THREE ESSAYS ON EQUITY VALUATION AND THE PREDICTIVE ABILITY OF QUANTITATIVE AND QUALITATIVE CORPORATE DISCLOSURES

By KATSIARYNA SUSLAVA

A Dissertation submitted to the

Graduate School-Newark

Rutgers, The State University of New Jersey

In partial fulfillment of the requirements

For the degree of Doctor of Philosophy

Graduate Program in Management

Written under the direction of

Professor Suresh Govindaraj

And approved by

Suresh Govindaraj (chair)

Joshua Livnat

Dan Palmon

Li Zhang

Newark, New Jersey

May 2018

ABSTRACT OF THE DISSERTATION

THREE ESSAYS ON EQUITY VALUATION AND THE PREDICTIVE ABILITY OF QUANTITATIVE AND QUALITATIVE CORPORATE DISCLOSURES

By KATSIARYNA SUSLAVA

Dissertation Director: Dr. Suresh Govindaraj

My dissertation centers on the study of qualitative corporate disclosures. I integrate the relevant theory from the linguistics and incorporate new tools and methodologies from the text mining literature. My research goal is to advance our understanding of how market participants analyze and interpret the qualitative aspect of firm disclosures. My dissertation takes a step towards this goal by studying voluntary disclosures in several areas of corporate communication. These areas are: preliminary earnings announcements (Form 8-K), conference call transcripts, and corporate governance disclosures.

The first essay studies qualitative order backlog (OB) disclosures in the preliminary earnings announcements. Despite the obvious potential for OB disclosures to predict future sales and stock returns, and the strong interest in OB data among market participants, these disclosures are not a part of the required audited financial statements, and OB disclosure is not required on a quarterly basis. Companies can choose to disclose OB in the earnings press release (Form 8-K) and they can also choose the format of these disclosures: quantitative or qualitative. Prior literature on the implications of order backlog for stock returns are both sparse and inconclusive (Rajgopal et al. (2003), Lev and Thiagarajan (1993). In my dissertation I address several questions related to OB disclosures, starting

with the question of whether OB disclosures are useful in predicting next-period sales. I then focus on managers' OB disclosure decisions in the annual as well as quarterly corporate filings. In particular, I examine the determinants of earlier and more frequent OB disclosures than the mandatory annual disclosure in Form 10-K, as well as whether these disclosures are presented in either quantitative or qualitative form. Finally, I study the incremental information content of OB disclosures (over and above other information released at the same time such as earnings, accruals, and other financial statements data) for future returns. I find that the backlog growth rate is positively and significantly associated with the next period sales. I show that the main determinants of voluntary OB disclosures are OB magnitude, prior OB disclosure habits, changes in OB, changes in the inventory levels, and the level of uncertainty faced by a firm. I provide evidence that the annual OB change signal is significantly associated with abnormal returns incrementally to earnings and accrual surprises both in the short-window and drift returns around the 4th-quarter preliminary earnings announcements, and around the Form 10-K filings. Finally, I find that there are significant market reactions to the quantitative and qualitative OB disclosures during quarterly earnings announcements beyond the market reactions to contemporaneous earnings surprises. This suggests that OB disclosures serve a useful role in interpreting the implications of the current earnings surprises on future returns.

The second essay examines the value relevance of euphemisms in the conference call transcripts. Euphemisms are "indirect words or phrase that people often use to refer to something embarrassing or unpleasant, sometimes to make it seem more acceptable than what it really is" (Hornby 2004). These are one of the linguistic tools used by managers to soften their explanation of poor company performance during conference calls. Prior studies in accounting and finance find evidence that managers use conference calls with investors not only to communicate financial results, but also to manage investor perception of firm performance. Managers tend to avoid taking responsibility for negative results by blaming external factors (for example, industry or weather) or by talking about it in an evasive and confusing manner. I extend these empirical studies by exploring how euphemisms are used during earnings conference calls to manage investor perception of company performance. This is the first study to document the use of euphemisms in corporate communication. I have built the first dictionary of euphemisms used in business discourse and shown that euphemisms are indeed used in conference calls (on average more than 70% of calls will have at least one euphemism) across various sectors and time periods. In my study I focus on the determinants of euphemism usage as well as investors' reaction to the use of euphemisms during conference calls. I predict and find that higher use of euphemisms is negatively associated with firm's operating performance. I also find that the use of euphemisms is perceived as a negative signal by investors and results in the immediate negative market reaction. However, due to the impression management aspect of euphemisms, investors underreact to the signal as they underestimate the severity of the problems faced by the company, which results in a delayed negative reaction to the content of a conference call.

In the third essay, I study the relationship between the length of director tenure and two main functions of the board: monitoring and advising. I examine whether corporate boards consisting of longer-serving directors are better able to fulfill these functions due to the firm-specific knowledge accumulation, or whether director performance suffers due to the deterioration of their technical knowledge and due to the decreasing independence of the board from managers. Using a sample of up to 3,000 firms over an 18-year period, the evidence suggests that board tenure is positively related to forward-looking measures of market value, with the relationship reversing after about 9 years on average. The detrimental effect of longer board tenure on market value is stronger for high growth firms, which is consistent with the deterioration of the board members' ability to provide useful advice on technical matters relating to the operations of a firm. I also find that board tenure is reflected in stock returns in a similar manner to market values, and that the declining effect of long board tenure is similarly more pronounced for dynamic, growing firms.

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the help of my committee members and professors I have worked with. First of all, I would like to give special thanks to my advisor Dr. Suresh Govindaraj. You are the main reason I decided to pursue a Ph.D. degree in the first place. You have been very attentive and supportive throughout my studies. You have been extremely generous with your time and talking to you helped me come up with ideas for my dissertation. I am very grateful for your continuous trust, support and patience. I also want to thank Dr. Joshua Livnat. You are a mentor to me and gave me a lot of confidence in the early stage of my research. You took time to patiently introduce me to the world of research and have inspire me to pursue my ideas in the space of textual analysis. I am indebted to Dr. Dan Palmon. As the department chair, you gave me a lot of support (moral and financial), which I truly appreciate. I am also grateful for the patient guidance, encouragement and trust from Dr. Li Zhang. Your help is vital in my academic career.

The five years it has taken to complete my dissertation has required support that extends beyond research. I am indebted to my parents, grandparents and friends. Your love and care motivate me every day.

TABLE OF CONTENTS

ESSAY 1: Market Reaction to Quantitative and Qualitative Order Backlog Disclosures

1. INTRODUCTION

The importance of Order Backlog (OB) for investors and financial analysts is easily gauged by the numerous searching questions and clarifications relating to OB in the popular press and conference calls.[1] This depth of interest suggests that market participants view OB related information as an indicator of future firm performance; in particular, as a predictor of future sales, future earnings, and stock (equity) returns. Despite the obvious potential for OB disclosures to predict future sales and stock returns, and the strong interest in OB data among market participants, the academic literature on the subject is sparse.

As with all financial disclosures, OB information should be interpreted contextually. An increase in OB may signify greater demand (good news) or production and supply issues (bad news); and conversely, decreases in OB could signify better production (good news) or decreased demand (bad news). Additionally, OB disclosures are mandatory in annual financial statements, but voluntary for quarterly or preliminary earnings reports, and can be either quantitative or qualitative in practice.

One reason for the scarcity of academic research relating to OB is that quarterly data or preliminary releases of OB disclosures are not easily available. Prior research has simply used annual data collected by Compustat. Additionally, tools to exploit the information content of qualitative disclosures were not widely available; the recent advances in the field of text mining has helped greatly in classifying and understating these disclosures. As a

[1] We note that Backlog information is also of immense importance in the macroeconomic literature (see for example Lahiri and Moore, 1992).

result, previous studies of OB disclosures suffer from the limitation that they use only quantitative annual data. We summarize the few existing studies relating to the information content of OB disclosures in the next section.

We address several questions related to OB disclosures, starting with the question of whether OB disclosures are useful in predicting next-period sales. We then focus on managers' OB disclosure decisions in the annual as well as quarterly corporate filings. In particular, we examine the determinants of earlier and more frequent OB disclosures than the mandatory annual disclosure in Form 10-K, as well as whether these disclosures are presented in either quantitative or qualitative form. Finally, we study the incremental information content of OB disclosures (over and above other information released at the same time such as earnings, accruals, and other financial statements data) for future returns. We focus primarily on disclosures of changes in OB, because this provides a directional element (increasing or decreasing), and because large directional changes in OB are more likely to be unexpected (OB surprises).

We first examine the information content of OB disclosures in predicting future sales, and study the factors that affect the decision to voluntarily disclose OB. We then examine the information content of OB disclosures on stock returns, but differently from prior studies. Specifically, we use three settings – (1) short-window returns when <u>annual</u> OB is disclosed in the preliminary earnings releases (or Form 8-K), (2) short-window returns when <u>annual</u> OB is disclosed in the financial statements (10-K filings), and (3) short-window returns around <u>quarterly</u> preliminary earnings announcements, where we use *quantitative* or *qualitative* backlog disclosures to derive the quarterly backlog signal. The extraction and use of qualitative information on backlogs is a novel addition to the existing literature.

We find that the backlog growth rate is positively and significantly associated with the next period sales. We show that the main determinants of voluntary OB disclosures are OB magnitude, prior OB disclosure habits, changes in OB, changes in the inventory levels, and the level of uncertainty faced by a firm. We provide evidence that the annual OB change signal is significantly associated with abnormal returns incrementally to earnings surprises (and accruals when appropriate) both in the short-window and drift returns around the 4^{th}-quarter preliminary earnings announcements, and around the Form 10-K filings. Finally, we find that there are significant market reactions to the *quantitative* and *qualitative* OB disclosures during quarterly earnings announcements beyond the market reactions to contemporaneous earnings surprises. This suggests that OB disclosures serve a useful role in interpreting the implications of the current earnings surprises on future returns.

We contribute to the academic literature in several ways. First, we provide persuasive evidence that OB changes are positive signals of future sales and stock returns. Second, our unique sample of quarterly OB disclosures allows us to investigate why managers make certain voluntary OB disclosure choices. Third, we are the first to provide empirical evidence on the importance of the *qualitative* OB disclosures in preliminary earnings announcements; thus, adding to a growing literature on the implications of qualitative disclosure for returns. Finally, we contribute to the existing literature on the usefulness of additional signals that are disclosed either with earnings, or separately, and can be used by investors to better interpret earnings news. The rest of this paper proceeds as follows. Section 2 reviews the literature on OB disclosures and develops the predictions we examine. Section 3 describes the samples and methodologies used in the study. Section 4 discusses the empirical results. Section 5 presents our conclusions.

2. PRIOR LITERATURE AND OUR STUDY IN CONTEXT

2.1 Prior Literature

The past literature on the implication of OB for future sales at the firm level is almost non-existent, and its information content for future stock returns is both sparse and somewhat inconclusive. It is generally understood that OB are contractual orders that have not yet been fulfilled by a firm, but are expected to be fulfilled and reported as sales in future periods. This metric is broadly accepted as a useful leading indicator of future sales and profits, both independently, and in conjunction with other indicators. As noted by Rajgopal, Shevlin, and Venkatachalam (2003), OB is estimated to be about 30 percent of total assets for the median sample firm that reports OB, thus making it economically significant. Therefore, it seems intuitive that OB is widely used by both analysts and forecasters to predict future firm earnings, and by investors to predict future returns. However, prior empirical research on the relationship between OB and market returns has shown contradictory results regarding both its significance and direction.

It is important to point out that even though OB is likely to be perceived as a value relevant disclosure, currently, the reporting of OB is not a part of required audited financial statements, and OB disclosure is not required in quarterly SEC filings. OB is mandated by the Securities and Exchange Commission (SEC) only in the annual Form 10-K. However, some companies choose to disclose information about their backlog either in the quarterly filings (Form 10-Q), or in the preliminary earnings press release (which since 2004 must be filed in a Current Report, Form 8-K), or both. To the best of our knowledge, there are no prior studies that examine why some firms voluntarily disclose OB information in their quarterly filings, while others only disclose it in the annual Form 10-K.

While intuition may suggest that OB increases should contribute to higher future earnings (a positive signal), an argument can also be made that OB may indicate production problems and inventory stockouts (a negative signal). Therefore, disclosures of large OB increases could be interpreted by investors as symptomatic of deeper problems, and lead to lowered expectations about future earnings and returns. Also, it is possible that investors overestimate the value and impact of OB disclosures on future earnings (a behavioral market inefficiency argument advanced by Rajgopal et al. (2003)). Consequently, it is not entirely clear how information relating to OB affects expectations among investors and analysts. As Livnat and Ryan (2011) correctly point out, backlog information has to be carefully interpreted within the context of firm’s sales growth, finished goods inventories, and total inventory growth. Different combinations of these variables lead to different interpretations and different forecasts for future sales, earnings, and stock returns.

Behn (1996) using annual disclosures of OB is one of the earliest papers to investigate and provide persuasive evidence that the change in OB provides investors with useful information about future earnings and contemporaneous stock returns. Lev and Thiagarajan (1993) identify annual, quantitative OB disclosures as one of twelve fundamental signals commonly used by analysts to determine the value of a firm’s stock. They interpret the OB signal contextually by not only controlling for sales growth but also other fundamentals including the macroeconomic climate. They show that a larger (smaller) increase in OB relative to the increase in sales is viewed positively as increasing (decreasing) future demand for the firm’s products and increasing (decreasing) the value of the firm’s stock.

Rajgopal et al. (2003) investigate whether the stock market efficiently values annual quantitative OB disclosures. Using the well-known Mishkin test (Mishkin 1983) of market efficiency, they show that the market overestimates the importance and value of OB disclosures on future earning, and, consequently, misprices the firm. To further corroborate this, and to blunt criticism that testing efficiency of financial markets is a joint test of model specification, Rajgopal et al. (2003) follow the Fama and Macbeth (1973) method of constructing zero-investment portfolios using short and long positions in deciles of OB levels, and show that their OB signal and future returns are negatively related. They conclude that investors over-value OB disclosures. A working paper by Gu, Wang, and Ye (2008) does not find evidence corroborating the findings of Rajgopal et al. (2003) that market investors overestimate the value of the level of OB signal. However, they do find evidence that investors underestimate the value relevance of the change in OB. While their finding is consistent with the earlier finding of Behn (1996) regarding the value relevance of the change in OB *vis-à-vis* the level of OB, their work is also limited to annual disclosures of OB. Francis, Schipper, and Vincent (2003) also find little evidence that the level of the OB signal is informative about future performance of the firm, especially after controlling for earnings disclosures. Gu and Huang (2010) use annual OB disclosures to construct an OB factor at the portfolio level and show that this factor can be used to explain portfolio momentum returns. They find that winner stocks (high momentum portfolio of stock) have higher positive changes in OB, while losers (low momentum portfolio of stock) experience the opposite. They also find that the OB factor is positively related to future growth in sales, investments, dividends, and return for the winner and loser portfolios. In summary, the existing literature offers conflicting views about the potential information of annual OB disclosure to investors and market values of firms.

2.2 Our Study

First, we test whether OB disclosures serve as leading indicators of future sales. Since sales forecasts are the cornerstone of the firms' budgeting process and financial analysts use expected sales to project expected earnings (Silhan and Frecka, 1986), sales forecasting benefits of OB information would indicate that this is a value relevant disclosure. In studying the incremental information content for predicting future firm sales, we control for both historical sales growth as well as inventory changes, both of which are known predictors of future sales.

Next, we examine the factors affecting voluntary OB disclosures. Firms have discretion over the *frequency* of OB disclosures: they can choose to disclose it either only in their annual filings or, in addition to these regulated disclosures, they might provide OB information in their quarterly filings. Since the format of the quarterly OB disclosures is not regulated, firms have further discretion over *how* they present the OB information to the investors. Firms can choose to disclose the current dollar or unit level of OB, the dollar or the percentage change of OB from a prior reporting period, changes in OB at the consolidated or segment level, or the overall direction of OB change in a qualitative statement. The following excerpts from earnings releases illustrate the diversity of OB disclosures among firms:

- In the earnings release, dated September 21, 2004, KB Homes, a homebuilding company, discloses backlog statistics both in dollars as well as in units and compares the results to prior year:

  "The dollar value of backlog at August 31, 2004 totaled approximately $4.82 billion, up 42% from August 31, 2003, and represents a strong pipeline of future revenues for the remainder of 2004 and into 2005. The Company's unit backlog at August 31, 2004 stood at 21,928, an increase of 5,356 units or 32% from 16,572 units at August 31, 2003."

- Imax Corp discloses only unit information about its order backlog (Form 8-K dated November 9, 2006):

  "At the present time, the Company has 24 systems in backlog scheduled for installation in 2007 and an additional eight systems that could be installed as early as December of that year."

- Texas Instruments management chooses to make a statement about the direction of the backlog change only, without quantifying it (Form 8-K dated April 23, 2012):

  "As we expected, our business cycle bottomed in the first quarter, and early signs of growth began to emerge," said Rich Templeton, TI's chairman, president and CEO. "Orders were up 13 percent, and backlog is growing again".

- Caterpillar Inc. discloses qualitative information about its backlog from the point of view of the company's segments (Form 8-K dated July 24, 2006):

  "Shipyards have healthy order backlogs, which should increase marine engine sales. Order backlogs at truck manufacturers currently cover nearly all production slots available through year-end…. we have some of the strongest order backlogs we've had in modern history in the larger end of our machine and engine and turbine product line."

Given that quarterly OB disclosures are voluntary in nature, managers might be disclosing OB to either communicate their knowledge of firm's performance or to manage reported performance for opportunistic reasons (Healy and Palepu 2001). Focusing on the informational aspect of OB disclosures, we predict that the OB magnitude would force managers to disclose it more frequently and in a more precise manner (quantitative presentation) because of its materiality to investors and stakeholders. Since OB should be understood contextually (Livnat and Ryan 2011) our second prediction is that managers might volunteer backlog information more frequently and in a more precise form if it helps shed light on other disclosures, such as inventory changes or current earnings/sales.

OB voluntary disclosure may be influenced by managers who attempt to opportunistically time the disclosure of good or bad news to investors (Aboody and Kasznik 2000, Suijs 2005). Since OB is an indicator of future demand, we predict that managers expedite disclosure of OB ***increases*** in the quarterly filings. Also, since OB is a forward-looking indicator of firm performance and prior research finds a negative relation between investor uncertainty and a firm's decision to disclose forward-looking information due to the fear of not achieving projections (Field et al. 2005), we expect less voluntary OB disclosures when uncertainty is high. Finally, disclosure choices tend to be sticky (Bozanic et al. 2017); therefore, we predict that if a firm chooses a certain OB disclosure pattern, it would continue to follow the same pattern in the future.

In studying the relationship of OB information with returns, we combine the Lev and Thiagarajan (1993) and Rajgopal et al (2003) studies. In contrast to prior studies, we focus on short window returns around the disclosures of backlog, as well as drift returns (90 days). If OB is indeed a value-relevant signal and can be used to predict future sales, it is reasonable to expect that users of financial statements will react to the new OB information upon its disclosure (either in the earnings press release – 8-K filings, or in the annual or quarterly filing – Form 10K/ 10Q). After controlling for context (see Livnat and Ryan 2011), we expect that the increases in OB will be viewed by investors as a positive signal of future demand. Therefore, we expect short window stock market reactions to be positively correlated with the initial OB disclosures either around preliminary earnings releases (Form 8-K), or around periodic SEC filings (Form 10-K/Q).

Since investors may be receiving and processing information about the OB levels of firms in either quantitative or qualitative form, or both, we construct an OB signal that captures not only quantitative, but also qualitative statements about OB. This type of OB metric will reflect more fully the information available to investors and is, therefore, likely to exhibit a positive and significant association between OB disclosures and short window stock returns around earnings announcements. Of course, this requires us to classify the qualitative OB disclosure as a positive or negative signal, both in itself and interactively with the quantitative OB signal. In instances where we are unable to reliably classify the qualitative OB disclosure as favorable or unfavorable, the OB signal's correlation with market returns may be insignificant.[2]

3. SAMPLE SELECTION AND RESEARCH DESIGN

3.1 Using Backlog Disclosures to Predict Future Sales Growth

We begin with all firms in Charter Oak Compustat Point-In-Time database (PIT)[3] in years between 1989 and 2015 that have positive annual inventory and cost of goods sold in the current and prior year. To reduce the bias caused by smaller firms, we restrict our sample to firms with annual assets and sales in excess of $50 million in the current year and annual assets in the previous and subsequent years in excess of $10 million. At each month end, we obtain the disclosures for the level of order backlog (if available), sales, and inventory. The use of Compustat PIT allows us to use the information that was available on the Compustat files at that month-end, and, therefore, it is not necessary to lag the annual financial information by four months, as is typically done by prior research.

We test the predictive ability of OB using two proxies for future sales growth – next-period sales (historical information) and analyst sales forecasts. For the first test, we use all observations as of the end of June each year; by then, recent annual data for virtually all of

---

[2] A similar problem for researchers occurs with qualitative management guidance.

[3] Charter Oak Compustat Add-On Database reports preliminary, un-restated, first-reported earnings filed with the SEC. This eliminates the discontinuities that result from subsequent restatements and provides a more accurate picture as to what fundamentals the firm disclosed to investors at a particular point in time.

the December and January fiscal year-end firms are already incorporated in the Compustat database. We denote by year *t* the year ending at time *t*, and *i* to indicate a particular firm. We calculate the percentage changes in OB for a firm *i* from year *t*−1 to year *t* ($BacklogCH\%_{it}$), the percentage change in sales ($SalesGr_{it}$) in the years *t*, the percentage change in sales ($SalesGrLead_{it+1}$) in the year *t+1*, and the percentage change in inventory from year *t*−1 to year *t* ($InvCH\%_{it}$). Our resulting dataset comprises of two sets of companies: one with backlog disclosures and one without.

To test the predictive ability of OB disclosures we perform Fama and MacBeth (1973) style regression analysis using well-known predictors of next-period sales such as current sales growth and inventory changes. For companies with OB disclosures we also add an explanatory variable for the backlog changes. Following Sun (2009), we control for disproportionate inventory increases using an indicator function that takes a value of 1 if a firm *i*'s days in inventory changes by more than 20 percent from the previous year; otherwise 0 ($Large_{it}$). Regression (1) is for companies without OB disclosures and Regression (2) – for the ones with OB disclosures:

$$SalesGrLead_{it+1} = \gamma_0 + \gamma_1 SalesGr_{it} + \gamma_2 InvCH\%_{it} + \gamma_3 Large_{it} + \varphi_{it};$$

$$SalesGrLead_{it+1} = \gamma_0 + \gamma_1 BacklogCH\%_{it} + \gamma_2 SalesGr_{it} + \gamma_3 InvCH\%_{it} + \gamma_4 Large_{it} + \varphi_{it}.$$

We want to compare the coefficients and the explanatory power of the two regressions. A stronger explanatory power of Regression (2) and a significantly positive coefficient for $BacklogCH\%_{it}$ would suggest that, on average, firms that provide backlog disclosures in their financial reports make it easier for investors to predict future sales growth.

For the second test, we merge our PIT sample with analyst sales forecasts from Institutional Brokers' Estimate System (I/B/E/S) for 1996-2015. We associate analyst sales forecast revisions with the annual data that were known prior to the forecast date. We restrict our sample to the forecasts that are further from the annual fiscal year-end, since the Compustat backlog data is annual and analyst forecasts close to year-end have the advantage of known quarterly sales. We require that analyst forecasts are at least 200 calendar days prior to the next fiscal period-end. To test the predictive ability of OB disclosures for the analyst forecasts, we use the same independent variables as in Regressions (1) and (2) and analysts' predictions of firms' sales growth in year *t+1* per I/B/E/S ($SalesGrLeadAn_{it+1}$) as dependent variables, where we divide the analyst forecast for sales at t+1 by actual IBES sales at year t:

$$SalesGrLeadAn_{it+1} = \gamma_0 + \gamma_1 SalesGr_{it} + \gamma_2 InvCH\%_{it} + \gamma_3 Large_{it} + \varphi_{it} ;$$

$$SalesGrLeadAn_{it+1} = \gamma_0 + \gamma_1 BacklogCH\%_{it} + \gamma_2 SalesGr_{it} + \gamma_3 InvCH\%_{it} + \gamma_4 Large_{it} + \varphi_{it} ; \qquad (4)$$

Similar to the first test, we expect that a stronger predictive power of Regression (4), and a significant positive coefficient for $BacklogCH\%_{it}$, would indicate that analysts incorporate backlog disclosures in their sales forecast analysis. We use Fama and Macbeth style regressions and run our test on the two set of firms: one without OB disclosures and one with OB disclosures.

3.2 Determinants of Backlog Disclosure Choices

As discussed earlier, managers make the following three choices when it comes to OB disclosures: (1) disclose OB during the 4th quarter preliminary earnings announcement (Form 8-K) or wait to disclose it in the annual report, as required by the SEC (Form 10-K);

(2) disclose OB only during the 4th quarter, as required by regulation or disclose it more frequently in the 1st, 2nd, or 3rd quarter; (3) in the preliminary earnings announcement, disclose the numeric information about OB– *quantitative* OB disclosure, or disclose it in a descriptive way, without providing specific OB numbers –*qualitative* OB disclosure. What determines these choices is the question addressed in this section.

Our sample for the first test (disclose 4th quarter results in the 8-K or wait and disclose only in the 10-K) consists of all firms that have the annual disclosure of the order backlog levels for the period 1988-2015 in the PIT database. The database identifies whether the backlog disclosure is available in the preliminary earning release, (update code 2), or only in the annual filings, Form 10-K (code 3). For our tests, we create a dummy variable *Prelim*, that is equal to one if a firm is a preliminary earnings backlog discloser and zero otherwise.

The sample to test the choices between annual and quarterly disclosures (the second test) and between the *quantitative* and *qualitative* OB disclosures (the third test) is drawn from preliminary quarterly earnings announcements filed with the SEC in Form 8-K. We downloaded preliminary earnings announcements (8-K filings) from the SEC website and extracted all paragraphs that specifically mentioned companies' order backlog in the 8-K filings from April 2004 to December 2015. Our sample begins in 2004 because the SEC had revamped its Form 8-K reporting requirements, expanding the list of items that must be reported (Lerman and Livnat, 2009). Our extraction engine is based on a full parser, so we analyze the full sentence and not just small fragments of it (like in a shallow parsing approach).[4] This enables us to write more general rules, and hence we need to write fewer rules. It also results in a higher level of accuracy compared to a shallow parsing approach.

[4] Shallow parsing means a focus on specific phrases, and not the full structure of the sentence. This causes rules to be more error- prone and specific.

We use examples of backlog disclosures that contain either specific mention of order backlog, or variations on it. For example, a firm may be using the term "unfilled orders" to indicate orders backlog. Similarly, one cannot use just the term "order" to search for information about order backlog, because management may have used the term "order" to describe past information, e.g., a decrease in customer orders last quarter. Therefore, we created specific extraction rules based on a hand-collected sample of OB disclosures. After the paragraphs related to OB were extracted, we extracted the numeric information that related to OB, including current and prior OB or percentage change and the period that spanned the OB change. Detailed explanations about the extraction process is provided in Appendix A.

Next, for each firm *i* at time *t*, a rater read each paragraph, verified the numerical OB information extracted by the parser, and assigned each backlog disclosure a binary tone variable ($BacklogTone_{it}$). The tone of backlog disclosure was assigned a value of 1 for a positive tone and 0 for a negative one. We have used the same rater for all the order backlog disclosures to ensure comparability in application for all firms. We examined the rating process on a small sample of 300 disclosures using another rater, and found the raters' consistency to be over 96 percent. The following examples illustrate the rating process for the backlog tone variable:

Positive $BacklogTone_{it}$ (assigned a value of 1):

- Steris Corp, 8-K, dated November 7, 2006: “Although Healthcare revenue growth for the quarter was modest, we have witnessed growing backlog and order trends that position us well for stronger second half performance, said Les C. Vinney, STERIS s president and chief executive officer.”
- Magnetek, Inc., 8-K, dated October 29, 2008: “Given our recent book-to-bill ratio and strong backlog coming into the second quarter, we continue to remain cautiously optimistic about our prospects for the remainder of fiscal 2009.”

- Titanium Metals Corp, 8-K, dated August 4, 2010: "Bobby D. O Brien, President and CEO, said, In late 2009, we began to see strengthening demand for our products as our backlog and customer order levels began reflecting increased manufacturing activity, particularly in the commercial aerospace supply chain."

Negative $BacklogTone_{it}$ (assigned a value of 0):

- NCI, Inc., 8-K, dated February 16, 2012: "The expectations on derived revenue from much of those contracts has decreased, so we took some backlog down related to that."
- Layne Christensen Co, 8-K, dated June 5, 2012: "We expect backlog to decline in the short term due to our efforts to increase margins and profitability."
- Vectren Corp, 8-K, dated May 3, 2012: "The lower backlog reflects some slowing in the demand for performance contracting projects."

Our resulting dataset of Form 8-K paragraphs with backlog disclosures consisted of the following information: (i) unique company identifier, (ii) 8-K issue date, (iii) the actual paragraph where the backlog is mentioned, (iv) prior period backlog amount (if disclosed), (ii) current period backlog amount (if disclosed), (iii) percentage change in order backlog (if disclosed), and (iv) the tone of the order backlog disclosure.

Next, we aggregated the dataset of 8-K paragraphs at the company level. If a company had several paragraphs with backlog disclosures in their 8-K, we used the paragraph with backlog information that contained the numerical information about backlog change for the most recent period. If no quantitative information was available, we used the paragraph with the qualitative tone variable. Overall, we have downloaded 102,440 firm-quarter filings of preliminary earnings announcements from the SEC website. About 10 percent of these filings have backlog disclosures, resulting in the sample of 10,406 firm-quarters.

For our second test (annual vs. quarterly disclosers), we used our 8-K sample to add an indicator variable (*Q*) to the PIT database sample; we assigned it a value of one if a firm disclosed OB in any of the quarterly filings (Q1, Q2, or Q3) and zero if management provides OB information only in the 4th quarter filings. For our third test, we used our 8-K sample and assigned each observation an indicator variable (*Quant*) equal to one if OB disclosures were quantitative and zero if OB disclosures were only qualitative. We obtain additional accounting information from PIT, stock price information is obtained from the Center for Research in Security Prices (CRSP) database. To eliminate the effect of small firms we exclude firms with market capitalization below $50 million.

To address the research question regarding the determinants of OB disclosure choices, we regress our dummies for management disclosure choices on the determinants of OB disclosures and additional control variables using Fama-MacBeth style Logit regressions:

$$Prelim_{it} = \gamma_0 + \gamma_1 Backlog_{it} + \gamma_2 Lag\_Prelim_{it} + \gamma_3 BacklogSurp_{it} + \gamma_4 InvSurp_{it} + \gamma_5 EarnVol_{it} + \gamma_6 SUE_{it} + \gamma_7 BM_{it} + \gamma_8 LagXRET_{it} + \gamma_9 ROE_{it} + \varphi \quad (5)$$

$$Q_{it} = \gamma_0 + \gamma_1 Backlog_{it} + \gamma_2 Lag\_Q_{it} + \gamma_3 BacklogSurp_{it} + \gamma_4 InvSurp_{it} + \gamma_5 EarnVol_{it} + \gamma_6 SUE_{it} + \gamma_7 BM_{it} + \gamma_8 LagXRET_{it} + \gamma_9 ROE_{it} + \varphi \quad (6)$$

$$Quant_{it} = \gamma_0 + \gamma_1 Backlog_{it} + \gamma_2 Lag\_Quant_{it} + \gamma_3 BacklogSurp_{it} + \gamma_4 InvSurp_{it} + \gamma_5 EarnVol_{it} + \gamma_6 SUE_{it} + \gamma_7 BM_{it} + \gamma_8 LagXRET_{it} + \gamma_9 ROE_{it} + \varphi \quad (7)$$

We use the following variables as determinants of OB disclosures to predict OB disclosure choices in a firm's filings:

Backlog$_{it}$	Used as a proxy for the materiality of OB and measured as firm's order backlog scaled by sales;
Lag_Prelim$_{it}$, *Lag_Q$_{it}$*, *Lag_Quant$_{it}$*	Used as proxies for the OB disclosure habits and measured as indicator variables Prelim, Q, and Quant from the prior period;

BacklogSurp$_{it}$	Used as a proxy for the *annual* OB news; measured as change in OB from year t−1 to year t scaled by average total assets during the quarter;
BacklogTone$_{it}$	Used as a proxy for the quarterly OB news; measured as an indicator variable equal to one if backlog increased from the most recent previous period available, zero otherwise. If numeric OB values are unavailable for the current period then a qualitative tone variable is used with 1 for positive tone and 0 otherwise;
InvSurp$_{it}$	Used as a proxy for the *annual* inventory growth and measured as firm's change in inventory from year t−1 to year t scaled by average total assets during the quarter;
Quart_InvSurp$_{it}$	Used as a proxy for the *quarterly* inventory growth and measured as change in the inventory level from previous quarter scaled by total assets at the end of the quarter;
EarnVol	Used as a proxy for firm's uncertainty and measured as standard deviation of the firm's earnings before extraordinary items, deflated by lagged total assets, measured over the prior 12 quarters.

We add control for the disclosed earnings surprise (*SUE*) and firm characteristics, such as growth (*B/M*), prior quarter market returns (*LagXret*), and profitability (*ROE*) (Bozanic et al. 2017).

