conglomerates' Earnings Predictability and Strategic Manipulation of Earnings

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 "Strategic Manipulation" 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	Forecast Dispersion
	(1)	(2)
Strategic Manipulation	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

Table 8: LTG, Strategic Manipulation of Earnings and Mutual Fund Performance

In this table, we construct calendar-time fund portfolio sorting based on HGCD (High-Growth Conglomerate Distorted, 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). HGCD is the investment weight in conglomerates with top decile LTG and strategic manipulation of earnings. HGC and HGCD 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, HGCD 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 IBES Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We define strategic manipulation of earnings 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 strategic manipulation of earnings are lagged one year. HGC and HGCD 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	0.609*	-0.008	0.087	0.043	0.015
	(1.855)	(-0.134)	(1.313)	(0.699)	(0.278)
2	0.545*	-0.024	-0.001	-0.017	-0.018
	(1.749)	(-0.467)	(-0.018)	(-0.383)	(-0.582)
3	0.526*	-0.035	-0.081	-0.094	0.001
	(1.707)	(-0.447)	(-1.298)	(-1.511)	(0.032)
4	0.508	-0.048	-0.087	-0.096	-0.025
	(1.627)	(-0.622)	(-1.258)	(-1.384)	(-0.703)
High	0.393	-0.155**	-0.179**	-0.209***	-0.095**
	(1.219)	(-2.017)	(-2.127)	(-2.906)	(-2.365)
High Minus	-0.216*	-0.147*	-0.266***	-0.252***	-0.11*
Low	(-1.909)	(-1.816)	(-2.858)	(-2.889)	(-1.793)

Panel B: Returns on funds sorted by their Active Investment Weights in High-Growth Conglomerates with Strategic Manipulation of Earnings (HGCD)

High-Growth Conglomerates Distorted (HGCD)	Raw Returns	Carhart	FF5+Mom	Ferson-Schadt	Objective Adjusted
Low	0.566*	-0.022	-0.021	-0.03	-0.037
	(1.845)	(-0.328)	(-0.299)	(-0.505)	(-0.773)
2	0.58*	-0.02	-0.071	-0.085	-0.041
	(1.872)	(-0.245)	(-0.896)	(-1.154)	(-0.997)
3	0.555*	-0.058	-0.07	-0.07	-0.008
	(1.688)	(-0.74)	(-0.889)	(-0.887)	(-0.164)
4	0.504	-0.065	-0.162*	-0.155*	-0.019
	(1.642)	(-0.699)	(-1.721)	(-1.79)	(-0.5)
High	0.325	-0.222**	-0.321***	-0.317***	-0.138***
	(1.014)	(-2.315)	(-3.029)	(-3.126)	(-2.867)
High Minus	-0.241**	-0.199***	-0.299***	-0.287***	-0.101
Low	(-2.182)	(-2.46)	(-3.353)	(-3.05)	(-1.422)

Table 9: LTG, Strategic Manipulation of Earnings 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 ΔDistortion and Conglomerate. The dependent variable here is the percentage of a stock's total shares outstanding held by mutual funds. We look at the mutual fund ownership of all firms in Column 1 and within the group of conglomerates in Column 2. We only include mutual funds with positive HGC when we construct the ownership level in Column 1 and mutual funds with positive HGCD when we construct the ownership measure in Column 2. ΔHighLTG dummy is set to 1 if a stock moves from the bottom 90% in quarter t-2 to the top decile of the long-term growth rates in quarter t-1 and 0 otherwise. ΔDistortion dummy is set to 1 if a conglomerate didn't strategically distort earnings in year y-2 but distorted earnings in year y-1 and 0 otherwise. Conglomerate dummy is set to 1 iff 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:	Mutual Fund Ownership Level (%)	
Sample Selection	All Firms	Only Conglomerates
	(1)	(2)
ΔHighLTG*Conglomerate	1.585***	
	(0.1833)	
ΔHighLTG * ΔDistortion		2.440***
		(0.4327)
ΔHighLTG	0.3222***	0.5847***
	(0.0705)	(0.1020)
ΔDistortion		0.2201**
		(0.0645)
Conglomerate	0.0042	
	(0.0913)	
Stock Return	-0.3500***	-0.1008
	(0.0443)	(0.0520)
Size	0.9158***	0.2551***
	(0.0454)	(0.0561)
BM	0.1615***	0.0499
	(0.0356)	(0.0479)
Firm Fixed effects	Yes	Yes
Year Quarter Fixed effects	Yes	Yes
Clustering by Firm and Year Quarter	Yes	Yes
Observations	251,157	59,285
Adjusted R^2	0.568	0.409

