Information in Order Backlog: Change versus Level

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Abstract

Information on order backlog has been disclosed in the notes to financial statements since 1970. However, it is not clear whether financial analysts understand its importance. Empirical researchers have pesented mixed evidence about the information of order backlog and how the analysts and investors react to it. We show that almost all information in order backlog is in the change, and that both the stock market and financial analysts substantially underreact to the information: While both the stock market and financial analysts partially understand the implication of an increase in order backlog on future sales growth, it appears as if they have no idea at all that the increase also implies better future profitability. This leads to an economically significant hedge return from a portfolio formed based on the change in order backlog. The results suggest that the disclosures of nonfinancial information and leading business indicators needs to be substantially improved.

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1. Introduction

Recent concerns about the change in the relevance of financial statements have led to substantial interest in non-financial disclosure and leading business indicators. One of the most important disclosures of this type is order backlog. However, existing research on the value relevance of order backlog produces mixed evidence. For example, Myers (1999) and Francis, Schipper, Vincent (2003) find weak or no evidence that order backlog predicts future performance of a firm, while Behn (1996) shows that stock market reacts to order backlog as if it is relevant.

Another important question is whether stock market incorporates fully these types of information. Empirical evidence shows that investors often underreact to financial information such as earnings (as in the case of post-earnings announcement drift, Bernard and Thomas, 1989), accruals, (Sloan, 1996), and inventory (Thomas and Zhang, 2002). It has been shown, however, that investors overreact to information in order backlog, leading to relatively low future return from high backlog firms, see, for example, Lev and Thiagarajan (1993) and Rajgopal, Shevlin, and Venkatachalam (2003). If investors react to nonfinancial information and leading indicators more than the financial statements, standard-setters may encourage more disclosures in terms of non-financial disclosures.

In this paper, we reconcile the results from different research on order backlog by studying two different measures of order backlog: the level and the change. We measure the change as the change in the ratio of order backlog to assets or sales. Our results show that almost all the information in order backlog is in the change, not in the level. This accounts for the relative insignificance of backlog in predicting future earnings change as observed in Myers (1999) and Rajgopal, et al. (2003).

We find that the change in order backlog provides important information about future earnings, but the stock market substantially underreacts to such information. On average, the portfolio based on the top and bottom deciles of the change in order backlog-to-assets ratio earns an abnormal return of 13% per year from 1971-2006. Therefore, the hedge return is not only statistically significant, it is also economically significant. This return is not diminished by the inclusion of various risk factors, such as the beta, size, and market-to-book ratio, and known market inefficiencies such as accruals and inventory information.

In the spirit of financial statement analysis (e.g. Penman (2004), Fairfield and Yohn (2002)), we decompose the change in earnings into sales growth and profitability change, and examine the implications of order backlog in depth. We find that the stock market partially recognizes the information content of order backlog on sales growth, but underreacts to it. However, even though the market partially recognizes the information from the change in order backlog, Mishkin tests show that the market behaves as if the change in order backlog has no information on future profitibility. We consider this as evidence that earnings increase resulting from backlog increase is of high quality and thus has a high earnings response coefficient, so that lagged partial response to the expected earnings change due to order backlog is as high as normal response to unexpected earnings change.

The results show that the market inefficiency is due to the lack of understanding of the information as well as the lack of publicity of the information. From the analysis, we observe that, however, the information efficiency of order backlog is improving over the years. Our further analysis suggests that such market inefficiency is at least partially related to financial analysts' inefficiency in recognizing the information in order backlog. Analysts' earnings forecasts only partially reflect the information in the change of order backlog.

The information in order backlog has long been reported in the Notes to Financial Statements. COMPUSTAT collected data for a large number of firms from annual reports going back to 1969. The information is quantitative and the format is relatively simple. Therefore, one can expect that investors and financial analysts are relatively familiar with them and the stock price should be relatively more efficient in incorporating the information than other types of information in the Notes. If the stock market is inefficient in incorporating this information, then it is less likely that investors would price efficiently other types of information, such as customer satisfaction (Ittner and Larcker, 1998) and patents (Deng and Lev, 1996). Inefficiency of stock market in incorporating order backlog would suggest that the disclosures of leading indicators need to be substantially enhanced. This raises substantial challenges on how to facilitate market efficiency with a better disclosure of leading business indicators. This paper suggests that such a disclosure should focus on the change, rather than the level, of the measures.

The remainder of this paper is organized as follows: Section 2 describes our test procedures. Section 3 descirbes the sample we use and presents the empirical results.

Section 4 concludes.

2. Data and Models

In this section we consider the models to use for evaluating the efficiency of order backlog. Lev and Thiagarajan (1993) define order backlog variable as the difference between the growth rate of order backlog and the growth rate in sales. While this attempts to measure the new information in order backlog, the variable is unstable for firms with small backlog. Myers (1999) and Rajgopal *et al.* (2003) overcome the problem by using the level of order backlog-to-average assets and includes lagged order backlog as a robustness study. Even through this captures the change in the order backlog, they focus on the level rather than change. Note that if the information of order backlog is in its change, then the coefficient of the lagged backlog would be opposite to that of the level.