3.3 Association between Backlog and Stock Returns

Using our samples for the annual and quarterly backlog disclosers, we study the stock market reaction to the OB disclosures as reflected in the immediate abnormal 3-days returns around the announcement date as well as in the 90-day period returns following the announcement. In our first set of tests, we perform univariate sorts of stocks based on our measure of backlog surprises (*BacklogSurp$_{it}$* for the annual and *BacklogTone$_{it}$* for the quarterly disclosures) and examine the pattern of excess stock returns. Similar to Lev and Thiagarajan (1993), we expect that firms with positive OB surprises will be associated with positive immediate and drift abnormal returns. Our measure for abnormal stock returns is the characteristic-adjusted excess return of a stock computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. It is the buy and hold return on a security minus the capitalization-weighted average buy and hold return on a portfolio of firms with similar size (three groups), B/M (three groups) and 11-month momentum (three groups). Short-window excess returns (*XretPrelim*) are calculated for the three-day window [-1, +1] around the disclosure date (day 0),[5] and abnormal drift returns (*XretDrift*) are calculated for a drift window, which begins two days after the annual disclosure of OB (day 0), and lasts through one day after the preliminary earnings announcement for the subsequent quarter (EA+1) (or 90 days if unavailable).

In our univariate sorts, for each firm *i*, we control for other accounting information around the disclosure date *t*: earnings (SUE_{it}) and, if approporiate, accrual surprises ($AccrSurp_{it}$). For the univariate sorts, we rank SUE_{it} and $AccrSurp_{it}$ annually into quintiles and assign them to the most positive surprise group if SUE_{it} ($AccrSurp_{it}$) is in the top (bottom) quintile ($SUE_{it}/AccrSurp_{it}$=1), most negative surprise group if SUE_{it} ($AccrSurp_{it}$) is in the bottom (top) quintile ($SUE_{it}/AccrSurp_{it}$=-1), and to the in-between group ($SUE_{it}/AccrSurp_{it}$=0) otherwise. Based on the prior literature on earnings and accrual surprises, we expect that firms in the positive surprise group ($SUE_{it}/AccrSurp_{it}$=1) will have higher abnormal immediate and drift returns than those in the negative accrual or earnings surprise group.

Next, we examine whether these signals (earnings, accrual, and backlog surprises) are substitutes for each other, or each contains incremental information over and above the others. We use an analysis of variance where the dependent variable is the abnormal return

[5] Day 0 is the preliminary earnings announcement date if OB is included in the preliminary earnings announcement, and the SEC 10-K filing date if it is first available in the 10-K filing.

and the independent variables are the assigned indicator variables for backlog, earnings and accrual surprises and the interactions of these indicator variables.[6] This is equivalent to three separate tests of equality of mean abnormal returns for the backlog surprise variable within each of the three earnings and accrual surprise levels. However, the analysis of variance allows us to combine the three tests into one test simultaneously and document which of the signals has incremental value. Following the prior literature and to eliminate the effect of inventory changes (Thomas and Zhang 2002), we also add a control for inventory increases ($InvSurp_{it}$), calculated as the change in the inventory level from the end of prior period scaled by the average total assets over the period [*t-1*, *t*].

Our analyses of variance consist of two regression specifications: one for the test of the interaction between backlog and earnings surprises (Regression (3a and 4a)) and one for the test of the interaction between backlog and accrual surprises (Regression (3b and 4b)). We perform these tests for immediate (Regressions (3a) and (3b)) and drift abnormal returns (Regressions (4a) and (4b)). Since accruals become known to the market only after 10-K filings, we run specifications (3b) and (4b) only for our 10-K sample.

$$XretPrelim\,[-1,+1]_{it} = \gamma_0 + \gamma_1 BacklogSurp_{it} + \gamma_2 SUE_{it} + \gamma_3 BacklogSurp_{it} \times SUE_{it} + \gamma_4 InvSurp_{it} + \varphi \tag{3a}$$

$$XretPrelim[-1,+1]_{it} = \gamma_0 + \gamma_1 BacklogSurp_{it} + \gamma_2 AccrSurp_{it} + \gamma_3 BacklogSurp_{it} \times AccrSurp_{it} + \gamma_4 InvSurp_{it} + \varphi \tag{3b}$$

$$XretDrif\,[2, EA+1]_{it} = \gamma_0 + \gamma_1 BacklogSurp_{it} + \gamma_2 SUE_{it} + \gamma_3 BacklogSurp_{it} \times SUE_{it} + \gamma_4 InvSurp_{it} + \varphi \tag{4a}$$

[6] We use PROC GLM in SAS for this analysis.

$$XretDrif[2, EA+1]_{it} = \gamma_0 + \gamma_1 BacklogSurp_{it} + \gamma_2 AccrSurp_{it} + \gamma_3 BacklogSurp_{it} \times AccrSurp_{it} + \gamma_4 InvSurp_{it} + \varphi \quad (4b)$$

In addition, we estimate the implications of the backlog surprises on the immediate and drift abnormal returns beyond the earnings, accruals, and inventory surprise in the two-way clustered panel regressions using the same regression specifications as above. In these regressions, we use normalized measures of earnings, accruals, and inventory surprise signals. We derive the normalized measures by ranking SUE_{it} and $AccrSurp_{it}$ into the deciles (0 to 9 in SAS) and $InvSurp_{it}$ into quintiles (0 to 5 in SAS), dividing the rank by 9 for SUE_{it} and $AccrSurp_{it}$ and by 4 for *InvSurp*, and subtracting 0.5. As a result, each observation is scaled between -0.5 and 0.5, and the coefficients on them have the natural interpretation of the abnormal returns on a hedge portfolio that is long the top earnings/accruals/inventory surprise group and short the bottom group. The backlog surprise signal is a binary variable equal to one if OB increased from the prior period and zero otherwise.[7] Because of cross-correlations of firms within a quarter and across quarters, the regression uses two-way clustering with firms and quarters as the clustering variables.

4. RESULTS

4.1 Using OB Disclosures to Predict Future Sales Growth

Descriptive statistics about the variables used in the first analysis are reported in Table 1. The first set of variables presents the statistics for our test that uses next period sales growth

---

[7] We could have used the transformed decile rank of the OB surprise instead of a binary variable to indicate an increase or decrease in OB. We chose to use the binary variable for ease of interpretation with the interaction between the earnings surprise and the OB surprise variables. Using the binary OB signal allows us to calculate the OB surprise without having to know the OB surprises of other firms. Finally, it meshes well with our qualitative OB signal where we have a binary variable of "optimistic" vs. "pessimistic" OB tone. We have also performed the analyses in this section with transformed rank OB surprise signal with slightly stronger results than those of the binary OB signal in the text.

as a proxy for sales forecast, while the second set is for the test sample that uses analyst sales forecasts from I/B/E/S.

There are 54,639 year-firms in Compustat from 1989-2015 that satisfy our sample selection criteria: positive annual inventory and cost of goods sold and annual assets and sales in excess of $50 million. Slightly less than half of these observations (20,446 observations) report their order backlog levels in their 10-K disclosures. Figure 1 examines how the proportion of firms with backlog disclosures changes through time. The time series suggest that while during 1989-1998 the number of firms with backlog disclosures grows up to 50 percent, this disclosure becomes less popular with time and less than 40 percent of firms have such disclosures in their 10-Ks after 2001. While the initial increase in the backlog disclosures can be attributed to the growing coverage of companies in Compustat, the subsequent decline might be related to the overall shift from the manufacturing-oriented to high-tech and service-related businesses in the US. An examination of the sample distribution by industry based on the 48-industry classification of Fama-French confirms the industry bias in order backlog disclosures. While in some industries all firms provide backlog disclosures (refer to Figure 2 for the list of top ten industries with the highest proportion of backlog disclosures), in some industries, such as Transportation, Insurance, Telecom, and Utilities, backlog disclosures are practically non-existent. This fluctuation of backlog disclosures across industries is consistent with a considerable cross-sectional variation of backlog levels ($Backlog_{it}$) and backlog growth rates ($Backlog_CH\%_{it}$). For example, although backlog level has a mean of $1,095 million and growth rate of 4 percent, it has a standard deviation of $9,289 million for the levels and 20 percent for the growth rate. In contrast, the other performance measures – sales ($SalesGr_{it}$) and inventory growth ($InvCH\%_{it}$) – have much smaller standard deviations and interquartile changes. A possible explanation for the difference in these statistics might be the difference in the accounting treatment between sales, inventory, and backlog. While sales and inventory are accrual-based measures, backlog disclosures do not have an accrual component and are based on the actual contracts not yet fulfilled by a firm.

Our sample for sales predictions based on the analyst forecasts has 244,650 observations, about four times more than the sample in Panel A. The sample size increases because we include all analyst forecasts for a given firm-year that are issued by the analysts at least 200 calendar days prior to the next fiscal period-end. This I/B/E/S-based sample includes larger companies: the means and medians for sales, inventory, backlog, assets, and market value variables are significantly larger than the ones for the first sample. This is consistent with a well-documented observation that analysts tend to follow larger companies.

Panel B presents the results of Spearman correlation. Consistent with our predictions, backlog growth rate is positively and significantly correlated with future sales growth (the correlation of 0.363). Other explanatory variables that are used in the regression analysis, such as growth in inventory and sales levels, also have significant correlation with the rate of sales growth.

Insert Table 1 here

The empirical results from the Fama-Macbeth average monthly cross-sectional regressions are reported in Table 2. In Panel A we use the next-period sales growth as a dependent variable, and in Panel B – growth based on analyst forecasts. Concentrating on the firms without backlog disclosures, we note that both current period sales and inventory growth rates are significant predictors of next period sales: 1 percent increase in current period sales is associated with 0.1 percent increase in next-period sales, while 1 percent increase in inventory – with an 0.6 percent increase. However, this association does not hold in the sample restricted to the larger firms, with analyst following in I/B/E/S: the explanatory variables are not significant and directionally inconsistent with the sample in Panel A.

Next, we examine firms that provide backlog disclosures in their annual filings. Consistent with our predictions, backlog growth rate is positively and significantly associated with the next period sales. The coefficient is positive and significant at the 1 percent confidence level for the first sample (Panel A) and indicates that 1 percent of backlog growth rate in the current period results in 0.3 percent sales increase in the next period. This association holds for a sample of larger firms: in the I/B/E/S-based sample (Panel B), the coefficient for backlog growth is smaller in magnitude, but is positive and statistically significant. Other independent variables are positive and significant only in the first sample, with inventory growth rate having an economically similar effect on the next period sales. Another interesting observation is that the explanatory power of our model for a sample of firms with backlog disclosures is significantly higher compared to the one without these disclosures (R-squared increases to 0.18 from 0.07 for the first sample and to 0.09 from 0.03 for the I/B/E/S-based sample).

Insert Table 2 here

To conclude, our evidence suggests that backlog disclosures are useful in predicting next-period sales. Backlog growth rates are predictive of analyst sales forecasts and historical sales growth. Including backlog growth rate in predictions of next-period sales significantly increases the overall explanatory power of the model.

4.2 Determinants of Backlog Disclosure Choices

Table 3 shows the descriptive statistics for our tests of OB disclosure determinants. Panel A examines the frequencies of OB disclosure choices for annual and quarterly filings. It appears that in the 4th quarter most firms choose to delay the disclosure of OB to the 10-K filing: we find that only 3,875 firm-years (17% of the sample) disclose OB in preliminary earnings announcements of the 4th quarter, while the rest (18,703 firm-years, 83% of the sample) disclose OB only in the required Form 10-K filings. We also find that most annual OB disclosers refrain from disclosing OB in their quarterly filings (1st, 2nd or 3rd quarter): only 32% of our sample chose to disclose OB quarterly. When it comes to the choice of OB quarterly disclosure format, most firms prefer quantitative backlog disclosures to only qualitative ones (7,347 firm-quarters have quantitative OB disclosures compared to 3,059 with only qualitative ones). Panel B provides descriptive statistics for the observations in our three samples. The number of observations varies across the three samples due to data availability: PIT database discloses OB since 1987, while our 8-K sample starts in 2004.

Comparing the three panels of Table 3, we see that the size of the order backlog is larger for firms that report OB in their quarterly earnings releases (54% of sales compared to 46% of sales for the annual disclosers). Most of the other variables have similar characteristics across the three samples, except for the Book/Market ratio, which is similar for the first two panels, but is much lower for firms in the third panel. This may be an indication that higher growth firms (lower B/M ratio) are more likely to disclose information about OB in their quarterly earnings releases.

Insert Table 3 here

Table 4 presents the results of our tests of the determinants of OB disclosures: Panel A examines the determinants of OB disclosures for preliminary earnings vs. 10K disclosers, Panel B looks at the quarterly vs. annual disclosers, and Panel C studies the determinants of OB disclosure format.

Insert Table 4 here

In all three cases, the materiality of OB (*$Backlog_{it}$*) and prior firm's disclosure habits (*Lag_Prelim_{it}, Lag_Q_{it}, Lag_Quant_{it}*) have a significant relation with firms' disclosure choices. Firms with larger backlog levels are more likely to disclose OB earlier after the 4th quarter ended, instead of waiting to disclose it in their Form 10-K. They are also more likely to voluntarily disclose OB information on a quarterly basis, and prefer quantitative over qualitative OB disclosures. OB disclosure choices are also very sticky: if a firm is an early OB discloser in the fourth quarter, if it reports OB quarterly, or if it reports OB in quantitative format, it is likely to stick to this practice in future periods. The nature of OB news (*$BacklogSurp_{it}$*) seems to have no effect on the firm decision to disclose the news early in the 4th quarter; however, it does matter for a firm's decision to disclose OB on quarterly basis: firms with better OB news are more likely to report OB in their quarterly filings. This is consistent with the voluntary disclosure literature; firms with good news are more likely to report them earlier. However, when it comes to firms' choice of quarterly OB format, firms with good news tend to choose qualitative disclosures (*$BacklogTone_{it}$*), which may be the result of the fact that most qualitative OB statements are positive (88% of qualitative disclosures are favorable vs. 70% for quantitative ones).

Backlog disclosures seem to be complementary to the changes in firms' inventory levels. If a firm experiences an increase in its inventory (*$InvSurp_{it}$*), it is more likely to report OB on a quarterly basis. It is also more likely to provide numeric information about OB in its quarterly disclosures (*$Quart\_InvSurp_{it}$*). This is consistent with the contextual nature of OB signal: if a firm has inventory increases and provides investors with information about its OB, investors are better able to assess the causes for the inventory growth. Growing OB in the face of inventory increases, for example, would point to improving demand for firm's products, rather than inventory overstock. When it comes to uncertainty (*EarnVol*), it seems that firms with higher uncertainty tend to report their OB in the required 10-K filings and do not rush to provide this information to investors in the preliminary earnings announcements. Since OB can be considered a forward-looking measure of operating performance, managers who face less predictable earnings might be reluctant to provide early disclosures of OB, as prior research shows that managers fear the cost of not reaching a projection (Graham et al. 2005). However, we do not find the earnings volatility to affect firms' decision to report the information in quarterly earnings announcements or whether to report OB quantitatively.

In summary, we find that managers are more likely to report OB voluntarily the more material OB is, and do so by reporting it earlier in the fourth quarter disclosure cycle (preliminary earnings announcements rather than Form 10-K filings), reporting it on a quarterly basis when there is no mandatory disclosure requirement, or by providing quantitative rather than qualitative statements about OB. We also find that managers are persistent in their voluntary disclosure decisions; they tend to continue their voluntary disclosure practices in prior periods. This is intuitive given the perceived costs of holding back disclosure and its signaling effects to market participants. We also find that voluntary OB disclosure is more likely to be provided to shed light on unusual inventory changes.

4.3 Association between Annual Backlog Disclosures and Stock Returns

In our third set of tests, our primary interest is the immediate abnormal returns in the [-1, +1] window around the disclosure date, day 0. Additionally, we also use drift abnormal returns to assess whether investors under-react to the OB information, in the same manner they under-react to earnings surprises. Descriptive data related to the variables used in these tests are reported in Table 5.

Insert Table 5 here

Consistent with our expectations, $BacklogSurp_{it}$ is positively correlated with the abnormal returns, both immediate (*XretPrelim*) and drift (*XretDrift*) for the early disclosers. This pattern also holds for the drift returns for the 10-K disclosers. We also find a positive and significant correlation between the backlog surprise with the earnings surprises (SUE_{it}), inventory surprises ($InvSurp_{it}$), and accrual surprises ($AccrSurp_{it}$). This suggests that growth in order backlog is more likely to indicate good news about the firm's economic environment.

Turning to Table 6, we show the abnormal short-window and drift returns contingent on the backlog and earnings signals. We assign the earnings surprise rank based on quintiles in the entire population of firms for that quarter, with -1 assigned to the most negative quintile of earnings surprises, +1 to the most positive quintile, and zero to all other observations. The backlog surprise signal is just a binary variable, obtaining 1 if OB grew during the year ($BacklogSurp_{it}$=1) and 0 if it declined ($BacklogSurp_{it}$=0). We present our results separately for the preliminary earnings and 10-K disclosers.

Insert Table 6 here

As can be seen in the table in the *All* row for the preliminary earnings disclosers, the 1,686 firm-year observations that had an OB decline ($BacklogSurp_{it}$=0), experienced an average abnormal market return of -0.2 percent in the three-day window around the earnings announcement, whereas those 2,231 observations with an OB increase experienced an average 3-day abnormal return of 0.8 percent. This would result in the positive 1 percent spread over the 3-day window. Furthermore, there are subsequent drift returns that are consistent with the backlog signal of -1.3 percent for the declining OB firms and 1.3 percent for the increasing OB firms. However, we need to consider the effects of the earnings surprise as well.

In the first row of Table 6, we provide information about the 885 firm-year observations in the most positive earnings surprise quintile. These firms are further separated into two groups based on the backlog signal: 554 firm-years have a positive backlog surprise, while 331 – a negative one. The firms with a favorable backlog surprise ($BacklogSurp_{it}$=1) have an immediate positive market reaction of 3.0 percent on average, while the 331 observations with an OB decrease have a significantly lower average abnormal return of 1.7 percent. We observe a similar pattern with the drift returns for these observations. Observations with OB declines experience an average drift of 0.1 percent and those with an OB increase an average drift of 2.2 percent. It appears that backlog disclosures help to more properly interpret the earnings surprise relationship with the immediate and subsequent drift returns.

Moving to the quintile of the most negative earnings surprises, SUE_{it} = -1, we observe a similar pattern. We find that an average immediate market reaction is again greater for firms that experienced an OB increase (-1.9 percent) than those that experienced an OB decline (-2.0 percent). Furthermore, the subsequent drift is quite different for these two groups, with 0.0 percent drift for the OB increases and -2.7 percent for the OB declines, indicating how the OB decline helps in interpreting the implications of the earnings surprise for future returns. Similarly, for all the non-extreme earnings surprises, i.e. where SUE_{it} = 0, we find that when OB increases, the average immediate market return is positive at 0.7

percent and a subsequent drift at 1.4 percent, whereas it is 0.2 percent and -0.1 percent for firms with an OB decline.

We perform a similar analysis for firms that disclosed their backlog information in the SEC 10-K filings. In addition to SUE_{it}, we add a tabulation by the accrual signal, as this information becomes available at the time of 10-K filing. As shown in prior literature (see, for example, Li and Ramesh (2009)), market reactions around 10-K filings are less pronounced than those around earnings announcements. However, we experience the same patterns as the one we see for preliminary earnings disclosers. Firms that had OB declines typically have lower immediate market reactions than those that had OB increases; subsequent drift returns are in the same direction. Moreover, the OB signal helps in the interpretation of the accruals signal; the OB signal is predictive of the immediate and drift returns within groups of firms with the same rankings based on accrual surprises.

Table 7 tests the statistical significance of our tabulation results. We use multivariate analysis of variance (General Linear Model) of the immediate and drift abnormal returns on the same groups of variables as we did in Table 6: backlog surprise, earnings surprise, and the interaction of the two, as well as backlog surprise, accrual surprise and their interaction. For 10-K disclosers we add a control for inventory surprises. The table provides results for both the immediate market reactions (dependent variable = *XretPrelim*) and for the drift (dependent variable = *XretDrift*), both for firms that disclose the OB in their preliminary earnings release (8-K) and in their annual filings (10-K).

Insert Table 7 here

As can be seen in the first column of Table 7, the immediate market reactions around earnings announcements are statistically different across the six groups (three groups formed on SUE_{it} and two – on $BacklogSurp_{it}$), with an F-statistic of 22.30, significant at 1 percent confidence level. Both earnings and backlog surprises contribute positively and significantly to the immediate market reaction: $BacklogSurp_{it}$ has F-statistics of 5.49, while the one for SUE_{it} is at 56.56. We observe a similar relationship when we examine the effect on the subsequent drift (8-K column under the *XretDrift* section), where both the backlog signal and SUE_{it} are positive and effective (F-statistic of 11.4 for $BacklogSurp_{it}$ and 2.93 for SUE_{it}).

Table 7 also provides the results of the analysis of variance for 10-K backlog disclosers. It shows that the six groups of earnings and OB signals have statistically different immediate abnormal returns (F-statistic of 8.62, 1 percent significance level). The sources for these differences can be attributed to both the backlog signal (F-statistic of 8.24) and the earnings surprises (F-statistic of 12.42). This relationship continues to hold for the drift returns: both backlog and earnings surprises contribute positively and significantly to explaining drift returns (F-statistics of 20.94 for $BacklogSurp_{it}$ and 4.99 for SUE_{it}).

Following the groups in Table 6, for 10-K disclosers we perform similar analysis for the accruals and backlog signals. The six groups indeed have statistically different means (F-statistic 3.35); however, only backlog contributes to the different means in a meaningful way (F-statistics of 7.83) for the short-window return around the 10-K filing date. A similar picture emerges for the drift after the 10-K filing date: the six groups are statistically significant (F-statistics of 6.85), and now both the accruals and the backlog signals are incrementally different across the six groups.

Table 8 provides more direct tests of the associations between returns, the backlog signal, earnings surprises and accruals. We use two-way clustering by firms and quarters to obtain the covariance of coefficient estimates and their associated t-statistics. As can be seen from the table, the backlog signal ($BacklogSurp_{it}$) is positively and significantly associated with immediate and drift returns both for 8-K and 10-K disclosers. A trading strategy that buys firms with backlog increases and sells the ones with the backlog decreases earns immediate abnormal returns of 0.3-0.6 percent in the three-day window and 2.3-2.7 percent over the three subsequent months, and it is statistically significant after controlling for earnings, accruals, and inventory surprises. Consistent with prior literature, the coefficient on SUE_{it} is positive and significant, while the coefficients on $AccrSurp_{it}$ and $InvSurp_{it}$ are negative and significant for the drift returns (Lev and Thiagarajan 1993, Abarbanell and Bushee 1997, Sloan 1996).

Insert Table 8 here

The results of this subsection indicate that the annual backlog signal can add incrementally beyond the earnings, accrual and inventory surprise signals in explaining immediate and drift abnormal returns. However, in the analyses here, we have used only annual levels of backlog to calculate our signal, and also have utilized only quantitative signals about backlog increases or declines, but not qualitative disclosures about OB. This extended analysis is provided in the next sub-section.

4.4 Association between Quarterly Backlog Disclosures and Stock Returns

We now perform similar tests of association between *quarterly* OB disclosures and stock returns. Table 9 provides descriptive statistics for the variables used in the test. The $BacklogTone_{it}$ variable is positive about 75 percent of the times and is positively and significantly correlated with earnings and inventory surprises and abnormal returns.

Insert Table 9 here

Panel A in Table 10 provides the average abnormal immediate and drift returns for various groupings of firm-quarters based on their earnings surprise and backlog tone. Consistent with our prior observations for the annual quantitative OB disclosures, both the immediate and drift returns are higher for the positive backlog tone ($BacklogTone_{it}$=1) than the negative signal ($BacklogTone_{it}$=0): 0.9 percent vs. -1.0 percent for the immediate returns, and 0.8 percent vs. -0.8 percent for the drift returns. We find that this pattern of higher immediate and drift returns for the positive backlog tone signal is also evident for each of the three groupings on SUE_{it}, indicating that the backlog tone signals are helpful to market participants in assessing the current earnings signals and their implications for future returns.

Panel B provides the statistical tests of the differences in the groups along the two signals and the incremental information in each of the signals. As can be seen from the table, the six groups have statistically different immediate returns, as well as subsequent drift returns (F-statistic 55.36 and 6.87, both significant at 1 percent level). We further find that both the earnings surprise and the backlog tone signals are incrementally significant in explaining the variability of immediate and subsequent drift returns.

Insert Table 10 here

Table 11 provides the results of the regressions of abnormal returns (short-window and drift) on the transformed earnings surprise rank and backlog tone signal, and the interaction between them, where we use quantitative and qualitative OB signals together and separately. To adjust for the cross-correlations in the panel data, we use two-way clustering for firms and quarters. As can be seen in Table 11, when we use both the quantitative and qualitative OB signals, both SUE_{it} and $BacklogTone_{it}$ signals are positively and significantly associated with short-window and drift returns. We observe similar results when we use quantitative backlog signal only: $BacklogTone_{it}$ is incrementally and significantly associated with the immediate and drift abnormal stock returns. The results for the qualitative $BacklogTone_{it}$ signal are statistically significant for immediate stock returns, but not for the drift.

Insert Table 11 here

Summing up the results of this sub-section, it seems that the backlog tone signal does incrementally add to the explanation of both immediate and subsequent drift returns beyond the contemporaneous earnings surprise. Investors seem to use not only annual backlog disclosures, but quarterly data as well. Finally, both qualitative and quantitative backlog disclosures seem to be value relevant to the investors.

5. CONCLUSIONS

Our study extends the current literature about order backlog along several dimensions. First, it establishes order backlog as a useful accounting variable in predicting next-period sales. Second, we find that the decision to disclose OB depends on several characteristics of OB itself, such as its magnitude, prior disclosure habits, and the OB news, as well as other aspects of the company's operations, such as changes in the inventory levels, and the uncertainty faced by the firm. Next, our study examines both short-window three-day returns around the disclosure of the OB signal and subsequent drift returns. It uses the annual OB disclosures compiled by Compustat, and the indications whether the annual OB disclosures were made in the preliminary earnings announcements or the SEC 10-K filings. The results of these analyses indicate that the OB signal can add incrementally beyond the earning, accrual, and inventory surprises in explaining immediate and drift abnormal returns. This study also examines OB disclosures in quarterly earnings announcements, as well as qualitative disclosures about OB in addition to quantitative OB disclosures. We find that quarterly OB disclosures are incremental to contemporaneous earnings surprise disclosures in explaining both immediate and subsequent abnormal returns. We also find that both quantitative and qualitative disclosures of OB in quarterly earnings announcements have value relevance for investors.

The results of this study are relevant to academics, investors, regulators and firms. They indicate that increases in OB are positively associated with future returns, helping to shed more light on prior academic studies. Investors may rely on OB signals that are captured not only in annual filings, but also in quarterly announcements, whether the signal is numeric or qualitative in nature. Regulators may require firms to provide OB information in quarterly intervals, whether quantitative or qualitative, because this information is beneficial to investors. Finally, managers of firms may find it beneficial to provide OB disclosures (quantitatively or qualitatively) in quarterly intervals (or even more frequently), thereby reducing information uncertainty about the firm, and as a consequence, potentially reducing its cost of capital.

REFERENCES

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

Aboody, D., and R. Kasznik. 2000. CEO stock options awards and the timing of corporate voluntary disclosures. *Journal of Accounting and Economics* 29, 73–100.

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

Bozanic, Z., D.T. Roulstone, and A. Van Buskirk. 2017. Management Earnings Forecasts and Other Forward-Looking Statements. Journal of Accounting & Economics, Forthcoming.

Daniel, K., M. Grinblatt, S. Titman and R. Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance* 52 (3): 1035-1058.

Fama, E. and J. Macbeth. 1973. Risk, Return and Equilibrium: Empirical Tests. *Journal of Political Economy* 81, 607–636.

Francis, J., K. Schipper and L. Vincent, 2003, "The relative and incremental information content of alternative to earnings performance measures," *Contemporary Accounting Research*, 20 (Spring 2003), 121-164.

Graham, J. R., C. R. Harvey, and S. Rajgopal. 2005. The Economic Implications of Corporate Financial Reporting. *Journal of Accounting & Economics* 40 (1-3):3-73.

Gu, L., and Huang, D., 2010, Sales order backlogs and Momentum Profits, *Journal of Banking and Finance*, 34, 1564−1575

Gu L., Z. Wang, and J, Ye. 2008. Information in Order Backlog: Change versus Level. *Working Paper Xiamen University*, Fujian.

Healy P.M., and G. K. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature, *Journal of Accounting and Economics,* 31, (1-3), 405-440

Lahiri, K. (Editor), and Moore, G.H. (Editor). 1992. Leading Economic Indicators: New Approaches and Forecasting, *Cambridge University Press*.

Lerman, A., and J. Livnat. 2010. The New Form 8-K Disclosures. *Review of Accounting Studies* 15, 752-778.

Lev, B., and S. Thiagarajan. 1993. Fundamental Information Analysis. *Journal of Accounting Research*, 31, 190-215.

Livnat, J., and S. G. Ryan. 2011. Accessing Inventory Management and Capacity Requirements Using Financial Reports. *Bridging the GAAP: Recent Advances in Finance and Accounting, World Scientific Series in Finance*: Volume 1. 93-119.

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

Rajgopal, S., T. Shevlin, and M. Venkatachalam. 2003. Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog. *Review of Accounting Studies*, 8, 461-492.

Silhan, P. A., and T. J. Frecka. 1986. On the Sales Forecasting Benefits of Form 10-K Backlog Information. *Journal of Business Finance & Accounting*, 13(3), 425-431.

Sloan, R. G. 1996. Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings? *The Accounting Review* 71, 3: 289-315.

Suijs, J. 2005. Voluntary Disclosure of Bad News. *Journal of Business Finance & Accounting*, 32: 1423–1435.

Sun, Y. 2010. Do MD&A Disclosures Help Users Interpret Disproportionate Inventory Increases? *The Accounting Review*, Vol. 85, No. 4, 1411-1440.

Thomas, J. K., and H. Zhang. 2002. Inventory changes and future returns. *Review of Accounting Studies* 7, 2–3: 163–187.

Xuejun Li, Edward, and K. Ramesh. 2009. Market Reaction Surrounding the Filing of Periodic SEC Reports. *The Accounting Review* 84, 4: 1171-1208.

Appendix A: Extracting Backlog information (A Technical Note)

The overall goal of our study is to extract information about changes in companies' backlog values, as reported in 8-K filings. In particular, for a given company report, we are interested in the most recent backlog value (in millions of dollars), the previous value, and in the length of time over which the change in backlog happened (discretized as quarterly ("Q"), semi-annual ("SA"), nine-months ("NINE"), or yearly ("Y") change).

In the simplest case, we have the following sentence: *"The Company said at the beginning of 1990 it has a record $22 million backlog of unfilled orders, compared to a $9.7 million backlog a year earlier"*. We would like to extract the triple (22, 9.7, Y), which would mean that the backlog has changed from $9.7 million to $22 million during a year. Frequently, one of the values is not stated explicitly: *"Order backlog at the end of 1989 stood at $1.88 billion, up 14 pc from a year earlier and up 3 pc from the 1989 third quarter"*. In this case, the prior backlog value can be calculated from the current value ($1.88 billion), the difference (14%), and the direction (up), producing the final triple (1880, 1825.24, Q). Note, that the more recent of the two possible prior values is used.

The extraction engine (EE) by itself does not perform the processing required to convert the money amounts to million-of-dollars numbers, analyze the dates, select the most recent value in a set, etc. Instead, this business-logic work is delegated to the post-processor. The EE performs only relation extraction, finding instances of semantic relations, and filling them with text values, copied verbatim from the input sentence. For our extraction process, we use one relation type – BacklogInfo; it has six text slots: Backlog, Value, Date, PriorValue, PriorDate, Difference, and two Boolean slots (Up /Down). From the EE perspective, the two sentences above should produce the following two relation instances:

BacklogInfo: Backlog = "*backlog*"
Value = "*$22 million*"
PriorValue = "*$9.7 million*"
PriorDate = "*a year earlier*"

BacklogInfo: Backlog = "*Order backlog*"
Value = "*$1.88 billion*"
Date = "*the end of 1989*"
PriorDate = ["*a year earlier*", "*the 1989 third quarter*"]
Difference = ["*14 pc*", "*3 pc*"]
UP = [true, true]

The BacklogInfo relation requires several entity types. Below we provide a set of rules developed in Java for each type.

