Review of Accounting Studies, 8, 461–492, 2003

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

SHIVARAM RAJGOPAL rajgopal@u.washington.edu
Department of Accounting, University of Washington, Box 353200, Seattle, WA 98195

TERRY SHEVLIN* shevlin@u.washington.edu
Department of Accounting, University of Washington, Box 353200, Seattle, WA 98195

MOHAN VENKATACHALAM vmohan@duke.edu
Fuqua School of Business, Duke University, P.O. Box 90120, Durham, NC 27708

Abstract. Although leading indicators are becoming increasingly important for equity valuation, disclosures of such indicators suffer from the absence of GAAP related guidance on content and presentation. We explicitly examine (i) whether one leading indicator—order backlog—predicts 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 exploits such overweighting generates significant future abnormal returns. However, such mispricing is not due to analysts' inability to incorporate order backlog into their earnings forecasts.

Keywords: leading indicator, backlog, mispricing, market efficiency, analyst forecasts

JEL Classification: M41, G14

In this study, we investigate whether capital 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. The market value of a firm's shares and analyst forecasts should reflect an unbiased expectation of future earnings. To the extent current earnings persist in the future, the link between current and future earnings is relatively apparent. However, in today's dynamic business environment, a substantial portion of future earnings may reflect the contribution of several leading indicators such as backlog (Behn, 1996), product market share (Amir and Lev, 1996), customer satisfaction (Ittner and Larcker, 1998a), patents (Deng et al., 1999), web traffic (Trueman et al., 2001; Rajgopal et al., 2003) or managerial actions (Rajgopal et al., 2002). Under generally accepted US accounting principles, such leading indicators are not recognized but are often disclosed in the firm's financial statements. When an economically significant portion of a firm's future earnings stems from leading indicators, the

*Corresponding author.

absence of explicit information about the contribution of such indicators to future earnings complicates the task of equity valuation.

Disclosure issues related to leading indicators have grown in importance in recent years. One reason for such focus is claims about the declining importance of accounting-based performance metrics such as earnings and equity book values (see Collins et al., 1997; Francis and Schipper, 1999; Brown et al., 1999; Lev and Zarowin, 1999). Further, the Jenkins Committee report (AICPA, 1994) and research on the lead–lag relation between stock prices and earnings (see Kothari, 2001) kindled an active interest among academics in understanding whether leading indicators of future earnings could potentially remedy the perceived fall in the value-relevance of earnings and book value. Several practitioners (e.g., Kaplan and Norton, 1996; Eccles et al., 2001) have called for a reporting framework that integrates traditional financial measures and leading indicators. Recently, national regulators such as the FASB (2001) and SEC (2001) and international regulators such as the Canadian Institute of Chartered Accountants (1995) and Institute of Chartered Accountants of England and Wales (2000) have published studies that discuss the possibility of mandating enhanced disclosures of leading indicators.

The increased importance of non-GAAP leading indicators raises the question of whether security prices reflect their unbiased contribution to future earnings. In an efficient market, the stock market correctly impounds the value of a leading indicator for future earnings. Hence, there ought to be no association between leading indictors and future stock returns. On the other hand, several characteristics of these leading indicators impede a clear understanding of their implications for future earnings. Most leading indicators are inherently idiosyncratic to specific industries and some are even specific to individual firms. Disclosure of such metrics is voluntary and is open to management discretion. Furthermore, the content and presentation of such disclosures are not standardized by GAAP. Many indicators are not denominated in dollars, rendering cross-firm comparison of such indicators difficult. Moreover, a recent FASB study (FASB 2001) found several problems in the extant disclosures: (i) indicators were presented in isolation without relating them to the context of the industry and the company; (ii) the measurement and presentation of some indicators were not consistent over time; (iii) some firms presented vague metrics such as "organization enhancing customers" or "image enhancing customers" without a concise definition of the metric or its measurement.

These complications raise the possibility that stock prices do not fully incorporate the contribution of leading indicators for future earnings. On account of uncertainty inherent in translating leading indicators to value creation, investors may excessively discount the contribution of such indicators to future earnings. Underpricing may also arise if investors are functionally fixated on current earnings—i.e., they mechanically accept firms' current earnings numbers at face value without adjusting for the long-term benefits of the underlying activities or processes captured by leading indicators.

In contrast, some observers have suggested that investors overestimate the benefits from leading indicators, especially in hot sectors of the economy such as Internet-intensive businesses or the wireless industry (Damodaran, 2001; D'Avolio et al., 2001). There is wide coverage of leading indicators such as POPS (population coverage), book-to-bill ratio or customer satisfaction indices in the media and some firms devote intensive marketing efforts to promote such indicators. As a result, the market may be overly optimistic about the contribution of such indicators to future earnings. The objective of our study is to explicitly examine whether investors appropriately account for the contribution of leading indicators to future earnings.

We choose order backlog as the leading indicator in our empirical tests because an investigation into the potential mispricing of a widely disseminated, dollar denominated leading indicator that is readily available and cross-sectionally comparable for a large number of firms across several industries gives the null of market efficiency the best possible chance of success. Moreover, order backlog is economically significant (30% of total assets for the median sample firm) and is somewhat standardized in its definition and disclosure. If the market has difficulty in interpreting the implications of order backlog for future earnings, it is more than likely that the market fails to fully appreciate the implications of non-dollar denominated, less widely disseminated, and less objective leading indicators such as customer satisfaction measures, web traffic, patents or firm- or industry-specific metrics such as manufacturing cycle time or time-to-market measures.

