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REVENUE MANAGEMENT: THE USE OF ORDER BACKLOG TO MEET REVENUE REPORTING TARGETS

By

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Jan – I Love You!
☺

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ABSTRACT

Prior studies show that the market rewards companies that meet earnings and revenue reporting targets. While findings of earnings management are abundant, the extant literature does not show that managers can smooth revenue recognition without violating GAAP. This study investigates the use of order backlog to manage revenue reporting. My results show that managers use order backlog to report positive revenue growth, to smooth revenue reporting, and to meet analysts' revenue forecasts. Managers also use order backlog to limit the magnitude of large positive forecast surprises and in so doing delay revenue recognition. This study adds to the earnings management literature, which typically focuses on earnings, by showing that managers also manipulate reporting to meet revenue targets. An implication of this study is that more expansive order backlog disclosure requirements could bring greater transparency to this type of revenue manipulation.

CHAPTER ONE

INTRODUCTION

A large body of research concludes that managers adjust accruals and take real economic actions to manipulate earnings. Managers manipulate earnings to report positive earnings, positive earnings growth, and to meet analysts' forecasts (e.g. Burgstahler and Dichev 1997; DeGeorge, Patel, and Zeckhauser 1999; Burgstahler & Eames 2006). Managers strive to meet earnings expectations to advance their careers and to increase the market value their companies (Graham, Harvey, and Rajgopal 2005). By meeting the markets earnings expectations managers can draw a positive market response (e.g. Skinner and Sloan 2002; Ertimur, Livnat, and Martikainen 2003). However, investors also adjust their valuations based on revenue announcements. For example, on April 23, 2013, Apple Inc. announced its first earnings decline in 10 years and one week later Facebook Inc. announced its earnings missed analysts' forecasts. Both companies announced revenues that beat analysts' forecasts (Reuters 2013; CNBC 2013). Reuters and CNBC also reported that investors bid up the price of the stock of both companies on the news that revenues were higher than expected. Companies can neutralize the market response to a negative earnings surprise with a positive revenue surprise and by meeting both revenue and earnings expectations, they can maximize the market response to earnings announcements (Ertimur, et al. 2003; Ghosh, Gu, and Jain 2005; Jegadeesh and Livnat 2006). These studies also argue that, in contrast to earnings, managers are unlikely to manipulate revenue and they provide evidence that in the presence of positive revenue growth, there is less earnings management. On the other hand, Stubben (2010) documents 173 instances of revenue manipulation that were targeted by the Securities and Exchange Commission's (SEC) accounting enforcement actions and Callen, Robb, and Segal (2008) documents 260 firm-years of improper revenue recognition from financial restatements. These two studies document revenue manipulation that employs methods that violate GAAP. Less egregious forms of revenue manipulation that fall within GAAP are more challenging to identify.

In this study, I use order backlog to examine revenue smoothing that occurs within the parameters of GAAP. Order backlog represents sales agreements that are made during the current fiscal year but remain unfulfilled at fiscal year-end.[1] Since 1970, the SEC's regulation §229 item 101(c) (VIII) has required public companies to disclose order backlog with their annual 10-K filings.[2] By aggressively filling orders and decreasing order backlog, managers can shift revenue that would otherwise be recognized in the next year into the current one.[3] Similarly, managers who slow the fulfillment of orders increase order backlog and defer revenue to the following year. Consequently, when new sales orders do not generate enough revenue to meet revenue reporting targets, managers can reduce order backlog to avoid negative revenue surprises.[4] By deferring revenue recognition companies can build a reserve or "cookie jar" of orders that can be used to generate revenue in the subsequent year. Such actions provide mangers

[1] Average annual order backlog for my 42 year sample ranges from 38% to 57% of annual revenues.
[2] SEC regulation §229 item 101(c) (VIII) "The dollar amount of backlog orders believed to be firm, as of a recent date and as of a comparable date in the preceding fiscal year, 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 the backlog. (There may be included as firm orders government orders that are firm but not yet funded and contracts awarded but not yet signed, provided an appropriate statement is added to explain the nature of such orders and the amount thereof. The portion of orders already included in sales or operating revenues on the basis of percentage of completion or program accounting shall be excluded.)" Since order backlog is a non-GAAP reporting metric it is not a part of the audited financial statements. Although order backlog is a non-GAAP metric, Statement of Auditing Standards AU §550 requires auditors of public companies to review 10-K filings and to report inconsistencies with a company's financial records.
[3] The SEC has documented these practices with firms that it has charged with failure to disclose order backlog (e.g. Securities and Exchange Commission vs. Comverse Technology Inc. and Securities and Exchange Commission vs. Mercury Interactive Inc.)
[4] I use the terms new sales orders, sales orders, and orders interchangeably for sales contracts that are obtained during the current reporting period.

with a means of reporting revenue growth that is inconsistent with the underlying economic conditions that generate growth. When firms report revenue growth despite a decline in the demand for its products, investors may be misled.

To investigate whether firms manipulate revenue, I model reductions in order backlog as a function of revenue before the effects of order backlog as measured against three revenue reporting targets: positive revenue growth, smooth revenue growth, and analysts' revenue forecasts. Each test result shows that when revenue before the effects of order backlog is insufficient to meet the revenue reporting target that managers reduce order backlog and thereby reduce or eliminate the revenue shortfall. These results also show that when revenue before the effects of order backlog can provide a large positive analysts' forecast surprise, managers build order backlog and postpone revenue recognition. I also present empirical evidence in the form of distributions that illustrate the differences in reported revenue and revenue before the effects of order backlog. The distributions of reported revenue have discontinuities at zero growth and at zero analysts' forecast errors whereas the distributions of revenue before the effects of order backlog do not have the discontinuities. The discontinuities that show more companies than expected just meet their reporting targets provide evidence of revenue management. This evidence is bolstered by a lack of discontinuities with measures that do not have reporting targets. To further consider the effect on reporting of changes in product demand, I perform additional testing. This testing shows that companies are 2.7 times more likely to report revenue growth than to report a revenue decline, despite a decline in orders, than they are to report a revenue decline when orders are growing. This factor increases to 3.7 for a sub-sample of companies with a history of reporting positive revenue growth.[5] I conclude from this evidence that managers use order backlog to time revenue recognition for the purpose of meeting revenue benchmarks.

This study expands our understanding of the sway mangers have on revenue recognition and its impact on the quality of financial reporting. I provide evidence that companies engage in real economic activities to time revenue recognition to meet revenue reporting targets without violating GAAP. An important implication of this evidence is that managers may not be willing to manipulate revenue merely to achieve earnings targets if in so doing they create a revenue reporting surprise – managers manipulate reporting to meet both revenue and earnings targets. I report the first evidence of a planned process where managers accumulate revenue for future recognition in the form of order backlog then use order backlog as needed to meet revenue reporting targets. This evidence is in contrast to prior research that asserts that unlike earnings, revenue is unlikely to be managed. This study also introduces the use of a non-GAAP metric, order backlog, to identify real earnings management activities. An important trend in earnings management research is the development and expansion of real economic activities. Using a non-GAAP metric to identify real earnings management reduces reliance on proxies such as abnormal cross sectional cash flows that can be subject to multiple interpretations. This research highlights the importance of understanding non-GAAP measures. This study also has implications for policy makers. While the SEC recognized more than 40 years ago that order backlog information is valuable to investors, the financial reporting for order backlog merely requires it be disclosed in annual reports filed with the SEC. Consequently investors who rely on quarterly reports to make decisions must wait several quarters before learning that reported

[5] Burgstahler and Dichev (1997) find that companies with a history of positive earnings growth are more likely to engage in earnings management to report positive growth than are companies are that do not have a history of growth.

revenue growth could have been derived from a reduction in order backlog. Also, the SEC does not govern privately owned companies that often use debt financing instead of equity financing. By not disclosing order backlog, managers of non-public companies can mislead creditors about the source of revenue growth. Additionally, without a GAAP order backlog disclosure requirement, companies can use their corporate counsel to make decisions about legal compliance with SEC regulations without oversight from auditors. If GAAP required disclosure then the audit function would help ensure disclosure compliance.[6] Consequently, the Financial Accounting Standards Board (FASB) may want to consider the costs and benefits of requiring companies to disclose order backlog in a more timely and prominent manner.

The rest of this paper is organized as follows. Section 2 provides the motivation for the research and develops the hypotheses. Section 3 explains the research design, the sample data, variable definitions, descriptive statistics, and the models used to test the hypotheses. Section 4 presents the empirical results and Section 5 concludes.

[6] The Statement of Auditing Standards AU §550 requires the auditor of public companies to review 10-K filings and to report inconsistencies with a company's financial records. However, auditors are not in a position to challenge legal opinions about whether the law pertains to a particular company.

CHAPTER TWO

MOTIVATION AND HYPOTHESES

2.1 Motivation

The purpose of financial reporting is to provide investors and creditors with information that is useful in making investment and credit decisions (Statement of Accounting Concepts No. 1, FASB, 1978).[7] To meet this purpose SFAC No. 1 states that financial reporting is to be evenhanded, neutral, and unbiased. Because financial reporting influences investors' decisions and reflects management's stewardship, managers have incentives to meet or beat reporting targets (Healy and Whalen 1999; Dechow and Skinner 2000; Graham, Harvey, and Rajgopal 2005). Incentives to meet reporting targets include attracting capital, meeting debt covenants, maximizing bonus plans, and building professional reputations (Dechow, Sloan, and Sweeny 1996; Healy and Whalen 1999; Graham, et al. 2005; McInnis and Collins 2011). Managerial reporting incentives can create conflicts of interests with stakeholders.

The study of manager-stakeholder conflicts of interest and the means by which managers exercise discretion over their firms' financial reporting is the primary focus of most earnings management research. Earnings management research documents that managers use discretionary accruals to smooth earnings around market expectations. Kasznik (1999) provides evidence that managers use accruals to increase (decrease) earnings when pre-managed earnings are below (above) management forecasts and that earnings management actions escalate with the expected magnitude of management forecast errors. Subsequent studies show that managers

[7] The Financial Accounting Standards Board (FASB) defines investor as anyone who has, in the past or may in the future, provide a company with resources.

manipulate earnings with the use of discretionary accruals to reduce analysts' forecast errors (e.g. Dechow Richardson and Tuna 2000; Abarnell and Lehavy 2003; Burgstahler and Eames 2006). Managers also use real earnings management techniques to increase earnings (Roychowdhury 2006). He states that real earnings management occurs when management diverges from normal business operations for the purpose of misleading financial statement users into thinking reporting targets have been met through the normal course of business. Addressing management's perspective on the tradeoff between accrual based and real activity based earnings management, Graham, et al. (2005) write "We find that managers would rather take economic actions that could have negative long-term consequences than make within-GAAP accounting choices to manage earnings. A surprising 78% of our sample admits to sacrificing long-term value to smooth earnings." Several studies identify cutting R & D expenses to increase earnings as a real earnings management technique (e.g. Bushee 1998; Roychowdhury 2006; Brown and Krull 2008; and Cohen and Zarowin 2010). Roychowdhury (2006) finds firms cut R & D expenses at year-end to avoiding reporting losses and Cohen and Zarowin (2010) finds firms cut R & D spending before issuing seasoned equity offerings (SEOs). Other real earnings management techniques include excess production to lower cost of goods sold and year-end marketing activities such as product discounts and enhanced credit terms to entice sales (Roychowdhury 2006; Cohen and Zarowin 2010). The research cited above shows that by participating in real activities as well as by manipulating accruals managers are willing and able to manage earnings.

These findings suggest that managers may manipulate other important reporting metrics as well. Managers have incentives to manipulate revenue for two reasons. First, revenue is typically the largest item reported on an income statement and it has a direct positive impact on earnings.[8] An income statement in its most basic form begins with revenue at the top and is offset by expenses generating gross margin, operating margin, EBITDA, and "street earnings." Second, evidence suggests that the FASB, managers, and investors consider revenue to be an important reporting metric independent of earnings. In its exposure draft on revenue recognition the FASB states that revenue is a crucial number to users of financial statements in assessing an entity's financial performance and position.[9] Jegadeesh and Livnat (2006) observe that about 95% of the companies that announce earnings also announce revenue. They also note that the level of detail typically provided with earnings announcements is sparse and that many other useful earnings components are not available until after companies file their financial statements and 10-Ks reports with the Securities and Exchange Commission (SEC). In their survey, Graham, et al. (2005) interview over 400 executives including Chief Financial Officers (CFOs) to determine the factors that influence their financial reporting decisions. The managers rank their two most important financial reporting metrics as earnings followed by revenue. Revenue is cited as the single most important reporting measure by 12% of the managers and it is ranked second by 32% of the managers. Managers also demonstrate the importance they place on revenue reporting by including revenue with their earnings announcements. Graham et al. (2005) report that managers are motivated to manage revenue reporting to meet market expectations and the extant literature shows investors generally respond more strongly to revenue surprises than to expenses surprises (e.g. Ertimur, Livnat, and Markikainen, 2003; Ghosh, Gu, and Jain 2005; Jegadeesh and Livnat 2006; Callen, Robb, and Segal 2008; Kama 2009). Ertimur, et al. (2003) find that all but value companies experience a positive market response when negative earnings

[8] For revenue to have positive earnings impact it is assumed that products and services are sold at a price above cost.
[9] The FASB financial series exposure draft, revenue recognition topic 605 issued June 24, 2010, revised November 14, 2011, and January 4, 2012 addresses proposed changes to existing revenue recognition rules.

surprises are accompanied by positive revenue surprises and that the market responds negatively to positive earnings surprises when accompanied by negative revenue surprises.[10] Ghosh, et al. (2005) report that companies with a history of revenue growth have higher earnings response coefficients (ERCs) and Jegadeesh and Livnat (2006) report higher ERCs for companies with a history of revenue surprises.