1. The BACKLOG entity, indicating the type of the backlog, is a closed type, containing a small number of predefined words and phrases. Its definition is as follows:

type atomic BACKLOG: rel; **type** nform_backlog : nform_namedentity;
wordclass skipnorm: Best wcAddLexicon =
DefNoun(([<5> (order | construction | funded | total | worldwide)] backlog),

```
        ([<5> (order | construction | funded | total | worldwide)] backlogs),
         (SYN.HEAD.FORM nform_backlog, SYN.HEAD.SPECIAL true,
          SYN.VAL.BACKLOG true, SYN.HEAD.BACKLOGRELWORD true,
          SEM <INDEX setindex, RESTR [<RELN BACKLOG, RELNOUN true>]>
))
```

2. The MONEYAMOUNT entity is defined using a generic set of rules for extracting numerical objects, together with a word class containing a set of known currencies. The definition is as follows:

```
wordclass skipnorm
wcCommonCurrency =%include(\wordclasses\wcCurrency.txt);
wordclass skipnorm :Best wcMoneyMagnitude = mln bln mil bil m b;

MoneyAmount :- <5> wcCommonCurrency Numeral [wcMoneyMagnitude];
MoneyAmount :- <5> [wcMoneyMagnitude] Numeral ["-"] wcCommonCurrency;
MoneyAmount :- <-1> Numeral wcNumeral_large;

type atomic MONEYAMOUNT : rel;
type nform_moneyamount : nform_namedentity;

Lexeme $<(cntn_lxm) SYN.HEAD <FORM nform_moneyamount, AGR.PER third
>,
              SEM <INDEX setindex, RESTR [<RELN MONEYAMOUNT>]>> :-
                     MoneyAmount [<-3> "to" MoneyAmount];
```

3. The PCVALUE entity is a "percentage" value, like "15.3%" or "14 pc". It is defined as follows:

```
type atomic PCVALUE : rel; type nform_pcvalue : nform_namedentity;
Lexeme $<(cntn_lxm) SYN.HEAD <FORM nform_pcvalue, AGR.PER third>,
              SEM <INDEX setindex, RESTR [<RELN PCVALUE>]>> :-
 Numeral ("pc" | "%" | "percent" | "percents" | "per" "cent" | "per" "cents");
```

4. The DATEPOINT entity is an extension of the generic DATE entity. Its definition is also rule-based, slightly more complex than the definitions of the entities above.

There are several ways in which the BacklogInfo relation can be expressed syntactically. In the most frequent case, the main meaning of the relation is carried by a verb, and is further qualified by various modifiers. The two sentences above are the examples of this relation. In the first sentence, it is the verb "have", with two NP arguments of types ORGANIZATION and BACKLOG ("Company has backlog"). In the second, it is the verb "stand", with one NP argument of type BACKLOG and another PP argument of type MONEYAMOUNT ("Backlog stood at $$"). Our EE parser captures the backlog relations from the text by analyzing the sentence structure and filling all needed fields with the relevant values.

Figure 1 Order Backlog Disclosures in Compustat by Year

Figure 1 plots the percentage of firms with backlog disclosures in Compustat over the sample period.

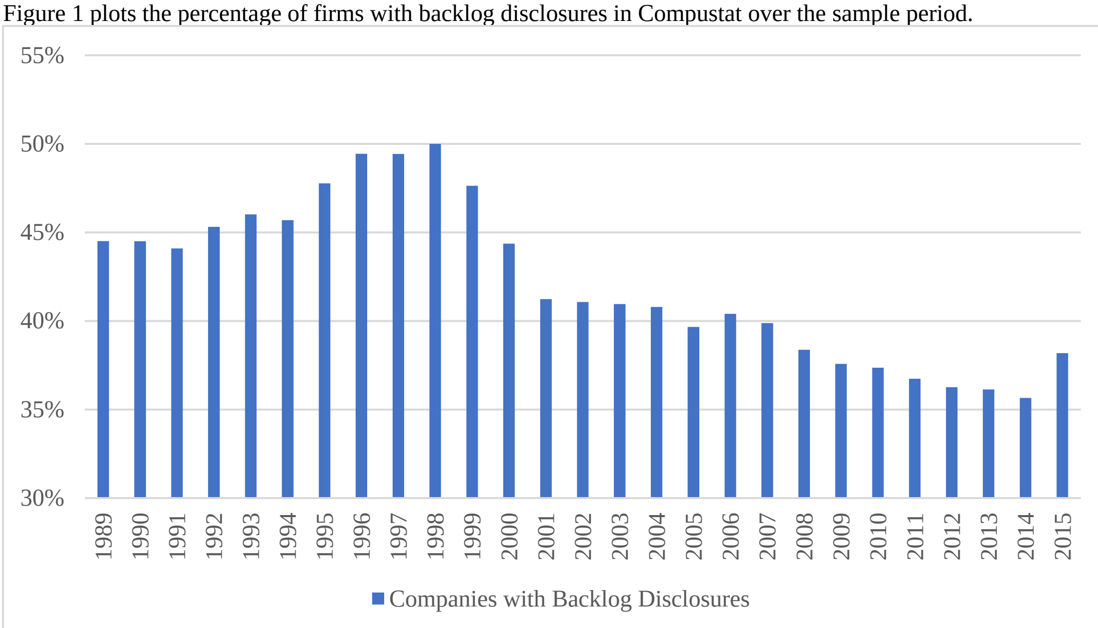


Figure 2 Top 10 Industries in Terms of Backlog Disclosure Prevalence

Figure 2 plots ten industries that have backlog disclosures most frequently. Industries are listed on the horizontal axis. The primary vertical axis (left hand-side) plots the number of unique companies in the industry in our sample with backlog disclosures - blue bars on the chart. The secondary vertical axis (right hand-side) plots the total number of unique companies in the industry in our sample – green line on the chart. We use Fama-French 48 industry classification for our analysis.

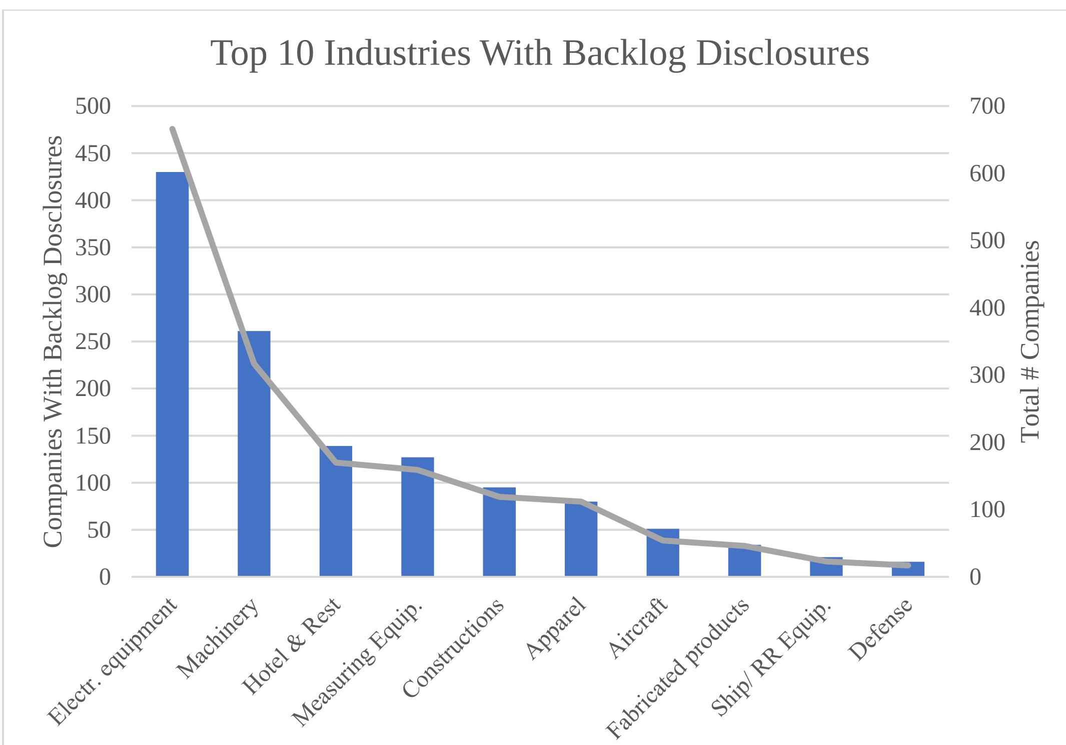


Table 1. Descriptive Statistics: Using Backlog to Predict Sales

Panel A: Descriptive Statistics

Variables	**N**	**Mean**	**Median**	**Std. Dev**	**1st Quartile**	**3rd Quartile**
Sales Predictions: Financials						
$Backlog_{it}$	20,446	1095.21	40.49	9289.88	0.00	207.00
$BacklogCH\%_{it}$	13,729	4%	1%	20%	-2%	7%
$Inventory_{it}$	54,639	939.64	70.87	10868.49	20.67	258.55
$InvCH\%_{it}$	54,639	2%	0%	6%	0%	3%
$InvDays_{it}$	54,639	89	66	99	30	111
$Sales_{it}$	54,639	4446.79	678.64	17157.96	236.92	2409.40
$SalesGr_{it}$	54,639	118%	109%	104%	100%	122%
$SalesGrLead_{it+1}$	54,639	112%	108%	104%	99%	119%
$Assets_{it}$	54,639	8254.57	724.56	62239.66	252.49	2715.00
MV_{it}	54,639	5279.96	693.45	19787.57	224.16	2588.60
Sales Predictions: Analysts						
$Backlog_{it}$	97,141	2902.39	57.10	19072.80	0.00	780.00
$BacklogCH\%_{it}$	54,944	4%	1%	18%	-2%	6%
$Inventory_{it}$	244,650	2505.55	216.90	20910.62	46.46	878.41
$InvCH\%_{it}$	244,650	1%	0%	4%	0%	2%
$InvDays_{it}$	244,650	90	63	108	27	109
$Sales_{it}$	244,650	10720.21	2603.64	27896.26	773.80	8777.10
$SalesGr_{it}$	244,650	116%	109%	62%	101%	121%
$SalesGrLeadAn_{it+1}$	244,650	100%	100%	52%	99%	101%
$Assets_{it}$	244,650	19560.91	3177.73	95496.69	939.76	11007.57
MV_{it}	244,650	16255.08	3733.51	39669.62	1140.32	13291.91

Panel B: Spearman Correlations

	Backlog	*BacklogCH%*	*Inventory*	*InvCH%*	*Sales*	*SalesGr*	*Assets*
Backlog	1						
BacklogCH%	0.181***	1					
Inventory	0.249***	-0.013***	1				
InvCH%	-0.042***	0.315***	0.120***	1			
Sales	0.186***	-0.015	0.808***	-0.056***	1		
SalesGr	-0.021	0.363***	-0.120***	0.439***	-0.130***	1	
Assets	0.272***	-0.004	0.725***	-0.093***	0.899***	-0.103***	1

***, **,* denote significance at 1%, 5% and 10% level.
This table provides descriptive statistics for our key variables used to predict next-period sales. The first set of variables in Panel A consists of annual financial statements data points that we use to predict next-period annual sales. This sample consists of all firms in Compustat for the years 1989-2015. The second set of variables consists of monthly data available to the analysts to predict sales. This sample consists of all firms in *IBES* database for the years 1996-2015. Financial information is from Compustat, and sales prediction information is from the I/B/E/S database.
Variable Definitions:

$Backlog_{it}$	=	firm *i's* order backlog (Compustat #98) in year *t*;
$BacklogCH\%_{it}$	=	firm *i*'s percentage change in backlog from year *t*−1 to year *t* (Compustat #98/lag (Compustat #98)- 1;
$Inventory_{it}$	=	firm *i's* inventory in year *t* (Compustat #3);
$InvCH\%_{it}$	=	firm *i*'s percentage change in inventory from year *t*−1 to year *t* (Compustat #3/lag (Compustat #3)- 1;
$InvDays_{it}$	=	firm *i*'s days in inventory, computed as (365/(Compustat #41/Compustat #3);
$Sales_{it}$	=	firm *i*'s sales in year *t* (Compustat #12);
$SalesGr_{it}$	=	firm *i*'s sales growth rate in year *t* (Compustat #12/lag(Compustat #12));
$SalesGrLead_{it+1}$	=	firm *i*'s sales growth rate in year *t+1*;
$SalesGrLeadAn_{it+1}$	=	analyst prediction of firm *i*'s sales growth rate in year *t+1* per I/B/E/S;
$Assets_{it}$	=	firm *i*'s total assets in year *t* (Compustat #6);
MV_{it}	=	market value of firm's common equity at time *t*.

Table 2. Regression Analysis: Using Backlog to Predict Sales

Panel A: Future Sales Growth Prediction Based on Historical Data

Dependent Variable = $SalesGrLead_{it+1}$

	Without Backlog Disclosures		With Backlog Disclosures	
Intercept	0.9893***	0.9878***	0.9753***	0.9626***
	(38.35)	(37.84)	(26.68)	(25.99)
$BacklogCH\%_{it}$			0.3532***	0.3516***
			(17.46)	(17.13)
$SalesGr_{it}$	0.1043***	0.1050***	0.0866***	0.0970***
	(4.94)	(4.87)	(2.84)	(3.13)
$InvCH\%_{it}$	0.7899***	0.6469***	0.5691***	0.3365***
	(14.55)	(8.90)	(7.63)	(4.30)
$Large_{it}$		0.3863***		0.6155***
		(3.19)		(4.54)
N	1,515	1,515	508	508
Cross-sections	27	27	27	27
R-squared	0.070	0.073	0.177	0.186

Panel B: Future Sales Growth Prediction Based on Analyst Forecast

Dependent Variable = $SalesGrLeadAn_{it+1}$

	Without Backlog Disclosures		With Backlog Disclosures	
Intercept	1.0107***	1.0100***	1.0129***	1.0098***
	(50.59)	(50.23)	(159.13)	(152.15)
$BacklogCH\%_{it}$			0.0544**	0.0270**
			(2.10)	(2.36)
$SalesGr_{it}$	-0.0015	-0.0008	-0.0133**	-0.0111*
	(-0.11)	(-0.06)	(-2.36)	(-1.92)
$InvCH\%_{it}$	-0.0569	-0.0329	-0.0040	0.1639
	(-1.43)	(-0.79)	(-0.07)	(1.54)
$Large_{it}$		-0.0835**		-0.2006*
		(-2.46)		(-1.75)
N	941	941	284	284
Cross-sections	201	201	189	189
R-squared	0.038	0.049	0.096	0.116

*, **, *** Indicate statistical significance at the 10 percent, the 5 percent, and the 1 percent confidence levels, respectively two-tailed.

Panel A presents the coefficient estimates from Fama-Macbeth style regressions of a firm's next-year sales growth on the annually reported sales, backlog and inventory variables. The sample consists of all 54,639 firm-years during 1989-2015. We separate our sample into firm-years without backlog disclosures and firm-years with backlog disclosures. Panel B presents the coefficient estimates from Fama-Macbeth style regressions of an analyst forecast of firm's next-year sales growth on the annually reported sales, backlog and inventory variables. The sample consists of 244,650 monthly analyst-forecasts during 1996-2015. We separate our sample into analyst-forecasts without backlog disclosures and analyst-forecasts with backlog disclosures. The coefficients are averages from annual cross-sectional regressions; these are time-series means with t-statistics (in parentheses) corresponding to the standard error of the mean. *N* denotes the average number of cross-sectional observations.

Variable Definitions:

$BacklogCH\%_{it}$	=	firm *i*'s percentage change in backlog from year *t*−1 to year *t* (Compustat #98/lag (Compustat #98)- 1;
$InvCH\%_{it}$	=	firm *i*'s percentage change in inventory from year *t*−1 to year *t* (Compustat #3/lag (Compustat #3)- 1;
$Large_{it}$	=	1 if firm *i*'s days in inventory changes by more than 20% from the previous year, otherwise 0;
$SalesGr_{it}$	=	firm *i*'s sales growth rate in year *t* (Compustat #12/lag(Compustat #12));
$SalesGrLead_{it+1}$	=	firm *i*'s sales growth rate in year *t+1*;
$SalesGrLeadAn_{it+1}$	=	analyst prediction of firm *i*'s sales growth rate in year *t+1* per I/B/E/S.

Table 3. Management Choices of Backlog Disclosures

Panel A: Management Discretion over Backlog Disclosure Choices

Backlog Disclosure Choices	Number of Firms	%	Sample Period
4th Quarter Disclosures:			
Disclose in the 8-K and 10-K filings	3,875	17%	
Disclose only in the 10-K filing	18,703	83%	
Total	22,578	100%	1987-2015
Quarterly vs. Annual Disclosures:			
Disclose on Quarterly Basis	2,855	32%	
Disclose on Annual Basis	6,015	68%	
Total	8,870	100%	2004-2015
Quarterly Disclosures:			
Disclose Quantitative Information	7,347	71%	
Disclose Qualitative Information	3,059	29%	
Total	10,406	100%	2004-2015

Panel B: Descriptive Statistics

Variables	N	Mean	Median	Std. Dev	1st Quartile	3rd Quartile
<u>4th Quarter Backlog Disclosures</u>						
$Prelim_{it}$	22,578	0.17	0.00	0.38	0.00	0.00
$Backlog_{it}$	22,578	0.46	0.26	0.58	0.12	0.53
$BacklogSurp_{it}$	22,578	0.05	0.01	0.55	-0.04	0.09
$InvSurp_{it}$	22,578	0.02	0.01	0.07	-0.01	0.04
$EarnVol_{it}$	22,578	3.21	0.98	7.79	0.42	2.57
SUE_{it}	22,578	0.00	-0.06	0.34	-0.28	0.28
B/M_{it}	22,578	0.67	0.55	0.47	0.34	0.86
Lag_XRET_{it}	22,578	-0.04	-0.03	0.27	-0.17	0.09
ROE_{it}	22,578	0.02	0.09	0.37	0.01	0.16
<u>Quarterly vs. Annual Disclosures</u>						
Q_{it}	8,870	0.32	0.00	0.47	0.00	1.00
$Backlog_{it}$	8,870	0.54	0.28	0.69	0.13	0.64
$BacklogSurp_{it}$	8,870	0.06	0.01	1.17	-0.02	0.08
$InvSurp_{it}$	8,870	0.01	0.00	0.06	-0.01	0.03
$EarnVol_{it}$	8,870	2.96	0.94	7.39	0.41	2.37
SUE_{it}	8,870	0.01	0.06	0.34	-0.28	0.28
B/M_{it}	8,870	0.62	0.52	0.42	0.33	0.78
Lag_XRET_{it}	8,870	-0.01	-0.01	0.22	-0.12	0.10
ROE_{it}	8,870	0.01	0.08	0.38	-0.01	0.15

Variables	N	Mean	Median	Std. Dev	1st Quartile	3rd Quartile
Quantitative vs. Qualitative Backlog Disclosures						
$Quant_{it}$	10,406	0.71	1.00	0.45	0.00	1.00
$Backlog_{it-1}$	10,406	0.67	0.37	0.94	0.15	0.79
$BacklogTone_{it}$	10,406	0.75	1.00	0.43	1.00	1.00
$Quart\_InvSurp_{it}$	6,506	0.02	0.01	0.07	0.00	0.04
$EarnVol_{it}$	10,406	2.86	0.83	6.96	0.37	2.34
SUE_{it}	10,406	0.01	0.06	0.33	-0.28	0.28
B/M_{it}	10,406	0.23	0.24	0.03	0.24	0.24
Lag_XRET_{it}	10,406	0.00	0.00	0.15	-0.09	0.08
ROE_{it}	10,406	0.01	0.03	0.09	0.01	0.04

***, **,* denote significance at 1%, 5% and 10% level.
This table presents our key variables used to test the determinants of backlog disclosure choices. Panel A tabulates the frequencies of three types of choices managers make in terms of backlog disclosures: disclose in 8-K vs. 10-K in the 4th quarter, disclose on quarterly vs. annual basis, disclose in quantitative vs. qualitative form in 8-K filings. Panel B provides descriptive statistics for the variables used in the tests. The first set of variables in Panel B consists of annual variable that we use to test the determinants of preliminary disclosures in the 4th quarter. This sample consists of all firms in Compustat that have backlog for the years 1987-2015. The second set of variables in panel B consists of variables that we use to test the determinants of quarterly vs. annual disclosures. This sample consists of all firms in Compustat that have backlog for the years 2004-2015. The third set of variables consists of all firms with 8-K filings that have backlog for the years 2004-2015. The correlation column reports correlation between backlog disclosure choice variable (*Prelim*, *Q* or *Quant*) and other variables.

Variable Definitions:

$Prelim_{it}$	=	an indicator variable equal to one if firm *i* discloses backlog in form 8-K in the 4th quarter and zero if a firm waits until 10-K filing to disclose its backlog.
Q_{it}		an indicator variable equal to one if firm *i* discloses backlog on quarterly basis and zero if a firm waits until the 4th quarter to disclose its backlog.
$Quant_{it}$		an indicator variable equal to one if firm *i* discloses quantitative information about its backlog in the 8-K filings and zero if a firm discloses qualitative information about its backlog in the 8-K filings.
$Backlog_{it}$	=	firm *i's* order backlog (Compustat #98) in year *t* divided by firm *i*'s sales in year *t* (Compustat #12);
$BacklogSurp_{it}$	=	firm *i*'s change in backlog from year *t*−1 to year *t* scaled by average total assets during the quarter; (Compustat #98-lag (Compustat #98)*2/(Compustat#6+ lag (Compustat #6));
$BacklogTone_{it}$	=	an indicator variable equal to one if backlog increased from the most recent previous period available, zero otherwise. If numeric OB values are unavailable for the current period then a qualitative tone variable is used with 1 for positive tone and 0 otherwise;
$InvSurp_{it}$	=	firm *i*'s change in inventory from year *t*−1 to year *t* scaled by average total assets during the quarter; (Compustat #3-lag (Compustat #3)*2/(Compustat#6+ lag (Compustat #6));
$Quart\_InvSurp_{it}$	=	Change in the inventory level from previous quarter scaled by total assets at the end of the quarter. (Compustat #3-lag (Compustat #3)*2/ (Compustat#6+ lag (Compustat #6)).

$EarnVol_{it}$	=	Standard deviation of the firm's earnings before extraordinary items (Compustat #58), deflated by lagged total assets, measured over the prior 12 quarters.
SUE_{it}	=	Earnings surprise calculated as the adjusted fully-diluted preliminary EPS before extraordinary items (Compustat#57) in the current quarter minus expected *EPS* for the quarter scaled by the standard deviation of EPS surprises in the prior 8 quarters. Expected *EPS* is the adjusted fully-diluted *EPS* in the same quarter of the prior year plus a constant growth term equivalent to the average *EPS* surprise in the prior 8 quarters;
B/M_{it}	=	Shareholders' equity (Compustat #144) divided by pre-earnings announcement market value.
Lag_XRET_{it}	=	Cumulative stock return measured from three trading days following the prior earnings announcement to three trading days before the current earnings announcement.
ROE_{it}		Earnings before extraordinary items (Compustat #58) divided by shareholders' equity (Compustat #144).

Table 4: Determinants of Backlog Disclosure Choices

Panel A: When do Managers Rush to Report Backlog in the 4th Quarter?

	Dependent Variable = $Prelim_{it}$				
$Intercept_{it}$	-2.3249***	-2.8082***	-2.8204***	-2.8329***	-2.8373***
	(-7.78)	(-11.36)	(-11.37)	(-11.23)	(-11.30)
$Backlog_{it}$	0.4224***	0.3203***	0.3164***	0.2846***	0.2727***
	(6.97)	(4.55)	(4.75)	(4.27)	(4.20)
Lag_Prelim_{it}		1.4290**	1.4395**	1.4837**	1.5009**
		(2.31)	(2.33)	(2.39)	(2.41)
$BacklogSurp_{it}$			0.0217	0.0214	0.0271
			(0.22)	(0.21)	(0.26)
$InvSurp_{it}$				-0.0014	-0.0115
				(-0.01)	(-0.09)
$EarnVol_{it}$					-0.0071*
					(-1.80)
SUE_{it}	-0.0122	0.0000	-0.0006	-0.0167	-0.0335
	(-0.12)	(0.00)	(-0.01)	(-0.14)	(-0.30)
B/M_{it}	-0.0953	-0.0435	-0.0305	-0.0344	-0.0023
	(-0.98)	(-0.42)	(-0.29)	(-0.33)	(-0.02)
Lag_XRET_{it}	-0.0834	-0.0811	-0.0951	-0.0689	-0.0470
	(-0.61)	(-0.66)	(-0.78)	(-0.65)	(-0.36)
ROE_{it}	0.2286*	0.2414*	0.2456*	0.2476*	0.2281*
	(1.68)	(1.74)	(1.78)	(1.79)	(1.67)
N	22,578	20,553	20,553	20,553	20,553

Panel B: When do Managers Disclose Backlog More Frequently?

	Dependent Variable = Q_{it}				
$Intercept_{it}$	-0.7598***	-1.7192***	-1.7343***	-1.7404***	-1.7357***
	(-7.90)	(-17.90)	(-17.12)	(-16.61)	(-16.52)
$Backlog_{it}$	0.4836***	0.3501***	0.2820***	0.2855***	0.2873***
	(20.13)	(10.91)	(7.56)	(8.18)	(8.12)
Lag_Q_{it}		2.6333***	2.6542***	2.6596***	2.6707***
		(10.87)	(10.85)	(10.84)	(10.82)
$BacklogSurp_{it}$			0.4345***	0.3931**	0.4059**
			(3.15)	(2.61)	(2.74)
$InvSurp_{it}$				0.1644*	0.1587
				(1.78)	(1.72)
$EarnVol_{it}$					-0.0011
					(-0.70)
SUE_{it}	0.0272	0.0309	-0.0208	-0.0280	-0.0223
	(0.44)	(0.51)	(-0.39)	(-0.47)	(-0.37)
B/M_{it}	-0.2227***	-0.2193*	-0.1478	-0.1479	-0.1524
	(-3.37)	(-1.84)	(-1.27)	(-1.24)	(-1.29)
Lag_XRET_{it}	0.0620	0.1050	0.0581	0.0620	0.0392
	(0.28)	(0.41)	(0.22)	(0.23)	(0.14)
ROE_{it}	0.4351***	0.4235***	0.3954***	0.3798***	0.3708***
	(4.30)	(4.83)	(4.47)	(4.40)	(4.33)
N	8,870	8,380	8,380	8,380	8,380

Panel C: When do Managers Choose Quantitative vs. Qualitative Backlog Disclosures?

	Dependent Variable = *$Quant_{it}$*				
$Intercept_{it}$	-0.4287*	-1.3212***	-0.4479	0.4116	0.5788
	(-1.75)	(-3.67)	(-1.18)	(0.90)	(1.17)
$Backlog_{it-1}$	2.7808***	1.7436***	1.7642***	0.6551***	0.6582***
	(12.26)	(10.78)	(10.58)	(6.63)	(6.73)
Lag_Quant_{it}		2.8404***	2.8287***	2.7527***	2.7535***
		(31.73)	(29.04)	(22.65)	(22.38)
$BacklogTone_{it}$			-0.8571***	-0.9472***	-0.9780***
			(-6.94)	(-6.05)	(-6.37)
$Quart\_InvSurp_{it}$				2.1759*	2.2034*
				(1.94)	(1.96)
$EarnVol_{it}$					0.0051
					(0.80)
SUE_{it}	-0.0882	-0.0701	-0.0194	-0.0635	-0.0735
	(-1.10)	(-0.71)	(-0.18)	(-0.37)	(-0.44)
B/M_{it}	1.6203	-0.1913	-1.0075	-1.9018	-2.5940
	(1.62)	(-0.13)	(-0.65)	(-1.05)	(-1.33)
Lag_XRET_{it}	0.1935	0.1575	0.3028	0.4614	0.5012
	(0.93)	(0.59)	(1.09)	(1.15)	(1.26)
ROE_{it}	0.4248	-0.9429	-0.7137	-0.9299	-0.6637
	(0.86)	(-1.56)	(-1.10)	(-0.88)	(-0.62)
N	10,406	9,052	9,052	6,506	6,506

The table reports the results of Fama-MacBeth style logistic regressions: in Panels A and B we run the regressions for each year and in Panel C – for each quarter. The averages are time-series means with t-statistics (in parentheses) corresponding to the standard error of the mean; statistically significant terms are bolded. *N* denotes the number of observations. ***, **, * denote significance at 1%, 5% and 10% level.

Variable Definitions:

$Prelim_{it}$ = an indicator variable equal to one if firm *i* discloses backlog in form 8-K in the 4th quarter and zero if a firm waits until 10-K filing to disclose its backlog.

Q_{it} an indicator variable equal to one if firm *i* discloses backlog on quarterly basis and zero if a firm waits until the 4th quarter to disclose its backlog.

$Quant_{it}$		an indicator variable equal to one if firm *i* discloses quantitative information about its backlog in the 8-K filings and zero if a firm discloses qualitative information about its backlog in the 8-K filings.
Lag_Prelim_{it}		$Prelim_{it}$ lagged by year.
Lag_Q_{it}		Q_{it} lagged by year.
Lag_Quant_{it}		$Quant_{it}$ lagged by quarter.
$Backlog_{it}$	=	firm *i's* order backlog (Compustat #98) in year *t* divided by firm *i*'s sales in year *t* (Compustat #12);
$BacklogSurp_{it}$	=	firm *i*'s change in backlog from year $t-1$ to year *t* scaled by average total assets during the quarter; (Compustat #98-lag (Compustat #98)*2/(Compustat#6+ lag (Compustat #6));
$BacklogTone_{it}$	=	an indicator variable equal to one if backlog increased from the most recent previous period available, zero otherwise. If numeric OB values are unavailable for the current period then a qualitative tone variable is used with 1 for positive tone and 0 otherwise;
$InvSurp_{it}$	=	firm *i*'s change in inventory from year $t-1$ to year *t* scaled by average total assets during the quarter; (Compustat #3-lag (Compustat #3)*2/(Compustat#6+ lag (Compustat #6));
$Quart\_InvSurp_{it}$	=	Change in the inventory level from previous quarter scaled by total assets at the end of the quarter. (Compustat #3-lag (Compustat #3)*2/ (Compustat#6+ lag (Compustat #6)).
$EarnVol_{it}$	=	Standard deviation of the firm's earnings before extraordinary items (Compustat #58), deflated by lagged total assets, measured over the prior 12 quarters.
SUE_{it}	=	Earnings surprise calculated as the adjusted fully-diluted preliminary EPS before extraordinary items (Compustat#57) in the current quarter minus expected *EPS* for the quarter scaled by the standard deviation of EPS surprises in the prior 8 quarters. Expected *EPS* is the adjusted fully-diluted *EPS* in the same quarter of the prior year plus a constant growth term equivalent to the average *EPS* surprise in the prior 8 quarters;
B/M_{it}	=	Shareholders' equity (Compustat #144) divided by pre-earnings announcement market value.
Lag_XRET_{it}	=	Cumulative stock return measured from three trading days following the prior earnings announcement to three trading days before the current earnings announcement.
ROE_{it}		Earnings before extraordinary items (Compustat #58) divided by shareholders' equity (Compustat #144).

Table 5. Descriptive Statistics: Association between Annual Backlog Disclosures and Stock Returns

Variables	N	Mean	Median	Std. Dev	1st Quartile	3rd Quartile
Backlog Disclosures in 8-Ks						
$BacklogSurp_{it}$	3,875	0.05	0.01	0.55	-0.04	0.09
SUE_{it}	3,875	-0.38	-0.02	4.00	-0.94	0.89
$InvSurp_{it}$	3,875	0.02	0.01	0.08	-0.01	0.04
$XretPrelim_{it}$	3,875	0.00	0.00	0.09	-0.04	0.04
$XretDrift_{it}$	3,875	0.00	-0.01	0.21	-0.11	0.09
Backlog Disclosures in 10-Ks						
$BacklogSurp_{it}$	14,065	0.05	0.01	1.02	-0.03	0.08
SUE_{it}	14,065	-0.37	-0.01	4.53	-0.96	0.89
$InvSurp_{it}$	14,065	0.01	0.01	0.06	-0.01	0.03
$AccrSurp_{it}$	13,785	-0.03	-0.02	0.07	-0.04	-0.01
$XretPrelim_{it}$	14,065	0.00	0.00	0.07	-0.03	0.02
$XretDrift_{it}$	14,065	0.00	-0.01	0.25	-0.14	0.11

***, **,* denote significance at 1%, 5% and 10% level.

This table provides descriptive statistics for our key variables used to test the association between backlog disclosures and stock returns. The first set of variables in are
disclosed by companies in the preliminary earnings announcements (Form 8-K). This sample consists of all firms that have preliminary backlog disclosures in Compustat
for the years 1988-2015. The second set of variables are disclosed by companies in the annual financial statement filings (Form 10-K). This sample consists of firms that
have annual backlog disclosures in Compustat for the years 1988-2015. Financial information is from Compustat, and market information is from the CRSP database.
The correlation column reports correlation between *BacklogSurp* and other variables.

Variable Definitions:

$BacklogSurp_{it}$	=	firm *i*'s change in backlog from year t−1 to year t scaled by average total assets during the quarter; (Compustat #98-lag (Compustat #98)*2/(Compustat#6+ lag (Compustat #6));

Table 7. GLM Evidence: Association between Backlog Disclosures and Stock Returns

	Dependent Variable = $XretPrelim_{it}$			Dependent Variable = $XretDrift_{it}$		
	8-K	10-K	10-K	8-K	10-K	10-K
$BacklogSurp_{it}$	0.0413***	0.0367***	0.0350***	0.4929***	1.3270***	1.7410***
	(5.49)	(8.24)	(7.83)	(11.40)	(20.94)	(27.48)
SUE_{it}	0.4257***	0.0554***		0.1266*	0.3163***	
	(56.56)	(12.42)		(2.93)	(4.99)	
$BacklogSurp_{it} \times SUE_{it}$	0.0078	0.0167**		0.0025	0.1245	
	(1.03)	(3.75)		(0.06)	(1.97)	
$AccrSurp_{it}$			0.0026			0.3000***
			(0.58)			(4.73)
$BacklogSurp_{it} \times AccrSurp_{it}$			0.0060			0.1570*
			(1.34)			(2.47)
$InvSurp_{it}$	0.0216*	0.0012	0.0003	0.0195	0.8215***	0.6300***
	(2.87)	(0.26)	(0.06)	(0.045)	(12.96)	(9.93)
N	3,875	14,065	14,065	3,875	14,065	14,065
R-squared	0.033	0.004	0.002	0.005	0.003	0.003
F-Value	22.30	8.62	3.55	3.56	7.31	6.85

*, **, *** Indicate statistical significance at the 10 percent, the 5 percent, and the 1 percent confidence levels, respectively two-tailed.