Table 10: Earnings Predictability and Strategic Manipulation of Earnings: 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: $Absolute\ Forecast\ Error_{i,t,f} = |\frac{Analyst\ Forecasted\ EPS_{i,t,f,m} - Real\ EPS_{i,t,f,m}}{P_{i,t}}|$. 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. Ex-ante Distortion is a dummy variable set to 1 if the frequency of strategic manipulation of earnings of the firm in pre-SFAS 131 period is above the median frequency 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 (3)	FD (4)
Post	-4.403	-1.765**
	(4.211)	(0.740)
Ex-Ante Distortion*Post	-5.009**	-1.151*
	(2.501)	(0.625)
Size	-0.342	-0.016
	(0.744)	(0.259)
Firm Age	-0.064*	-0.026**
	(0.035)	(0.013)
Analyst Coverage	-0.070	-0.049
	(0.260)	(0.095)
BM	-0.070	0.520
	(1.113)	(0.740)
Firm Fixed effects	Yes	Yes
Fiscal Year Fixed effects	Yes	Yes
Clustering by Firm	Yes	Yes
Observations	452	452
R^2	0.504	0.537
Adjusted R^2	0.360	0.403

Table 11: Return Predictability: Strategic Manipulation of Earnings, Forecast Revision and Changes in Sentiment

In Table 11 Panel A, we construct 2*2 independent calendar-time portfolios sorted by forecast revision(downward or upward) and strategic manipulation of earnings (yes or no) using the sub-sample of only conglomerates with top decile long-term growth rates(LTG). In Table 11 Panel B, we construct 2*2 independent calendar-time portfolios sorted by changes in sentiment (positive or negative) and strategic manipulation of earnings (yes or no) using the sub-sample of only conglomerates with top decile LTG. 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 IBES Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. Changes in sentiment is positive if the sentiment measure for the firm in month t is higher than that in month t-1 and negative otherwise. The firm level sentiment is calculated as the average value of Event Sentiment Score from RavenPack dataset. Forecast revision is downward if the long-term growth rate for the firm in year y-1 is lower than that in year y-2 and upward otherwise. LTG and changes in sentiment 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 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 in June to Dec of year y. We only show the results of groups with top decile LTG for Panel A and groups with top decile LTG for Panel B. 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.

Panel A: One-Year Returns Based on Forecast Revision for High Growth Conglomerates

Strategic Manipulation	Forecast Revision	Raw Returns	FF5+Mom	Q-factor	Mispricing
	Downward	0.044	-0.925***	-0.847***	-1.143***
Distorted		(0.119)	(-2.808)	(-2.547)	(-3.37)
	Upward	0.854***	-0.347	-0.284	-0.317
		(2.505)	(-1.172)	(-0.843)	(-1.114)
	Downward	1.096***	0.167	0.31	0.033
Not Distorted		(2.563)	(0.498)	(0.921)	(0.095)
	Upward	0.836*	-0.361	-0.049	-0.277
		(1.723)	(-0.805)	(-0.109)	(-0.495)

Panel B: One-Year Returns Based on Change in Sentiment for High Growth Conglomerates

Strategic Manipulation	Change in Sentiment	Raw Returns	FF5+Mom	Q-factor	Mispricing
	Negative	0.326	-0.535	-0.336	-0.762*
Distorted		(0.573)	(-1.227)	(-0.798)	(-1.749)
	Positive	-0.077	-1.03***	-0.839**	-1.027**
		(-0.143)	(-2.741)	(-2.231)	(-2.321)
	Negative	0.323	0.052	0.331	0.75
Not Distorted		(0.501)	(0.103)	(0.509)	(1.049)
	Positive	0.062	-0.596	-0.206	0.003
		(0.091)	(-1.128)	(-0.33)	(0.004)

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.