In this paper, we consider the change in the ratio of order backlog-to-assets (ΔBKLG) and compare its information content with the level (BKLG). This definition measures the new information in order backlog. To evaluate the information in order backlog, we estimate the following model

$$Y_{t+1} = \omega_o + \omega_1 Y_t + \omega_2 \Delta \mathrm{BKLG}_t + \omega_3 \mathrm{BKLG}_t + \text{Control Variables} + \varepsilon, \qquad (1)$$

where Y is the dependent variable such as sales growth (SaleGr), profitability measure (return on assets, ROA), the total earnings, and the contemporaneous stock return. This allows us to measure the information content of order backlog on different operating performance measures of the firm. We consider sales growth because order backlog is basically information about future sales. The control variables include the lagged market-to-book ratio, the change in the inventory-to-assets ratio, and accruals-to-assets ratio. Since we expect that an increase in order backlog is associated with future sales growth and an increase in future profit margin, therefore we have

$$\text{Hypothesis I: } \omega_2 > 0$$

in all cases when the dependent variable is sales growth or profit measure. Since we expect the new information to be in the change of order backlog, we expect that ΔBKLG to be substantially more significant than BKLG.

Our second step of the analysis includes the prediction of abnormal return based on the information in order backlog. We use the size-adjusted return (SAR) and evaluate the abnormal return of the level and change of order backlog,

$$\mathrm{SAR}_{t+1} = \beta_o + \beta_1 Y_t + \beta_2 \Delta\mathrm{BKLG}_t + \beta_3 \mathrm{BKLG}_t + Control\ Variables + \varepsilon, \tag{2}$$

where Y_t includes both sales growth and profitability measure. The control variables include accruals and market-to-book ratio.

While the hedge return and regression (2) provide some ideas about market efficiency with regard to the information in order backlog, a more formal test of efficiency is through the Mishkin test (Mishkin, 1983) following Sloan (1996) and Xie (2001). Consider the joint model,

$$\begin{aligned} Y_{t+1} &= \omega_o + \omega_1 Y_t + \omega_2 \Delta\mathrm{BKLG}_t + \omega_3 \mathrm{BKLG}_t + \varepsilon_{t+1} \\ \mathrm{SAR}_{t+1} &= \beta_o + \beta_1 (Y_{t+1} - \omega_o^* - \omega_1^* Y_t - \omega_2^* \Delta\mathrm{BKLG}_t - \omega_3^* \mathrm{BKLG}_t) + \varepsilon'_{t+1}. \end{aligned} \tag{3}$$

Here Y_t is future earnings, future sales growth, or future earnings. The Mishkin test for the market efficiency with regard to order backlog evaluates the null hypothesis that $\omega_2 = \omega_2^*$ and $\omega_3 = \omega_3^*$. If the null hypothesis holds, then the market correctly weights at period t the impact of order backlog on future value of Y, Y_{t+1}, so that unexpected return SAR_{t+1} is correlated only with the unexpected value of Y. Given Hypothesis (I) that $\omega_2 > 0$, if $\omega_2^* < \omega_2$, the stock market underreact to the information in the change in order backlog. Empirical research shows that the stock market underreacts to accounting information such as earnings, accruals, and inventory change, we expect the same effect to hold for backlog information, that is,

$$\text{Hypothesis II: } \omega_2^* < \omega_2.$$

This hypothesis is qualitatively different from Rajgopal, *et al.* (2003) who find that stock market overreact to the level of order backlog, that is, $\omega_3 > \omega_3^*$.

In Hypothesis I we hypothesize that an increase in order backlog signals an increase in both the future profit and future sales growth. It has been observed empirically that sales growth has an additional valuation effect than profit increase (Swaminathan and Weintrop, 1991, Ghosh, Gu, and Jain, 2003), we expect that the abnormal stock return depends on both unexpected profit and unexpected sales growth. To test this, we extend the Mishkin test in equation (3) to test two variables,

$$\begin{aligned}
\text{SaleGr}_{t+1} &= \omega_o + \omega_1 \text{SaleGr}_t + \omega_2 \Delta\text{BKLG}_t + \omega_3 \text{BKLG}_t + \varepsilon_{t+1} \\
\text{EARN}_{t+1} &= \rho_o + \rho_1 \text{EARN}_t + \rho_2 \Delta\text{BKLG}_t + \rho_3 \text{BKLG}_t + \varepsilon_{t+1} \\
\text{SAR}_{t+1} &= \beta_o + \beta_1(\text{SaleGr}_{t+1} - \omega_1^* \text{SaleGr}_t) + \delta_1(\text{EARN}_{t+1} - \rho_1^* \text{EARN}_t) \\
&\quad - \beta_2 \Delta\text{BKLG}_t - \beta_3 \text{BKLG}_t + \varepsilon'_{t+1}.
\end{aligned} \tag{4}$$

Market efficiency for lagged sales growth and earnings requires that $\omega_1^* = \omega_1$ and $\rho_1^* = \rho_1$, and for change in order backlog, it requires that

$$\beta_2 = \beta_1\omega_2 + \delta_1\rho_2.$$

When the stock market has an overall underreaction to order backlog, we expect that $\beta_2 < \beta_1\omega_2 + \delta_1\rho_2$. The test statistics based on likelihood ratios are given in the tables.

