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Contingent Information Content of Order Backlog and the Direction of Sales Change

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Abstract: We examine the contingent information content of order backlog and the direction of sales change. The more significant the order backlog, the less likely it is for future sales and thus earnings to decrease. As a result, an additional unit of order backlog predicts a more significant increase in future earnings and stock price when the firm also reports a sales decrease. The contingency of the information content is so significant that a sales decrease is no longer bad news when a firm reports above the top fiftieth percentile of order backlog relative to average assets. Our results support a contextual fundamental analysis theory in which the implication of an accounting measure can depend on other accounting information, and the impact of the context can be strong enough to overturn the qualitative interpretation.

Keywords: Order backlog, Contextual fundamental analysis, Sales decrease, Leading indicator

1. Introduction

Prior research documents the usefulness of order backlog (i.e., the dollar amount of unfilled orders) to investors and analysts for evaluating future firm performance (Rajgopal et al. 2003) dating back to 1970 when the Securities Exchange Commission (SEC) began to require order backlog disclosure in the 10-K. The information content of order backlog, however, can be ambiguous without a context as a growing order backlog can indicate either a future sales increase or an inefficiency that delays the production process. In response to investors' demand to understand the contextual information content of order backlog, we often observe that firms emphasize order backlog to cast a positive outlook on future revenue, especially when their current performance is sluggish. Consistent with disclosure practice, prior literature has examined the contextual information content of accounting measures. Following the literature examining the information content of accounting measures in context, we examine whether a leading indicator, such as order backlog, can have extended information content depending on the direction of sales change. For the sample of the US firms between 1970 and 2016, our research design allows examination of inter-dependence of the information content of order backlog and a sales decrease in explaining future earnings and stock returns. We find that a sales decrease, a reliable indicator of negative future returns and earnings growth, is no longer bad news when significant order backlog suggests a sales decrease is likely temporary. The significance of the contextual information content of order backlog and a sales decrease suggests that it is necessary to consider context, which is often other accounting information, to understand the information content of 10-K disclosures.

Order backlog predicts, on average, an increase in future earnings. Recognizing order backlog as a leading indicator of future performance (Ittner et al. 1997), order backlog exhibits a positive association with future earnings (Dechow et al. 2011; Behn 1996; Rajgopal et al. 2003). Studies have also found that investors react to order backlog (Jiambalvo et al. 2002; Rajgopal et al. 2003). In these studies, order backlog is currently unfilled orders that represents future revenue likely to be recognized following a firm's normal operating cycle.

Although the literature has established the information content of order backlog on average, it is often ambiguous in varying circumstances. On the one hand, an unusually significant increase can imply an increasing demand. On the other hand, the significant increase may indicate congestion or disruption in the supply chain, resulting in a firm’s inability to completely fulfill their performance obligation to customers. Conversely, a significant decrease in order backlog may indicate a shortening operating cycle, suggesting a more efficient operation or decreasing future demand. Investors who need to evaluate the information content of order backlog are likely to demand context to understand the information content of order backlog.

In response, companies increasingly provide additional information about order backlogs in their press releases or earnings announcements, suggesting the importance of contingent information content regarding order backlog. For example, in 2018, big rigs and truck factory backlogs soared on an increase in demand.[1] The manufacturers could not build fast enough due to supply chain issues that negatively affected their stock price. The market reaction indicates that despite order backlog having a significantly positive effect on future earnings (Rajgopal et al. 2003), the short-term market reaction to order backlog can be contingent on other information. As they reported a relatively large order backlog, Daimler Trucks North America

[1] article available at https://www.wsj.com/articles/get-in-line-backlog-for-big-rigs-stretches-to-2019-1534500005 and https://www.wsj.com/articles/heavy-duty-truck-factory-backlogs-soar-on-surging-orders-1530783005

clarified in a press release that they would be able to turn order backlog into sales. Other companies such as General Electric, Caterpillar, Salesforce, and Airbus, to name a few, have also provided press releases to guide the market on order backlog issues and expectations to address investors' concerns of sluggish demand.[2]

Consistent with the disclosure practice of providing context to interpret accounting signals, prior literature has examined the contextual information content of accounting measures. Ample evidence exists in the literature that documents how economic conditions, as well as a history of accounting information, determines the information content of accounting information (Beneish et al. 2001). Banker et al. (1993) show that the information content of discontinuing dividends depends on not only the prior history of dividends but also capital expenditures. Among many others, Barth et al. (1999) document that investors react more strongly to earnings surprises that are consecutive and Schmalz and Zhuk (2019) find that the market reactions to earnings surprises are stronger during economic downturns. Chen et al. (2019) show that adjustment costs affect the sensitivity of cost and earnings to managerial expectations on future sales. Recently, Chang et al. (2018) show that the bullwhip effect distorts demand information up the supply chain, which reduces order backlog's ability to predict earnings for upstream suppliers.

Following the literature examining the contingent information content of accounting measures, we examine the ability of order backlog to predict future earnings and stock returns when a firm experiences a concurrent sales decrease. An extensive stream of literature

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[2] articles available at https://www.wsj.com/articles/backlog-and-revenue-growth-power-salesforce-results-1543356152, https://www.wsj.com/articles/ge-power-has-a-92-billion-backlog-for-new-boss-thats-a-problem-11550068479, https://www.reuters.com/article/us-caterpillar-supplychain-analysis/why-caterpillar-cant-keep-up-with-a-boom-in-demand-idUSKCN1IO0FW,https://www.ft.com/content/a495bc06-49a6-11e9-bbc9-6917dce3dc62

documents that accounting and operational decisions following a sales decrease affect the behavior of earnings (Anderson et al. 2003; Anderson et al. 2007; Weiss 2010; Banker, Basu and Byzalov 2016; Banker, Basu, Byzalov, et al. 2016; Banker et al. 2018; Hwang et al. 2016 among many others). While a sales decrease can be a situational business context, it also has information content that depends on other accounting information or context such as order backlog. A sales decrease may imply a further decrease in demand that triggers a scaling down of capacity resources (Anderson et al. 2003; Banker et al. 2014). However, when a firm reports an order backlog with a sales decrease, the order backlog can indicate that the downturn is likely to be temporary, thereby reducing the negative implications of a sales decrease. Hence, a unit of order backlog conditional on a concurrent sales decrease is likely to be a more important piece of positive information on future earnings than a sales increase.

Using a broad cross-section of samples between 1970 and 2016, we examine the ability of order backlog to predict future earnings and stock returns when a firm's concurrent sales decrease. To examine the interdependence of information content of order backlog and a sales decrease, we examine the interaction terms of order backlog and a sales decrease in the regressions of future earnings and abnormal returns. Throughout our analyses, we employ both firm fixed effects and Fama-MacBeth regressions for robustness. For abnormal stock returns, we also employ both Fama-MacBeth regressions and a calendar-portfolio approach for robustness following an extensive literature of stock return predictability. We recognize that regression coefficients of order backlog levels may represent the time-varying differences in the normal operating cycle of industry or firm. To mitigate potential confounding effects, we conduct cross-sectional analyses, including an examination of the cash-conversion cycle. Additionally, we directly estimate the conditional information content of a sales decrease and order backlog at different levels of order backlog to allow non-linear effects of a sales decrease and order backlog using high-order polynomials of order backlog.

Our results show that although order backlog is predictive of future earnings, it is even more predictive of future earnings when it coincides with a sales decrease. The contingent information content of a sales decrease and order backlog is so strong that a sales decrease, a reliable indicator of negative future stock returns, is no longer a negative indicator when a firm also reports significant order backlog.

Our findings suggest that one should analyze an accounting signal's information content, not in isolation but in the context of other signals, consistent with a call for a more holistic approach in the fundamental analysis literature (Sloan 2019). Although contextual fundamental analysis literature is extensive, the interdependency of the information content between contemporaneous accounting information has received much less attention. One of a few examples is the literature on the information content of revenue growth documenting that the stock market reacts strongly to earnings growth backed by revenue growth (Ertimur et al. 2003; Ghosh et al. 2005; Jegadeesh and Livnant 2006). We extend this stream of literature to document the interdependency of the accounting information content of order backlog and the direction of sales change, showing that information content of accounting information depends on other accounting information concurrently available, and the contingent information content is strong enough to overturn the qualitative interpretation of an accounting signal.

The remainder of the paper is as follows: Section 2 discusses the related literature and hypotheses development, Section 3 outlines the sample selection criteria and research design, Section 4 presents the empirical findings, and Section 5 summarizes and concludes the paper.

2. Prior Literature and Hypothesis Development

2.1 Prior Literature

2.1.1 Order Backlog as a Leading Indicator

Leading indicators of future performance are relevant to managers, investors, regulators, academics, and both public and private stakeholders because they have the potential to explain aspects of future performance that earnings alone cannot explain. Francis and Schipper (1999) find that the explanatory power of earnings levels and changes for returns has decreased over time. Barth et al. (2018) find non-earnings disclosures provide more information in recent years. This increases the importance of leading indicators such as order backlog in predicting future earnings and stock returns (Rajgopal et al. 2003). Several non-GAAP metrics are regarded as leading indicators of future performance. Customer satisfaction is an example of a non-GAAP metric that can be used as a leading indicator of future performance. Ittner and Larcker (1998) show that greater customer satisfaction leads to better future performance. Similar results are extended to order backlog. Lev and Thiagarajan (1993), Behn (1996), Feldman et al. (2018), and Rajgopal et al. (2003) all show that order backlog, a leading indicator, is useful in predicting future earnings and is incorporated into stock prices. Order backlog is informative in predicting earnings per share, and analysts use order backlog as a non-GAAP metric when forecasting future earnings.

2.1.2 Information Content of a Sales Decrease

Prior research examines the stock market reactions to unexpected earnings and sales, documenting the persistence of future earnings growth as the incremental information of unexpected sales over unexpected earnings. Ertimur et al. (2003) and Ghosh et al. (2005) find that market reactions to the earnings surprises are stronger when the sales surprises accompany earnings surprises, establishing the inter-dependency of the information content of earnings and sales. Jegadeesh and Livnat (2006) document the information content of sales incremental to the earnings surprises. They find that revenue surprises can indicate persistent growth of future sales and earnings, suggesting that a sales increase or decrease is likely to imply a further increase or decrease in the next periods.

