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Changes in Order Backlog and Future Returns

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Abstract

This paper examines whether investors recognize the implications of changes in order backlog, a non-GAAP leading indicator, for future performance. A hedge portfolio strategy taking a long position in the highest decile of order backlog change and a short position in the lowest decile of order backlog change earns 13.7 percent in the year after the hedge portfolio is formed. Moreover, analysts' forecast errors are large and negative (overoptimistic) for firms experiencing declines in order backlog. Overall, our evidence indicates that analysts underreact to the information in changes in order backlog. In addition, the market does not appear to see through the relation between changes in order backlog and future performance and underweights the implications of order backlog, which contrasts with the findings of Rajgopal, Shevlin, and

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Venkatachalam (2003).

Keywords: order backlog, non-GAAP indicator, analyst optimism

INTRODUCTION

This paper examines whether stock prices reflect information regarding changes in order backlog. Order backlog is the aggregate of the sales price of orders received from customers less the revenue recognized. It represents the unfulfilled portion of contractual orders and is an important leading indicator of future sales and earnings.

Although information about order backlog is not included in financial statements, it has been considered useful for the task of equity valuation. Ample anecdotes suggest that investors use order backlog as a meaningful indicator of future business prospects.[1)] Also, prior studies indicate that changes in order backlog are most closely watched in software, semiconductors, steel, and aircraft manufacturers (Lev and Thiagarajan 1993; Chandra Procassini, and Waymire 1999). For example, Lev and Thiagarajan (1993) find that the percentage change in sales less the percentage change in order backlog, an earnings management proxy, is associated with abnormal returns. Penman (2007) also stresses that a decline in order backlog is one of the red flag indicators for valuation analysis in his financial statement textbook, suggesting that order backlog is an important value driver.

Recently, Rajogpal, Shevlin, and Venkatachalam (2003), hereafter RSV (2003), examine whether market participants fully incorporate the implications of *the level of order backlog* relative to the level of operations (average total assets) for future earnings during the sample period of 1981-1999. They provide evidence suggesting that the stock market overweights the contribution of order backlog in predicting future earnings. They find that firms

1) Several analysts sell investment advice using this information. For example, such recommendations are included in “Companies and Finance the Americas” (*Financial Times*, 7/18/2002), “Meet ITT, the Defense Play” (*Business Week*, 11/7/2001), “Barron’s Mutual Fund Forum” (*Barron’s*, 6/2/1997), “Corporate Performance 1997 Review: 2nd Quarter” (*Wall Street Journal*, 8/4/1997), and “Swelling Backlog Sets for a Surge in Earnings” (*Barron’s*, 8/19/1991).

with higher order backlog earn lower future returns, which is inconsistent with Lev and Thiagarajan (1993)'s conjecture that higher order backlog is a good signal for future sales and earnings.

The level of order backlog is associated with product cycles. Firms with long product cycles tend to have higher order backlogs, while those firms with short product cycles are likely to have lower order backlogs. Consequently, the levels of order backlog may not be comparable across industries. For example, the level of order backlog for Boeing in the fiscal year of 1998 is more than 300 percent of its average total assets. The level of order backlog to the operation level is relatively high because of its long product cycle. By contrast, the level of order backlog for Nike in the same year is 79 percent of its average total assets. This difference does not necessarily indicate that Boeing will have a more favorable future performance than Nike. Indeed, Nike shows a marginal increase in order backlog, while Boeing suffers a 70 percent decrease in order backlog relative to that of the previous year. Thus, we believe that the results by RSV (2003) are confounded by the use of the level variable without considering the level of order backlog being a function of product cycles.

In this study, we reexamine the relation between order backlog and future returns using a change variable. More specifically, we investigate whether stock prices fully recognize the implications of changes in order backlog for future performance. Changes in order backlog represent an indicator for future performance free of measurement errors (associated with product cycles). Also, there are a substantial number of anecdotes suggesting that this measure is often used for equity valuation.

Using a sample of 32,738 firm-years for the sample period of 1971-1999, we find that stock prices act as if investors underreact to the implications of changes in order backlog. In other words, firms with steep increases in order backlog experience positive future, abnormal returns, while firms with steep declines in order backlog suffer negative future abnormal returns. A hedge portfolio strategy taking a long position in the stocks of firms in the highest decile of order backlog change and a short position in the stocks of firms in the lowest decile of order backlog change generates a 13.7 percent return in the following 12 months, on average, during the sample period of 1971-1999. We find evidence regarding the stability of the abnormal returns to the trading strategy. The hedge portfolio return is positive in 26 of the 29 years examined. Furthermore, we find that analysts' forecast errors contribute to the mispricing of order backlog changes. The forecast errors for firms with high declines in order backlog are larger (more optimistic) than the forecast errors for firms with high increases in order backlog. This evidence is consistent with the notion that analysts do not fully incorporate the implications of changes in order backlog into their forecasts, and investors overprice those stocks with high declines in order backlog. This finding also suggests that analysts play an important role in the market's underreaction to order backlog.