Panel A: 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)
	Conglomerates Minus Single-Segment Firms	-10.404**	-13.747**	-2.984	-6.343
		(-2.07)	(-2.478)	(-0.729)	(-1.296)
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)
	Conglomerates Minus Single-Segment Firms	1.138	-1.794	-0.312	-1.721
		(1.048)	(-1.197)	(-0.102)	(-1.048)
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)

Panel B: Comparing Conglomerates with Single-Segment Firms

Long-Term Growth Rate (LTG)		Raw Returns	FF5+Mom	Q-factor	Mispricing
High Growth Firms	Conglomerates	-3.166	-14.736***	-12.996***	-1.987
		(-0.779)	(-2.729)	(-2.854)	(-0.337)
	Single-Segment Firms	2.26	-4.422	-3.886	-2.612
		(0.614)	(-0.862)	(-0.585)	(-0.292)
	Conglomerates Minus Single-Segment Firms	-5.426	-10.314*	-9.11	0.625
		(-1.358)	(-1.675)	(-1.18)	(0.067)
Low Growth Firms	Conglomerates	15.312***	0.27	4.098	-0.492
		(4.783)	(0.08)	(1.295)	(-0.087)
	Single-Segment Firms	16.419***	5.73	0.543	6.911
		(5.534)	(1.358)	(0.147)	(1.298)
	Conglomerates Minus Single-Segment Firms	-1.108	-5.46*	3.555*	-7.403
		(-0.544)	(-1.886)	(1.659)	(-1.508)
High Growth Minus Low Growth	Conglomerates	-18.478***	-15.006**	-17.095***	-1.495
		(-6.091)	(-2.421)	(-3.894)	(-0.21)
	Single-Segment Firms	-14.159***	-10.152**	-4.429	-9.523
		(-2.851)	(-2.016)	(-0.692)	(-1.094)

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.

Panel A

	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: Earnings Predictability and Forecast Horizon: Conglomerates vs Pseudo-Conglomerates

In this table, we divide our sample based on the forecast horizons (1 year, 2 years, and Long-term(3-5 years)). We only keep firms with forecasts for all horizons (1 year, 2 year, and 3-5 years) and everything else is the same as in Table 2. The dependent variable here is the absolute forecast error (AFE) and forecast dispersion (FD). 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: $Absolute\ Forecast\ Error_{i,t,f} = \left|\frac{Analyst\ Forecasted\ EPS_{i,t,f,m} - Real\ EPS_{i,t,f,m}}{P_{i,t}}\right|$. 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. Using actual earnings per share as an alternative deflator does not change our conclusions and replacing the forecasted EPS consensus with the mean value of forecasted EPS doesn't harm our main results, either. A firm with segments in two different FF-48 industries is defined as a conglomerate. We require the total sales of all segments within a firm to be larger than 80% of the firm-level sale. 3-5Year is a dummy variable set to 1 if the forecast horizon is the 3-5 years forecast horizon 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 FF-48 industry times year fixed effects and standard errors are clustered by industry and year.

Dependent variable:	AFE (Absolute Forecast Error)				Forecast Dispersion			
Sample	1Year	2Year	3-5Years	ALL	1Year	2Year	3-5Years	ALL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3-5Years_Dummy				5.470^{***}				1.384^{***}
				(0.750)				(0.274)
Conglomerate	-1.815^{***}	-3.190^{***}	-4.074^{***}	-2.259^{***}	-0.485^{***}	-0.996^{***}	-1.171^{***}	-0.722^{***}
	(0.516)	(0.664)	(0.848)	(0.612)	(0.157)	(0.235)	(0.301)	(0.210)
3-5Years_Dummy*Conglomerate				-2.583^{***}				-0.532^{*}
				(0.553)				(0.272)
Size	-0.211	-0.814^{***}	-0.606^{**}	-0.731^{***}	-0.201^{***}	-0.332^{***}	-0.108	-0.260^{***}
	(0.151)	(0.178)	(0.246)	(0.143)	(0.050)	(0.072)	(0.076)	(0.046)
Firm Age	0.000	0.002	0.017	0.008	-0.001	0.001	0.003	0.001
	(0.006)	(0.010)	(0.014)	(0.009)	(0.002)	(0.003)	(0.005)	(0.003)
Analyst Coverage	-0.017	0.027	-0.053	0.059^{**}	0.007	0.035^{**}	-0.017	0.031^{***}
	(0.028)	(0.041)	(0.113)	(0.026)	(0.009)	(0.016)	(0.044)	(0.010)
Book-Market	0.658^{***}	1.911^{***}	4.028^{***}	2.186^{***}	0.437^{***}	0.812^{***}	1.093^{***}	0.779^{***}
	(0.233)	(0.532)	(0.810)	(0.468)	(0.121)	(0.187)	(0.182)	(0.144)
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Fiscal Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Double Clustering by Industry and Fiscal Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,356	13,356	13,356	40,068	13,356	13,356	13,356	40,068
Adjusted R^2	0.423	0.517	0.529	0.453	0.457	0.568	0.543	0.454

