Does Stock Market Appreciate the Implication of Order Backlog for Future Earnings? A Re-examination

by

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Abstract:

Rajgopal, Shevlin, and Venkatachalam (2003) examine whether order backlog predicts future earnings and whether analyst forecast incorporates the contribution of order backlog to future earnings. They find order backlog information contain additional information about future earnings over current earnings. A hedge portfolio based on the decile ranking of the level of order backlog yield an average abnormal return of 5.8% per year over the 19-year period. They also find that analysts fully capture the marginal predicting power of order backlog for future earnings. Overall, there is a strong tendency for firms to remain in the neighborhood of the deciles in the previous year.

In this paper, we first argue that the level of order backlog is not comparable across firms. Then, we present transition matrices to show that firms have a strong tendency to remain in the neighborhood of the deciles, based on the level of order backlog, in the previous year. Therefore, it is hard to argue that a hedge portfolio based on the decile ranking of the level of order backlog could earn persistent abnormal returns. We further argue that in a cross sectional model and given current earnings, a better measurement of the order backlog information to test whether this leading indicator predicts future earnings is the change in order backlog, not the level of it. This issue is important since the evidence of market inefficiency could be due to the uncontrolled industry factor or other firm characteristics. In addition, the results that analysts seem to fully appreciate the implication of order backlog for future earnings could be due to the measurement error of the explanatory variable.

Our results show that change in order backlog, not the level of order backlog, which has incremental information about future earnings over current earnings. In addition, financial analysts are not able to adequately appreciate the implication of order backlog information about future earnings.

**Keyword:** order backlog, leading indicator, future earnings, rational pricing
1. INTRODUCTION

Francis, Schipper, and Vincent (2003) find that order backlog has no incremental information content over bottom line numbers in explaining concurrent stock returns. Since many of the non-GAAP performance metrics are industry-specific, they believe that industry-by-industry examination is the proper way to test the superiority of non-GAAP metric relative to GAAP earnings. However, their result on the order backlog for homebuilding industry is based on 210 samples spanning an eleven year sample period. The small sample size could be a reason for the insignificant result.

Rajgopal, Shevlin, and Venkatachalam (2003, RSV hereafter) examine whether order backlog predicts future earnings and whether analyst forecast incorporates the contribution of order backlog to future earnings. Their Mishkin test shows that stock market over-prices backlog information. A hedge portfolio based on the decile ranking of the level of order backlog (deflated by total asset) for the 19-year test period yield 13 positive and 6 negative abnormal returns. The average abnormal return is 5.8% over the 19-year period. Finally, they also find that analysts fully capture the marginal predicting power of order backlog for future earnings.

Since order backlog is readily available for a large number of firms across many industries, RSV contend that their choice of order backlog as the leading indicator (non-GAAP metric) in their investigation into the potential mispricing of leading indicators gives the null of market efficiency the best possible chance of success. The assumption underlies this statement is that order backlog information is cross-sectionally comparable.

In this paper, we argue that the level of order backlog, deflated or not, is not comparable across firms and therefore, in a cross sectional model and given current earnings, a better measure of the order backlog information to test whether this leading indicator predicts future earnings is the change in order backlog, not the level of it. This issue is important since the evidence of market inefficiency could be due to the uncontrolled industry factor or other firm characteristics. In addition, the results that analysts seem to fully appreciate the implication of order backlog for future earnings could be due to the measurement error of the explanatory variable.

The rest of the paper is organized as follows: In Section 2, we discuss the proper measure of order backlog information in a cross sectional model. In Section 3 we describe the data and research design. In section 4, we discuss the empirical results. Section 5 provides conclusions.

2. Discussion of proper measure for order backlog information

In this section, we first argue that the level of order backlog is not comparable across firms. Then, we present some statistics to show that a trading strategy based on the level of order backlog is not likely to earn persistent abnormal returns. Also, given the current earnings, we argue for and propose the use of the change in order backlog in a cross sectional model to test its marginal information effect about future earnings.
Order backlog in different industries

Firms with longer operating cycle tend to have larger order backlogs. Consider the following two footnote disclosures taken from annual reports of Lockheed Martin’s and Cisco System:

**Lockheed Martin’s, December 31, 2000—**

“...backlog was $56.4 billion compared with $45.9 billion at the end of 1999...Of our total 2000 year-end backlog, approximately $40.7 billion, or 72%, is not expected to be filled within one year...”