Our paper is different from RSV (2003) in that we provide compelling evidence of the market's underreaction to information on order backlog, inconsistent with RSV's overreaction explanation. We also provide corroborate evidence that the market's underreaction is in part attributable to analysts' bias in forecasts. We add more evidence to a growing body of literature on market inefficiency. This also enables us to better understand how the market perceives the order backlog-related signals. In addition, our paper contributes to the literature on the disclosure of non-GAAP leading indicators (Lev and Thiagarajan, 1993; Chandra, Procassini and Waymire, 1999) by providing evidence that order backlog is value-relevant and useful to investors.

Our findings have several disclosure implications for regulators and auditors with respect to order backlog, more broadly, non-GAAP leading indicators. Despite its recognized importance as a nonfinancial measure in valuation, the current GAAP does not require firms to disclose information on order backlog in their financial statements. This lack of information on non-GAAP leading indicators in turn deters investors from making informed decisions. Put differently, the information outside financial statements, such as changes in order backlog, are hidden from investors who would might wish to interpret their implications for valuation. Our findings highlight the importance of fully disclosing fundamental value drivers, in particular, non-GAAP leading indicators.

We note some caveats in this paper. Caution should be used when interpreting the results in this study. Order backlog must be disclosed in the Management Discussion and Analysis (MD & A) only if it is material. Our analyses are conditional on the existence of backlog data on COMPUSTAT.[2] Thus, our results may not be generalized to all COMPUSTAT firms. In addition, it is possible that unobservable firm characteristics related to changes in order backlog could cause the findings in this study. We will leave this issue for future research.

The remainder of the paper is organized as follows. Section 2 reviews prior literature on non-GAAP leading indicators. Section 3 describes our empirical procedures, including the sample selection and variable definitions. In section 4 we present the empirical results. The final section concludes the study.

LITERATUER REVIEW

There is a voluminous literature on non-GAAP leading indicators. Recent studies include customer satisfaction measures (Ittner and Larcker 1998), patent data (Deng, Lev, and Narin 1999), market penetration (Amir and Lev 1996), and eyeball measures in the internet industry (Trueman, Wong, and Zhang 2000). Ittner and Larcker (1998) examine the value relevance of customer satisfaction measures using customer, business-unit, and firm-level data and find that the relations between customer satisfaction measures and future accounting performance are positive and statistically significant. Deng, Lev, and Narin (1999) relate patent citation data to book-to-market ratios and firms' stock prices. Deng, Lev, and Narin (1999) find that patent citation data are positively related to investor growth expectations, but they find a somewhat weaker relation between patent citation data and stock prices. Amir and Lev (1996) examine the value-relevance in the wireless communication industry. They find that earnings, book values, and cash flows are generally irrelevant while nonfinancial measures such as POPs (growth potential) and market penetration determine

2) In our unreported results, we find that the mean market capitalization for firms with order backlog is smaller that that for the overall COMPUSTAT sample.

cellular values. Trueman, Wong, and Zhang (2000) find that while bottom-line net income is not significantly associated with stock prices, unique visitors and page views provide incremental explanatory power for stock prices, consistent with those who claim that financial information is of limited use in the valuation of internet stocks. These studies suggest that nonfinancial measures can be leading indicators of financial performance.

Even though order backlog is frequently used for valuation purposes in practice and is economically significant, the literature on order backlog is limited. Lev and Thiagarajan (1993) examine the value-relevance of various fundamental signals for future performance identified in Value Line analyst reports, such as receivables growth, inventory growth, capital expenditures, gross margin, etc. They consider the difference between sales changes and order backlog changes as one of 13 fundamental signals. They view an excess percentage change in order backlog over percentage change in sales as a bad signal and interpret this to result from poor management or opportunistic earnings management (which is prevalent in high-tech industries). They find that order backlog is value-relevant and has a positive association with future earnings. Also, this earnings management measure is associated with future returns.[3)] Relatedly, Liu, Livnat, and Ryan (1996) provide evidence that backlog disclosure is useful in predicting future sales.

Chandra, Procassini, and Waymire (1999) report significant stock price movements on the release dates of aggregate industry data for new orders and shipments (the industry book-to-bill ratio) by the Semiconductor Industry Association (SIA) each month. The industry information released is positively correlated with earnings changes in the subsequent, quarterly earnings announcements of firms within the industry. This study provides evidence that order backlog is a value-relevant indicator.

A recent study by RSV (2003) investigates whether the market incorporates the implications of order backlog, using the level of order backlog during the sample period of 1981-1999. They find that the level of order backlog is negatively related to future returns. In addition, they show that analysts efficiently process

3) Lev and Thiagarajan (1993) find that excess inventory growth is a bad signal and that order backlog is incremental to inventory changes to capture future performance.

this information, using the Mishkin test. However, they find evidence suggesting that the market places excessive emphasis on the order backlog signal because the extent to which order backlog predicts a firm's future earnings is not clear. Their results suggest that investors do not use value-relevant information provided by analysts.