Our empirical tests use the Mishkin (1983) framework to examine whether market participants incorporate into stock prices 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 is 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 and 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 and 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 result is consistent with market participants not appreciating the fact that analyst forecasts already incorporate information in order backlog.

Our study extends two areas of prior research. First, we contribute to the literature that documents a relation between stock prices and leading indicators. 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. However, recent research raises doubts about that assumption. In particular, survey evidence presented by Ittner and Larcker (1998b) suggests that even managers question the quality of leading indicator information. Furthermore, a field study conducted by Banker et al., (2000) indicates that managers, let alone investors, cannot fully articulate the link between leading indicators and firm value.

The evidence we present suggests that the market misprices leading indicators although sophisticated information intermediaries such as analysts fully appreciate these disclosures. To the extent such abnormal returns imply that there are costs associated with the limited disclosure of information on order backlog (such as estimated future earnings from backlog), we believe that our findings 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). Second, we extend prior research by Sloan (1996) that examines market efficiency with respect to earnings, accruals, and cash flows, to leading indicators and their contribution to future earnings.

The remainder of the paper is organized as follows. In Section 1, we briefly describe the difficulties associated with disclosures of leading indicators, prior research and institutional details on order backlog. Section 2 discusses the sample while Section 3 presents the experimental procedures employed and the findings. Section 4 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 5 provides some concluding remarks.

1. Background

1.1. Disclosure Issues on Leading Indicators

In recent years, academics, practitioners and regulatory bodies have called for increased disclosure of leading indicators by firms (e.g., AICPA, 1994; Eccles et al., 2001; Lev, 2001). These groups argue that traditional financial measures such as book value and earnings have reduced relevance for valuation purposes, especially in rapidly evolving technology-based industries.[1] Survey evidence suggests that professional analysts use leading indicators reported in firms' financial reports (Previts et al., 1994). Concurrently, several firms have adopted the use of leading indicators for internal performance evaluation (Ittner and Larcker, 1998b). Given the increasing importance of leading indicators for valuation and managerial compensation purposes, many practitioners have called for a disclosure framework that integrates leading indicators with traditional financial measures (Kaplan and Norton, 1996; Eccles et al., 2001).

Extant disclosures of leading indicators are subject to several limitations (Eccles et al., 2001; FASB, 2001). First, disclosures of leading indicators are voluntary in nature and are hence not available for all firms. Second, the types of measures disclosed and the reporting formats used vary both in the cross-section and across time. Third, leading indicators are often industry-specific and sometimes even firm-specific. Fourth, survey evidence reported in Ittner and Larcker (1998b) indicates that (i) executives have concerns about the quality of leading indicators in certain areas such as employee performance, environment and innovation; and (ii) executives view financial information to be of higher quality than leading indicator data. Finally, two recent studies cast doubt on whether managers, let alone investors, can fully articulate the links between leading indicators and firm value (Banker et al., 2000; Ittner and Larcker, 1998b). For example, in a field study covering the hotel industry, Banker et al., (2000) find that while managers are aware of a relation between customer satisfaction and firm profitability, they did not fully appreciate the nature and the timing of this relation. These limitations raise questions about the relevance and reliability of disclosures related to leading indicators.

Research on the value-relevance of leading indicators suggests that such indicators are perhaps relevant and reliable enough for researchers to detect an association between leading indicators and contemporaneous stock prices. In the wireless industry, Amir and Lev (1996) find that income statement and balance sheet information explain little of the cross-sectional variation in the market values of wireless firms. However, two leading indicators—service area population (a product market size measure) and population penetration (a product market share measure) —are highly value-relevant incremental to traditional financial measures. For a broad cross-section of industries, Behn (1996) finds that unfulfilled order backlogs are value-relevant. Other examples of research that documents value-relevance of leading indicators include Ittner and Larcker (1998a) on customer satisfaction, Chandra et al., (1999) on the book-to-bill ratio in the semi-conductor industry, Deng et al., (1999) on patent counts, Hughes (2000) on sulfur dioxide emissions, and Francis et al., (2003) on airline load factors, home building order backlog, and same stores sales. Research on Internet firms related to web traffic, loyalty, and the quality of online customer experience (e.g., Trueman et al., 2001; Demers and Lev, 2001; Rajgopal et al., 2002, 2003) highlights the importance of leading indicators for emerging high-technology firms.

Most of the cited value-relevance research rests, however, on two important assumptions. First, the value-relevance of the leading indicator is usually assumed to be indicative of future earnings or future growth options in the firm. Many of the cited studies do not test whether these leading indicators predict realized future earnings.[2] Second, all the cited studies assume market efficiency in assessing the relevance and reliability of leading indicators. However, the assumption of market efficiency, even with respect to widely disseminated financial measures such as earnings and accruals, has been challenged (e.g., Bernard and Thomas, 1990; Sloan, 1996). Further, a recent commentary by the AAA Financial Accounting Standards Committee (2002, p. 357) raises questions about investors' ability to use leading indicators appropriately in firm valuation.

We explicitly examine both these assumptions in the current study. In particular, we model the association between a leading indicator (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.