A growing literature examines how the context of a sales decrease can influence the behavior of earnings. Banker, Basu, and Byzalov (2016) find that earnings, on average, decrease 23.3 cents per dollar of a sales decrease and rise by 5.9 cents per dollar of a sales increase because a sales decrease can trigger the impairment of assets. Banker, Basu, Byzalov, et al. (2016b) show that firms hire additional workers when sales increase, but layoffs are delayed when sales decrease to give managers time to determine whether the sales decrease is temporary, which shows that the asymmetric timeliness of earnings can be attributable to operational decisions of managers facing a sales decrease. Banker and Liang (2017) show that managerial decisions after a sales decrease can affect earnings persistence and forecast accuracy. Hwang et al. (2016) find that inventory increases during a sales decrease predict higher future sales than during a sales increase. Sales decreases also have an asymmetric effect on accounts receivable, inventory, and accounts payable (Banker et al. 2018). Related literature also finds that utilizing the information available from a sales decrease improves forecast accuracy (Banker and Chen 2006).

The literature also suggests that other information can reduce the uncertainty resulting from a sales decrease. Anderson et al. (2003) document sticky cost behavior. Sticky costs occur when costs increase at a higher rate when sales increase than the rate at which costs decrease when sales decrease. On average, a sales decrease predicts sticky cost behavior. Dierynck et al.

(2012) and Kama and Weiss (2013) document that incentives to manage earnings decrease the degree of cost stickiness. Chen et al. (2012) suggest that empire-building behavior incentives increase the degree of cost stickiness. Banker et al. (2013) document that strong employment protection increases the average cost stickiness for 19 OECD countries. These moderators, if readily observable, clarify how managers make accounting and operating decisions during periods of declining sales and reduce uncertainty resulting from a sales decrease.

2.2 Hypothesis: Interdependence of Information Content of Order Backlog and a Sales Decrease

Although the market reaction studies document that on average a sales decrease is negative news to future earnings and returns, it is unclear whether a sales decrease alone can unambiguously imply either a further increase or a decrease in future earnings. Even if a firm undergoes a permanent decrease in sales, management may efficiently reduce slack resources and improve profitability despite a permanent decrease in sales. Conversely, a temporary decrease in sales does not guarantee recovery of earnings in the next period. The firm may need to invest to meet increasing demand, and future earnings may not increase at all if the recovery or increase in the demand is not large enough.

Order backlog with a sales decrease can narrow down the possible states of a business because it reduces the possibility of permanently negative shocks to demand. Given the uncertainty of a firm's next year's sales, additional units of order backlog are likely to decrease the likelihood that a consecutive decrease in sales will occur in the next period. Managers, weighing their expectations on future sales, are more likely to remain optimistic and induce sticky cost behavior when order backlog exists (Banker et al. 2014). As a result, a firm's current earnings are more suppressed when an order backlog exists, and the firm's earnings in the next year are likely to increase when a firm fulfills the order backlog obligation.

The incremental positive news that order backlog conveys should be more significant when sales decrease. In other words, a sales decrease is less likely bad news for future earnings when a firm reports a significant order backlog. Order backlog implies a boost of sales in the future period within the firm's capacity to fulfill the order backlog obligation. When sales decrease, order backlog reduces the downside risk of a further decrease in sales. Each unit of order backlog during a sales decrease, as a result, provides two forms of positive news: 1) a boost in future sales, and 2) a reduction of the downside risk that sales will further decrease. The hypothesis representing the contingent information content of order backlog and a sales decrease is as follows:

HYPOTHESIS 1. *An additional unit of order backlog predicts more positive future earnings and abnormal stock returns when a firm concurrently reports a sales decrease than a sales increase.*

Specifically, we expect that one-year-ahead earnings and abnormal returns explained by an additional unit of order backlog will be greater for firms that experience a concurrent sales decrease. Consistent with our expectation of order backlog's influence on future earnings when sales decrease, we expect a sales decrease to be less bad news for the stock price as backlog becomes more significant.

3. Sample Selection and Research Design

3.1 Sample Selection

We sample 254,079 firm-years from the intersection of Compustat and CRSP from 1970-2016. We require non-missing order backlog (Compustat OB) and truncate variables used in the regression models at 1% and 99%. We also require firm-years to have positive sales for year t and t−1 and positive average total assets, yielding a total of 64,306 firm-years. To examine the information content of order backlog on stock returns, we require stock returns to be available for the previous year for at least for 126 trading days and the event window of 63 trading days (one quarter) beginning with four months after the year-end, yielding 44,991 firm-years. The intersection of IBES yields the most restricted samples of 18,445 and 19,500 firm-years before and after the 10-K filing we obtain from the Compustat CO_FILEDATE file.

We present descriptive statistics in Table 1. We deflate the main variables, Income Before Extraordinary Items Available for Common Stock (Compustat $IBCOM$) adjusted for special items (Compustat SPI) as $IBCOM - SPI * 0.65$ (Bradshaw and Sloan 2002, So 2013) and order backlog by the average total assets. Deflating by a common variable allows us to examine the relations between future earnings and order backlog as well as future returns on assets and a sales decrease. Order backlog exhibits variations in the sample. The first 29th percentiles of $BKLG$ is zero, while the interquartile range of order backlog deflated by average assets ($BKLG$) is 0.48. ROA_{t+1} has a mean of 3%, a median of 5%, and an interquartile range of 8.8%.

[INSERT TABLE 1 HERE]

3.2 Research Design

We examine whether order backlog has incremental information content for future earnings and returns when a firm also reports a sales decrease. Building on Rajgopal et al. (2003), we employ a one-year ahead earnings prediction model augmented by a sales decrease indicator and controlling for the asymmetric persistence of loss (Li and Mohanram 2014) and cross-sectional determinants of future earnings (Hou et al. 2012, So 2013). We estimate the following model of ROA_{t+1} to estimate the information content of order backlog conditioned on a sales change.

$$ROA_{i,t+1} = \beta_0 BKLG_{i,t} + \beta_1 DEC_{i,t} + \beta_2 BKLG_{i,t} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t} \quad (1)$$

Subscripts i and t are the indicators for a firm and a fiscal year, and ROA and $BKLG$ are earnings and order backlog deflated by average assets (Compustat $(AT_{t-1} + AT_t)/2$), respectively. Dec is a 1 for firms that have a sales decrease and a zero otherwise. The coefficient $\beta_0 > 0$ reflects the positive relation with future earnings (e.g., Rajgopal et al. 2003). Our coefficient of interest is β_2 for the interaction of $BKLG$ and Dec. If order backlog, conditional on a sales decrease, is more informative in predicting an increase in future earnings, we expect the coefficient to be significantly positive. We include the following control variables: returns on assets(ROA_t), a loss indicator ($NEGE$), the interaction of ROA_t and $NEGE$, the magnitudes of positive and negative accruals (ACC^+ and ACC^-), asset growth (AG), a dividends indicator (DD), dividends (DIV), book-to-market (BTM), market capitalization ($Ln(MV)$), and Leverage. Detailed variable description and variable construction information are available in Appendix A.

In an additional test, we replace our main variables with interactions of the third order polynomials of order backlog and changes in revenue to measure the marginal effects of order backlog on future earnings in a less restrictive model. We estimate the marginal effects of a sales decrease indicator on the future returns of assets for each percentile of order backlog. The variation of the marginal effect for order backlog percentiles shows how the significance of order backlog alters the implications of a sales decrease.

To examine information content of order backlog on future stock returns, we estimate the following Fama-MacBeth regression of monthly size adjusted returns beginning with four months after the year-end.

$$Ret_{0i} = \alpha_0 BKLGvar_{i,t} + \alpha_1 DEC_{i,t} + \alpha_2 BKLGvar_{i,t} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t} \quad (2)$$

Subscripts i and t are the indicators for a firm and a fiscal year, $BKLGvar$ represents $BKLG$ or $BKLG^{Tr.TER}$, which is a tercile rank transformed variable (e.g., zero order backlog = 0, low order backlog = 0.5, and high order backlog = 1). α_2 measures the incremental information of order backlog conditional on a sales decrease for future stock returns. To mitigate the effects of delisting, our returns incorporate available delisting returns in CRSP daily returns. To remove confounding effects from market capitalization, we adjust returns by subtracting corresponding size-decile portfolio returns. In addition to the control variables included in Equation 1, we include explanatory variables for stock returns such as prior returns (RET_{-1} and $RET_{-12,-2}$) for momentum effects, market beta ($Beta$) for systematic risk, idiosyncratic volatility ($IVOL$) for volatility risk, and illiquidity ($ILLIQ$) for liquidity risk.

Additionally, we estimate the information content of order backlog following the calendar-portfolio approach using Fama-French (2015) five-factor and Carhart (1997) four-factor models. We construct 2×3 portfolios based on the direction of sales change and magnitude of order backlog (No backlog disclosure, low, and high backlog portfolios). Assuming that the cross-sectional distribution of order backlog becomes available within four months of the December year-end (Rajgopal et al. 2003), our event window is 63-trading days (e.g., one quarter) starting from May 1st. We expect market reactions to a sales decrease to be negative for low backlog portfolios but negligibly small for high backlog portfolios where high backlog mitigates negative news from a sales decrease.

4. Empirical Findings

4.1 Information Content of Order Backlog for Future Earnings

Table 2 shows the information content of order backlog on future earnings. The coefficients of order backlog in Column (1) and (2) are positive, which is consistent with Rajgopal et al. (2003). The sales decrease indicator in Column (2) exhibits a negative coefficient, suggesting that a sales decrease without a backlog is more likely to imply a decrease in future profitability. The coefficient of the interaction of $BKLG$ and Dec is positive, showing that order backlog conditional on a sales decrease has greater information content, and makes a sales decrease less negative news for future earnings.

[INSERT TABLE 2 HERE]

Figure 1 shows how a significant amount of order backlog reported can change the information content of a sales decrease. A sales decrease predicts a decrease in future ROA by 0.58% without order backlog. However, the negative news from a sales decrease is mitigated by order backlog. At about the fiftieth percentile of order backlog and above, on average, the impact of a sales decrease on the next year's ROA is not significantly different from zero. This suggests that a sales decrease is no longer bad news for the next year's profitability when a firm reports a significant amount of order backlog.

[INSERT FIGURE 1 HERE]

4.2 Information Content of Order Backlog for Future Stock Returns

Table 3 presents Fama-MacBeth regressions of monthly size-adjusted returns from four months after the year-end. Column (1) reports results with order backlog deflated by assets ($BKLG$) and Column (2) reports the results with tercile transformed deflated order backlog. Column (1) shows that the coefficient of the interaction of order backlog and a sales decrease indicator is strongly positive, suggesting that order backlog is especially positive news for a firm reporting a sales decrease. The coefficient of $BKLG^{Tr.TER} \times Dec$ in Column (2) represents the incremental information content of order backlog conditional on a sales decrease measured in abnormal returns over a month. While a sales decrease predicts negative abnormal returns of 1%, the portfolio of stocks in the top fifty percentiles of $BKLG$ earns additional 1.6% relative to stocks in the bottom fifty percentiles, showing that the order backlog mitigates the negative news of a sales decrease.