Table A4: Fama-Macbeth Regressions for Return Predictability

This table shows Fama-Macbeth Regressions. The dependent variable is the monthly six-factor alpha cumulated over the periods of future 12 months or 24 months. 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. High Growth is a dummy variable set to 1 if the forecast-implied growth rate for the firm is in top quintile in the cross-section and 0 otherwise. Downward is a dummy variable, meaning downward revision in analyst forecasts, set to 1 when the forecast-implied growth rate for the firm in year t-1 is lower than that in year t-2 and 0 otherwise. Manipulation&Down is Manipulation multiplied by Downward. We report Newey-West t-stats.

Dependent Variable	One-year Alpha			Two-year Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
High Growth	-0.063***	0.001	-0.041**	-0.098**	0.001	-0.079**
	(0.021)	(0.022)	(0.020)	(0.038)	(0.063)	(0.039)
Distortion		-0.012			-0.012	
		(0.013)			(0.022)	
High Growth* Distortion		-0.072*			-0.150**	
		(0.041)			(0.073)	
Down&Manipulation			0.004			-0.004
			(0.012)			(0.022)
High Growth* Down& Distortion			-0.070**			-0.149***
			(0.029)			(0.031)
Size	-0.022**	- 0.022**	-0.021**	-0.045**	-0.049**	-0.046**
	(0.011)	(0.010)	(0.010)	(0.018)	(0.019)	(0.017)
Firm Age	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Analyst Coverage	0.003	0.003	0.003	0.006*	0.007**	0.006**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
BM	0.006	0.003	0.006	0.009	-0.000	0.011
	(0.014)	(0.015)	(0.012)	(0.025)	(0.028)	(0.023)
Constant	0.122	0.108	0.115	0.252**	0.266**	0.263**
	(0.075)	(0.067)	(0.071)	(0.109)	(0.114)	(0.107)
Observations	11,761	7,243	9,371	11,180	6,988	8,962
R-squared	0.037	0.069	0.047	0.043	0.079	0.050
F	3.210	1.658	2.409	3.395	2.313	5.657

Table A5: LTG, Strategic Manipulation of Earnings and Mutual Fund Performance

In this table, we construct calendar-time fund portfolio sorting based on HGCND (High-Growth Conglomerate Not Distorted, quarter 1 (low) to 5 (high)). HGCND is the active investment weight in conglomerates with top 10% long-term growth rate (LTG) and without strategic manipulation of earnings. 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, HGCND 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 IBES Unadjusted U.S. Detail file and the detailed construction is provided in Variable Definition. We define strategic manipulation of earnings 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 strategic manipulation of earnings are lagged one year. HGCWD 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 Distorted Earnings (HGCWD)	Raw Returns	Carhart	FF5+Mom	Ferson-Schadt	Objective Adjusted
Low	0.61*	0.001	0.057	0.046	0.018
	(1.85)	(0.015)	(0.885)	(0.667)	(0.298)
2	0.56*	-0.021	0.001	-0.032	-0.014
	(1.771)	(-0.318)	(0.012)	(-0.591)	(-0.398)
3	0.516*	-0.047	-0.055	-0.083	-0.024
	(1.678)	(-0.678)	(-1.019)	(-1.557)	(-0.532)
4	0.531*	-0.03	-0.057	-0.072	-0.006
	(1.671)	(-0.37)	(-0.76)	(-0.937)	(-0.161)
High	0.484	-0.059	-0.033	-0.056	-0.04
	(1.601)	(-1.492)	(-0.81)	(-1.559)	(-1.464)
High Minus Low	-0.126	-0.06	-0.09	-0.103*	-0.058
	(-1.464)	(-1.129)	(-1.591)	(-1.66)	(-1.311)