Given the market inefficiency hypothesized in (I) and (II), it is interesting to see whether such inefficiency is related to financial analysts. To evaluate whether the analysts take the order backlog into consideration in creating their earnings estimate, we use the model

$$\begin{aligned} \text{EARN}_{t+1} &= \omega_o + \omega_1\text{EARN}_t + \omega_2\Delta\text{BKLG}_t + \omega_3\text{BKLG}_t + \varepsilon_{t+1} \\ FE_{t+1} &= \gamma_o + \gamma_1\text{EARN}_t + \gamma_2\Delta\text{BKLG}_t + \gamma_3\text{BKLG}_t + \varepsilon'_{t+1}, \end{aligned} \quad (5)$$

where FE_{t+1} is the earnings estimate for year $t+1$. If analysts partially recognize the effect of order backlog, we expect that $\gamma_2 < \omega_2$ and $\gamma_3 < \omega_3$.

4. Empirical Results

In this section we evaluate the hypothesis that investors and financial analysts underreact to the information in the change of order backlog. Our results can be summarized as follows:

- An increase in order backlog represents favorable information about both future sales growth and profitability. The level of order backlog contains much less information.
- Investors underreact to the information, leading to substantial abnormal return for a hedge portfolio based on the change in order backlog. They behave as if the

information has only impact on sales growth but no impact on profitability.

- The underreaction may be related to the bias in financial analysts, who also behave as if the information has no impact on profitability.

The data required for the estimation are obtained from COMPUSTAT 2006. We use firms that have reported non-zero order backlog (COMPUSTAT item #98). The information is available starting from 1969. We use the data from 1971-2006. For each given year t, a firm is included in the sample if it reports order backlog, sales revenue, assets, earnings for both year t and $t-1$, and has earnings for year $t+1$. For each variable, the bottom and top 1% of the observations are deleted to control for outliers. The final sample consists of 28,225 observations.

We conduct the analysis with all variables scaled by average total assets. Order backlog BKLG is calculated as a fraction of the order backlog (COMPUSTAT item #98) relative to assets. The change in order backlog is calculated as

$$\Delta\text{BKLG}_t = \frac{\text{Order Backlog}_t}{\text{Assets}_t} - \frac{\text{Order Backlog}_{t-1}}{\text{Assets}_{t-1}}.$$

Since order backlog also represents future sales volume, we also consider using sales revenue as the scaling factor. The results are very similar and are thus not reported. The accruals are calculated as defined by Sloan (1996),

$$\text{Accruals} = \Delta(\text{CA} - \text{Cash}) - \Delta(\text{CL} - \text{SL}) - \text{DEP},$$

where CA is the current assets (#4), Cash is the cash and short-term investments (#1), CL is the current liabilities (#5), SL is the debt in current liabilities (#34), and DEP is the depreciation and amortization expenses. Using this definition of accruals allows us to use data before 1987 when the statement of cash flow are not available.

The stock return data are obtained from the CRSP database. For each year, the future return is measured from 4 months after the fiscal yearend. Both the raw return and size-adjusted return are used.

The data for analysts' estimate are obtained from IBES database. Only firms with December yearend are used. We use the mean earnings estimate at June of the same year. Since we use the total assets to deflate both the earnings estimates and actual earnings, we only include firms with number of shares reported in IBES. This is because IBES adjusts the per-share number using most recent share bases, while COMPUSTAT uses historical share basis. While there is some difference between the IBES actual earnings and COMPUSTAT earnings (Abarbanell and Lehavy, 2000), using either one of them produces effectively identical results in our case. Therefore, we will continue to use COMPUSTAT actual earnings. After removing the top and bottom one percentile of the variables, the sample consists of 4466 firm-years.

Table 1 gives the descriptive statistics of the variables used. The mean backlog-to-assets ratio is 50.6% in the firms considered. Thus the level of backlog is substantial to these firms. Note that the standard deviation in ΔBKLG is slightly less than half that of BKLG. Thus when economically speaking, the coefficient of ΔBKLG needs to be twice that of BKLG to achieve the same economic significance.

Table 2 presents the regression results of model (1) based on one-year ahead sales growth, profitability as measured by ROA, and the earnings change. The models are estimated using Fama-MacBeth method (Fama and MacBeth, 1973), so that the coefficients presented are the average values from annual regressions, and the t-ratios are based on the time series standard deviation of the coefficient estimates. For sales growth, the simple regression on lagged sales growth yields an R^2 of 5.4%. However, including the change in and the level of order backlog increase the R^2 to 15.5%, almost tripling the R^2. This indicates that the information in order backlog is highly significant for explaining future sales growth. For firms with order backlog, it is indeed as important as the lagged sales growth. Comparing the difference between ΔBKLG and BKLG, one finds that the coefficient on the change in order backlog (ω_2=0.348, t=22.2) is much more significant than that for the level (ω_2=0.038, t=4.1). Therefore, we can say that the information in order backlog is mainly in the change of the measure, not the level. The last column includes the accruals and book-to-market ratio as control variables. A high value in B/M ratio indicates a low growth perspective, and thus shows a negative association with future revenue growth. High accruals are considered to be associated with growth firms (McNichols, 2002), as confirmed by the model. The inclusion of these two control variables, however, causes almost no change in the significance of order backlog. Therefore, the information in lagged order backlog is incremental to these control variables.