Although RSV (2003) show the economic significance of order backlog, the level of order backlog could be a noisy predictor of future performance. The level of order backlog is associated with product cycles such that firms with long product cycles tend to have high order backlogs. By comparison, changes in order backlog filter this noise and provide a cross-sectionally comparable measure. This measure is also different than an earnings management proxy, sales changes less order backlog changes, suggested by Lev and Thiagarajan (1993), which captures the amount of unrealized sales recorded in the current year. Thus, an empirical examination of whether investors understand the implications of backlog using changes in order backlog is warranted.

SAMPLE SELECTION

Our initial sample of 41, 325 firm-years includes all firms with a non-zero order backlog from the year 2000 COMPUSTAT for the period of 1971-1999. We then delete 8,587 firm-year observations for which return data are not available from CRSP. This results in a final sample of 32,738 firm-year observations and 3,812 firms. To conduct an analysis that requires analysts' forecasts in IBES datasets, we match our sample with the IBES datasets. Our sample size reduces to 13,223 observations for the analysis of analyst forecast errors because of data availability. Our study uses annual, one-year-ahead earnings forecasts (FY1) from the I/B/E/S summary file.

Order backlog represents the dollar value of orders that are unfulfilled and are scheduled to be delivered in the future. The variable of interest in this study is order backlog change. We define order backlog change as follows:

$DBKLG_t$ = Backlog (data98) of year t deflated by average total assets in year t – Backlog (data98) of year t-*1* deflated by average total assets in year t-1.

We define two measures of analyst forecast errors as follows:

$$FERR1_{it} = (A_{it} - F_{it}) / |A_{it}| \text{(FERR1)}$$
$$FERR2_{it} = (A_{it} - F_{it}) / PRICE_{it} \text{(FERR2)}$$

where A_{it} = Actual EPS for firm i in year t,
F_{it} = median analyst forecast for firm i in year t,
$PRICE_{it}$ = stock price for firm i when the consensus is issued.

To eliminate outlier effects, we delete the forecast errors at the top 1 percent and the bottom 1 percent.[4] Table 1 provides statistics on changes in order backlog, returns, and forecast errors in the sample. Descriptive statistics related to changes in order backlog are reported in Panel A of table 1. The mean (median) value of order backlog changes is -0.014 (-0.007) for the whole sample. This indicates that order backlog change is on average -1.4% of average total assets. The breakdown of the sample into the three time periods is also provided. Although the COMPUSTAT coverage increases in recent years, the number of the order backlog observations remains stable across years. The standard deviation of order backlog change is 1.12, suggesting that the variable varies substantially during the sample period.

Panel B of table 1 reports the industry composition of the sample. Consistent with RSV (2003), the manufacturing industry (whose SIC codes range from 2000 to 3900) accounts for a large number of observations, about 78 percent of the sample. The service industry comprises another 8 percent of the sample.

Panel C of table 1 presents the descriptives of returns and forecast errors. The average of raw returns (size-adjusted returns) is 18.2% (16.6%). FERR1 (FERR2) for the average firm is -0.312 (-0.016), suggesting that analysts are on average optimistic.

In our untabulated results, we find that the level of order backlog (in the sample) varies substantially across industries.

4) FERR1 is likely to be exaggerated if the denominator is close to zero. We also eliminate firm-years where the absolute value of actual eps is less than 5 cents. The results are qualitatively similar.

Table 1. Descriptive Statistics

Panel A: Distribution of Order Backlog Changes						
	N	Mean	Std	Median	Quartile 1	Quartile 3
All	32,738	-0.0143	1.1185	-0.0065	-0.0090	0.0063
1971-1980	9,707	0.0100	0.4507	0.0029	-0.0860	0.0952
1981-1990	11,732	-0.0279	0.3923	-0.0141	-0.1044	0.0531
1991-1999	11,299	-0.0210	1.8139	-0.0077	-0.0813	0.0501

Panel B: Industry Composition						
	N	Mean	Std	Median	Quartile 1	Quartile 3
Mineral	306	0.0065	0.7125	-0.0090	-0.1033	0.0591
Construction	1,044	-0.0236	0.7248	-0.0094	-0.2080	0.1277
Manufacturing	25,640	-0.0182	1.1187	-0.0059	-0.0860	0.0624
Transport., Comm., Utilities	454	-0.0594	0.6578	-0.0087	-0.1174	0.0692
Wholesale Trade	1,071	0.0507	1.9038	-0.0071	-0.0743	0.0495
Retail Trade	230	-0.0152	0.1801	-0.0086	-0.0506	0.0156
Finance, Insurance, Real Estate	855	-0.0439	0.7205	-0.0084	-0.0672	0.0245
Service	2,824	0.0147	1.1311	-0.0077	-0.1352	0.1001
Other	314	-0.0236	0.2664	-0.0121	-0.1062	0.0510

Panel C: Distribution of Returns and Forecast Errors						
	N	Mean	Std	Median	Quartile 1	Quartile 3
Raw Returns	32,738	0.182	0.743	0.055	-0.217	0.403
Size Adjusted Returns	32,738	0.166	0.249	0.143	-0.006	0.307
FERR1	11,292	-0.312	1.284	-0.005	-0.162	0.035
FERR2	12,658	-0.016	0.066	-0.0002	-0.009	0.002

The size-adjusted returns are computed by subtracting the raw return on a size-matched portfolio formed from size-decile groupings provided by CRSP.