1.2. 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 SEC 10-K filing 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 2). 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 equals 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 disclosures made by the company in its 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 US 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 market participants 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) have a backlog-to-annual sales ratio in excess of 100%. Although firms are required by Item 101(c) (VIII) of SEC regulations S-K to disclose the proportion of backlog not scheduled to be executed in the next fiscal year, Compustat does not code that information. Hence, we are unable to use that data in our empirical tests. However, 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. We relax the one-lag structure assumption in our sensitivity analyses.

Even if backlog is economically significant, market participants may not use backlog disclosures unless such disclosures are reliable. Previous studies provide evidence that backlog disclosures are value-relevant in general (Behn, 1996; Chandra et al., 1999), and are useful in predicting future sales (Liu et al., 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 market participants fully appreciate the association between order backlog and future earnings.

2. 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 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.

2.1. 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).

$EARN_t$ = 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.

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.

Following Sloan (1996), we control for Fama and 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 (MVE), measured at four months after fiscal year-end.

$LnBM_t$ = the natural log of the ratio of book value of common equity to the market value of common equity (BM), measured at four months after fiscal year-end.[3]

$BETA_t$ = 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.[4]

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

Descriptive data related to these variables are reported in Panels A and B 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. Panel C presents data on the potential relation between order backlog deflated by assets (i.e., BKLG) and other firm characteristics such as backlog deflated by sales, earnings, cash flows, and accruals, Fama and French (1992) risk factors, and other variables shown to predict future returns. In particular, we form

Table 1. Descriptive statistics
Panel A: Primary variables

Variable	*N*	Mean	Std. dev.	Median	1st quartile	3rd quartile
EARN	21,891	0.00	0.18	0.04	– 0.02	0.08
ACC	13,012	– 0.04	0.15	– 0.03	– 0.08	0.02
OPCF	13,012	0.04	0.16	0.06	– 0.00	0.11
BKLG	21,891	0.46	1.36	0.30	0.15	0.57
SAR	21,891	0.01	0.72	– 0.09	– 0.35	0.20
EPS	11,259	0.03	0.22	0.06	0.03	0.08
FEPS	11,259	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	21,891	1.09	22.01	0.63	0.04	1.00
LnBM	21,891	– 0.73	1.45	– 0.51	– 1.09	– 0.01
BETA	21,891	1.15	0.79	1.12	0.73	1.54
MVE (million $)	21,891	458.77	4,319.68	43.25	13.13	158.22
LnSIZE	21,891	3.89	1.87	3.77	2.57	5.06
EP	21,891	– 0.00	0.05	0.05	– 0.01	0.08
Sales growth	16,404	0.27	3.20	0.10	0.01	0.22

Table 1. Continued.

Panel C: Summary statistics for firm characteristics sorted on backlog deflated by assets (BKLG)

	Decile									
	1	2	3	4	5	6	7	8	9	10
BKLG	0.045	0.098	0.149	0.203	0.262	0.336	0.434	0.576	0.824	1.672
Backlog/sales	0.067	0.121	0.169	0.224	0.273	0.328	0.420	0.541	0.720	1.312
EARN	−0.020	−0.005	−0.004	−0.001	0.008	0.005	−0.002	−0.001	0.001	0.002
ACC	−0.042	−0.040	−0.043	−0.045	−0.046	−0.052	−0.040	−0.043	−0.042	−0.044
OPCF	0.030	0.038	0.042	0.042	0.052	0.050	0.028	0.031	0.038	0.037
BM	0.781	0.740	0.745	1.084	0.756	0.746	0.705	0.806	0.922	0.731
LnBM	−0.757	−0.711	−0.722	−0.642	−0.638	−0.680	−0.749	−0.769	−0.792	−0.860
BETA	1.107	1.115	1.123	1.162	1.156	1.181	1.209	1.182	1.166	1.144
MVE (million $)	493.778	909.453	377.267	468.029	257.631	392.619	325.249	318.755	484.233	560.779
SIZE	0.995	0.979	0.962	0.938	0.947	0.919	0.879	0.851	0.831	0.711
EP	−0.078	−0.052	−0.054	−0.002	−0.029	−0.042	−0.072	−0.023	0.350	−0.042
Sales growth	0.243	0.218	0.336	0.348	0.208	0.373	0.204	0.193	0.338	0.187

Panel D: Pearson correlation of backlog deflated by assets (BKLG) with firm characteristics

	Backlog/ Sales	EARN	ACC	OPCF	BM	LnBM	BETA	MVE	SIZE	EP	Sales Growth
ρ	0.53**	0.02**	−0.00	−0.00	0.01	−0.03**	0.01	0.01	0.01	0.01	−0.01
(p-value)	(0.00)	(0.00)	(0.86)	(0.87)	(0.20)	(0.00)	(0.37)	(0.59)	(0.50)	(0.19)	(0.56)

Table 1. Continued.
Panel E: Industry composition

Industry	Obs	%	Mean Backlog
Mining and construction	753	3.44	0.74
Food	91	0.42	0.25
Textiles, printing and publishing	2,046	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	11,802	53.91	0.45
Computers	4,020	18.36	0.49
Transportation	89	0.41	0.36
Utilities	162	0.74	0.90
Retail	827	3.78	0.32
Services	1,014	4.63	0.77
Other	487	2.74	0.66
Total	21,891	100.00	0.46