**Cisco Systems, September 19, 2002—**

“...the backlog of orders for its networking equipment has shrunk 30 percent, prompting speculation that the firm's sales will be weak this quarter. ...order backlog on Sept. 9 declined to $1.4 billion from $2 billion a year earlier...Order backlog, which includes orders for products to be shipped within 90 days...”

Most of the Lockheed Martin’s order backlogs will not be filled within one year due to the long production process for airplanes. In contrast, Cisco Systems’ product and service need much less time to complete. Also, discussing from the demand side, consumers of electronic devices usually would not book a product that will be delivered many months in the future because their product life cycle is normally much shorter than other goods. Even in recession time with clouded future, Lockheed Martin’s could still have relatively much higher order backlog. Therefore, for firms like Lockheed Martin’s, the use of dollar amount to measure order backlog in a cross-sectional model would always predict higher future incomes because of their relatively high level of order backlogs. If the stickiness in the level of order backlog is a general phenomenon, it is hard to imaging a trading strategy based on the level of order backlog could earn abnormal returns year after year.

To examine, on average, how sticky firms are in the level of order backlog, at the end of each year firms are ranked into deciles based on the magnitude of their order backlog (deflated by sales). Table 1 presents the transition matrices of decile ranking thus formed. The rows of table 1 correspond to year t decile rankings and the columns correspond to year t+1 decile rankings. The second last column reports total number of firm-years for each decile in year t.

The numbers in the last column are the sums of the number of firms which have change in ranking less or equal to one from year t to year t+1. For example, 430 (91.88%) in the second row of the last column means that among the 468 firms ranked 0 (D=0) in year t, 430 firms (91.88%) have decile rankings equal to 0 or 1 in year t+1. Thus, about 92% of firms have change in ranking less or equal to one. Similarly, for the top ranked firm-years (D=9) in year t, 95.64% are in the top 2 ranked deciles (D=8, 9) in the following year. Overall, there is a strong tendency for firms to remain in the neighborhood of the deciles in the previous year. Such stickiness is perhaps because that the level of order backlog is closely tied to the operating cycle and trading practice of individual firms.
Table 2 reports transition matrices for decile ranking based on the change in order backlog (difference in the magnitude of order backlog deflated by sales). Bench marking on the order backlog in the previous year, the transition show much less stickiness. There are two worth noting patterns in this table. First, note on the four transition percentages among extreme decile rankings in two consecutive years. For firms in the extreme deciles (D=0, 9), there is a tendency that they remain in the extreme deciles next year. This pattern is possibly due to two effects. For some firms, extreme change in order backlog tends to reverse and for some other firms, it persists in the next year. Also, middle ranking firms (D=4, 5, and 6) in year t show a consistent pattern that they have a tendency to remain in middle ranking next year.¹

We also inspect the distribution of the means of order backlog information for individual firms to examine whether they are comparable across firms or not. For each variable listed on the first column of Table 3, the second and third columns of the table show respectively, the variance (V) across all firm-years and the mean of the variances (MV) of each firm. For the first variable, the level of order backlog before any deflation, note that V is much larger than MV. This indicates that the means of the level of backlog of individual firms, are not comparable. But also note that for the second variable, the change in order backlog, V is only 1.5 times the magnitude of VM.

Since the use of deflators in cross sectional studies is often necessary, we examine the relative magnitude of V and VM for the last six variables in Table 3, the backlog information after deflation by sales, average assets and assets at the beginning of the period. Note that, for the deflated change-in-order-backlogs, the variables used in this study, V and VM are quite comparable. In contrast, the V and VM of the deflated level-of-order-backlogs are still not comparable. For the primary variable used in RSV, V is 0.3528, which is about 5.5 times as large as VM.

**Seasonality and order backlog in different segments within industries**

One way to alleviate industry difference is of course to test the theory industry-by-industry. However, order backlog could still be segment-specific. Up-stream firms in an industry get orders booked earlier than do down-stream firms. Partners in different stages of the value chains share the total revenues from terminal customers. Therefore, if there is seasonality in the sales to terminal customers, the order backlog could also exhibit similar seasonality. But if we measure only at year-end for the order backlog information, the levels of order backlog for up-stream firms could be quite different from that of down-stream firms.