[INSERT Table 3 HERE]

To verify the incremental abnormal returns of order backlog conditional on a sales decrease, we estimate abnormal returns over the quarterly window using a calendar-portfolio approach. Table 4 shows that sales decrease is particularly bad news for the stocks in the bottom fifty percentiles. Column (3) reports a -2.76% long-short portfolio difference in returns compounded over the quarterly window between sales decreases and increases with low order backlog. By contrast, the long-short portfolio returns over the quarter are not significantly different from zero for high order backlog portfolios of firms with a concurrent sales decrease or increase. The results suggest that a sales decrease is no longer bad news when the amount of order backlog reported is significantly large.

[INSERT Table 4 HERE]

Figure 2 shows the results from daily window estimations of abnormal returns. The top line represents the cumulative abnormal returns of taking a long position on sales decrease stocks and short position on sales increase stocks among firms with high order backlog. Consistent with the results in Table 4, a sales decrease does not have a negative market reaction when order backlog is high. The bottom line represents the cumulative abnormal returns of taking a long position on sales decrease stocks and short position on sales increase stocks among firms with low order backlog portfolios. By contrast, the long-short portfolio returns among low order backlog portfolios show negative market reactions to a sales decrease. The negative market reaction is mostly concentrated in the first 30-trading days.

[INSERT Figure 2 HERE]

4.3 Cross-Sectional Analyses on the Contingent Information Content of Order Backlog

Table 5 shows the cross-sectional variations of the information content of order backlog. We find that order backlog increases future earnings more when a firm reports a sales decrease, which is consistent with our primary analyses. The cross-sectional analysis also shows that order backlog is a more significant predictor of a future earnings increase when a firm has a longer cash conversion cycle. In our sample, firms in the long-term contract industries such as insurance, defense, aircraft, and heavy equipment manufacturing industries following Fama-French industry classification exhibit relatively longer cash conversion cycles, and their order backlogs are more likely to represent persistent future revenue within their operating cycles. In contrast, we find a negative coefficient on the interaction of $BKLG$ and the ratio of order backlog to sales (BTR). The result is consistent with an unusually high order backlog to sales ratio indicating temporary congestion in operations. The result is also consistent with non-linear analyses in Appendix B.9 showing the decreasing marginal information content of order backlog. Lastly, we find that order backlog indicates a more significant increase in earnings when the firm also exhibits growth in assets. This is consistent with firms expanding their businesses with the intent of fulfilling unfilled orders to boost revenue in the future. However, when a firm reports a sales decrease and at the same time expands its asset base, the order backlog negatively predicts future earnings. This result suggests that those firms may engage in empire building (Chen et al. 2012).

[INSERT Table 5 HERE]

4.4 Additional Analyses and Robustness Checks

We compile additional information for our main analyses and robustness checks in Appendix B, including coefficients of control variables.

Appendix B.1 presents the correlation matrix. Appendix B.2, B.3, and B.4 present coefficients of control variables in Table 2, 3 and 5, respectively. B.5 reports Fama-MacBeth regressions of ROA_{t+1} following Equation 1 with control variables. B.6 shows the robustness of the regressions of Ret_0 after including standardized unexpected earnings as an additional control variable. In Appendix B.7 and Appendix B.8, we report how analysts react to order backlog.

4.4.1 Sell-Side Analysts' Use of Backlog Information

We find that the median analyst forecasts impound greater information content of order backlog after the announcement of a 10-K that reports order backlog. Appendix B.7 shows that the coefficients of $BKLG^{TR.TER}$ are 0.015 and 0.039 before and after the release of 10-K, respectively. The coefficients of $BKLG^{TR.TER}$ in Appendix B.8 suggest that analysts reduce forecast errors by incorporating order backlog information released in the 10-K. Column (2) reports 0.021 as the coefficient of $BKLG^{TR.TER}$, while Column (4) reports -0.009, which is less than half of the coefficients in the period before the announcement of order backlog in the 10-K.

The results suggest that analysts recognize the information of order backlog and incorporate it into the earnings forecasts. The analysts' earnings forecasts are more sensitive to order backlog disclosure after the release of 10-K than before. However, we do not find evidence that analysts incorporate contingent information of order backlog conditional on a sales decrease.

Analyst forecasts or analyst forecasts errors are not sensitive to the interaction between order backlog and a sales decrease indicator.

4.4.2 Information Content of Order Backlog by Magnitude

Appendix B.9 shows that the marginal information content of order backlog conditional on the direction of sales change under a flexible specification based on the scale of order backlog. We find decreasing marginal information content of order backlog contingent on the direction of sales change. Information content of the additional unit of order backlog decreases in the scale of order backlog. The contingent information content of order backlog when sales decrease is most significant when the magnitude of order backlog is small relative to total assets.

4.4.3 Reversal of Overreaction/Underreaction or Mispricing

We extend the window for measuring abnormal returns to one-year, and we do not find a reversal of abnormal returns. The results (untabulated) suggest that positive abnormal returns of order backlog conditional on a sales decrease in Fama-MacBeth regressions and incrementally positive returns of a sales decline for high order backlog portfolios are likely to reflect mispricing that investors resolve as they realize the implications of order backlog.

4.4.4 Information Content of Order backlog over Sample Periods

We examine variations of the information content of order backlog over time. Consistent with Rajgopal et al. (2003), between 1981 and 1999, order backlog predicts negative returns, although we do not find statistically significant results. Across three sample periods (e.g., 1997-1980, 1981-1999, 2000-2016), we find consistently positive coefficients of $BKLG^{TR.TER} \times Dec$ in the model of future returns. The results (untabulated) suggest that although the order backlog is on average positive news for future earnings as prior literature finds, the contingent information content is often substantial enough to overturn the sign of regression coefficients as we find in Table 5.

5. Summary and Conclusion

We investigate whether order backlog has information content contingent on the direction of sales change. We find that an additional unit of order backlog is a more informative leading indicator of future earnings when sales decrease, which is consistent with our theory that order backlog not only represents likely future sales but also reduces the likelihood of consecutive sales decreases. Significant order backlog mitigates the negative impact on the stock price from a sales decrease. A sales decrease, on average, represents a -1% monthly abnormal returns. A sales decrease in the presence of significant order backlog, however, no longer indicates a negative abnormal stock return.

Our findings suggest that the information content of multiple accounting measures may depend on each other and the total information content is greater than the sum of the information content of interrelated accounting measures. It is consistent with the disclosure practice of order backlog by Airbus, Boeing, Salesforce, GE, and Caterpillar where managers may complement order backlog disclosure with other sources of information to help investors better understand the context. In our study, we provide insight that a sales decrease does not imply a persistent decline of earnings when firms disclose significant order backlogs in the context of a sales decrease. Future research may continue to extend the contextual fundamental analysis literature on the contingent information content of accounting measures in a variety of settings from valuation models to the market anomalies that can depend on context.

Further research can also examine the interrelation of order backlog and other accounting disclosures in a new disclosure environment created by ASC 606 (Accounting Standards

Codification 606) for the US GAAP and IFRS 15 for International Financial Reporting Standards. Order backlog disclosure in our sample period is governed by Item 101(c)(1)(viii) of Regulation S-K. ASC 606, a new regulation effective since 2018 requires firms to disclose when order backlog is likely to be recognized in revenue. IFRS 15, also effective since 2018, requires the disclosure of the estimated transaction price for the remaining performance obligations (i.e., order backlog) in addition to the timing. The expanded disclosure may affect the information content of order backlog, analyst behavior, and market reactions.

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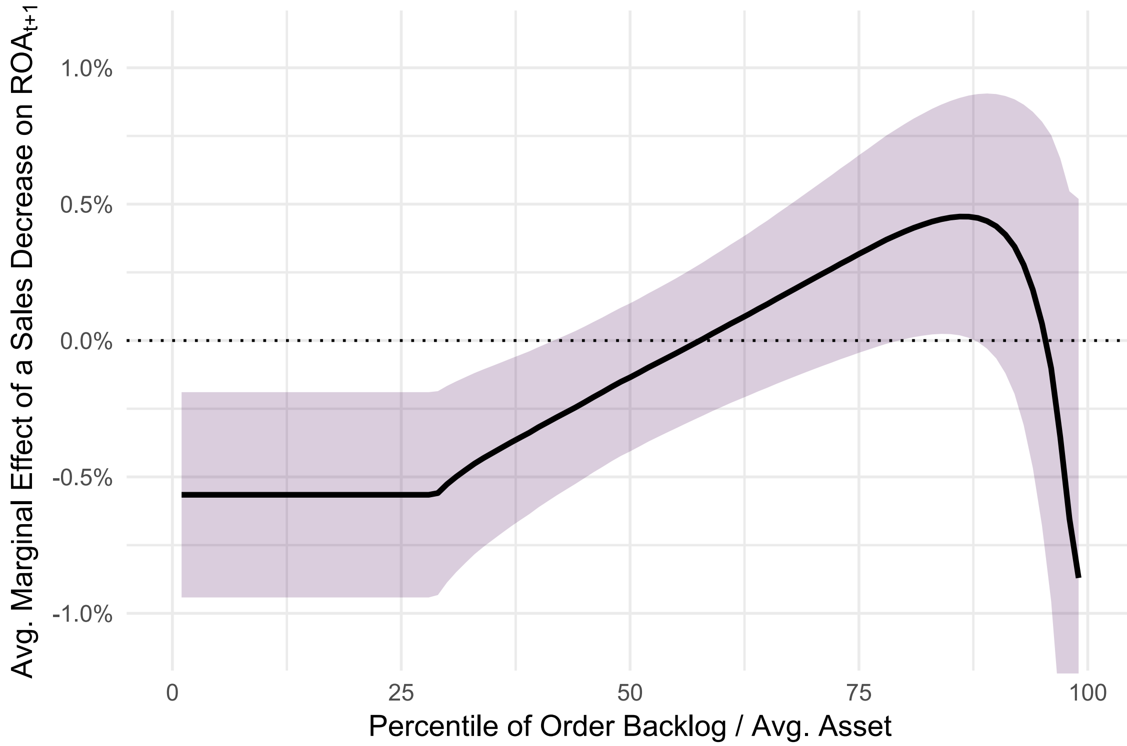
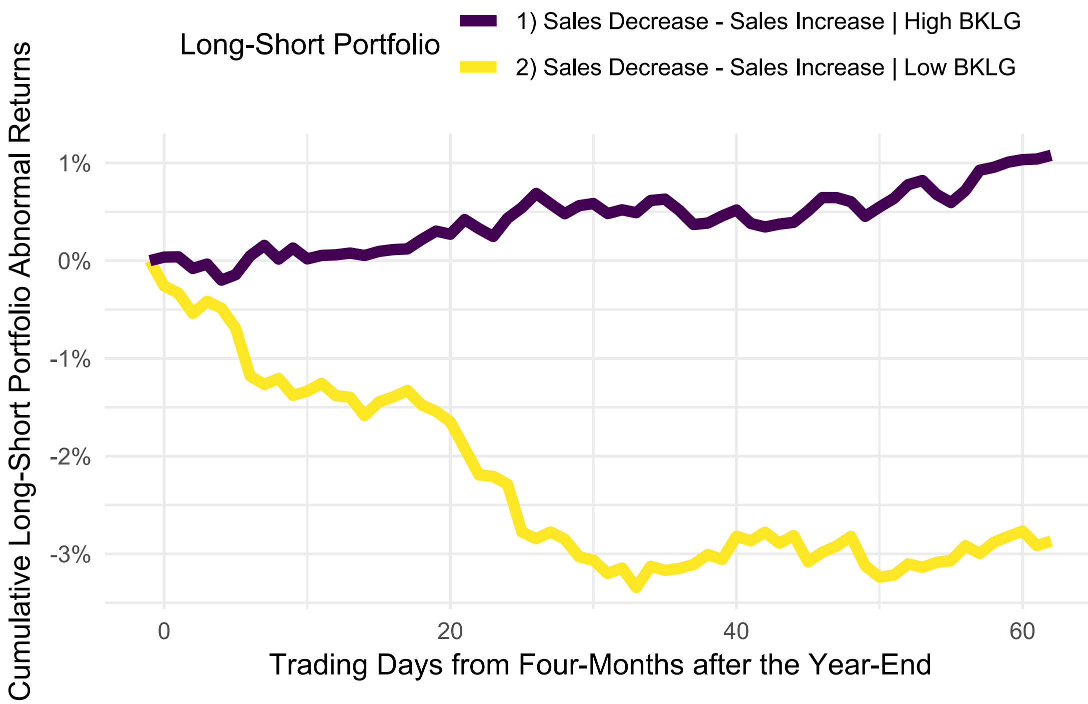
Figure 1 Contingent Information Content of a Sales Decrease