In panel C, the number of observations used to compute ACC, OPCF and Sales growth is 13,012, 13,012 and 16,404 respectively. The number of observations used for other statistics in panel C is 21,891. 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.
LnBM = the natural logarithm of the ratio of the book to market ratio (BM) 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 (MVE) 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).

ten portfolios sorted on order backlog (deflated by assets) and report the means of various characteristics of firms in these portfolios. We find that backlog deflated by sales closely follows the distribution of backlog deflated by assets. Other than that, there are no clear patterns between BKLG and the reported firm characteristics. Thus, the descriptive evidence presented in panel C indicates prima facie that BKLG is not strongly related to other well documented anomalies, although we investigate this issue in greater depth later in the paper. The correlations reported in panel D confirm that indication. In Panel E 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. Empirical Analyses

We present the empirical tests in several stages. In Sections 3.1 and 3.2, 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 for future earnings. In Section 3.3, we investigate whether abnormal returns can be earned by exploiting investors' misweighting of the contribution of order backlog to future earnings. In Section 4, we examine whether equity analysts use backlog information in an efficient manner while forecasting future earnings. Finally, we also assess whether market inefficiencies with respect to backlog are present after controlling for information in analysts' forecasts.

3.1. 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, 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 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 extend the earnings forecasting equation in Sloan (1996) to incorporate the implications of order backlog for future earnings as follows (firm subscripts suppressed):

$$\mathrm{EARN}_{t+1} = \omega_0 + \omega_1\ \mathrm{EARN}_t + \omega_2\ \mathrm{BKLG}_t + \varepsilon_{t+1}. \quad (1)$$

The coefficient ω_1 represents earnings persistence while ω_2 captures the incremental contribution of current order backlog for future earnings. Note that backlog is denominated in sales dollars. Hence, ω_2 incorporates the joint effect of (i) the probability of conversion of order backlog into future sales; and (ii) the accounting rate of return (margins) on such converted sales. For the purposes of our analyses, we assume ω_2 is a cross-sectional constant.[5]

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

$$\mathrm{SAR}_{t+1} = \beta_0 + \beta_1\ \mathrm{UEARN}_{t+1} + v_{t+1}, \tag{2}$$

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

$$\mathrm{UEARN}_{t+1} = \mathrm{EARN}_{t+1} - E(\mathrm{EARN}_{t+1}). \tag{3}$$

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

$$\mathrm{SAR}_{t+1} = \beta_0 + \beta_1(\mathrm{EARN}_{t+1} - \omega_0^* - \omega_1^*\ \mathrm{EARN}_t - \omega_2^*\ \mathrm{BKLG}_t) + v_{t+1}. \tag{4}$$

We refer to equation (4) as the returns equation. 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 is warranted.

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):

$$2^* n^* \ln(\mathrm{SSR}^{\mathrm{c}}/\mathrm{SSR}^{\mathrm{u}}), \tag{5}$$

where q is the number of constraints imposed by market efficiency; n is the number of observations in each equation; $\mathrm{SSR}^{\mathrm{c}}$ is the sum of squared residuals from the constrained weighted system; and $\mathrm{SSR}^{\mathrm{u}}$ is the sum of squared residuals from the unconstrained weighted system.

3.2. 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 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

Table 2. Nonlinear generalized least squares estimates of the relation between abnormal stock return and the information contained in order backlog for future earnings (21,891 firm year observations spanning years 1981–1999).

$$\text{EARN}_{t+1} = \omega_0 + \omega_1 \text{ EARN}_t + \omega_2 \text{ BKLG}_t + \varepsilon_{t+1}, \quad (1)$$

$$\text{SAR}_{t+1} = \beta_0 + \beta_1(\text{EARN}_{t+1} - \omega_0 - \omega_1^* \text{ EARN}_t - \omega_2^* \text{ BKLG}_t) + v_{t+1}. \quad (4)$$

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

*/** represent 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*.

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.[6]

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 ($p < 0.01$). While 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), recall 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, probably because some of the backlog may not convert to future sales or may convert at lower margins. This suggests that order backlog is incrementally informative about future earnings even after controlling for information in past earnings.

Of most importance is that 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.[7]

3.3. 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 et al., 2001). Second, because the coefficients are estimated from a set of contemporaneous observations, 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 a value ranging between zero and one. We estimate the following cross-sectional OLS regression for each of the 19 years in the sample:

$$\text{SAR}_{t+1} = \gamma_0 + \gamma_1 \, \text{BKLG}_t^{\text{dec}} + \phi_{t+1}. \tag{6}$$

The basic idea behind the Fama and MacBeth (1973) regressions is to project the size-adjusted returns on the intercept and the $\text{BKLG}_t^{\text{dec}}$ 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 $X = [1, \text{BKLG}_t^{\text{dec}}]$, 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 of 5.8% to a trading strategy based on order backlog is both statistically and economically significant.