RSV did a sensitivity check on their Mishkin test results for the durable manufacturers and computers industries. As we will show that even for a much finer classification of industries, the levels of order backlog could still be not comparable across firms. To demonstrate this idea, we

¹ The transition matrices for decile rankings based on order backlog information deflated by assets and average assets show very similar patterns.
choose three two-digit industry groups with the most sample sizes—industries 35, 36, and 38. The last six columns of Table 3 show V and VM of order-backlog variables of the three industries. Note that the V and VM for the level-of-order-backlog variables are not comparable. Besides, for industries 36 and 38, V is still much larger than VM after any deflation. But for change in order backlog deflated by sales, the primary variable used in this study, the Vs and VMs are comparable across all industries listed on the table.

In fact, among other factors, length of the operating cycle, seasonality, product mix, credit policy, and sales strategy all affect year-end measure of order backlog. One could always argue that order backlog is firm specific or even firm-year specific. We believe there are trade-offs among single-firm time-series models, industry-by-industry cross-sectional models, and large sample cross-sectional models across many industries. The purpose in this study is only limited to the use of large sample cross-sectional models to re-examine the important issues raised by RSV.

**Measure for order backlog information in a cross-sectional model**

The way the information regarding level of order backlog at year-end transforms into earnings of the next year is not comparable for firms in different industries, for firms in different segments within industries, or even for firm-years sampling from the same company. If there is a linkage between year-end order backlog and the realized earnings in the next year, then current earnings should contain information regarding the level of order backlog in the previous period (lagged order backlog). Consequently, a model that includes both current earnings and change in order backlog as predictor for future earnings could minimize problems introduced by the use of the level of order backlog.

The disclosure requirement in item 101(c) (VIII) of SEC regulation S-K seems to be in agreement with our argument by requiring the disclosure of “…the dollar amount of backlog orders believed to be firm, as of a recent date and as of a comparable date in the preceding fiscal year…” Also, the way order backlog information mentioned in most conference calls is consistent with the SEC’s requirement. The example of Cisco Systems reported above clearly demonstrates that an increase in order backlog (change in order backlog) is an indication that future period will be better than the operating result of this period.

3. **RESEARCH DESIGN**

We re-examine the following three questions addressed by RSV: (i) whether order backlog predicts future earnings, (ii) whether market participants rationally price order backlog information, and (iii) whether financial analysts correctly incorporate order backlog into their earnings forecast. Given the current period earnings, we will test whether the use of change in order backlog, instead of level of order backlog to test, is a better measure in a cross-sectional model.

3.1 **Sample Selection**
We collect financial data from the Compustat industrial annual file and the stock return and share data from the Center for Research in Security Prices (CRSP) monthly stock and CRSP indices & deciles databases. The sampling period is 24 years, from 1982 to 2005. For this sample period, we delete firm-year observations that: (1) are non-NYSE, non-AMEX firms and non-NASDAQ firms; (2) are non-calendar year firms; (3) order backlog information are not available; (4) have negative sales; (5) are in financial sectors; (6) are outliers in the upper and lower 1% of distributions of change in order backlog and the current order backlog; (7) have other missing financial data and missing stock return data. The final available sample comprises of 7,243 firm-years, representing 767 firms.

For the tests of analysts’ use of order backlog information, we extract analysts’ consensus earnings forecasts from I/B/E/S summary history - summary statistics file and stock price data from I/B/E/S summary history- actuals and pricing & ancillary file. The accompanying realized earnings are also from the same tape (Abarbanell and Lehavy (2000)). We then merge data from I/B/E/S and order backlog data from Compustat. The final available sample comprises of 4,261 firm-years.