The statements and actions by managers coupled with the markets' response to revenue reporting shows that managers have incentives to manipulate revenue reporting. Although an extensive amount of research finds that earnings are managed within GAAP, the extant literature suggests that revenue is not subject to such systematic manipulation. Ertimur, et al., (2003) argue that revenue is harder to manage and that their results showing the market responds negatively to small positive earnings surprises unless they are accompanied by positive revenue surprises is consistent with investors believing the earnings surprise is likely a result of expense manipulation. Ghosh et al., (2005) point out that the known methods mangers use to increase revenue such as channel stuffing, bill and hold, and buy-back arrangements violate GAAP, often require an outside organization's participation, and are subject to more stringent scrutiny by auditors and the Securities and Exchange Commission (SEC). In contrast to revenue management, Ghosh et al., (2005) observe that managing expenses such as bad debt reserves and restructuring charges do not involve outside organizations, frequently comply with GAAP, and consequently can be more difficult to detect than revenue management. Addressing bad debt reserves, Jackson and Liu (2010) argue that the discretionary nature of accrued expenses coupled with the conservative nature of accounting creates an environment where managers can build excess reserves over time then reverse their reserves when needed to meet earnings targets.

[10] Ertimur, Livnat, and Martikainen (2003) separate their sample into two groups based where the firm is in its life cycle. Firms in the latter stages of their life cycle are classified as value firms.

The characteristics associated with manipulating revenues and expenses are examined by Nelson, Elliott, and Tarpley (2002). In their survey, they ask 253 auditors from a Big 5 accounting firm to recall attempts by managers to manipulate accounting numbers. Nelson, et al. (2002) concludes attempts at managing reserves are likely to be unstructured, follow discretionary rules, often reduce income and are less likely to be adjusted by auditors. They find that while attempts at accelerating revenue recognition also occur frequently auditors are more likely to make adjustments to prevent manipulation. Nelson, et al. (2002) also concludes that more accounting structure such as that for revenue recognition results in less earnings management.

The accounting structure for revenue transactions is addressed by the American Accounting Association (AAA) in its response to a FASB Exposure Draft on Revenue Recognition (Topic 605). The AAA response points out that while there are over 100 revenue recognition polices currently in place they do not feel the large number of rules are a problem as the FASB asserts. The AAA argues that the current polices, although large in number, meet the needs of stakeholders and facilitate identifying and preventing aggressive revenue recognition practices. They also express concern that by introducing estimation into the revenue recognition process that manipulative reporting practices will increase and they cite evidence of manipulation with expense estimation such as that provided by Jackson and Liu (2010) as support for their concern.

Several studies investigate whether earnings management is less pervasive for revenue than it is for expenses. Ghosh et al., (2005) examine companies with earnings growth for differences in the level of earnings management activities between revenue-growth companies and expense-reduction companies. They find that revenue-growth companies are less likely to manage earnings through total accruals, working capital accruals, abnormal accruals, special items, or share repurchases. They also find that revenue-growth companies have higher earnings quality as measured by earnings persistence. Jegadeesh and Livnat (2006) examine earnings quality for companies with positive earnings surprises. Their results show that positive earnings surprises coupled with positive revenue surprises have higher earnings persistence (earnings quality) than positive earnings surprises without accompanying positive revenue surprises. Roychowdhury (2006) uses an abnormal cash flow model to conclude that to avoid reporting losses managers provide year-end price cuts and/or lenient credit terms to boost year-end sales. Roychowdhury (2006) deemed the sales terms be a deviation from normal business practices and unsustainable. One criticism of this earnings management method is that year-end price cutting when profits are down may just reflect good business practices (Gunny 2010). Year-end price cutting also has limited efficacy as managers cannot accurately gauge the effects of marketing programs aimed at boosting year-end sales (Zang 2012). She also points out that managers cannot use marketing programs to build a reserve or "cookie jar" of revenue for future use as they can with discretionary accruals. Consequently, this methodology does not provide management with a smoothing mechanism.

The Treadway Commission, the literature, and anecdotal evidence from SEC filings suggest that managers can use order backlog to manage revenue. The Treadway Commission Report on Fraudulent Reporting (1987) states that a change in business practices such as a decrease in order backlog could result in a decrease in the quality of sales reporting. The Treadway Commission's report also describes a hypothetical situation where a manager increases sales by reducing order backlog; "The CEO, under pressure to continue increasing sales, has the shipping department work longer hours in the days prior to the end of the quarter."

They cite this example as the kind of circumstance that warrants a more in depth investigation into revenue reporting. Lev and Thiagarajan (1993) also observe that a decrease in order backlog may indicate a form of earnings management where companies report revenue in excess of their actual product demand as measured by new sales orders. To my knowledge, no one has provided evidence that managers use order backlog to meet revenue targets.

To illustrate the potential effectiveness of order backlog as a means to manage revenue Toro Company provides an example of how variations among new sales orders and changes in order backlog affect reported revenue. Toro Company reported annual revenue growth every year from 1994 to 2007 – fourteen straight years of revenue growth. At the beginning of its fourteen year growth period, in 1994, Toro Company's order backlog was equal to 20% of its revenue but, by 2007 Toro had reduced its order backlog to 3.7% of revenue. The following year Toro Company's reported no revenue growth, and in 2009, Toro reported its first revenue decline in sixteen years. If Toro Company would have continued to maintain its 1994 level of order backlog, then Toro Company would have reported a revenue decline thirteen years earlier.[11] Without adjusting order backlog Toro Company would have reported revenue declines in three of the fourteen years that it reported revenue growth. Given the 14 consecutive years of reported revenue growth, these actions also indicate that every time orders were low and revenues would have declined, Toro reduced its order backlog and avoided reporting a revenue decline.

An example of the use of order backlog to manipulate revenue was documented by the SEC. The SEC filed suit against Mercury Interactive, Inc. (now a part of Hewlett Packard) on May 31, 2007 charging that they had not disclosed order backlog as the SEC regulations

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[11] Sales and order backlog were obtained from Compustat (SALE & OB respectively) and *ORDERS* were calculated following Behn (1996): $OB_{it} + SALE_{it} - OB_{it-1} = ORDERS_{it}$.

require.[12] The SEC accused Mercury of using a “secret” order backlog to manipulate revenue in order to meet or beat analysts’ forecast every quarter between 1997 and 2001. The SEC provided evidence to show that management built its secret order backlog by halting shipments to fill orders once analysts’ targets had been met. The SEC produced emails and documentation of conversations between the CFO (Abrams) and the CEO (Landan) including these comments by Abrams:

> “We need to stop shipping in Europe and ROW now[13]. If we do that, we have the flexibility to recognize anywhere from about 37.5 to 40M, even more if you want (up to 42). Let's discuss. No matter what we do, we can show whatever EPS we want. We would accrue some of 1999 expenses that can be related to 1998 in one way or another.”

In their complaint the SEC documented that in the years 1999 and 2000 Mercury had used order backlog to shift 32% and 39% of its annual revenue between accounting periods. Additionally, for internal purposes, the company maintained historical comparisons between reported revenues and “normalized” revenues. Their “normalized” revenues were GAAP revenues with the effects of order backlog manipulation removed. The SEC pointed out that Mercury’s practice of using order backlog to smooth revenue did not violate GAAP rules per se but, they added that by failing to disclose its order backlog, Mercury had concealed the source of its revenue which misled investors and violated securities regulation §229 item 101(c) (VIII). Mercury, its directors, Abrams, and Landon, subsequently agreed to settlements that included

[12] The defendants included Mercury, its directors, and its officers: CEO Amnon Landon, and CFO Sharlene Abrams who were charged with two accounts of violating security laws – failure to disclose order backlog and back dating stock options. The litigation has continued for over six years.
[13] ROW is an acronym for Rest of the World. Companies with global operations often organize along geographical lines such as North America, Asia, Latin America, and Europe with ROW representing locations that do not fall into their defined geographical categories.

large fines and the executives were barred from serving as an officers or directors of public companies. [14]

Dell Inc. has also been the subject of recent SEC investigations.[15] Dell Inc.'s 10-K filing for 2011 did not disclose order backlog. But their 10-K filing included a statement about order backlog that said in part "Our business model generally gives us flexibility to manage product backlog at any point in time by expediting shipping or prioritizing customer orders toward products that have shorter lead times, thereby reducing product backlog and increasing current period revenue." [16] This statement suggests that Dell Inc. has the ability to use order backlog to smooth revenue should it choose to do so.

This anecdotal evidence suggests that managers can use order backlog to manage revenue reporting. These examples also suggest that managers view order backlog as a cookie jar and that they use it as such. In fact, they can do so without penalty if they disclose order backlog. By reducing their order backlog, e.g. in the manner suggested by Dell Inc., managers can increase their reported revenue. Conversely, managers can stop or slow their order fulfillment process when revenue reaches a target level e.g. Mercury Interactive, Inc. By slowing order fulfillment, managers can build a reserve of sales orders (order backlog) to be used as needed in future

[14] On September 8, 2008, Mercury (Hewlett Packard) agreed to pay a $28,000,000 dollar fine and its outside directors each agreed to pay $100,000 fines. On March 20, 2009 Mercury's CFO, Sharlene Abrams, agreed to pay a fine of $2,712,914 and to be permanently barred from serving as an officer, a director or an accountant of a public company. On February 21, 2013, Mercury's CEO, Ammon Landon, agreed to pay a fine of $7,317,500 and to be barred for five years from serving as an officer or director of a public company. All of the settlement agreements covered two accounts of violating securities regulations – failure to disclose order backlog and back dating stock options. The penalties were not allocated between the two charges. I reviewed the original lawsuit filing and subsequent filings, along with the settlement agreements but was unable to find any evidence that suggested one violation was considered to be more egregious than the other.

[15] On July 22, 2010 the SEC filed suit against Dell Inc. charging them with "various disclosure and accounting violations…from 2001 to 2006."

[16] Dell Inc.'s statement in its entirety: "PRODUCT BACKLOG - We believe that product backlog is not a meaningful indicator of net revenue that can be expected for any period. Our business model generally gives us flexibility to manage product backlog at any point in time by expediting shipping or prioritizing customer orders toward products that have shorter lead times, thereby reducing product backlog and increasing current period revenue. Moreover, product backlog at any point in time may not translate into net revenue in any subsequent period, as unfilled orders can generally be canceled at any time by the customer."

periods in the manner described by Dell. By adjusting order backlog levels, managers can smooth revenue to meet reporting targets for extended periods.

Managers say they are willing to shift revenue between accounting periods if they can do so without violating GAAP (Graham et al. 2005). Their survey asks managers about actions they would take to meet a target if permitted to do so by GAAP. Forty percent of the managers indicated that they would be willing to accelerate revenue recognition while only 27.9% of the managers said they would be willing to draw down on reserves that had been previously set aside. On the other hand, several cited studies provide evidence that in contrast to earnings, revenue is unlikely to be managed. Other cited papers claim that revenue might be managed using order backlog but those papers do not offer support for their claims. However, those claims are consistent with the noted anecdotal evidence of the use of order backlog to smooth revenue. Whether companies manage revenue and if so how they can manage revenue remain unanswered questions.

2.2 Hypotheses

This study investigates whether mangers use order backlog to manage revenue for the purpose of meeting or beating revenue reporting targets. Graham et al. (2005) reports that managers consider revenue to be an important reporting metric and that they consider reporting positive growth, smooth growth, and meeting analysts' forecasts to be important reporting thresholds. Several empirical studies report that the market rewards companies that report revenues that meet these thresholds (e.g. Ertimur, et al. 2003; Ghosh, Gu, and Jain 2005; Jegadeesh and Livnat 2006; Kama 2009). While arguing that revenue is not managed these studies show that investors consider positive growth, smooth reporting, and analysts' forecasts to be important reporting targets. These targets are also often cited as incentives to manipulate reporting in earnings management studies.

When new sales orders generate insufficient revenue to constitute positive revenue growth, managers can reduce the level of order backlog to diminish or eliminate negative revenue growth. Thus my first hypothesis, stated in the null form:

H1. Decreases in order backlog are not associated with reporting positive revenue growth.