Panel B of Table 2 shows the results for profitabilty change (ROA). As expected, profitability change is negatively related to the lagged ROA due to mean reversion in profitability (Nissim and Penman, 2001). The level of order backlog (BKLG) is insignificant (ρ_3 = 0.004, t=1.5) when adding together with the change (ΔBKLG). The inclusion of order backlog information increases R^2 from 14% to 15.6%. The increase in R^2 is not high but ΔBKLG is highly significant ($\rho_2 = 0.055$, t=15.5). A high B/M ratio reflects a negative business environment and thus have a negative coefficient (-0.013, t=-9.4). High accruals indicate low earnings quality (Sloan, 1996) and thus also have a negative effect on future profitability. Adding B/M ratio and accruals in the regression as control variables indeed makes ΔBKLG more significant. Note that ΔBKLG is the second most significant variable in the regression with the control variables. Thus the change in order backlog represents important information about a firm's future profitability change. Given that an increase in order backlog is likely to be caused by an increase in demand, it is not surprising that an increase in ΔBKLG is associtd with higher future demand, and hence give the firm rooms to improve profitibility.

Combining the results in sales growth and profitability change we get the earnings change in panel C of Table 2. The results are basically similar to panel B. This is because the change in profit margin typically dominates the change in sales growth. One percent decrease in ROA have much higher impact on earning than one percent increase in sales. Therefore we observe that ΔBKLG remains highly significant while BKLG is insignificant, with and without the control variables. This indicates that the useful information about 1-year ahead earnings change is in ΔBKLG, rather than in BKLG.

Given the information in order backlog, we now investigate how investors react to it. Table 2(D) gives a regression of contemporaneous stock return on earnings, sales growth, order backlog, and control variables. When contemporaneous change and level of order backlog are added to the model separately, they are both significant. When they are both added, ΔBKLG remains significant (coefficient=0.313, t=4.0), while the level $BKLG$ becomes insignificant (coefficient=0.015, t=1.0). When beginning book-to-market ratio and beginning accruals are added, the significance of ΔBKLG and BKLG has little change. The results reconfirm that the information in order backlog is in the change, ΔBKLG, rather than BKLG. As shown in Behn (1996), the stock price incorporates at least part of the information in ΔBKLG.

In this paper, we focus on whether the stock market fully incorporates the information in the change in order backlog, that is, whether the change in order backlog predicts future return. Table 3 (A-B) shows that average future return and size-adjusted future return of portfolios formed on the deciles of the change in order backlog, together with the level of order backlog, inventory change, book-to-market ratio, and accruals. The hedge portfolio that takes a long position on stocks in the top decile of ΔBKLG and a short position on the stocks in the bottom decile gives an average annual return of 13% over the period of 1971-2006. The size-adjusted return from the same hedge portfolio is 12.9%. As a comparison, the hedge portfolio formed on the top and bottom deciles of the level of order backlog gives a raw return of 2% and size-adjusted return of 4.5%. Thus the hedge return from the change portfolio is substantially higher than that from the level portfolio. The evidence shows that investors fail to appreciate the information in the change of order backlog.

The hedge return of 13% based on the top and bottom deciles of ΔBKLG is quite substantial, compared to the hedge portfolio formed on the top and bottom deciles in inventory change (5.7% raw return and 6.6% size adjusted return), book-to-market ratio

(12.7% raw return and 6.9% size-adjuted return) and the accruals (20% raw return and 17.7% size-adjusted return). The results for these other variables are consistent with what have been found in other research.

To evaluate the extent to which these variables explain the anomaly in order backlog, we construct portfolio returns based on combinations of two factors at a time: ΔBKLG versus B/M ratio and ΔBKLG versus accruals. From Table 4, we observe that the portfolio return is still increasing in ΔBKLG for each B/M classification and for each accruals classification. The hedge raw returns for the highest−lowest ΔBKLG groups for the five B/M grouping are 8.9%, 7.9%, 3.9%, 15.9%, and 8.7%. For the five accruals groupings, the hedge returns are 7.8%, 6.5%, 10.4%, 11.9%, and 6.5%. Similar values are observed for size-adjusted returns. Based on these values, it is clear that the abnormal returns of different variables studied here are not uncorrelated. However, the change in order backlog does produce abnormal return that is not explained by the B/M ratio or accruals.