3.2 Research Model and Variable Measurement

As in RSV, we employ Mishkin (1983) framework to test for (i) whether order backlog predicts future earnings, (ii) whether market participants rationally price order backlog information. We estimate the following three sets of equations:

\[
NI_{t+1} = \beta_0 + \beta_1 NI_{t} + \beta_2 BKLG_{t} + \sigma_{t+1} \quad (1-1)
\]
\[
ARE_{t+1} = a_0 + a_1 \cdot (NI_{t+1} - \beta_0 - \beta_1 NI_{t} - \beta_2 BKLG_{t}) + \varrho_{t+1} \quad (1-2)
\]
\[
NR_{t+1} = \alpha_0 + \alpha_1 NI_{t} + \alpha_2 \Delta BKLG_{t} + \varepsilon_{t+1} \quad (2-1)
\]
\[
ARE_{t+1} = b_0 + b_1 \cdot (NR_{t+1} - \alpha_0 - \alpha_1 NI_{t} - \alpha_2 \Delta BKLG_{t}) + \nu_{t+1} \quad (2-2)
\]
\[
NI_{t+1} = \theta_0 + \theta_1 NI_{t} + \theta_2 \Delta BKLG_{t} + \theta_3 BKLG_{t} + \zeta_{t+1} \quad (3-1)
\]
\[
ARE_{t+1} = c_0 + c_1 \cdot (NI_{t+1} - \theta_0 - \theta_1 NI_{t} - \theta_2 \Delta BKLG_{t} + \theta_3 BKLG_{t}) + \tau_{t+1} \quad (3-2)
\]

Where

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2 To form a hedge portfolio, we need order backlog information available in the same month of the year. As a result, we retain only calendar year firms.
3 We delete the observations with negative sales, because order backlog information is deflated by sales.
4 We obtain 199,980 firm-year observations from Compustat industrial annual file, delete 58,460 observations for non-NYSE, non-AMEX firms and non-NASDAQ firms, 82,107 observations for non-calendar year firms, 16,124 observations for financial-related industries, 3,360 observations with negative sales, and 29,810 observations with missing order backlog information. Thus, the initial available financial data is 10,110 firm-years.
5 We obtain 1,229,793 observations from I/B/E/S, delete 420,273 observations for non-calendar year firms and 740,959 observations for the median consensus earnings forecast per share not reported at the fourth month (April) after the end of previous fiscal year.
\[ NI_{it} = \text{Income before extraordinary items (Compustat \#18) of firm } i \text{ at time } t \]
\[ BKLG_{it} = \text{Order backlog divided by sales firm } i \text{ at time } t. \]
\[ \Delta BKLG_{it} = \text{Change in order backlog divided by sales of firm } i \text{ at time } t \text{ (i.e., } (BKLG_{it} - BKLG_{t-1})/SALE_i). \]
\[ ARE_{it+1} = \text{the market-adjusted abnormal stock return of firm } i \text{ at time } t+1. \]

Each set of equations consists of a forecast equation and a return equation. If we take the second system of equations as example, equation (2-1) is the forecast equation and equation (2-2) is the return equation. The forecasting coefficient \( \alpha_i \) measures the earnings persistence while the coefficient \( \alpha_2 \) represents the incremental contribution of change in order backlog information for future earnings. If coefficient \( \alpha_2 \) is statistically significant, it means that change in order backlog has incremental information over current earnings when predicting future earnings.

Model (2-2) estimates the valuation coefficients that the market investors appear to assign to earnings \( (\alpha_i^*) \) and change in order backlog information \( (\alpha_2^*) \) relatively to their abilities to predict one-year-ahead earnings. If the valuation coefficient \( (\alpha_2^*) \) is greater/smaller than the forecasting coefficient \( (\alpha_2) \), then the Mishkin test suggests that investors overprice/underprice the implication of change in order backlog information for one-year-ahead earnings. The interpretation of the coefficients from the other two systems of equations is similar.

### 3.2.2 I/B/E/S Data Test--How do the Analysts use the information of Backlog?

In this part, we examine how financial analysts, the sophisticated market intermediaries, use order backlog information when they generate earnings forecasts. In addition, we will explore how efficiently these analysts use order backlog information in predicting future earnings.