When new sales orders generate insufficient revenue to constitute smooth revenue reporting, managers can reduce order backlog to produce smoother revenue reporting.[17] Thus my second hypothesis, stated in the null form:

H2. Decreases in order backlog are not associated with reporting smooth revenue growth.

When new sales orders generate insufficient revenue to meet analysts' forecasts, managers can reduce order backlog to diminish or eliminate negative revenue surprises. Thus my third hypothesis, stated in the null form:

H3. Decreases in order backlog are not associated with meeting analysts' revenue forecasts.

[17] I define the smooth revenue target in Section 3.2.

Burgstahler and Eames (2006) find that firms manage earnings downward after achieving a small positive forecast surprise. When new sales orders provide sufficient revenue to beat analysts' revenue forecasts, managers can defer revenue recognition and build order backlog by slowing or stopping order fulfillment. Hence, my fourth hypothesis, stated in the null form:

H4. Increases in order backlog are not associated with beating analysts' revenue forecasts.

Taken together H3 and H4 predict that managers will use order backlog to minimize analysts' forecast errors.

CHAPTER THREE

RESEARCH DESIGN

3.1 Sample Selection

My sample covers the years 1970 through 2012 and includes companies from Compustat. The sample period begins in 1970 to coincide with the implementation of the SEC's regulation requiring order backlog disclosures and 1970 is also the year Compustat began providing order backlog data. I use annual data because the SEC's order backlog disclosure requirement only applies to annual 10-K filings.[18] I require non-zero data for beginning and ending order backlog. And, I eliminate financial institutions, insurance companies, and utilities. These selection criteria provide a sample of 43,493 firm-years. Under the SEC's regulations companies are required to disclose the amount of order backlog that is to be recognized as revenue in the following year. I screen disclosures that may fall outside this parameter by dropping 2,518 observations where order backlog exceeds reported revenue for both the current year and for the following year. This results in a sample of 40,975 firm-years. I use this sample to perform my initial data analysis and to test my positive revenue growth hypothesis. But to test the revenue smoothing hypothesis I require four consecutive years of revenue data. This requirement results in a sample of 34,841. Finally, to test the analysts' forecast hypotheses I require analysts' revenue forecasts from Institutional Brokers Estimate System (I/B/E/S). This requirement limits the useable firm-years to 1997 through 2012 and reduces the sample to 7,575 firm-year observations.[19]

[18] An analysis of the Compustat quarterly data file shows that 10Q order backlog disclosures are too sparse to be usable.
[19] I/B/E/S did not begin reporting analyst's revenue forecast until 1997.

3.2 Variable Definitions

Since my hypotheses are built on incentives to change order backlog, I calculate a revenue measure that excludes the effects of changes in order backlog levels. This measure is then compared with revenue targets to identify firm-years when managers have incentives to manipulate the level of order backlog. To remove the effects of changes in order backlog from revenue I begin with Behn (1996) who defines the relation among four key variables; beginning order backlog (OB_{it-1}), new sales orders ($ORDERS_{it}$), reported revenue ($SALES_{it}$) and ending order backlog (OB_{it}):

$$OB_{it-1} + ORDERS_{it} = SALES_{it} + OB_{it} \tag{1}$$

Equation 1 shows that OB_{it-1} and $ORDERS_{it}$ are the sources of $SALES_{it}$ and OB_{it}. Moreover, it shows that OB_{it} is the residual or remainder of the sources of revenue after revenue is recognized. Similarly, Figure 1 illustrates the sources of $SALES_{it}$ and how order fulfillment determines both $SALES_{it}$ and OB_{it}. Thus, both equation 1 and Figure 1 show that by increasing (decreasing) the amount of filled orders companies can increase (decrease) $SALES_{it}$ which in turn decreases (increases) OB_{it}. Thus, firms can use the order fulfillment process shift revenue between accounting periods and OB_{it} is the residual. If management increases $SALES_{it}$ by reducing OB_{it} then $SALES_{it}$ will exceed $ORDERS_{it}$ by the amount OB_{it} is reduced. On the other hand, if management increases OB_{it} then revenue recognition will be deferred by a like amount. By rearranging the variables in equation 1 it can be shown that $SALES_{it}$ consists of OB_{it-1} plus $ORDERS_{it}$ and is reduced by the residual OB_{it}:

$$SALES_{it} = OB_{it-1} + ORDERS_{it} - OB_{it} \tag{2}$$

By combining OB_{it} and OB_{it-1} to form changes in order backlog it can be seen that $SALES_{it}$ is a positive function of $ORDERS_{it}$ and a negative function of increases in OB_{it}:

$$SALES_{it} = ORDERS_{it} - (OB_{it} - OB_{it-1}) \tag{3}$$

From Figure 1 and equations 1 - 3 it can be seen that when OB_{it-1} equals OB_{it} that $ORDERS_{it}$ equal $SALES_{it}$. The effect that changes in order backlog have on ($SALES_{it}$) is removed in equation 4:

$$ORDERS_{it} = SALES_{it} \tag{4}$$

Equations 3 and 4 show that if companies do not change the level of *OB,* then *ORDERS* equal *SALES*. A comparison of $ORDERS_{it}$ with $SALES_{it}$ is provided by Figure 2. Figure 2 graphs the total un-scaled amount of $ORDERS_{it}$ and reported revenue from 1970 through 2012. This comparison shows that with cross sectional pooling $ORDERS_{it}$ and $SALES_{it}$ map closely for the 42 year sample period. From the aggregate amounts presented in Figure 2 there does not appear to be evidence of revenue management but this does not imply that firm level data would be so well matched, especially if firms use order backlog to manage revenue.

When a firm's *ORDERS* do not provide sufficient revenue to meet performance expectations firms can tap into *OB* to either reach their target or to reduce their shortfall. Using firm specific data I compare *ORDERS* with revenue targets, to determine *ex ante* firm-years with incentives to manage revenue. Bartov (1993) uses an *ex ante* measure of pre-tax income before the inclusion of gains or losses from the sale of assets to test his hypotheses. Similarly, I use an *ex ante* measure of revenue that excludes revenue attributed to changes in *OB*. To distinguish firm-years with revenue growth incentives I use the indicator variable *GROW_SUSPECT* that identifies firm-years where $ORDERS_{it}$ are less than $SALES_{it-1}$. This indicator variable equals one when the condition is true and zero otherwise. To identify firm-years with smooth revenue reporting incentives I first construct a measure for smooth revenue (*SMOOTH_REVENUE* $_{it}$). Jegadeesh and Livnat (2006) use a random walk with a seasonal adjusted drift to calculate expected quarterly revenue. To calculate an annual measure for smooth revenue (*SMOOTH_SALE* $_{it}$) I adjust their model to use annual revenue ($SALES_{it}$):

$$SMOOTH\_SALE_{it} = SALES_{it-1} + \frac{1}{2}\sum_{j=1}^{2}\left(SALES_{it-j} - SALES_{it-j-1}\right) \qquad (5)$$

To identify firm-years with incentives to smooth revenue reporting I use the indicator variable *SMOOTH_SUSPECT*. $SMOOTH\_SUSPECT_{it}$ equals one for firm-years where $ORDERS_{it}$ are less than $SMOOTH\_SALE_{it}$ (equation 5) and zero otherwise. I use two indicator variables to identify the two analysts' forecast incentives. First, PRE_MISS_{it} identifies firm-years where new $ORDERS_{it}$ are less than the analysts' mean revenue forecast (FC_SALE_{it}). Second, PRE_BEAT_{it} identifies firm-years when $ORDERS_{it}$ exceed the analysts' mean forecasts (FC_SALE_{it}) by more than 2%. The two percent threshold is chosen following Burgstahler and Eames (2006) who find that firms manage earnings downward after achieving a small positive earnings surprise. Equation 3 shows that when ending order backlog is less than beginning order backlog that reported revenue is increased. To identify this condition I use OBR_{it} which equals one when the change in order backlog is negative and zero otherwise.

3.3 Descriptive Statistics

Figure 3 shows the percentage of Compustat firms disclosing order backlog by year. In 1970, the first year the SEC required disclosure, 23% of all firms disclosed order backlog.

The ratio of order backlog disclosures rose to 38% percent of all firms by 1982 and then steadily declined until 2001 when disclosing firms accounted for 20% of all firms. The percent of firms disclosing order backlog for the 33 year sample period is 28%. To illustrate the economic importance of order backlog Figure 4 displays order backlog as a percentage of firm revenue and as a percentage of firm assets. From 1970 to 2000 the amount of order backlog ranged from 38% to 51% of revenue. Until 2000 the percentage of order backlog to revenue remained around 40% then it began ascending to 57% of revenue. The average firm has started every year in the sample period with sales orders on hand equaling between 38% and 57% of its annual revenue. Order backlog also represents a material amount from a balance sheet perspective as it averages 40% of total assets during the sample period.

Table 1 displays the percentage of firms reporting order backlog by industry. To categorize the industries I use the Fama French 49 industry classifications. Table 1 shows manufacturing oriented industries have the highest percent of firms disclosing order backlog with aerospace and ship building at 81% and 77% respectively but, the list is diverse with technology, textiles, and clothing having disclosure rates at or above 46% of the firms in those industries.

3.4 Model

The relation among *OB*, *ORDERS*, and *SALES* as described in equations 1 - 4 allow me to examine the relation between *OBR* and meeting revenue targets based on *ex ante* incentives. My first hypothesis predicts that decreases in order backlog are associated with reporting positive revenue growth. Specifically, I predict a positive association with *OBR* and *ORDERS* providing insufficient revenue to report positive growth. The second hypothesis predicts that decreases in order backlog are associated with reporting smooth revenue growth. I predict a positive association with *OBR* and *ORDERS* providing less revenue than needed to meet smooth revenue reporting expectations. My third and fourth hypotheses predict that increases and decreases in order backlog are associated with meeting or beating analysts' revenue forecasts. Specifically, I predict a positive association with *OBR* and *PRE_MISS*. I also predict a negative association with *OBR* and *PRE_BEAT*.

To test these hypotheses I use the following multivariate logistic regression:

$$Prob(OBR_{it} = 1) = f(\alpha + \beta_1 SUSPECT_{it} + \beta_2 MTB_{it} + \beta_3 \Delta EMP_{it} + \beta_4 \Delta PPE_{it} + \beta_5 \Delta IND\_OB_{it} + \beta_6 ROA_{it} + \beta_7 LOG\_MVE_{it} + \beta_8 \Delta INVT_{it} + \varepsilon_{it}) \quad (6)$$

Estimated coefficients are expected to be positive for *SUSPECT* where *SUSPECT* represents *GROW_SUSPECT* for my first hypothesis, *SMOOTH_SUSPECT* for my second hypothesis, *PRE_MISS* for my third hypotheses and a negative estimated coefficient is predicted for *PRE_BEAT,* my fourth hypothesis

where:

OBR = an indicator variable to identify firm-years that reduce OB. *OBR* equals 1 when ($OB_{it} - OB_{it-1}$) is negative, otherwise *OBR* equals 0. OB is order backlog from Compustat.

GROW_SUSPECT = an indicator variable to identify firms whose new sales orders (*ORDERS*) are less than the prior year's reported revenue.

ORDERS = $OB_{it} + SALES_{it} - OB_{it-1}$ where *SALES* is SALE from Compustat and *OB* is previously defined.

SMOOTH_SUSPECT = an indicator variable to identify firms whose new sales orders (*ORDERS*) are less than *SMOOTH_SALE*. *SMOOTH_SALE* is defined by equation 3 and *ORDERS* is previously defined.

PRE_MISS = an indicator variable to identify firms whose new sales orders (*ORDERS*) miss the analysts' revenue forecasts: PRE_MISS_{it} equals 1 when $[ORDERS_{it} - FC\_SALE_{it}] / FC\_SALE_{it}$ is < 0.00, Otherwise PRE_MISS_{it} equals 0. *FC_SALE* and *ORDERS* are previous defined.

PRE_BEAT = an indicator variable to identify firms whose new sales orders (*ORDERS*) beats the analysts' revenue forecasts by 2% or more: PRE_BEAT_{it} equals 1 when $[ORDERS_{it} - FC\_SALE_{it}] / FC\_SALE_{it}$ is ≥ 0.02, otherwise PRE_BEAT_{it} equals 0. *FC_SALE* and *ORDERS* are previous defined. Two percent is chosen following Burgstahler and Eames (2006) who find that firms manage earnings downward after achieving a small positive earnings surprise. The distribution of forecast errors (Figure 6) shows that 0% to 2% is the most populated range of positive forecast errors management achieves.