Table A6: Return Predictability and Strategic Manipulation of Earnings: Pre & Post SFAS 131

This table shows future one-month returns pre and post SFAS 131 for the group of high LTG conglomerates with strategic manipulation of earnings. 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)

Table A7: Stock Return Predictability: Change in Sentiments

We construct 2 dependent calendar-time portfolios sorted by changes in sentiment (positive or negative) using the sub-sample of only conglomerates with top decile long-term growth rates (LTG). We identify a firm as a conglomerate if the firm has segments in at least two distinct Fama-French 48 industries. Changes in sentiment is positive if the sentiment measure for the firm in year y-1 is higher than that in year y-2 and negative otherwise. The firm level sentiment is calculated as the average value of Event Sentiment Score from RavenPack dataset. The future stock return is measured over a one-year horizon. 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.

Change in Sentiment	Raw	FF5+Mom	Q-factor	Mispricing
Positive	-0.451	-1.135	-1.208	-1.301
	(-0.684)	(-3.39)	(-3.232)	(-3.462)
Negative	0.224	-0.676	-0.643	-0.453
	(0.371)	(-2.181)	(-1.872)	(-1.354)
Positive Minus	-0.675	-0.46	-0.565	-0.849
Negative	(-1.607)	(-1.22)	(-1.309)	(-1.724)

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 sale, 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)[32] 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

[32] 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.

and consists of business segments from 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 sale.

After we obtain the matched sample at the segment level, we aggregate segment level data into firm level weighted by the segment sale 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 sale 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 all tables in Appendix B uses the sample including “stand-alone pseudo”.

Table B1: Matching Accuracy and Summary Statistics for Conglomerates and Pseudo-Conglomerates Matched by CEM

In this table, we report the matching accuracy of segment sale and analyst coverage for conglomerates and pseudo-conglomerates. Segment sale is from Compustat. 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. In Panel B, 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 matched standalone firms for 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. Cash is defined as cash plus short-term investment divided by total book assets. 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 long-term forecasts (3-5 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.

Panel A: Matching Accuracy

	Before Matching			After Matching		
	0	1	SMD	0	1	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)	

Table B2: Absolute Forecast Errors, Forecast Dispersion, Forecast Horizon, and Conglomerates

In this table, we divide our sample of conglomerates and pseudo-conglomerates matched by CEM based on the forecast horizons (1 year, 2 years, and Long-term(3-5 years)). The dependent variable here is the absolute forecast error (AFE) and forecast dispersion (FD). 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. Using actual earnings per share as an alternative deflator does not change our conclusions and replacing the forecasted EPS consensus with the mean value of forecasted EPS doesn't harm our main results, either. A firm with segments in two different FF-48 industries is defined as a conglomerate. We require the total sales of all segments within a firm to be larger than 80% of the firm-level sale. 3-5Year is a dummy variable set to 1 if the forecast horizon is the 3-5 years forecast horizon 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 FF-48 industry times year fixed effects and standard errors are clustered by industry and year.