Notes: We estimate firm fixed effects regressions of ROA_{t+1} on the interaction of the third order polynomials of order backlog deflated by total assets ($BKLG_t$) and the indicator for sales decline (*Dec*) with control variables in Equation 1. We evaluate the average marginal effects of a sales decline indicator on ROA_{t+1} at each percentile of $BKLG_t$ (Order backlog divided by average assets).

Figure 2 Information Content of Order Backlog Conditional on Sales Change about Future Stock Returns



Notes: We estimate seemingly unrelated regression using Fama-French Five-Factor model (Fama and French 2015) as in Equation 3 for 1971-2017. Every year we partition stocks into six portfolios by the direction of sales change (*Dec*) and the terciles of the magnitude of order backlog deflated by average assets (High, Low, and Zero $BKLG_t$). The figure shows cumulative abnormal returns of the two long-short portfolios: 1) Sales Decrease and High BKLG − Sales Increase and High BKLG, 2) Sales Decrease and Low BKLG − Sales Increase and Low BKLG. The long-short portfolio returns of the portfolio 1) represent the information content of a sales decrease when order backlog is high, and 2) represents that of a sales decrease when order backlog is low. The difference of the abnormal returns of the two portfolios represent the incremental information content of order backlog when sales decrease.

TABLE 1
Descriptive Statistics

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
ROA_{t+1}	0.03	0.17	0.002	0.05	0.09
ROA_t	0.03	0.14	0.01	0.05	0.08
BKLG	0.36	0.53	0.00	0.17	0.48
Dec	0.27	0.44	0	0	1
CCC	95.83	457.95	50.48	97.11	150.59
BTR	0.29	0.41	0.00	0.15	0.38
NEGE	0.22	0.41	0	0	0
ACC^+	0.03	0.07	0.00	0.00	0.02
ACC^-	0.06	0.09	0	0.03	0.1
AG	0.18	0.51	-0.02	0.08	0.21
DD	0.60	0.49	0	1	1
DIV	0.01	0.02	0	0	0.01
BTM	0.90	0.76	0.39	0.67	1.15
Ln(MV)	4.30	2.27	2.61	4.08	5.83
Leverage	0.23	0.18	0.07	0.20	0.34
Ret_0	-0.004	0.14	-0.08	-0.01	0.05
$Ret_{0, 11}$	-0.07	0.51	-0.35	-0.12	0.12
$BKLG^{TER}$	2.08	0.79	1.00	2.00	3.00
$BKLG^{Tr.TER}$	0.54	0.39	0.00	0.50	1.00
Ret_{-1}	-0.001	0.15	-0.08	-0.01	0.06
$Ret_{-12, -2}$	-0.05	0.46	-0.32	-0.10	0.12
Beta	0.86	0.61	0.43	0.81	1.23
IVOL	0.03	0.02	0.02	0.03	0.04
ILLIQ	94.64	286.38	2.81	17.69	90.71
SUE	-0.05	1.19	-0.92	-0.02	0.86
AF_{t+1}	0.06	0.14	0.02	0.05	0.09
FE_{t+1}	-0.02	0.11	-0.01	-0.001	0.003
Following	1.96	0.88	1.10	1.95	2.64
Turnover	1.71	0.87	1.12	1.75	2.33
Disp	0.01	0.03	0.001	0.003	0.01

Notes: Table 1 shows the descriptive statistics for variables. Details of variable definitions and variable construction are available in Appendix A.

TABLE 2
Information Content of Order Backlog for Future Earnings

	ROA_{t+1} (1)	ROA_{t+1} (2)
BKLG	0.043***	0.042***
	(0.003)	(0.003)
Dec		-0.007***
		(0.002)
BKLG×Dec		0.005**
		(0.002)
Adjusted R^2	0.612	0.613
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Control Variables	Yes	Yes
Observations	64,306	64,306

Notes: We estimate the following model of future *ROA* to estimate the information content of order backlog conditioned on a sales change:

$$ROA_{i,t+1} = \beta_0 BKLG_{i,t} + \beta_1 DEC_{i,t} + \beta_2 BKLG_{i,t} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t}$$

, where i and t are the indicators for a firm and a fiscal year, respectively. We include following control variables: returns on assets(ROA_t), a loss indicator (*NEGE*), the interaction of ROA_t and *NEGE*, the magnitudes of positive and negative accruals (ACC^+ and ACC^-), asset growth (*AG*), a dividends indicator (*DD*), dividends (*DIV*), book-to-market (*BTM*), market capitalization (*Ln(MV)*), and *Leverage*. Detailed variable description and construction are available in Appendix A. Standard errors in the parentheses are robust to the clustering of errors by firm. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

TABLE 3
Information Content of Order Backlog for Future Stock Returns

	Ret_0 (1)	Ret_0 (2)
BKLG	0.050	
	(0.131)	
$BKLG^{Tr.TER}$		-0.200
		(0.287)
Dec	-0.413	-0.998***
	(0.257)	(0.358)
BKLG×Dec	0.777***	
	(0.299)	
$BKLG^{Tr.TER}\times Dec$		1.616***
		(0.434)
Adjusted R^2	0.057	0.056
Control Variables	Yes	Yes
Observations	44,991	44,991

Notes: We estimate following Fama-MacBeth regression of size-decile adjusted returns for a month after four months after the year-end to estimate the information content of order backlog conditioned on a sales change:

$$Ret_{0i} = \alpha_0 BKLGvar_{i,t} + \alpha_1 DEC_{i,t} + \alpha_2 BKLGvar_{i,t} \times DEC_{i,t} + \sum\beta Controls_t + \varepsilon_{i,t}$$

, where i and t are the indicators for a firm and a fiscal year, $BKLGvar$ is $BKLG$ or $BKLG^{Tr.TER}$ for column (1) and (2), respectively. The dependent variables are in percentage. We include following control variables: returns on assets(ROA_t), a loss indicator (*NEGE*), the interaction of ROA_t and *NEGE*, the magnitudes of positive and negative accruals (ACC^+ and ACC^-), asset growth (*AG*), a dividends indicator (*DD*), dividends (*DIV*), book-to-market (*BTM*), market capitalization (*Ln(MV))*, *Leverage*, monthly size-adjusted returns for one-month before the event-window and the compounded size-adjusted returns for the previous year excluding the previous month's returns (Ret_{-1} and $Ret_{-2,\,-12}$), *Beta*, idiosyncratic volatility (*IVOL*), and illiquidity (*ILLIQ*). Detailed variable description and construction are available in Appendix A. The dependent variable is in percentage. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

TABLE 4

Abnormal Returns of Order Backlog Portfolios Conditional on the Direction of Sales Change

	Five-Factor Model			Four-Factor Model		
	Decrease	Increase	Dec. − Inc.	Decrease	Increase	Dec. − Inc.
	(1)	(2)	(3)	(4)	(5)	(6)
High	0.70	0.07	0.63	0.04	-0.51	0.54
	(0.71)	(0.49)	(0.78)	(0.72)	(0.51)	(0.78)
Low	-1.90*	0.86	-2.76**	-1.42	1.23*	-2.65**
	(1.13)	(0.63)	(-1.17)	(1.13)	(0.64)	(-1.17)
No BKLG	-0.57	0.27	-0.84	-0.55	0.05	-0.60
	(0.48)	(0.25)	(-0.53)	(0.49)	(0.24)	(-0.53)
High-Low	2.60**	-0.79	3.39**	1.46	-1.74**	3.19**
	(1.30)	(-0.82)	(1.41)	(1.33)	(-0.86)	(1.41)