MTB	=	the market to book value of equity, $[(PRCC\_f_{it} * CSHO_{it})/CEQ_{it}]$ where *PRCC_f* is the closing share price at fiscal year-end, *CSHO* is the number of shares outstanding and *CEQ* is the book value of common ordinary equity. *PRCC_f, CSHO*, and *CEQ* are from Compustat.
ΔEMP	=	the annual change in the number of employees scaled by total assets, $[(EMP_{it}-EMP_{it-1})/ AT_{it-1}]$ where *EMP* is the number of employees and *AT* is previously defined. *EMP* and *AT* are from Compustat.
ΔPPE	=	the annual change in property plant and equipment scaled by total assets, $[(PPEGT_{it} – PPEGT_{it-1})/AT_{it-1}]$ where *PPEGT* is gross property plant and equipment from Compustat and *AT* is previously defined.
ΔIND_OB	=	the mean annual change in *OB*, scaled by total assets, and calculated by industry, $[(OB_{it}- OB_{it-1})/ AT_{it-1}]$ where *OB* and *AT* are previously defined. Industry is categorized using the Fama French 49 industrial classifications.
ROA	=	is income before extraordinary items scaled by total assets (IB_{it}/AT_{it-1}) where *IB* is income before extraordinary items from Compustat and *AT* is previously defined.
LOG_MVE	=	the natural logarithm of the market value of equity $(PRCC\_f_{it} * CSHO_{it})$ both variables are previously defined.
$\Delta INVT$	=	the annual change in inventory scaled total assets, $(INVT_{it}-INVT_{it-1}) /AT_{it-1}$ where *INVT* is inventory from Compustat and *AT* is previously defined.

To consider non-revenue target related factors that can affect order backlog levels, the model incorporates several control variables. Following previous earnings management studies that investigate variations in accounting amounts, I include variables to control for the effects of differences in firm growth, industry, performance, and size e.g. Roychowdhury (2006); Cohen, Dey, and Lys (2008); and Jackson and Liu (2010). To account for firm growth, I use the market to book value of equity (*MTB*), changes in employment (Δ*EMP*), and changes in property, plant and equipment (Δ*PPE*).[20] I predict negative estimated coefficients for the three growth variables. Negative estimated coefficients indicate that higher growth firms are more likely to also grow their order backlog. To account for industry, the model includes industry changes in order backlog (Δ*IND_OB*). I predict a negative estimated coefficient for Δ*IND_OB*. A negative estimated coefficient indicates that a firm in an industry that is building order backlog is less likely to reduce its own order backlog. I use income before extraordinary items scaled by assets (ROA) to control for performance. This metric follows Roychowdhury (2006) and Gunny (2010). The model also includes log of the market value of equity (*LOG_MVE*) to control for size. I do not predict the sign of the estimated coefficients for *ROA* or *LOG_MVE*. In addition to the effects of firm characteristics, Chapman & Steenburgh (2010) argues that when firms cut prices at year-end to increase earnings, as identified by Roychowdhury (2006), their true incentive may be inventory clearance. Reducing order backlog to clear inventory is a logical extension of this argument. Therefore, the model includes inventory changes (Δ*INVT*). A negative estimated coefficient would be consistent with reductions in order backlog resulting in lower inventory.

[20] Changes in employment and PPE could also indicate management's intention to change the level of order backlog for non-revenue management business reasons.

3.5 Propensity-Score Matching

I use propensity-score matching to develop data samples that reduce differences in the control variables between the *SUSPECT* and the non-*SUSPECT* observations.[21] Logistic models are the most customary method of calculating propensity scores (Lawrence, Minutti-Meza, and Zhang, 2011). I calculate propensity scores for *SUSPECT* firm-years using the following multivariate logistic regression (see Heckman Navarro-Lozano, 2004 for more details on this procedure):

$$Prob(SUSPECT_{it} = 1) = f(\alpha + + \beta_1 MTB_{it} + \beta_2 \Delta EMP_{it} + \beta_3 \Delta PPE_{it} + \beta_4 \Delta IND\_OB_{it} + \beta_5 ROA_{it} + \beta_6 LOG\_MVE_{it} + \beta_7 \Delta INVT_{it} + \varepsilon_{it}) \quad (7)$$

where the variables are described with equation 6. I include all of the control variables from my primary models in this regression (see the discussion above about the choice of these variables). The *PSCORE* is the predicted probability from equation 7 that a firm year will be *SUSPECT*. Matched pairs are formed by choosing an observation from the *SUSPECT* observations and choosing an additional observation from the non-*SUSPECT* observations with the closest *PSCORE*. Matching is designed to minimize the differences in *PSCORE* for the pairings (Armstrong, Jagolinzer, and Larcker, 2009). Matching is performed by year and is done without replacement. I require a minimum match of one decimal point and drop observations that do not meet this criterion[22]. The cutoff of one decimal point is used to maximize the number of

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[21] I use *SUSPECT* to refer to the four suspect variables: *GROW_SUSPECT, SMOOTH_SUSPECT, PRE_MISS, and PRE_BEAT.*

[22] The matching process is reiterative starting with matches at 8 decimal places. Of the four sample groups 48 was the largest number of matches that used the one decimal point criterion cutoff for accuracy.

observations and minimize the variable differences between the *SUSPECT* and non-*SUSPECT* observations. Table 2 shows the variable means, medians and *p*-values for differences in means and medians for the *SUSPECT* and non-*SUSPECT* observations for both the full samples and the propensity-score matched samples.

Panel A of Table 2 provides a comparison of the mean and median of each control variable with the *GROW_SUSPECT* and the non-*GROW _SUSPECT* observations. The full sample shows that the variable means and medians for the *GROW_SUSPECT* observations are smaller than they are for the non-*GROW _SUSPECT* observations and the differences are large and statistically significant (*p*-value < 0.0001). In comparison, in the propensity-score matched sample the differences in the variable means and medians are smaller and only 2 of the 7 measures have mean differences that are statistically significant. Panels B, C, and D of Table 2 provide the same comparisons for the *SMOOTH_SUSPECT*, *PRE_MISS*, and *PRE_BEAT* samples respectively. In each case, it can be seen that the large differences in the control variable means and medians between the *SUSPECT* observations and non_*SUSPECT* observations in the full sample are reduced or eliminated with the propensity-score matching.

CHAPTER FOUR

RESULTS

4.1 Test of Hypotheses Using Distributions

Numerous studies have used scaled earnings distributions to show earnings management to report earnings growth (e.g. Burgstahler and Dichev 1997; DeGeorge, Patel, and Zeckhauser 1999; Brown and Caylor 2005; and Jacob and Jorgensen 2007). Following these studies I construct a scaled distribution of changes in reported revenue and of changes measured by new sales orders over the prior year's reported revenue. Since revenues have a target of positive growth, a discontinuity in distribution at zero growth would be consistent with revenue management. On the other hand, growth as measured with *ORDERS* does not have a target so there is no reason to expect a discontinuity at zero growth. These distributions are shown in Figure 5.

Figure 5 displays a histogram using the distributions of year over year changes in reported revenue ($SALES_{it} - SALES_{it-1}$) and in growth measured by ($ORDERS_{it} - SALES_{it-1}$) scaled by beginning total assets (AT_{it-1}). For these distributions I use interval widths of 0.020 and for presentation purposes I truncate the graphs at -0.10 and 1.40 but, the entire sample is used to draw statistical inferences. Panel A of Figure 5 shows the distribution for scaled revenue changes ($SALES_{it} - SALES_{it-1}$)/($AT_{it-1}$). The figure shows a near bell shape distribution that peaks to the right of zero revenue growth. The distributions at zero revenue growth show a discontinuity. Relative to a smooth distribution it appears that the number of companies reporting small revenue increases is greater than expected while number of companies reporting revenue declines is less than expected. Following Burgstahler and Dichev (1997) I confirm the statistical significance of this discontinuity using standardized differences.[23] The small revenue decline interval has a standardized difference of -1.94 indicating statistical significance for the fewer than expected observations in this interval.[24] In contrast, the small revenue increase interval has a standardized difference of 3.27 indicating statistical significance for the greater than expected observations in this interval. Burgstahler and Dichev (1997) interpreted a similar discontinuity in the distribution of scaled earnings changes as evidence of earnings management.

Next I perform this analysis using scaled changes in new sales orders over reported revenue ($ORDERS_{it} - SALES_{it-1}$)/($AT_{it-1}$). Panel B Figure 5 shows the distribution for growth represented by new sales orders. This distribution appears similar in shape to the distribution for reported revenue, except, the discontinuity at zero has disappeared. The lack of a discontinuity is confirmed by the standardized differences for small decrease (0.25) and small increase (0.15) intervals that are not significantly different than zero. The presence of a discontinuity at zero growth for reported revenue suggests revenue management to avoid reporting a *SALES* decline. Since managers have an incentives to report positive revenue growth this interpretation is bolstered by the lack of a discontinuity at zero growth as measured by $ORDERS_{it} - SALES_{it-1})/AT_{it-1}$ that does not have a target. The difference between *ORDERS* and *SALES* is explained by changes in *OB* (Equations 1 and 4). Changes in order backlog explain the presence of discontinuity at zero growth for *SALES* and its disappearance with *ORDERS*. This figure provides evidence that managers use order backlog to avoid reporting a revenue decline.

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[23] The expected number of firms in an interval is the average of the two immediately adjacent intervals. The variance approximates $Np_i(1 - p_i) + (1/4)\, N(p_{i-1} + p_{i+1})(1 - p_{i-1} - p_{i+1})$ where N is the sum of the number of firms and p_i is the probability that a firm goes into interval i.
[24] Statistical significance is measured at 95% using a one tailed test.

DeGeorge, Patel, and Zeckhauser (1999) use distributions of analysts' earnings forecast errors to provide evidence of earnings management to meet analysts' forecasts. I adapt their methodology for use with revenue forecasts. I create two distributions of forecast errors using the mean analysts' FC_SALE_{it}. The first forecast error calculation uses $SALES_{it}$ and the second calculation uses $ORDERS_{it}$. I divide the forecasts errors into intervals of one percent. Figure 6 shows the distribution of sales order forecast errors with an overlay of the distribution of reported revenue forecast errors.

The distribution for reported revenue forecast errors shows that 63.2% of the errors are within 3% of zero and 53.4 percent are within 2% of zero but, the forecast errors are not distributed equally around zero. For both the 2% and 3% range approximately 58% of the errors are positive and approximately 42% of the errors are negative. To test the statistical significance of these differences I calculate standardize differences for the two revenue intervals adjacent to zero. The standardize differences for just missing the forecast (3.45) and just beating it (12.85) indicate that more companies than expected either just miss or just beat. Prior research has interpreted similar inequalities around zero forecast errors for earnings to be evidence of earnings management to meet or beat analysts' earnings forecasts e.g. DeGeorge et al. (1999); Burgstahler and Eames (2006). While Graham et al. (2005) report that managers not only manage earnings to meet analysts' forecasts they also try to influence the forecast.

The distribution of the new sales order forecast error is presented as an overlay in Figure 6. While this distribution also peaks at just beating the forecast the peak is far less pronounced and the distribution is broader and does not have the level clustering around zero forecast error that is present with reported revenue. Whereas reported revenue has 63.2% of the distribution within 3% of zero the new sales order distribution has 28% of the distribution is within 3% of zero and 20% is within 2% of zero. The standardized differences for the 1% intervals adjacent to zero are 0.37 for just missing and 2.04 just beating. The higher level of clustering around zero errors for *SALES* versus that of *ORDERS* is accounted for by changes in *OB*. These results suggest that when *ORDERS* fail to provide sufficient revenue to meet analysts' forecast, *OB* is reduced to increase *SALES*. Conversely, when new sales orders provide sufficient revenue to beat analysts' forecast, order backlog is increased to reduce reported revenue. These two assertions are tested using logistic regression model.

4.2 Test of Hypotheses Using Regressions

Panel A of Table 3 presents the results of the multivariate logistic regression model for the full samples. OBR_{it} is regressed on the $SUSPECT_{it}$ variables and the group of control variables. The *GROW_SUSPECT* model appears to be well specified. Based on chi-square tests, the estimating capacity of the model is significant (p-value < 0.0001). The generalized R^2 and max-rescaled R^2 of 21.4 and 28.9 respectively, indicate the fit of the model. Consistent with my first hypothesis *GROW_SUSPECT* has a positive estimated coefficient and is highly significant (p-value < 0.0001). The positive estimated coefficient is indicative of companies reducing order backlog and increasing reported revenue when *ORDERS* are insufficient to provide positive revenue growth. The control variables ΔEMP, ΔPPE, ΔIND_OB, *ROA, LOG_MV,* and $\Delta INVT$ are highly significant and with the exception of ΔPPE the sign of the estimated coefficients match their predictions.

The *SMOOTH_SUSPECT* model also appears to be well specified. Based on chi-square tests, the estimating capacity of the model is significant (p-value < 0.0001). The generalized R^2

and max-rescaled R^2 of 20.8 and 28.0 respectively, indicate the fit of the model. Consistent with my second hypothesis *SMOOTH_SUSPECT* has a positive estimated coefficient and is highly significant (p-value < 0.0001). The positive estimated coefficient is indicative of companies reducing order backlog and increasing revenue when *ORDERS* are insufficient to provide smooth revenue reporting. The control variables ΔEMP, ΔPPE, ΔIND_OB, *LOG_MV,* and $\Delta INVT$ are highly significant and the sign of the estimated coefficients match their predictions.