FERR1 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year $t + 1$) divided by the absolute value of actual eps.

FERR2 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year $t + 1$) divided by price.

For example, the means of the level of order backlog for the construction industry and service industry are 141 percent and 108 percent of average total assets, respectively. The means for manufacturing and finance are 52 percent and 33 percent, respectively, relative to average total assets. Transportation (which includes aircraft and ship building) maintains a mean of 115 percent of average total assets. These results support the view that the level of order backlog depends on the typical industry product cycle. This also suggests that RSV employ a noisy measure for the tests of market efficiency.

To test market efficiency, portfolio returns are constructed by compounding monthly returns on CRSP. To ensure that all the necessary accounting variables are known to the market, we match the accounting variables for all fiscal years ending in calendar year *t* and form decile portfolios 4 months after the fiscal year end where order backlog changes are reported. Then, we examine the subsequent performance of our portfolios for one year using returns data from CRSP. Stock returns are measured as compounded buy-hold returns, inclusive of dividends and other distributions. Following conventional practice, we replace firm returns with the corresponding size decile returns if the firm is delisted during the portfolio-holding period. But if a firm is established in the middle of the accumulation period, we start to accumulate returns from the first month it appears. Within each portfolio, we equally weight all the stocks and compute returns using the annual buy-and-hold strategy. Size-adjusted returns are the firm’s raw returns less the returns of the corresponding size decile, where size is measured using market capitalization at the fiscal year end.

EMPIRICAL RESULTS

Do Stock Prices Fully Incorporate the Information in Order Backlog Changes?

As noted above, we investigate whether the stock market acts as if it appreciates the implication of changes in order backlog.[5)]

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5) In an untabulated analysis, we also confirm that the change of order backlog is positively related with future earnings.

Table 2. Percentage Stock Returns for Portfolios on Order Backlog Changes: 1971-1999

	N	Mean Raw Returns	Mean Size-adjusted Returns	Median Raw Returns	Median Size-adjusted Returns
Low	3,262	0.0960	-0.0650	-0.0278	-0.1611
2	3,273	0.1600	-0.0032	0.0168	-0.1096
3	3,280	0.1484	-0.0199	0.0429	-0.0916
4	3,276	0.1948	0.0263	0.0611	-0.0637
5	3,271	0.1714	0.0052	0.0693	-0.0679
6	3,281	0.1986	0.0320	0.0793	-0.0449
7	3,278	0.1986	0.0332	0.0795	-0.0526
8	3,278	0.2041	0.0372	0.0794	-0.0512
9	3,275	0.2187	0.0487	0.0625	-0.0745
High	3,264	0.2361	0.0722	0.0705	-0.0528
High-Low		0.1401**	0.1372**	0.0983††	0.1083††

** denotes significance at the 0.01 level using a two-tailed t-test.
†† denotes significance at the 0.01 level using a two-tailed wilcoxon ranksum test.
The size-adjusted returns are computed by subtracting the raw return on a size-matched portfolio formed from size-decile groupings provided by CRSP.
The high-low return is the return from investing long in the highest order backlog change portfolio and investing short in the lowest order backlog change portfolio for zero net investment.

To address this issue, we form portfolios in the sample period with respect to changes in order backlog and examine whether these portfolios generate differential returns. For each year from 1971 to 1999, firms are sorted on the magnitude of order backlog changes and put in decile portfolios based on changes in order backlog. The returns are accumulated beginning 4 months after the fiscal year end.

In untabulated analysis, we replicate RSV (2003) and find a significant negative relation between the level of order backlog and size-adjusted returns ($p = 0.04$), consistent with RSV (2003). Table 2 reports raw returns and size-adjusted returns to the investment position based on changes in order backlog over the 29 years. The results show that both raw returns and size-adjusted returns are generally monotonically increasing with changes in order backlog. Portfolio returns range from 10% ($p < 0.01$) for the lowest order backlog change portfolio to 24% ($p < 0.01$) for the highest order backlog change portfolio. The mean (median) raw return difference between the highest and lowest decile portfolios is 14.0% (9.8%). On a size-adjusted basis, the mean (median) difference is 13.7% (10.8%). The mean return to a hedge portfolio taking a long position in the highest portfolio (biggest increases in order backlog) and a short position in the lowest portfolio is 14.0% on a raw return basis and 13.7% on a size-adjusted basis. The difference is statistically significant (p-value < 0.01). In an unreported analysis, there is evidence of the predicted, positive relation for the second year following portfolio formation. The remaining two columns in table 2 provide median portfolio returns. The results are generally consistent with those obtained in the means.

