Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog

Shivaram Rajgopal
Assistant Professor
Department of Accounting
University of Washington
Box 353200
Seattle, WA 9819
Tel: 206 543 7525
Fax: 206 685 9392
E-mail: rajgopal@u.washington.edu

Terry Shevlin
Deloitte and Touche Professor
Department of Accounting
University of Washington
Box 353200
Seattle, WA 98195
Tel: 206 543 7223
Fax: 206 685 9392
E-mail: shevlin@u.washington.edu

and

Mohan Venkatachalam
Assistant Professor of Accounting
Graduate School of Business
Stanford University
Stanford, CA 94305
Tel: 650 725 9461
Fax: 650 725 0468
E-mail: vmohan@gsb.stanford.edu

December 18, 2001

We thank Jennifer Francis, John Hand, Ed Maydew, Michael Mikhail, Madhav Rajan, Richard Willis and workshop participants at Duke University, Columbia University, and the 2001 University of Texas-Dallas symposium on business valuation for helpful comments. We appreciate financial support from the Accounting Development Fund at the University of Washington and the Graduate School of Business, Stanford University.

Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog

Abstract

A number of recent studies assume market efficiency and interpret an association between stock returns and leading indicators as evidence of the contribution of such indicators to future earnings. We explicitly examine (i) whether one leading indicator – order backlog – has predictive ability for future earnings, and (ii) whether market participants correctly incorporate such predictive ability in determining share prices. We find that the stock market overweights the contribution of order backlog in predicting future earnings and a hedge strategy that takes positions on the cross-sectional distribution of backlog generates significant future abnormal returns. Additional analysis indicates that the market mispricing is not due to analysts' inability to incorporate order backlog into their earnings forecasts.

Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog

1. Introduction

In this study, we examine whether market participants, i.e., investors and analysts, incorporate the implications of one leading indicator – order backlog – for future earnings in an efficient manner when determining stock prices and earnings forecasts. Claims about the declining importance of accounting-based performance metrics such as earnings and equity book values stimulated a number of studies that examine the value-relevance of accounting performance measures over the last four decades (see Collins, Maydew, and Weiss 1997; Francis and Schipper 1999; Brown, Lo, and Lys 1999; Lev and Zarowin 1999). Concurrently, the Jenkins Committee report (AICPA 1994) kindled an active interest among academics and practitioners in understanding whether leading indicators of future earnings could potentially remedy the perceived fall in the value-relevance of earnings and book value. Recent examples of value-relevant leading indicators examined in the literature include product market size and market penetration information in the wireless industry (Amir and Lev 1996), customer satisfaction measures (Ittner and Larcker 1998), patents (Deng, Lev and Narin 1999), the book-to-bill ratio in the semi-conductor industry (Chandra, Procassini, and Waymire 1999) and web traffic measures in the Internet industry (Trueman, Wong, and Zhang 2001). These studies assume that security prices are set in an efficient market and accordingly interpret the value-relevance of the leading indicators as an early signal of the link between such indicators and future earnings.

Given the recent regulatory interest in mandating enhanced disclosures of non-GAAP leading indicators (e.g., FASB 2001; SEC 2001), practitioner interest in the subject (e.g., Eccles et al. 2001), and a flurry of new evidence questioning market efficiency with respect to GAAP information (e.g., Sloan 1996; Chan, Lakonishok, Sougiannis 2000; and Xie 2001), it is worthwhile to entertain the alternate hypothesis that the stock market possibly misprices non-GAAP leading indicators. It is especially important to examine this alternate hypothesis because very few of the referenced value-relevance studies explicitly test the association between non-GAAP leading indicators and realized future earnings. The association between leading indicators and stock prices is usually taken as evidence that the market must be pricing (correctly) the implication of such leading indicators for future earnings. Hence, we investigate whether market participants price leading indicators in a manner consistent with their contribution to future earnings.

We choose order backlog as the leading indicator in our empirical tests for several reasons. Most leading indicators tend to be specific to a particular industry (e.g., web traffic in the Internet sector or the book-to-bill ratio for semi-conductor industry). While there are distinct advantages to industry-specific analysis, it often constrains researchers to grapple with small samples and generalizability concerns. Moreover, firms tend to make disclosures of several leading indicators (e.g., manufacturing cycle time or time-to-market measures) that do not easily lend themselves to cross-sectional comparisons even across firms in the same industry. Many of the non-GAAP measures such as patents and cycle time are not denominated in dollars further impairing comparability across industries. In contrast, order backlog represents cross-sectionally comparable information that is already denominated in dollars and is readily available for a large number of firms that span several industries.[1] Perhaps the most important motivation behind our

[1] The tradeoff to this advantage is that in an effort to conserve statistical power, we constrain our predictive coefficient of backlog to future earnings to be the same across industries.

focus on backlog is that an investigation into potential mispricing of a widely disseminated dollar denominated leading indicator such as order backlog gives the null of market efficiency the best possible chance of success. If the market has difficulty in interpreting the implications of order backlog for future earnings, it is more than likely that the market may fail to fully appreciate the implications of non-dollar denominated leading indicators such as customer satisfaction measures, web traffic and patents.

Our empirical tests use the Mishkin (1983) framework employed by a number of recent studies that investigate whether accounting information is fully impounded in stock prices (e.g., Sloan 1996; Burgstahler, Jiambalvo, and Shevlin 2001; Beaver and McNichols 2001; Xie 2001). We examine whether market participants incorporate the predictive ability of order backlog for future earnings. The results indicate that the stock market behaves as if backlog contributes more to future earnings than that implied by the cross-sectional association between backlog and future earnings.

To corroborate findings from the Mishkin (1983) test, we assess whether abnormal future returns can be earned by taking positions on current order backlog. We find that a Fama-MacBeth (1973) type hedge strategy based on taking positions on order backlog can earn abnormal returns of 7.7% as compared to 16.6% abnormal returns that can be earned from Sloan's (1996) accrual-based anomaly. Moreover, abnormal returns based on order backlog are robust to the inclusion of Fama-French (1992) risk factors and are *incremental* to abnormal returns earned from Sloan's (1996) accrual anomaly.

Next, we examine whether the failure of equity investors to correctly incorporate the implications of order backlog for future earnings is at least partially explained by the failure of sophisticated information intermediaries such as equity analysts to incorporate the contribution of backlog to future earnings when generating earnings forecasts. Our results suggest otherwise. We find that median consensus analysts' forecasts correctly incorporate the information contained in backlog for future earnings. Finally, we find that even after controlling for information in analysts forecasts for future earnings investors continue to place weight on order backlog information. This is consistent with market participants not appreciating the fact that analyst forecasts already incorporate information in order backlog.

Our study contributes to the literature that documents a relation between stock prices and leading indicators. As noted before, the association between leading indicators and stock prices is usually taken as evidence that the market correctly prices the contribution of such leading indicators to future earnings. The evidence we present suggests that the market misprices leading indicators. This finding can potentially inform standard setting bodies during their deliberations on standardizing or enhancing the disclosure of non-GAAP leading indicators (see FASB 2001, SEC 2001). While sophisticated market intermediaries such as analysts appear to understand the link between order backlog and future earnings, the market as a whole does not appear to fully appreciate that link. We speculate about possible implications of our research for regulators in the concluding section of the paper.

The remainder of the paper is organized as follows. In Section 2, we briefly describe prior research on the value-relevance of leading indicators and provide institutional details on order backlog. Section 3 discusses the sample while section 4 presents the experimental procedures employed and the findings. Section 5 investigates whether equity analysts appreciate the role of backlog in forecasting future earnings and how the stock market interprets backlog in the presence of analyst forecasts. Section 6 provides some concluding remarks.

2. Background

2.1 Prior Research on Leading Indicators

Research by Amir and Lev (1996) represents an early example of investigation into the value-relevance of non-GAAP leading indicators of future earnings.[2] Consistent with arguments that financial information is of limited use to investors of firms in rapidly evolving technology-based industries they find that income statement and balance sheet information explain little of the cross-sectional variation in the market values of wireless firms. In the absence of value-relevant financial information they explore nonfinancial information that are considered important for wireless firms, i.e., service area population (a product market size measure) and population penetration (a product market share measure) and document that both measures are value-relevant. However, Amir and Lev (1996) are careful to note that they do not transform these product market measures into financial values before incorporating them into the value-relevance equation. Such a transformation would have to rely on the relation between the leading indicator and future earnings. We explicitly examine that relation for one leading indicator (order backlog) in this study.

Appealing to the reduced importance of income statement and balance sheet information, a number of other studies have examined the value-relevance of non-GAAP leading indicators in other contexts, usually dominated by technology intensive industries. Some examples include Ittner and Larcker (1998) on customer satisfaction, Chandra, Procassani, and Waymire (1999) on the book-to-bill ratio in the semi-conductor industry and Deng, Lev, and Narin (1999) on patent counts. Francis, Schipper, and Vincent (2001) investigate the relative and incremental

[2] Lev and Thiagarajan (1993), Abarbanell and Bushee (1997, 1998), Ou and Penman (1989) are examples of research that focuses predominantly on GAAP-based leading indicators of future earnings.

information content of several non-GAAP leading indicators (such as passenger miles and load factors for airlines and backlog for homebuilding industries) vis-à-vis GAAP measures such as earnings and cash flows for various industries.   Research on Internet firms has also examined a number of non-GAAP leading indicators of future earnings such as web traffic, loyalty, and the quality of online customer experience (e.g., Trueman, Wong, and Zhang 2001; Demers and Lev 2001; Rajgopal, Venkatachalam, and Kotha 2001).[3]

The value-relevance of the leading indicator is usually assumed to be indicative of future earnings or future growth options in the firm. However, most of the cited studies do not test whether these leading indicators predict realized future earnings. One plausible reason for such an omission is that many of the technology-intensive industries examined have long gestation lags from product conception to profitability and are hence likely to report negative earnings in the short-run. Moreover, equity analysts usually do not forecast future earnings beyond three years and the near-term forecasts of future earnings in technology intensive industries may still be negative.