Dependent variable:	AFE				FD			
Sample	1Year	2Year	Long-Term	ALL	1Year	2Year	Long-Term	ALL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3-5Years				5.229***				0.943***
				(0.533)				(0.183)
Conglomerate	-0.539**	-0.465	-1.321***	-0.316	-0.095	-0.233**	-0.586**	-0.170**
	(0.264)	(0.409)	(0.455)	(0.249)	(0.077)	(0.094)	(0.231)	(0.081)
3-5Years*Conglomerate				-1.622***				-0.320**
				(0.442)				(0.149)
Size	-2.964***	-5.192***	-4.432***	-3.985***	-0.254***	-0.240***	-0.361***	-0.238***
	(0.305)	(0.476)	(0.454)	(0.263)	(0.039)	(0.027)	(0.120)	(0.031)
Firm Age	0.008	0.008	-0.031	-0.009	0.004*	0.005*	0.016	0.005*
	(0.009)	(0.011)	(0.021)	(0.011)	(0.002)	(0.003)	(0.010)	(0.003)
Analyst Cover	0.056**	0.308***	0.366***	0.166***	0.012	0.006	0.058**	0.010*
	(0.025)	(0.049)	(0.105)	(0.022)	(0.007)	(0.009)	(0.025)	(0.006)
BM	0.588**	0.339	0.083	0.327	0.225***	0.282***	0.353*	0.353***
	(0.282)	(0.421)	(0.571)	(0.261)	(0.068)	(0.082)	(0.202)	(0.087)
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Fiscal Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Double Clustering by Industry and Fiscal Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,847	18,941	8,685	48,473	15,986	13,629	3,937	33,552
R^2	0.318	0.362	0.400	0.267	0.326	0.344	0.431	0.248
Adjusted R^2	0.174	0.220	0.185	0.203	0.153	0.163	0.080	0.162

Table B3: Earnings Volatility

In this table, we report the cross-sectional regression of earnings volatility (EV) on a Conglomerate dummy with controls for various firm characteristics. Earnings volatility (EV) is the standard deviation of all historical earnings per share (EPS) for each firm. Earnings/Price volatility (EPV) is the standard deviation of all historical EPS divided by stock price in the same year. Conglomerate is a dummy variable that is one if the firm is a conglomerate and =0 for matched pseudo conglomerate. Sales is the mean value of the aggregated segment level sales revenue. Cash Holding is defined as cash plus short-term investment divided by total book assets. Segment is the number of segments that the conglomerate operates across the Fama-French 48 (FF-48) industries. BM the logarithm of the ratio book value to market value of equity. All variables are the time-series mean within a firm. We include FF-48 industry fixed effects and standard errors are clustered by industry.

	Dependent variable:							
	EV				EPV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conglomerate	-4.762***	-5.121***	-5.007***	-2.544*	-2.264***	-2.361***	-2.186***	-0.487
	(0.552)	(0.787)	(0.691)	(1.328)	(0.281)	(0.394)	(0.379)	(0.611)
Cash Holding			9.908**	19.336**			5.549**	12.050***
			(4.599)	(8.132)			(2.428)	(4.196)
Sales			0.001	0.001			-0.003**	-0.003**
			(0.004)	(0.004)			(0.001)	(0.001)
Segment			0.042	0.049			0.025	0.030
			(0.082)	(0.082)			(0.025)	(0.024)
BM			0.344	0.353			0.606**	0.613**
			(0.456)	(0.460)			(0.306)	(0.310)
Conglomerate*Cash				-17.401**				-12.001***
				(7.572)				(3.893)
Constant	6.396***				2.718***			
	(0.390)				(0.198)			
Industry Fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Clustering by Industry	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	3,791	3,791	3,526	3,526	3,796	3,796	3,530	3,530
R^2	0.019	0.051	0.051	0.058	0.017	0.045	0.045	0.056
Adjusted R^2	0.019	0.015	0.011	0.018	0.017	0.008	0.004	0.015

Table B4: Coibion-Gorodnichenko Regressions for EPS

This table runs Coibion-Gorodnichenko Regressions for EPS for conglomerates and pseudo-conglomerates matched by CEM. 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}. We include firm fixed effects and year fixed effects and standard errors are clustered by firm and year.