Notes: We estimate Fama-French factor regressions of portfolios based on the direction of sales change and order backlog magnitude. On May 1st of each year from 1971 to 2016, we sort firms based on order backlog into terciles. 1st tercile include zero-order backlog stocks (No BKLG), the second (Low) and the third (High) include stocks with the bottom and the top fifty percentiles of order backlog. Independently, we sort firms by the direction of sales change (e.g., Decrease and Increase relative to the firm's previous year's sales). We construct value-weighted portfolios of size-decile adjusted daily returns based on the market capitalization on April 30th each year and measure abnormal returns for the first 63 trading days since May 1st to measure the information content of order backlog available from 10-K disclosure. Panel A and B present results from Five-factor model (Fama and French 2015) and four-factor model (Carhart 1997, Fama and French 1993), respectively. The five factors include market premium, size, value, profitability, and investment. We estimate seemingly unrelated regression of six portfolios' daily size-decile adjusted returns on the five factors for 63 trading days since the four months after the year-end:

$$SizeAdjRet_{i,t} = \alpha_i + \beta_i Mkt_{i,t} + s_i SMB_{i,t} + h_i HML_{i,t} + r_i RMW_{i,t} + c_i CMA_{i,t} + \varepsilon_{i,t} \quad (3)$$

and the four factors include market premium, size, value, and momentum:

$$SizeAdjRet_{i,t} = \alpha_i + \beta_i Mkt_{i,t} + s_i SMB_{i,t} + h_i HML_{i,t} + u_i UMD_{i,t} + \varepsilon_{i,t} \quad (4)$$

, where i = 1, …, 6 is indicator for six portfolios constructed based on order backlog and the direction of sales change (1=No BKLG/Increase),2=Low/Increase, 3=High/Increase, 4=No BKLG/Decrease, 5=Low/Decrease, 6=High/Decrease). We report compounded long-short portfolio returns in percentage for the quarterly window from May 1st. Standard errors are in parentheses. High-Low indicates long-short portfolio returns of High minus Low for sales increase and decrease partitions, respectively. Column (3) Dec. − Inc indicates the long-short portfolio returns of Column (1) minus Column (2). High-Low row of Column (3) measures the incremental information content of order backlog when sales decrease. ***, **, and represent significance at the 1%, 5%, and 10% level, respectively.

TABLE 5
Cross-Sectional Variations of Information Content of Order Backlog

	ROA_{t+1} (1)	ROA_{t+1} (2)
BKLG	0.051***	0.008***
	(0.006)	(0.002)
Dec	-0.007***	-0.006***
	(0.002)	(0.002)
BKLG×Dec	0.008***	0.010***
	(0.003)	(0.003)
BKLG×CCC	0.0001***	0.0001***
	(0.00004)	(0.00002)
BKLG×BTR	-0.024***	-0.005**
	(0.003)	(0.002)
BKLG×AG	0.016***	0.020***
	(0.003)	(0.004)
BKLG×Dec×AG	-0.034***	-0.060***
	(0.012)	(0.017)
Adjusted R^2	0.614	0.537
Firm Fixed Effects	Yes	No
Year Fixed Effects	Yes	No
Control Variables	Yes	Yes
Observations	64,306	64,306

Notes: We estimate following model of future ROA to estimate the information content of order backlog conditioned on a sales change:

$$\begin{cases} ROA_{i,t+1} = \beta_0 BKLG_{i,t} + \sum\beta Controls_t + \varepsilon_{i,t} \\ \beta_0 = \lambda_0 + \lambda_1 Dec_{i,t} + \lambda_2 CCC_{i,t} + \lambda_3 BTR_{i,t} + \lambda_4 AG_{i,t} + \lambda_5 AG_{i,t} DEC_{i,t} \end{cases} \tag{5}$$

, where i and t are the indicator for a firm and a fiscal year, respectively.
. Column (1) and (2) show the results of fixed effects and Fama-MacBeth regressions, respectively. We include following control variables: returns on assets(ROA_t), a loss indicator (*NEGE*), the interaction of ROA_t and *NEGE*, Cash Conversion Cycle (*CCC*), Order Backlog to Sales (*BTR*), the magnitudes of positive and negative accruals (ACC^+ and ACC^-), asset growth (*AG*), a dividends indicator (*DD*), dividends (*DIV*), book-to-market (*BTM*), market capitalization (*Ln(MV)*), and *Leverage*. Detailed variable description and construction are available in Appendix A. Standard errors in the parentheses are robust to the clustering of errors by firm for Column (1). Column (2) reports Fama-MacBeth standard errors. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix A Variable Definition and Construction

Variable	Description and Construction
ROA_{t+1}	Income Before Extraordinary Items Available for Common Stock (Compustat *IBCOM*) adjusted for special items (Compustat *SPI*) as $IBCOM - SPI \times 0.65$ (Bradshaw et al. 2018, Bradshaw and Sloan 2002, So 2013) for year t divided by average total assets (Compustat $(AT_{t-1} + AT_t)/2$).
ROA_t	*ROA* for fiscal year t.
BKLG	Order Backlog (Compustat *IB*) divided by average total assets.
$BKLG^{TER}$	Backlog tercile portfolio indicator constructed for each fiscal year. One being zero order backlog, two being bottom fifty percentiles of non-zero order backlog, and three being the top fifty percentiles of non-zero order backlog.
$BKLG^{Tr.TER}$	Tercile order backlog rank transformed variable defined by $(BKLG^{TER} - 1)/2$.
Dec	An indicator variable being one for a sales decline in fiscal year t when Compustat $REVT_t < REVT_{t-1}$ and zero otherwise.
CCC	Cash conversion cycle defined by the operating cycle, the sum of the days inventories outstanding and accounts receivables outstanding (Dechow et al. 1998), less days accounts payables outstanding (Wang 2019). 360 × (Outstanding Average Inventories/*COGS* + Average Accounts Receivables/Sales − Average Accounts Payables/*COGS*), where inventories (*INVT*), accounts receivables (*RECT*), accounts payables (*AP*), sales (*REVT*), costs of goods sold (*COGS*) are from Compustat.
BTR	Ratio of order backlog (Compustat *BKLG*) to sales (Compustat *REVT*).
NEGE	An indicator variable for a loss being one when Compustat $IBCOM < 0$ and zero otherwise.
ACC^{+}	Magnitude of positive accruals (So 2013). We define accruals following (Sloan 1996) prior to 1988 and following Hribar and Collins (2002) starting from 1988 as in (Hou et al. 2015). Accruals prior to 1988 are defined by $(\Delta ACT - \Delta CHE) - (\Delta LCT - \Delta DCL - \Delta TXP) - DP$ from Compustat where *DLC*, *TXP*, and *DP* are zero if missing. Accruals following since 1988 are defined as net income (Compustat *NI*) minus net cash flow from operations (Compustat *OANCF*).
ACC^{+}	Magnitudes of negative accruals (So 2013).
AG	Asset growth defined by $\Delta Total\ Assets$ (Compustat $AT)/Total\ Assets_{t-1}$ following (Cooper et al. 2008).
DD	An indicator variable being one if Dividends for common and ordinary shares (Compustat *DVC*) are positive and zero otherwise.
DIV	Dividends for common and ordinary shares divided by average total assets.
BTM	Book value of equity following (Davis et al. 2000) divided by market value available from Compustat $PRCC\_F \times CSHO$).
Ln(MV)	log of market value available from Compustat.
Leverage	Average of long-term debt and current portion of long-term debt (Compustat $DLTT + DLC$) divided by average total assets.
Ret_0	Event-window monthly size-adjusted returns after four months from the year-end. We adjust returns for size-decile portfolio returns available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french. We include delisting returns for missing daily returns when available as $(1 + RET) \times (1 + DLRET) - 1$ from CRSP and calculate daily size-decile portfolio adjusted returns for each

	trading date by subtracting corresponding size-decile portfolio returns from individual stock returns, and compound the size-decile portfolio adjusted returns for the month.
$Ret_{0,11}$	Annual size-adjusted returns for 12-months after four months from the year-end. We compound daily size-decile portfolio adjusted returns for the one-year window.
Ret_{-1}	Monthly size-adjusted returns for one-month before the event-window.
$Ret_{-12,-2}$	Compounded size-adjusted returns for the previous year before the event-window excluding the previous month's returns.
Beta	Market beta estimated from a regression of raw daily delisting adjusted returns of a stock on the excess return of value-weight market portfolio returns for the one-year window before the event-window. We require the stock has available data for at least 126 trading days.
IVOL	Idiosyncratic volatility based on (Ang et al. 2006). Standard deviation of a regression of raw daily delisting adjusted returns of a stock on the excess return of value-weight market portfolio returns, Fama-French SMB and HML factors for the one-year window before the event-window. We require the stock has available data for at least 126 trading days.
ILLIQ	(Amihud 2002) illiquidity measure calculated by average of absolute raw daily delisting adjusted returns divided by dollar trading volume (CRSP absolute value of *PRC* multiplied by *VOL*) multiplied by one million.
SUE	Standardized Unexpected Earnings (*SUE*) based on (Bernard and Thomas 1989, 1990) calculated by $(EPS_q - EPS_{q-4} - \mu_{q-7,q})/\sigma_{q-7,q}$, where EPS is earnings per share from Compustat *EPSPXQ* and $\mu_{q-7,q}$, $\sigma_{q-7,q}$ are mean and standard deviation of the seasonal difference of EPS ($EPS_q - EPS_{q-4}$) over the past eight quarters, respectively.
AF_{t+1}	Median analyst forecasts for street-earnings per share t+1 issued over three-month window after the 10-K filing date (Compustat Filedate from CO_FILEDATE file available from Wharton Research Data Service) of year t multiplied by the number of shares outstanding (CRSP *SHROUT*/1,000) at the forecast announcement date and divided by average total assets for year t.
FE_{t+1}	Median analyst forecast error defined by actual IBES street-earnings per share t+1 minus median analyst forecasts t+1 issued over the three-month window multiplied by the number of shares outstanding (CRSP *SHROUT*/1,000) at the forecast announcement date and divided by average total assets for year t.
Following	Log of the sum of the number of analyst forecasts over the three-month window.
Turnover	Daily average of trading volume (CRSP *VOL*) divided by shares outstanding (CRSP *SHROUT*) over the one-year window ending one-day before the event-window.
Disp	Standard deviation of analyst forecasts for street-earnings per share t+1 issued over three-month window after the 10-K filing date (Compustat Filedate from CO_FILEDATE file available from Wharton Research Data Service) for year t multiplied by the number of shares outstanding (CRSP *SHROUT*/1,000) at the forecast announcement date and divided by average total assets for year t.

Notes: The average of a balance sheet item is the average between the current fiscal year t and the previous year t−1, and the variables represent the value of the current fiscal year t unless stated otherwise.