In contrast, we explicitly test the association between leading indicators (in our case, order backlog) and one-year-ahead realized earnings and assess whether stock prices fully reflect this association. We also assess whether analyst forecasts incorporate the contribution of backlog to future earnings and whether the stock market correctly interprets such analyst forecasts. To the extent that market prices do not appropriately reflect the implications of such leading indicators for future earnings, our results suggest that information in leading indicators can be exploited to earn abnormal returns.

---

[3] Another stream of research uses proprietary or field study data to document a link between revenues and non-financial indicators such as customer satisfaction (Banker et al. 2000) and product quality (Nagar and Rajan 2001). However, these studies do not assess whether the stock market fully appreciates the nature of such a link.

2.2 Institutional Details about Order Backlog

Order backlog represents contractual orders that are unfulfilled but are scheduled to be executed in later accounting periods. Item 101(c) (VIII) of SEC regulations S-K requires disclosure, to the extent material, of the

> "dollar amount of the order backlog believed to be firm, as of a recent date and as of a comparable date in the preceding fiscal year, together with an indication of the portion thereof not reasonably expected to be filled within the current fiscal year, and seasonal or other material aspects of backlog."

Order backlog information is usually neither audited nor reviewed, although under AICPA Statement on Auditing Standards No. 8 the auditor is required to read the 10-K to determine whether it is consistent with the financial statements.

Order backlog disclosures are commonly concentrated in a few industries such as durable manufacturing and computers (see sample description in Section 3). These disclosures usually include data about backlog at the end of the current and previous fiscal year, the percentage likely to be recognized in revenues in the subsequent year and backlog numbers for significant segments of the business. To illustrate, Motorola's 10-K for the fiscal year ended December 31, 2000 contains the following disclosure about its backlog position:

> Motorola's aggregate backlog position, including the backlog position of subsidiaries through which some of its business units operate, as of the end of the last two fiscal years, was approximately as follows:
>
> December 31, 2000.. $9.62 billion
> December 31, 1999.. $9.92 billion
>
> Except as previously discussed in this Item 1, the orders supporting the 2000 backlog amounts shown in the foregoing table are believed to be generally firm, and approximately 94% of orders on hand at December 31, 2000 are expected to be shipped during 2001. However, this is a forward-looking estimate of the amount expected to be shipped, and future events may cause the percentage actually shipped to change.

Motorola's backlog represents 26% of its fiscal 2000 sales and 23% of total assets at 2000 fiscal year-end. It is also interesting to note that Motorola expects 94% of its backlog to be reflected in next year's earnings. In contrast, Lockheed Martin's backlog will take longer to get reflected in future earnings as is evident from the following backlog disclosures made by the company in their fiscal 2000 10-K:

> At December 31, 2000, our total negotiated 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. These amounts include both unfilled firm orders for our products for which funding has been both authorized and appropriated by the customer (Congress in the case of U.S. Government agencies) and firm orders for which funding has not been appropriated.

Lockheed Martin's backlog for fiscal 2000 is 222% of sales and 186% of total assets. Two observations can be made from a review of these disclosures. First, backlog numbers are economically significant enough to expect investors to pay attention to them when forecasting a firm's future earnings. Second, the number of years of annual earnings that would be affected by backlog at any year-end is likely to vary by industry. Our empirical tests assume that, in the cross-section, year-end backlog substantially feeds into one-period ahead future earnings. We report results related to one lag because only a small proportion (7%) of our sample (discussed in the next section) had a backlog-to-annual sales ratio in excess of 100%. Moreover, unreported analyses suggest that backlog follows a random-walk process. Thus, the assumption that backlog maps into future earnings with just one lag seems reasonable. However, in our sensitivity analyses we relax the one-lag structure assumption.

Even if backlogs are economically significant, backlog disclosures may not be used by investors in forecasting future earnings unless such disclosures are reliable. Previous studies provide evidence that backlog disclosures are value-relevant in general (Behn 1995; Chandra et al. 1999), and are useful in predicting future sales (Liu, Livnat, and Ryan 1996). Lev and Thiagarajan (1993) use the proportion of sales changes to order backlog changes as a revenue management proxy to predict (and find) a negative contemporaneous association between returns and such proportion. However, none of the cited papers tests whether the market participants fully appreciate the association between order backlog and future earnings.

3. Sample Selection, Variable Measurement and Descriptive Statistics

In this section, we provide descriptive data for the sample, which includes all firm-years satisfying our data requirements. The empirical analyses use firms with non-zero order backlog information during the period 1981-1999 available from the 2000 COMPUSTAT active and research data tapes. We obtain 29,574 firm-year observations for which financial statement data are available. We eliminate 7,218 firm-year observations for which stock price and return data are unavailable from the 2000 CRSP tapes. To avoid the undue influence of extreme observations we eliminate 465 firm-years in the extreme upper and lower 1% of the order backlog distribution. Thus, our final sample comprises of 21,891 firm-year observations representing 3,170 firms. For analysis that requires accruals and operating cash flows data we use a reduced sample of 13,012 observations because we are able to obtain operating cash flows from SFAS 95 disclosures only since 1989.

3.1 Primary Variables

$BKLG_t$ = Backlog (Compustat #98) in year *t* scaled by average total assets (calculated as the arithmetic mean of total assets at the beginning and end of the fiscal year).[4]

$EARN_t$ = Income before extraordinary items (Compustat #18) in year *t* scaled by average total assets.

$OPCF_t$ = Operating cash flows (Compustat #308) in year *t* scaled by average total assets.

[4] Although the disclosure of the proportion of backlog that is not expected to be filled in the next fiscal year is required by Item 101(c) (VIII) of SEC regulations S-K, Compustat does not code that information. Hence, we are unable to use that data in our empirical tests.

ACC_t = Accruals measured as the difference between $EARN_t$ and $OPCF_t$.

SAR_{t+1} = Size-adjusted security return, measured as the realized security return from CRSP, cumulated over 12 months beginning with the fourth month after the end of fiscal year *t*, minus the corresponding mean return for all CRSP firms in the same market capitalization decile at the end of year *t*.

Descriptive data related to these variables are reported in Panel A of Table 1. Backlog for the average (median) firm is 46% (30%) of average total assets. The earnings for an average (median) firm are 0% (4%) of average total assets. Backlog is a large proportion of average total assets relative to earnings (as a proportion of total assets) because backlog represents future sales. On average, accruals are negative, consistent with depreciation being a dominant accrual for these firms. In Panel C we provide the industry composition for our sample firms. Note that a substantial number of observations (over 70% of the sample) come from two industries - durable manufacturing and computers (discussed further below).

3.2 Control Variables

Following Sloan (1996), we control for Fama-French (1992) factors (size, book-to-market and beta) and prior-year earnings scaled by share price (Basu 1977) to rule out alternate explanations for any anomalous security returns. In particular, we consider four variables:

$SIZE_t$ = the natural log of the market-value of common equity measured at four months after fiscal year-end.

BM_t = the natural log of the ratio of book value of common equity to the market value of common equity, measured at four months after fiscal year-end.[5]

[5] Whenever the equity book value is negative we replace the BM variable with the lowest number from the distribution of natural log of the book to market ratio.

$BETA_t$ = the CAPM beta estimated from a regression of raw monthly returns on the CRSP value-weighted monthly return index over a period of 60-months ending four months after each firm's fiscal year-end.[6]

EP_t = earnings per share divided by stock price measured at four months after fiscal year-end.

4. Empirical Analyses

We present the empirical tests in several stages. In sections 4.1 and 4.2 we estimate the historical relation between backlog and future earnings, and the relation between backlog and future earnings implicit in security prices. A comparison of these historical and market-inferred weights using the Mishkin (1983) test indicates whether investors correctly appreciate the importance of order backlog to future earnings. In section 4.3 we investigate whether abnormal returns can be earned by exploiting investors' misweighting of the contribution of order backlog to future earnings. In section 5, we examine whether equity analysts use backlog information in an efficient manner while forecasting future earnings. We also assess whether market inefficiencies with respect to backlog are present after controlling for information in analysts forecasts.

4.1. Mishkin Test

Our initial empirical tests employ the Mishkin (1983) framework to test whether the stock market is efficient in impounding the information contained in backlog for future earnings. This framework, first introduced by Sloan (1996) to the accounting literature, has since been used by a number of studies that test for market efficiency. We infer mispricing if the valuation

[6] In estimating the beta we require that monthly return data are available for a minimum of 10 months to enable efficient estimates.

coefficient attributed to backlog by market participants is different from the weight in the association between backlog and future earnings.