This table presents the analysis of variance where the dependent variable is the abnormal return and the independent variables are the indicator variables for backlog, earnings, inventory, and accrual surprises. This is equivalent to separate tests of equality of mean abnormal returns for the backlog surprise variable within each of the earnings surprise and accrual surprise levels (top and bottom quintiles, and everything else). We use SAS GLM procedures to perform these tests. Panel A uses immediate abnormal returns as a dependent variable, while Panel B uses drift abnormal returns. The sample for 8-K disclosures consists of all firms that have preliminary backlog disclosures in Compustat for the years 1988-2015. The sample for 10-K disclosures consists of all companies with annual backlog disclosures in Compustat for the years 1988-2015. The coefficients a re averages from GLM-style regressions; these are time-series means with F-statistics (in parentheses). *N* denotes the total number of observations.

Variable Definitions:

$BacklogSurp_{it}$ = 1 if *BacklogSurp* is positive, zero otherwise;

ESSAY 2: "Stiff Business Headwinds and Unchartered Economic Waters": The Use of Euphemisms in Earnings Conference Calls

1. Introduction

Corporate verbal communication with investors has two purposes: to relay facts about company performance (informational purpose) and to influence investors' views (promotional purpose or impression management). Promotional aspects of verbal communications may aim to influence news stories, analyst reports and ultimately investors' view of company value. Regulators recognize that these verbal communications may lead to mispricing and have called for a revision of language used by companies to communicate with investors. An example of such regulatory effort is SEC's Plain English Handbook, which contains guidelines on companies' verbal disclosures. The handbook calls for clearer and more informative disclosures by avoiding long sentences, superfluous words, jargon, passive voice, and abstract words (SEC 1998). The regulators' concerns are shared by academic community, as researchers in accounting and finance find evidence that firms may opportunistically use verbal cues to influence investors' reaction to the reported information (e.g. Henry (2008), Rutherford (2005), Zhou (2014), Larcker and Zakolyukina (2012), Lee (2016)). This paper extends these studies by exploring how euphemisms are used during earnings conference calls to manage investor perception of company performance.

Hornby 2010 defines euphemisms as indirect words or phrases that people use to refer to something unpleasant to make it sound more acceptable than what it really is (Hornby 2010). For example, when politicians talk about tax increases, they might use a euphemism – "revenue enhancement" (Lutz 1996). Euphemisms reflect a speaker's ideology of positive self-presentation – discourse participant's motivation to protect the interests of social group they belong to (van Dijk 1998, van Dijk 2002). In the context of earnings conference calls, the use of euphemisms in the discourse of the call participants is indicative of some unfavorable news about the company that call participants try to present in more favorable light to the investors. I focus on the determinants of euphemism usage as well as investors' reaction to the use of euphemisms during conference calls. I predict that higher use of euphemisms is negatively associated with firm's operating performance. I also hypothesize that the use of euphemisms is perceived as a negative signal by investors and results in the immediate negative market reaction. However, due to the impression management aspect of euphemisms investors underreact to the signal as they underestimate the severity of the problems faced by the company. This results in a negative delayed reaction to the content of a conference call.

To develop a proxy for euphemism usage, I have created my own dictionary of euphemisms and euphemistic expressions. My dictionary is based on two published dictionaries of euphemisms and is extended with expressions that I hand collect by reading through 100 randomly selected conference call transcripts. Using my dictionary and commercially available Visual Information Extraction Platform (VIP) software, I parse 78,115 earnings conference call transcripts for U.S. companies over the period from March 2002 to December 2016 and extract instances of euphemism usage in each call.

I test my predictions with univariate and regression analyses controlling for other sources of information around the conference call date, such as earnings surprises and the overall tone of the conference call. First, I show that firm financial performance is negatively associated with the extent of euphemisms during a call, while the level of uncertainty faced by a firm has the opposite relationship. It appears that firms would try to talk their way out of poor operating results, but remain silent when these results are harder to explain. In addition, firms that use euphemisms are more likely to be older firms with limited growth opportunities and complex operations. Second, I find a negative association between my measure of euphemisms usage and immediate stock market reaction around the conference call date. I also find that firms with more euphemisms during the conference calls continue to experience a negative market reaction over the course of the subsequent quarter. These finding indicate that firms that try to mitigate the tone of conference call disclosures using euphemisms appear to be hiding bad news, which is ultimately revealed in the future. My findings are robust to firm size, regression specification, and to using levels, changes, and variability of euphemisms as proxies for the euphemism usage.

This paper makes contributions on several fronts. This is the first study to document the use of euphemisms in corporate communication. I have built the first dictionary of euphemisms used in business discourse and show that euphemisms are indeed used in conference calls (on average more than 70% of calls will have at least one euphemism) across various sectors and time periods. Second, I contribute to the emerging literature on the promotional aspect of conference calls by introducing euphemisms as another linguistic tool used by conference call participants to influence investors' perception of company performance. In this regard, I add a measure to the literature that compliments existing proxies for the promotional aspect of corporate communication. Third, while earnings conference calls remain a voluntary disclosure, they still make up part of a bigger corporate communication space that is of interest to regulators. Regulators remain concerned that managers might use linguistic cues to influence investors' reaction to corporate announcements. This study provides initial evidence consistent with regulatory concerns that the promotional aspect is indeed a part of corporate communication.

The rest of the paper proceeds as follows: Section 2 defines euphemisms and discusses their properties; Section 3 examines prior research; Section 4 develops the hypotheses; Section 5 describes the source of the data and the construction of the euphemism measure in detail; Section 6 discusses the empirical results; Section 7 describes the robustness tests; Section 8 concludes the paper.

2. Euphemisms

Euphemisms are mild, vague, or periphrastic expressions that are used as substitutes for blunt or disagreeable expressions; additionally, euphemisms once meant or still mean something else (Holder 2008). For example, the expression *open a can of worms* is a euphemistic expression that means "to inadvertently create numerous problems while trying to solve one". It comes from the action of fisherman who would buy a can with bait from a bait store only to discover how easy it is to open it but difficult to close. It is a euphemism because it: 1) refers to something else, 2) talks about something unpleasant, and, 3) is a mild way of saying that someone's actions led to multiple problems. In English, euphemistic expressions belong to a semantic category of fixed expressions or idioms - groups of words that are used together by the language speakers and have a meaning that is different from the meaning of individual words in the phrase. It should be noted that not all fixed expressions are euphemisms. For example, *kill two birds with one stone* or *hit the nail on the head* are idioms, but they are not euphemism, because they do not refer to something unpleasant.

Humans have always used euphemisms to camouflage harsh realities and to avoid offending the audience (Allen and Burridge 1991). People employ euphemistic terms in the discourse to talk about the phenomena they find embarrassing (e.g., *rest room* is a euphemism for lavatory, even though no one goes there to rest (Holder 2008)), terrifying (e.g., euphemisms for death include *fall asleep*, *rest*, *depart, check out*, *close your eyes* (Holder 2008)), offensive (e.g., in educational circles drop-outs are referred to as *early leavers* and lazy students are renamed *back-rowers* (Rahimi 2006)) or sensitive (e.g., *glass ceiling* means discrimination at work (Holder 2008)). In the context of corporate disclosures, euphemisms are also likely to be used to refer to something embarrassing (e.g., *we hit some speed bumps*, talking about failure to meet financial targets), unpleasant (e.g., *we continue to right-size our business*, talking about personnel layoffs), or difficult to predict and control (e.g. *currency headwinds will remain our main challenge*, talking about unfavorable currency movements).

Language is a social practice that varies over time and across social groups (Fairclough 1995). Since euphemisms are a part of language, they also have this temporal and social variability. Halmary 2011 illustrates how euphemisms change over time by tracing the name for the American Association on Intellectual and Developmental Disabilities back to the previous century. This non-profit professional organization has changed its name four times. When it was founded in 1876, it was named the American Association of Medical Officers of Institutions for Idiotic and Feebleminded Persons. Later, words “idiotic” and “feebleminded” were deemed offensive, and in 1933 the organization was renamed to a more euphemistic version – the American Association on Mental Deficiency. This title was deemed offensive again in 1987 and the name was changed to the American Association on Mental Retardation. However, with time “mental retardation” also ceased to be considered a euphemism and the name was changed again in 2006 to its current title (Halmary 2011).

In addition to the variability through time, euphemisms also vary with the speaker background. For example, it is reasonable to expect that people who are exposed to sports will more frequently use euphemisms that come from literal expressions in athletics (for example, *behind the eight ball*, “to be in difficulty”, or *throw a curve ball*, “to introduce something unexpected”). A speaker might also be accustomed to the use of some specific euphemisms due to his country of origin. For example, a euphemistic expression *rebase dividends*, meaning “to lower dividends” is typical for speakers of British English. Some euphemisms are used differently even within the same country. For example, a euphemism *kiss-off*, meaning “a summary dismissal or demotion”, is called a *New York kiss-off* by those living on the west coast, while those in New England call it a *California kiss-off* (Holder 2008). I will consider the social and temporal variability of euphemisms in my test design by controlling for fixed effects and examining not only levels, but also changes in the usage of euphemisms.

Critical Discourse Analysis (“CDA”), a stream of research in linguistics and sociology, develops a framework that explains why people would use of euphemisms in their speech. CDA suggests that individuals belong to certain power relationships in a society and aim to sustain and secure these relationships. These relationships form individual’s ideological prejudices, which are the attitudes a group of people hold about certain issues. Individuals’ power relationships and ideologies are created and naturalized via the use of language. The very same event or phenomenon can be presented entirely differently by people belonging to different parties and mental models. In sum, according to CDA, language is the main domain of ideology and struggle for power; it is a tool to manipulate the presentation of reality in a way that is ideologically suitable for the speaker (van Dijk 1998, van Dijk 2002, Rahimi 2006). CDA identifies several tools that speakers can use to promote their ideology in text. For example, a speaker can use numbers excessively to sound more credible (‘number game’), enhance or exaggerating meaning (‘hyperbole’), say something and mean something else (‘irony’), or avoid naming unpleasant phenomena directly (‘euphemisation’) (van Dijk 2002). CDA identifies euphemisms as a type of ideological “power language” that is used in discourse to manipulate unpleasant reality by presenting it in a better, mitigated fashion.

3. Literature Review

Accounting and finance literature clearly indicates that verbal communication by market participants has relevant information that is incremental to the quantitative information about firms. The value of qualitative information has been documented for various channels of investor communication: media news (Tetlock (2007), Tetlock et al. (2008)), analyst reports (Huang et al. (2016), Franco et al. (2015)), and internet message boards

(Das and Chen 2007). These findings have been also extended to corporate reporting; researchers show value relevance of verbal cues in the context of earnings press releases (Demers and Vega (2010), Henry (2008), Davis et al. (2012)), Forms 10-Q and 10-K (Feldman et al (2010), Loughran and McDonald (2011)), chairman's letters (Abrahamson and Amir (1996), Smith and Taffler (2000)), auditor reports (Uang et al. (2006)), and loan agreements (Bozanic 2016). More recently accounting research has focused on the linguistic study of conference call transcripts, which is a more spontaneous form of corporate disclosure and includes verbal cues for both managers and analysts. Consistent with prior studies of the qualitative aspect of business communication, research shows that the verbal content of conference call transcripts conveys important, value-relevant information (for example, Bushee et al. (2003), Brockman et al. (2014), Druz et al. (2015), Chen et al. (2016), Price et al. (2012)).

Text portions of investor communication can be used not only to inform investors of corporate events (informational purpose), but also to manage investor impression of company performance (promotional purpose) (Henry 2008). Prior studies explicitly examine the promotional aspect of verbal communication in letters to shareholders (e.g., Hildebrandt and Snyder 1981, Rutherford 2005), chairman's statements (e.g., Clatworthy and Jones, 2006), 10-K reports (e.g., Li 2008, Loughran and McDonald 2011), and shareholder meetings (Li and Yermack 2016). Researchers recognize that conference call disclosures are especially fruitful ground for this stream of research due to their spontaneous nature (Larcker and Zakolyukina 2010).

Earlier work on conference call disclosures uncover various verbal communication techniques used by managers with the goal of promoting a more favorable impression of company performance. For instance, Zhou (2014) shows that executives play a blame game during conference calls by attributing poor performance to external factors, such as weather and economic environment. He finds evidence that this impression management results in investor under reaction to negative information. Lee (2016) studies another linguistic trick used by managers to cover up underperformance during the Q&A session of conference calls. He finds that managers prepare their answers to analyst questions in advance and use scripted answers to analysts' question, in effect, repeating portions of the management discussion section. Larcker and Zakolyukina (2012) find that executives that try to cover up accounting misstatements tend to use more references to general knowledge, fewer non-extreme positive emotional words, and fewer shareholder value references. My paper extends prior studies on the promotional aspect of verbal communication in conference call transcripts by introducing a new linguistic cue used to manage investor perception – euphemisms.

4. Hypotheses Development

My first question is related to the determinants of the euphemism usage in the earnings calls. Prior literature documents that the tone of corporate disclosures is determined by the firm's operating performance: the sentiment is more positive when a company reports growing and positive earnings and beats analysts' forecasts (Huang et al. 2014). Since euphemisms are phrases that are used to refer to something *unpleasant*, I hypothesize that in the context of earnings conference calls they are used to talk about poor financial results and, therefore, firms with poor operating performance would have more euphemisms in their conference calls.

Prior research also finds that qualitative disclosures are related to the uncertainty faced by the firm. Bozanic et al. (2017) find that managers tend to prefer qualitative forward-looking statements when uncertainty is high. Borochin et al. (2017) show that negative tone of conference call is associated with higher implied volatility of firms' stock options. Given that euphemisms are *indirect* phrases, it can be hypothesized that higher levels of uncertainty would be reflected in the higher euphemism usage, as these firms would find it harder to communicate precise information about firm's performance and would instead use roundabout ways of talking about the operating results and forecasts. At the same time, existing research finds that managers might choose to withhold information when uncertainty is high (Karamanou and Vafeas 2005). When it comes to conference calls disclosures, prior studies find that managers might even explicitly refuse to answer analyst questions (e.g., Hollander et al. 2010). Managers might choose to avoid providing information at the times of uncertainty, since it might be costly to them; therefore, it is also reasonable to hypothesize that conference calls for firms with more uncertain operations would have fewer euphemisms. Therefore, I do not make a prediction regarding the direction of this association. My first set of hypotheses follows:

H1A: Operating performance is negatively related to on the use of euphemisms in the earnings conference call.

H1B: Uncertainty has a strong effect on the use of euphemisms in the earnings conference call.

My remaining hypothesis are related to investor response to the use of euphemisms on the call. On one hand, prior studies show that qualitative information in conference calls generates measurable market reaction (e.g., Price et al. 2012, Zhou 2014, Chen et al. 2016). A high usage of euphemisms in a call might signal negative information about the firm to investors and lead to a negative market reaction at the time of conference call. On the other hand, investors might view euphemisms as vague and non-verifiable statements and discard them in assessing firm value. I hypothesize that:

H2: Higher use of euphemisms in conference call transcripts is associated with a negative price reaction at the conference call date.

Prior research shows that investors underreact to the qualitative information in the conference calls (e.g. Lee 2016). It is shown that investor react more slowly to less tangible information (Cohen et al. 2010, Bozanic et al. 2012). Since the use of euphemisms during an earnings call is a qualitative and intangible measure, investors might not fully incorporate this information in the stock prices immediately. Investor underreaction might be also due to the indirect nature of euphemisms. Euphemisms are used to soften the negative tone of discussion by avoiding naming an unpleasant reality directly. For example, if investors hear about *lumpiness* in sales or some economic *headwinds* in the last quarter, they might perceive this as less alarming news than, for example, a loss of a large client or a drop in sales. As such, I hypothesize that:

H3: Use of euphemisms during conference calls leads to negative drift in subsequent returns.

While I expect that investors are underreacting to the use of euphemisms, I understand that investors might also be able to see through the linguistic tricks used by the call participants. After all, euphemisms are fixed, idiomatic expressions that are easily understood by speakers of language. Therefore, it is possible that investors will correctly price in the information content of euphemisms during the call.

5. Sample selection and measure of euphemism usage

Sample selection

For my study, I use a comprehensive set of conference call transcripts provided by Thomson Reuters Street Events database. The database covers 275,361 full-text conference call transcripts from 7,007 US and international firms during 2002-2016. The database maintains a history of transcripts for various corporate meetings: earnings conference call, shareholder meetings, sales updates, analyst meetings, and guidance conference calls. It includes date, unique company identifiers, and verbatim transcript of the meeting.

To construct my sample for the study, I exclude transcripts of international companies (60,445) and with missing names (20,574). For this study, I focus on the earnings conference calls, so I also exclude transcripts of all other events from my sample (73,643). I further restrict my sample to earnings conference calls that occur within one day or on the same day as the earnings release; this eliminates another group of transcripts from my sample (22,263). Finally, I match firms in Thomson Reuters database with identifiers in CRSP, I/B/E/S, and Compustat Point-In-Time database[8]. I limit my sample to firms that have analyst following in I/B/E/S and positive book value of equity.

My final sample includes 78,115 earnings conference calls for 3,183 unique US firms during 2002-2016. Figure 1 shows that my sample is increasing over the years: it includes about 1,200 firm-years in 2002 and grows to over 2,500 in 2011-2016. This increase is due to the data provider expanding its coverage and due to more firms choosing to hold conference calls after Regulation FD (Mayew 2008). Table 1 provides descriptive statistics for the firms/ earnings calls in my sample. Due to the requirement that firms have analyst coverage in I/B/E/S, my sample is biased towards larger firms: the mean (median) market value is $5.9 billion ($1.4 billion) and the average analyst following is 7.

Measurement for euphemism usage

---

[8] Charter Oak Compustat Add-On Database reports preliminary, un-restated, first-reported earnings filed with the SEC. This eliminates the discontinuities that result from subsequent restatements and provides a more accurate picture as to what fundamentals the firm disclosed to investors at a particular point in time.

I based the initial list of euphemistic words and phrases on the euphemisms that are classified as business or commerce in the two published dictionaries of euphemisms: Oxford Dictionary of Euphemisms by R.W. Holder and Dictionary of Euphemisms and Other Doubletalk by Hugh Rawson. I should note that not all euphemisms identified in the published dictionaries as related to the business world would be considered euphemisms in the context of earnings conference calls. For example, Holder identifies a phrase *home equity loan* as a business euphemism, which in effect means a second mortgage. However, if a financial services company is reporting growth in their portfolio of home equity loan, they are not using this expression to make it sound more palatable. Therefore, I examine each euphemism, its definition and the examples of its usage in sentences that the dictionaries provide to make sure they will remain euphemisms in the context of earnings calls.

In addition to using the published dictionaries of euphemisms, I examined 100 random conference call transcripts and expanded the list with euphemisms I identified in the transcripts that are omitted from the published dictionaries. To address the concern that a hand-collected word list can be confounded by researcher's subjectivity, I presented the list to a group of twelve investment professionals who read financial disclosures, such as earning releases, conference call transcripts, 10-Ks, and 10-Qs, as part of their work duties. The investment professionals were presented with the definition of what is a euphemism by Holder (2008) and with passages from conference call transcripts that had euphemisms. Next, the professionals were asked to indicate words or phrases that were euphemisms in each passage. Only words that were marked as euphemisms by the investment professionals were included in the list used for testing. Finally, I cross-checked the list of euphemisms against the Loughran and McDonald dictionary[9]. If euphemisms were already included in the Loughran and McDonald dictionary (for example, euphemism *challenging* is already a part of their list), I excluded them from my list of euphemisms. The final list of euphemisms consists of 110 words and phrases and is available upon request.

After I finalized my list of euphemisms, I used VIP software to create rules in Python that would extract instances of euphemisms from the conference call transcripts. VIP has

[9] While Loughran and McDonald dictionary does not have a separate category for euphemisms, their list of negative words includes some euphemisms.

several features that allow users to create rules that capture compound words and phrases in text. In Appendix 1 I show VIP features that I used to create my rules. The first example shows that VIP rules recognize a grammatical relationship in the sentence. In this case *tight* is a euphemism that is used to describe profit margins that are decreasing and the VIP rule ensures that the software will capture exactly this relationship: the word *margin* defined by a verb *be* and a predicate *tight*. The second example shows that VIP rules will capture euphemistic phrases that have negation and keep track of them as a separate group of euphemisms (this feature is called *polarity* in VIP). For example, if a manager says that they *didn't fall out of bed*, VIP software will count this phrase as an instance of a euphemistic phrase with negation. This feature allows me to calculate the euphemism score more precisely by subtracting these negations from the overall euphemism score. For example, if an analyst asks if managers *fell out of bed*, and managers answer by saying that they *didn't fall out of bed*, the resulting euphemism score for this interaction will be zero. Another useful feature is VIP's capacity to create semantic rows, a list of words that can be used in a euphemistic phrase. This feature helps me capture only phrases, in which a word works as a euphemism. For example, if I take a word *soft*, it would be a euphemism if the call participants talk about *soft sales* or a *soft quarter*. However, if a word *soft* is followed by a word *pretzel*, it is not a euphemism and it should not be captured in the euphemism measure. The semantic row feature in VIP software allows to add all possible variations of euphemistic phrases in a rule. Some additional feature of VIP include punctuation and tagging capacity and are illustrated in Appendix 1.

To better understand euphemisms that are captured using VIP technology and how polarity is assigned, I have selected some extracts captured by VIP in Appendix 2. In all examples, the euphemisms captured by VIP software are underlined and in bold. In the first example, VIP assigns negative polarity to euphemism *headwinds* because it is not surrounded by negation. However, in the second example, the polarity is switched to a positive one because euphemism *price pressure* appears after a negative particle *not*. In addition to capturing direct negation with *not* or *no*, VIP has a list of verbs that imply negation. For example, in the third example the presence of a verb *offset* changes the polarity of euphemism *price pressure*.

Next, using my set of rules, I parse the conference call corpus using VIP batch process, which calculates how many times each euphemism occurs in each transcript. To give readers a sense of most frequently encountered euphemisms, Figure 2A shows top ten euphemisms identified by VIP, and Figure 2B lists euphemisms that are most likely to be repeated in a transcript. Euphemisms *have an issue* and *headwind* are most likely to occur in a transcript: 3.3% of all transcripts mention *having an issue* and 2.7% having *headwinds* at least once. Most frequently repeated euphemisms within a transcript are *headwinds* (repeated on average 11 times per transcript) and *price pressure* (repeated 8 times on average). After capturing the euphemism instances in the body of a transcript, the program then identifies the polarity of euphemisms. Since euphemisms refer to bad news, euphemisms are assigned a negative polarity by default. VIP software will change euphemism polarity to a positive one if a euphemism is used in a negative sentence or if there is a word/phrase that flips the meaning of the sentence. Finally, VIP program outputs the following information: the count of euphemisms with negative polarity and the count of euphemisms with positive polarity for each of the conference call transcripts. Using this output, I calculate the measure of euphemism usage (*EUPH*) for each conference call as the total number of euphemisms with negative polarity less the total number of euphemisms with positive polarity.

As shown in Table 1, on average, *EUPH* is equal to 2: the mean (median) for *EUPH* is 2.4 (2.0). An examination of *EUPH* distribution suggests that its frequencies exhibit substantial skewness caused by outliers. Only top quartile of conference calls has more than three euphemisms during the call, but within this group there are some calls with substantial amount of euphemisms (euphemism count can reach up to thirty euphemisms per conference call). To learn more about the properties of my euphemism measure I examine how it varies across sectors. Specifically, I calculate the average percentage of calls with at least one euphemism by sector. Figure 3 shows that companies that belong to more cyclical types of sectors (Materials, Industrials, and Consumer Products) use euphemisms more frequently. In contrast, companies that belong to less volatile sectors, such as Utilities and Telecommunication, tend to use fewer euphemisms. This observation is consistent with my hypothesis that euphemisms in earnings calls are used to soften the delivery of negative news, a verbal skill that can be helpful to managers of highly cyclical sectors. I also explore the time series variability of the euphemism measure to examine how it is correlated with the stock market fluctuations over the years. I plot the average *EUPH* measure and the contemporaneous stock market returns on Russell 3000 index for each year (refer to Figure 4). The plot indicates that stock market performance is negatively associated with the euphemism measure across time for my sample. The use of euphemisms increases in the period of economic downturns, as is clearly visible during the period of around 2007-2009. This observation is consistent with my prediction that earnings calls have more euphemisms when firms are going through tough times.

6. Empirical Results

Determinants of Euphemism Usage

My first question is what determines the use of euphemisms in an earnings call, and specifically how operating performance and uncertainty affect the euphemism usage. I examine this question by running the following logistic regression:

$$EUPH\_USAGE_{jt} = \beta_1 TONE_{jt} + \beta_2 Log(LENGTH)_{jt} + \beta_3 SUE_{jt} + \beta_4 EARN_{jt} + \beta_5 EPS_{GROWTH} + \beta_6 LOSS_{jt} + \beta_7 RET_{jt} + \beta_8 BM_{jt} + \beta_9 Log(Firm\_Age)_{jt} + \beta_{10} STD\_EARN_{jt} + \beta_{11} STD\_FORECAST_{jt} + \beta_{12} STD\_RET_{jt} + \beta_{13} Log(Analyst)_{jt} + \beta_{14} Log(SEG\_NUM)_{jt} + \beta_{15} Log(Size)_{jt} + f_{jt} + \varepsilon_{jt} \quad (1)$$

The dependent variable (EUPH_USAGE) is an indicator for whether an earnings call has the total number of euphemisms that is in the top quartile for all firms for that quarter. I control for qualitative information in the transcript with *TONE*, the number of positive minus the number of negative words in a conference call, scaled by the sum of the positive and the negative words (based on the Loughran and McDonald dictionary) and with *LENGTH*, the number of all words in the call. For explanatory variables, I use established tone determinants that are available to investors at the time of earnings call: measures for currently available fundamental information, growth opportunities, uncertainty, and complexity (Huang et al. 2014 and Brockman et al. 2015). The determinants for company performance are *SUE*, the difference between the actual earnings reported per IBES and the median earnings preliminary estimate, divided by the standard deviation of the actual earnings for the last eight quarters; *EARN*, earnings before extraordinary items scaled by beginning total assets; *EPS_GROWTH*, earnings before extraordinary items in the quarter minus the earnings in the same quarter in the previous year, divided by the earnings in the same quarter in the previous year, *LOSS*, an indicator variable equal to 1 when *EARN* is negative, and is 0 otherwise; and *RET*, the buy and hold monthly returns for 3 months preceding a conference call. To proxy for the uncertainty of firm operations I include *STD_EARN*, the standard deviation of firm earnings over the last five years; *STD_FORECAST*, the standard deviation of analysts' earnings forecasts for the quarter that are outstanding the day before quarter's earnings are announced; and *STD_RET*, the standard deviation of RET over the 3 months preceding the conference call. I further include book-to-market ratio (*BM*) and firm age to capture information about growth opportunities. The number of analyst (*ANALYST*), business segments (*SEG_NUM*), and the market value of equity (*SIZE*) proxy for operating complexity of the firm. The variable f_{jt} represents a vector of fixed effects that includes year-quarter and Fama French industry dummies.

Table 2 presents the results for the regression using three specifications: only with financial variables, only with textual variables, and a combined specification. My first hypothesis (H1A) states that firms with poor operating performance will have more euphemisms in their calls. I find that firms that resort to the use of euphemisms have more negative earnings surprises: the *SUE* coefficient is negative and significant. These companies have also experienced decline in earnings (the coefficient on *EPS_GROWTH* is negative and significant) and are likely to report negative earnings for the quarter (positive and significant coefficient on *LOSS*). Higher use of euphemisms is also associated with negative returns in the three months preceding the call (*RET*). These results confirm the empirical prediction that firm's performance is negatively related with the use of euphemisms during the calls. My second prediction explores how uncertainty influences the use of euphemisms on the call. I find that my proxies for uncertainty, such as variability of earnings (*STD_EARN*), analyst forecasts (*STD_FORECAST*), and returns (*STD_RET*) are negatively related to the use of euphemisms. In other words, call participants will use fewer euphemisms when uncertainty is high. This evidence seems to support prior findings that call participants might refuse to answer tough questions in situations when firm performance is volatile (Hollander et al. 2010). In the same regression, I also include controls for size, growth, and complexity of firm's informational environment. The empirical results show a strong positive association between firm size (*SIZE*) and complexity (*ANALYST* and *SEG_NUM*) and a negative association with firm's growth opportunities (positive and significant coefficients for *FIRM_AGE* and *BM*).

In the second specification, I investigate how textual characteristics of earnings calls relate to *EUPH*. The results show that *TONE* is negatively related to my measure of euphemisms, indicating that when call participants are more optimistic, they are less likely to use euphemisms. This is consistent with my prior findings that *EUPH* is reflective of poor quarterly performance and, therefore, negative news discussed on the call. I also find that the length of the transcript has a positive association with *EUPH*, providing evidence that call participants tend to be more talkative when they resort to the use of euphemisms to explain firm performance. In the third specification, I combine the textual and quantitative variables and the results hold. To summarize, firms that have more euphemisms during their earnings calls are likely to be large, mature firms with complex operations that are going through the period of poor operating performance. Earnings calls for these firms are likely to have a pessimistic tone and tend to be lengthier.

Investor Reaction to the Euphemisms

Next, I examine how investors react to the use of euphemisms around the conference call date. Specifically, I test my second hypothesis whether investors react negatively to the higher use of euphemisms in the earnings call. I use both univariate and regression analysis to test this prediction.

Univariate tests

As part of my univariate testing, I examine the pattern of immediate and drift abnormal returns on portfolios constructed according to the measure of euphemism usage. I construct portfolios by sorting all firms into four groups each quarter based on their euphemism count (*EUPH*). I calculate abnormal return, using the Daniel et al. (1997) methodology. In this approach, abnormal return is the buy and hold return on a security minus the capitalization-weighted average buy and hold return on a portfolio of firms with similar size (3 groups), B/M (3 groups) and 11-month momentum (3 groups). For immediate returns (*XRET_PRELIM*), I estimate cumulative abnormal return for each observation over the interval [-1, +1], where day 0 is the preliminary earnings announcement date. I estimate post-announcement abnormal return (*XRET_DRIFT*) from 2 days after the preliminary earnings announcement date through 1 day before the subsequent quarter's preliminary earnings announcement. I also examine the pattern of earning surprises ranked into quartiles (*iSUE*) across the ranked euphemism quartiles. The results are presented in Table 3, Panel A.

Consistent with my expectations about short-window reaction around the earnings announcement, firms with higher level of euphemisms during the call earn, on average, lower excess returns. *XRET_PRELIM* is monotonically decreasing across the four groups with the mean excess returns of +1.0% for *iEUPH1* (calls with the lowest euphemism usage) and -0.7% for *iEUPH4* (highest euphemism usage during a call), resulting in the statistically significant spread of 1.7%. I observe a similar pattern for the drift returns: stocks with higher euphemism usage during conference calls continue to experience lower subsequent returns for three months after the conference call date. *XRET_DRIFT* is +1.1% for *iEUPH1* and monotonically decrease to 0.2% for *iEUPH4*, resulting in a statistically significant difference of 0.9%. The distribution of the average earnings surprises across *iEUPH* quartiles further confirms my empirical findings regarding the association between *EUPH* and operating results: firms with more euphemisms have lower earnings surprises. I also re-perform similar analysis for my measure of tone. The results are consistent with prior literature: *TONE* is positively associated with contemporaneous and forward-looking returns as well as earnings surprises. All in all, the evidence implies that the *EUPH* factor works at identifying stocks with lower immediate and subsequent returns and poor financial performance.

Next, I perform the cross-tabulation analysis, when I control for the overall tone of the conference call (*TONE*) and earnings surprises (*SUE*) to ensure that *EUPH* is incremental to these other determinants of stock returns. I rank *TONE* and *SUE* quarterly into four groups so that stocks with more positive sentiment and more positive earnings surprises are ranked higher (*iTONE* and *iSUE*). Panel B of Table 3 presents average excess returns after sorting observation by both *EUPH* and *TONE*. Specifically, the rows correspond to quartiles based on the *TONE* measure, while the columns correspond to the euphemism usage quartiles. The table consists of sixteen portfolios each reporting the average excess return for observations that are similar both in the extent of euphemism usage and the overall sentiment. The bottom row represents the spread returns by the euphemism usage quartile and the far-right column shows the spread returns by the sentiment quartile. As the table shows, if I hold the overall tone of the call constant, the mean excess returns monotonically decrease for companies with more euphemisms during their conference calls. For example, if we look at the calls with the most negative tone (*iTONE1*), theses calls earn, on average, an immediate negative excess return of -1.4%. However, my measure of euphemisms usage allows to further differentiate within this group. Calls with the lowest level of euphemisms (*iEUPH1*) have an average immediate excess return of -0.5%, and as the level of euphemisms increases, the excess returns start to drop to -1.1% for *iEUPH2*, -1.6% for *iEUPH3*, and -2.5% for *iEUPH4*. This observation holds for both immediate and drifts returns and works across all quartiles formed on the sentiment measure.