Furthermore, we examine whether this hedge portfolio strategy generates positive, abnormal returns across years. Figure 1 demonstrates the annual hedge portfolio return for each of the 29 years in the sample. The returns used to generate the plot are size-adjusted returns. The average of the 29 years is the mean size-adjusted return of 13.7% in table 2. Figure 1 illustrates that the hedge portfolio earns a positive return in 26 years out of the 29 years, suggesting that the relation between changes in order backlog and abnormal returns is not time-specific. The years producing a negative return are 1971, when the return was -0.09%; 1977, when the return was -0.05%; and 1999, when the return was -8.2%.[6)]

However, changes in order backlog might also reflect risk factors for individual stocks. Hence, the results in this section might not show the pure effect from changes in order backlog on stock returns. To check this possibility, we examine whether changes in order backlog are forecast in excess of those predicted by commonly used proxies for risk. To examine empirically the incremental effect of backlog changes on the predictability of abnormal returns, we run the following Fama and MacBeth-type cross-sectional regressions (Fama and French 1992) to control for risk factors.

6) Although not reported in Table 2, a hedge portfolio in fiscal 2000 produced 0.88% when the available return data were used.

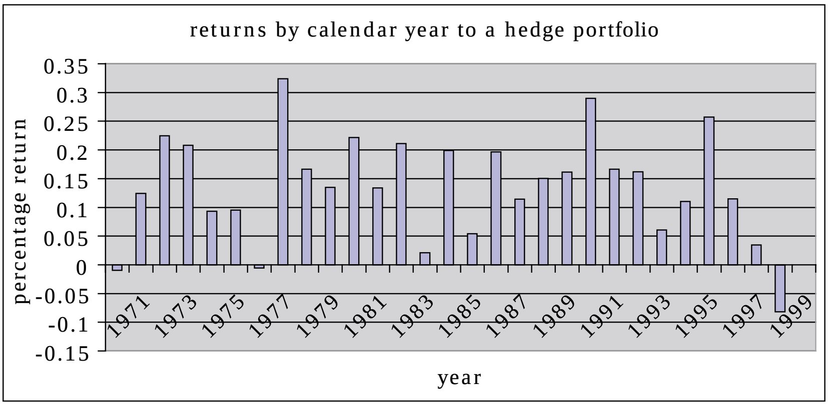


Figure 1. Returns by Calendar Year to a Hedge Portfolio
This figure presents mean returns to a hedge portfolio taking a long position in the stock of firms in the highest decile of order backlog change and a short position in the stock of firms in the lowest decile of order backlog change. Order backlog change is the difference in order backlogs (relative to average total assets) between year *t* and year *t* - 1.0.

$$RET_{it+1} = \beta_0 + \beta_1 DBKLG_{it} + \beta_2 LSIZE_{it} + \beta_3 BETA_{it} + \beta_4 BP_{it} + \beta_5 LEV_{it} + \beta_6 EP_{it}$$

where RET_{it+1} is one-year, buy-and-hold raw returns; $DBKLG_{it}$ is change in order backlog; $LSIZE_{it}$ is the log of size; $BETA_{it}$ is CAPM beta, measured by estimating the market model on the prior 60 monthly stock returns; BP_{it} is the book-to-market ratio; LEV_{it} is leverage, defined as the ratio of total assets to the book value of equity; and EP_{it} is the earnings-to-price ratio.

Table 3 provides additional evidence on the robustness of the association between changes in order backlog and returns. This table displays the mean coefficients from estimating the coefficients of the 29 regressions during the sample period from 1971 to 1999. For each year, we run a regression of returns on changes in order backlog and other risk factors. The means of the estimated coefficients are presented with *t*-statistics. *T*-statistics are computed using the ratio of the mean coefficient to the standard deviation of the annual coefficients. Table 3 reports the results from the regressions of returns on change in order backlog and a variety of other variables that have been shown to

Table 3. Mean Coefficient Estimates For Regression of Returns on Order Backlog Changes and Other Firms Characteristics: 1971-1999

$RET_{it+1} = \beta_0 + \beta_1 DBKLG_{it} + \beta_2 LSIZE_{it} + \beta_3 BETA_{it} + \beta_4 BP_{it} + \beta_5 LEV_{it} + \beta_6 EP_{it}$

Variable	Coefficients			
Intercept	0.194**	0.199**	0.179**	0.177**
DBKLG	0.065**	0.065**	0.064**	0.064**
LSIZE	-0.016**	-0.016**	-0.016**	-0.018**
BETA			0.017	0.018
BP	0.035**	0.035**	0.040**	0.037**
LEV		-0.001**	-0.001**	-0.001**
EP				0.050