Similar to prior research, we jointly estimate a forecasting specification for the leading indicator and the rational expectations pricing specification. We begin with a forecasting specification that links backlog to future earnings (firm subscripts suppressed):

$$EARN_{t+1} = \omega_0 + \omega_1\ EARN_t + \omega_2\ BKLG_t + \varepsilon_{t+1} \qquad (1)$$

Next, we assume that the market reacts to unexpected earnings conditioned on last year's earnings and order backlog. That is:

$$SAR_{t+1} = \beta_0 + \beta_1\ UEARN_{t+1} + \nu_{t+1} \qquad (2)$$

where $UEARN_{t+1}$, the unexpected earnings variable, is decomposed into realized earnings, $EARN_{t+1}$, and expected earnings, $E(EARN_{t+1})$ with $E(.)$ as the expectation operator:

$$UEARN_{t+1} = EARN_{t+1} - E\ (EARN_{t+1}) \qquad (3)$$

We substitute the linear prediction of $EARN_{t+1}$ in equation (1) for expected earnings $E(EARN_{t+1})$ embedded in equation (3), and rewrite equation (2) as:

$$SAR_{\ t+1} = \beta_0 + \beta_1\ (EARN_{t+1} - \omega_0^* - \omega_1^*\ EARN_t - \omega_2^*\ BKLG_t) + \nu_{t+1} \qquad (4)$$

We refer to equation (4) as the returns equation in the paper. Market efficiency with respect to backlog imposes the constraint that ω_2^* from the returns equation (4) is the same as ω_2 from forecasting equation (1). This nonlinear constraint requires that the stock market rationally anticipate the implications of current order backlog for future earnings. If $\omega_2 > \omega_2^*$ the market assesses a lower contribution of backlog to future earnings than that warranted by the underlying cross-sectional association of backlog and future earnings. On the other hand, if $\omega_2 < \omega_2^*$ the market assesses a higher contribution of backlog to future earnings than that warranted by the underlying cross-sectional association.

The two equations in the system are estimated using iterative weighted non-linear least squares (Mishkin 1983). Market efficiency is tested using a likelihood ratio statistic which is distributed asymptotically chi-square (q):

$$2*n* \ln (SSR^c / SSR^u) \qquad (5)$$

where

q = the number of constraints imposed by market efficiency,
n = the number of observations in each equation,
SSR^c = the sum of squared residuals from the constrained weighted system, and
SSR^u = the sum of squared residuals from the unconstrained weighted system.

4.2. Mishkin Test Results

Our initial analyses compare the historical relation between backlog and realized earnings to the relation between backlog and earnings expectations embedded in security prices. Table 2 reports the historical relation between realized earnings, $EARN_{t+1}$, and order backlog, $BKLG_t$, and the stock market's implicit weighting of order backlog. The coefficient on earnings in the forecasting equation, ω_1 is 0.581 and is statistically significant and different from zero. This coefficient represents the persistence of the accounting rate of return on assets and is less than unity implying thereby that accounting rates of return are mean-reverting (Beaver 1970; Freeman et al. 1982). The coefficient on earnings in the returns equation (4), ω_1^* is 0.536, but is only weakly different from its counterpart in the forecasting equation (1): the likelihood test for market efficiency on annual earnings ($\omega_1 = \omega_1^*$) is a marginal 3.81 (significance level = 0.05). Thus, we detect traces of inefficiency in the market's evaluation of earnings.[7]

[7] While this result may appear inconsistent with Sloan's (1996) finding of market efficiency with respect to information in past earnings, our unreported results using observations from two sub-samples used later in the paper (sample of SFAS 95 accrual data discussed later in section 4.3.2 and analyst forecast sample discussed in section 5) indicate no market inefficiency with respect to the time-series properties of earnings. Furthermore, we cannot find abnormal returns to the EP anomaly, thereby suggesting market efficiency with respect to past earnings.

Turning to the role of backlog, we find that the coefficient on BKLG in the forecasting equation, ω_2, is positive (coefficient = 0.008) and statistically significant ($p < 0.01$).[8] This suggests that order backlog is incrementally informative about future earnings even after controlling for information in past earnings. However, the coefficient on BKLG in the returns equation, ω_2^*, is over four times larger than that in the forecasting equation and is statistically significant (coefficient = 0.039, $p < 0.01$). The difference between the two coefficients is statistically significant (likelihood ratio test statistic = 12.06, $p < 0.00$). Thus the stock market appears to place a higher weight on order backlog relative to the weight inherent in the association between backlog and future earnings.[9]

4.3. Abnormal Returns to Hedge Strategy

The preceding section uses the Mishkin test to demonstrate that the stock market overprices backlog information. However, the Mishkin test is not direct evidence of market inefficiency for at least two reasons (see Beaver and McNichols 2001; Wahlen 2001). First, model misspecification or the assumptions implicit in the Mishkin procedure (such as linearity of the model specification, and efficient stock market pricing of omitted variables) may cause an illusion of market inefficiency (see Kraft, Leone and Wasley 2001). Second, the coefficients are

[8] The magnitude of the coefficient on order backlog (0.008) may appear to be small relative to the magnitude on the earnings coefficient (0.536). Note, however, that order backlog is denominated in sales dollars. To convert order backlog into comparable earnings dollars, we divide the coefficient on backlog, 0.008, by the median return on sales for our sample firms (2.6%). This conversion is equivalent to estimating the backlog coefficient after multiplying the backlog variable by the median return on sales. The resulting quotient is a coefficient of 0.31. Thus, the incremental impact of order backlog for future earnings (0.31) is comparable in magnitude to the coefficient on lagged earnings (0.536). The impact of backlog is lower because some of the backlog may not convert to future sales or may convert at lower margins.

[9] In untabulated results using decile rankings of BKLG and EARN instead of actual values, we continue to find that the stock market does not appear to rationally anticipate the lower contribution of backlog for future earnings. That is $\omega_2^* > \omega_2$ and the likelihood ratio statistic to test the equality of ω_2^* and ω_2 is 11.63 ($p < 0.01$).

estimated from a set of contemporaneous observations i.e., the procedure suffers from a "look-ahead" bias. Investors do not know the implications (i.e., the weight) of backlog for future earnings until later in the sample period. Hence, we turn to an additional test, the ability of portfolios formed on the cross-sectional distribution of backlog to predict future abnormal returns.

The strategy we implement relies on the construction of zero-investment portfolios (Fama and MacBeth 1973). Portfolios are formed as follows: First, for each year from 1981 to 1999, we calculate the scaled decile rank for $BKLG_t$ for each firm. In particular, we rank the values of $BKLG_t$ into deciles (0,9) each year and divide the decile number by nine so that each observation related to $BKLG_t$ takes the value ranging between zero and one. We estimate the following separate cross-sectional OLS regression for each of the 19 years in the sample:

$$SAR_{t+1} = \gamma_0 + \gamma_1 BKLG_t^{dec} + \varphi_{t+1} \qquad (6)$$

The basic idea behind the Fama-MacBeth (1973) regressions is to project the size-adjusted returns on the intercept and the $BKLG_t^{dec}$ variable for each cross section and then aggregate the estimates over the 19 years. Tests of statistical significance of γ_1 are based on the standard error calculated from the distribution of the individual yearly coefficients. This test overcomes bias due to cross-sectional correlation in error terms but assumes independence in error terms across time (Bernard 1987).

Coefficient γ_1 represents the size-adjusted abnormal return to a zero-investment portfolio optimally formed to exploit the information in the backlog variable. This is because the weights assigned to each firm in the $BKLG^{dec}$ variable represented by the rows of the matrix $(X'X)^{-1}X'$, where $X = [1, BKLG^{dec}{}_t]$, sum to zero. Because the portfolio weights are determined without foreknowledge of future abnormal returns, we are investigating executable trading strategies.

Our strategy involves taking positions in firms that have reported results within 4 months of the fiscal-year end to allow for the determination of portfolio weights from $(X'X)^{-1}X'$ used to ascertain the investment positions. Thus, firms receiving negative weights are sold short and firms with positive weights are bought. The long and short positions are closed after one year. The abnormal returns, represented by coefficient γ_1, are comparable to abnormal returns to a zero-investment portfolio with long (short) positions in firms within the lowest (highest) deciles of backlog (see Bernard and Thomas, 1990).

Results from the Fama-MacBeth regressions reported in Table 3 generally confirm the findings from the Mishkin test. There is a negative relation (coefficient = -0.058) between BKLG and future returns that is statistically significant (t-statistic of 2.38, $p < 0.05$). The negative sign on the coefficient on BKLG is consistent with the difference in historical and security-market weightings of the contribution of current backlog to future earnings documented using the Mishkin framework. Because the market overestimates the future earnings implications of backlog we should observe negative abnormal returns for portfolios ranked on backlog. Thus, the abnormal return to a trading strategy based on order backlog is 5.8%.

4.3. Robustness Checks and Sensitivity Analyses

4.3.1. Controlling for Fama-French Factors and the Basu (1977) Anomaly

Prior research has shown that future abnormal returns are associated with other variables, such as firm size (SIZE), book-to-market ratio (BM), and systematic risk (BETA). Fama and French (1992) conjecture that these variables reflect unknown risk factors and hence, are associated with future expected returns. It is possible that abnormal returns related to backlog are not independent of returns observed in connection with the Fama-French factors. We also include the earnings-to-price ratio (EP) to control for the earnings-price anomaly documented by Basu (1977).

To assess whether the backlog anomaly generates incremental returns to the Fama-French factors and the Basu anomaly, we estimate the following regression:

$$SAR_{t+1} = \gamma_0 + \gamma_1 \, BKLG^{dec}_t + \gamma_2 \, SIZE^{dec}_t + \gamma_3 \, BETA^{dec}_t + \gamma_4 \, BM^{dec}_t + \gamma_5 \, EP^{dec}_t + \varphi_{t+1} \quad (7)$$

where $SIZE^{dec}_t$, $BETA^{dec}_t$, and BM^{dec}_t relate to scaled decile ranks (ranging from 0 to 1) for the three Fama-French factors. EP^{dec}_t refers to scaled decile ranks of the earnings-price ratio. In the regression specification (7), coefficient γ_1 represents the *incremental* size-adjusted abnormal return to a zero-investment portfolio in the backlog variable.