Table 5 shows similar conclusion using a regression method with the size-adjusted return (SAR). The results are based on Fama-MacBeth method. In the simple regression of SAR, ΔBKLG is highly significant (coefficient=0.154, t=4.59), while the level BKLG is not significant (coefficient=0.032, t=1.76) at 5% level. BKLG becomes slightly less significant in a multiple regression with ΔBKLG. The control variable B/M ratio has a positive coefficient (0.025, t=1.96) while the accruals variable has a negative coefficient (−0.443, t=−4.48). The inclusion of these two factors reduces the significance of the variable ΔBKLG only slightly. Therefore the abnormal return from change in order backlog cannot be explained by the book-to-market ratio or the accruals phenomenon.

Table 6 gives a more rigorous test of market efficiency based on the Mishkin test. Panel A gives the estimation based on earnings. As in the Fama-MacBeth regression in Table 2, future earnings shows strong positive association with lagged earnings (coefficient=0.665, t=119). From the return model, lagged earnings has a relative coefficient of $\omega_1^* = 0.639$. The difference shows a slight market underreaction to earnings, but the Mishkin test is not significant (p-value=0.265).

From the table, the earnings equation shows that future earnings is strongly associated with the change in order backlog (coefficient=0.061, t=21.2). However, the return model shows almost no association with ΔBKLG (coefficient=0.003, t=0.3). This indicates that investors use an unexpected earnings that is measured relative to lagged earnings but not with ΔBKLG. In other words, investors are surprised by any future earnings change that is predictable by ΔBKLG. It appears as if the stock market has totally no idea at all that an increase in order backlog would increase future earnings. The Mishkin test reject market efficiency in ΔBKLG with a χ^2=32.56 (p-value=0).

The observation that the stock market appears to have anticipated no earnings increase from an increase in backlog conflicts with earlier observation from contemporaneous return that the market partially incorporates the information in backlog change. An interpretation (and an explanantion) is that the quality of earnings increase from backlog increase is higher, so that its earnings response coefficient is higher for this part of earnings than for average unexpected earnings. That is, the market responds more to this portion of earnings increase. This is not suprising as earnings increase from backlog increase in more likely to be due to growth in sales revenue, which is deemed to have higher quality (Ghosh, Gu, and Jain, 2005). Since the models do not (and cannot) allow for different earnings response coefficient (β_1) for different type of earnings, partial response to the earnings from backlog change can be equal to the average response to unexpected earnings, leading to the observation that stock market appears to have no idea about the earnings change due to backlog.

As observed in Table 2, the stock market also appears to slightly underreact to information in the level of order backlog. It also appears as if the stock market has no idea that BKLG predicts future return. But since BKLG has a much weaker relationship to future earnings, the market inefficiency is also less significant (χ^2=5.13, p-value=0.023).

Table 6 Panel B show the results of market efficiency tests with regard to sales growth. Sales growth are positively autocorrelated, with the coefficient of lagged sales growth of 0.263 (t=45.3). The market appears to overreact to this, so that $\rho_1 < \rho_1^*$. The Mishkin test rejects market efficiency in lagged sales growth with a χ^2=14.5 (p-value=0). The market behaves as if the sales growth is much more persistent than it actually is. This phenomenon is well documented in the glamor versus value stocks literature, which shows that the glamor stocks (with high growth rate) tend to have low future return (Lakonishnok, Shleifer, Vishny, 1994).

From the table, we again observe that sales growth is highly correlated with ΔBKLG (coefficient=0.345, t=53.0). Market recognizes about half of the dependence, with

$\rho_2^* = 0.178$ (t=4.7). Therefore, the Mishkin test strongly rejects the hypothesis of market efficiency, with χ^2=19.35 and p-value=0. For the level of BKLG, the market efficiency hypothesis is rejected also, with χ^2=6.91 and p-value of 0.009. Even though the level is weakly correlated with future sales growth, stock market behaves as if this is no relationship between them.

Panels C of Table 6 provides a joint test of market efficiency assuming that the abnormal return is related to both unexpected earnings and unexpected sales growth. The results suggest that the stock market underreacts to lagged earnings news, since the hypothesis that $\omega_1^* = \omega_1$ is rejected, and $\hat{\omega}_1^* < \hat{\omega}_1$. This result is not surprising given the well-known phenomenon of post-earnings announcement drift (Bernard and Thomas, 1989). The result also indicates market overreaction on sales growth (χ^2=41.92, p-value=0), and underreaction to the change (χ^2=15.72, p-value=0) and the level (χ^2=8.20, p-value=0.004) of order backlog.

To investigate what leads to the market inefficiency in order backlog, we consider how financial analysts react to the information in Table 7. Note that the data set is substantially smaller due to the requirement of analysts' estimate data. Using Fama-MacBeth regressions over the 21 years from 1985 to 2006, we again observe that actual earnings is strongly associated with the change in order backlog (coefficient=0.063, p-value=5.44) but not associated with the level (coefficient=0.010, p-value=0.34). The table shows that analysts' estimates are insignificantly associated with ΔBKLG (coefficient=−0.008, t=−1.73). This suggests that analysts totally ignore the information in ΔBKLG, which leads to a significantly positive association between the analyst's forecast error and

ΔBKLG.

The results also suggest that analysts respond negatively to a high level of order backlog (coefficient=−0.1, t=−4.97), although the forecast error is much less associated with level. Such a result seems counterintuitive. A further investigation indicates that the negative association between analysts' estimate and the level of order backlog is related to analysts' pessimism on certain sectors and the strong mean reversal of negative earnings firms.