** denotes significance at the 0.01 level using a two-tailed t-test.
t-statistic is computed as the ratio of the mean of the annual coefficients to the standard error from the coefficients distribution.
Regression coefficients are estimated for each year of the sample period. Coefficients are the mean of regression estimates over 29 regressions from 1971-1999.
R_{it+1} is one-year buy-and-hold raw returns.
$DBKLG_{it}$ is change in order backlog.
$LSIZE_{it}$ is the log of size.
$BETA_{it}$ is CAPM beta. It is estimated from regression of monthly raw returns on risk free rates and value weighted portfolio over a 60 month period before the portfolio is formed.
BP_{it} is book-to-market ratio.
LEV_{it} is leverage defined as total assets to book value of equity.
EP_{it} is earnings to price ratio.

predict returns (i.e., size, beta, book-to-market, leverage, and earnings-to-price). As expected, the mean coefficient on changes in order backlog is positive and statistically significant (the t-statistics range from 5.03 to 5.71 and the p-values are less than 0.01). The coefficients on the variables are interpreted as abnormal returns after controlling for other factors. We also repeat the analysis using size-adjusted returns (untabulated), and the results are quite similar. Thus, the predictability of future returns using changes in order backlog is incremental to the returns expected from risk factors. Our evidence indicates that the market places less weight on changes in order backlog for future performance. In other words, the market underreacts to the news embedded in changes in order backlog in predicting future performance.

Overall, the positive relation between changes in order backlog and abnormal returns is statistically significant. Changes in order backlog predict returns in excess of the returns expected from risk factors. These results suggest that the market underestimates the implications of changes in order backlog for future performance, which is inconsistent with RSV (2003).

Do Analysts Fully Incorporate the Information in Order Backlog Changes?

In this section, we examine whether analysts are efficient in processing the information contained in changes in order backlog. Specifically, to gain insights into investors' mispricing of order backlog, we examine the pattern of analysts' forecast errors. RSV (2003) suggest that analysts fully appreciate the implications of the level of order backlog for future earnings. Using a change variable, which is less subject to a measurement error, we reexamine RSV (2003).

Thus, an investigation into the role of analysts' forecasts in the relation adds to our understanding of whether analysts' systematic bias is attributable to mispricing. In fact, an abundance of prior research suggests that security analysts do not fully incorporate accounting information in their forecasts. For example, Mendenhall (1991), Abarbanell and Bernard (1992), and Eastwood and Nutt (1999) find that analysts underreact to past earnings information. Klein (1990), Lys and Sohn (1990), and Abarbanell (1991) present evidence that analysts underreact to past stock prices.

To test whether analysts' bias contributes to the mispricing of changes in order backlog, we examine the relation between changes in order backlog and analysts' forecast errors. If analysts fully incorporate the implications of changes in order backlog, then their forecast errors should not be related to changes in order backlog.

Using the IBES annual summary file, we measure the forecast errors for fiscal year t+1. We use the median forecast as the consensus forecast. Then, we relate changes in order backlog in fiscal year t to the forecast errors in fiscal year t+1. To ensure that analysts have order backlog information for fiscal year t, we

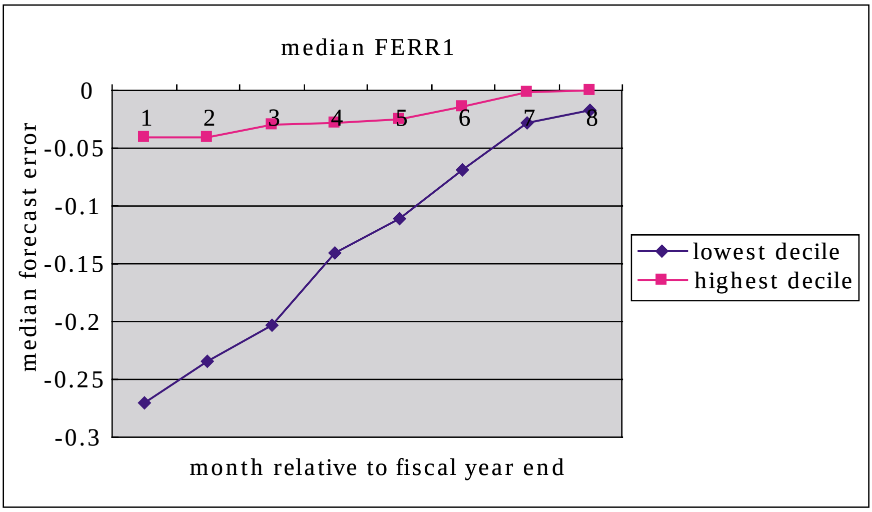
Table 4. Forecast Errors for Portfolios on Order Backlog Changes

	N	Mean *FERR*1	Median *FERR*1	N	Mean *FERR*2	Median *FERR*2
Low	1,129	-0.5226	-0.0174	1,132	-0.0596	-0.0012
2	1,246	-0.6264	-0.0237	1,247	-0.0375	-0.0015
3	1,334	-0.4346	-0.0049	1,339	-0.0580	-0.0002
4	1.360	-0.2999	-0.0097	1,363	-0.0356	-0.0006
5	1,376	-0.3254	-0.0074	1,374	-0.0216	-0.0004
6	1,351	-0.4681	0.0000	1,350	-0.0172	0.0000
7	1,349	-0.2134	-0.0054	1,347	-0.0234	-0.0004
8	1,267	-0.3330	0.0000	1,269	-0.0167	0.0000
9	1,197	-0.3926	0.0000	1,196	-0.0211	0.0000
High	1,042	-0.4519	0.0000	1,042	-0.0221	0.0000
High-Low		0.0707	$0.0174^{\dagger\dagger}$		0.0375**	$0.0012^{\dagger\dagger}$