Results reported in panel B of Table 3 indicate that incremental abnormal returns related to BKLG persist after controlling for potentially confounding variables. However, controlling for Fama-French factors and the Basu anomaly reduces the incremental return to the BKLG based hedge portfolio to 4.8% from 5.8% in panel A with no controls. Turning to the control variables, it is interesting to note that there is a statistically significant size-adjusted incremental return of 8.3% to the SIZE based hedge portfolio. Although this result is somewhat curious, it is consistent with Foster, Olsen and Shevlin (1984), Bernard (1987), and Shevlin and Shores (1993) who find that the use of size-adjusted raw returns does not appear to ensure a perfect control for size. We also find a positive incremental return to the BM portfolio of 7.5%. The signs of abnormal returns on the SIZE and BM portfolios are consistent with those observed by Fama and French (1992).

4.3.2. Controlling for the Accrual Anomaly

In this section, we assess whether the BKLG related anomaly is distinct from the anomaly documented by Sloan (1996). Sloan (1996) shows that a hedge portfolio strategy based on accruals can earn abnormal returns in subsequent periods because the stock market overweights the persistence of the accruals for future earnings. Sloan (1996) and a few subsequent papers such as Xie (2001) infer the accruals component of earnings from balance sheet accounts such as current assets and current liabilities. However, Collins and Hribar (2000) demonstrate that accruals calculated from cash flow numbers reported by firms under SFAS 95 are less susceptible to the contaminating influences of acquisitions, mergers, and divestitures than accruals deduced from balance sheet information. Hence, we further restrict our sample to only firm-years for which SFAS 95 cash flow data are available.

In Table 4, we repeat the analysis of the forecasting equation (1) and returns equation (4) on the reduced sample of 13,012 observations after decomposing earnings into SFAS 95 derived cash flow component scaled by average assets (OPCF) and accruals scaled by average assets (ACC). Similar to Sloan (1996) we find that the market overweights the accruals component and underweights the cash flow component of total earnings in the returns equation. Specifically, the coefficient on operating cash flows in the forecasting equation, ω_{1a}, is 0.726, whereas the coefficient on operating cash flows in the returns equation, ω_{1a}*, is 0.586 and the difference is significant at conventional levels (likelihood ratio statistic = 11.84, $p < 0.01$). The coefficient on accruals in the forecasting equation, ω_{1b}, is 0.390 whereas its counterpart in the returns equation, ω_{1b}*, is 0.557 (likelihood ratio statistic = 15.31, $p < 0.01$). Most important, however, the market continues to overweight BKLG in the returns equation (ω_2 is 0.005) compared to the weight on BKLG in the forecasting equation (ω_2* is 0.052) and the difference is statistically significant (likelihood ratio statistic is 13.91, $p < 0.00$). Thus, the BKLG anomaly is incremental to the accruals anomaly documented by Sloan (1996).

To ensure that abnormal returns can be earned from the BKLG anomaly incremental to those from the accrual anomaly, we augment the Fama-Macbeth type equation (7) with an additional regressor, ACC^{dec}_{t}. This variable represents accruals for year t divided by average assets ranked into deciles (0,9) each year and scaled by nine so that each observation takes a value ranging between zero and one.

Panel A of Table 5 reports the results of assuming hedge positions on order backlog for the reduced sample of firm-years with SFAS 95 data. It turns out that the hedge portfolio return for the reduced sample is higher at 8.1% as compared to the full sample return of 5.8% reported earlier. Systematic differences between the reduced sample and the full sample could potentially account for the higher return on the backlog variable in the reduced sample. For example, we find that firms in the reduced sample are systematically larger on average (t-statistic to assess difference in means is 11.43) and have smaller CAPM betas (t-statistic for difference of means is 7.54).

Panel B of Table 5 shows that the introduction of Fama-French factors and both the Sloan and the Basu anomaly do not affect abnormal returns from the BKLG anomaly.[10] A zero-investment strategy on BKLG variable earns incremental abnormal returns of 7.7%.[11] In contrast, Sloan's accrual strategy appears to earn an incremental abnormal return of 16.6%. Notice that the negative coefficient on the accruals variable is consistent with the market overreacting to accruals. Thus, the BKLG strategy earns as much as 46% of the returns from

[10] We also control for industry differences by including industry dummies and our inferences are unaltered.

[11] Transactions costs are unlikely to be a major hurdle in exploiting the BKLG anomaly. If a trader wants to exploit the accrual and the BKLG anomaly, the incremental costs of exploiting the BKLG anomaly are likely to be trivial. The positions that the trader needs to take to exploit the accrual anomaly can be netted against those that he needs to take to exploit the BKLG anomaly, thereby requiring a single trade to achieve the optimal weights in all portfolios.

Sloan's anomaly.[12]

4.3.3. Additional Sensitivity Analyses

In this section we conduct two additional tests to further assess the robustness of our results. In the first test, we consider the sensitivity of our analysis to the assumption of a single-lag relation of backlog for future earnings. It is quite likely that backlog follows a more complicated process and investors may also use a more sophisticated expectations model. As a result our estimates of the weights implicit on backlog in the estimation equation (ω_2) and valuation weight placed by investors on backlog (ω_2^*) may be biased. However, following Mishkin (1983, 49) and Abel and Mishkin (1983, 10), Sloan (1996) argues that the tests of cross-system non-linear constraints remain valid tests of market efficiency regardless of whether the forecasting equation has omitted variables (such as a second-lag backlog term). Abel and Mishkin (1983, 11) and Mishkin (1983, 51) also point out that if the model generating the dependent variables (earnings at t+1 in our setting) is incorrectly specified, then the standard errors-in-variables problem arises, meaning estimates of the valuation equation weights, ω_1^* and ω_2^*, will be inconsistent, and the test will have lower power. Rejection of the null hypothesis of efficiency with a test of known low power would be an even stronger case against efficiency. Thus, our inferences about the degree to which information in prior backlogs is incorporated into

[12] The magnitude of the abnormal return on Sloan's strategy is larger than the 10.4% that he documents. This possibly occurs for four reasons. First, Collins and Hribar (2000) show that accruals backed out of balance sheet accounts such as current assets and current liabilities, as computed by Sloan, instead of SFAS 95 data tend to understate the extent of abnormal returns that can be earned from Sloan's anomaly. Second, Sloan's (1996) sample comes from the years 1962-1991 whereas our sample covers the years 1989-1999. Thus, time-period specific issues might have also influenced our findings. Third, Sloan (1996) focuses only on the lowest and highest deciles whereas we focus on Fama and Macbeth (1973) type trading strategy that assigns weights to firms in every decile. In Sloan's (1996) study if one were to focus on the extreme quintiles as opposed to extreme deciles one could earn abnormal returns of 16.7%. Finally, our reduced sample is an intersection of firms with backlog data and SFAS 95 data. Hence, the abnormal returns may be different for firms with non-zero backlog.

the earnings expectations process are likely to be robust to the actual time series process and the form of investor expectations.

Furthermore, as Soffer and Lys (1999) point out in their appendix 3, ω_2 can be viewed as a weighted average of the extent to which future earnings are related to prior backlog lags that are correlated with the first lag. Similarly, ω_2* can be viewed as a weighted average of the extent to which investors have incorporated information from prior backlog lags that are correlated with the first lag. Thus, we capture in a single measure, the degree to which all information correlated with the first lag is incorporated into earnings expectations. Considering that the correlation between first-lag of backlog and the second-lag is very high ($\rho = 0.87$) in our sample, we argue that modeling the first lag alone is reasonable for the purpose of assessing deviation from market efficiency with respect to the information in order backlog.

Notwithstanding the above arguments, we incorporate a second-lag of backlog into the earnings estimation equation (1) and (4) and test whether the weights placed by the market on both lags of backlog in equation (4') below are consistent with weights in the forecasting equation (1').

$$EARN_{t+1} = \omega_0 + \omega_1\, EARN_t + \omega_2\, BKLG_t + \omega_3\, BKLG_{t-1} + \varepsilon_{t+1} \qquad (1')$$

$$SAR_{t+1} = \beta_0 + \beta_1\, (EARN_{t+1} - \omega_0^* - \omega_1^*\, EARN_t - \omega_2^*\, BKLG_t - \omega_3^*\, BKLG_{t-1}) + \nu_{t+1} \qquad (4')$$

The joint test of efficiency (i.e., $\omega_2 = \omega_2^*$; $\omega_3 = \omega_3^*$) is rejected at conventional levels. More important, the results (unreported) indicate that the market prices $BKLG_{t-1}$ (not $BKLG_t$) in an inefficient manner. This result is probably not surprising given the high correlation between $BKLG_t$ and $BKLG_{t-1}$. An implication of this finding is that abnormal returns can be earned on BKLG positions for a period longer than one year. Indeed, we do observe (results not reported) the presence of abnormal returns on $BKLG^{dec}$ portfolios for three years into the future, after which the abnormal returns are no longer statistically significant. The disappearance of abnormal returns after three years also suggests that an omitted risk factor cannot explain our findings.

In the second sensitivity check, we estimate the earnings forecasting equation (1) and the returns equation (4) separately for two main industry groups in our sample – durable manufacturers and computers. Separate estimation by industry does not constrain the predictive ability of order backlog for future earnings to be a cross-sectional constant. In unreported results, we find that the market overweights backlog relative to its contribution to future earnings in both industries. Hence, our reported results are not due to the assumption of homogeneity on the conversion of backlog across industries.