Panel C of Table 3 is the counterpart of Panel B: it uses *SUE* signal instead of *TONE* sentiment in the portfolio construction. The table shows that my measure of euphemism usage works across all groups of earnings surprises. Holding the earnings surprises constant, the mean excess returns for the quartile with the lowest number of euphemisms during a conference call are greater than those with the highest quartile across all portfolios.

The results of univariate testing suggest that my measure of euphemism usage is negatively related to immediate and drift excess returns. Further, the information content of this signal is incremental to earnings news and the overall tone of the conference call.

Regression tests

Next, I test my hypothesis by running the panel regression with cumulative abnormal returns in the 3-day window around the conference call to test investors' initial reaction to the use of euphemisms on the call. Specifically, the regression is:

$$XRET\_PRELIM_{j,t} = \beta_1 EUPH_{jt} + \beta_2 TONE_{jt} + \beta_3 Log(LENGTH)_{jt} + \beta_4 SUE_{jt} + \beta_5 EPS\_GROWTH_{jt} + \beta_6 Log(Assets)_{jt} + \beta_6 BM_{jt} + \beta_6 STD\_EARN_{jt} + f_{jt} + \varepsilon_{jt} \quad (2)$$

The main variable of interest in this regression is my measure of euphemism usage (*EUPH*); I expect it to have a negative coefficient consistent with my hypothesis that investors prefer conference calls with fewer euphemisms. I control for the qualitative characteristics of the call with TONE and LENGTH. The measure of earnings surprises (*SUE*) and earnings growth (*EPS-GROWTH*) control for operating performance.

Additionally, I include controls for firm size (*ASSETS*, the total assets at the earnings announcement date), growth (*BM*), and operating risk (*STD_EARN*). My measures for euphemism usage (*EUPH*), call sentiment (*TONE*), and earnings surprises (*SUE*) are normalized between -0.5 and 0.5 following Feldman et al 2010. The remaining variables are winsorized at 1 and 99 percent. Finally, to control for the intertemporal variation of euphemisms and industry related omitted variable bias, I control for quarter and industry fixed effects.

The result is presented in Table 4. As can be seen from the results of the first specification, the coefficient on *EUPH* (-0.015) is negative and highly statistically significant (t=-16.84); a hedged portfolio that is long the top quartile of EUPH in the quarter and short the bottom quartile earns an excess return of 1.5%. The coefficient on the control for earnings surprises (0.089) loads positively, which is consistent with prior studies. In specification 2, I add my proxy for the overall tone of the conference call: *TONE* is positively related to abnormal contemporaneous returns and is statistically significant, consistent with prior studies. Including the proxy for the overall tone reduces the coefficient on *EUPH* slightly, but it remains significant with the hedged return of 1.23% at the 99% level. The third regression includes a set of control variables for size, growth and operating risk; the coefficient for EUPH is still negative and statistically significant. This result provides further support for H2: the negative investor response indicates that call participants using an elevated level of euphemisms is perceived as a negative signal about firm performance by market participants.

The second test of investor reaction investigates whether investors fully incorporate the information contained in the euphemisms used during the call; I use a similar specification as the immediate market return regression:

$$XRET\_DRIFT_{j,t} = \beta_1 EUPH_{jt} + \beta_2 TONE_{jt} + \beta_3 Log(LENGTH)_{jt} + \beta_4 SUE_{jt} + \beta_5 XRET\_PRELIM_{jt} + \beta_6 EPS\_GROWTH_{jt} + \beta_7 Log(Assets)_{jt} + \beta_8 BM_{jt} + \beta_9 STD\_EARN_{jt} + f_{jt} + \varepsilon_{jt} \quad (3)$$

The dependent variable is 3-month drift returns (*XRET_DRIFT*), which matches the return until the next quarterly earnings announcement. The results of the regression are presented in Table 5. I find that companies that had conference calls with more euphemisms continue to experience negative returns during the subsequent quarter: the coefficient on *EUPH* is negative and significant at the 1% level. This result holds as I add controls for the overall sentiment of the call (*TONE*) and firm fundamentals. In terms of economic magnitude, the euphemism measure can generate return predictability comparable to *SUE* and *TONE*: the coefficient on EUPH is 0.8% while the one of SUE is at 0.4% and TONE – 1.2%. To summarize, the results of analysis in the section show that a higher usage of euphemisms in conference calls is negatively related to the immediate and drift excess returns and that these market reactions are incremental to the established signals based on earnings surprises and the overall sentiment of a call.

Changes in euphemism usage over time and market reaction

I examine the role of euphemism usage on immediate and delayed market reactions by focusing on the levels of euphemisms in each conference call. However, prior studies of non-quantitative disclosures find that the changes of those disclosures from the recent past and not the levels might be a more relevant variable to examine (Demers and Vega (2007), Feldman et al (2010), Davis et al. (2012)). Researchers argue that non-financial disclosures do not vary significantly from period to period, as managers tend to modify them slightly, and that a word choice for a particular company can depend on the industry or a specific company. When it comes to the conference calls, one can, similarly, argue that the habits of call participants might bias the level of some words during a conference call. For example, if a call participant tends to repeat some words in his speech and if these words happen to be a part of researcher's dictionary, this would bias the count of these words for that specific conference call. Also, when it comes to euphemisms, the frequency of these words in speech depends on the social background of a speaker. For example, prior studies of euphemisms show people with certain professional backgrounds, such as politics and law, are more likely to use euphemisms in their speech (Lutz 1996). Additionally, if a call participant is not a native English speaker, he or she might use fewer euphemisms all together. Prior studies find that non-native English speakers might not be fully aware of euphemisms and their cultural meaning (Plancic 2009, Damen 1984).

To mitigate the concern that company-specific use of euphemisms might bias my cross-sectional comparison of tone levels, I conduct an additional analysis using the change of euphemism level as a proxy for euphemism measure. Following Feldman et al (2010), I calculate the change in euphemism measure (*CH_EUPH*) as the difference between euphemism measure in the current quarter and the average euphemism measure in the previous four quarters. I expect the coefficient to be negative, meaning that higher usage of euphemisms on the call compared to the prior four quarters leads to more negative returns and vice versa. Next, I run the following regressions:

$$XRET\_PRELIM_{j,t} = \beta_1 CH\_EUPH_{jt} + \beta_2 CH\_TONE_{jt} + \beta_3 Log(LENGTH)_{jt} + \beta_4 SUE_{jt} + \beta_5 EPS\_GROWTH_{jt} + \beta_6 Log(Assets)_{jt} + \beta_6 BM_{jt} + \beta_6 STD\_EARN_{jt} + f_{jt} + \varepsilon_{jt} \quad (4)$$

$$XRET\_DRIFT_{j,t} = \beta_1 CH\_EUPH_{jt} + \beta_2 CH\_TONE_{jt} + \beta_3 Log(LENGTH)_{jt} + \beta_4 SUE_{jt} + \beta_5 XRET\_PRELIM_{jt} + \beta_6 EPS\_GROWTH_{jt} + \beta_7 Log(Assets)_{jt} + \beta_8 BM_{jt} + \beta_9 STD\_EARN_{jt} + f_{jt} + \varepsilon_{jt} \quad (5)$$

I use similar controls and model specifications as in Models 2 and 3, except for the *TONE* variables. Following Feldman et al. 2010, I control for the change in the overall tone of a conference call (*CH_TONE*) and use this variable in place of the level *TONE* signal. The change in tone is calculated as the difference between the tone sentiment signal in a company's conference call and the mean sentiment signal in the company's conference calls held within the preceding 370 calendar days.

Table 6 presents the results of the regression for returns around the preliminary earnings announcements (*XRET_PRELIM* – specifications 1-2) and the drift returns (*XRET_DRIFT* – specifications 3-4). In all specifications, the coefficient on *CH_EUPH* is consistently negative: the hedged portfolio returns on the euphemism signal is around -0.3% in the three-day window and -0.2% in the following quarter. The association holds controlling for earnings surprises, a well-documented measure of tone change (Feldman et al. 2010), and other firm controls. The results of this test further confirm my findings that investors treat the use of euphemisms as a negative signal.

7. Robustness Tests

My research is not without inherent limitations. In this section, I present the results of additional tests to check the robustness of main results. Specifically, I consider whether my results are driven by the regression specification, sample selection and the construct of the euphemism measure.

First, I check the sensitivity of my results to the regression specification. I re-perform my main tests for market reactions using Fama-MacBeth style regressions (Fama and MacBeth, 1973) for both levels and changes of my euphemism measure. Table 7 presents the results for immediate and drift returns around the conference call date regressed on *EUPH/ CH_EUPH*, *TONE*, *SUE* and other controls. The results of Fama-MacBeth style regressions confirm my findings that both levels and changes in levels of euphemism usage are negatively related to the abnormal returns both around and subsequent to the conference call date. The coefficients on *EUPH* and *CH_EUPH* remain negative and statistically significant for immediate and drift returns and are similar in magnitude to the coefficients observed in the panel regression specifications.

The relationship between *EUPH* and returns might change with firm size. To alleviate the concern that my results are driven by a well-documented size anomaly (Fama and French 1993, 2014), I perform my tests on the sub-sample of conference calls that exclude small-cap firms. I define small-cap companies as companies with market capitalization less than $500 million. Table 8 reports the results for the association between my measure of euphemism usage and stock returns for a subsample that excludes small-cap firms. The association between the level of euphemisms and excess stock returns remains at the same level of statistical significance (1% level) and magnitude as the results reported for the full sample in Table 4 and Table 5. Similarly, the statistical and economic significance of the association between my measurement of euphemism change and excess returns remains unaffected by the exclusion of small-cap stocks. When it comes to using drift returns as a dependent variable, the association also holds. All in all, the main takeaway from Table 8 is that my results on the association between my measure of euphemism usage and excess stock returns are robust to the size anomaly.

My results might also be driven by the choice of the main explanatory variable. I use the total count of euphemisms to capture the extent of euphemism usage during a conference call. Using the sum to capture the effect of euphemism usage might capture a repetition of the same popular euphemisms by different call participants and confound the effect of euphemism variability during a conference call. To ensure that my results are not driven by my choice of explanatory variable, I perform the tests using an alternative measure of euphemism usage that captures the variability of these words on the call. To construct this measure (EUPH_VAR) I count the number of distinct euphemisms in each conference call; this way if a euphemism is repeated more than once, it is counted as one euphemism occurrence. Table 9 reports the results. The first specification shows the results of my baseline regression, using the level of euphemism variability. The coefficient on *EUPH_VAR* is negative and significant in the regression specifications with immediate market returns (*XRET_PRELIM*) as a dependent variable and controlling for the earnings surprises, the tone, and firm fundamentals. The effect of *EUPH_VAR* is also meaningful for the three-month drift returns. This supports my earlier conclusion that a less (more) extensive use of euphemisms during a conference call leads to higher (lower) immediate and drift abnormal returns. Additionally, I test the effect of change in the euphemism variability during a given call versus the previous four-quarter average (*CH_EUPH_VAR*). The results continue to support my earlier conclusion that the increased level of euphemism usage is associated with lower immediate and drift excess returns. The coefficients remain negative and statistically significant in both specifications.

8. Conclusion

This study uses the earnings conference call setting to test the role of euphemisms in corporate communication. The research documents that firms use euphemisms more extensively when the companies perform badly, have complex operations and fewer growth opportunities. However, firms with risky and uncertain operations tend to use fewer euphemisms during the calls, consistent with prior findings that managers tend to withhold information when the operating results are hard to explain. I also find that the extent of euphemisms in the conference call contains value-relevant information. I show that my measure of euphemism usage is negatively associated with short-window returns around the date of the conference call and with the subsequent 90-day drift returns. My results are robust to controlling for the earnings surprises, the overall tone of the conference call, the size of the firm, and two alternative measurements of euphemism usage – the change in the euphemism level and the variability of euphemisms.   Collectively, these results suggest that the overall use of euphemism in the conference call setting is indicative of negative information about the company performance. However, due to the strong promotional aspect of euphemistic words, the negative news is only gradually absorbed by market participants. Investors are pacified with euphemistic terms and, as a result, underestimate the extent of bad news that a company is reporting.

My results contribute to the growing stream of accounting literature that examines the promotional aspect of corporate communication, and provide evidence on a specific type of linguistic tricks scrutinized by regulators. Even though, the results suggest that euphemism usage in conference calls poses a material detrimental effect to market participants, it remains unclear whether managers and analysts use euphemisms intentionally to mislead investors. The impact of managerial compensation as well as analyst' career success on their linguistic habits represents a promising area for future research on euphemisms.

REFERENCES

Abrahamson E, Amir E. The Information Content of the President's Letter to Shareholders. Journal of Business Finance & Accounting. October 1996; 23 (8):1157-1182.

Allan, K., K. Burridge. 1991. Euphemism & Dysphemism: Language Used as a Shield and as a Weapon. Oxford University Press, Oxford.

Bozanic, Z., L. Cheng, T. Zach. 2016. Soft Information in Loan Agreements. Working paper, Fisher College of Business, Eller College of Management.

Brochet, F., M. Loumioti, G. Serafeim. 2015. Speaking Of the Short-Term: Disclosure Horizon and Managerial Myopia. Review of Accounting Studies 20: 1122-1163.

Brockman P, Unlu E. Earned/contributed capital, dividend policy, and disclosure quality: An international study. Journal of Banking & Finance. July 2011; 35(7):1610-1625.

Brockman, P., X. Li, S.M. Price. 2015. Differences in Conference Call Tones: Managers versus Analysts. Financial Analyst Journal 71; 24-42.

Bushee, B. J., D. A. Matsumoto, and G. S. Miller. 2003. Open Versus Closed Conference Calls: The Determinants and Effects Of Broadening Access To Disclosure. Journal of Accounting and Economics 34 (1–3):149-180.

Chen, S., S. Hollander, and K. Law. 2016. In Search of Interaction Working paper. University of Texas at Austin.

Clatworthy, M., M. Jones. 2006. Differential patterns of textual characteristics and company performance in the chairman's statement. Accounting, Auditing & Accountability Journal. August 2006; 19 (4):493-511.

Cohen, L., D. Lou, and C. Malloy. 2014. Playing Favorites: How Firms Prevent the Revelation of Bad News. Working paper, Harvard University.

Damen, L. 1984. Overcoming the Pollyanna Syndrome. Cross Currents 11.1.

Daniel, K., M. Grinblatt, S. Titman and R. Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. Journal of Finance 52 (3): 1035-1058.

Das S, Chen M. Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web. Management Science. September 2007; 53 (9):1375-1388.

Davis, A. K., J. M. Piger, L. M. Sedor. 2012. Beyond the Numbers: Measuring the Information Content of Earnings Press Release Language. Contemporary Accounting Research, 29(3), 845-868

Demers, E., C. Vega 2010. Soft Information in Earnings Announcements: News or Noise? INSEAD Working Papers Collection, (33), 1-67.

Druz, M., A. Wagner, R. Zeckhauser. 2015. Tips and tells from managers: How the market reads between the lines of conference calls. NBER Working Paper No. 20991.

Fairclough, N. 1995. Critical discourse analysis. London: Longman.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., and K. R. French. 2014. A five-factor asset pricing model. Working paper, Booth School of Business, University of Chicago.

Fama, E. F., and J. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Feldman, R., S. Govindaraj, J. Livnat, B. Segal. 2010. Management's tone change, post earnings announcement drift and accruals, Review of Accounting Studies 15, 915–953.

Franco G., O. Hope, D. Vyas, Y. Zhou. Analyst Report Readability. Contemporary Accounting Research. Spring2015 2015; 32 (1).

Frankel, R., M. Johnson, and D. J. Skinner. 1999. An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium. Journal of Accounting Research, Vol. 37, No. 1, pp. 133-150.

Halmari, H. 2011. Political correctness, euphemism, and language change: The case of 'people first' Journal of Pragmatics, Volume 43, Issue 3, February 2011, Pages 828-840.

Henry, E. 2008. Are Investors Influenced By How Earnings Press Releases Are Written? Journal of Business Communication 45.4.

Hildebrandt, H., Snyder R. The Pollyanna Hypothesis in Business Writing: Initial Results, Suggestions for Research. Journal of Business Communication. Winter 81 1981; 18(1):5-15

Holder, R.W. 2008. Oxford Dictionary of Euphemisms. Oxford University Press.

Hornby, A.S. 2010. Oxford Advanced Learner's Dictionary. 8th edition. Oxford: O.U.P.

Huang, X., S.H. Teoh, and Y. Zhang. 2014. Tone Management. The Accounting Review 89, 1083-1113.

Huang, A., R. Lehavy, A. Zang, and R. Zheng. 2016. Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. Working paper.

Karamanou, I., and N. Vafeas. 2005. The Association between Corporate Boards, Audit Committees, and Management Earnings Forecasts: An Empirical Analysis. Journal of Accounting Research 43 (3):453-486.

Kelner, D. 1992. The Persian Gulf TV War. Boulder, Colorado: West view Press.

Larcker, D. F., Zakolyukina, A. A. 2012. Detecting Deceptive Discussions in Conference Calls. Journal of Accounting Research, 50(2), 495-540.

Lee, J. 2016. Can Investors Detect Managers' Lack of Spontaneity? Adherence to Predetermined Scripts during Earnings Conference Calls. Accounting Review. Jan2016, Vol. 91 Issue 1.

Li, F. 2008. Annual Report Readability, Current Earnings, And Earnings Persistence. Journal of Accounting & Economics 45, No. 2/3: 221-247.

Li, Y., D. Yermack. 2016. Evasive Shareholder Meetings. Journal of Corporate Finance 38, 318-334.

Loughran, T., B. McDonald. 2011. “When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks.” The Journal of Finance 66.

Lutz, W. 1996. The New Doublespeak. Why No One knows what anyone’s Saying Anymore. Harper Collins Publishers.

Mayew, W. J. 2008. Evidence of Management Discrimination among Analysts during Earnings Conference Calls. Journal of Accounting Research, June 2008, Vol. 46, Issue 3.

Mayew, W. J., N. Y. Sharp, M. Venkatachalam. 2011. Using Earnings Conference Calls to Identify Analysts with Superior Private Information. AAA 2010 Financial Accounting and Reporting Section (FARS) Paper.

Plancic, B., Zanchi Z. 2009. Political Correctness – A Challenge to EFL Teaching. Strani Jezici 38.2.

Price, S. M., J. S. Doran, D. R. Peterson, and B. A. Bliss. 2012. Earnings Conference Calls and Stock Returns: The Incremental Informativeness of Textual Tone. Journal of Banking & Finance, 36, pp. 992-1011.

Rahimi, A., Sahragard R. A. 2006. Critical Discourse Analysis of Euphemisation and Derogation in Emails on the Late Pope. Linguistics Journal, January 2006. Volume 2.

Rawson, H. 1995. Dictionary of Euphemisms and Other Doubletalk: being a compilation of linguistic fig leaves and verbal flourishes for artful users of the English language. Castle Books.

Rutherford, B.A. 2005. Genre Analysis of Corporate Annual Report Narratives. A Corpus Linguistics- Based Approach. Journal of Business Communication, Volume 42, Number 4, October 2005, 349-378.

Smith, M., R. J. Taffler. 2000. The chairman's statement - A content analysis of discretionary narrative disclosures. Accounting, Auditing & Accountability Journal, Vol. 13 Iss.: 5, pp.624 - 647

Tetlock, P. C. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. The Journal of Finance, 62(3), 1139–1167.

Tetlock, P. C., Saar-Tsechansky, M., Macskassy, S. 2008. More than Words: Quantifying Language to Measure Firms' Fundamentals. Journal of Finance, 63(3), 1437–1467.

U.S. Securities and Exchange Commission. 1998. A plain English handbook: How to create clear SEC disclosure documents. Available from the U.S. Securities and Exchange Commission Web site, https://www.sec.gov/pdf/handbook.pdf

Uang J., D. Citron, S. Sudarsanam, R. Taffler. Management Going-concern Disclosures: Impact of Corporate Governance and Auditor Reputation. European Financial Management. November 2006; 12 (5): 789-816.

van Dijk, T. A. 1998. Critical discourse analysis. Retrieved from: http://www.hum.uva.nl/teun/ cda.htm

van Dijk, T. A. 2002. The discourse knowledge interface. Paper for a book edited by Gilbert Weiss and Ruth Wodak. Theory and interdisciplinarity in CDA.

van Dijk, T. A. 1997. Political discourse and political cognition. Congress Paper on Political Discourse, Aston University July 1997. Retrieved from: http://www.let.uva.nl~teun

van Dijk T. A. 2005. Politics Ideology and Discourse. Volume on Politics and Language 2005. pp. 728-740. 2005.

Widdowson, H. 2000. Critical Practices: On Representation and the Interpretation of Text. In: S. Sarangi & Malcolm Coulthard (Eds.), Discourse and social life. Harlow: Pearson Education.

Zhou, D. 2014. The Blame Game. Working paper, June 6, 2014.

Appendix 1: Examples of VIP Rules

This table exhibits some examples of VIP rules that I wrote to capture instances of euphemisms in the corpus of conference call transcripts. The rules show some features of VIP software that helped me create rules that can capture euphemisms and euphemistic phrases, accounting for punctuation, semantic rows, and grammatical structure of sentences.

VIP Features	VIP Rule	Conference Call Extract Captured by the Rule
Identifies phrases by recognizing grammatical relationships	(0: Lemma=tight PRD->1) + (1: Lemma=be A1<-2) + (2: Lemma=margin) => {AddProp(1.SENTIMENT=NEG); AddProp(1.NOMERGE=true); AddProp(1.EVENT=Euph_margintight); AddLink(1.SentWord->0); AddLink(1.SentWord->2);}	*PHH Corporation, November 11, 2005, Terence W. Edwards, CEO*: **Margins are** very, very **tight** by historical standards. And I would tell you now that we're -- into the month of October they're tighter still.
Identifies negations	(0: Lemma=bed pobj->1) + (1: Lemma=of prep->2) + (2: Lemma=out DIR->3) + (3: Lemma=fall) => {AddProp (3.SENTIMENT=NEG); AddProp(3.EVENT=Euph_falloutofbed); AddLink(3.SentWord->0); AddLink(3.SentWord->1); AddLink(3.SentWord->2);}	*Walgreen, June 22, 2010, Greg Wasson, CEO:* When we removed Duane Reade and in light of the 5.9% new store growth, our SG&A trend is pretty consistent with where we've been over the last two or three years. We certainly **didn't fall out of bed**. We certainly know that there's opportunity, we're going to keep pushing. The goal I have, I've given this team is make sure that that two year stack yea
Has tagging capacity	(0: Lemma=ball pobj->1 det<-2 nummod<-3) + (1: Lemma=behind) + (2: Lemma=the) + (3: NERTag=CARDINAL) => {AddProp(1.SENTIMENT=NEG); AddProp(1.NOMERGE=true); AddProp(1.EVENT=Euphemism_behindball); AddLink(1.SentWord->0); AddLink(1.SentWord->2); AddLink(1.SentWord->3);}	*United States Steel Corp, June 26, 2011, John Surma, CEO*: In the first quarter we had a disruption at our industrial gas supplier at our Great Lakes Works and that got us sort of **behind the eight ball** on inventory coverage. So we didn't have as many tons available in the spot market in the second quarter as we might have liked.
Allows creation of semantic rows	(0: Lemma=soft amod->1) + (1: Lemma=(market | April | August | December | demand | environment | February | January | July | June | March | May | month | November | October | orders | Q1 | Q2 | Q3 | Q4 | quarter | sales | September | year)) => {AddProp(1.SENTIMENT=NEG); AddProp(1.NOMERGE=true); AddProp(1.EVENT=Euphemism_softmarket); AddLink(1.SentWord->0);}	*Carlisle Companies, July 19, 2005, Richmond McKinnish, CEO*: What was really disappointing to us was the earnings. We had several significant actions, which reduced our earnings in the quarter. The first was a layoff at our Pennsylvania tire plant, where we recognized the **soft demand** in lawn and garden.
Accounts for punctuation, compound word	(0: Lemma=_ punct->1) + (1: Lemma=up det<-2 compound<-3) + (2: Lemma=the) + (3: Lemma=hang) =>	*St. Jude Medical, July 19, 2006, Bruce Nudell, Sanford Bernstein, Analyst*: Good morning, Dan. Two questions.

	{AddProp(1.SENTIMENT=NEG); AddProp(1.NOMERGE=true); AddProp(1.EVENT=Euphemism_hangup); AddLink(1.SentWord->0); AddLink(1.SentWord->2); AddLink(1.SentWord->3);}	One is, we did a little survey work, and it was certainly inadequate to sample the waterfront. But it suggested that the issue in referral may be even below the cardiologist's level, affecting better preserved patients who are seemingly doing well, you know, not routinely managed by cardiologists. Just your thought about where <u>**the hang-up**</u> in the referral chain might be.

Appendix 2: Examples of Sentences with Euphemisms

This table exhibits extracts with some most frequently used euphemisms from the conference call transcripts. VIP software captures these instances and assigns polarity to each case. Euphemisms have a negative sentiment because they are used to present unpleasant reality in a more positive light. Therefore, I assign negative sentiment to all euphemism rules in VIP. However, VIP software will identify negation in the sentence structure and might change the polarity for some cases from negative to positive. Most examples below have negative polarity. The second example shows how euphemisms can be classified as having a positive polarity, while third example shows examples of euphemisms both with positive and negative polarity within a conference call paragraph.

Company/ Call Date	Examples	Polarity
TriQuint Semiconductor Inc. July 27, 2011	*Ralph Quinsey, CEO*: With **cloudier near-term visibility** and **some headwinds**, we are forecasting flat revenue in Q3, but I anticipate returning to strong sequential growth in Q4.	NEG
Micron Technology December 22, 2005	*Tim Luke, Lehman Brothers, Analyst*: That makes sense. Any color just with respect to pricing and how that may play out in terms of gross margin outlook? *Steve Appleton, Micron Technology, CEO*: Very difficult to project what's going to happen with respect to pricing. If you paid attention to some of the news that's been out in the public on spot market pricing in the DRAM area just in the past week or so, it appears to have stabilized at a level that's much lower than we would have hoped for. But it appears to have stabilized. Our contract renegotiations that occurred midmonth with our big OEMs resulted in flat pricing. So it appears that we're through the storm, anyway, on the strong price reductions that we have seen in the DRAM area. And on the NAND Flash area, there's really **not much price pressure** at all. Prices are relatively stable. In the CMOS image sensor area, we are kind of in a sole-source situation with virtually all of our customers. So there's **not a lot of commodity-type price pressure** there, either.	POS
Lennox International April 26, 2011	*Bob Hau, CFO*: We now **expect commodity headwind** of $45 million to $50 million for the full year, weighted more to the first half of the year. We also expect to fully **offset this commodity headwind** on a full year basis through pricing actions we've taken.	NEG/ POS
Brooks Automation February 1, 2005	*Bob Woodbury, CFO*: Our inventories are still somewhat stalled. We have an 18, $19 million amount sitting in deferred. I would like to get that more than half of that value reduced the course of this year. We did have as I alluded to on the call, **we had some timing issues** just because of the literally the holidays, where we had almost $5 million in cash land January 3 in our lock boxes; again all held by holidays. DSO's we're still trying to drive back into a 60-day normalized value. Again, take 10 off of the inventories. Again we ate into payables a little bit this quarter, but the focus on balance sheet with operating profitability is somewhat of a daily mantra here.	NEG
Polo Ralph Lauren February 4, 2009	*Roger Farah, COO*: The proactive measures we've taken to scale back inventory levels across channels to manage our expenses, and to execute our day to day operations with a high level of precision and agility have helped to mitigate the dramatic **pullback** in consumer spending that occurred during the quarter.	NEG
Halliburton Company February 20, 2003	*Douglas Foshee, CFO*: Now I want to give you a little more detail by segment on our operating results. In the Energy Services Group, quarterly revenues were $1.7 billion, a 10% decrease year-over-year and a 2% increase sequentially. The	NEG

	year-over-year revenue decrease is attributable to the decline in U.S. activity, **pricing pressures**, and importantly, our contribution of Halliburton subsidy assets to SubSea 7.	
Union Pacific Corp July 21, 2011	*Scott Group, Wolfe Trahan Co, Analyst*: And just the last question is on intermodal, I understand that the contract loss, but if I look at your volumes, they are **flattish**. Your western competitor's up 10. I'm guessing there's more than just a contract loss driving that spread and any additional color you can give would be great on why you're seeing kind of **flattish** intermodal volumes, particularly on the domestic side given the strength we're seeing from JP Hunt and Hub.	NEG
Syntel, Inc. November 7, 2009	*David Mackey, SVP Finance*: As we have been pretty consistent in saying over the last year we certainly expected a lot of these headwinds to come back on the cost side of our business when the demand environment started to improve. So things like wage increases, utilization levels, and as you mentioned before, the currency, these will all create headwinds. In terms of the magnitude, we are going to have **to wait and see** exactly what that means.	NEG
Dentsply International July 27, 2005	*Bill Jellison, CFO*: However, these positives were offset in the quarter by lower precious metal sales and the unleveraged start-up costs of our new anesthetic facility. Rates are expected to only improve slightly the by the end of 2005 due to the negative impact of the precious metal product mix, primarily the result of the **soft** German dental **market** and the higher unleveraged start-up costs for the anesthetic facility.	NEG
CNA Financial Corp July 28, 2005	*Scott Frost, HSBC, Analyst*: Yes, I think I may have **missed something here**, and I apologize if I have. But you're saying the Corporate and other Non-Core, the results were largely driven by the tax settlement. Excluding those results you would've shown a fairly significant deterioration. And I'm not sure I understand -- and again, I apologize if **I've missed it here** -- what drove that deterioration. Is that the right way to look at that? *Stephen W. Lilienthal, CEO*: No, I don't think it is. You -- there are two things in the Corporate results. One is the tax settlement, which is a 115 good guy. And the other is the commutation of the reinsurance, which is a $36 million the other way. So, if you take those two things out, you'll see relatively, you know, consistent numbers. *Scott Frost:* So, 115 less 35, that's around what, I mean--. *Stephen W. Lilienthal:* 79. *Scott Frost*: OK. So, excluding that, your net income would have been 2 versus 58 in 2004, right? *Stephen W. Lilienthal* Yes. And there were a lot of investment gains in 2004, which accounts for the majority of the difference. - *Scott Frost*: OK. All right. So that's the main driver is lower investment gains. OK. Thank you.	NEG
PCTEL April 29, 2005	*Marty Singer, CEO*: The **lumpiness** in 2004 with RFS (*type of product*) was largely due to an error that I made, and that was being unrealistically bullish about our opportunities in the third quarter for government sales, and secondly, we had **lumpiness** because after we introduced Clarify, we had an algorithm glitch in the first quarter of 2004 that led to some significant delays in rolling out that product in a -- in a strong way. And so there was a real **hiccup** in the Clarify rollout.	NEG
LMI Aerospace November 8, 2010	*Ed Dickinson, CFO*: Good morning everybody and thanks for joining the call today. As Ron said, the third quarter was a bit of a **transitional quarter** in both segments, and as we prepare ourselves for expected growth with new work and both -- and	NEG

	production rates as well. I will go through the financial results and try to explain a few of the unusual items during the quarter. **Sales** for the quarter **were light**, as we generated $52.3 million in the quarter, down from $58.7 million the prior year and down sequentially from $55.6 million.	
Marriott International October 6, 2005	*Bill Crow, Raymond James, Analyst*: Right. Finally on the syn fuel, **not to beat a dead horse**, but is there any way that it could be dilutive to the $3 to $3.10 range next year, or you think you can manage it so that you're not surprised by the end of year fuel price spike or something that would eliminate your profits to date?	NEG

Appendix 3: Variable Definitions

EUPH	The number of euphemisms in a conference calls. For regression analysis EUPH is normalized between -0.5 and 0.5 by ranking it into the quartiles (0 to 3) by fiscal quarter, dividing the rank by 3 and subtracting 0.5.
TONE	The measure of sentiment based on the number of positive minus the number of negative words in a conference call, scaled by the sum of the positive and the negative words; the list of positive and negative words is based on the Loughran and McDonald dictionary. For regression analysis TONE is normalized between -0.5 and 0.5 by ranking it into the deciles (0 to 9) by fiscal quarter, dividing the rank by 9, and subtracting 0.5.
LENGTH	The number of words in a conference calls.
CH_EUPH	The difference between the EUPH in a company's conference call and the mean EUPH in the company's conference calls held within the preceding 370 calendar days. For regression analysis CH_EUPH is normalized between -0.5 and 0.5 by ranking it into the quartiles (0 to 3) by fiscal quarter, dividing the rank by 3 and subtracting 0.5.
CH_TONE	The difference between the TONE in a company's conference call and the mean TONE in the company's conference calls held within the preceding 370 calendar days. For regression analysis CH_TONE is normalized between -0.5 and 0.5 by ranking it into the deciles (0 to 9) by fiscal quarter, dividing the rank by 9, and subtracting 0.5.
EUPH_VAR	The number of distinct euphemisms in a conference call. For regression analysis EUPH_VAR is normalized between -0.5 and 0.5 by ranking it into the quartiles (0 to 3) by fiscal quarter, dividing the rank by 3 and subtracting 0.5.
CH_EUPH_VAR	The difference between the EUPH_VAR in a company's conference call and the mean EUPH_VAR in the company's conference calls held within the preceding 370 calendar days. For regression analysis CH_EUPH_VAR is normalized between -0.5 and 0.5 by ranking it into the quartiles (0 to 3) by fiscal quarter, dividing the rank by 3 and subtracting 0.5.
SUE	The difference between the actual earnings reported per IBES and the median earnings preliminary estimate, divided by the standard deviation of the actual earnings for the last eight quarters. For regression analysis SUE is normalized between -0.5 and 0.5 by ranking it into the deciles (0 to 9) by fiscal quarter, dividing the rank by 9, and subtracting 0.5.
EARN	Earnings before extraordinary items deflated by beginning total assets.
EPS_GROWTH	The earnings before extraordinary items in the quarter minus the earnings in the same quarter in the previous year, divided by the earnings in the same quarter in the previous year.
LOSS	Indicator variable equal to 1 if current period earnings are negative.
RET	The buy and hold monthly returns for 3 months preceding a conference call.
BM	Shareholder's equity divided by pre-earnings announcement market value.
FIRM_AGE	The number of years since a firm is first listed in CRSP database.
STD_EARN	The standard deviation of EARN over the last five years.
STD_FORECAST	The standard deviation of analysts' earnings forecasts for the quarter that are outstanding the day before quarter's earnings are announced.
STD_RET	The standard deviation of RET over the last 3 months preceding a conference call.
ANALYST	The number of analysts in IBES which issue earnings forecast for the firm.
SEG_NUM	The number of business segments.