3.4. Robustness Checks and Sensitivity Analyses

3.4.1. 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. Although panels C and D of Table 1 report the absence of strong relations between BKLG and the Fama–French factors, to be consistent with standard practice in recent asset-pricing literature, we investigate whether abnormal returns related to backlog are 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:

$$\mathrm{SAR}_{t+1} = \gamma_0 + \gamma_1\,\mathrm{BKLG}_t^{\mathrm{dec}} + \gamma_2\,\mathrm{SIZE}_t^{\mathrm{dec}} + \gamma_3\,\mathrm{BETA}_t^{\mathrm{dec}} + \gamma_4\,\mathrm{LnBM}_t^{\mathrm{dec}} + \gamma_5\,\mathrm{EP}_t^{\mathrm{dec}} + \varphi_{t+1}, \tag{7}$$

where $\mathrm{SIZE}_t^{\mathrm{dec}}$, $\mathrm{BETA}_t^{\mathrm{dec}}$, and $\mathrm{LnBM}_t^{\mathrm{dec}}$ relate to scaled decile ranks (ranging from 0 to 1) for the three Fama–French factors. $\mathrm{EP}_t^{\mathrm{dec}}$ 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.

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).

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

$$SAR_{t+1} = \gamma_0 + \gamma_1 \ BKLG_t^{dec} + \gamma_2 \ SIZE_t^{dec} + \gamma_3 \ BETA_t^{dec} + \gamma_4 \ LnBM_t^{dec} + \gamma_5 \ EP_t^{dec} + \varphi_{t+1}. \quad (7)$$

Parameter	Pred. Sign	Means from Annual Regressions ($N = 19$)		Number of Years Coefficient Positive/Negative	Number of Years Coefficient Significantly ($p < 0.05$) Positive/Negative
Panel A: Univariate regressions					
γ_0	?	0.042	(1.85)	12/7	3/3
γ_1	−	− 0.058*	(− 2.38)	6/13	0/10
Panel B: Regressions after controlling for risk factors					
γ_0	?	0.027	(0.73)	10/9	4/2
γ_1	−	− 0.048*	(− 2.12)	5/14	1/10
γ_2	−	− 0.083**	(− 3.22)	6/13	0/8
γ_3	+	0.043	(0.78)	8/11	0/6
γ_4	+	0.075*	(2.26)	15/4	10/1
γ_5	+	− 0.014	(− 0.31)	11/8	6/3

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

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.

$LnBM^{dec}$ = 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.

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 et al. (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 LnBM portfolio of 7.5%. The signs of abnormal returns on the SIZE and LnBM portfolios are consistent with those observed by Fama and French (1992).[8]

3.4.2. *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 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, Hribar and Collins (2002) 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 the 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 0.052) compared to the weight on BKLG in the forecasting equation (ω_2 is 0.005) 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, $\text{ACC}^{\text{dec}}_t$. 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.

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 (13,012 firm year observations spanning 1989–1999).

$$\text{EARN}_{t+1} = \omega_0 + \omega_{1a}\ \text{OPCF}_t + \omega_{1b}\ \text{ACC}_t + \omega_2\ \text{BKLG}_t + \varepsilon_{t+1}, \qquad (1')$$

$$\text{SAR}_{t+1} = \beta_0 + \beta_1\ (\text{EARN}_{t+1} - \omega_0 - \omega^*_{1a}\ \text{OPCF}_t - \omega^*_{1b}\ \text{ACC}_t - \omega^*_2\ \text{BKLG}_t) + v_{t+1}. \qquad (4')$$

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

*/** represent 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.
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.

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.[9] A zero-investment strategy on BKLG variable earns incremental abnormal returns of 7.7%.[10] 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 Sloan's anomaly.[11]

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).

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

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

Parameter	Pred. Sign	Means from Annual Regressions ($N = 11$)		Number of Years Coeff. Positive/ Negative	Number of Years Coeff. Significantly ($p < 0.05$) Positive/Negative
Panel A: Univariate Regressions					
γ_0	?	0.069	(1.94)	7/4	3/0
γ_1	−	−0.081*	(−2.18)	3/8	0/6
Panel B: Regressions after Controlling for Risk Factors					
γ_0	?	0.103	(1.63)	7/4	5/6
γ_1	−	−0.077*	(−2.43)	3/8	0/6
γ_2	−	−0.049	(−1.45)	4/7	0/2
γ_3	+	0.129	(1.51)	8/3	4/2
γ_4	+	0.035	(0.65)	6/5	4/2
γ_5	+	−0.022	(−0.39)	5/6	5/3
γ_6	−	−0.166**	(−5.30)	0/11	0/9

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

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.

$LnBM^{dec}$ = 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.

3.4.3. Additional Sensitivity Analyses

In this section, we conduct several additional tests to further assess the robustness of our results. We begin by considering 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) and Abel and Mishkin (1983), 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) and Mishkin (1983) 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 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 equations (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′).

$$\text{EARN}_{t+1} = \omega_0 + \omega_1 \text{ EARN}_t + \omega_2 \text{ BKLG}_t + \omega_3 \text{ BKLG}_{t-1} + \varepsilon_{t+1}, \qquad (1')$$

$$\begin{aligned}\text{SAR}_{t+1} = \beta_0 + \beta_1(&\text{EARN}_{t+1} - \omega_0^* - \omega_1^* \text{ EARN}_t - \omega_2^* \text{ BKLG}_t \\ &- \omega_3^* \text{ BKLG}_{t-1}) + v_{t+1}.\end{aligned} \qquad (4')$$

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.