5. Do Analysts Appreciate the Implications of Backlog for Future Earnings?

In this section we explore whether sophisticated market intermediaries, such as equity analysts, understand the implications of order backlog for future earnings when they generate earnings forecasts. Lev and Thiagarajan (1993) identify order backlog as one of the fundamental variables that analysts appear to use beyond GAAP information. Francis, Schipper, and Vincent (2001) isolate order backlog as a leading indicator in the home-building industry based on their assessment of the industry reports, analyst reports and popular press articles. Research by Barth, Kaznik, and McNichols (2001) suggests that financial analysts likely aid investors' assessment of non-GAAP information. Hence, arguments made in the prior literature support the conjecture that analysts incorporate backlog data into their earnings forecasts. On the other hand, other research (Klein 1990; Abarbanell 1991; Mendenhall 1991; Abarbanell and Bernard 1993; Ali, Klein, and Rosenfeld 1992) finds that analysts do not fully utilize available information efficiently while setting earnings forecasts. Thus, whether analysts incorporate order backlog efficiently in a manner consistent with the cross-sectional association of backlog to future earnings is an open question.

To address this question we regress future earnings on scaled decile ranks of backlog and compare the coefficient on backlog ranks with the coefficient from a regression of analyst forecast of future earnings on these backlog ranks. Specifically, we estimate the following specifications:

$$EPS_{t+1} = \delta_0 + \delta_1 EPS_t + \delta_2 BKLG^{dec}_t + \mu_{t+1} \quad (8)$$

$$FEPS_{t+1} = \lambda_0 + \lambda_1 EPS_t + \lambda_2 BKLG^{dec}_t + \eta_{t+1} \quad (9)$$

$$FERR_{t+1} = (\delta_0 - \lambda_0) + (\delta_1 - \lambda_1) EPS_t + (\delta_2 - \lambda_2) BKLG^{dec}_t + (\mu_{t+1} - \eta_{t+1}) \quad (10)$$

where EPS_{t+1} is earnings per share for the fiscal year t+1 scaled by stock price at the end of fiscal year t, $FEPS_{t+1}$ if the forecasted year t+1 earnings per share made four months after the end of year t (deflated by stock price at four months after the end of year t), and $FERR_{t+1}$ is the forecast error computed as the difference between EPS_{t+1} and $FEPS_{t+1}$.[13] We use backlog ranks as opposed to backlog scaled by average assets to avoid concerns about mismatch in the scalar used for EPS and FEPS variables.[14]

Coefficients δ_1 and δ_2 represent the information content of past earnings and backlog in forecasting future earnings. Coefficients λ_1 and λ_2 represent weights that analysts attach to past earnings and backlog, respectively. The coefficients on the forecast error specification indicate

[13] Consistent with a long tradition in analyst forecast research (e.g., Ali et al. 1992 and Abarbanell and Bernard 1993), we scale the median analyst forecast by market price and not by average total assets (as in the previous sections of the paper). Scaling by average total assets, which is obtained from COMPUSTAT tapes, requires a conversion of the per-share forecast numbers to a net income number. This can be accomplished by multiplying the number of outstanding shares in I/BE/S by the forecast per share. However, data on the number of shares outstanding for a significant number of firm-years are missing in the I/B/E/S tapes. In an effort to conserve as many firm-year observations as possible for our empirical analyses, we scale the analyst forecast by lagged market price per share. To be consistent with the scaler for analyst forecasts, we scale the earnings variables in equations (8), (9), and (10) by stock price as well.

[14] As a sensitivity check, we use actual order backlog scaled by average total assets and find that our inferences are unaffected.

the difference between the implied weight on backlog (past earnings) for future earnings and the analysts' weights on backlog (past earnings) in forecasting future earnings. If analysts fail to adequately incorporate the implications of backlog for future earnings the coefficient on BKLG (i.e., δ_2-λ_2) in equation (10) will be different from zero.

To conduct the analysis, we obtain analysts' consensus earnings forecasts from I/B/E/S. Because the definition of accounting earnings in I/B/E/S is often different from that in the COMPUSTAT tapes (Abarbanell and Lehavy 2000) we obtain realized earnings from I/B/E/S for the purpose of this analysis. This also ensures comparability between analysts' forecasts and realized earnings. From the I/B/E/S tapes we are able to obtain analyst forecasts for 11,259 observations for the period 1981-1999. Descriptive statistics relating to forecast earnings and corresponding reported earnings are presented in panel A of Table 1.

Table 6 reports the results of estimating equations (8)–(10). We report mean estimates from annual cross-sectional regressions. Test-statistics and significance levels of the mean estimates are determined using inter-temporal tests (see Bernard, 1987). The estimated coefficient on past earnings per share in earnings forecasting equation (8), i.e., δ_1, is 0.488 (see Panel A of Table 6). The earnings persistence based on I/B/E/S earnings variables is comparable to the earnings persistence of 0.58 obtained using earnings scaled by average total assets (see Table 2). However, the coefficient on past earnings per share in the analysts' forecasting equation (9), i.e., λ_1, is just 0.221 (see Panel B of Table 6). As is evident from Panel C of Table 7, the difference (δ_1 - λ_1) is statistically significant at the 1% level (coefficient = 0.267, t = 2.99). This result is consistent with prior research (Ahmed, Nainar, and Zhou 2001) that finds analysts under-estimate the time-series persistence of earnings.

As with the results obtained earlier we find that order backlog information has implications for future earnings ($\delta_1 = 0.016$, $t = 3.29$). Consistent with the hypothesis that analysts' forecasts incorporate information in order backlog in addition to information in past realized earnings we find that the coefficient on order backlog, λ_2, in equation (9) is statistically positive (coefficient = 0.017, $t = 5.07$). Furthermore, there is no statistical difference between the two coefficients. That is, the coefficient ($\delta_2 - \lambda_2$) reported in Panel C is not statistically significantly different from zero. Thus, the results indicate that analysts use backlog information to forecast future earnings in a manner consistent with the association between backlog and future earnings.

If analysts correctly incorporate the implication of backlog for future earnings, then why do we observe abnormal returns on order backlog positions? One possibility is that the stock market overweights backlog information only in firms with low analyst coverage.[15] Walther (1997) and Elgers, Lo, and Pfeiffer (2001) find that the market does not correctly impound the information in analyst forecasts when firms are covered by fewer analysts. However, we find (in untabulated analyses) that the backlog anomaly is robust in firms with high analyst coverage (proxied by firms where number of analysts covering a firm is above the median) as well.

Another possibility is that investors fixate on order backlog even though analyst forecasts efficiently impound the future-earnings effects of backlog. To assess this possibility, we estimate the following regressions:

$$EPS_{t+1} = \alpha_0 + \alpha_1 EPS_t + \alpha_2 FEPS_{t+1} + \alpha_3 BKLG^{dec}{}_t + \phi_{t+1} \qquad (11)$$

$$SAR_{t+1} = \zeta_0 + \zeta_1 (EPS_{t+1} - \alpha_0 - \alpha_1^* EPS_{it} - \alpha_2^* FEPS_{t+1} - \alpha_3^* BKLG^{dec}{}_t) + \pi_{t+1} \qquad (12)$$

[15] In untabulated results, we find evidence of the stock market overweighting backlog in firms *without* analyst coverage, i.e., the sub-sample of firms for which we do not have I/B/E/S forecasts.

Equations (11) and (12) are estimated using the Mishkin procedure described earlier. In equation (11), the coefficient α_3 is predicted to be statistically insignificant because the median analyst forecast, $FEPS_{t+1}$, already incorporates the forecast of future earnings from backlog. If investors correctly appreciate the role of order backlog as it relates to future earnings, we would expect to observe α_3^* in equation (12) to be insignificant as well.

Table 7 reports the results of estimating equations (11) and (12). Coefficient α_3 is statistically insignificant, as expected. Thus, backlog is not incrementally useful for forecasting future earnings over analyst forecasts because analysts already efficiently incorporate backlog information in their forecasts. However, coefficient α_3* in the returns equation (12) is positive and statistically significant consistent with market mispricing information in order backlog. The likelihood ratio test to assess the equality of coefficient α_3 and α_3* can be comfortably rejected at conventional levels of significance (12.15, $p < 0.00$). Thus, it appears that the stock market fixates on order backlog although equity analysts appear to correctly use backlog information in forecasting future earnings. The simultaneous existence of analysts' efficiency with respect to public information and the stock market's inefficiency with respect to the same public information is not without precedent. Doukas, Kim and Pantzalis (2001) find that analysts' forecasts and revisions do not exhibit the value-glamour anomaly documented for the stock market as a whole by Lakonishok, Shleifer and Vishny (1994) and La Porta, Lakonishok, Shleifer and Vishny (1997).

A couple of other findings from equations (11) and (12) are worthy of comment. Consistent with Sloan (1996), we find that the market does not misweight earnings persistence as the likelihood ratio test cannot reject the equality of earnings coefficient α_1 and α_1* at conventional levels of significance (likelihood ratio statistic is 0.00, $p = 0.96$). However, the stock market appears to misweight the role of analyst forecasts in predicting future realized earnings. Coefficient α_2 on analyst forecasts in the earnings-equation (11) is 0.764 whereas coefficient α_2* on analyst forecasts in the returns-equation (12) is higher at 1.310 and the difference is statistically significant (likelihood ratio test = 8.64, $p < 0.00$). Thus, stock market participants appear to overweight the role of analyst forecasts in predicting future earnings. Prior literature (e.g., Walther 1997; Elgers, Lo, and Pfeiffer 2001) also provides evidence consistent with investors failing to correctly impound analysts' forecasts although these papers find that investors underweight analyst forecasts.

6. Conclusions

Previous research has interpreted the value-relevance of leading indicators in an efficient market context as indicative of future earnings prospects of firms. We explore the alternate hypothesis that the stock market possibly misprices these leading indicators. We examine one aspect of such mispricing by investigating whether security prices rationally anticipate the role of current backlog for future earnings.