Based on RSV, we build the following three sets of equations.

\[
\begin{align*}
\{ \text{EPS}_{it+1} &= \omega_{e0} + \omega_{f1} \text{EPS}_{it} + \omega_{j2} BKLG_{it} + \varepsilon_{it+1} \ldots \quad (4-1) \\
\text{FEPS}_{it+1} &= \omega_{fe0} + \omega_{fe1} \text{EPS}_{it} + \omega_{fe2} BKLG_{it} + \mu_{it+1} \ldots \quad (4-2) \\
\text{FERR}_{it+1} &= (\omega_{e0} - \omega_{fe0}) + (\omega_{e1} - \omega_{fe1}) \text{EPS}_{it} + (\omega_{e2} - \omega_{fe2}) BKLG_{it} + (\varepsilon_{it+1} - \mu_{it+1}) \ldots \quad (4-3) \\
\} \\
\{ \text{EPS}_{it+1} &= \delta_{e0} + \delta_{e1} \text{EPS}_{it} + \delta_{e2} \Delta BKLG_{it} + \mu_{it+1} \ldots \quad (5-1) \\
\text{FEPS}_{it+1} &= \delta_{fe0} + \delta_{fe1} \text{EPS}_{it} + \delta_{fe2} \Delta BKLG_{it} + \nu_{it+1} \ldots \quad (5-2) \\
\text{FERR}_{it+1} &= (\delta_{e0} - \delta_{fe0}) + (\delta_{e1} - \delta_{fe1}) \text{EPS}_{it} + (\delta_{e2} - \delta_{fe2}) \Delta BKLG_{it} + (\mu_{it+1} - \nu_{it+1}) \ldots \quad (5-3) \\
\} \\
\{ \text{EPS}_{it+1} &= \gamma_{e0} + \gamma_{e1} \text{EPS}_{it} + \gamma_{e2} \Delta BKLG_{it} + \gamma_{e3} BKLG_{it} + \xi_{it+1} \ldots \quad (6-1) \\
\text{FEPS}_{it+1} &= \gamma_{fe0} + \gamma_{fe1} \text{EPS}_{it} + \gamma_{fe2} \Delta BKLG_{it} + \gamma_{fe3} BKLG_{it} + \psi_{it+1} \ldots \quad (6-2) \\
\text{FERR}_{it+1} &= (\gamma_{e0} - \gamma_{fe0}) + (\gamma_{e1} - \gamma_{fe1}) \text{EPS}_{it} + (\gamma_{e2} - \gamma_{fe2}) \Delta BKLG_{it} + (\gamma_{e3} - \gamma_{fe3}) BKLG_{it} + (\xi_{it+1} - \psi_{it+1}) \quad (6-3)
\end{align*}
\]
where

\[ EPS_i \times \] earnings per share as reported by I/B/E/S, scaled by stock price firm i at time t.
\[ FEPS_{it+1} = \] I/B/E/S median consensus for time t + 1 earnings forecast per share reported four months after the end of previous fiscal year firm i at time t, scaled by stock price.
\[ FERR_{it+1} = \] the forecast error computed the difference between \( EPS_{it+1} \) and \( FEPS_{it+1} \) firm i at time t (i.e., \( EPS_{it+1} - FEPS_{it+1} \)).

In model (5-1), coefficient \( \delta_1 \) represents the earnings persistence and coefficient \( \delta_2 \) captures the incremental contribution of change in order backlog information for future earnings. In model (5-2), coefficient \( \delta_{f1} \) and \( \delta_{f2} \) represents the weights that analysts use the past earnings and change in order backlog information for predicting future earnings, respectively. If the coefficient \( \delta_{f2} \) is significantly different from zero, it implies that the analysts factually incorporate change in order backlog information when forecasting future earnings. The coefficients on model (5-3) indicate the difference between the forecasted weights and the analysts’ weights on the past earnings \( (\delta_1 - \delta_{f1}) \) and change in order backlog information \( (\delta_2 - \delta_{f2}) \) in forecasting future earnings. If the coefficient \( (\delta_2 - \delta_{f2}) \) is significantly different from zero, it means that the analysts fail to adequately appreciate the implication of change in order backlog information for future earnings. The other two sets of equations can be interpreted in a similar way.

4. EMPIRICAL RESULTS

This section is organized as follows. In sub-section 4.1, we briefly describe the descriptive statistics and correlation analysis of model variables. In sub-section 4.2 we present the Mishkin test results for the implication of different backlog information to predict future earnings. Then, in sub-section 4.3, we examine how analysts use order backlog information in generating earnings forecasts. Finally, in sub-section 4.4 we report the evidence for the hedge-portfolio test.