Recall that the coefficient mapping BKLG to future earnings (EARN), is constrained to be a cross-sectional constant in equation (1). To assess whether our results are sensitive to that assumption, we perform two sensitivity checks. First, 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. Second, we estimate future earnings from BKLG and investigate whether investors misprice such earnings. In particular, we construct a new variable, BKLG-GM, defined as the product of BKLG and the gross margin percentage ($1-$cost of goods sold/sales) and substitute that variable in place of BKLG in equations (1) and (4).[12] The unreported results of the Mishkin test indicate that the market continues to overweight the relation between BKLG-GM and future earnings. In particular, coefficient ω_2 on BKLG-GM in equation (1) is 0.020 whereas investors price BKLG-GM at 0.118 (coefficient ω_2^*) and the difference is statistically significant (likelihood ratio statistic $= 9.80$, $p < 0.00$). Taken together, our reported results are not due to the assumption of homogeneity on the conversion of backlog across industries.

Finally, we assess whether our results are sensitive to the deflator used to scale order backlog, by using sales as a deflator instead of average total assets in equations (1) and (4). The untabulated results from this procedure are similar to those reported in the paper.[13]

4. 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 et al. (2003) isolate order backlog as a leading indicator in the home-building industry based on their assessment of industry reports, analyst reports and popular press articles. Research by Barth et al. (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 et al. 1992) finds that analysts do not fully utilize available information efficiently while setting earnings forecasts. Thus, whether analysts incorporate order backlog 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. We estimate the following specifications:

$$\mathrm{EPS}_{t+1} = \delta_0 + \delta_1 \ \mathrm{EPS}_t + \delta_2 \ \mathrm{BKLG}_t^{\mathrm{dec}} + \mu_{t+1}, \tag{8}$$

$$\mathrm{FEPS}_{t+1} = \lambda_0 + \lambda_1 \ \mathrm{EPS}_t + \lambda_2 \ \mathrm{BKLG}_t^{\mathrm{dec}} + \eta_{t+1}, \tag{9}$$

$$\mathrm{FERR}_{t+1} = (\delta_0 - \lambda_0) + (\delta_1 - \lambda_1) \ \mathrm{EPS}_t + (\delta_2 - \lambda_2) \ \mathrm{BKLG}_t^{\mathrm{dec}} + (\mu_{t+1} - \eta_{t+1}), \tag{10}$$

where FERR is the forecast error computed as the difference between EPS_{t+1} and FEPS_{t+1}, EPS_{t+1} is earnings per share for the fiscal year $t+1$ scaled by stock price at the end of fiscal year t, and 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).[14] We use backlog ranks as opposed to backlog scaled by average assets to avoid concerns about mismatch in the scaler used for EPS and FEPS variables.[15]

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 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., $\delta_2 - \lambda_2$) 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 procedure 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 again determined using inter-temporal t-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'

Table 6. Summary regression statistics of the relation between scaled decile rankings of order backlog and analysts' earnings forecasts and forecast errors (11,259 firm year observations spanning 1981–1999).

$$\mathrm{EPS}_{t+1} = \delta_0 + \delta_1\ \mathrm{EPS}_t + \delta_2\ \mathrm{BKLG}_t^{\mathrm{dec}} + \mu_{t+1}, \tag{8}$$

$$\mathrm{FEPS}_{t+1} = \lambda_0 + \lambda_1\ \mathrm{EPS}_t + \lambda_2\ \mathrm{BKLG}_t^{\mathrm{dec}} + \eta_{t+1}, \tag{9}$$

$$\mathrm{FERR}_{t+1} = (\delta_0 - \lambda_0) + (\delta_1 - \lambda_1)\ \mathrm{EPS}_t + (\delta_2 - \lambda_2)\ \mathrm{BKLG}_t^{\mathrm{dec}} + (\mu_{t+1} - \eta_{t+1}). \tag{10}$$

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)

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

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.

$\mathrm{BKLG}^{\mathrm{dec}}$ = order backlog divided by average total assets, transformed to a scaled-decile variable with values ranging from 0 to 1.

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 $(\delta_1 - \lambda_1)$ is statistically significant at the 1% level (coefficient $= 0.267$, $t = 2.99$). This result is consistent with prior research (Ahmed et al., 2002) 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 significantly different from zero. Thus, the results indicate that analysts use backlog information to forecast

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 (11,259 firm year observations spanning 1981–1999).

$$\mathrm{EPS}_{t+1} = \alpha_0 + \alpha_1\ \mathrm{EPS}_t + \alpha_2\ \mathrm{FEPS}_{t+1} + \alpha_3\ \mathrm{BKLG}_t^{\mathrm{dec}} + \phi_{t+1}, \tag{11}$$

$$\mathrm{SAR}_{t+1} = \zeta_0 + \zeta_1(\mathrm{EPS}_{t+1} - \alpha_0 - \alpha_1^*\ \mathrm{EPS}_t - \alpha_2^*\ \mathrm{FEPS}_{t+1} - \alpha_3^*\ \mathrm{BKLG}_t^{\mathrm{dec}}) + \pi_{t+1}. \tag{12}$$

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

*/** represent 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.
$\mathrm{BKLG}^{\mathrm{dec}}$ = 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.