We find that market expectations are inconsistent with the traditional efficient markets view that stock prices fully reflect publicly available information about the association between current leading indicators and future earnings. In particular, the market behaves as though the contribution of backlog to future earnings is larger than that warranted by the earnings prediction model. This anomaly can be exploited to earn abnormal hedge strategy returns and such returns are incremental to returns expected on account of Fama-French factors, Basu's (1977) earnings-price anomaly and Sloan's (1996) accrual anomaly.

We probe deeper to evaluate whether analysts correctly appreciate the role of backlog in predicting future earnings. We find that analysts incorporate backlog information into their equity forecasts in a manner consistent with the relation between backlog and future earnings. However, investors appear to value backlog incremental to analyst forecasts that already include the implications of backlog for future earnings. Thus, the backlog anomaly persists in spite of analyst forecast efficiency possibly because the stock market fixates on order backlog information.

Our findings have several implications. The assumption of market efficiency in prior studies on the value-relevance of non-GAAP indicators may be open to question. Because investors have trouble appreciating the future-earnings implications of backlog for a set of relatively mature industries such as durable manufacturers and computers, it may not be a stretch to conjecture that investors perhaps over-value leading indicators in technology-intensive and early-stage businesses focused on wireless operations and the Internet. It is also worth noting that stock analysts in these industries often rely on ratios based on such indicators in their reports (e.g., price-to-POPS ratio in the wireless industry and price-to-eyeballs ratio in the Internet sector). Moreover, regulators cite evidence on the value-relevance of non-GAAP leading indicators (see FASB 2001 and SEC 2001) in policy papers that recommend enhanced disclosure of forward-looking information. Given the documented over-weighting of backlog information, perhaps standard-setting bodies could consider asking firms to report explicit data about how leading indicators might map into future earnings. An example of such disclosure might be the expected margins on order backlog. We hasten to add that policy recommendations based on empirical archival research are hazardous on account of difficulties associated with extrapolation of results from one study and the complex balancing of social costs and benefits of increased disclosure.

A limitation of our paper is that while we document an anomaly with respect to non-GAAP leading indicators, we do not provide a testable alternative to market efficiency. Behavioral models, proposed by Barberis, Shleifer, and Vishny (1998) and Daniel, Hirschleifer and Subramanyam (1998), suggest a few first steps in that direction. Barberis et al. (1996) is motivated by two judgment-related biases documented in psychology research: (i) the representativeness bias of Kahneman and Tversky (1982) which argues that people attach too much weight to recent patterns in the data and too little to the properties of the population that generates the data, and (ii) the conservatism bias due to Edwards (1968) which argues that people are slow in updating models in the face of new evidence. In Daniel et al. (1996) mispricing is caused by informed investors who suffer from over-confidence and self-attribution. Overconfidence leads them to exaggerate the precision of their private signals about a stock's value. Biased self-attribution causes them to place a lower weight on public signals about value, especially when the public signals contradict their private signals. Assessing whether these behavioral explanations can successfully explain the anomaly documented here or other anomalies, is a challenge for future research.

References

Abarbanell, J. 1991. Do analysts' forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics* 14, 147-165.

Abarbanell, J., and V. Bernard. 1993. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *Journal of Finance* 47, 1187-1207.

Abarbanell, J., and B. Bushee. 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35 (Spring), 1-24.

Abarbanell, J., and B. Bushee. 1998. Abnormal returns to a fundamental analysis strategy. *The Accounting Review* (January), 19-45.

Abarbanell, J., and R. Lehavy. 2000. Differences in commercial database reported earnings: Implications for inferences concerning analyst forecast rationality, the association between prices and earnings, and firm reporting discretion. Working paper, University of North Carolina at Chapel Hill and University of California, Berkeley.

Abel, A., and F. Mishkin. 1983. An integrated view of tests of rationality, market efficiency and the short run neutrality of monetary policy. *Journal of Monetary Economics* 11 (January), 3-24.

Ahmed, A.S., K. Nainar, and J. Zhou. 2001. Do analysts' forecasts fully reflect the information in accruals? Working paper, Syracuse University.

Ali, A., A. Klien, and J. Rosenfeld. 1992. Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS. *The Accounting Review* 67, 183-198.

American Institute of Certified Public Accountants (AICPA) 1994. *Improving business reporting – A customer focus: Meeting the information needs of investors and creditors*. New York, NY.

Amir, E., and B. Lev. 1996. Value-relevance of nonfinancial information: The wireless communications industry. *Journal of Accounting and Economics* 22, 3-30.

Barth, M.E., R. Kaznik, and M. F. McNichols. 2001. Analyst coverage and intangible assets *Journal of Accounting Research* (forthcoming).

Banker, R., G. Potter, and D. Srinivasan. 2000. An empirical investigation of an incentive plan that includes nonfinancial performance measures. *The Accounting Review* 75: 65-92.

Barberis, N., A. Schleifer, and R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* (September): 49(3): 307-343.

Basu, S. 1977. The investment performance of common stocks in relation to their price to earnings ratios: A test of the efficient markets hypothesis. *Journal of Finance* 32, 663-662.

Beaver, W.H. 1970. The time series behavior of earnings. *Journal of Accounting Research* 8 (June/September), 319-346.

Beaver, W.H., and M.F.McNichols. 2001. Do stock prices of property casualty insurers fully reflect information about earnings, accruals, cash flows, and development? *Review of Accounting Studies* (forthcoming).

Behn, B.K. 1996. Value implications of unfilled order backlogs. *Advances in Accounting* 14, 61-84.

Bernard, V. 1987. Cross-sectional dependence and problems in inference in market-based accounting research. *Journal of Accounting Research* 25 (Spring), 1-48.

Bernard, V., and J. Thomas, 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Brown, S., K. Lo, and T. Lys. 1999. Use of R^2 in accounting research: Measuring changes in value relevance over the last four decades. *Journal of Accounting & Economics* 28, 83-115.

Burgstahler D., J. Jiambalvo, and T. Shevlin. 2001. Do stock prices fully reflect the implications of special items for future earnings? Working paper, University of Washington.

Chan, L.K.C, J. Lakonishok, and T. Sougiannis. 2000. The stock market valuation of research and development expenditures. *The Journal of Finance* 56(6): 2431-2456.

Chandra U., A. Procassini, and G. Waymire. 1999. The use of trade association disclosures by investors and analysts: Evidence from the semiconductor industry. *Contemporary Accounting Research*, 643-670.

Collins, D.W., and P. Hribar. 2000. Earnings-based and accrual-based market anomalies: one effect or two? *Journal Of Accounting And Economics* 29, 101-123.

Collins, D.W., E.L. Maydew, and I.S. Weiss. 1997. Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting & Economics* 24, 39-67

Daniel, K, D. Hirshleifer, and A. Subramanyam. 1998. Investor psychology and security market under- and overreactions. *The Journal of Finance* 53(6): 1839-1885

Demers, E., and B. Lev. 2000. A rude awakening: Internet value drivers in 2000, *Review of Accounting Studies* 6 (July/Sep), 331-359.

Deng, Z, B. Lev, and F. Narin. 1999. Science and technology as predictors of stock performance *Financial Analysts Journal* 55 (May/Jun), 20-32.

Doukas, J.A., C. Kim, and C. Pantzalis. 2001. A test of the errors-in-expectations explanation of the value/glamour stock returns performance: Evidence from analysts' forecasts. *The Journal of Finance* (forthcoming).

Eccles, R.G., R. H. Herz, M. Keegan, D.M.H. Phillips. 2001. *The Value Reporting Revolution: Moving Beyond the Earnings Game*. John Wiley & Sons, NY.

Edwards, W. 1968. Conservatism in human information processing, in B.Kleinmutz (ed.), *Formal Representation of Human Judgement*, New York, John Wiley and Sons.

Elgers, P.T., M.H. Lo, and R.J. Pfeiffer. 2001. Delayed security price adjustments to financial analysts' forecasts of annual earnings. *The Accounting Review* (forthcoming).

Fama, E. and K. French. 1992. The cross-section of expected returns. *Journal of Finance* 47 (June): 427-466.

Fama, E. and J. Macbeth. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 71 (May/June), 607-636.

FASB report Business and Financial Reporting: Challenges from the New Economy 2001.

Foster, G., C. Olsen, and T. Shevlin. 1984. Earnings releases, anomalies, and the behavior of security returns. *The Accounting Review* 59, 574-604.

Francis J., and K. Schipper. 1999. Have financial statements lost their relevance? *Journal of Accounting Research,* Autumn 37, 319-352.

Francis, J., K. Schipper, and L. Vincent. 2001. The relative and incremental information content of alternative (to earnings) performance measures. Working paper, Duke University and Northwestern University.

Freeman, R., J. Ohlson, and S. Penman. 1982. Book rate-of-return and prediction of earnings changes: An empirical investigation. *Journal of Accounting Research* 20 (Autumn), 3-42.

Ittner, C. and D. Larcker. 1998. Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research* 36 (Supplement), 1-36.

Kahneman, D. and A.Tversky. 1982. Intuitive predictions: Biases and corrective procedures. Reprinted in Kahneman, Slovic, and Tversky, *Judgement Under Uncertainity*: *Heuristics and Biases* Cambridge University Press, Cambridge, England.

Klein, A. 1990. A direct test of the cognitive bias theory of share price reversals. *Journal of Accounting and Economics* 13, 155-166.

Kraft, A., A. Leone, and C. Wasley. 2001. On the use of Mishkin's rational expectations approach to testing efficient-markets hypotheses in accounting research. Working paper, University of Rochester.