The *PRE_MISS* model also appears to be well specified. Based on chi-square tests, the estimating capacity of the model is significant (p-value < 0.0001). The generalized R^2 and max-rescaled R^2 of 44.5 and 60.5 respectively, indicate the fit of the model. Consistent with my third hypothesis *PRE_MISS* has a positive estimated coefficient and is highly significant (p-value $<$ 0.0001). The positive estimated coefficient is indicative of companies reducing order backlog and increasing reported revenue when *ORDERS* are insufficient to meet analysts' revenue forecasts.

The *PRE_BEAT* model appears to be well specified too. Based on chi-square tests, the estimating capacity of the model is significant (p-value < 0.0001). The generalized R^2 and max-rescaled R^2 of 41.0 and 55.4 respectively, indicate the fit of the model. Consistent with my fourth hypothesis *PRE_BEAT* has a negative estimated coefficient and is highly significant (p-value $<$ 0.0001). The negative estimated coefficient is consistent with companies increasing order backlog and reducing reported revenue when new sales orders exceed analysts' forecast by 2% or more. The control variables *MTB*, ΔEMP, ΔIND_OB, and $\Delta INVT$ are highly significant and the sign of the estimated coefficients match their predictions.

Panel B of Table 3 presents the results of the multivariate logistic regression model for the propensity-score matched samples. OBR_{it} is regressed on the $SUSPECT_{it}$ variables and the group of control variables. The four models seem well specified. Based on chi-square tests, the estimating capacity of each of the models is significant (p-value < 0.0001). The generalized R^2s and max-rescaled R^2s range from 13.4 and 17.9 respectively, to 41.6 and 55.6 indicating the models fit. The logistic regression results using the matched samples are consistent with those of the full sample. *GROW_SUSPECT*, *SMOOTH_SUSPECT*, and *PRE_MISS* each have positive estimated coefficients as predicted and are significant at (p-value < 0.0001). The estimated coefficient for *PRE_BEAT* is negative as predicted and it is significant at (p-value < 0.0001).

4.3 Comparison of New Sales Order Growth with *Ex Post* Revenue Reporting

An alternative interpretation to the *GROW_SUSPECT* results shown in Table 3 is that companies with declining demand reduce *OB* as a consequence of economic circumstances. To address this issue I investigate changes in *OB* and in reported revenue around zero growth. I begin by examining how increases and decreases in $ORDERS_{it}$ over the $SALES_{it-1}$ relate to changes in *OB* and to changes in *SALES*. Univariate analyses of these relations are shown in Table 4 using the full sample of 40,975 firm-years. Panel A Table 4 provides a comparison of sales order growth ($ORDERS_{it} - SALES_{it-1}$) with growth in order backlog ($OB_{it} - OB_{it-1}$). This panel shows a sharp distinction between companies that generate $ORDERS_{it}$ that are greater than $SALES_{it-1}$ and those companies that fail do so. Companies with positive growth build OB_{it} 74% of the time. In contrast, companies with negative growth reduce OB_{it} 75% of the time. The apparent disparity between building and reducing order backlog could be indicative of revenue management where companies that generate positive growth can defer revenue for future recognition and companies that generate negative growth accelerate revenue recognition to increase reported revenue. However, this information could also merely reflect changes in demand for the companies' products. Therefore I examine comparisons of sales order growth ($ORDERS_{it} - SALES_{it-1}$) with reported revenue growth ($SALES_{it} - SALES_{it-1}$). These results are shown in Panel B.

Panel B indicates that when $ORDERS_{it}$ exceed $SALES_{it-1}$ companies report negative revenue growth 6.8% of the time. Conversely, when $ORDERS_{it}$ fall short of $SALES_{it-1}$, companies report positive revenue growth 18% of the time. These differences are statistically significant with p-value of <.0001 for the chi-square. Companies are 2.7 times more likely to report revenue growth despite a decline in orders than to report a revenue decline when orders are growing. This disparity is consistent with the use of order backlog to manage revenue reporting. To further test the influence of incentives on *ex post* reporting I examine companies with a history of revenue growth.

When Burgstahler and Dichev (1997) use a subsample of companies with a history of growth they find the discontinuity at zero growth is larger for the growth subsample than it is for the total sample. They interpret this to mean that companies with a history of growth have greater incentives to manage earnings. To test the influence of a history of positive revenue growth on revenue reporting Panel C Table 4 uses a subsample of companies that reported positive revenue growth in the prior year. Using this subsample Panel C shows that companies with sales orders that exceed last year's sales report revenue decreases 5.5% of the time. In contrast, with the subsample for the condition where sales orders have decreased the companies report positive revenue growth 20.2% of the time. These differences are highly significant with a p-value of <.0001 for the chi-square. With the presence of greater incentives companies are 3.7 times more likely to report revenue growth despite a decline in *ORDERS* than to report a *SALES* decline when *ORDERS* are growing. Incentives associated with a history of revenue growth appear to influence reporting positive revenue growth. Panels B and C provide evidence that supports the notion that companies use *OB* to report revenue increases when *ORDERS* do not provide a sufficient source of revenue for positive *SALES* growth.

4.4 Robustness Testing of the Revenue Growth Hypothesis

To further investigate the impact of changes in demand on order backlog reductions I perform additional robustness testing. Using changes in order backlog assumes that expected order backlog follows a random walk. Since, companies with extremely large changes in demand may have less flexibility they need to be interpreted more cautiously. In robustness testing, I repeat my analyses using subsamples partitioned into deciles based on changes in demand (i.e., $\Delta ORDERS_{it}$) to distinguish observations that have (do not have) extremely large increases in demand. A decile-by-decile approach provides insight into whether evidence of smoothing occurs throughout the population of firms (and regardless of the change in demand for its products) rather than being driven by firms with extreme values where managerial discretion may have a relatively smaller role. To perform these tests I use the full growth sample of 40,975. To calculate $\Delta ORDERS$ I use the annual change scaled by total assets. The additional lagged data requirement with this calculation causes a loss of 4,841 firm-years that result in a sample of 36,134 firm-year observations. Table 5 shows the robustness testing results. Deciles consist of 3,613 firm-year observations (four deciles have 3,614 firm-year observations) and $GROW\_SUSPECT_{it}$ observations range from 3,202 for the decile with the smallest $\Delta ORDERS$ to 257 for decile with the largest $\Delta ORDERS$. The estimated coefficients $GROW\_SUSPECT_{it}$ are positive as predicted and they are statistically significant at 99% for nine of the ten deciles and statistically significant at 90% for the remaining decile. Consistent with hypothesis 1, these results along with those presented in Table 4 provide evidence that the *OB* changes are not merely a result of changes in product demand but are instead made to meet revenue reporting targets.

Additional untabulated robustness testing was performed using pairwise tests for each hypothesis. In all four cases the *SUSPECT* variable has a signed estimated coefficient as predicted and p-values of < 0.0001. The outcomes from the untabulated tests are consistent with the previously reported results.

CHAPTER FIVE

CONCLUSION

This paper adds to our understanding of financial reporting in several ways. First, prior research reports that managers and investors consider revenue to be an important reporting metric independent of earnings. Prior research does not provide evidence that managers can time revenue recognition to meet revenue targets and several studies show a decline in earnings management when revenue growth is present. My study provides empirical evidence that managers use the order fulfillment process in conjunction with order backlog to accelerate and to defer revenue recognition around three revenue reporting targets: positive revenue growth, smooth revenue growth, and analysts' revenue forecast. Second, prior earnings management research typically focuses on earnings without accounting for how the markets' response to different earnings components can affect earnings management decisions. My paper finds that managers time revenue recognition to meet revenue targets and that they do so independently of earnings targets. This result suggests that managers may be unlikely to create revenue surprises to meet earnings targets. Future researchers may want to consider the influence of revenue reporting targets on earnings management activities. Third, earnings management studies often rely on estimation models of accruals, discretionary accruals, individual accrual accounts, and cash flows to identify both accrual manipulation and real earnings management activities. These estimation models typically use revenue as a predicting variable. Future researchers may want to consider that revenue may also be a manipulated variable. Fourth, real earnings management techniques are often associated with activities that have not been shown to be repeatable (e.g.

Roychowdhury, 2006 questions whether companies that engage in real activities can do so continuously). My study identifies a real activity that managers can use to either accelerate or defer revenue recognition in a manner that provides a revenue smoothing mechanism that can be used repeatedly over multiple accounting periods. Finally, my paper provides empirical evidence that revenue management can be identified using a non-GAAP reporting metric.

My research also has implications for policy setters. Prior research shows that investors use revenue growth to gauge future earnings growth – earnings growth coupled with revenue growth signals persistent earnings growth. When companies report revenue growth derived from a reduction in order backlog then the growth implications that are associated with revenue do not necessarily reflect the existing underlying economic conditions. The SEC recognizes that investors need order backlog information to evaluate revenue growth and the SEC has required order backlog disclosure since 1970 but, the SEC's disclosure requirement is limited to the annual 10-K filing and order backlog disclosure is not required under GAAP. Annual order backlog disclosure, as the SEC requires, appears to be inadequate. The literature has documented that investors respond to revenue news that accompanies quarterly earnings announcements but under current regulations investors cannot ascertain the source of quarterly revenue growth. Currently, as an SEC legal requirement, the decision about whether to disclose order backlog can be based on the advice of legal counsel. Consequently, the disclosure decision is not subject to the review of an auditor. On the other hand, if order backlog disclosure were required by GAAP, then the audit function would also help ensure compliance with disclosure requirements. Order backlog disclosure under GAAP would also obligate auditors to perform more stringent testing of order backlog than is currently required under the SEC's regulations. Also, under GAAP companies would be required to disclose order backlog on a quarterly basis. With both order backlog and revenue data investors could determine the source of quarterly revenue growth. Given the interpretation of revenue growth as a signal of future earnings growth it appears unlikely that investors would value revenue growth that is garnered from growth in new sales orders the same as revenue growth that is derived from reducing order backlog. While earnings management techniques such as the use of discretionary accruals may be difficult to detect, revenue manipulation with order backlog could be made visible to investors on a quarterly basis if GAAP were to require order backlog disclosure.

APPENDIX A

VARIABLE DEFINITIONS

AT	=	total assets from Compustat.
OB	=	order backlog from Compustat.
SALES	=	revenue from Compustat.
L_SALE	=	prior year revenue from Compustat.
SMOOTH_SALE	=	defined by equation 3.
FC_SALE	=	*FC_SALE* is the last mean revenue forecast prior to fiscal year-end from I/B/E/S.
ORDERS	=	$OB_{it} + SALES_{it} – OB_{it-1}$ where *OB* and *SALES* are previously defined.
Δ*ORDERS*	=	$(ORDERS_{it} – ORDERS_{it-1})/AT_{it-1}$ where *ORDERS* and *AT* are previously defined,
OBR	=	an indicator variable for OB reduction. *OBR* equals 1 when $(OB_{it} – OB_{it-1})$ is negative, otherwise *OBR* equals 0. OB is previously defined.
PRE_MISS	=	an indicator variable to identify firms whose new sales orders (*ORDERS*) miss the analysts' revenue forecasts: PRE_MISS_{it} equals 1 when $[ORDERS_{it} – FC\_SALE_{it}] /FC\_SALE_{it}$ is < 0.00, Otherwise PRE_MISS_{it} = 0. *FC_SALE* and *ORDERS* are previous defined.
PRE_BEAT	=	an indicator variable to identify firms whose new sales orders (*ORDERS*) beats the analysts' revenue forecasts by 2% or more: PRE_BEAT_{it} equals 1 when $[ORDERS_{it}–FC\_SALE_{it}] /FC\_SALE_{it}$ is ≥ 0.02, otherwise PRE_BEAT_{it} equals 0. *FC_SALE* and *ORDERS* are previous defined. Two percent is chosen following Burgstahler and Eames (2006) who find that firms manage earnings downward after achieving a small positive earnings surprise.
GROW_SUSPECT	=	an indicator variable to identify firms whose new sales orders (*ORDERS*) are less than the prior year's reported revenue.
SMOOTH_SUSPECT	=	an indicator variable to identify firms whose new sales orders (*ORDERS*) are less than *SMOOTH_SALE*.
MTB	=	the market to book value of equity, $[(PRCC\_f_{it} * CSHO_{it})/CEQ_{it}]$ where *PRCC_f* is the closing share price at fiscal year-end, *CSHO* is the number

of shares outstanding and *CEQ* is the book value of common ordinary equity. *PRCC_f, CSHO*, and *CEQ* are from Compustat.