5. Conclusions

This paper studies the information in order backlog. We find that almost all the information in order backlog lies in the change in the ratio of order backlog-to-assets ratio, and the level (or the dollar value) of the order backlog is much less informative compared to the change.

Our results indicate that an increase in the order backlog-to-assets ratio predicts both higher future sales growth and higher future profitability. The stock market responds favorably to the information, but fails to incorporate all the information. Indeed, the stock return responds to the predicted increase in profitability due to order backlog as if it was completely unpredicted. This leads to substantial hedge return using portfolios formed based on the change in order backlog-to-assets ratio.

The apparent anomaly in order backlog is partly due to the inefficiency in financial analysts' earnings estimates. Analysis of the estimates indicates that analysts fail to incorporate much of the predicted profitability increase into their estimates.

The market inefficiency raises interesting questions about the disclosure of leading indicator information. The analysis suggests that investors, including sophisticated financial analysts, have substantial difficulties in understanding the prediction roles in order backlog. Therefore, a more and better disclosure of the information is much needed. Given that order backlog is a relatively traditional and popular leading indicator, it is likely that the issue is even more important for other leading indicators that are less well known.

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Table 1: Summary Statistics

Variable	Mean	Stdev	10-th Percentile	Median	90-th Percentile
RET	0.178	0.759	-0.448	0.048	0.857
SAR	-0.002	0.704	-0.634	-0.121	0.670
BKLG	0.506	0.542	0.079	0.330	1.129
ΔBKLG	-0.013	0.227	-0.226	-0.005	0.187
EARN	0.037	0.098	-0.063	0.051	0.130
ΔEARN	0.002	0.090	-0.085	0.008	0.075
ΔROA	-0.008	0.089	-0.096	-0.001	0.066
SaleGr	0.084	0.227	-0.167	0.089	0.335
Accruals	-0.020	0.102	-0.134	-0.018	0.099
B/M Ratio	0.901	0.695	0.248	0.725	1.813
FEARN	0.061	0.058	0.013	0.057	0.122

For all variables except FEARN, the total number of observations is 28225, spanning from 1971-2006. For FEARN (analysts' mean earnings estimate scaled by average assets), the number of observations is 4466, spanning from 1985-2006. The variables are defined as follows:

RET:	12-month buy and hold return beginning 4 months after fiscal year-end
SAR:	12-month buy and hold return beginning 4 months after fiscal year-end less corresponding size portfolio buy and hold return.
BKLG:	order backlog divided by average total assets.
ΔBKLG:	$BKLG_t$-$BKLG_{t-1}$
EARN:	income before extraordinary items and discontinued operations divided by average total assets.
SaleGr:	Change in sales revenue divided by lagged sales revenue.
Accruals:	the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable), less depreciation expense.
B/M Ratio:	the ratio of the book to market value measured at the beginning of the abnormal return accumulation period.
FEARN:	I/B/E/S analysts' mean earnings estimate scaled by average assets;

Table 2: Information in Order Backlog

The models are estimated using the Fama-MacBeth approach with data from 1971-2006. Each column represents one model. Each coefficient is the average of the corresponding coefficient from 29 annual regressions. Given in the parentheses are the t-ratios calculated from the time series of annual coefficients.

	A: Dependent Variable: Sales Growth		
LagEARN	0.230 (16.2)	0.300 (23.7)	0.231 (22.0)
ΔBKLG		0.348 (22.2)	0.337 (21.9)
BKLG		0.038 (4.1)	0.033 (3.9)
Accruals			0.184 (11.5)
B/M Ratio			-0.052 (12.3)
Average R^2	5.4%	15.5%	17.7%
	B: Dependent Variable: Change in ROA		
LagEARN	-0.341 (0.34)	-0.336 (35.8)	-0.306 (26.8)
ΔBKLG		0.055 (15.5)	0.055 (16.4)
BKLG		0.004 (1.5)	0.003 (1.3)
Accruals			-0.112 (12.4)
B/M Ratio			-0.013 (9.4)
Average R^2	14.0%	15.6%	17.5%
	C: Dependent Variable: Future Earnings		
LagEARN	0.679 (53.7)	0.683 (54.3)	0.715 (50.9)
ΔBKLG		0.055 (17.2)	0.055 (18.8)
BKLG		0.003 (1.1)	0.002 (0.7)
Accruals			-0.131 (14.9)
B/M Ratio			-0.019 (12.5)
Average R^2	12.2%	13.7%	16.6%