SIZE	The market value of equity at the fiscal quarter end.
ASSETS	The total assets at the earnings announcement date.
XRET_PRELIM	The buy-and-hold return on a stock minus the average return on a matched size-B/M-momentum portfolio in the interval [-1, +1], where day 0 is the preliminary earnings announcement date. For regression analysis when XRET_PRELIM is used as a dependent variable, it is normalized between -0.5 and 0.5 by ranking it into the deciles (0 to 9) by fiscal quarter, dividing the rank by 9, and subtracting 0.5.
XRET_DRIFT	The buy-and-hold return on a stock minus the average return on a matched size-B/M-momentum portfolio from 2 days after the preliminary earnings announcement date through 1 day before the subsequent quarter's preliminary earnings announcement.

Figure 1 Sample Size

Figure 1 plots the number of firms over the sample period (*N*). The sample consists of all US firms in Thompson Reuter's conference calls database for the years 2002-2016 that hold earnings conference calls within one day or on the same day as the earnings release.

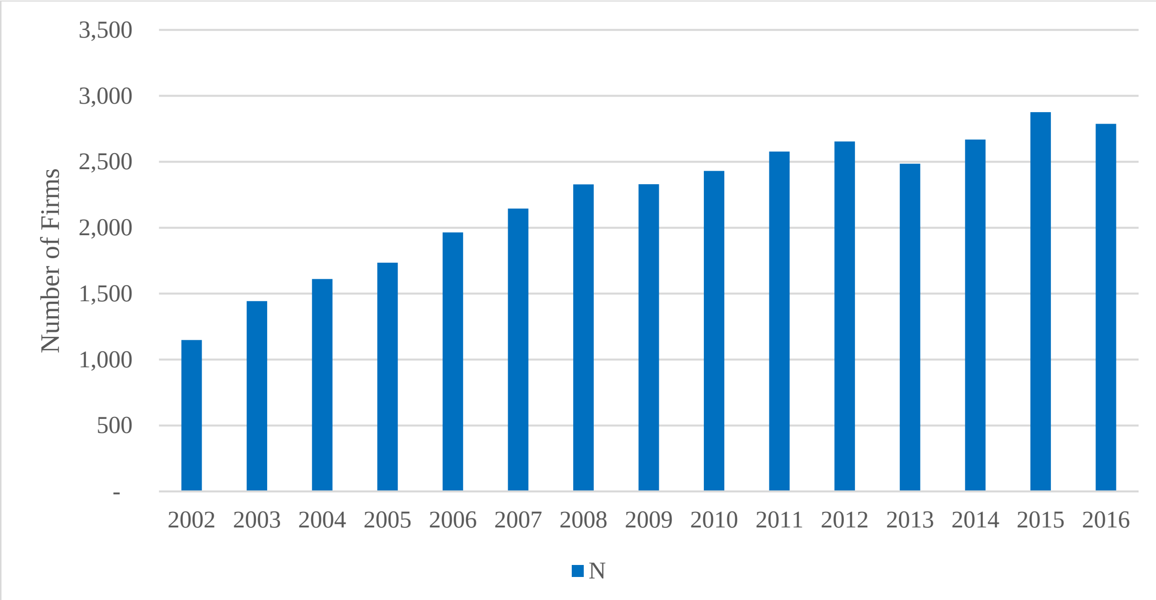
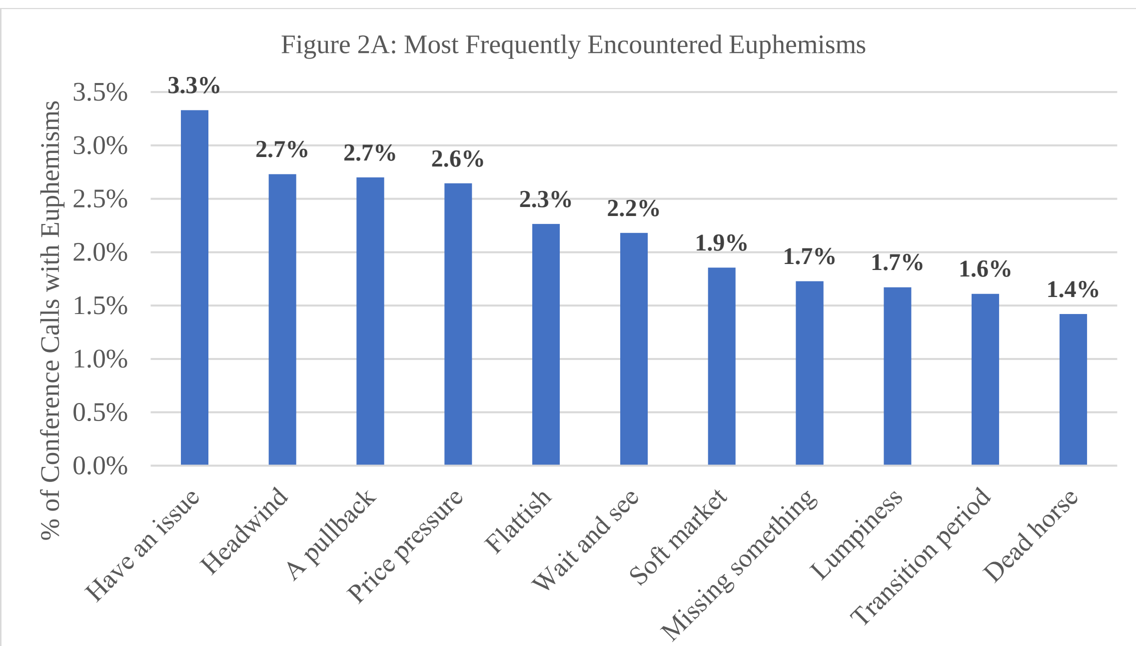


Figure 2 Most Frequently Used Euphemisms

Figure 2 shows mostly frequently used euphemisms. Figure 2A shows euphemisms that are most likely to be used at least once in a transcript. Figure 2B shows ten most frequently repeated euphemisms.



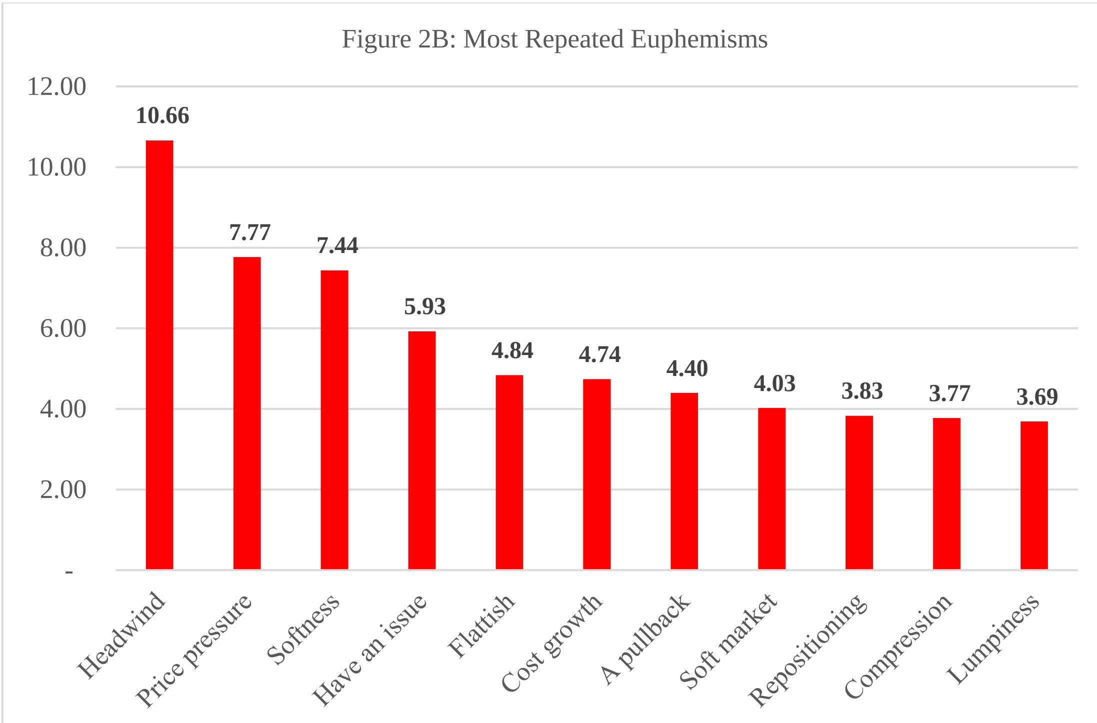


Figure 3 Uses of Euphemisms by Sector

Figure 3 plots the proportion of conference calls that have euphemisms by sector.

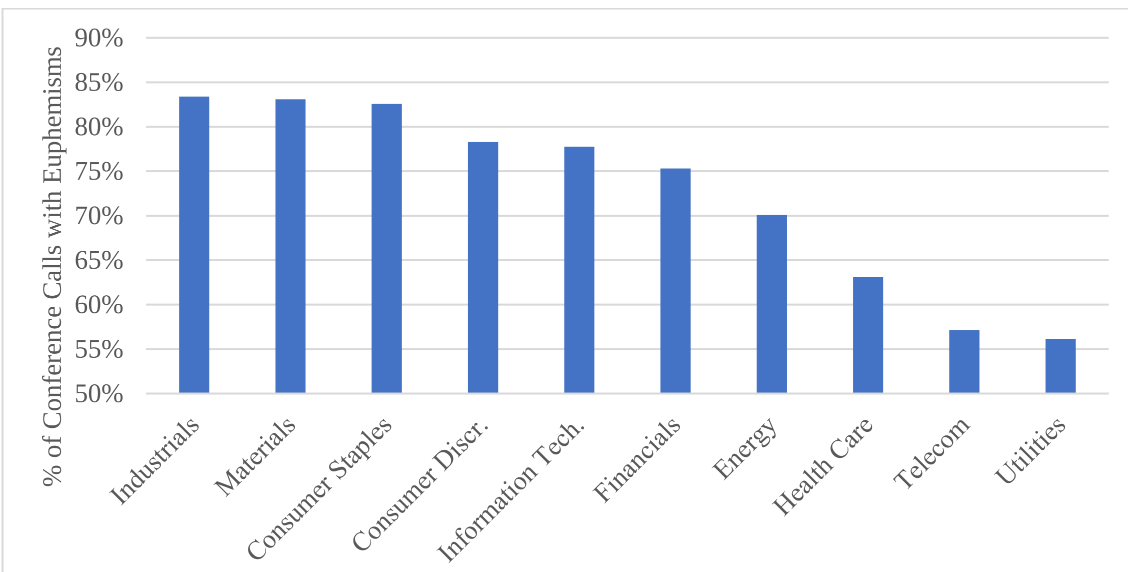


Figure 4 Russell 3000 Returns and Proportion of Calls with Euphemisms

Figure 4 plots Russell 3000 returns for the period covered by the sample of conference calls and the proportion of conference calls that have euphemisms (*Euph %*).

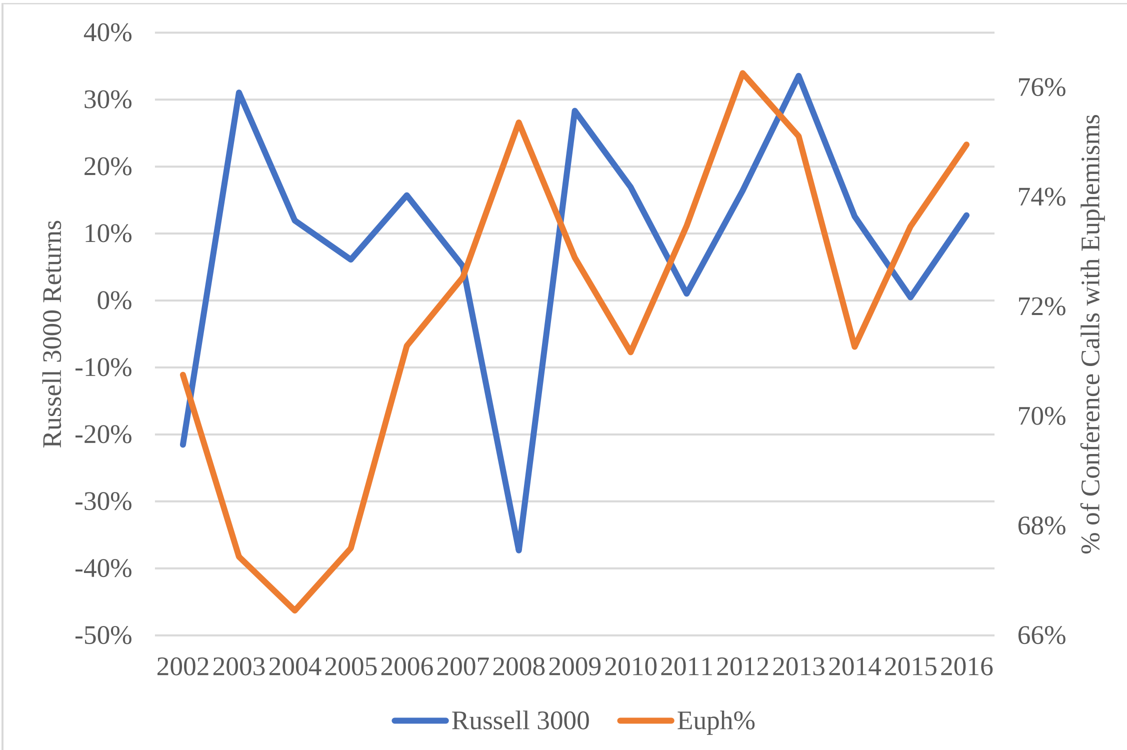


Table 1: Summary Statistics

This table reports summary statistics for variables used in the paper. Individual variable definitions are outlined in Appendix 3.

Variable	N	Mean	Median	Std Dev	Q1	Q3
EUPH	78,115	2.386	2.000	2.853	0.000	3.000
TONE	78,115	0.175	0.187	0.210	0.036	0.325
LENGTH	78,115	7119.755	7138.000	2350.126	5432.000	8670.000
CH_EUPH	72,403	0.105	0.000	2.581	-1.251	1.252
CH_TONE	72,403	0.003	0.007	0.159	-0.097	0.106
EUPH_VAR	78,115	1.855	2.000	1.673	1.000	3.000
CH_EUPH_VAR	72,403	0.049	0.000	1.577	-1.000	1.000
SUE	78,115	0.005	0.000	33.868	0.000	0.002
EARN	78,115	0.018	0.037	0.151	0.007	0.076
EPS_GROWTH	78,115	0.255	0.026	3.637	-0.506	0.409
LOSS	78,115	0.214	0.000	0.410	0.000	0.000
RET	78,115	-0.029	0.004	0.251	-0.143	0.115
BM	78,115	0.569	0.459	0.451	0.272	0.735
FIRM_AGE	78,115	44.422	28.000	42.102	13.000	65.000
STD_EARN	78,115	0.062	0.062	0.183	0.012	0.062
STD_FORECAST	78,115	0.044	0.019	0.072	0.010	0.044
STD_RET	78,115	0.026	0.023	0.014	0.016	0.032
ANALYST	78,115	7.348	5.000	6.191	3.000	10.000
SEG_NUM	78,115	2.338	1.000	1.775	1.000	3.000
ASSETS	78,115	8581.551	1666.218	23010.721	478.213	5641.797
SIZE	78,115	5945.848	1425.190	14356.049	499.838	4339.191
XRET_PRELIM	78,115	0.003	0.002	0.087	-0.037	0.043
XRET_DRIFT	78,115	0.006	0.000	0.202	-0.091	0.092

Table 2: Determinants of Euphemism Usage

This table shows the logistic regression results of the euphemism usage on financial and textual variables. The dependent indicator variables (EUPH_USAGE) are for conference calls for which EUPH is over the 75th percentile value for all firms for that quarter. Individual variable definitions are outlined in Appendix 3. For simplicity, quarter and industry dummies are included in the regression, but not reported in the tables. Industry fixed effect is at Fama French's 48 industries classification. p-values are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Variables	EUPH_USAGE	EUPH_USAGE	EUPH_USAGE
Textual Variables			
TONE		-0.5998***	-0.6139***
		(0.0000)	(0.0000)
Log (LENGTH)		2.4705***	2.1936***
		(0.0000)	(0.0000)
Financial Variables			
SUE	-0.3736***		-0.2273***
	(0.0000)		(0.0000)
EARN	0.1495		0.2108*
	(0.2103)		(0.0941)
EPS_GROWTH	-0.0046		-0.0030
	(0.1332)		(0.3390)
LOSS	0.1426***		0.1563***
	(0.0000)		(0.0000)
RET	-0.3890***		-0.2452***
	(0.0000)		(0.0000)
BM	0.3460***		0.2551***
	(0.0000)		(0.0000)
Log (FIRM_AGE)	0.1258***		0.1459***
	(0.0000)		(0.0000)
STD_EARN	-0.1963		-0.2932**
	(0.1353)		0.0391
STD_FORECAST	-0.9747***		-1.2202***
	(0.0000)		(0.0000)
STD_RET	-4.8907***		-9.1697***
	(0.0000)		(0.0000)
Log (ANALYST)	0.3913***		0.1211***
	(0.0000)		(0.0000)
Log (SEG_NUM)	0.1553***		0.1281***
	(0.0000)		(0.0000)
Log (SIZE)	0.1580***		0.0394***
	(0.0000)		(0.0000)
No. Obs.	78,115	78,115	78,115
Quarter FE	YES	YES	YES
Industry FE	YES	YES	YES
Pseudo R-squared	13.50%	17.20%	17.90%

Table 3: Abnormal Returns and Earning Surprises for the Sentiment Signals

This table reports mean excess returns and earning surprise around conference call for portfolios of firms based on the sentiment signals, ranked into quartiles. Panel A tabulates mean excess returns and earnings surprises for the two measures of sentiment. Panel B shows the mean excess returns for portfolios of firms based on the double sorts of TONE and EUPH. Panel C shows the mean excess returns for portfolios of firms based on the double sorts of EUPH and SUE. For this analysis, EUPH, TONE, and SUE are ranked each fiscal quarter into four groups with the corresponding quartile rankings referred to as iEUPH, iTONE and iSUE. Individual variable definitions are outlined in Appendix 3. N is the number of observations in each group for each signal. t-statistics are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Panel A: Mean Excess Return and Earnings Surprises around the Date of the Conference Calls

iEUPH	XRET_ PRELIM	XRET_ DRIFT	iSUE	iTONE	XRET_ PRELIM	XRET_ DRIFT	iSUE
1 (L)	1.0%	1.1%	1.539	1 (L)	-1.4%	0.0%	1.277
2	0.6%	0.9%	1.528	2	-0.3%	0.5%	1.454
3	0.2%	0.5%	1.500	3	0.8%	1.0%	1.581
4 (H)	-0.7%	0.2%	1.433	4 (H)	2.1%	1.2%	1.686
L-H	1.7%***	0.9%***	0.106***	H-L	3.5%***	1.2%***	0.409***
(t-stat)	(18.47)	(4.60)	(9.66)	(t-stat)	(40.32)	(5.57)	(37.23)

Panel B: Cross Tabulation of Mean Excess Return on the Ranked EUPH and TONE sentiment signals

XRET_PRELIM

iTONE	iEUPH1	iEUPH2	iEUPH3	iEUPH4	L-H
1	-0.5%	-1.1%	-1.6%	-2.5%	2.0%
2	0.6%	-0.1%	-0.3%	-1.3%	1.9%
3	1.3%	1.0%	0.6%	0.1%	1.2%
4	2.3%	2.5%	2.1%	1.3%	1.0%
H-L	2.8%	3.6%	3.7%	3.8%	

XRET_DRIFT

1	0.2%	0.0%	0.1%	-0.4%	0.6%
2	0.9%	0.9%	0.0%	0.0%	0.9%
3	1.2%	1.2%	0.9%	0.3%	0.9%
4	1.8%	1.2%	0.7%	0.7%	1.1%
H-L	1.6%	1.2%	0.6%	1.1%	

Panel C: Cross Tabulation of Mean Excess Return on the Ranked EUPH and SUE signals

XRET_PRELIM

iSUE	iEUPH1	iEUPH2	iEUPH3	iEUPH4	L-H
1	-2.5%	-3.4%	-3.9%	-5.1%	2.6%
2	0.0%	-0.4%	-0.7%	-1.4%	1.4%
3	2.1%	2.0%	1.5%	1.1%	1.0%
4	3.9%	4.0%	3.8%	3.3%	0.6%
H-L	6.4%	7.4%	7.7%	8.4%	

XRET_DRIFT

1	0.6%	0.0%	0.1%	0.0%	0.6%
2	1.1%	1.0%	0.6%	0.0%	1.1%
3	0.7%	0.4%	0.5%	0.2%	0.5%
4	1.7%	1.9%	0.5%	0.4%	1.3%
H-L	1.1%	1.9%	0.4%	0.4%	

Table 4: Panel Regression: Immediate Investor Reactions to the Euphemism Usage

The table reports the results of the panel regression of the excess buy-and-hold return around the conference call dates on EUPH and other control variables. The dependent variables (XRET_PRELIM) are the buy-and-hold returns on a stock minus the average return on a matched size-B/ M-momentum portfolio in the interval [-1, +1], where day 0 is the preliminary earnings announcement date. Individual variable definitions are outlined in Appendix 3. For simplicity, quarter and industry dummies are included in the regression, but not reported in the tables. Industry fixed effect is at Fama French's 48 industries classification. t-statistics are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Variables	XRET_PRELIM	XRET_PRELIM	XRET_PRELIM
EUPH	-0.0146***	-0.0123***	-0.0121***
	(-16.84)	(-14.22)	(-13.92)
TONE		0.0317***	0.0265***
		(32.19)	(26.41)
Log (LENGTH)	-0.0007	-0.0030***	-0.0048***
	(-0.76)	(-3.41)	(-5.07)
SUE	0.0892***	0.0849***	0.0848***
	(95.80)	(90.84)	(90.17)
EPS_GROWTH			0.0001
			(0.08)
Log (ASSETS)			0.0008
			(0.49)
BM			-0.0176***
			(-24.97)
STD_EARN			-0.0042***
			(-2.52)
No. Obs.	78,115	78,115	78,115
Quarter FE	YES	YES	YES
Industry FE	YES	YES	YES
R-squared	11.26%	12.37%	13.85%

Table 5: Panel Regression: Subsequent Investor Reaction to the Euphemism Usage

The table reports the results of the panel regression of the excess buy-and-hold subsequent returns on EUPH and other control variables. The dependent variables are XRET_DRIFT, which is the buy-and-hold return on a stock minus the average return on a matched size-B/M-momentum portfolio from 2 days after the preliminary earnings announcement date through 1 day before the subsequent quarter's preliminary earnings announcement. Individual variable definitions are outlined in Appendix 3. For simplicity, quarter and industry dummies are included in the regression, but not reported in the tables. Industry fixed effect is at Fama French's 48 industries classification. t-statistics are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Variables	XRET_DRIFT	XRET_DRIFT	XRET_DRIFT
EUPH	-0.0084***	-0.0076***	-0.0093***
	(-3.96)	(-3.60)	(-3.27)
TONE		0.0112***	0.0128***
		(4.60)	(5.07)
Log (LENGTH)	-0.0016	-0.0024	-0.0009
	(-0.73)	(-1.11)	(-0.41)
SUE	0.0049**	0.0038	0.0027
	(2.01)	(1.57)	(1.11)
XRET_PRELIM	0.0161***	0.0147***	0.0126***
	(6.63)	(6.01)	(5.01)
EPS_GROWTH			0.0004*
			(1.95)
Log (ASSETS)			0.0001
			(0.27)
BM			0.0054***
			(3.04)
STD_EARN			0.0021
			(0.50)
No. Obs.	78,115	78,115	78,115
Quarter FE	YES	YES	YES
Industry FE	YES	YES	YES
R-squared	0.46%	0.49%	0.51%

Table 6: Panel Regression: Market Reaction to the Changes in Euphemism Usage

The table reports the results of the panel regression of the excess buy-and-hold immediate and subsequent returns on the changes in the sentiment signals and other control variables. The dependent variables are XRET_PRELIM and XRET_DRIFT. XRET_PRELIM is the buy-and-hold returns on a stock minus the average return on a matched size-B/ M-momentum portfolio in the interval [-1, +1], where day 0 is the preliminary earnings announcement date. XRET_DRIFT is the buy-and-hold return on a stock minus the average return on a matched size-B/M-momentum portfolio from 2 days after the preliminary earnings announcement date through 1 day before the subsequent quarter's preliminary earnings announcement. Individual variable definitions are outlined in Appendix 3. For simplicity, quarter and industry dummies are included in the regression, but not reported in the tables. Industry fixed effect is at Fama French's 48 industries classification. t-statistics are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Variables	XRET_PRELIM	XRET_PRELIM	XRET_DRIFT	XRET_DRIFT
CH_EUPH	-0.0034***	-0.0034***	-0.0025***	-0.0025***
	(-12.72)	(-12.33)	(-3.54)	(-3.26)
CH_TONE	0.0347***	0.0327***	0.0157***	0.0165***
	(36.41)	(34.02)	(6.55)	(6.77)
Log (LENGTH)	-0.0037***	-0.0053***	-0.0036*	-0.0018
	(-4.35)	(-5.62)	(-1.73)	(-0.74)
SUE	0.0851***	0.0848***	0.0024	0.0017
	(88.51)	(87.10)	(0.95)	(0.67)
XRET_PRELIM			0.0123***	0.0111***
			(4.88)	(4.26)
EPS_GROWTH		0.0001		0.0004**
		(0.93)		(2.09)
Log (ASSETS)		-0.0005***		-0.0003
		(-2.38)		(-0.57)
BM		-0.0202***		0.0053***
		(-28.40)		(2.96)
STD_EARN		-0.0078***		0.0055
		(-3.74)		(1.06)
No. Obs.	72,403	72,403	72,403	72,403
Quarter FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared	13.31%	14.89%	0.53%	0.55%

Table 7: Robustness Test: Fama-MacBeth Regressions of Excess Returns on the Euphemism Signal

The table presents the results of Fama-McBeth style regression of the excess immediate (XRET_PRELIM) and subsequent drift (XRET_DRIFT) buy-and-hold return around the conference call dates on euphemism signal. XRET_PRELIM is the buy-and-hold return on a stock minus the average return on a matched size-B/ M-momentum portfolio in the interval [-1, +1], where day 0 is the preliminary earnings announcement date. XRET_DRIFT is the buy-and-hold return on a stock minus the average return on a matched size-B/ M-momentum portfolio from 2 days after the preliminary earnings announcement date through 1 day after the subsequent quarter's preliminary earnings announcement. Individual variable definitions are outlined in Appendix 3. The table reports average coefficients from the quarterly cross-sectional regressions. The averages are time-series means with t-statistics computed using the standard error of the mean. Significance levels are based on the standard error of the coefficient across the quarterly regressions in a manner of Fama and MacBeth (1973). ***, **, * denote significance at 1%, 5% and 10% level.

Variables	XRET_PRELIM	XRET_PRELIM	XRET_DRIFT	XRET_DRIFT
EUPH	-0.0114***		-0.0098***	
	(-10.07)		(-3.93)	
CH_EUPH		-0.0037***		-0.0031***
		(-10.35)		(-3.44)
TONE	0.0272***		0.0111***	
	(20.08)		(4.18)	
CH_TONE		0.0325***		0.0161***
		(18.39)		(4.46)
Log (LENGTH)	-0.0064***	-0.0056***	-0.0009	-0.0001
	(-3.80)	(-4.66)	(-0.29)	(-0.26)
SUE	0.0805***	0.0819***	0.0009	0.0019
	(25.74)	(31.47)	(0.26)	(0.63)
XRET_PRELIM			0.0043	0.0046
			(1.03)	(1.41)
EPS_GROWTH	0.0001	0.0002	0.0001*	0.0001*
	(0.57)	(1.17)	(1.69)	(1.88)
Log (ASSETS)	0.0004	-0.0001	0.0001	0.0001
	(1.38)	(-0.04)	(0.08)	(0.25)
BM	-0.0197***	-0.0230***	0.0052	-0.0006
	(-11.20)	(-12.00)	(0.90)	(-0.11)
STD_EARN	-0.0003	-0.0108*	0.0147	0.0199
	(-0.04)	(-1.92)	(0.70)	(0.81)
No. Obs.	78,115	72,403	78,115	72,403
No. Regressions	55	53	55	53
Quarter FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared	19.78%	20.93%	1.1%	1.2%

Table 8: Robustness Tests: Firms with Market Cap> $500M

The table reports the results of the panel regression of the excess buy-and-hold immediate and subsequent returns on the sentiment signals and other control variables for the sample that excludes small-cap firms: firms with market capitalization less than $500 M. The dependent variables are XRET_PRELIM and XRET_DRIFT. XRET_PRELIM is the buy-and-hold returns on a stock minus the average return on a matched size-B/ M-momentum portfolio in the interval [-1, +1], where day 0 is the preliminary earnings announcement date. XRET_DRIFT is the buy-and-hold return on a stock minus the average return on a matched size-B/M-momentum portfolio from 2 days after the preliminary earnings announcement date through 1 day before the subsequent quarter's preliminary earnings announcement. Individual variable definitions are outlined in Appendix 3. For simplicity, quarter and industry dummies are included in the regression, but not reported in the tables. Industry fixed effect is at Fama French's 48 industries classification. t-statistics are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Variables	XRET_PRELIM	XRET_PRELIM	XRET_DRIFT	XRET_DRIFT
EUPH	-0.0119***		-0.0079***	
	(-13.65)		(-3.82)	
CH_EUPH		-0.0031***		-0.0023***
		(-11.71)		(-3.71)
TONE	0.0256***		0.0078***	
	(25.10)		(3.21)	
CH_TONE		0.0300***		0.0073***
		(30.51)		(3.14)
Log (LENGTH)	-0.0040***	-0.0048***	-0.0001	-0.0001
	(-3.97)	(-4.76)	(-0.00)	(-0.40)
SUE	0.0824***	0.0817***	-0.0046*	-0.0047*
	(79.00)	(76.03)	(-1.75)	(-1.76)
XRET_PRELIM			0.0038	0.0033
			(1.52)	(1.28)
EPS_GROWTH	-0.0000	0.0000	0.0003	0.003
	(-0.12)	(0.21)	(1.48)	(1.26)
Log (ASSETS)	0.0040*	0.0001	0.0001	-0.0004
	(1.79)	(0.24)	(0.15)	(-0.75)
BM	-0.0222***	-0.0243***	0.0141***	0.0131***
	(-24.42)	(-26.67)	(6.53)	(6.09)
STD_EARN	-0.0092***	-0.0072**	0.0091	0.0178**
	(-2.75)	(-2.01)	(1.15)	(2.09)
No. Obs.	54,451	51,792	54,451	51,792
Quarter FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared	14.32%	14.95%	0.61%	0.64%

Table 9: Robustness Tests: Alternative Measure of Euphemism Usage

The table reports panel regression results for the sample, using variability of euphemism usage (*EUPH_VAR*) as an alternative measure of euphemism usage in a conference call. The dependent variables are XRET_PRELIM and XRET_DRIFT. XRET_PRELIM is the buy-and-hold returns on a stock minus the average return on a matched size-B/ M-momentum portfolio in the interval [-1, +1], where day 0 is the preliminary earnings announcement date. XRET_DRIFT is the buy-and-hold return on a stock minus the average return on a matched size-B/M-momentum portfolio from 2 days after the preliminary earnings announcement date through 1 day before the subsequent quarter's preliminary earnings announcement. Individual variable definitions are outlined in Appendix 3. For simplicity, quarter and industry dummies are included in the regression, but not reported in the tables. Industry fixed effect is at Fama French's 48 industries classification. t-statistics are reported in parenthesis. Significance level: *** p < 0.01, ** p < 0.05, * p <0.1.