Lakonishok, J, A. Shleifer, and R. W. Vishny. 1994. Contrarian investments, extrapolation, and risk. *The Journal of Finance*, 49, 1541-1578.

La Porta, R, J. Lakonishok, A. Shleifer, and R.W. Vishny. 1997. Good news for value stocks: Further evidence on market efficiency. *The Journal of Finance*, 50, 1715-1742.

Lev, B. and S. R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31 (Autumn), 190-215.

Lev, B. and P. Zarowin. 1999. The boundaries of financial reporting and how to extend them. *Journal of Accounting Research*, 353-385.

Liu, C., J. Livnat, and S.G. Ryan. 1996. Forward-looking financial information: The order backlog as a predictor of future sales. *The Journal of Financial Statement Analysis* (Fall), 89-99.

Mendenhall, R. 1991. Evidence on the possible underweighting of earnings-related information. *Journal of Accounting Research* 29, 170-179.

Mishkin, F. 1983, A Rational Expectations Approach to Macroeconometrics: Testing Policy Ineffectiveness and Efficient-Markets Models. Chicago: University of Chicago Press.

Nagar, V. and M. Rajan. 2001. The revenue implications of financial and operational measures of product quality. *The Accounting Review* 76 (October), 495-513.

Ou, J., and S.H. Penman. 1989. Financial statement analysis and the prediction of stock returns. *Journal of Accounting and economics* 11, 295-330.

Rajgopal, S., M. Venkatachalam, and S. Kotha. 2001. Does the quality of online customer experience create a sustainable competitive advantage for e-commerce firms? Working paper, University of Washington and Stanford University.

Securities and Exchange Commisson. 2001. Division of Corporation Finance

Current Accounting and Disclosure Issues, Prepared by Accounting Staff Members in the Division of Corporation Finance. March 31, http://www.sec.gov/divisions/corpfin/acctdisc.htm#P466_96509

Shevlin, T.S. and D. Shores. 1993. Firm size, security returns, and unexpected earnings: The anomalous signed-size effect. *Contemporary Accounting Research* 10, 1-30.

Sloan R.G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* (July), 1-27.

Soffer, L.C. and T. Lys. 1999. Post-earnings announcement drift and the dissemination of predictable information. *Contemporary Accounting Research*, 16, 305-331.

Trueman, B. F.Wong and X. Zhang. 2001. The eyeballs have it: Searching for the value in Internet stocks. *Journal of Accounting Research* 38 (supplement), 137-162.

Wahlen, J.M. 2001. Do stock prices of property casualty insurers fully reflect information about earnings, accruals, cash flow and development? Analysis, synthesis and extension. *Review of Accounting Studies* (forthcoming).

Walther, B. 1997. Investor sophistication and the market earnings expectations. *Journal of Accounting Research* 35, 157-192.

Xie H. 2001 Are discretionary accruals mispriced? A reexamination. *The Accounting Review* 76 (Jul), 357-373.

Table 1

Descriptive Statistics

Panel A: Primary Variables

Variable	N	Mean	Std.dev.	Median	1st quartile	3rd quartile
EARN	21891	0.00	0.18	0.04	-0.02	0.08
ACC	13012	-0.04	0.15	-0.03	-0.08	0.02
OPCF	13012	0.04	0.16	0.06	-0.00	0.11
BKLG	21891	0.46	1.36	0.30	0.15	0.57
SAR	21891	0.01	0.72	-0.09	-0.35	0.20
EPS	11259	0.03	0.22	0.06	0.03	0.08
FEPS	11259	0.07	0.10	0.07	0.05	0.10

Panel B: Risk Factors and Control Variables

Variable	N	Mean	Std.dev.	Median	1st quartile	3rd quartile
BM	21891	-0.73	1.45	-0.51	-1.09	-0.01
BETA	21891	1.15	0.79	1.12	0.73	1.54
SIZE	21891	3.89	1.87	3.77	2.57	5.06
EP	21891	-0.00	0.05	0.05	-0.01	0.08

Table 1 (continued)

Panel C: Industry Composition

Industry	Obs	%	Mean Backlog
Mining and construction	753	3.44	0.74
Food	91	0.42	0.25
Textiles, Printing and Publishing	2046	9.35	0.32
Chemicals	336	1.54	0.30
Pharmaceuticals	171	0.78	0.17
Extractive Industries	140	0.64	0.43
Durable manufacturers	11802	53.91	0.45
Computers	4020	18.36	0.49
Transportation	89	0.41	0.36
Utilities	162	0.74	0.90
Retail	827	3.78	0.32
Services	1014	4.63	0.77
Other	487	2.74	0.66
Total	21891	100.00	0.46

The variables are defined as follows:

EARN = income before extraordinary items and discontinued operations divided by average total assets.
OPCF = net cash flows from operating activities from SFAS 95 scaled by average total assets.
ACC = total operating accruals (EARN *minus* OPCF) scaled by average total assets.
BKLG = order backlog divided by average total assets.
SAR = size adjusted abnormal returns computed as the buy and hold raw return *minus* the buy and hold return on a size matched decile portfolio of firms cumulated over 12 months beginning with the fourth month after the end of fiscal year t.
EPS = earnings per share as reported by I/B/E/S, scaled by share price at four months after the end of previous fiscal year.
FEPS = I/B/E/S median consensus earnings forecast per share reported four months after the end of previous fiscal year scaled by share price.
BM = the natural logarithm of the ratio of the book to market ratio measured at the beginning of the abnormal return accumulation period.
BETA = systematic risk estimated from regression of monthly raw returns on value weighted portfolio over a 60-month return period prior to the abnormal return accumulation period.
SIZE = the natural logarithm of the market value of common equity measured at the beginning of the abnormal return accumulation period.
EP = earnings to price ratio (stock price measured at the beginning of the return accumulation period).

Table 2

Nonlinear generalized least squares estimates of the relation between abnormal stock return and the information contained in order backlog for future earnings (21891 firm year observations spanning years 1981-1999)

$$EARN_{t+1} = \omega_0 + \omega_1\ EARN_t + \omega_2\ BKLG_t + \varepsilon_{t+1} \quad (1)$$

$$SAR_{t+1} = \beta_0 + \beta_1\ (EARN_{t+1} - \omega_0 - \omega_1^*\ EARN_t - \omega_2^*\ BKLG_t) + \nu_{t+1} \quad (4)$$

Parameter	Pred. Sign	Estimate	Asymptotic Standard Error
ω_0	?	-0.001	0.001
ω_1	+	0.581**	0.005
ω_1^*	+	0.536**	0.023
ω_2	+	0.008**	0.002
ω_2^*	+	0.039**	0.009
β_0	?	0.027**	0.007
β_1	+	1.088**	0.033

Test of Market Efficiency:	$\omega_1 = \omega_1^*$	$\omega_2 = \omega_2^*$
Likelihood ratio statistic	3.81	12.06
Marginal significance level	0.05	0.00

Note: */** represents statistical significance at 5%/1% levels two-tailed.

The variables are defined as follows:

EARN = income before extraordinary items and discontinued operations divided by average total assets.

BKLG = order backlog divided by average total assets.

SAR = size adjusted abnormal returns computed as the buy and hold raw return *minus* the buy and hold return on a size matched decile portfolio of firms cumulated over 12 months beginning with the fourth month after the end of fiscal year t.

Table 3

Summary regression statistics of the relation between abnormal stock return and scaled order backlog decile rankings after controlling for Fama-French risk factors and EP anomaly (Fama and Macbeth 1973 approach)

$$SAR_{t+1} = \gamma_0 + \gamma_1 \, BKLG^{dec}_t + \varphi_{t+1} \quad (6)$$

$$SAR_{t+1} = \gamma_0 + \gamma_1 \, BKLG^{dec}_t + \gamma_2 \, SIZE^{dec}_t + \gamma_3 \, BETA^{dec}_t + \gamma_4 \, BM^{dec}_i + \gamma_5 \, EP^{dec}_i + \varphi_{t+1} \quad (7)$$

Parameter	Pred. Sign	Means from Annual Regressions (N=19)	Number of years Positive/ (Negative)
Panel A: Univariate Regressions			
γ_0	?	0.042 (1.85)	12/(7)
γ_1	-	-0.058* (-2.38)	6/(13)
Panel B: Regressions after Controlling for Risk Factors			
γ_0	?	0.027 (0.73)	10/(9)
γ_1	-	-0.048* (-2.12)	5/(14)
γ_2	-	-0.083** (-3.22)	6/(13)
γ_3	+	0.043 (0.78)	8/(11)
γ_4	+	0.075* (2.26)	15/(4)
γ_5	+	-0.014 (-0.31)	11/(4)

Note: */** represents statistical significance at 5%/1% levels two-tailed.
t-statistic (in parenthesis) is computed as the ratio of the mean of the annual coefficients to the standard error calculated from the distribution of annual coefficients.

Table 3 (continued)

The variables are defined as follows:

SAR	= size adjusted abnormal returns computed as the buy and hold raw return *minus* the buy and hold return on a size matched decile portfolio of firms cumulated over 12 months beginning with the fourth month after the end of fiscal year t.
$BKLG^{dec}$	= order backlog divided by average total assets, transformed to a scaled-decile variable with values ranging from 0 to 1.
$SIZE^{dec}$	= the natural logarithm of the market value of common equity measured at the beginning of the abnormal return accumulation period, transformed to a scaled-decile variable with values ranging from 0 to 1.
$BETA^{dec}$	= systematic risk estimated from regression of monthly raw returns on value weighted portfolio over a 60-month return period prior to the abnormal return accumulation period, transformed to a scaled-decile variable with values ranging from 0 to 1.
BM^{dec}	= the natural logarithm of the ratio of the book to market ratio measured at the beginning of the abnormal return accumulation period, transformed to a scaled-decile variable with values ranging from 0 to 1.
EP^{dec}	= earnings to price ratio (stock price measured at the beginning of the return accumulation period), transformed to a scaled-decile variable with values ranging from 0 to 1.