** denotes significance at the 0.01 level using a two-tailed *t*-test.
†† denotes significance at the 0.01 level using a two-tailed wilcoxon ranksum test.
*FERR*1 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year *t*+1) divided by the absolute value of actual eps.
*FERR*2 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year *t*+1) divided by price.
The high-low forecast error is the difference between the forecast error in the highest order backlog change portfolio and the forecast error in the lowest order backlog change portfolio.

start to track their forecast errors from 7 months before the fiscal year end of year *t*+1. If analysts' forecasts fully reflect the information embedded in changes in order backlog, we expect that their forecast errors are not associated with changes in order backlog.

Table 4 provides the forecast errors across portfolios ranked on changes in order backlog at the fiscal period end of year *t*+1. Consistent with analyst bias in forecasts, there is a significant, positive relation between changes in order backlog and the forecast errors, except for the mean forecast errors (*FERR*1). The median forecast error from *FERR*1 in the lowest decile is 0.0174 (the optimistic bias is 1.74% relative to actual earnings) and that in the highest decile is 0.000 (almost unbiased). The difference in the forecast errors between the highest and lowest decile



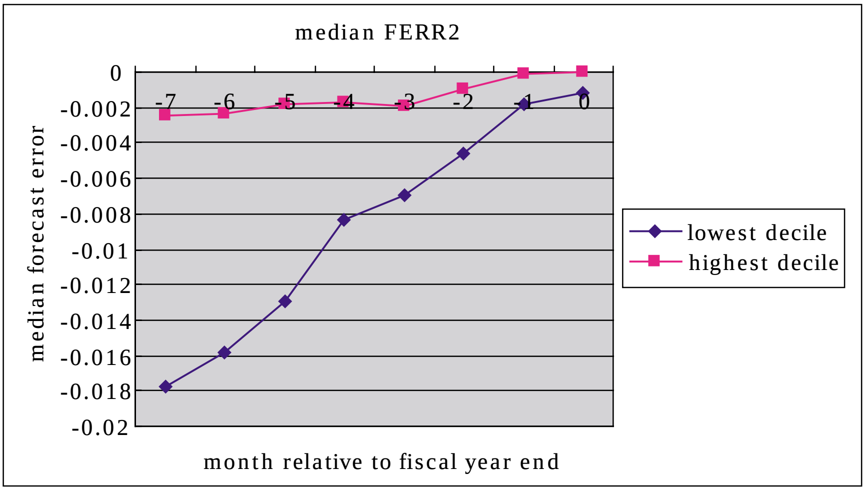


Figure 2. Analyst Forecast Errors for Deciles of Order Backlog Change Portfolios.

This figure presents median forecast errors in the next year after forming portfolios on ranked order order backlog changes. Month 0 is the month of the fiscal year end of year t+1. *FERR*1 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year t+1) divided by the absolute value of actual eps.

*FERR*2 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year t+1) divided by price.

portfolios is significant (p-value < 0.01). The fifth and sixth columns in Table 3 manifest the relation more clearly. The mean (median) forecast error from *FERR2* in the lowest decile is -0.0596 (-0.0012).[7)] In contrast, the mean (median) forecast error from *FERR2* in the highest decile is -0.0221 (0.000). The mean and median differences of the forecast errors between the highest and lowest decile portfolios are statistically significant (p-value < 0.01). Put differently, when the second forecast error (*FERR2*) is used, the mean (median) optimistic bias in the lowest decile is 5.9% (0.12%) relative to price, while the mean (median) optimistic bias in the highest decile is 2.2% (0.000%) relative to price.

To further investigate the pattern of forecast errors across changes in order backlog, we compute the median forecast errors from 7 months before fiscal year *t*+1. Figure 2 plots analysts' forecast errors (*FERR1* and *FERR2*, respectively) for fiscal year *t*+1 over the 7 months following the announcement of results in year t. It illustrates the behavior of the median forecast errors in the highest and lowest deciles of changes in order backlog. The most recent *FERR1* (*FERR2*) in the graph correspond to -0.017 (-0.001) for the lowest decile and 0.00 (0.00) for the highest decile in Table 4. Consistent with prior literature, optimism in analysts' forecasts decreases as the fiscal period end nears. The optimistic bias of the lowest decile (relative to the highest decile) is pronounced at all points in time. This suggests that analysts' overoptimism persists into year *t*+1 (over which returns are computed) for firms in the lowest decile group.