Appendix B.1 Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) ROA_{t+1}	1.00	0.69	0.08	-0.18	0.00	0.00	-0.45	-0.01	-0.23	-0.02
(2) ROA_t	0.69	1.00	0.07	-0.26	0.01	-0.03	-0.65	0.08	-0.46	0.09
(3) *BKLG*	0.08	0.07	1.00	-0.04	0.03	0.85	-0.06	0.10	-0.07	0.05
(4) *Dec*	-0.18	-0.26	-0.04	1.00	0.03	0.02	0.32	-0.12	0.24	-0.25
(5) *CCC*	0.00	0.01	0.03	0.03	1.00	0.05	0.02	0.04	0.01	-0.01
(6) *BTR*	0.00	-0.03	0.85	0.02	0.05	1.00	0.01	0.05	-0.03	0.04
(7) *NEGE*	-0.45	-0.65	-0.06	0.32	0.02	0.01	1.00	-0.06	0.37	-0.11
(8) ACC^{+}	-0.01	0.08	0.10	-0.12	0.04	0.05	-0.06	1.00	-0.27	0.31
(9) ACC^{-}	-0.23	-0.46	-0.07	0.24	0.01	-0.03	0.37	-0.27	1.00	-0.16
(10) *AG*	-0.02	0.09	0.05	-0.25	-0.01	0.04	-0.11	0.31	-0.16	1.00
(11) *DD*	-0.21	-0.25	-0.01	0.07	0.04	0.02	0.31	0.09	0.15	0.08
(12) *DIV*	0.19	0.23	-0.02	-0.04	0.01	-0.04	-0.22	-0.06	-0.10	-0.05
(13) *BTM*	-0.05	-0.06	-0.05	0.17	0.04	-0.06	0.09	-0.08	0.01	-0.18
(14) *Ln(MV)*	0.20	0.25	-0.04	-0.14	-0.10	0.04	-0.28	-0.13	-0.08	0.06
(15) *Leverage*	-0.09	-0.10	-0.09	0.01	0.06	-0.08	0.09	0.02	0.01	-0.01
(16) Ret_0	0.07	0.01	0.00	0.00	0.00	0.00	-0.01	-0.03	0.01	-0.01
(17) $Ret_{0,\,11}$	0.16	0.06	0.01	-0.01	-0.01	0.01	-0.06	-0.06	0.01	-0.05
(18) $BKLG^{TER}$	0.03	0.01	0.66	0.04	0.12	0.66	0.00	0.09	-0.07	0.00
(19) $BKLG^{Tr.TER}$	0.03	0.01	0.66	0.04	0.12	0.66	0.00	0.09	-0.07	0.00
(20) Ret_{-1}	0.09	0.01	0.02	0.00	-0.01	0.01	-0.01	-0.03	0.02	0.00
(21) $Ret_{-12,\,-2}$	0.26	0.14	0.05	-0.08	-0.02	0.03	-0.13	-0.02	-0.03	0.02
(22) *Beta*	0.08	0.08	0.03	-0.06	-0.01	0.06	-0.06	0.01	0.00	0.07
(23) *IVOL*	-0.31	-0.37	-0.03	0.15	0.04	-0.03	0.40	0.08	0.21	0.01
(24) *ILLIQ*	0.03	0.03	0.00	0.00	0.00	-0.03	-0.03	0.01	-0.05	-0.03
(25) *SUE*	0.09	0.07	0.02	-0.05	0.00	0.01	-0.10	0.02	-0.08	0.01
(26) AF_{t+1}	0.45	0.49	0.03	-0.13	-0.02	-0.04	-0.31	0.05	-0.11	0.09
(27) FE_{t+1}	0.32	0.14	0.00	-0.01	-0.03	-0.01	-0.13	-0.09	0.00	-0.04
(28) *Following*	0.10	0.15	-0.05	-0.04	-0.12	-0.01	-0.11	-0.12	0.02	-0.03
(29) *Turnover*	0.02	0.03	-0.05	-0.01	-0.08	0.00	0.04	0.01	0.10	0.12
(30) *Disp*	-0.29	-0.25	-0.01	0.05	0.04	0.02	0.25	0.07	0.07	0.05

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) ROA_{t+1}	-0.21	0.19	-0.05	0.20	-0.09	0.07	0.16	0.03	0.03	0.09
(2) ROA_t	-0.25	0.23	-0.06	0.25	-0.10	0.01	0.06	0.01	0.01	0.01
(3) *BKLG*	-0.01	-0.02	-0.05	-0.04	-0.09	0.00	0.01	0.66	0.66	0.02
(4) *Dec*	0.07	-0.04	0.17	-0.14	0.01	0.00	-0.01	0.04	0.04	0.00
(5) *CCC*	0.04	0.01	0.04	-0.10	0.06	0.00	-0.01	0.12	0.12	-0.01
(6) *BTR*	0.02	-0.04	-0.06	0.04	-0.08	0.00	0.01	0.66	0.66	0.01
(7) *NEGE*	0.31	-0.22	0.09	-0.28	0.09	-0.01	-0.06	0.00	0.00	-0.01
(8) ACC^+	0.09	-0.06	-0.08	-0.13	0.02	-0.03	-0.06	0.09	0.09	-0.03
(9) ACC^-	0.15	-0.10	0.01	-0.08	0.01	0.01	0.01	-0.07	-0.07	0.02
(10) *AG*	0.08	-0.05	-0.18	0.06	-0.01	-0.01	-0.05	0.00	0.00	0.00
(11) *DD*	1.00	-0.65	-0.04	-0.27	0.07	-0.01	-0.06	-0.01	-0.01	-0.01
(12) *DIV*	-0.65	1.00	-0.08	0.21	-0.17	0.00	0.04	-0.01	-0.01	0.00
(13) *BTM*	-0.04	-0.08	1.00	-0.43	0.11	0.02	0.02	-0.03	-0.03	0.03
(14) *Ln(MV)*	-0.27	0.21	-0.43	1.00	-0.12	0.01	0.09	-0.10	-0.10	0.01
(15) *Leverage*	0.07	-0.17	0.11	-0.12	1.00	0.00	-0.02	-0.12	-0.12	0.02
(16) Ret_0	-0.01	0.00	0.02	0.01	0.00	1.00	0.28	0.00	0.00	0.05
(17) $Ret_{0, 11}$	-0.06	0.04	0.02	0.09	-0.02	0.28	1.00	0.01	0.01	0.07
(18) $BKLG^{TER}$	-0.01	-0.01	-0.03	-0.10	-0.12	0.00	0.01	1.00	1.00	0.01
(19) $BKLG^{Tr.TER}$	-0.01	-0.01	-0.03	-0.10	-0.12	0.00	0.01	1.00	1.00	0.01
(20) Ret_{-1}	-0.01	0.00	0.03	0.01	0.02	0.05	0.07	0.01	0.01	1.00
(21) $Ret_{-12, -2}$	-0.05	0.03	-0.11	0.14	-0.03	0.02	0.05	0.03	0.03	-0.01
(22) *Beta*	0.01	-0.04	-0.18	0.38	-0.05	0.00	0.05	0.05	0.05	0.02
(23) *IVOL*	0.39	-0.29	0.16	-0.49	0.07	-0.01	-0.09	0.00	0.00	0.03
(24) *ILLIQ*	-0.11	0.09	0.13	-0.21	-0.01	0.00	-0.01	0.00	0.00	-0.01
(25) *SUE*	0.00	0.00	-0.02	0.01	-0.01	0.00	0.01	0.01	0.01	0.01
(26) AF_{t+1}	-0.05	0.09	-0.17	0.12	-0.06	0.01	0.01	0.01	0.01	0.03
(27) FE_{t+1}	-0.07	0.05	-0.03	0.12	-0.01	0.06	0.13	-0.03	-0.03	0.04
(28) *Following*	-0.11	0.10	-0.22	0.69	-0.01	-0.01	0.04	-0.15	-0.15	0.02
(29) *Turnover*	0.25	-0.20	-0.18	0.34	-0.08	-0.02	0.02	-0.09	-0.09	0.04
(30) *Disp*	0.13	-0.08	-0.03	-0.14	-0.06	-0.05	-0.09	0.05	0.05	-0.03

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
(1) ROA_{t+1}	0.26	0.08	-0.31	0.03	0.09	0.45	0.32	0.10	0.02	-0.29
(2) ROA_t	0.14	0.08	-0.37	0.03	0.07	0.49	0.14	0.15	0.03	-0.25
(3) *BKLG*	0.05	0.03	-0.03	0.00	0.02	0.03	0.00	-0.05	-0.05	-0.01
(4) *Dec*	-0.08	-0.06	0.15	0.00	-0.05	-0.13	-0.01	-0.04	-0.01	0.05
(5) *CCC*	-0.02	-0.01	0.04	0.00	0.00	-0.02	-0.03	-0.12	-0.08	0.04
(6) *BTR*	0.03	0.06	-0.03	-0.03	0.01	-0.04	-0.01	-0.01	0.00	0.02
(7) *NEGE*	-0.13	-0.06	0.40	-0.03	-0.10	-0.31	-0.13	-0.11	0.04	0.25
(8) ACC^{+}	-0.02	0.01	0.08	0.01	0.02	0.05	-0.09	-0.12	0.01	0.07
(9) ACC^{-}	-0.03	0.00	0.21	-0.05	-0.08	-0.11	0.00	0.02	0.10	0.07
(10) *AG*	0.02	0.07	0.01	-0.03	0.01	0.09	-0.04	-0.03	0.12	0.05
(11) *DD*	-0.05	0.01	0.39	-0.11	0.00	-0.05	-0.07	-0.11	0.25	0.13
(12) *DIV*	0.03	-0.04	-0.29	0.09	0.00	0.09	0.05	0.10	-0.20	-0.08
(13) *BTM*	-0.11	-0.18	0.16	0.13	-0.02	-0.17	-0.03	-0.22	-0.18	-0.03
(14) *Ln(MV)*	0.14	0.38	-0.49	-0.21	0.01	0.12	0.12	0.69	0.34	-0.14
(15) *Leverage*	-0.03	-0.05	0.07	-0.01	-0.01	-0.06	-0.01	-0.01	-0.08	-0.06
(16) Ret_0	0.02	0.00	-0.01	0.00	0.00	0.01	0.06	-0.01	-0.02	-0.05
(17) $Ret_{0,\,11}$	0.05	0.05	-0.09	-0.01	0.01	0.01	0.13	0.04	0.02	-0.09
(18) $BKLG^{TER}$	0.03	0.05	0.00	0.00	0.01	0.01	-0.03	-0.15	-0.09	0.05
(19) $BKLG^{Tr.TER}$	0.03	0.05	0.00	0.00	0.01	0.01	-0.03	-0.15	-0.09	0.05
(20) Ret_{-1}	-0.01	0.02	0.03	-0.01	0.01	0.03	0.04	0.02	0.04	-0.03
(21) $Ret_{-12,\,-2}$	1.00	0.14	-0.13	-0.02	0.17	0.12	0.12	0.04	0.07	-0.05
(22) *Beta*	0.14	1.00	-0.11	-0.20	0.01	-0.01	0.00	0.28	0.50	0.07
(23) *IVOL*	-0.13	-0.11	1.00	0.01	-0.04	-0.14	-0.16	-0.27	0.17	0.25
(24) *ILLIQ*	-0.02	-0.20	0.01	1.00	0.01	0.01	-0.01	-0.23	-0.33	-0.02
(25) *SUE*	0.17	0.01	-0.04	0.01	1.00	0.04	0.04	0.01	-0.03	-0.02
(26) AF_{t+1}	0.12	-0.01	-0.14	0.01	0.04	1.00	0.19	0.08	0.03	-0.40
(27) FE_{t+1}	0.12	0.00	-0.16	-0.01	0.04	0.19	1.00	0.07	0.01	-0.42
(28) *Following*	0.04	0.28	-0.27	-0.23	0.01	0.08	0.07	1.00	0.44	-0.06
(29) *Turnover*	0.07	0.50	0.17	-0.33	-0.03	0.03	0.01	0.44	1.00	0.05
(30) *Disp*	-0.05	0.07	0.25	-0.02	-0.02	-0.40	-0.42	-0.06	0.05	1.00