ΔEMP	=	the annual change in the number of employees scaled by total assets, $[(EMP_{it}-EMP_{it-1})/\ AT_{it-1}]$ where *EMP* is the number of employees and *AT* is previously defined. *EMP* and *AT* are from Compustat.
ΔPPE	=	the annual change in property plant and equipment scaled by total assets, $[(PPEGT_{it} - PPEGT_{it-1})/AT_{it-1}]$ where *PPEGT* is gross property plant and equipment from Compustat and *AT* is previously defined.
ΔIND_OB	=	the mean annual change in *OB*, scaled by total assets, and calculated by industry, $[(OB_{it}-\ OB_{it-1})/\ AT_{it-1}]$ where *OB* and *AT* are previously defined. Industry is categorized using the Fama French 49 industrial classifications.
ROA	=	is income before extraordinary items scaled by total assets (IB_{it}/AT_{it-1}) where *IB* is income before extraordinary items from Compustat and *AT* is previously defined.
LOG_MVE	=	the natural logarithm of the market value of equity $(PRCC\_f_{it} * CSHO_{it})$ both variables are previously defined.
$\Delta INVT$	=	the annual change in inventory scaled total assets, $(INVT_{it}INVT_{it-1})\ /AT_{it-1}$ where *INVT* is inventory from Compustat and *AT* is previously defined.

APPENDIX B

FIGURES

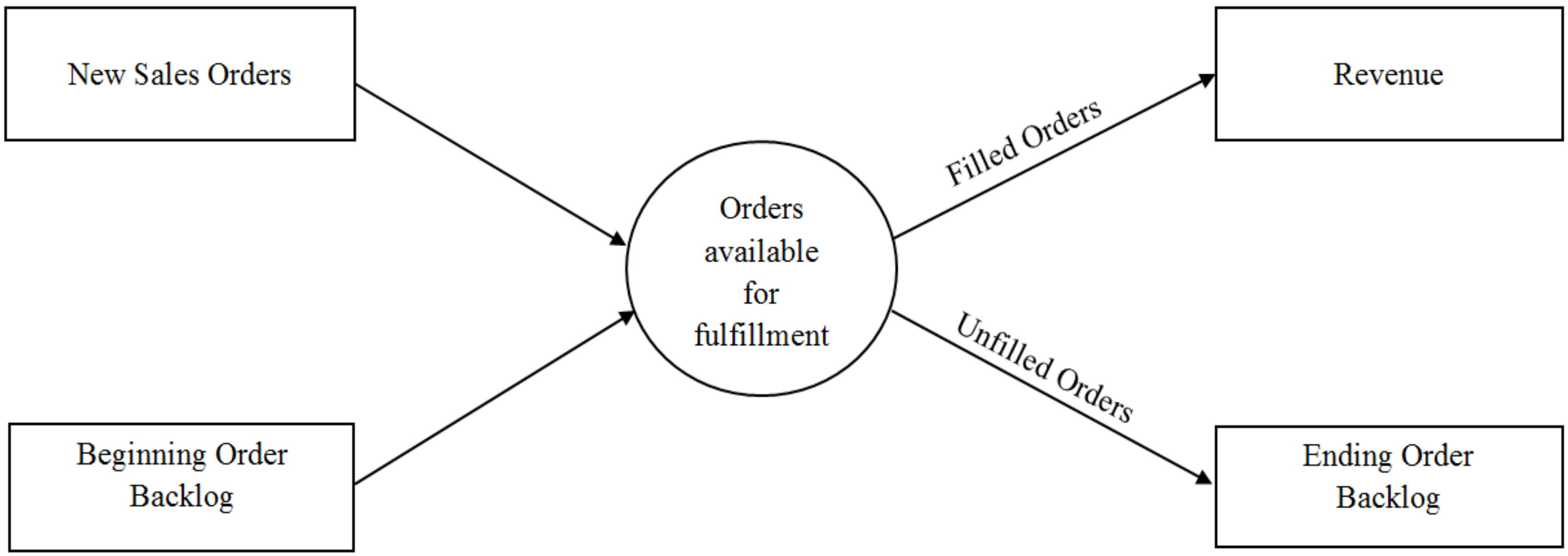


Figure 1. Flow chart of order fulfillment.

This chart shows the relation among four variables; beginning order backlog (OB_{it-1}), new sales orders ($ORDERS_{it}$), ending order backlog (OB_{it}), and revenue ($SALES_{it}$). Order backlog and revenue are the Compustat variables OB and SALES respectively. New sales orders ($ORDERS_{it}$) are calculated using equations 1 thru 4. From this equation and the flow chart it can be seen that when beginning order backlog (OB_{it-1}) equals ending order backlog (OB_{it}) that new sales orders ($ORDERS_{it}$) equal revenue ($SALES_{it}$). This chart illustrates that by increasing (decreasing) the amount of filled orders companies can increase (decrease) revenue ($SALES_{it}$) which in turn decreases (increases) order backlog (OB_{it}). By increasing or decreasing order backlog (OB_{it}) companies shift revenue ($SALES_{it}$) between accounting periods.

Figure 2. Total un-scaled revenue and new sales orders.

The amounts are un-scaled totals for each year. Revenue is Compustat data item Sale and new sales orders (ORDERS) are calculated using equations 1 thru 4. OB is the Compustat data item for order backlog. Beginning and ending order backlog data are required to calculate new sales orders (ORDERS) so firm years missing this data are excluded and financial institutions, insurance companies, and utilities are eliminated. Under the SEC's regulations firms are required to disclose the amount of order backlog that is expected to be recognized as revenue in the following year. I eliminate disclosures that may fall outside this parameter by dropping 2,518 observations where order backlog exceeds reported revenue for the current year or for the following year. These selection criteria provide a sample of 40,975 firm years. For each firm year the percentages are of order backlog divided by revenue and total assets respectively.

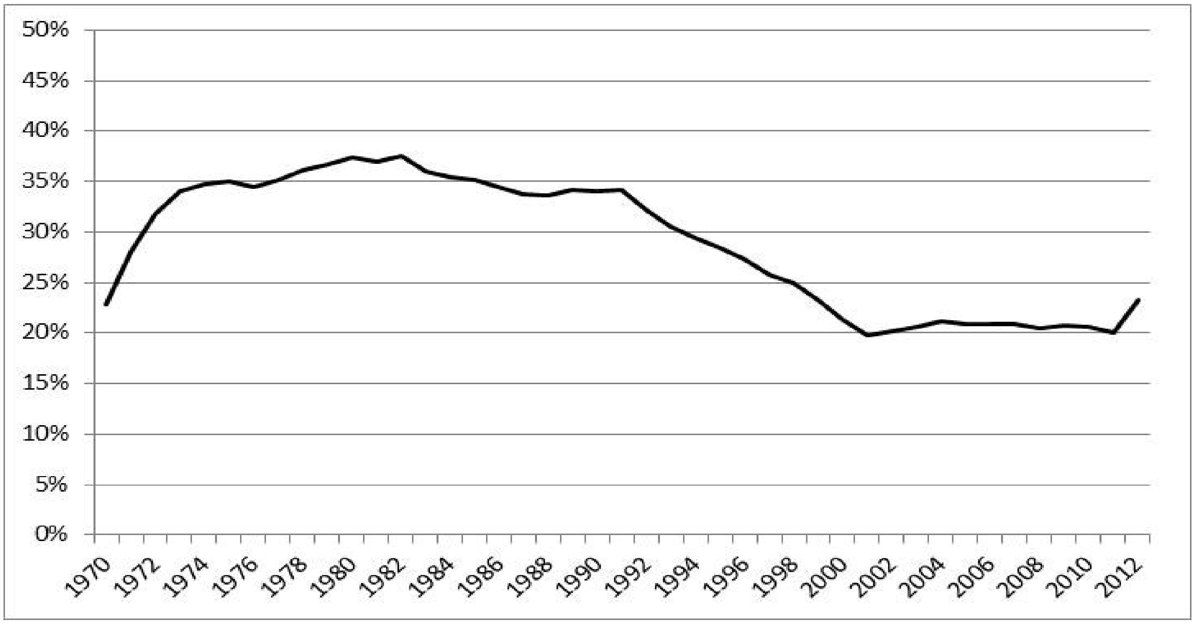


Figure 3. Percentage of firms disclosing order backlog.

Since 1970 SEC regulation §229 item 101(c) (VIII) has required public companies to disclose order backlog amounts with their 10-K filings. Under this regulation companies are required to disclose the amount of order backlog that is expected to be recognized as revenue in the subsequent year. To coincide with the implementation of the SEC's regulation the sample covers the years 1970 through 2012 and includes firms from Compustat. I use annual data because the SEC's order backlog disclosure requirement only applies to annual 10-K filings.[25] I require two consecutive firm years of data and I eliminate financial institutions, insurance companies, and utilities. These selection criteria provide a sample 40,975 firm years disclose order backlog. The percentage is calculated by dividing the number of firms with order backlog disclosures by the total number of firms by year.

[25] An analysis of the Compustat quarterly data file shows that 10Q order backlog disclosures are too sparse to be useable.

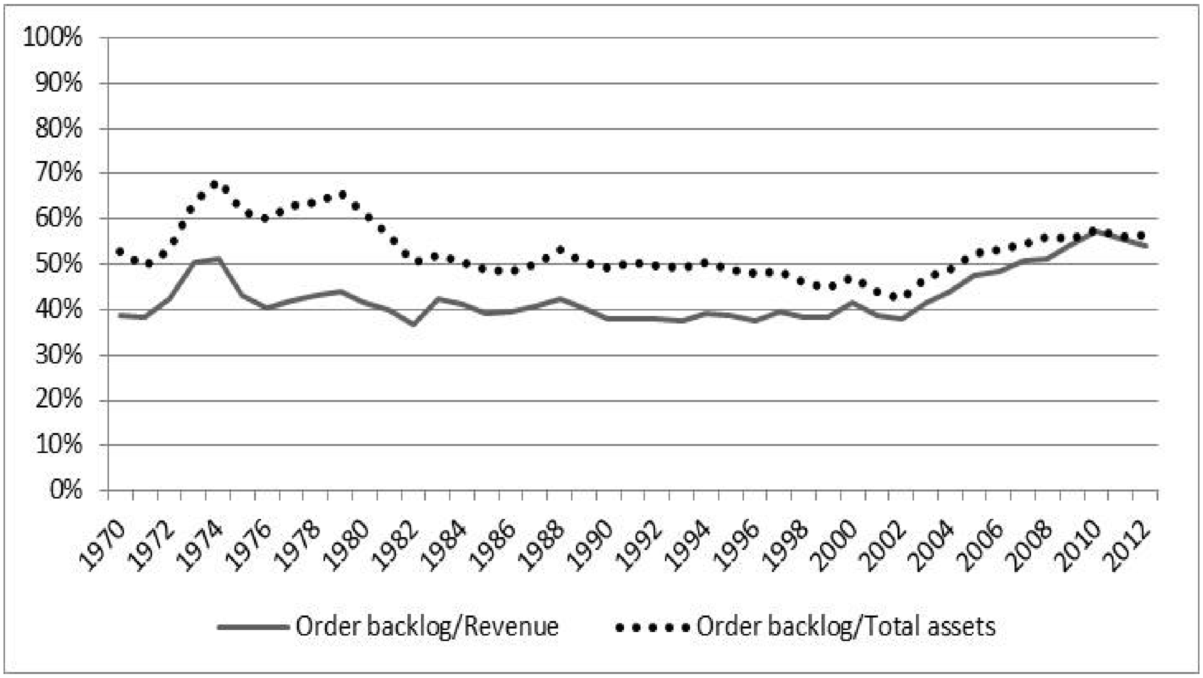
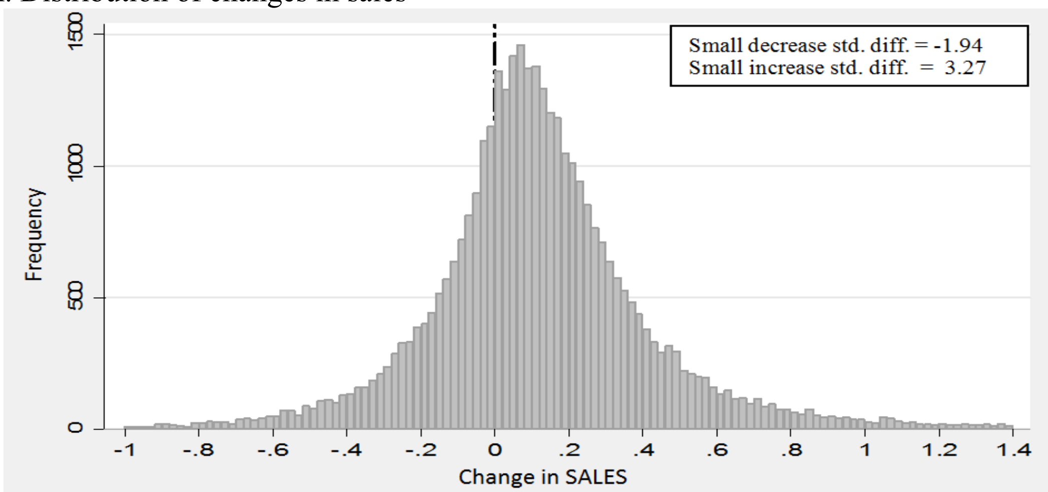


Figure 4. Order backlog as a percentage of revenue and total assets.