To formally test the relation between changes in order backlog and the forecast errors, we sort changes in order backlog into 10 groups and estimate the following regression:

$$FERR2_{it+1} = \beta_0 + \beta_1 RDBKLG_{it}$$

where $FERR2_{it+1}$ is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year *t*+1)

7) The forecast error deflated by price is more frequently used in the literature because the earnings deflator close to zero induces undue influence on the forecast error. For example, Abarbanell and Lehavy (2003), Bradshaw, Richardson, and Sloan (1999), and Brown (2001) compute the forecast error scaled by price.

Table 5. Regressions of Forecast Errors on Order Backlog Change

Panel A: FERR1	$FERR1_{it+1} = \beta_0 + \beta_1 RDBKLG_{it}$		
Month relative to the fiscal period end of year t + 1	β_0	β_1	Adj-R^2
-7	-0.989**	0.050**	0.004
-6	-0.886**	0.038**	0.003
-5	-0.823**	0.035**	0.003
-4	-0.702**	0.027**	0.002
-3	-0.644**	0.026**	0.002
-2	-0.558**	0.020**	0.001
-1	-0.441**	0.014**	0.001
0	-0.376**	0.014**	0.001
Panel B: FERR2	$FERR1_{it+1} = \beta_0 + \beta_1 RDBKLG_{it}$		
Month relative to the fiscal period end of year t + 1	β_0	β_1	Adj-R^2
-7	-0.068**	0.004**	0.003
-6	-0.104**	0.010*	0.000
-5	-0.062**	0.004**	0.002
-4	-0.059**	0.004**	0.002
-3	-0.056**	0.004**	0.002
-2	-0.052**	0.003**	0.001
-1	-0.050**	0.003**	0.001
0	-0.050**	0.004**	0.001

* denotes significance at the 0.05 level using a two-tailed t-test.
** denotes significance at the 0.01 level using a two-tailed t-test.
*FERR*1 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year t+1) divided by the absolute value of actual eps.
*FERR*2 is the forecast error defined as actual earnings less the median forecast (at the fiscal period end of year t+1) divided by price.
Month 0 is the month for the fiscal period end of year t+1. Month-1 is one month before the fiscal period end.
$RDBKLG_{it}$ is the portfolio decile

divided by price, and $RDBKLG_{it}$ is the portfolio decile ranking.

Table 5 provides statistical significance of the relation between changes in order backlog and analysts' forecast errors. We regress the forecast errors on the decile portfolio ranking of changes in order backlog from 7 months before the fiscal end of year t+1. Panel A of table 5 report the results from *FERR1*. The intercept is negative and statistically different from zero (p-value < 0.01), indicating that analysts' forecasts are on average optimistic. The coefficient on the decile ranking is positive and statistically significant. This means that analysts tend to be overoptimistic about low-decile portfolios (relative to high-decile portfolios). This pattern persists through the periods from -7 before the fiscal year end t+1 to the fiscal year end t+1. In Panel B of table 5, we also find similar results using *FERR2*. This evidence suggests that even though information on order backlog is publicly available, analysts do not adjust for their bias related to order backlog. Analysts appear to be more optimistic about those firms with steep declines in order backlog, consistent with the results from stock prices.

Taken together, the results are consistent with the conjecture that analysts' forecasts do not fully reflect the implications of changes in order backlog. The consensus forecast is more likely to be upwardly biased for low-decile portfolios. This upward bias contributes to the underperformance of low-decile portfolios. The evidence that changes in order backlog are not impounded in analysts' forecasts suggests that analysts contribute to the mispricing of order backlog.

CONCLUSIONS

Motivated by RSV (2003)'s evidence about investors overweighting information on order backlog and the use of a level variable (which may not be comparable across industries), we reexamine the relation between order backlog and future returns. Specifically, using changes in order backlog from the COMPUSTAT files from 1971 to 1999, we examine whether the market fully reflects the implications of changes in order backlog for future earnings. We confirm that order backlog numbers are economically significant when forecasting a firm's future earnings (untabulated).

However, contrary to RSV (2003), we find evidence that investors underreact to information embedded in order backlog changes. We find that changes in order backlog predict returns over those anticipated using risk proxies during the sample period. Our findings also demonstrate that professional investment intermediaries do not "see through" the information associated with changes in order backlog. They appear to be optimistic about firms with steep declines in order backlog, thus contributing to the overvaluation of those stocks.

In summary, we want to highlight the importance of the transparent disclosure of non-GAAP leading indicators. In this paper, we do not investigate why analysts and the market do not efficiently process information regarding changes in order backlog for future earnings. One interpretation of our results is that the disclosure of non-GAAP leading indicators is not transparent, and thus investors do not fully appreciate the implications of order backlog changes.[8)]

Consistently, a random examination of information on order backlog from financial statements in the sample firms shows a wide variation of disclosure quality. It would be useful to gain additional insights into whether firms use order backlog disclosure strategically and the extent to which the return predictability using changes in order backlog is a result of this behavior. We are hoping that future research sheds light on understanding this issue.

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8) Glassman, former SEC commissioner, indicated that firms need to increase in transparency of disclosures in non-GAAP financial information in his 2003 speech.

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