Dependent Variable:	$(EPS_{t+3}/EPS_t)^{1/3} - LTG_t$			$(EPS_{t+4}/EPS_t)^{1/4} - LTG_t$			$(EPS_{t+5}/EPS_t)^{1/5} - LTG_t$		
Independent Variable	LTG_t-LTG_{t-1}	LTG_t-LTG_{t-2}	LTG_t-LTG_{t-3}	LTG_t-LTG_{t-1}	LTG_t-LTG_{t-2}	LTG_t-LTG_{t-3}	LTG_t-LTG_{t-1}	LTG_t-LTG_{t-2}	LTG_t-LTG_{t-3}
Panel A: All Firms									
Revision	-0.458***	-0.466***	-0.474***	-0.462***	-0.470***	-0.458***	-0.460***	-0.473***	-0.459***
	(0.007)	(0.014)	(0.009)	(0.007)	(0.012)	(0.007)	(0.008)	(0.010)	(0.007)
Observations	28,456	25,880	23,851	28,457	25,880	23,851	28,459	25,882	23,852
Adjusted R^2	0.355	0.317	0.315	0.459	0.406	0.396	0.524	0.474	0.466
Panel B: All Firms									
Revision	-0.654***	-0.495***	-0.681***	-0.711***	-0.493***	-0.696***	-0.730***	-0.489***	-0.714***
	(0.033)	(0.016)	(0.034)	(0.029)	(0.013)	(0.029)	(0.028)	(0.008)	(0.026)
Conglomerate	-0.019***	0.038***	-0.015***	-0.018***	0.038***	-0.017***	-0.016***	0.038***	-0.015***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Revision*Conglomerate	0.361***	0.135***	0.380***	0.461***	0.109***	0.436***	0.500***	0.074**	0.468***
	(0.057)	(0.037)	(0.054)	(0.051)	(0.032)	(0.047)	(0.048)	(0.035)	(0.043)
Observations	28,456	25,880	23,851	28,457	25,880	23,851	28,459	25,882	23,852
Adjusted R^2	0.365	0.319	0.328	0.477	0.408	0.415	0.544	0.476	0.487
Panel C: Only High Growth Firms									
Revision	-0.775***	-0.599***	-0.771***	-0.839***	-0.612***	-0.796***	-0.801***	-0.580***	-0.754***
	(0.036)	(0.024)	(0.045)	(0.030)	(0.025)	(0.040)	(0.029)	(0.023)	(0.039)
Conglomerate	-0.081***	-0.041*	-0.055	-0.063***	-0.015	-0.048	-0.050**	0.001	-0.031
	(0.025)	(0.021)	(0.035)	(0.021)	(0.021)	(0.029)	(0.019)	(0.019)	(0.026)
Revision*Conglomerate	0.334***	0.319***	0.302***	0.427***	0.325***	0.394***	0.404***	0.246***	0.370***
	(0.063)	(0.066)	(0.081)	(0.055)	(0.046)	(0.074)	(0.053)	(0.048)	(0.073)
Observations	5,565	4,816	4,388	5,565	4,816	4,388	5,566	4,817	4,388
Adjusted R^2	0.414	0.349	0.390	0.519	0.432	0.461	0.572	0.490	0.513
Panel D: Only Conglomerates									
Revision	-0.299***	-0.393***	-0.325***	-0.254***	-0.402***	-0.273***	-0.226***	-0.420***	-0.243***
	(0.030)	(0.046)	(0.030)	(0.024)	(0.029)	(0.024)	(0.025)	(0.039)	(0.024)
manipulation	0.015	0.002	0.002	0.008	0.001	0.000	0.008	0.007	0.004
	(0.012)	(0.012)	(0.013)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Revision* manipulation	0.036	0.080	0.068	0.039	0.019	0.057	-0.001	-0.037	0.006
	(0.044)	(0.093)	(0.043)	(0.039)	(0.067)	(0.034)	(0.040)	(0.066)	(0.037)
Observations	15,474	12,909	12,900	15,475	12,909	12,900	15,476	12,910	12,901
Adjusted R^2	0.341	0.276	0.289	0.458	0.390	0.391	0.524	0.475	0.467
Panel E: Only High Growth Conglomerates									
Revision	-0.521***	-0.196***	-0.547***	-0.444***	-0.260***	-0.451***	-0.401***	-0.299***	-0.411***
	(0.065)	(0.053)	(0.072)	(0.056)	(0.049)	(0.067)	(0.057)	(0.045)	(0.059)
manipulation	0.013	0.034	0.020	0.002	-0.010	-0.021	0.034	-0.002	0.021
	(0.048)	(0.061)	(0.055)	(0.040)	(0.048)	(0.045)	(0.030)	(0.037)	(0.039)
Revision* manipulation	0.115	-0.172	0.066	0.044	-0.034	0.080	-0.040	-0.042	-0.054
	(0.094)	(0.130)	(0.126)	(0.080)	(0.103)	(0.086)	(0.070)	(0.084)	(0.087)
Observations	3,080	2,335	2,331	3,080	2,335	2,331	3,080	2,335	2,331
Adjusted R^2	0.344	0.253	0.315	0.440	0.349	0.389	0.495	0.411	0.444