See Figure 2 for sample selection criteria. The variables are Compustat data items Order backlog (OB), revenue (SALES), and total assets (AT). For each firm year the percentages are of order backlog divided by revenue and by total assets respectively. The mean percentage for each year is shown.

Panel A. Distribution of changes in sales



Panel B. Distribution of changes in sales orders

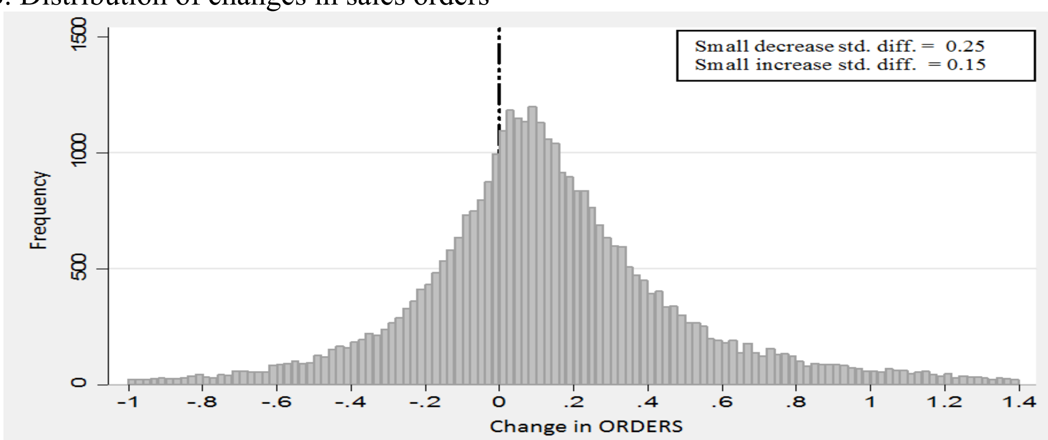


Figure 5. Distribution of year over year changes in reported *SALES* and in *ORDERS*.

Panel A is a histogram of scaled changes in reported *SALES*. Reported *SALES* changes are calculated by subtracting $SALES_{it-1}$ from $SALES_{it}$ where *SALES* is the Compustat data item for revenue. The change is scaled by AT_{it-1} the Compustat data item for total assets. The panel B histogram of scaled changes in orders is calculated by subtracting $SALES_{it-1}$ from $ORDERS_{it}$ (equations 1 thru 4). The change is scaled by AT_{it-1}. I use bin widths of 0.020 and calculate the statistical significance of the expected discontinuity with a t-statistic (commonly referred to as a "standardized difference") which equals the difference between the actual and expected number of firms in the small loss interval (and small profit interval) divided by the difference's estimated standard deviation (e.g. Burgstahler and Dichev 1997; McAnally, Srivastava, and Weaver 2008). The dashed line indicates the demarcation between negative and positive revenue growth. The expected number of firms in an interval is the average of the two immediately adjacent intervals. The variance approximates $Np_i(1 - p_i) + (1/4) N(p_{i-1} + p_{i+1})(1 - p_{i-1} - p_{i+1})$ where N is the sum of the number of firms and p_i is the probability that a firm goes into interval *i*. Distributions are cutoff at -1 and 1.4 for presentation purposes only, statistical differences are based on the complete sample.

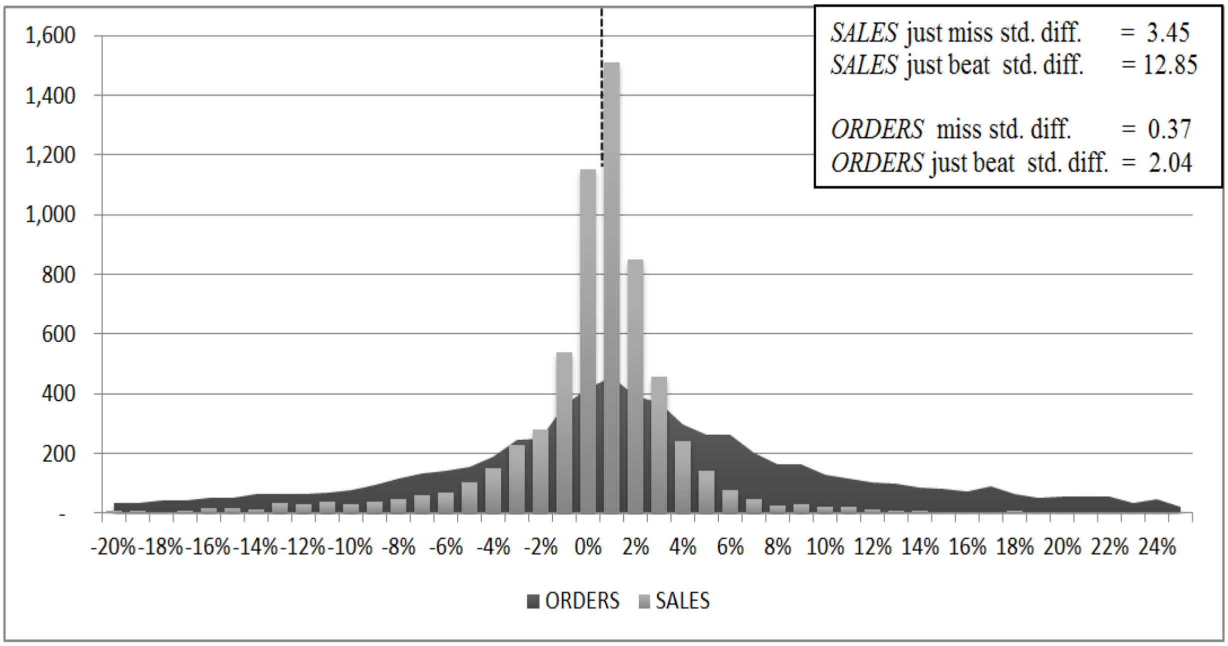


Figure 6. Analysts forecast errors using reported revenue and orders.

Orders and sales measured against analysts' revenue forecasts forecast errors are measured in intervals of 1%. This histogram requires analysts' revenue forecasts from Institutional Brokers Estimate System (I/B/E/S). This requirement limits the useable years to 1997 through 2012 and reduces the sample to 7,575 firm year observations and is a sub-set of the sample used in Figures 3 and 4. Earnings management studies often use 1 cent which is consistent with how the business press reports forecast errors. The business press reports revenue forecast errors in terms of percent of forecast. I use one percent intervals for the bin widths and the calculation for standardized differences is described with Figure 6. The revenue forecast error is determined by subtracting the difference between revenue (Compustat data item Sale) and the latest mean analysts' revenue forecast prior to fiscal year-end (I/B/E/S data item Meanest) and dividing by the analysts' revenue forecast. This method is also used to calculate the forecast errors for sales orders (*ORDERS*) –which are defined by equation 1. For presentation purposes the histogram is truncated at -20% and 25% but the standardize differences are based on the entire sample. The dashed line is at the point of zero forecast errors. Calculations for the standardized differences are described with Figure 6.

APPENDIX C

TABLES

Table 1. Number of order backlog disclosures by industry.

Industry	*N*	Order backlog disclosures Disclosures	Non-Disclosures	Disclosures %
Aircraft	1,349	1,089	260	81%
Shipbuilding	440	338	102	77%
Measuring & Control Equipment	4,505	3,205	1,300	71%
Defense	349	247	102	71%
Machinery	7,671	5,170	2,501	67%
Construction	2,597	1,699	898	65%
Electrical Equipment	3,533	2,172	1,361	61%
Semi-Condutors & Electronics	11,426	7,012	4,414	61%
Fabricated Products	995	538	457	54%
Textiles	1,800	912	888	51%
Apparel	3,312	1,531	1,781	46%
Computers	4,787	2,192	2,595	46%
Constructions Materials	5,992	2,362	3,630	39%
Steel Works	3,698	1,444	2,254	39%
Rubber & Plastic Products	2,325	874	1,451	38%
Automobiles & Trucks	3,556	1,288	2,268	36%
Consumer Goods	4,837	1,530	3,307	32%
Recreation	1,881	536	1,345	28%
Business Supplies	3,552	984	2,568	28%
Other	3,361	848	2,513	25%
Medical Equipment	5,393	1,345	4,048	25%
Business Services	9,480	2,182	7,298	23%
Computer Software	11,572	2,466	9,106	21%
Chemicals	4,279	686	3,593	16%
Wholesale	8,440	1,352	7,088	16%
Shipping Containers	748	73	675	10%
Real Estate	2,889	274	2,615	9%
Printing & Publishing	1,910	156	1,754	8%
Agriculture	813	65	748	8%
Personal Services	2,069	158	1,911	8%
Pharmaceutical Products	8,098	533	7,565	7%
Coal	424	27	397	6%
Entertainment	3,004	152	2,852	5%
Mining & Extraction	1,751	88	1,663	5%
Food Products	4,326	174	4,152	4%
Retail	11,478	322	11,156	3%
Healthcare	2,862	77	2,785	3%
Candy & Soda	561	15	546	3%
Transportation	5,532	130	5,402	2%
Restaurants & Lodging	3,953	88	3,865	2%
Tobacco Products	271	5	266	2%
Precious Metals	1,788	18	1,770	1%
Beer & Liquor	923	3	920	0%
Total	164,530	46,360	118,170	28%

See Figure 2 for a description of the sample selection criteria. Table one shows the number of firm year observations disclosing order backlog (Compustat data item OB) by industry using the Fama-French 49 industry classifications. Observations counted under Disclosures include all firm years with positive order backlog and Non-Disclosures are the remainder.

Table 2. Comparison of covariates with full and propensity-score matched samples.

Panel A. *GROW_SUSPECT* sample: means and medians for full and matched samples.

	Full *GROW_SUSPECT* Sample						Propensity-Score Matched Sample					
	SUSPECT (*N = 12,762)*		Non-*SUSPECT* (*N = 28,213)*		Difference in mean	Difference in median	*SUSPECT* (*N = 8,295)*		Non-*SUSPECT* (*N = 8,295)*		Difference in mean	Difference in median
Variable	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]
MTB	1.820	1.108	2.305	1.579	0.0001	0.0001	1.907	1.213	1.865	1.262	0.2743	0.0045
Δ*EMP*	-1.994	-0.832	2.393	0.739	0.0001	0.0001	-0.845	-0.433	-0.643	-0.116	0.0001	0.0001
Δ*PPE*	0.009	0.013	0.065	0.042	0.0001	0.0001	0.024	0.019	0.024	0.022	0.6025	0.0001
Δ*IND_OB*	0.042	0.027	0.086	0.061	0.0001	0.0001	0.049	0.035	0.050	0.040	0.3699	0.0015
ROA	-0.032	0.009	0.052	0.063	0.0001	0.0001	-0.002	0.021	0.000	0.034	0.2889	0.0001
LOG_MVE	3.497	3.330	4.210	4.021	0.0001	0.0001	3.900	3.727	3.729	3.575	0.0001	0.0001
Δ*INVT*	-0.019	-0.013	0.046	0.024	0.0001	0.0001	-0.002	-0.003	-0.001	0.000	0.4106	0.0001

Panel B. *SMOOTH_SUSPECT* sample: means and medians for full and matched samples.

	Full *SMOOTH_SUSPECT* Sample						Propensity-Score Matched Sample					
	SUSPECT (*N = 14,689)*		Non-*SUSPECT* (*N = 19,972)*		Difference in mean	Difference in median	*SUSPECT* (*N = 10,056)*		Non-*SUSPECT* (*N = 10,056)*		Difference in mean	Difference in median
Variable	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]
MTB	1.783	1.207	2.163	1.503	0.0001	0.0001	1.888	1.336	1.861	1.337	0.3542	0.9326
Δ*EMP*	-1.252	-0.442	2.163	0.691	0.0001	0.0001	-0.166	-0.111	0.006	0.090	0.0001	0.0001
Δ*PPE*	0.023	0.021	0.056	0.037	0.0001	0.0001	0.034	0.027	0.032	0.024	0.0830	0.0009
Δ*IND_OB*	0.047	0.031	0.088	0.063	0.0001	0.0001	0.057	0.040	0.057	0.046	0.9073	0.0001
ROA	0.002	0.030	0.048	0.060	0.0001	0.0001	0.025	0.041	0.022	0.042	0.0527	0.7350
LOG_MVE	3.888	3.720	4.298	4.101	0.0001	0.0001	4.252	4.092	4.132	3.936	0.0001	0.0001
Δ*INVT*	-0.006	-0.003	0.041	0.023	0.0001	0.0001	0.010	0.004	0.009	0.006	0.3194	0.0001

Panel C. *PRE_MISS* sample: means and medians for full and matched samples.