Notes: The upper and the lower triangles show Spearman and Pearson correlation coefficients, respectively.

Appendix B.2 Information Content of Order Backlog for Future Earnings

	ROA_{t+1} (1)	ROA_{t+1} (2)
BKLG	0.043***	0.042***
	(0.003)	(0.003)
Dec		-0.007***
		(0.002)
BKLG×Dec		0.005**
		(0.002)
ROA_t	0.896***	0.889***
	(0.024)	(0.025)
NEGE	0.002	0.003
	(0.003)	(0.003)
ROA_t×*NEGE*	-0.465***	-0.458***
	(0.042)	(0.042)
ACC^+	-0.064***	-0.062***
	(0.020)	(0.020)
ACC^-	0.135***	0.138***
	(0.016)	(0.016)
AG	-0.011***	-0.011***
	(0.002)	(0.003)
DD	0.002	0.002
	(0.001)	(0.001)
DIV	-0.096**	-0.087**
	(0.040)	(0.040)
BTM	-0.017***	-0.017***
	(0.001)	(0.001)
Ln(MV)	-0.010***	-0.010***
	(0.001)	(0.001)
Leverage	-0.017**	-0.018**
	(0.008)	(0.008)
Adjusted R^2	0.612	0.613
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	64,306	64,306

Notes: We estimate the following model of future ROA to estimate the information content of order backlog conditioned on a sales change:

$$ROA_{i,t+1} = \beta_0 BKLG_{i,t} + \beta_1 DEC_{i,t} + \beta_2 BKLG_{i,t} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t}$$

, where i and t are the indicators for a firm and a fiscal year, respectively. We include following control variables: returns on assets(ROA_t), a loss indicator (*NEGE*), the interaction of ROA_t and *NEGE*, the magnitudes of positive and negative accruals (ACC^+ and ACC^-), asset growth (*AG*), a dividends indicator (*DD*), dividends (*DIV*), book-to-market (*BTM*), market capitalization (*Ln(MV)),* and *Leverage*. Detailed variable description and construction are available in Appendix A. Standard errors in the parentheses are robust to the clustering of errors by firm. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.3 Information Content of Order Backlog for Future Stock Returns

	Ret_0 (1)	Ret_0 (2)
BKLG	0.050	
	(0.131)	
$BKLG^{Tr.TER}$		-0.200
		(0.287)
Dec	-0.413	-0.998***
	(0.257)	(0.358)
$BKLG \times Dec$	0.777***	
	(0.299)	
$BKLG^{Tr.TER} \times Dec$		1.616***
		(0.434)
ROA_t	2.179	2.025
	(2.138)	(2.153)
NEGE	0.054	0.001
	(0.352)	(0.344)
$ROA_t \times NEGE$	-0.365	-0.141
	(3.086)	(3.065)
ACC^+	-3.499*	-3.327*
	(1.792)	(1.811)
ACC^-	1.327	1.344
	(1.445)	(1.421)
AG	-0.027	0.041
	(0.282)	(0.271)
DD	0.134	0.131
	(0.224)	(0.220)
DIV	-3.430	-4.163
	(5.773)	(5.788)
BTM	0.256	0.228
	(0.217)	(0.214)
Ln(MV)	-0.009	-0.013
	(0.079)	(0.080)
Leverage	-0.098	-0.207
	(0.478)	(0.470)
Ret_{-1}	3.757***	3.691***
	(1.036)	(1.038)
$Ret_{-12,-2}$	0.994**	0.983**
	(0.406)	(0.409)
Beta	-0.152	-0.165
	(0.327)	(0.318)
IVOL	-31.238**	-30.502**
	(12.837)	(12.813)
ILLIQ	-0.001	-0.001*
	(0.0003)	(0.0003)
Constant	0.541	0.755

	(1)	(2)
	(0.951)	(0.988)
Adjusted R^2	0.057	0.056
Observations	44,991	44,991

Notes: We estimate following Fama-MacBeth regression of size-decile adjusted returns for a month after four months after the year-end to estimate the information content of order backlog conditioned on a sales change:

$Ret_{0i} = \alpha_0 BKLGvar._{i,t} + \alpha_1 DEC_{i,t} + \alpha_2 BKLGvar._{i,t} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t}$

, where i and t are the indicators for a firm and a fiscal year, $BKLGvar.$ are $BKLG$ and $BKLG^{Tr.TER}$ for column (1) and (2), respectively. The dependent variables are in percentage. Detailed variable description and construction are available in Appendix A. The dependent variable is in percentage. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.4 Cross-Sectional Variations of Information Content of Order Backlog

	ROA_{t+1} (1)	ROA_{t+1} (2)
BKLG	0.051^{***}	0.008^{***}
	(0.006)	(0.002)
Dec	-0.007^{***}	-0.006^{***}
	(0.002)	(0.002)
BKLG×Dec	0.008^{***}	0.010^{***}
	(0.003)	(0.003)
BKLG×CCC	0.0001^{***}	0.0001^{***}
	(0.00004)	(0.00002)
BKLG×BTR	-0.024^{***}	-0.005^{**}
	(0.003)	(0.002)
BKLG×AG	0.016^{***}	0.020^{***}
	(0.003)	(0.004)
BKLG×Dec×AG	-0.034^{***}	-0.060^{***}
	(0.012)	(0.017)
ROA_t	0.884^{***}	1.075^{***}
	(0.025)	(0.025)
NEGE	0.003	0.002
	(0.003)	(0.003)
ROA×NEGE	-0.453^{***}	-0.335^{***}
	(0.042)	(0.053)
CCC	-0.0001^{**}	-0.000
	(<0.001)	(0.000)
BTR	0.026^{***}	-0.013^{**}
	(0.009)	(0.005)
ACC^{+}	-0.073^{***}	-0.131^{***}
	(0.020)	(0.017)
ACC^{-}	0.137^{***}	0.145^{***}
	(0.016)	(0.016)
AG	-0.016^{***}	-0.023^{***}
	(0.003)	(0.003)
DD	0.002	-0.003^{***}
	(0.001)	(0.001)
DIV	-0.084^{**}	-0.090^{***}
	(0.041)	(0.034)
BTM	-0.016^{***}	-0.0004
	(0.001)	(0.001)
Ln(MV)	-0.010^{***}	0.003^{***}
	(0.001)	(0.0005)
Leverage	-0.019^{**}	0.004
	(0.008)	(0.004)
Constant		-0.025^{***}
		(0.004)
Adjusted R^2	0.614	0.537

	(1)	(2)
Firm Fixed Effects	Yes	No
Year Fixed Effects	Yes	No
Observations	64,306	64,306

Notes: We estimate following model of future *ROA* to estimate the information content of order backlog conditioned on a sales change:

$$\begin{cases} ROA_{i,t+1} = \beta_0 BKLG_{i,t} + \sum\beta Controls_t + \varepsilon_{i,t} \\ \beta_0 = \lambda_0 + \lambda_1 Dec_{i,t} + \lambda_2 CCC_{i,t} + \lambda_3 BTR_{i,t} + \lambda_4 AG_{i,t} + \lambda_5 AG_{i,t} DEC_{i,t} \end{cases}$$

, where i and t are the indicator for a firm and a fiscal year, respectively. Column (1) and (2) show the results of fixed effects and Fama-MacBeth regressions, respectively. We include following control variables: returns on assets(ROA_t), a loss indicator (*NEGE*), the interaction of ROA_t and *NEGE*, Cash Conversion Cycle (*CCC*), Order Backlog to Sales (*BTR*), the magnitudes of positive and negative accruals (ACC^+ and ACC^-), asset growth (*AG*), a dividends indicator (*DD*), dividends (*DIV*), book-to-market (*BTM*), market capitalization (*Ln(MV)*), and *Leverage*. Detailed variable description and construction are available in Appendix A. Standard errors in the parentheses are robust to the clustering of errors by firm for Column (1). Column (2) reports Fama-MacBeth standard errors. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.5 Fama-MacBeth Regression of ROA_{t+1}

	ROA_{t+1} (1)	ROA_{t+1} (2)
BKLG	0.011^{***}	0.010^{***}
	(0.001)	(0.001)
Dec		-0.003^{**}
		(0.001)
BKLG×Dec		0.005^{**}
		(0.002)
ROA_t	1.089^{***}	1.085^{***}
	(0.026)	(0.025)
NEGE	0.002	0.003
	(0.003)	(0.003)
ROA×NEGE	-0.341^{***}	-0.338^{***}
	(0.053)	(0.053)
ACC^{+}	-0.118^{***}	-0.117^{***}
	(0.016)	(0.016)
ACC^{-}	0.147^{***}	0.148^{***}
	(0.016)	(0.016)
AG	-0.018^{***}	-0.018^{***}
	(0.003)	(0.003)
DD	-0.003^{***}	-0.004^{***}
	(0.001)	(0.001)
DIV	-0.096^{***}	-0.094^{***}
	(0.035)	(0.034)
BTM	-0.001	-0.001
	(0.001)	(0.001)
Ln(MV)	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)
Leverage	0.005	0.005
	(0.005)	(0.004)
Constant	-0.025^{***}	-0.023^{***}
	(0.005)	(0.005)
Adjusted R^2	0.529	0.53
Observations	64,306	64,306