Table B5: Analyst Forecast Errors, Forecast Horizon, and Conglomerate

Here, we regress analyst forecast errors on forecast horizons (FH) and conglomerate dummy(=1 if conglomerate and =0 for matched pseudo conglomerate). The proxy of analyst forecast error is constructed as follows. For each firm-year, 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. Using actual earnings per share as an alternative deflator does not change our conclusions and replacing the forecasted EPS consensus with the mean value of forecasted EPS also doesn't harm our main results: $Analyst\ Forecast\ Error_{i,t,f} = \left|\frac{Analyst\ Forecasted\ EPS_{i,t,f,m} - Real\ EPS_{i,t,f,m}}{P_{i,t}}\right|$. Size is the log value of firm market capitalization in millions. Analyst coverage is the number of analysts covering the firm. Ret is the stock return in the current year. Age is the age of a firm. BM ratio is book value of equity divided by market value of equity. FDispersion is the standard deviation of the analyst forecasted EPS. 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:				
	Matched Sample	Match Sample With >3 Horizon	Match Sample With All Horizon	Before 2000 (Inclusive)	After 2000 (Exclusive)
	(1)	(2)	(3)	(4)	(5)
FH	0.043***	0.047***	0.046***	0.048***	0.047***
	(0.007)	(0.006)	(0.009)	(0.011)	(0.006)
Conglomerate	0.021***	0.034***	0.063***	0.034***	0.035***
	(0.006)	(0.007)	(0.018)	(0.010)	(0.007)
Cash	0.120***	0.156***	0.168*	0.079*	0.189***
	(0.027)	(0.031)	(0.090)	(0.039)	(0.040)
Size	-0.390*	-0.610**	-0.965*	-0.836***	-0.640*
	(0.205)	(0.274)	(0.486)	(0.192)	(0.330)
Analyst Coverage	-0.001***	-0.0001	0.001**	0.001*	-0.001
	(0.0003)	(0.0003)	(0.001)	(0.0004)	(0.001)
Ret	-0.018**	-0.018**	-0.044**	-0.020	-0.018*
	(0.007)	(0.007)	(0.017)	(0.013)	(0.009)
Age	-0.001***	-0.001***	-0.001*	-0.001**	-0.001***
	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Log(Bm ratio)	0.016***	0.006	-0.018*	0.011	0.001
	(0.005)	(0.005)	(0.010)	(0.008)	(0.006)
FDispersion	1.131***	1.081***	0.723***	1.110***	1.051***
	(0.054)	(0.062)	(0.191)	(0.109)	(0.076)
FPI*Conglomerate	-0.024***	-0.026***	-0.024***	-0.022***	-0.028***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.005)
Firm Fixed effects	Yes	Yes	Yes	Yes	Yes
Industry*Fiscal Year Fixed effects	Yes	Yes	Yes	Yes	Yes
Clustering by Fiscal Year	Yes	Yes	Yes	No	No
Clustering by Industry	Yes	Yes	Yes	Yes	Yes
Observations	88,894	64,766	18,098	24,739	40,027
R^2	0.265	0.312	0.518	0.381	0.302
Adjusted R^2	0.226	0.269	0.468	0.321	0.261

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) to 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 1 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 Strategic Manipulation of Earnings

Here, we follow Chen, *et al.,* (2016) to construct an alternative measure of strategic manipulation of earnings. 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)[33]. 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 conglomerate is just below the discontinuity cutoff, it's unlikely

[33] 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.

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 2B 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 6 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 managerial manipulation assures our previous finding that managerial manipulation 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)
Strategic Manipulation	-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