4.1 Descriptive Statistics

4.1.1 Descriptive Statistics for Mishkin Test

Table 1 reports the descriptive statistics of the variables in the first part of the empirical test (Mishkin test). In panel A, the statistics for change in order backlog information (\( \Delta BKLG \)) and
the current order backlog information (\( BKLG \)) are not deflated by sales. The mean of \( BKLG \) is approximately 738 millions, and the median is about 21 millions. Additionally, the mean and the median of \( \Delta BKLG \) are approximately 38 millions and 0, respectively.\(^6\) It implies that, on average, order backlog increases by 5% during the sample year. The mean (median) of income before extraordinary items (\( NI \)) is 69 millions (8 millions).

The descriptive statistics on panel B are for the deflated variables used in the model. The mean (median) of \( \Delta BKLG \) is 2.51% (0%) of sales. The mean (median) of \( BKLG \) is 0.2829 (0.1667) of sales, which is similar to the result reported in RSV. The mean and the median of income before extraordinary items scaled by beginning total assets are 4.68% and 5.50%, respectively. Statistics for stock returns show that sample firms are quite successful in the sampling period: the market-adjusted abnormal stock return, on average, is 0.1025, and the raw return average is 0.2336 (in panel A).

Table 6 reports Pearson and Spearman correlation among model variables. High correlation between current and next year’s income before extraordinary items is expected due to the persistence of earnings. Note specially that, the correlations between \( \Delta BKLG \) and future stock returns are significant and larger then the insignificant correlations between \( BKLG \) and future returns. The unconditional correlation between \( \Delta BKLG \) and \( BKLG \) is significant (Pearson=0.41; Spearman=0.32). This implies that \( BKLG \) and \( \Delta BKLG \) could be a surrogate for each other.

4.1.2 Descriptive Statistics for I/B/E/S Data Test

Table 5 reports the descriptive statistics in the second part of empirical process (I/B/E/S data test). In panel A, \( \Delta BKLG \) and \( BKLG \) are not deflated by sales. Since analysts are more interested in large firms, the descriptive statistics of these two variables are comparable but larger than those reported in the panel A of table 1. The mean of \( EPS \) is 0.8189, and the median is 0.6700. The mean and the median of I/B/E/S median consensus for analysts’ earnings forecast per share (\( FEPS \)) are 1.0963 and 0.7700, respectively. The analysts seem to be over-optimistic in predicting future earnings.

From panel B, we report the descriptive statistics of the variables used in the models. The mean (median) of \( \Delta BKLG \) is 2.41% (0%) of sales. The mean (median) of \( BKLG \) is 27.25% (16.38%) of sales. The mean and the median of \( EPS \) scaled by stock price are 0.0429 and 0.0556, respectively. The mean of \( FEPS \) scaled by stock price is 0.0593, and the median is

\(^6\) Rajgopal, Shevlin, and Venkatachalam (2003) delete observation with zero order backlog information. Following out argument for the change in order backlog, order backlog equal to zero still provides additional information regarding future earnings.
0.0617. In addition, the analysts’ forecast error, on average, is -0.0197. RSV report similar optimistic estimates of earnings per share by analysts but the distribution of $FEPS$ in their study is slightly more skewed.

Table 7 reports Pearson and Spearman correlation between model variables used in the second part of empirical process (I/B/E/S data test). We find similar correlation pattern between current and next year $EPS$ as on Table 6. The unconditional correlation between $EPS$ in year $t$ and $FEPS$ is quite high (Pearson=0.51; Spearman=0.61). It is as expected for analysts will certainly use current realized earnings as a bench mark to forecast future earnings. In addition, the unconditional correlation between $FEPS$ and $\Delta BKLG$ is 0.06 (0.03). Note particularly on the Pearson correlations between $BKLG$ and future $EPS$ and $FEPS$ is 0.01276 and 0.02572. With a correlation to future earnings close to zero, it is hard to imaging a hedge portfolio based only on $BKLG$ can yield significant abnormal stock returns.