D: Dependent Variable: Contemporaneous Return

EARN	1.179 (5.2)	1.155 (5.4)	1.170 (5.3)	1.159 (5.4)	1.113 (5.4)
LagEARN	-0.750 (3.5)	-0.705 (3.8)	-0.724 (3.6)	-0.704 (3.8)	-0.573 (3.4)
SaleGr	0.239 (4.1)	0.301 (4.2)	0.244 (4.0)	0.299 (4.1)	0.332 (4.4)
LagSaleGr	-0.129 (3.4)	-0.118 (3.5)	-0.131 (3.4)	-0.116 (3.5)	-0.050 (1.8)
ΔBKLG		0.315 (4.1)		0.313 (4.0)	0.303 (3.9)
BKLG			0.060 (3.0)	0.015 (1.0)	0.021 (1.3)
Accruals					-0.310 (3.6)
B/M Ratio					0.052 (3.5)
Average R^2	8.8%	10.1%	9.5%	10.4%	11.3%

Table 3: Portfolio Returns Based on Order Backlog

The table gives 12-month buy and hold raw return and size-adjusted return beginning 4 months after fiscal year-end. The returns are averaged over 1971-2006. The deciles are based on ranking of each variable within each year from low to high. Highest=highest decile; Lowest=lowest decile.

	Deciles									
	Lowest	2	3	4	5	6	7	8	9	Highest
Variable	A: Raw Return									
ΔBKLG	0.098	0.167	0.148	0.161	0.154	0.189	0.190	0.195	0.215	0.228
BKLG	0.162	0.132	0.135	0.202	0.189	0.191	0.179	0.182	0.194	0.182
ΔINV	0.193	0.198	0.176	0.189	0.162	0.216	0.163	0.167	0.150	0.136
B/M ratio	0.122	0.139	0.123	0.165	0.161	0.184	0.190	0.208	0.210	0.249
Accruals	0.263	0.249	0.199	0.188	0.177	0.183	0.146	0.147	0.130	0.063
	B: Size-adjusted Return									
ΔBKLG	-0.095	-0.021	-0.035	-0.016	-0.020	0.014	0.012	0.013	0.027	0.034
BKLG	-0.032	-0.055	-0.053	0.021	0.009	0.008	-0.003	-0.001	0.009	0.013
ΔINV	-0.007	0.012	0.000	0.021	-0.009	0.035	-0.011	-0.015	-0.041	-0.073
B/M ratio	-0.046	-0.026	-0.041	-0.005	-0.012	0.004	0.005	0.010	0.004	0.023
Accruals	0.049	0.059	0.024	0.012	0.009	0.004	-0.029	-0.033	-0.056	-0.128

Table 4: Portfolio Returns Based on Order Backlog

The table gives 12-month buy and hold raw return and size-adjusted return beginning 4 months after fiscal year-end. The returns are averaged over 1971-2006. The groupings are based on ranking of each variable within each year from low to high. Highest=highest decile; Lowest=lowest decile.

Raw Return

	B/M Ratio					Accruals				
ΔBKLG	Lowest	2	3	4	Highest	Lowest	2	3	4	Highest
Lowest	0.100	0.114	0.155	0.136	0.200	0.216	0.171	0.147	0.074	0.082
2	0.126	0.096	0.171	0.157	0.216	0.228	0.186	0.135	0.163	0.057
3	0.124	0.158	0.157	0.204	0.204	0.247	0.187	0.178	0.141	0.086
4	0.133	0.162	0.194	0.216	0.248	0.307	0.188	0.197	0.159	0.118
Highest	0.189	0.193	0.184	0.285	0.287	0.294	0.236	0.252	0.193	0.147

Size-adjusted Return

	B/M Ratio					Accruals				
ΔBKLG	Lowest	2	3	4	Highest	Lowest	2	3	4	Highest
Lowest	-0.090	-0.069	-0.026	-0.057	-0.017	0.008	-0.009	-0.050	-0.109	-0.108
2	-0.030	-0.064	-0.001	-0.038	0.000	0.032	0.004	-0.032	-0.011	-0.129
3	-0.018	0.003	-0.019	0.020	-0.009	0.047	0.019	0.016	-0.030	-0.098
4	-0.024	0.003	0.021	0.028	0.033	0.106	0.019	0.027	-0.018	-0.070
Highest	0.011	0.015	0.001	0.086	0.068	0.089	0.049	0.070	0.009	-0.045

Table 5: Testing the Abnormal Return of Order Backlog

The dependent variable is 12-month buy and hold size-adjusted return beginning 4 months after fiscal year-end. The models are estimated using the Fama-McBeth approach using data from 1971-2006. Each column represent one model. Each coefficient is the average of the corresponding coefficient from 29 annual regression. Given in the parentheses are the t-ratios calculated from the time series of annual coefficients.

				Dependent variable: SAR
ΔBKLG	0.154 (4.59)		0.146 (4.74)	0.136 (4.49)
BKLG		0.032 (1.76)	0.021 (1.23)	0.029 (1.75)
B/M Ratio				0.025 (1.96)
Accruals				−0.443 (4.48)

Table 6: The Mishkin Test of the Efficiency of Stock Market
with regard to the Information in Order Backlog

Each panel gives the estimates for one system of equations. The coefficients are estimated from each equation separately. The χ^2 is based on the likelihood ratio test (Mishkin, 1983) for each individual constraint that the difference is zero.