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.[16] Walther (1997) and Elgers et al., (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 analyzes) 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 its future-earnings effects. To assess this possibility, we estimate the following regressions:

$$\text{EPS}_{t+1} = \alpha_0 + \alpha_1 \text{ EPS}_t + \alpha_2 \text{ FEPS}_{t+1} + \alpha_3 \text{ BKLG}_t^{\text{dec}} + \phi_{t+1}, \quad (11)$$

$$\text{SAR}_{t+1} = \zeta_0 + \zeta_1 \left(\text{EPS}_{t+1} - \alpha_0 - \alpha_1^* \text{ EPS}_{it} - \alpha_2^* \text{ FEPS}_{t+1} - \alpha_3^* \text{ BKLG}_t^{\text{dec}}\right) + \pi_{t+1}. \quad (12)$$

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 et al., (2002) find that analysts' forecasts and revisions do not exhibit the value-glamour anomaly documented for the stock market as a whole by Lakonishok et al., (1994) and La Porta et al., (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 et al., 2001) also provides evidence consistent with investors failing to correctly impound analysts' forecasts, although these papers find that investors underweight analyst forecasts.

5. Conclusions

Previous research has interpreted the value-relevance of leading indicators in an efficient market context as indicative of future earnings prospects of firms. However, the content and presentation of the disclosures related to leading indicators is not standardized by GAAP. A recent FASB report finds that extant disclosures of such indicators are patchy and inconsistent. Hence, 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 is not a stretch to conjecture that investors likely 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; 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.

Acknowledgments

We thank an anonymous referee, Bruce Behn, Bokhyeon Baik, Jennifer Francis, John Hand, Pat Hopkins, Ed Maydew, Michael Mikhail, Steve Penman (editor), Madhav Rajan, Richard Willis and workshop participants at Duke University, Columbia University, the 2001 University of Texas-Dallas symposium, University of California at Irvine, and the 2002 BMAS conference at the University of Texas-Austin and the 2002 AAA meetings at San Antonio for helpful comments. We appreciate financial support from the Accounting Development Fund at the University of Washington, Fuqua School of Business, Duke University and the Graduate School of Business, Stanford University.

Notes

1. Recent research (Collins et al., 1997; Francis and Schipper, 1999) appears to support this claim. However, others question whether financial measures have lost relevance over time (Brown et al., 1999; Landsman and Maydew, 2002; Core et al., 2003).
2. 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.
3. 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.
4. In estimating the beta we require that monthly return data be available for a minimum of 10 months to enable efficient estimates.
5. We examine the implications of this assumption in sensitivity analyses (Section 3.4.3).
6. 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 in Section 3.4.2 and analyst forecast sample in Section 4) indicate no market inefficiency with respect to the time-series properties of earnings. Furthermore, as reported below, we do not find abnormal returns to the EP anomaly, thereby suggesting market efficiency with respect to past earnings.
7. 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 ($p < 0.01$).
8. We do not observe any significant time-based clustering of significant coefficients. Out of 10 significant coefficients in Table 3 related to BKLG, four coefficients (1983, 1985, 1987 and 1989) are significant before 1990 and the remaining coefficients (1991, 1993, 1994, 1995, 1998 and 1999) are significant after 1990. In Table 5 (to follow), the six significant coefficients are in 1989, 1990, 1992, 1994, 1995 and 1999.
9. We also control for industry differences by including industry dummies and our inferences are unaltered.
10. 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.
11. 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, Hribar and Collins (2002) 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 sample comes from the years 1962–1991, whereas our sample in these tests

covers the years 1989–1999. Thus, time-period specific issues might have also influenced our findings. Third, Sloan 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 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.

12. We use gross margins in lieu of return on sales because a significant number of observations have negative earnings.
13. Another potential sensitivity analysis is to examine the returns to a backlog strategy around subsequent earnings announcements, which is particularly relevant when the release of tradable information such as accruals (about predictable earnings changes) is assumed to be concentrated in announcement periods. However, this assumption is unlikely to hold in our context. This is because information about the extent of conversion of backlog into future sales, and hence, earnings, may not necessarily be revealed around earnings announcements given that (i) retailers provide periodic same store sales data, (ii) automobile manufacturers provide monthly vehicle sales information, and (iii) airline manufactures (e.g., Boeing) issue press releases about aircraft deliveries. Hence, information about the contribution of backlog for future earnings is likely to be incorporated in stock price at various times throughout the year, not just around earnings announcements.
14. Consistent with a long tradition in analyst forecast research (e.g., Ali et al., 1992; 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/B/E/S by the forecast per share. However, data on the number of shares outstanding for a significant number of firm-years is missing in the I/B/E/S tapes. In an effort to conserve as many firm-year observations as possible for our empirical analyzes, we scale the analyst forecast by lagged market price per share. To be consistent with the scalar for analyst forecasts, we scale the earnings variables in equations (8)–(10) by stock price as well.
15. As a sensitivity check, we use actual order backlog scaled by average total assets and find that our inferences are unaffected.
16. In untabulated results, we find evidence of the stock market continuing to overweight backlog in firms without analyst coverage, i.e., the sub-sample of firms for which we do not have I/B/E/S forecasts.

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 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 Michigan.

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, 3–24.

Ahmed, A. S., K. Nainar, X. Zhang and J. Zhou. (2002). "Do Analysts' Forecasts Fully Reflect the Information in Accruals?" Working paper, Syracuse University.

Ali, A., A. Klein 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: AICPA.

American Accounting Association (AAA), Financial Accounting Standards Committee. (2002). "Recommendations on Disclosure of Nonfinancial Performance Measures." *Accounting Horizons* 16, 353–362.