Variables	XRET_PRELIM	XRET_PRELIM	XRET_DRIFT	XRET_DRIFT
EUPH_VAR	-0.0124***		-0.0082***	
	(-13.75)		(-3.61)	
CH_EUPH_VAR		-0.0096***		-0.0043**
		(-11.86)		(-2.15)
TONE	0.0265***		0.0129***	
	(26.42)		(5.12)	
CH_TONE		0.0328***		0.0169***
		(34.14)		(6.93)
Log (LENGTH)	-0.0045***	-0.0052***	-0.0011	-0.0002
	(-4.69)	(-5.49)	(-0.49)	(-0.52)
SUE	0.0849***	0.0849***	0.0028	0.0018
	(90.20)	(87.13)	(1.12)	(0.69)
XRET_PRELIM			0.0127***	0.0113***
			(5.05)	(4.35)
EPS_GROWTH	0.0001	0.0001	0.0004**	0.0004**
	(0.10)	(0.95)	(1.96)	(2.09)
Log (ASSETS)	0.0001	-0.0005**	0.0000	-0.0002
	(0.45)	(-2.39)	(0.19)	(-0.52)
BM	-0.0174***	-0.0202***	0.0055***	0.0053***
	(-24.72)	(-28.41)	(3.10)	(2.97)
STD_EARN	-0.0042**	-0.0080***	0.0022	0.0054
	(-2.51)	(-3.82)	(0.51)	(1.04)
No. Obs.	78,115	72,403	78,115	72,403
Quarter FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared	13.85%	14.87%	0.49%	0.53%

ESSAY 3: Do Directors Have a Use-By Date?

Examining the Impact of Board Tenure on Firm Performance

1. INTRODUCTION

The length of time company directors stay on board ("board tenure") is a controversial issue that has attracted the attention of professional investors, regulators, and academics. The call by institutional investors for board "refreshment" – allowing new members to enter the board – is driven by the desire for a more diverse mix of board members and by the conventional wisdom that long-serving board members become entrenched[10]. The thinking is that entrenchment leads to cozy relationships between board members and executives, thereby diminishing the ability of board members to effectively represent shareholders' interests. A regulatory solution to this issue would be to limit director tenure by imposing a tenure limit.

The corporate governance literature that examines the relationship between board tenure and firm market value is scant and characterized by inconsistent findings. Some studies find that longer board tenure is detrimental to firm value, as it leads to the decrease of board independence (Vafeas 2003), governance problems (Berberich 2011), and lack of critical thinking by board members (Coles et al. 2015). On the other hand, a different stream of literature finds that board tenure is improving board's functionality, as longer-tenured board members are less susceptible to pressure by managers (Beasley 1996, Schnake et al. 2005), are more knowledgeable about company operations (Rutherford 2007), and are more likely to curb opportunistic behavior by managers (Hamouda et al. 2013 and Dou et al. 2015). One potential reason for the inconsistent empirical findings may be related to the small samples used by these studies. Most existing studies are limited to case studies,

[10] Some recent news articles about investors' concern regarding the length of directors' tenure include Frances (2016), Murphy (2016), Stein (2016), and Vekshin (2015).

extreme cases (e.g. companies with fraud or financial statement restatements), and specific industries. Another possible explanation for the inconsistent results is the inherent endogeneity of board selection, as board members might prefer to stay longer on boards of a better-performing companies, or shareholders of good companies might be reluctant to refresh a board when things are not "broken". This leads to strikingly opposite results even when researchers use very similar samples for their testing. For example, using the sample of S&P 1,500 firms, Dou et al. (2015) finds that extended tenure is favorable for company performance. However, Huang (2013), using the same sample of firms over the same period, finds that beyond a certain threshold board tenure becomes detrimental to firm value.

In this paper, we view board tenure[11] as a measure of how stable a certain mix of director capital[12] has been, and study how it impacts board effectiveness in value creation through its advisory and monitoring functions. On one hand, longer board tenure signals that the shareholders have appointed and maintained a board with the relevant mix of board capital. Therefore, increasing tenure of a board can be viewed as a proxy for an able and well-functioning board that is positively contributing to firm value. However, even if a board has a relevant mix of capital to perform its duties effectively, this ability might be diminished by the board's incentives to monitor managers. As board members' tenure increases, they become more connected to the firm's management (Vafeas 2003) and less motivated to effectively monitor managers. In addition to the indirect effect of board tenure on monitoring incentives, board tenure might have a direct effect on the relevance of board

[11] Our measure of board tenure is the **average** board tenure of all independent board members of a given company, at a given year; therefore, our predictions and tests relate to this overall measure of board tenure and not to the tenure of individual directors.
[12] Following Hillman and Dalziel (2003), we define board capital as board member's ability to perform their organizational functions.

capital. With time, as a firm is changing, board capital might become stale and less relevant to the needs of the firm. Therefore, extreme values of board tenure can be signaling both boards' disincentives to effectively monitor management and the staleness of board capital. This can lead to the negative impact of board tenure on firm value, and this latter effect is likely to be especially pronounced for fast-growing firms, where changing firm needs and strategic directions may cause faster deterioration of board capital.

In our study, we consider the relationship between board tenure and firm market value, as measured by both contemporaneous and forward-looking market-to-book ratios and stock returns. We study this relationship using an extensive sample of U.S. firm over 1996-2016. We find that longer average board tenure is positively related to both contemporaneous and future market-to-book. However, this relationship reverses at a certain point, roughly after eight to nine years of average board tenure. Beyond this "benchmark" for the average board tenure, we observe a deterioration in valuation that is especially significant for growing firms. For the stock return-based tests, we find that board tenure is reflected in stock returns in a similar manner to market values, and that the declining effect of long board tenure is similarly more pronounced for dynamic, growing firms. We also find that an investment strategy that holds long positions in stocks of companies with long board tenure (more than 12 years of average tenure) and short positions in companies with short board tenure (less than two years of average tenure) earns statistically significant abnormal returns ranging between 0.49 and 0.70 percent per month.

Overall, our results are consistent with the inverted U shape for Tobin's Q established by Huang (2013), who finds that nine years is a point in director's tenure after which the positive relationship between the board tenure and firm value starts to deteriorate. However, our study is different from Huang (2013), as we contribute to the existing literature along several dimensions. First and most important, we show that the relationship between board tenure and firm value is reflected in forward-looking measures of equity value - next-period market-to-book and next month abnormal returns, while Huang (2013) uses a contemporaneous measure of firm value only. By using forward-looking measures of firm value and stock returns we are also mitigating the endogeneity problems inherent in prior studies. Second, we disentangle the effect of tenure on the board's ability (board capital) by showing how a company's growth options determine the relationship between board tenure and firm value. We show that firm attributes, such as its growth rate, impacts the optimal average board tenure, suggesting that a uniform regulation limiting board tenure across companies and at all times may not be desirable. Finally, we have the largest sample used to-date to test the relevance of board tenure – up to 3,800 individual firms over a 20-year period.

The remainder of our paper is organized as follows. Section II discusses the prior literature in the area, and Section III follows with hypotheses development. In Section IV, we describe the research design and the data used in the study. Section V presents the empirical results, with Section VI providing additional robustness tests on the relationship of firm value and board tenure. Section VII concludes.

2. PRIOR LITERATURE

There is a substantial literature on the importance of tenure in explaining the performance of decision makers in different professions. For mutual fund managers, Chevalier (1999) finds that longer tenure helps them retain their job, as these managers are less likely to be terminated based on their performance, compared to younger portfolio managers. This "entrenchment" of longer-tenured managers stems from their higher than average performance early in their career: in effect, they are branded as having superior skills and abilities going forward. However, their outperformance is mainly due to chance and later results in mean reversion (Porter et al. 2012). For credit analysts, tenure matters when it comes to their tenure covering specific firms for the rating agency: their optimism increases and accuracy decreases with tenure covering the firm (Fracassi et al. 2015). Auditors' tenure contributes to firm value up to a certain point in time, as reflected in equity risk premium, with the relationship reversing at the extreme values of tenure (Boone et al. (2008). CEO tenure is negatively affecting firm performance in dynamic industries because prolonged tenure CEOs tend to develop a relatively fixed paradigm of managing the firm and unwillingness to accept new information or initiate strategic changes (McClelland et al. 2012). Politicians seem to be more effective in later periods of their tenure, as elections draw nearer. Ghosh (2006) finds that both property crimes and violent crimes in India go up in the initial years of an incumbent politician's tenure and then decline in the later periods of their tenure, closer to re-election. Tenure does not seem to matter when it comes to academic performance. For example, Li et al. (2010) find that the productivity (total number of papers) and impact (citations of papers) of the economics and finance faculty from top twenty-five schools remains consistent before and after they attain tenure.

Prior literature looks for evidence that board tenure is a board characteristic that can have an impact on firm performance and firm value by influencing the director monitoring or advising functions. Empirical papers find contradictory results about the relationship between tenure and board's monitoring function. Some researchers argue that seasoned board members over time become friendlier with managers and lose their ability to objectively examine managers' actions, thus decreasing the level of board independence and contributing to the erosion of firm value. Board tenure is thus viewed as a proxy for the extent to which outside directors are affiliated with management. For example, Vafeas (2003) claims that, in time, directors might be co-opted by managers when directors become less mobile and less attractive to other companies. He finds that directors who stay on the board the longest are significantly more likely to have a fiduciary relation with the firm (so called "grey directors" – bankers, consultants, lawyers), are more likely to be affiliated with managers from the beginning of their board tenure, and tend to have more power and more equity ownership in the firm. Finally, he finds that this lack of independence is positively related to the amount of CEO's salary. Following similar argument about the increasing lack of oversight by complacent board members, Berberich et al. (2011) find a positive association between director tenure and the probability that a company will experience some governance problems, such as bankruptcies, major litigations, major accounting restatements, or corporate scandals.

On the other hand, another stream of literature argues that longer-tenured board members are in a better position to scrutinize senior managers because they are less susceptible to peer pressure and are less likely to be controlled by managers. Two event studies ((Beasley 1996) and (Schnake et al. 2005)) examine firms with corporate governance problems: Beasley (1996) looks at firms with cases of fraud while Schnake et al. (2005) examine firms with 10-K investigations. Both studies find that longer board service increases the outside directors' ability to monitor managers more effectively to prevent fraud or 10-K investigations. An association study by Sharma (2011) examines the role of board tenure in controlling managerial discretion over the use of excess cash flow as measured by the dividend payout policy. She argues that dividend policy is one area where conflicts between management and shareholders may occur and the board is the ultimate internal governance mechanism charged with protecting shareholders' interests. She finds that the tenure of independent directors is positively related to the likelihood of a dividend payout. Bonini et al. (2015) find some evidence that longer-tenured board members (with tenure over 20 years) are better at monitoring management actions because they gather and store valuable information about the firm and can share it with other independent directors. They find that such firms are more profitable and have higher market value.

Similarly, researchers that examine how tenure affects the board’s advisory function find inconsistent results. On one hand, an argument is made that longer tenure of board members allows them to learn more information about the operations of the company, making it easier for them to understand the firm’s unique economic environment and financial reports, resulting in their improved ability to provide more informed advice to the management team. This, in turn, should result in a better-run firm. Studies that examine information-gathering practices of board members provide some support for this line of argument. For example, Rutherford et al. (2007) find that longer-tenured boards exchange information more frequently, as measured by the number of board committees. Additionally, a group of studies provide empirical evidence that better informed boards, as proxied by board tenure, provide better advice to managers that enhances the value of the firm. For instance, Muller-Kahle et al. (2011) show that financial service companies that chose to specialize in subprime lending and, and as a result, were negatively affected by subprime loan defaults had board members with less tenure, as compared to “smart” firms that avoided these risky business practices. Howton (2006) finds that firms with longer tenure boards are more likely to survive after an IPO vs. firms that fail or are acquired, and Hamouda et al. (2013) show that more seasoned boards are more likely to curb predatory insider trading practices around share repurchase announcements.

On the other hand, some studies of the relation between tenure and advisory function of the board hypothesize that board members might become complacent and stop learning about the firm’s operations the longer they stay on board. For instance, Coles et al. (2015) introduce a measure of *groupthink* – a way of thinking by cohesive groups where peer-pressure overrides the need for critical thinking. In the study *groupthink* is proxied by the length and the degree of overlap of board tenure. The study does not find support for the blanket prediction that *groupthink* has a negative effect on value for all types of firms, as measured by contemporaneous Tobin Q. However, the study does find evidence that the effect of groupthink on firm value is negative in dynamic industries, firms with smaller boards, and in firms that have boards with fewer outside connections. This is consistent with the idea that, holding group cohesion constant, the tendency to suffer from groupthink is harder to overcome in smaller boards and in boards with fewer outside connections.

Several studies in the area look at the interaction of both monitoring and advisory functions with board tenure and study how it is reflected in firm value. Huang (2013) finds that the relationship between board tenure and contemporaneous firm value (measured by Tobin Q) is in the shape of an inverted U that reaches a peak at about nine years. He finds that the value of companies initially rises, as directors acquire firm-specific knowledge early in their tenure. However, this continues only up to a certain threshold of tenure beyond which independence losses outweigh the learning gains and board tenure becomes detrimental to firm value. Dou et al. (2015) find that directors' performance improves with extended tenure. They find that longer-serving directors have a higher level of commitment, are better at controlling CEO turnover and CEO pay, have lower likelihood of intentionally misreporting earnings, and are also more likely to restrict the expansion of resources under CEO control (acquisitions are more rare and of higher quality).

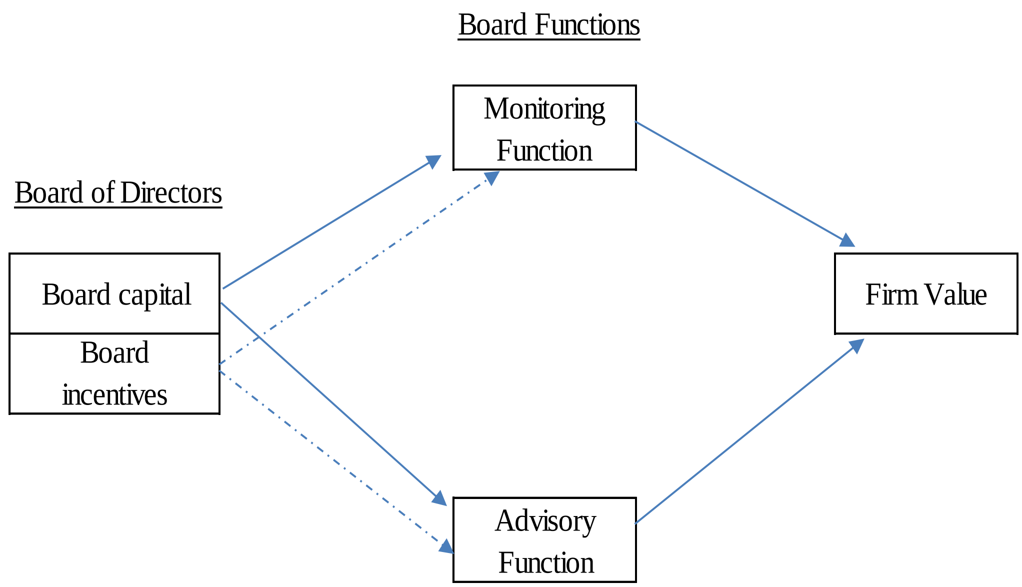
Huang (2013) is the closest to our study, so we need to emphasize our contributions beyond his study. Board tenure might be endogenously related to firm performance (Hermalin and Weisbach 1998), as board members might choose to stay on the board longer or investors might choose not to refresh a board if a firm is performing well. In comparison to Huang (2013), our use of forward-looking measures of firm value allows us to better address the concerns of endogeneity to identify the value of board tenure. In terms of sample size, our paper has the largest sample compared to all prior studies that mostly concentrate on extreme cases (i.e., fraud or accounting restatements) or on specific industries, which limits their sample size and brings into question the generalization of the results to the general population.

3. HYPOTHESIS DEVELOPMENT

We examine the relationship between board tenure and firm value within the framework developed by Hillman and Dalziel (2003) that considers both the direct effect of board capital on the monitoring and advisory functions of the board and the moderating effect of board incentives. Boards have two main functions: monitoring management on behalf of shareholders (monitoring function) and providing resources to the firm (advisory function). Effective monitoring by the boards lowers agency costs which in turn results in enhanced firm value (Fama 1980). Provision of resources by the board contributes to firm value by helping reduce dependency between the organization and external contingencies, diminish uncertainty for the firm, and lower transaction costs (Pfeffer and Salancik 1978). In order to be able to perform these two functions well, a board needs relevant board capital that consists of human capital (i.e. expertise, experience, knowledge of board members) and relational capital (i.e. connections that board members have to other organizations, prestige of directors, influence with political organizations, etc.).

While board capital is the board's ability to perform the two main board functions, board incentives influence the efforts that directors exercise in performing these functions. They can motivate board members to, for example, be more proactive in reaching out to their external connections to secure more favorable financing terms for the company. It should be noted that if a director has an incentive, but does not have the ability (for example, a director does not have the right banking connection in the example above), s/he will not be able to perform this board function (i.e. secure good financing terms for the firm). In other words, board members' ability to perform their functions are limited by the board's capital, and board incentives can only moderate boards' effectiveness in performing these functions. Exhibit 1 illustrates the relationship between the components of the theoretical framework described above.

Exhibit 1 Board of Directors and Firm Value



Boards with the relevant capital have the ability to monitor management and provide additional resources for the firm thus contributing positively to firm value. When investors are unhappy with director ability (capital), they refresh the board with a more relevant mix of board capital. Therefore, board tenure is a measure of how long a certain mix of director capital has been unchanged, and, in effect, longer board tenure signals that shareholders have appointed a board with the relevant mix of board capital. Increasing board tenure can be viewed as a proxy for an able and well-functioning board that is positively contributing to firm value. This leads to our first hypothesis in the following form:

Hypothesis 1: Longer board tenure indicates that shareholders have selected board members with appropriate monitoring and resource provision abilities to meet the needs of the firm that contribute to the appreciation of firm value. Therefore, we expect a positive relationship between board tenure and firm value.

Both board capital and incentives determine the board performance. If a board has the ability to perform monitoring, this ability might be enhanced or diminished by board's incentives to monitor managers. As board members' tenure increases, they become more connected to the firm's management through business dealings and social connections, and, as a result, more dependent of management. Board dependence on management will then act as a disincentive to monitor managers, negatively affecting the relationship between the boards' ability to monitor and the actual monitoring of management. This, in turn, will lead to the increasing agency costs between managers and owners and will negatively impact shareholder value. In addition to the indirect effect of board tenure on monitoring incentives, board tenure might have a direct effect on the relevance of board capital. With time, as a firm is changing, board capital might become stale and less able to meet the needs of the firm. Without refreshing the board capital in time, shareholders might be running the risk of ending up with a mix of board capital that no longer meets the needs of the firm. Therefore, extreme values of board tenure can be, on one hand, signaling boards' disincentives to effectively monitor management and, on the other hand, the staleness of board capital. This leads to our second hypothesis:

Hypothesis 2: Beyond certain tenure threshold, we expect a reversal in the relationship between board tenure and firm value as board member's capital becomes stale and board's dependence on firm management creates disincentives for board members to monitor managers.

As we have outlined above, board capital determines its ability to perform its two main functions. In equilibrium, board capital maximizes firm value by providing required monitoring and advising services for a particular firm. However, as a firm changes its business strategy, shareholders will need to "rebalance" board capital and possibly appoint new board members that have the most appropriate human and relationship capital to meet the new needs of a firm. We expect that this rebalancing of board capital should happen more frequently for fast-growing firms, and those firms that do not rebalance in time will suffer from the deterioration in firm value. This reasoning leads to our third hypothesis:

Hypothesis 3: The reversal of the positive relationship between board tenure and firm value is more pronounced for fast-growing firms.

4. SAMPLE AND RESEARCH DESIGN

4.1 Sample Selection

The board data in this study is from the Capital IQ database for 1996 to 2016. It is extracted from the *CIQ_Professional* table, which includes data about professionals associated with various organizations. We first extract all observations with a valid *CompanyID* (it is used to link to the Compustat and CRSP databases), a valid *PersonID* (it links the individual across years and companies), and a valid start date. We identify board members as individuals with the following titles (*Profunctionname* in the table): "Chairman of the Board", "Co-Chairman of the Board", and "Member of the Board of Directors".[13] We restrict our sample to independent board members only, i.e. those who are unemployed by the firm[14]. For each director-year observation, we then calculate the length of director board tenure. If an individual was elected to the board, for instance, in 1998, we use 1998 to calculate that person's tenure in 1999 (one year later) and onwards. This way, in 2005 that person's tenure is seven years.

The dataset includes additional items such as director age, the ending date for the director position, whether the individual is a current board member, and the year in which the firm was founded. If the ending date is missing and the individual is a current board member, we set the end-year to be 2017. If the ending date is missing and the individual is not a current board member, we set the end-year to equal the start year. We delete observations where the start year is earlier than the year the firm was founded or prior to 1945. To test

---

[13] Some companies have advisory boards, so it is important to focus on members of the board of directors.
[14] The results are unchanged when we include all board members in our tests.

the accuracy of the sample data, we examine the data for four companies, two large and two small, in the late 1990's and in the late 2010's against the proxy statements available in the SEC EDGAR database. We found a very high accuracy for the latter years, and some missing board members (less than 25 percent) for the early years.

We obtain accounting data from the Compustat Point-in-Time database[15] and stock return data from the Center for Research in Security Prices (CRSP) database. We require all companies in our sample to be incorporated in the US, have a positive book value and to be founded at least five years before we begin tracking their board tenure. To reduce the bias caused by smaller firms, we require a market value in excess of $100 million, and a minimum of three independent members on the board. Throughout our research we standardize accounting and stock return variables to a normal distribution, bound between plus and minus three to deal with outliers in the data. As a robustness check, we re-perform our tests using winsorized variables and the results are unchanged. For all other level-based variables we use the natural logarithm to manage outliers.

4.2 Research Design

To test our hypotheses, we focus on the relationship between board tenure and two measures of firm performance: 1) firm value, as proxied by market-to-book; and 2) stock returns.

4.2.1 Firm Value and Board Tenure

[15] Charter Oak Compustat Add-On Database reports preliminary, un-restated, first-reported earnings filed with the SEC. This eliminates the discontinuities that result from subsequent restatements and provides a more accurate picture as to what fundamentals the company disclosed to investors at a particular point in time.

We examine the relationship between firm value and board tenure in both univariate and multivariate settings. For the univariate test, we rank all firms in our sample into deciles based on the average board tenure ("tenure deciles"). We industry-adjust the measure of firm value by subtracting, annually, the median market-to-book for the firm's industry using the Fama-French 48-industry classification. We then examine the median values of the industry-adjusted market-to-book values across different tenure deciles. Next, we examine the relationship between board tenure and firm value in a multivariate setting. First, we estimate the relationship between board tenure and contemporaneous firm value to test prior findings by researchers on a larger sample of firms[16]. To do this, we estimate variations of the following model:

$$Market/\,Book_{it} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it} \quad (1)$$

We calculate our main variable of interest, *Tenure,* by taking the average board tenure of all independent board members for each firm for each year. In order to account for the expected non-monotonic relationship of a particular form of board tenure and market value, we also include a squared *Tenure* term. We include control variables that capture both firm and board characteristics previously shown to be related to firm value. For board controls we include *Board size*, the number of independent directors on the board, *Average Age*, the average age of independent directors on the board, *Connections*, the average number of boards that directors are serving on, including the current firm board, and *Chair CEO*, an indicator when the CEO also serves as board chair. Yermack (1996) establishes the value relevance of board size. We add Average *Age* as a control variable to disentangle the effect

[16] The largest sample used in the previous studies of board tenure is the one used by Huang (2013). It includes all firms in S&P 1500 over the period 1998 to 2010 – 13,989 firm-year observations. In comparison, our sample consists of 34,082 firm-year observations over the period 1996-2016.

of board tenure from the director's age. Well-connected boards likely add to firm value by providing better advice to managers, due to for information transmission between companies (Larcker 2013) and their ability to affect business relationships with other firms; *Connections* controls for this enhanced advisory function due to the board centrality. Goyal and Park (2002) show that CEO duality (*Chair CEO*) makes it harder for boards to dismiss an ineffective CEO and results in the inferior firm performance.

For firm controls, we use Annual sales (*Sales12m*), firm age (*Firm Age*), and number of business segments (*SegNum*) to control for size and complexity, which may affect the advisory role of board members. Growth opportunities of the firms are captured by *Intangible*s (scaled by Total Assets), *Leverage* (scaled by Total Assets), and *R&D* intensity (scaled by Sales). Firm profitability is controlled by two *ROA* variables – one for current and one for next period. We also include standard deviation of daily stock returns during the prior calendar year (*StdRet*), as a proxy for firm stability. We rely on prior studies to select firm and board controls, such as Hermalin and Weisbach (1988), Denis and Sarin (1999), Bhagat and Black (2001), and Baker and Gompers (2003).

Model (1) is first estimated as a panel regression with industry and year fixed effects[17]. Next, to examine the stability of the relationship between board tenure and firm value through time, we run cross-sectional regressions annually and calculate the time-series average of the coefficients and report t-statistics using the time-series standard error of the mean.

A common concern in empirical corporate governance research is the impact of reverse causality. When it comes to board tenure, directors might be interested in staying longer

[17] As a robustness check, we estimate the model with firm and year fixed effects; the results remain unchanged.

on the boards of better performing firms, or firms with good performance might be reluctant to "refresh" the board, following a *do-not-fix-what-ain't-broken* line of reasoning. As an attempt to address this endogeneity concern we use forward (instead of contemporaneous) values of market-to-book as a dependent variable in model (1) (an approach adopted by Hermalin and Weisbach (1991)). Following Rajgopal and Shevlin (2002), we use contemporaneous values of market-to-book as an additional dependent variable:

$$Market/\,Book_{it+1} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Market/\,Book_{it} + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it} \qquad (2)$$

Next, we test the effect of the growth option on the value relevance of board tenure using panel regressions and Fama and MacBeth (1973) style regressions on firm-level data. We modify model (1) by adding an interaction of growth option proxies with a squared *Tenure* term and by including the growth option proxy as a control variable. Specifically, we estimate:

$$Market/\,Book_{it} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Tenure_{it}^2 \times Growth\ Proxy + Growth\ Proxy\ Dummy + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it} \qquad (3)$$

We use four proxies for firm growth options: (i) *R&D*, an indicator variable equal to one if the firm's ratio of research and development expenses to sales is over the 75th percentile value for all firms for that year. We choose the 75th percentile value because the median R&D for the firms in the sample is zero. The level of R&D captures the extent of resources that the company dedicates to development of new products. (ii) *SalesGrowth1*, an indicator variable equal to one if a firm's sales growth is above the median value of other firms in that year. Sales growth captures the scale of growth experienced by the company. (iii) *SalesGrowth3*, an indicator variable equal to one if firm's three-year sales growth is above the median value of other firms for the year. We use *SalesGrowth3* to capture longer-run growth effects. (iv) *Fluidity*, an indicator variable equal to one if firm's Fluidity score is above the median value of other firms for the year. Fluidity score is a growth measure developed by Hoberg, Phillips, and Prabhala (2014) and is available from the online data at http://cwis.usc.edu/projects/industrydata/industryconcen.htm. It is derived from the descriptions of general business in the firms' annual financial statements, and it reflects tactics adopted by the competitor firms. Fluidity score is higher when the words in the firm's business description overlap more with the words of the rivals' business description. Hoberg et al. (2014) argue that fluidity scores capture changes in rival firms' products and reflect the pressures firms face from the competitor firms.

4.2.2 Stock Returns And Board Tenure

In our second set of tests, we investigate the relationship between board tenure and stock returns. All of these return-based tests focus on the ability of board tenure to explain future one-month abnormal stock returns. Evaluating the ability of board tenure to explain future stock returns is a strong test to further address concerns surrounding causality and endogeneity.

First, we perform simple univariate sorts of stocks based on board tenure, and examine the pattern of excess stock returns. This allows us to examine any linear and non-linear relationships between board tenure and future stock returns. Each month we separate all firms into quintiles and deciles based on *Tenure*. We carry forward the board tenure measure computed at the end of a calendar year over the next 12 months. We use three different measures of abnormal stock returns. First, *X_RET* is the excess stock return, defined as the monthly raw stock return in excess of the capitalization-weighted market return. Second, *DGTW_RET* is the characteristic adjusted excess return of a stock computed using the Daniel et al. (1997) methodology. In Daniel's approach, *DGTW_RET* is the buy and hold return on a security minus the capitalization-weighted average buy and hold return on a portfolio of firms with similar size (three groups), B/M (three groups) and 11-month momentum (three groups). Third, *FF_RET* is a measure of risk adjusted return, defined as the intercept of a four-factor model that includes three Fama-French factors and momentum (see Fama and French (1993) and Carhart (1997)):

$$Rp_t - Rf_t = a + b \cdot [Rm_t - Rf_t] + s \cdot SMB_t + h \cdot HML_t + u \cdot UMD_t + e_t \tag{4}$$

Second, we examine the relationship between firm abnormal returns (*DGTW_RET*) and board tenure in a multivariate setting. We use a Fama and MacBeth (1973) style regression model, including the previously described board and firm controls:

$$DGTW\_RET_{it+1} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it} \tag{5}$$

Each month end, we estimate the cross-sectional regression Model (5). We then calculate the time-series average of the coefficients and report t-statistics using the time-series standard error of the mean coefficient.

In our third set of stock return tests, we examine the value relevance of board tenure for predicting stock returns of high growth firms using Fama-MacBeth regressions on firm-level data:

$$\begin{aligned} DGTW_{RET}{}_{it+1} &= \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Tenure_{it}^2 \times Growth\ Proxy + Growth\ Proxy\ Dummy \\ &+ Board\ Controls_{it} + Firm\ Controls_{it} \\ &+ \epsilon_{it} \end{aligned} \tag{6}$$

We use five proxies for firm growth options similar to Model (3) and add *Market-to-Book* as an additional proxy for growth. *Market-to-Book* is defined as an indicator variable equal to one if firm's market-to-book ratio is above the median value of other firms for the year. Market-to-book ratio is higher for high growth firms as market price is factoring a higher expected future growth for the firm and a higher return on its assets.

5. RESULTS

5.1 Summary Statistics

Figure 1 plots the firm-year observations for our sample. Our final sample comprises of 638,717 firm-month observations, with 1,335 individual firms at the beginning of our sample period (year 1996) going up to 3,802 in 2006 and coming down after the financial crisis to 3,152 individual firms in 2016.

Insert Figure 1 here

Table 1 presents important firm and board characteristics of companies in our sample. An average independent director serves on the board for six years (*Tenure* has 6.7 mean and 6.0 median), is 58 years old, and sits on three boards (mean for *Connections* is 2.80). Boards have seven independent directors on average and in about 36% of firms the CEO also serves as board chair. Our sample firms are fairly large, with average market capitalization of $5.9 billion and sales of $4.4 billion.

Insert Table 1 here

Examining the correlations of *Tenure* with firm characteristics, we note that firms with longer-tenured board members are older (correlation of 34 percent with *Firm Age*), more profitable (7 percent correlation with *ROA*) with low-volatile stock returns (negative correlation of 19 percent with *StdRet*). All this confirms our expectation that board tenure is a proxy for firm stability. The correlation of *Tenure* and our proxies for firm growth are all negative, which is consistent with the hypothesis that higher *Tenure* is more damaging to high-growth firms. Panel B reports the correlation between our various proxies for growth: these variables have generally positive correlations with each other.

5.2 Board Tenure and Firm Value

In this section, we test our hypothesis of the effects of board tenure on firm value, proxied by Market-to-Book. We focus on three issues: effect of board tenure on contemporaneous firm value, effect of board tenure on forward-looking measure of firm value, and the effect of board tenure on the value of high-growth firms. Our analysis for each is discussed below.

For our univariate tests, we rank firms each year into deciles based on the board tenure and examine the values of industry-adjusted Market-to-Book values across the deciles. Figure 2 plots the average and median board tenure values across the deciles. The length of director tenure ranges from less than 2 years (first decile) to more than 14 years (highest decile). Figure 3 shows how firm values change across the tenure deciles. Initially, firm value is increasing with the length of director tenure: for example, if a firm has a high director turnover (firms in the lowest decile of tenure – D1), it is valued about 5% lower than other firms in the industry in terms of its market-to-book ratio. However, if directors remain on board for four to five years (D3-D4), firm's valuation is at par with its peers. The highest valuation premium (3% above the median for the industry) is achieved by the boards with nine years of tenure, after which the valuation ratio starts to decline.

Insert Figures 2 and 3 here

Next, we test our hypothesis in a multivariate setting. Table 2 presents the results of panel regressions for Model (1). In the first specification, we include only board tenure as a dependent variable and observe an insignificant statistical relationship. However, once we include a squared tenure term in the second specification, the coefficient on *Tenure* become statistically significant and positive, while the coefficient on the squared *Tenure* term is significantly negative. As we include further controls in regression (3) and (4), we see that the coefficients for *Tenure* and squared *Tenure* term remain significant at the 1% level. This confirms our prediction that, on average, board tenure is positively related to firm value, but the contribution to firm value begins decreasing at some point and longer board tenure beyond this critical point becomes a drag on firm valuation.

The coefficients on firm controls in the regression are consistent with our expectations: controls for size (*Sales*, *SegNum*) are negative and significant, while controls for growth (*Intangibles*, *Leverage*, *R&D, and ROA*) are positive and significant. Consistent with our expectations, *StdRet*, our additional control for stability, is negative and significant. Turning to board controls, we find that *Average Age* is negatively related to market value, which is consistent with the expected associations in the corporate governance literature that older directors are less active in monitoring managers' performance (e.g., Core et al. 1999). For *Board Size* we observe a positive relationship, contrary to the association established by Yermack (1996), which can be explained by the differences in the time frame between our studies. We observe a positive and significant coefficient for *Connections*, which is consistent with findings by Larcker (2013). Companies that have a CEO who is also a chair of the board seem to be valued higher: the coefficient on *Chair CEO* is positive and significant. This finding contradicts Goyal and Park 2002, which again might be due to the differences between the sample periods and sample sizes.