Panel A:

$$\text{EARN}_{t+1} = \omega_o + \omega_1 \text{EARN}_t + \omega_2 \Delta\text{BKLG}_t + \omega_3 \text{BKLG}_t + \varepsilon_{t+1}$$
$$\text{SAR}_{t+1} = \beta_o + \beta_1(\text{EARN}_{t+1} - \omega_o - \omega_1^* \text{EARN}_t - \omega_2^* \Delta\text{BKLG}_t - \omega_3^* \text{BKLG}_t) + \varepsilon'_{t+1}$$

		Coefficient		Coefficient		Difference	χ^2	P-value
EARN			β_1	2.114 (50.1)				
LagEARN	ω_1	0.665 (119)	ω_1^*	0.639 (27.8)	$\omega_1 - \omega_1^*$	0.026	1.24	0.265
ΔBKLG	ω_2	0.061 (21.2)	ω_2^*	0.003 (0.3)	$\omega_2 - \omega_2^*$	0.057	32.56	0.000
BKLG	ω_3	0.007 (5.2)	ω_3^*	-0.003 (0.8)	$\omega_3 - \omega_3^*$	0.011	5.13	0.023

Panel B:

$$\text{SaleGr}_{t+1} = \rho_o + \rho_1 \text{SaleGr}_t + \rho_2 \Delta\text{BKLG}_t + \rho_3 \text{BKLG}_t + \varepsilon_{t+1}$$
$$\text{SAR}_{t+1} = \beta_o + \beta_1(\text{SaleGr}_{t+1} - \rho_o - \rho_1^* \text{SaleGr}_t - \rho_2^* \Delta\text{BKLG}_t - \rho_3^* \text{BKLG}_t) + \varepsilon'_{t+1}$$

		Coefficient		Coefficient		Difference	χ^2	P-value
SaleGr			β_1	0.596 (30.7)				
LagSaleGr	ρ_1	0.263 (45.3)	ρ_1^*	0.390 (11.8)	$\rho_1 - \rho_1^*$	-0.127	14.5	0.000
ΔBKLG	ρ_2	0.345 (53.0)	ρ_2^*	0.178 (4.7)	$\rho_2 - \rho_2^*$	0.167	19.35	0.000
BKLG	ρ_3	0.043 (13.6)	ρ_3^*	-0.004 (0.20)	$\rho_3 - \rho_3^*$	0.046	6.91	0.009

Panel C:

$$\text{EARN}_{t+1} = \omega_o + \omega_1 \text{EARN}_t + \omega_2 \Delta\text{BKLG}_t + \omega_3 \text{BKLG}_t + \varepsilon_{t+1}$$
$$\text{SaleGr}_{t+1} = \rho_o + \rho_1 \text{SaleGr}_t + \rho_2 \Delta\text{BKLG}_t + \rho_3 \text{BKLG}_t + \varepsilon_{t+1}$$
$$\text{SAR}_{t+1} = \beta_o + \beta_1(\text{EARN}_{t+1} - \omega_1^* \text{EARN}_t) + \delta_1(\text{SaleGr}_{t+1} - \rho_1^* \text{SaleGr}_t) - \beta_2 \Delta\text{BKLG}_t - \beta_3 \text{BKLG}_t + \varepsilon'_{t+1}.$$

		Coefficient		Coefficient		Coefficient
EARN					β_1	1.904 (41.3)
LagEARN	ω_1	0.665 (119)			ω_1^*	0.601 (11.8)
SaleGr					β_2	0.246 (11.9)
LagSaleGr			ρ_1	0.263 (45.3)	ρ_1^*	0.788 (39.4)
ΔBKLG	ω_2	0.061 (21.2)	ρ_2	0.345 (53.0)	β_2	0.111 (5.1)
BKLG	ω_3	0.007 (5.2)	ρ_3	0.043 (13.6)	β_3	−0.005 (0.5)

Test of Efficiency:	$\omega_1 = \omega_1^*$	$\rho_1 = \rho_1^*$	$\beta_1\omega_2 + \beta_2\rho_1 = \beta_2$	$\beta_1\omega_3 + \beta_2\rho_3 = \beta_3$
Difference:	$\omega_1 - \omega_1^*$	$\rho_1 - \rho_1^*$	$\beta_1\omega_2 + \beta_2\rho_1 - \beta_2$	$\beta_1\omega_3 + \beta_2\rho_3 - \beta_3$
Estimated Difference:	0.065	−0.525	0.089	0.030
Likelihood Ratio Test (χ^2)	5.82	41.92	15.72	8.20
P-value	0.016	0	0	0.004

Table 7: Analysts Forecast and Order Backlog

The models are estimated using the Fama-McBeth approach using data from 1985-2006. The total number of observations is 4466. Each column represent one model. Each coefficient is the average of the corresponding coefficient from 29 annual regression. Given in the parentheses are the t-ratios calculated from the time series of annual coefficients.

	Dependent Variable		
	Actual Earnings	Earnings Estimate	Forecast Error
LagROA	0.667 (16.3)	0.304 (16.5)	0.364 (10.5)
ΔBKLG	0.063 (5.44)	−0.008 (1.73)	0.071 (6.19)
BKLG	−0.001 (0.34)	−0.010 (4.97)	0.009 (2.05)