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. Kasznik and M. F. McNichols. (2001). "Analyst Coverage and Intangible Assets." *Journal of Accounting Research* 39, 1–34.

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.

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, 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* 6, 197–220.

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, 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 and Economics* 28, 83–115.

Canadian Institute of Chartered Accountants. (1995). *Performance Measures in the New Economy*. Toronto, Canada: CICA.

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* 16, 643–670.

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 and Economics* 24, 39–67

Core, J., W. Guay and A. VanBuskirk. (2003). "Market Valuations in the New Economy: An Investigation of What Has Changed." *Journal of Accounting and Economics* 34, 43–67.

D'Avolio, G., E. Gildor and A. Shleifer. (2001). "Technology, Information Production, and Market Efficiency." Working paper, Harvard Institute of Economic Research.

Damodaran, A. (2001). *The Dark Side of Valuation: Valuing Old Tech, New Tech and New Economy Companies*. New Jersey: Financial Times Prentice Hall.

Demers, E. and B. Lev. (2000). "A Rude Awakening: Internet Value Drivers in 2000." *Review of Accounting Studies* 6, 331–359.

Deng, Z, B. Lev and F. Narin. (1999). "Science and Technology as Predictors of Stock Performance." *Financial Analysts Journal* 55, 20–32.

Doukas, J. A., C. Kim and C. Pantzalis. (2002). "A Test of the Errors-in-Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts." *The Journal of Finance* 57, 2143–2165.

Eccles, R. G., R. H. Herz, M. Keegan and D. M. H. Phillips. (2001). *The Value Reporting Revolution: Moving Beyond the Earnings Game*. New York: John Wiley & 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* 76, 613–632.

Fama, E. and K. French. (1992). "The Cross-section of Expected Returns." *Journal of Finance* 47, 427–466.

Fama, E. and J. Macbeth. (1973). "Risk, Return and Equilibrium: Empirical Tests." *Journal of Political Economy* 71, 607–636.

Financial Accounting Standards Board. (2001). *Business and Financial Reporting: Challenges from the New Economy*. New York: FASB.

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* 37, 319–352.
Francis, J., K. Schipper and L. Vincent. (2003). "The Relative and Incremental Information Content of Alternative (to Earnings) Performance Measures." *Contemporary Accounting Research* 20, 121–164.
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, 3–42.
Hribar, P. and D. W. Collins. (2002). "Errors in Estimating Accruals: Implications for Empirical Research." *Journal of Accounting Research* 40, 105–134.
Institute of Chartered Accountants in England and Wales. (2000). *New Measures for the New Economy*. London: ICAEW.
Ittner, C. and D. Larcker. (1998a). "Are Nonfinancial Measures Leading Indicators of Financial Performance? An Analysis of Customer Satisfaction." *Journal of Accounting Research* 36, 1–36.
Ittner, C. and D. Larcker. (1998b). "Innovations in Performance Measurement: Trends and Research Implications." *Journal of Management Accounting Research* 10, 205–238.
Kaplan, R. and D. Norton. (1996). *The Balanced Scorecard*. Boston: Harvard Business Press.
Klein, A. (1990). "A Direct Test of the Cognitive Bias Theory of Share Price Reversals." *Journal of Accounting and Economics* 13, 155–166.
Kothari, S. P. (2001). "Capital Markets Research in Accounting." *Journal of Accounting and Economics* 31, 105–231.
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.
Landsman, W. and E. Maydew. (2002). "Has the Information Content of Quarterly Earnings Announcements Declined in the Past Three Decades?" *Journal of Accounting Research* 40, 797–808.
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. (2001). *Intangibles: Management, Measurement, and Reporting*. Washington, D.C.: Brookings Institution Press.
Lev, B. and S. R. Thiagarajan. (1993). "Fundamental Information Analysis." *Journal of Accounting Research* 31, 190–215.
Lev, B. and P. Zarowin. (1999). "The Boundaries of Financial Reporting and How to Extend Them." *Journal of Accounting Research* 37, 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.
Previts, G., R. Bricker, T. Robinson and S. Young. (1994). "A Content Analysis of Sell-Side Financial Analyst Company Reports." *Accounting Horizons* 8, 55–70.
Rajgopal, S., M. Venkatachalam and S. Kotha. (2002). "Managerial Actions, Stock Returns and Accounting Earnings: The Case of Business-to-Business Internet Firms." *Journal of Accounting Research* 40, 529–556.
Rajgopal, S., M. Venkatachalam and S. Kotha. (2003). "The Value Relevance of Network Advantages: The Case of E-commerce Firms." *Journal of Accounting Research* 41, 135–162.
Securities and Exchange Commisson, Division of Corporation Finance. (2001). *Current Accounting and Disclosure Issues*. Washington, D.C.: SEC.
Shevlin, T. 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* 71, 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, 137–162.

Wahlen, J. M. (2001). "Discussion of 'Do Stock Prices of Property Casualty Insurers Fully Reflect Information About Earnings, Accruals, Cash Flow and Development?"' *Review of Accounting Studies* 6, 221–228.

Walther, B. (1997). "Investor Sophistication and the Market's Earnings Expectations." *Journal of Accounting Research* 35, 157–192.

Xie, H. (2001). "Are Discretionary Accruals Mispriced? A Reexamination." *The Accounting Review* 76, 357–373.