4.2 Mishkin Test Results -- the Implication of Different Backlog Information to Future Earnings

4.2.1 Mishkin Test Results -- change in order backlog Information

Panel A in Table 8 reports the jointly estimated coefficients for model (1-1) and (1-2) obtained in the first stage (no constraints). Then, we jointly estimate model (1-1) and (1-2) again in the second stage, after imposing the rational pricing constraints (i.e., $\alpha_i = \alpha_i^*$, where $i = 1$ and/or 2). In panel B, overall model test reveals a significant likelihood ratio statistics of 42.939 (p<0.000) and suggests that we reject the null hypothesis that the market rationally prices incomes before extraordinary items ($NI$) and $\Delta BKLG$ to their implications for one-year-ahead earnings.

Also from panel A, the valuation coefficient ($\alpha_i^*$=0.5380) of $NI$ is larger than the forecasting coefficient ($\alpha_i=0.2462$) and the reaction ratio is 219%, suggesting that the stock market overprices incomes before extraordinary items relative to its ability to predict one-year-ahead earnings. The reaction ratio is statistically significant.

Turning to the variable of change in order backlog information, the coefficient on $\Delta BKLG$ in forecasting equation is positive ($\alpha_2 = 0.0809$) and statistically significant. Dividing the coefficient ($\alpha_2=0.0809$) by the median of return on sales (0.0393) for our sample$^7$

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$^7$ The return of sale is computed with income before extraordinary items divided by sales. The result is not tabulated.
and then multiplying by the median of order backlog divided by sales, the resulting coefficient is 0.3372. Thus, the incremental contribution of $\Delta BKLG$ in predicting future earnings is slightly larger than the magnitude of the coefficient on earnings persistence (0.2462). The result suggests that change in order backlog information has incremental contribution in forecasting future earnings after controlling for current earnings.

The valuation coefficient on $\Delta BKLG$ ($\alpha_2^*=-0.2232$) is negative and smaller than the forecasting coefficient ($\alpha_2=0.0809$). It means that the market underprices change in order backlog information (the reaction ratio=-376%). The difference between the two coefficients is statistically significant (likelihood ratio test statistic= 9.28, p= 0.002). Thus, the stock market appears not to appreciate the implication of change in order backlog information for future earnings then places a lower weight on change in order backlog information.

### 4.2.2 Mishkin Test Results -- the Current Order Backlog Information

We replicate the model of RSV (Table 2 on page 474) with our sample and the result is shown in Table 9$^8$. As compared to their results, the forecasting coefficient of $BKLG$ in our research is insignificantly ($\beta_2 = 0.0066$), as compared to their significant result (slope coefficient= 0.008). Turning to the comparison of the results of the tests of valuation equations, the null hypothesis that the stock market rationally price order backlog information can not be rejected at any conventional significance level (p-value= 0.906)$^9$. We believe that, given the knowledge of current earnings and in a cross sectional model, the level of order backlog information provides no incremental contribution in predicting future earnings. We conjecture that the marginal predicting power of the level of order backlog is only a surrogate of the change in order backlog.

### 4.2.3 Mishkin Test Results -- change in order backlog v.s. level of order backlog

In Table 10, we incorporate the two leading indicators simultaneously to test our conjecture

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$^8$ Our sample period is 1982-2005. We delete non-calendar year firms and retain the observation with zero order backlog information. In Rajgopal, Shevlin, ane Venkatachalam (2003), the sample period is from 1981to 1999. They did not delete non-calendar year firms and they delete the observation with zero order backlog information.

$^9$ We run model (2-1) and (2-2) again with our sample that is deleted the observation with zero order backlog information (it is not unreported), the result dose not change. The forecasting coefficient on $BKLG$ changes to be negative and is not significant. The other coefficients are bigger than the coefficients in Table 9.
that level of order backlog provides no marginal contribution in predicting future earnings.

In panel A of Table 10, either the coefficient of forecasting equation or the coefficient of valuation equation on variable \( NI \), the similar to those in Table 8 and Table 9. Turning to the comparison of the two leading indicators, the coefficient on \( \Delta BKLG \) in forecasting equation is still significantly positive (\( \theta_2 = 0.0883 \)) and of a similar magnitude. However, the forecasting coefficient of \( BKLG \) is still not significant and the sign of the coefficient even changes to negative (\( \theta_3 = -0.0063 \)).