	Full *PRE_MISS* Sample						Propensity-Score Matched Sample					
	SUSPECT (*N = 3,305)*		Non-*SUSPECT* (*N = 4,207)*		Difference in mean	Difference in median	*SUSPECT* (*N = 2,500)*		Non-*SUSPECT* (*N = 2,500)*		Difference in mean	Difference in median
Variable	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]
MTB	2.402	1.762	2.962	2.195	0.0001	0.0001	2.540	1.883	2.505	1.937	0.5764	0.2134
Δ*EMP*	-0.040	-0.063	0.855	0.298	0.0001	0.0001	0.184	0.044	0.315	0.159	0.0009	0.0001
Δ*PPE*	0.025	0.017	0.045	0.028	0.0001	0.0001	0.032	0.021	0.034	0.022	0.4081	0.1746
Δ*IND_OB*	0.040	0.027	0.077	0.052	0.0001	0.0001	0.047	0.032	0.051	0.043	0.2544	0.0002
ROA	-0.002	0.037	0.060	0.064	0.0001	0.0001	0.039	0.053	0.032	0.048	0.0355	0.0128
LOG_MVE	5.963	5.825	6.463	6.381	0.0001	0.0001	6.273	6.102	6.193	6.137	0.0950	0.5338
Δ*INVT*	0.000	0.000	0.032	0.015	0.0001	0.0001	0.011	0.005	0.011	0.005	0.6793	0.3363

Panel D. *PRE_BEAT* sample: means and medians for full and matched samples.

	Full *PRE_BEAT* Sample						Propensity-Score Matched Sample					
	PRE_BEAT (*N = 3,447)*		Non-*SUSPECT* (*N = 4,128)*		Difference in mean	Difference in median	*PRE_BEAT* (*N = 2,536)*		Non-*SUSPECT* (*N = 2,536)*		Difference in mean	Difference in median
Variable	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]	Mean	Median	Mean	Median	*p*-value[a]	*p*-value[a]
MTB	3.065	2.243	2.428	1.811	0.0001	0.0001	2.710	2.116	2.772	2.062	0.3457	0.1158
Δ*EMP*	0.986	0.365	0.028	-0.015	0.0001	0.0001	0.454	0.234	0.356	0.131	0.0059	0.0001
Δ*PPE*	0.049	0.030	0.025	0.018	0.0001	0.0001	0.036	0.025	0.039	0.024	0.1338	0.5744
Δ*IND_OB*	0.082	0.056	0.043	0.030	0.0001	0.0001	0.061	0.051	0.056	0.039	0.1706	0.0001
ROA	0.062	0.066	0.009	0.042	0.0001	0.0001	0.044	0.056	0.051	0.062	0.0222	0.0003
LOG_MVE	6.462	6.358	6.064	5.953	0.0001	0.0001	6.358	6.280	6.455	6.311	0.0412	0.5744
Δ*INVT*	0.037	0.018	0.002	0.001	0.0001	0.0001	0.017	0.011	0.018	0.009	0.4633	0.1294

[a] All *p*-values based on two tailed test. Variables are defined in Appendix A

Table 3. Logistic estimates for order backlog reductions regressed on revenue reporting suspect variables

$Prob(OBR_{it} = 1)$

$= f(\alpha + \beta_1 SUSPECT_{it} + \beta_2 MTB_{it} + \beta_3 \Delta EMP_{it} + \beta_4 \Delta PPE_{it} + \beta_5 \Delta IND\_OB_{it} + \beta_6 ROA_{it} + \beta_7 LOG\_MVE_{it} + \beta_8 \Delta INVT_{it} + \varepsilon_{it})$

Panel A Full samples

SUSPECT =		*GROW_SUSPECT*		*SMOOTH_SUSPECT*		*PRE_MISS*		*PRE_BEAT*	
N =		40,975		34,841		7,575		7,575	
Variable	Predicted sign[a]	Estimated coefficient	p-value[b]	Estimated coefficient	p-value[b]	Estimated coefficient	p-value[b]	Estimated coefficient	p-value[b]
Intercept		-0.657	0.0001***	-0.600	0.0001***	-1.867	0.0001***	1.350	0.0001***
SUSPECT	+	1.854	0.0001***	1.543	0.0001***	3.567	0.0001***	-3.661	0.0001***
MTB	–	-0.001	0.8831	-0.002	0.6715	-0.059	0.0001***	-0.037	0.0080***
ΔEMP	–	-0.042	0.0001***	-0.049	0.0001***	-0.082	0.0003***	-0.098	0.0001***
ΔPPE	–	0.473	0.0012***	-0.531	0.0016***	-0.275	0.6045	0.289	0.0001***
ΔIND_OB	–	-2.570	0.0001***	-2.712	0.0001***	-2.387	0.0001***	-2.150	0.0001***
ROA		0.343	0.0001***	-0.083	0.3397	0.143	0.3524	-0.089	0.5382
LOG_MVE		-0.031	0.0001***	-0.051	0.0001***	-0.006	0.7847	-0.054	0.0042***
ΔINVT	–	-1.511	0.0001***	-2.668	0.0001***	-3.043	0.0001***	-2.988	0.0001***
Chi-Square		9,304	0.0001***	7,675	0.0001***	4,356	0.0001***	3,873	0.0001***
Generalized R^2		0.214		0.208		0.445		0.410	
Max - Rescaled R^2		0.289		0.280		0.605		0.554	

Panel B Propensity-score matched samples

SUSPECT =		*GROW_SUSPECT*		*SMOOTH_SUSPECT*		*PRE_MISS*		*PRE_BEAT*	
N =		16,590		20,112		5,000		5,072	
Variable	Predicted sign[a]	Estimated coefficient	p-value[b]	Estimated coefficient	p-value[b]	Estimated coefficient	p-value[b]	Estimated coefficient	p-value[b]
Intercept		-0.645	0.0001***	-0.540	0.0001***	-1.545	0.0001***	1.562	0.0001***
SUSPECT	+	1.765	0.0001***	1.434	0.0001***	3.455	0.0001***	-3.607	0.0001***
MTB	–	0.005	0.5	-0.010	0.2333	-0.040	0.0269**	-0.028	0.0925*
ΔEMP	–	-0.053	0.0001***	-0.072	0.0001***	-0.200	0.0001***	-0.219	0.0001***
ΔPPE	–	1.287	0.0001***	-0.558	0.0016***	-0.634	0.3091	0.503	0.4018
ΔIND_OB	–	-2.219	0.0001***	-2.402	0.0001***	-2.878	0.0001***	-1.453	0.0011***
ROA		0.879	0.0001***	-0.132	0.3668	0.995	0.0060***	0.826	0.0161**
LOG_MVE		-0.020	0.0269**	-0.046	0.0001***	-0.042	0.0994*	-0.110	0.0001***
ΔINVT	–	-1.562	0.0001***	-2.625	0.0001***	-1.408	0.1474	-1.063	0.2465
Chi-Square		3,151	0.0001***	2,892	0.0001***	2,688	0.0001***	2,399	0.0001***
Generalized R^2		0.173		0.134		0.416		0.377	
Max - Rescaled R^2		0.230		0.179		0.556		0.518	

[a] Predicted sign for *PRE_BEAT* is -.

[b] ***, **, * Statistical significant at the 0.01, 0.05, and 0.1 levels respectively. Based on one-tailed tests for signed predictions and, two-tailed tests otherwise. Variables are defined in Appendix I.

Table 4. Cross tabulations: *OB* changes, *SALES* changes and *GROW_SUSPECT*

Panel A *OB* changes and *GROW_SUSPECT*.

N Col %	*OB*	*GROW_SUSPECT* Non-*SUSPECT*	*SUSPECT*	Total
	Increase	20,711 74.2%	3,176 25.2%	23,887
	Decrease	7,217 25.8%	9,431 74.8%	16,648
	Total	27,928	12,607	40,535

Chi-square = 8,605, p-value <0.0001

Panel B. *SALES* changes and *GROW_SUSPECT*.

N Col %	*SALES*	*GROW_SUSPECT* Non-*SUSPECT*	*SUSPECT*	Total
	Increase	26,034 93.2%	2,264 18.0%	28,298
	Decrease	1,894 6.8%	10,343 82.0%	12,237
	Total	27,928	12,607	40,535

Chi-square = 23,344, p-value <0.0001

Panel C. Sub-sample of firms with positive revenue growth the prior year – *SALES* changes and *GROW_SUSPECT*.

N Col %	*SALES*	*GROW_SUSPECT* Non-*SUSPECT*	*SUSPECT*	Total
	Increase	17,932 94.5%	1,509 20.2%	19,441
	Decrease	1,048 5.5%	5,947 79.8%	6,995
	Total	18,980	7,456	26,436

Chi-square = 15,162, p-value <0.0001

I drop 440 firm-years that have no change in *OB*. The panel A cross tabulation reports positive (negative) growth for order backlog (Compustat data item OB) and sales orders (Equations 1 thru 4) Positive (negative) growth for order backlog is determined by subtracting OB_{it-1} from OB_{it}. Growth for sales orders is determined by subtracting $SALES_{it-1}$ from $ORDERS_{it}$. Reported revenue growth in Panel B is calculated the same as order backlog using $SALES_{it-1}$ and $SALES_{it}$. Panel C is a sub-sample of firms where $SALES_{it-1}$ minus $SALES_{it-2}$ is positive.

Table 5. Logistic estimates for order backlog reductions regressed on revenue growth suspect variables using Δ*ORDERS* deciles.

N = 36,134	Decile	1	2	3	4	5	6	7	8	9	10
Decile *N*		3,613	3,613	3,614	3,613	3,614	3,613	3,614	3,613	3,614	3,613
(*SUSPECT N*)		(3,202)	(2,825)	(2,424)	(1,862)	(1,397)	(1,025)	(829)	(580)	(417)	(257)
Variable	Pred sign	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]	Coeff. p-value[a]
Intercept		0.840	0.861	0.513	0.027	-0.045	-0.619	-0.711	-1.080	-1.771	-2.499
		0.0001***	0.0001***	0.0001***	0.777	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
GROW_SUSPECT	+	1.143	0.475	0.150	0.240	0.595	1.002	1.319	1.706	2.203	3.145
		0.0001***	0.0002***	0.087*	0.0017***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
MTB	–	0.013	-0.038	-0.014	0.041	0.047	0.071	0.105	0.051	0.065	0.034
		0.4548	0.0201**	0.480	0.0172**	0.0001***	0.0001***	0.0001***	0.0064***	0.0032***	0.0955
Δ*EMP*	–	-0.042	-0.024	-0.009	-0.017	-0.013	-0.025	-0.042	-0.020	-0.024	-0.002
		0.0003***	0.0647*	0.4824	0.2308	0.0755*	0.0755*	0.0016***	0.1111	0.0783	0.8606
Δ*PPE*	–	1.814	1.993	0.842	1.165	1.361	2.097	1.438	1.456	1.107	0.348
		0.0018***	0.0005***	0.1182	0.0302**	0.0001***	0.0001***	0.0117***	0.0112***	0.0716	0.5661
Δ*IND_OB*	–	-1.407	-1.256	-1.443	-1.736	-1.906	-0.976	-2.339	-3.782	-5.304	-4.739
		0.0004***	0.0016***	0.0007***	0.0001***	0.0328**	0.0328**	0.0001***	0.0001***	0.0001***	0.0001***
ROA		2.227	1.513	1.257	1.128	1.976	1.002	1.946	2.227	2.065	0.333
		0.0001***	0.0001***	0.0001***	0.0008***	0.011***	0.011***	0.0001***	0.0001***	0.0002***	0.4944
LOG_MVE		0.089	0.041	0.041	-0.019	-0.125	-0.138	-0.190	-0.175	-0.086	0.010
		0.0037**	0.0631*	0.0358*	0.2606	0.0001***	0.0001***	0.0001***	0.0001***	0.0079***	0.7850
Δ*INVT*	–	-0.336	0.193	-0.107	0.226	-0.507	0.338	0.680	-0.116	0.727	-0.208
		0.6304	0.7803	0.8763	0.7428	0.6548	0.6548	0.3584	0.8808	0.3160	0.7420
Chi-Square		130	91	49	48	116	122	178	168	154	194
		0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
Generalized R2		0.037	0.026	0.014	0.014	0.034	0.035	0.051	0.048	0.044	0.055
Max - Rescaled R2		0.074	0.042	0.020	0.019	0.046	0.051	0.077	0.813	0.872	0.138

These regressions use the full sample of 40,975 as described with Figure 2 but less 4,841 observations that were dropped to meet the data requirements for lagged *ORDERS* the resulting sample contains 36,134 observations. Deciles are calculated by using the scaled change in *ORDERS*. Variables are defined in Appendix I.

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