Notes: Appendix B.5 shows the average coefficients over fiscal years between 1970 and 2016 and (Fama and MacBeth 1973) standard errors. Detailed variable description and construction are available Appendix A. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.6 Returns over the Sample Period after Controlling for SUE

	Ret_0
	(1)
$BKLG^{Tr.TER}$	-0.212
	(0.297)
Dec	-0.918^{**}
	(0.369)
$BKLG^{Tr.TER} \times Dec$	1.677^{***}
	(0.422)
ROA_t	1.206
	(2.379)
NEGE	0.078
	(0.364)
$ROA_t \times NEGE$	4.008
	(4.741)
ACC^+	-2.570
	(2.054)
ACC^-	0.802
	(1.459)
AG	-0.019
	(0.343)
DD	0.223
	(0.221)
DIV	-3.922
	(5.853)
BTM	0.184
	(0.247)
Ln(MV)	-0.051
	(0.076)
Leverage	-0.142
	(0.606)
SUE	-0.006
	(0.061)
$Ret-1$	3.261^{***}
	(0.974)
$Ret-1_{2,-2}$	0.934^{**}
	(0.434)
Beta	-0.079
	(0.325)
IVOL	-32.853^{**}
	(12.937)
ILLIQ	-0.001^{**}
	(0.0003)
Constant	0.920
	(0.982)
Adjusted R^2	0.057

Observations	40,018

Notes: The monthly abnormal return predicted by order backlog and the sales decline are robust after Controlling for the fourth quarter *SUE*. Appendix B.6 shows the average coefficients over fiscal years between 1970 and 2016 and (Fama and MacBeth 1973) standard errors. Detailed variable description and construction are available Appendix A. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.7 Analyst Earnings Forecasts before and after 10-K Release Date

	AF_{t+1} *Before* (1)	AF_{t+1} *After* (2)
$BKLG^{Tr.TER}$	0.015*	0.039***
	(0.008)	(0.009)
Dec	-0.006**	-0.010**
	(0.003)	(0.004)
$BKLG^{Tr.TER} \times Dec$	0.002	0.006
	(0.004)	(0.007)
ROA_t	0.522***	0.503***
	(0.026)	(0.032)
NEGE	0.009*	0.007
	(0.005)	(0.007)
$ROA_t \times NEGE$	-0.082	-0.021
	(0.085)	(0.112)
ACC^{+}	0.078***	0.008
	(0.023)	(0.038)
ACC^{-}	0.058***	0.107***
	(0.016)	(0.020)
AG	0.010***	0.009***
	(0.002)	(0.003)
DD	-0.001	-0.0002
	(0.004)	(0.005)
DIV	0.211**	0.175*
	(0.102)	(0.102)
BTM	-0.014***	-0.028***
	(0.003)	(0.004)
Ln(MV)	0.024***	0.017***
	(0.002)	(0.003)
Leverage	-0.013	-0.003
	(0.012)	(0.015)
Adjusted R^2	0.669	0.705
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	18,972	20,142

Notes: We estimate the following analyst forecast model to estimate the information content of order backlog impounded in the analyst earnings forecasts before and after the 10-K release date:

$$AF_{t+1i} = \beta_0 BKLG_{i,t}^{Tr.TER} + \beta_1 DEC_{i,t} + \beta_2 BKLG_{i,t}^{Tr.TER} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t} \quad (6)$$

, where i and t are the indicators for a firm and a fiscal year, respectively. Column (1) and (2) show the results with analyst forecasts issued before and after the announcement of 10-K for each firm-year, respectively. Detailed variable description and construction are available in Appendix A. Standard errors in the parentheses are robust to the clustering of errors by firm. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.8 Analyst Earnings Forecast Errors before and after 10-K Release Date

	FE_{t+1} Before (1)	FE_{t+1} Before (2)	FE_{t+1} After (3)	FE_{t+1} After (4)
$BKLG^{Tr.TER}$	0.033^{***}	0.021^{**}	-0.002	-0.009^{*}
	(0.009)	(0.009)	(0.006)	(0.005)
Dec	-0.007^{*}	-0.006	-0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.003)
$BKLG^{Tr.TER}\times Dec$	0.003	0.004	0.001	-0.0003
	(0.005)	(0.005)	(0.004)	(0.004)
ROA_t	-0.033	-0.0003	0.036^{*}	0.050^{***}
	(0.030)	(0.027)	(0.019)	(0.018)
NEGE	-0.014	-0.009	-0.011^{**}	-0.006
	(0.009)	(0.008)	(0.006)	(0.005)
$ROA_t\times NEGE$	0.055	-0.174	-0.127^{**}	-0.185^{***}
	(0.138)	(0.125)	(0.058)	(0.059)
ACC^{+}	0.015	0.055	-0.077	-0.052
	(0.050)	(0.051)	(0.055)	(0.053)
ACC^{-}	0.108^{***}	0.092^{***}	0.037^{**}	0.035^{*}
	(0.029)	(0.029)	(0.018)	(0.018)
AG	-0.008^{***}	-0.004	-0.004^{**}	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)
DD	0.004	0.005	0.005	0.003
	(0.006)	(0.006)	(0.006)	(0.005)
DIV	0.036	0.127^{*}	0.005	0.014
	(0.066)	(0.077)	(0.045)	(0.040)
BTM	-0.031^{***}	-0.014^{*}	-0.019^{***}	-0.013^{**}
	(0.007)	(0.007)	(0.006)	(0.006)
Ln(MV)	-0.013^{***}	-0.012^{***}	-0.011^{***}	-0.009^{***}
	(0.003)	(0.004)	(0.003)	(0.003)
Leverage	-0.007	-0.0002	-0.007	-0.008
	(0.017)	(0.016)	(0.014)	(0.013)
Ret_{-1}		0.053^{***}		0.017^{***}
		(0.009)		(0.006)
$Ret_{-12,-2}$		0.047^{***}		0.016^{***}
		(0.005)		(0.002)
Beta		0.006		0.001
		(0.004)		(0.002)
IVOL		-1.178^{***}		-0.354^{**}
		(0.319)		(0.175)
ILLIQ		0.00002^{**}		0.00000
		(0.00001)		(0.00001)
Turnover		-0.004		-0.001
		(0.003)		(0.002)
Following		0.003^{*}		0.002
		(0.002)		(0.001)

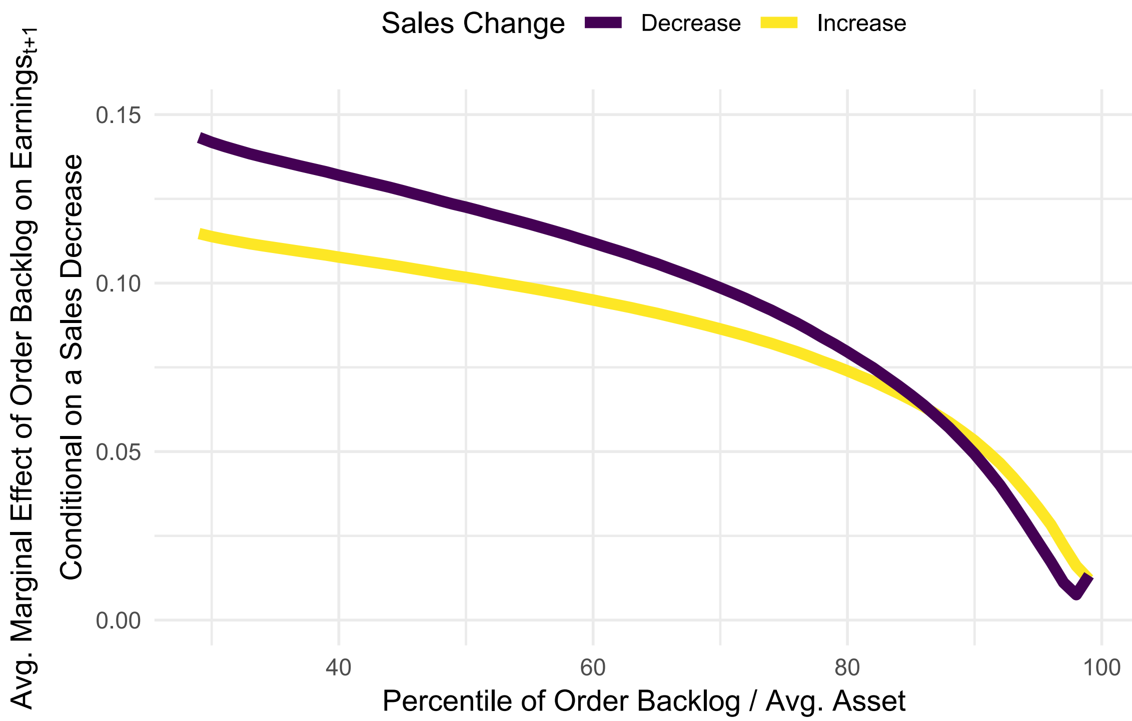
Disp		-1.293**		-1.005***
		(0.540)		(0.265)
Adjusted R^2	0.426	0.471	0.441	0.483
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	18,647	18,445	19,839	19,500

Notes: We estimate the following analyst forecast error model to estimate the information content of order backlog not impounded in the analyst earnings forecasts before and after the 10-K release date:

$$FE_{t+1i} = \beta_0 BKLG_{i,t}^{Tr.TER} + \beta_1 DEC_{i,t} + \beta_2 BKLG_{i,t}^{Tr.TER} \times DEC_{i,t} + \sum \beta Controls_t + \varepsilon_{i,t} \quad (7)$$

, where i and t are the indicators for a firm and a fiscal year, respectively. Column (1) and (2) show the results of the forecast error models with analyst forecasts issued before and after the announcement of 10-K for each firm-year, respectively. Detailed variable description and construction are available in Appendix A. Standard errors in the parentheses are robust to the clustering of errors by firm. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Appendix B.9 Contingent Information Content of Order Backlog by the Direction of Sales Change



Notes: We estimate firm fixed effects regressions of ROA_{t+1} on the interaction of the third order polynomials of order backlog deflated by total assets ($BKLG_t$) and the indicator for sales decline (*Dec*) with control variables in Equation 1. We evaluate the marginal effects of order backlog at each percentile of $BKLG_t$ conditional on the direction of sales change.