Table 4

Nonlinear generalized least squares estimates of the relation between abnormal stock return and the information contained in order backlog for future earnings after controlling for differential implications of accrual component of earnings (13012 firm year observations spanning 1989-1999)

$$EARN_{t+1} = \omega_0 + \omega_{1a} OPCF_t + \omega_{1b} ACC_t + \omega_2 BKLG_t + \varepsilon_{t+1} \quad (1')$$

$$SAR_{t+1} = \beta_0 + \beta_1 (EARN_{t+1} - \omega_0 - \omega_{1a}^* OPCF_t - \omega_{1b}^* ACC_t - \omega_2^* BKLG_t) + \nu_{t+1} \quad (4')$$

Parameter	Pred. Sign	Estimate	Asymptotic Standard Error
ω_0	?	-0.014**	0.003
ω_{1a}	+	0.726**	0.008
ω_{1a}^*	+	0.586**	0.040
ω_{1b}	+	0.390**	0.009
ω_{1b}^*	+	0.557**	0.042
ω_2	+	0.005*	0.003
ω_2^*	+	0.052**	0.013
β_0	?	0.035**	0.010
β_1	+	1.104**	0.046

Test of Market Efficiency:	$\omega_{1a} = \omega_{1a}^*$	$\omega_{1b} = \omega_{1b}^*$	$\omega_2 = \omega_2^*$
Likelihood ratio statistic	11.84	15.31	13.91
Marginal significance level	0.00	0.00	0.00

Note: */** represents statistical significance at 5%/1% levels two-tailed.

The variables are defined as follows:

BKLG = order backlog divided by average total assets.
OPCF = net cash flows from operating activities divided by average total assets.
ACC = total operating accruals (EARN *minus* OPCF) divided by average total assets.
SAR = size adjusted abnormal returns computed as the buy and hold raw return *minus* the buy and hold return on a size matched decile portfolio of firms cumulated over 12 months beginning with the fourth month after the end of fiscal year t.

Table 5

Summary regression statistics of the relation between abnormal stock return and scaled order backlog decile rankings after controlling for Fama-French risk factors and the EP and accrual anomalies (Fama and Macbeth 1973 approach)

$$SAR_{t+1} = \gamma_0 + \gamma_1 \, BKLG^{dec}_t + \varphi_{t+1} \quad (6)$$

$$SAR_{t+1} = \gamma_0 + \gamma_1 \, BKLG^{dec}_t + \gamma_2 \, SIZE^{dec}_t + \gamma_3 \, BETA^{dec}_t + \gamma_4 \, BM^{dec}_t + \gamma_5 \, EP^{dec}_t + \gamma_6 \, ACC^{dec}_t + \varphi_{t+1} \quad (7')$$

Parameter	**Pred. Sign**	**Means from Annual Regressions (N=11)**	**Number of years Positive/ (Negative)**
Panel A: Univariate Regressions			
γ_0	?	0.069 (1.94)	7/(4)
γ_1	-	-0.081* (-2.18)	3/(8)
Panel B: Regressions after Controlling for Risk Factors			
γ_0	?	0.103 (1.63)	7/(4)
γ_1	-	-0.077* (-2.43)	3/(8)
γ_2	-	-0.049 (-1.45)	4/(7)
γ_3	+	0.129 (1.51)	8/(3)
γ_4	+	0.035 (0.65)	6/(5)
γ_5	+	-0.022 (-0.39)	5/(6)
γ_6	-	-0.166** (-5.30)	0/(11)

Note: */** represents statistical significance at 5%/1% levels two-tailed.
t-statistic (in parenthesis) is computed as the ratio of the mean of the annual coefficients to the standard error calculated from the distribution of annual coefficients.

Table 5 (continued)

The variables are defined as follows:

SAR	= size adjusted abnormal returns computed as the buy and hold raw return *minus* the buy and hold return on a size matched decile portfolio of firms cumulated over 12 months beginning with the fourth month after the end of fiscal year t.
$BKLG^{dec}$	= order backlog divided by average total assets, transformed to a scaled-decile variable with values ranging from 0 to 1.
$SIZE^{dec}$	= the natural logarithm of the market value of common equity measured at the beginning of the abnormal return accumulation period, transformed to a scaled-decile variable with values ranging from 0 to 1.
$BETA^{dec}$	= systematic risk estimated from regression of monthly raw returns on value weighted portfolio over a 60-month return period prior to the abnormal return accumulation period, transformed to a scaled-decile variable with values ranging from 0 to 1.
BM^{dec}	= the natural logarithm of the ratio of the book to market ratio measured at the beginning of the abnormal return accumulation period, transformed to a scaled-decile variable with values ranging from 0 to 1.
EP^{dec}	= earnings to price ratio (stock price measured at the beginning of the return accumulation period), transformed to a scaled-decile variable with values ranging from 0 to 1.
ACC^{dec}	= total operating accruals (EARN *minus* OPCF) divided by average total assets, transformed to a scaled-decile variable with values ranging from 0 to 1.

Table 6

Summary regression statistics of the relation between scaled decile rankings of order backlog and analysts' earnings forecasts and forecast errors
(11259 firm year observations spanning 1981-1999)

$$EPS_{t+1} = \delta_0 + \delta_1\, EPS_t + \delta_2\, BKLG^{dec}_t + \mu_{t+1} \qquad (8)$$

$$FEPS_{t+1} = \lambda_0 + \lambda_1\, EPS_t + \lambda_2\, BKLG^{dec}_t + \eta_{t+1} \qquad (9)$$

$$FERR_{t+1} = (\delta_0 - \lambda_0) + (\delta_1 - \lambda_1)\, EPS_t + (\delta_2 - \lambda_2)\, BKLG^{dec}_t + (\mu_{t+1} - \eta_{t+1}) \qquad (10)$$

Parameter	Pred. Sign	Means from Annual Regressions (N=19)
Panel A: EPS Equation		
δ_0	?	0.006 (1.27)
δ_1	+	0.488** (4.86)
δ_2	+	0.016** (3.29)
Panel B: Forecast EPS Equation		
λ_0	?	0.062** (12.34)
λ_1	+	0.221** (7.24)
λ_2	+	0.017** (5.07)
Panel C: Forecast Error Equation		
$\delta_0 - \lambda_0$	-	-0.055** (-8.15)
$\delta_1 - \lambda_1$	?	0.267** (2.99)
$\delta_2 - \lambda_2$	?	-0.001 (-0.24)

Note: */** represents statistical significance at 5%/1% levels two-tailed.
t-statistic (in parenthesis) is computed as the ratio of the mean of the annual coefficients to the standard error calculated from the distribution of annual coefficients.

Table 6 (continued)

The variables are defined as follows:

EPS	= earnings per share as reported by I/B/E/S, scaled by share price at four months after the end of previous fiscal year.
FEPS	= I/B/E/S median consensus earnings forecast per share reported four months after the end of previous fiscal year scaled by share price.
FERR	= forecast error computed as EPS *minus* FEPS.
$BKLG^{dec}$	= order backlog divided by average total assets, transformed to a scaled-decile variable with values ranging from 0 to 1.

Table 7

Nonlinear generalized least squares estimates of the relation between abnormal stock return and the information contained in order backlog for future earnings after controlling for the information contained in analysts' earnings forecasts
(11259 firm year observations spanning 1981-1999)

$$EPS_{t+1} = \alpha_0 + \alpha_1 EPS_t + \alpha_2 FEPS_{t+1} + \alpha_3 BKLG^{dec}{}_t + \phi_{t+1} \quad (11)$$

$$SAR_{t+1} = \zeta_0 + \zeta_1 (EPS_{t+1} - \alpha_0 - \alpha_1^* EPS_t - \alpha_2^* FEPS_{t+1} - \alpha_3^* BKLG^{dec}{}_t) + \pi_{t+1} \quad (12)$$

Parameter	Pred. Sign	Estimate	Asymptotic Standard Error
α_0	?	-0.033**	0.004
α_1	+	0.162**	0.007
α_1^*	+	0.164**	0.054
α_2	+	0.762**	0.021
α_2^*	+	1.260**	0.173
α_3	0	0.001	0.001
α_3^*	0	0.019**	0.005
ζ_0	?	0.058**	0.011
ζ_1	+	0.383**	0.029

Test of Market Efficiency:	$\alpha_1 = \alpha_1^*$	$\alpha_2 = \alpha_2^*$	$\alpha_3 = \alpha_3^*$
Likelihood ratio statistic	0.00	8.64	12.15
Marginal significance level	0.96	0.00	0.00

Note: */** represents statistical significance at 5%/1% levels two-tailed.

The variables are defined as follows:

EPS = earnings per share as reported by I/B/E/S, scaled by share price at four months after the end of previous fiscal year.
FEPS = I/B/E/S median consensus earnings forecast per share reported four months after the end of previous fiscal year scaled by share price.
FERR = forecast error computed as EPS *minus* FEPS.
$BKLG^{dec}$ = order backlog divided by average total assets, transformed to a scaled-decile variable with values ranging from 0 to 1.
SAR = size adjusted abnormal returns computed as the buy and hold raw return *minus* the buy and hold return on a size matched decile portfolio of firms cumulated over 12 months beginning with the fourth month after the end of fiscal year t.