The results so far are consistent with our assertion that it is the change in order backlog which provides for marginal predicting power over current earnings, not the level of order backlog.

The valuation coefficient on \( \Delta BKLG \) (\( \theta_2^* = -0.2846 \)) is negative and smaller than the forecasting coefficient (\( \theta_2 = 0.0883 \)). This is similar to the evidence in Table 8. Furthermore, the valuation coefficient (\( \theta_3^* = 0.0519 \)) on \( BKLG \) after controlling variable \( \Delta BKLG \) is still not significant.

4.3 I/B/E/S Data Test Results --How do the Analysts use the information of Backlog?

In this section, we examine how the analysts, the sophisticated market intermediaries, use order backlog information when they generate earnings forecasts. We test how efficient they use the order backlog information for predicting future earnings as well. In table 11, the results of actual EPS equation (i.e., model (4-1), model (5-1), and model (6-1)) are consist and comparable with the results forecasting equation in Table 8, Table 9, and Table 10, except that the earnings persistence coefficients (coefficients of \( NI \)) are larger than those in Table 8, Table 9, and Table 10.

Table 11 also reports the results of earnings forecast equations (i.e., model (4-2), model (5-2), and model (6-2)). The coefficient on change in order backlog information (\( \Delta BKLG \)) is statistically significant (\( \delta_{ef2} = 0.0229 \)) in model (4-2). Thus, the analysts do use change in backlog to generate their earnings forecast, but we still do not know whether or not they can use it in an efficient way. Furthermore, the coefficient on the level of order backlog information (\( BKLG \)) in model (6-2) is statistically significant (\( \omega_{ef2} = 0.0064 \)). This is consistent with the results in RSV (Table 6 in their paper). However, when we incorporate the two backlog variables simultaneously in model (6-2), the coefficient on \( \Delta BKLG \) is still statistically significant (\( \gamma_{ef2} = 0.0175 \)) but the coefficient on \( BKLG \) is not insignificant (\( \gamma_{ef3} = 0.0041 \)).
Table 12 Results of Abnormal Stock Returns to Portfolio of $\Delta$BKLG in Next Year after Portfolio Formation.

<table>
<thead>
<tr>
<th>Fama-French Parameters</th>
<th>Highest portfolio</th>
<th>Lowest portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Monthly Average t-value</td>
<td>Monthly Average t-value</td>
</tr>
<tr>
<td>Intercept ($\alpha_p$)</td>
<td>0.001360 0.30</td>
<td>0.000169 0.06</td>
</tr>
<tr>
<td>Market factor ($b_p$)</td>
<td>1.22036*** 11.87</td>
<td>1.02400*** 15.23</td>
</tr>
<tr>
<td>Size factor ($s_p$)</td>
<td>0.000002 0.18</td>
<td>-0.000007 -0.87</td>
</tr>
<tr>
<td>Book-to-market factor ($h_p$)</td>
<td>-0.000001 -0.18</td>
<td>0.000004 0.87</td>
</tr>
<tr>
<td>Hedge (note3)</td>
<td>0.0145 (p=0.826)</td>
<td></td>
</tr>
</tbody>
</table>

Note 1: Asterisks indicate significant at 10% level (*), 5% level (**), and 1% level (***)..

Note 2: Portfolio deciles are formed annually based on the ranking of growth in long-term net operating assets ($GrLTNOA$). We estimate the following Fama and French (1993) regression:

$$R_p - R_f = \alpha_p + b_p (R_m - R_f) + s_p (SMB) + h_p (HML) + \varepsilon_p$$

Where $R_p$ = the value-weighted monthly return on the $GrLTNOA$ portfolio; $R_f$ = the one-month Treasury bill rate at the beginning of the month; $R_m$ = the value-weighted monthly return on all NYSE and AMEX stocks; $SMB$ = the difference between value-weighted monthly returns of portfolios of small and large stocks (below or above the median of all NYSE and AMEX); $HML$ = the difference between value-weighted monthly returns of high and low book-to-market stocks (above and below the 70 percent and 30 percent fractiles of book-to-market, respectively).

Note 3: It’s annual abnormal returns and p value for F test is in the parentheses.