Insert Table 2 here

As a robustness check, we examine model (1) cross-sectionally for each year in our sample. The coefficients from the annual regressions, as well as average coefficients and Fama-Macbeth t-statistics are reported in Table 2 Panel B. We only show the coefficients and t-statistics for *Tenure* and *Tenure Squared*; but indicate for each regression whether industry, firm, and board controls are included. Similar to our panel regression results, we continue to observe a positive and significant coefficient for *Tenure* and negative and significant coefficient for the squared *Tenure* term for most years in our sample.

We recognize that our results might be affected by possible endogeneity of our board tenure constructs. As an attempt at addressing these endogeneity concerns, we estimate the statistical association between *Tenure* and firm value using next-period market-to-book as a dependent variable, while controlling for market-to-book ratios in the current year. The results (presented in Table 3) continue to confirm our prediction of a positive relationship between *Tenure* and firm value (positive and significant coefficient for *Tenure*), with the relationship deteriorating beyond a certain point (negative and significant coefficient for the squared term). The results in Table 3 suggest that our findings in Table 2 are robust to potential econometric problems induced by endogenous independent variables. Furthermore, it reveals that while board tenure effects are associated with contemporaneous market-to-book, the market does not appear to fully appreciate the importance of board tenure and the positive effect of tenure persists in the forward-looking measure of equity value. This finding strengthens our expectation that the positive effect of board tenure is also reflected in stock returns.

Insert Table 3 here

The results of our analysis of value relevance of board tenure for growth firms are presented in Table 4 (Panel A shows the results of panel regressions and Panel B – Fama-MacBeth style regressions). The results indicate that tenure is negatively related to firm value for high-growth firms: the coefficients on the interaction of all growth proxy dummies and the squared *Tenure* term are negative for all proxies and significant in most cases. In all four specifications, *Tenure* remains positively associated with firm value, while the squared *Tenure* term remains negative, which is consistent with our previous findings. Overall, the results in Table 4 provide evidence that confirms our prediction that longer *Tenure* is detrimental to the market value of high growth firms beyond a certain point. Our growth option analysis provides some evidence that the relationship between board tenure and firm value can be further refined by factoring in additional firm-specific attributes.

Insert Table 4 here

5.3 Board Tenure and Stock Returns

The analysis presented above suggests that increasing board tenure is positively related to firm value up to a certain point, after which board tenure becomes a drag on firm valuation. This relationship holds for both contemporaneous and forward-looking measure of market value. The latter finding, in particular, suggests that a similar relationship may hold for stock returns. If so, this would allow for a portfolio strategy that exploits the information content of board tenure. We investigate this further by studying the hypothetical portfolio returns investors could have generated by buying firms with certain board tenure attributes.

The first two columns in Table 5 present average abnormal monthly returns (*X_RET* and *DGTW_RET*) for quintiles and deciles of portfolios formed based on *Tenure*. Both measures of abnormal returns are increasing monotonically to the middle of the *Tenure* range with the highest value at sixth decile: 0.41 percent monthly return for X_RET and

0.26 for DGTW_RET. In deciles seven through ten, both *X_RET* and *DGTW_RET* start to flatten out and decline. The magnitude of the spread return earned by investor who takes a long position in the highest quintile/ decile of stocks ranked on *Tenure* and a short position in the lowest groups range from 0.70 percent to 0.49 percent per month (statistically significant at the 1% level). However, it appears a more appealing strategy would be to go long on the firms in the middle groups of stock sorted on tenure, while shorting firms within the lowest *Tenure* group (monthly returns on this strategy would be up to 0.74 percent for *X_RET* and 0.72 percent for *DGTW_XRET*).

Our additional measure of abnormal returns is the intercept (*FF_RET*) of a four-factor model that includes three Fama-French factors and momentum, as specified in Model (4). The intercept from these regressions follows a pattern that is similar to that of *X_RET* and *DGTW_RET*: the spread abnormal returns range from 0.51% for the quintiles of *Tenure* portfolios (Panel A) to 0.72% for the deciles (Panel B).

Insert Table 5 here

Figure 4 plots *X_RET*, *DGTW_RET* and *FF_RET* for the deciles of portfolios formed on board tenure. For all three measures the pattern is similar to the inverted U-shape for market value observed in Figure 3. These results verify that the relationship observed between board tenure and firm value is also reflected in various measures of excess stock returns.

Insert Figure 4 here

Next we test whether the relationship between stock returns and board tenure holds in a multivariate setting. Following Fama and MacBeth (1973), we regress characteristic-adjusted excess returns (*DGTW_RET*) on *Tenure* and the squared *Tenure* term, including firm, board and industry controls, as specified in Model (5). We use time-series means and t-statistics for statistical inference. As Table 6 reveals, the coefficient on *Tenure* is positive and significant across all specifications, verifying an overall positive relationship between *Tenure* and excess returns. For regression (1), we find that in a univariate regression board tenure is positively related to future returns and is significant, unlike our findings for market-to-book.

Insert Table 6 here

The relationship between board tenure and future returns can be strengthened by including a quadratic tenure term. In regression (2) we include a squared board tenure term and find the coefficient on board tenure is now two times the size as the comparable coefficient in regression (1). Moreover, the squared term in regression (2) is negative and significant at the 5% level. Once we control for firm and board effects, the board tenure coefficients and significance are only modestly reduced, demonstrating the strength of the result. This confirms our prediction that board tenure is a positive for firms up to a certain point; however, after that further benefits do not arise for shareholders.

We now revisit our predictions that for high-growth firms the deterioration of firm value will show at the earlier stages of board tenure. We investigate whether the evidence from Table 4 suggesting that long board tenure is especially damaging to the market value of high-growth companies also holds for stock returns. Table 7 repeats the analysis performed in Table 4, adding one more proxy for growth – *Market-to-Book*. Specifically, we regress our measure of excess stock returns (*DGTW_RET*) on the interaction of the squared *Tenure* term and the growth dummy, keeping all other controls used in model (4). The results in Table 7 are weaker but consistent with the evidence uncovered previously in Table 4: the coefficient on the interaction variable is negative and statistically significant in one specification, while the rest of proxies seem to be statistically insignificant. The *Tenure* term is consistently positive and significant, while the squared term remains negative and significant.

Insert Table 7 here

6. ROBUSTNESS TESTS

Our research is not without inherent limitations. This section presents the results of additional tests to check the robustness of the main results. Specifically, we consider whether our results are driven by: 1) our sample selection, 2) our design of board tenure measure, 3) behavior of executive board members, 4) our selection of linear model to capture nonlinear relationship between firm value and board tenure, and 5) adverse selection of long-tenured board members. Additionally, in order to align our monthly return tests with the tests that use book-to-market as a dependent variable, we perform tests of the relationship between board tenure and stock returns by using annual stock returns as our dependent variable.

6.1 Sample Selection

Our results might be driven by the sample selection. First, we have fewer observations in the early years of our sample. Additionally, it is possible that the database started counting the length of tenure from the point of time that a director is added to the database. This would bias tenure in the early years of our sample to be shorter than it actually was. In order to address this concern, we separate our sample into two groups: a group of observations for the period of 1996-2003 and a group of observations for the period of 2004-2014. We test whether the relationship between board tenure and firm value and monthly returns holds for the two groups: Panel A of Table 8 reports the regression results. For both sub-periods we find results that are consistent with our main findings. In particular, board tenure is positively related to firm value up to a certain point, after point the positive relationship reverses. This reversal is reflected in the negative coefficient of the squared *Tenure* term.

Insert Table 8 here

The relationship between board tenure and firm value may also change with firm size, consistent with the well-documented size anomaly (e.g., Fama and French (1993, 2014)). To ensure that the paper's results are not driven by small-cap stocks, we re-perform our tests on the sub-samples of large-cap and small-cap stocks (we define large-cap companies as companies with market capitalization larger than the median market capitalization for the full sample in each year). The results in Panel A of Table 8 show that our findings hold both for large-cap and small-cap stocks: the board tenure has an inverted U-shape relationship with firm value for both sub-samples.

6.2 Our Design Of Board Tenure Measure

Another concern is that our main explanatory variable might be misspecified. Bonini et al. (2015) argue that using the average to capture the effect of long board tenure of the directors might be confounding the effect of a single long tenure, as it gets diluted by the tenure of the other board members with short or average tenures. To ensure that the paper's results are not driven by our choice of the main explanatory variable, we perform several additional robustness checks.

First, we replace the average board tenure with the median board tenure in our tests. Panel B1 of Table 8 presents the results of our baseline regression, using median as our main explanatory variable (*Med Tenure*). The coefficient on *Med Tenure* is positive and significant at the 1% level, while the coefficient on the squared term is negative and significant. In unreported results we also find that using median board tenure results also shows that the negative effect of the squared term is especially pronounced for high-growth firms. The results show that our findings are robust to using median as an alternative main explanatory variable.

Insert Table 8 here

Second, in order to further address the criticism that average board tenure might be a noisy measure, we examine whether our results are robust to different levels of standard deviation of board tenure. We separate our sample based on the median value of standard deviation of board tenure and re-run our baseline regression for the two sub-samples. Panel B1 shows the results for firms with high and low standard deviation of board tenure. *Tenure* and *Tenure Squared* terms retain their signs consistent with the main findings for both companies with high and low standard deviations of board tenure.

Finally, we test the effect of long board tenure on firm performance by using the proportion of long-serving directors as a dependent variable. For each company, we calculate the number of directors with tenure greater than 15 years[18] ("long-serving directors") and divide it by the total number of directors on the board in that year. We re-run regression (1) replacing average board tenure terms with the percentage of long-serving directors. The resulting coefficient on the dependent variable of interest is negative and significant at the 1% level, which supports our earlier conclusion that extreme terms of board tenure are detrimental to the firm values.

[18] Our choice of 15 years is consistent with the average value for the top decile in Figure 2. This cutoff point is also consistent with the definition of long-tenured directors in Bonini et al. (2015).

Our main results might also be driven by companies with extremely low board tenure. As can be seen in Figure 3, companies that belong to the first decile of the average board tenure have significantly lower market-to-book than the ones in deciles two or three. In order to address the criticism that our results might be driven by these outliers, we re-run our main results excluding firms that fall into decile one of average board tenure. The first column of Panel B2 shows that our results still hold if we restrict our test sample in this way: *Tenure* and *Tenure Squared* terms retain their signs and remain statistically significant at the 1% level. We further test the sensitivity of our results to the presence of low board-tenure companies in our sample by excluding firms both in decile one and two from our sample: the results are presented in column two of Panel B2. Even though the statistical significance of both *Tenure* and *Tenure Squared* terms weakens, the direction of the relationship between them and firm value remains unchanged.

6.3 Use Of Linear Model

Standard linear models might be inappropriate to capture the relationship between firm value and a corporate governance construct due to potential nonlinearities between corporate governance measures and other variables. In order to address this concern, we perform an additional test to confirm that the reversal in the relationship between board tenure and firm value is correctly captured by the squared *Tenure* term.

We partition our sample into two groups. Each year, we create a high board tenure group of firms, and a corresponding low board tenure group. High board tenure firms are the ones that have average board tenure that exceeds the 75^{th} percentile of board tenure for that year; low board tenure firms are the rest of the firms in our sample. We then estimate Model (1) as a panel regression, and also in a cross-sectional form, for each group of firms. We modify Model (1) by excluding the squared board tenure term because we would like to capture the point where the linear relationship between board tenure and firm value changes by creating the two groups of firms. Panel C of Table 8 presents the results of our test. We find that for our low board tenure sample board tenure is positively and significantly related to firm value. However, for our high board tenure sample, board tenure is negatively and significantly related to firm value. These results confirm our findings that board tenure and firm value are positively related, with the relationship reversing at longer terms of board tenure.

Insert Table 8 here

6.4 Adverse Selection Of Long-Tenured Board Members

It may be argued that long-tenured board members remain on their boards because they are not offered better board memberships on other firms, and therefore cannot upgrade their board memberships into more prestigious boards (similar to the lemon argument by Akerlof (1970)). To assess whether this is the case, we identify all cases in our universe where a board member has added another board membership during the year. We then compare the new board membership to an average of the prior board memberships along several dimensions.

In unreported results, we find that the new firm that is added is typically smaller in terms of market value than the average firm in which the board member had membership in the prior year. It also is less profitable in terms of ROE, net income scaled by book value of equity, and has a lower B/M (book to market value of equity) ratio. We find a similar pattern when a board membership is dropped. The dropped firm is typically smaller and has lower ROE and B/M ratio than the remaining firms in which the board member retains membership.

We also examine the average tenure of board members who added one more board membership, and compare it to the average tenure of all other board members in the same firms. We find that the person who added a board membership had a board tenure that was shorter than the average of other members by just 0.3 years. Thus, our data does not support the conjecture that inferior board members remain on the board because they are not offered better opportunities.

6.5 Board Tenure And Annual Stock Returns

Our tests of board tenure and monthly stock returns are consistent with the prevailing asset pricing methodology. However, it can be argued that because board tenure variable is measured annually, next year annual stock returns might be a more appropriate dependent variable for the tests. To address this, we re-run our tests of stock returns and board tenure using excess annual stock returns as a dependent variable. Table 9 presents the results for all four specifications. *Tenure* term remains positive and significant, as we add firm and board controls, while *Tenure Squared* is consistently negative and significant in most specifications. These results confirm our prior findings regarding the relationship between board tenure and stock returns.

Insert Table 9 here

7. CONCLUSIONS

Understanding the relationship between average board tenure and firm value is of fundamental importance to practitioners, academics and regulators. Calls of institutional and activist investors to “refresh the boards” and limit director tenure are shaping the regulatory environment. But these actions are not supported by a consistent set of results in the corporate governance literature.

This paper studies the value relevance of board tenure using the largest sample of firms compared to previous studies in the literature. We find considerable support for the notion that longer board tenure is positively related to future stock returns, as well as contemporaneous and future firm value. The market rewards firms with long-serving boards with a ‘stability’ premium. However, over time, the effectiveness of two primary board functions – monitoring and advising management – deteriorates. Tenure has a direct negative effect on the boards’ ability to keep up with the firm growth and a moderating effect on the board’s incentive to monitor managers. Effectiveness of board members peaks at average tenure of about nine years, at which point board tenure begins to become a drag on the company valuation relative to the nine year tenure. This reduction in effectiveness is especially pronounced for high-growth firms for which up-to-date knowledge of company operations is especially important for the company’s success.

We add to the existing literature in a number of ways. First, our findings are less prone to the biases that characterize prior studies in the area: our large sample of firms across 20 years and various industries addresses some of the small sample issues of prior studies. Second, we use forward-looking measures of firm value to test the value-relevance of board tenure in an attempt to mitigate the endogeneity problem. Third, we examine the effect of board tenure on firm returns, which allows us to suggest a viable portfolio strategy based on the length of board tenure. Finally, we provide some evidence regarding the effect of tenure on high growth firms that partially explains the nonlinear relationship between board tenure and firm value.

REFERENCES

Akerlof, G. A. 1970. The Market for 'lemons': quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84, 3, 488–500.

Baker, M., and P. Gompers. 2003. The determinants of board structure at the initial public offering. *Journal of Law and Economics* 46, 569–598.

Beasley, M. S. 1996. An empirical analysis of the relation between the board of director composition and financial statement fraud. *The Accounting Review* 71 (4): 443-465.

Berberich, G., and F. Niu. 2011. Director business, director tenure and the likelihood of encountering corporate governance problem. Working paper, Wilfrid Laurier University.

Bhagat, S., and B. Black. 2001. The non-correlation between board independence and long term firm performance. *Journal of Corporation Law* 27, 231–274.

Bonini, S., J. Deng, M. Ferrari, and K. John. 2015. 'Til death do us part: the long tenured directors' puzzle. Working paper, Stevens Institute of Technology, New York University, University of Modena.

Boone, J., I. Khurana, and K. Raman. 2008. Audit firm tenure and the equity risk premium. *Journal of Accounting, Auditing & Finance*, 23, 1, 115-140.

Carhart, M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52, 56–82.

Chevalier, J., and G. Ellison. 1999. Career concerns of mutual fund managers. *Quarterly Journal of Economics*, 114, 2, 389-432.

Coles, J., D. Naveen, and L. Naveen. 2015. Board Groupthink. Working paper, University of Utah, Drexel University, and Temple University.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance* 52 (3): 1035-1058.

Denis, D., and A. Sarin. 1999. Ownership and board structures in publicly traded corporations. *Journal of Financial Economics* 52, 187–223.

Donoher, W. J., and R. Reed. 2007. Employment capital, board control, and the problem of misleading disclosures. *Journal of Managerial Issues* 19 (3): 362-378.

Dou, Y., S. Sahgal, and E. J. Zhang. 2015. Should independent directors have term limits? The role of experience in corporate governance. Working paper, University of New South Wales.

Fama, E. 1980. Agency problems and the theory of the firm. *Journal of Political Economy*, 88: 288-307.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Fama, E. F., and K. R. French. 2014. A five-factor asset pricing model. Working paper, Booth School of Business, University of Chicago.

Fama, E. F., and J. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81, 607–636.

Fracassi, C., S. Petry, and G. A. Tate. 2015. Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics*, Forthcoming

Francis, T., and J.S. Lublin. 2016. Big investors question corporate board tenures. *The Wall Street Journal*, March 23, 2016.

Ghosh, A. 2006. Electoral cycles in crime in a developing country: evidence from the Indian States. Working paper, Mathematical Policy Research, Inc.

Goyal, V.K., and C.W. Park. 2002. Board leadership structure and CEO turnover. *Journal of Corporate Finance* 8, 49–66.

Hamouda, F., and M. B. Arab. 2013. Board of directors and insider trading with share repurchase programs. *Journal of Management & Governance* 17 (2): 405-418.

Hermalin, B., and M. Weisbach. 1988. The determinants of board composition. *Rand Journal of Economics* 19, 589–606.

Hermalin, B., and M. Weisbach. 1991. The effect of board composition and direct incentives on firm performance. *Financial Management* 20, 101–112.

Hermalin, B.E., Weisbach, M.S., 1998. Endogenously chosen boards of directors and their monitoring of the CEO. *American Economic Review* 88, 96–118.

Hillman, A.J., Dalziel, T. 2003. Boards of directors and firm performance: integrating agency and resource dependence perspectives. Academy of Management Review, Vol. 28, 3, 383-396.

Hoberg, G., G. M. Phillips, and N. Prabhala. 2014. Product market threats, payouts, and financial flexibility. *Journal of Finance*, 69, 1, 293-324.

Howton, S. W. 2006. Effect of governance characteristics on the state of the firm after an initial public offering. *Financial Review* 41 (3): 419-433.

Huang, S. 2013. Zombie boards: board tenure and firm performance. Working paper, Singapore Management University.

Klein, A. 1998. Firm performance and board committee structure. *Journal of Law and* Economics 41, 137–165.

Larcker, D. F., E. C. So, and C. Y. Wang. 2013. Boardroom centrality and firm performance. *Journal of Accounting & Economics*, 55, 2-3, 225-250.

Li, S., and H. Ou-Yang. 2010. Explicit incentives, implicit incentives, and performance: evidence from academic tenure. Working paper, Wilfrid Laurier University and Cheung Kong Graduate School of Business.

McClelland, P., V. Barker, and W. Oh. 2012. CEO career horizon and tenure: future performance implications under different contingencies. *Journal of Business Research,* 65, 9, 1387-1393.

McDonald, M., and J. Westpal. 2003. Getting by with the advice of their friends: CEOs' advice networks and firms' strategic responses to poor performance. *Administrative Science Quarterly* 48, 1-32.

Miller, D. 1991. Stale in the saddle: CEO tenure and the match between organization and environment. *Management Science* 37, 34-52.

Muller-Kahle, M. I., and K. B. Lewellyn. 2011. Did board configuration matter? The case of US subprime lenders. *Corporate Governance: An International Review* 19 (5): 405-417.

Murphy, M. 2016. Directors say 'Yes' to term, age limits, yet practice remains rare: survey. *The Wall Street Journal*, January 19, 2016.

Pfeffer, J., and G. Salancik. 1978. The external control of organizations: a resource-dependence perspective. New York: Harper & Row.

Porter, G., and J. Trifts. 2012. The best mutual fund managers: testing the impact of experience using a survivorship bias free dataset. *Journal of Applied Finance*, 22, 1, 105-117.

Rajgopal, S., and T. Shevlin. 2002. Empirical evidence on the relation between stock option compensation and risk taking. *Journal of Accounting and Economics* 33, 145–171.

Rutherford, M. A., and A. K. Buchholtz. 2007. Investigating the relationship between board characteristics and board information. *Corporate Governance: An International Review* 15 (4): 576-584.

Sharma, V. 2011. Independent directors and the propensity to pay dividends. *Journal of Corporate Finance* 17 (4): 1001-1015.

Schnake, M. E., W. B. Fredenberger, and R. J. Williams. 2005. The influence of board characteristics on the frequency of 10-k investigations of firms in the financial services sector. *Journal of Business Strategies* 22 (2): 101-117.

Stein, M.L. 2016. Investors question independence of long-stay directors. *The Wall Street Journal*, February 23, 2016.

Vafeas, N. 2003. Length of board tenure and outside director independence. *Journal of Business Finance & Accounting* 30 (7/8): 1043-1064.

Vekshin, A. 2015. Calpers pushes boards to clear room for the young and ethnic. *Bloomberg Politics*, November 12, 2015.

Yermack, D., 1996. Higher market valuation of companies with a small board of directors. *Journal of Financial Economics* 40, 185–212.

Figure 1 Sample Size

Figure 1 plots the number of firms over the sample period. We require firms to be founded at least five years before we begin tracking their board tenure. Also, we require a market value in excess of $100 million, a minimum of three members on the board, and a positive book value.

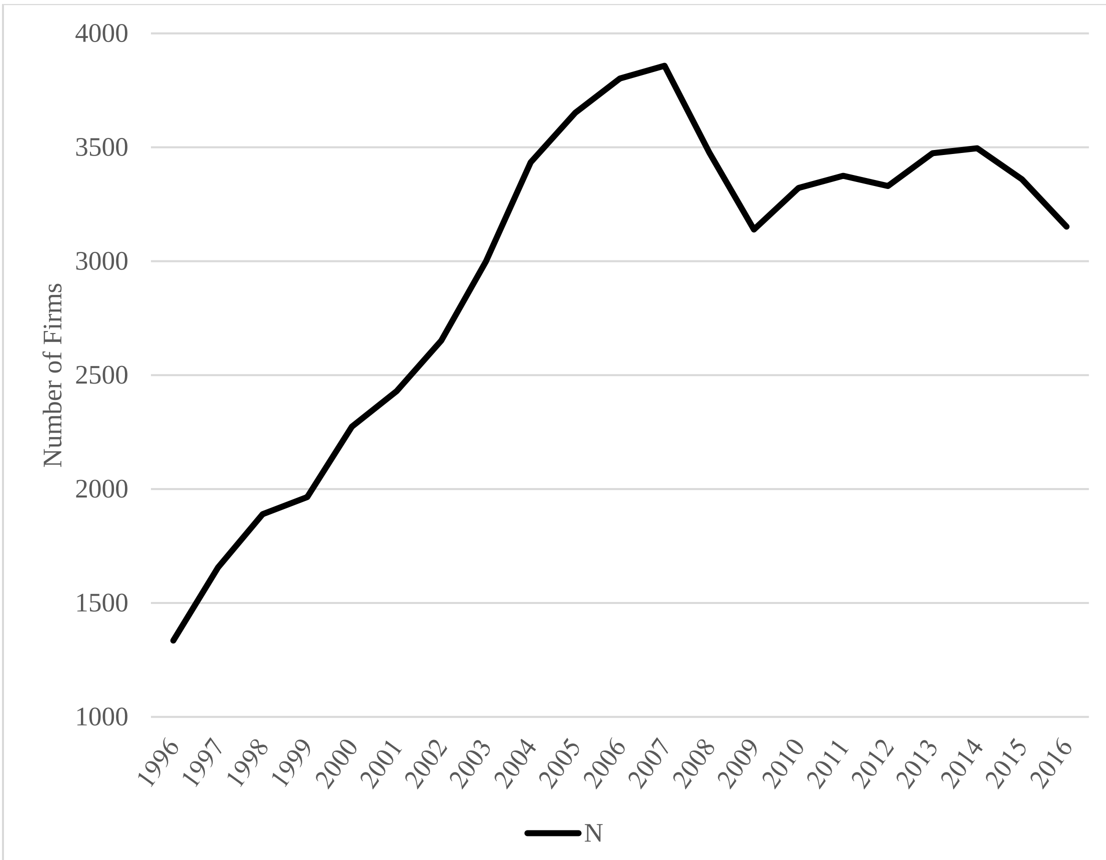


Figure 2 Average and Median Board Tenure by Deciles

Figure 2 plots average and median board tenure (in years) for groups of firms formed based on board tenure. We rank firms each year into deciles based on the board tenure for each firm. The average and median tenure is calculated for each decile.

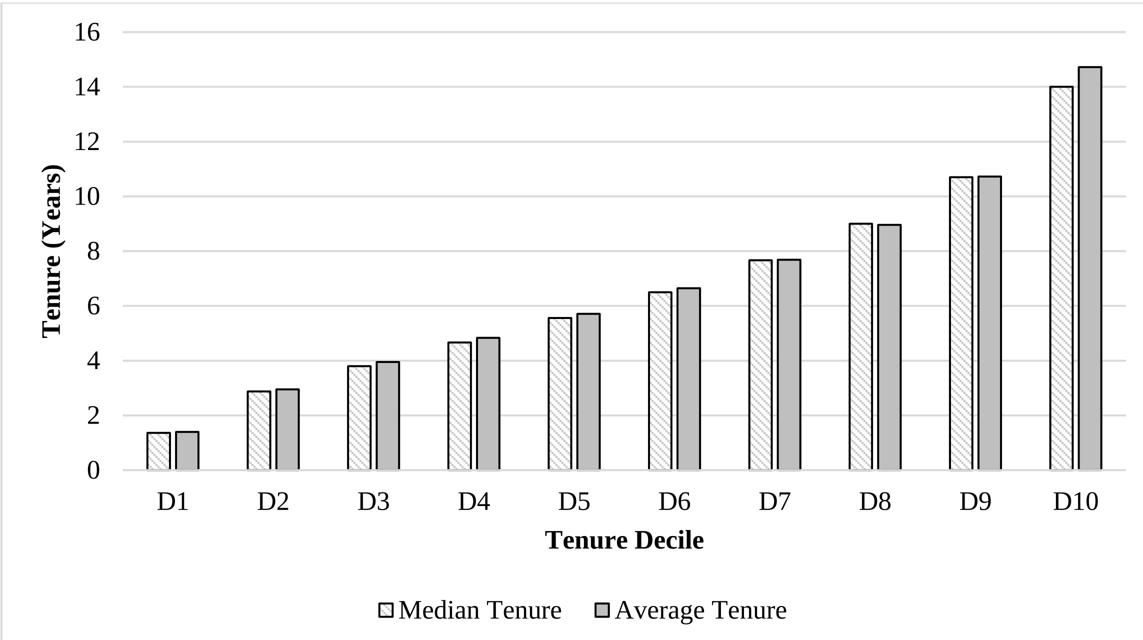


Figure 3 Market-to-Book Sorted by Tenure Deciles

Figure 3 plots median Market-to-Book value for portfolios of firms formed based on the board tenure. Market-to-Book values are annually adjusted by subtracting the median value for the industry, using Fama-French 48 industry classifications. Portfolios are formed by ranking firms each year into deciles based on the average board tenure for the firm.

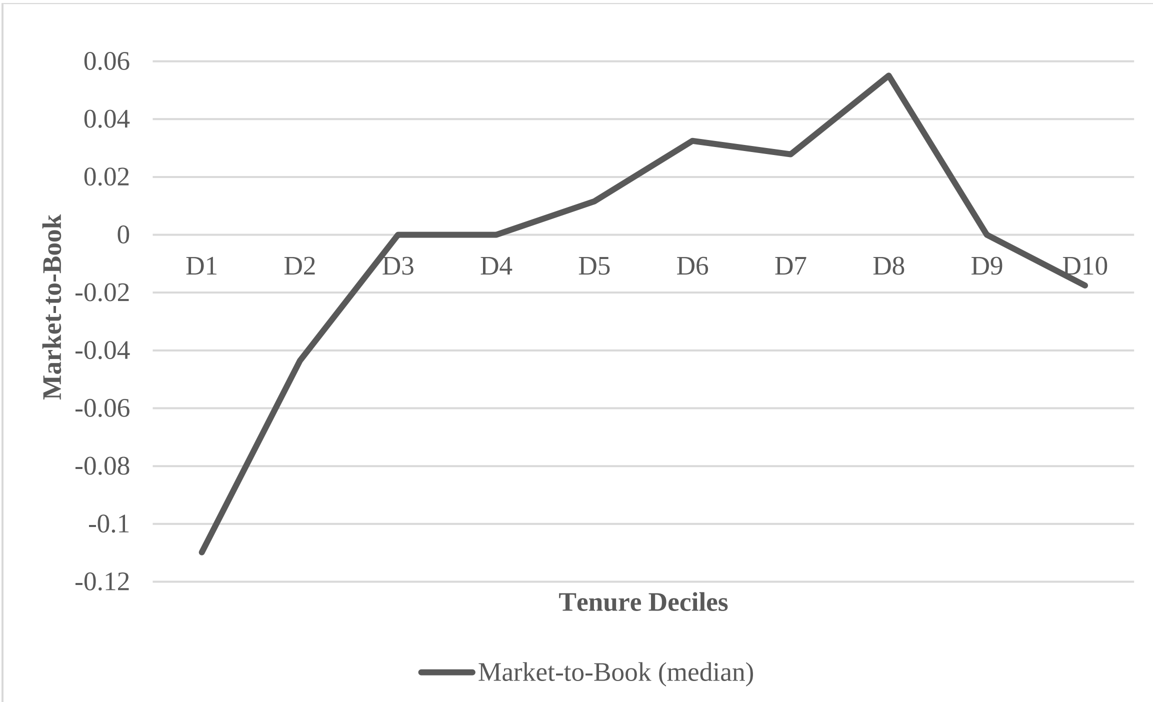


Figure 4 Excess Returns on Firms Sorted by Tenure Deciles

Figure 4 plots average excess returns (*XRET*), characteristic adjusted returns (*DGTW RET*), and risk-adjusted returns (*FF RET*) for portfolios of firms formed based on the average board tenure. The portfolios are formed by ranking firms each month into deciles based on the average board tenure for the firm.

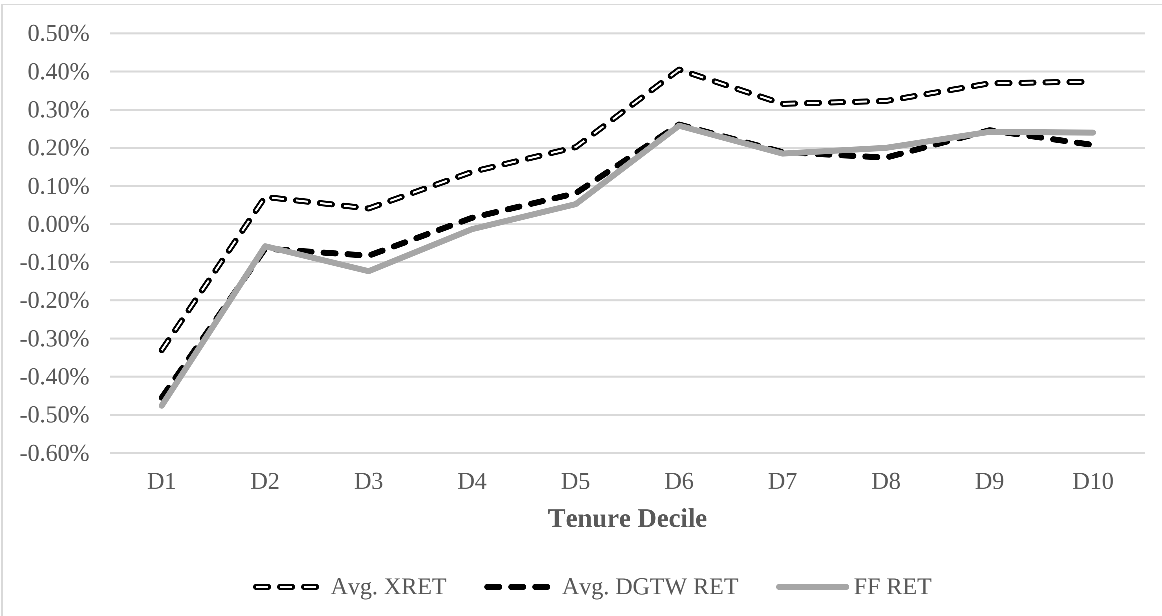


Table 1
Descriptive Statistics and Correlations

The table below provides descriptive statistics for our key variables. The sample consists of all firms on *Capital IQ* database for the years 1996-2016. The board information is from Capital IQ, financial information is from Compustat, and market information is from the CRSP database. *Tenure* is the average of the tenure of all independent directors sitting on the board. An individual director's tenure is calculated as the year of annual meeting minus the start year of directorship minus any breaks in the service of directorship. *Med Tenure* is the median of the tenure of all independent directors sitting on the board. *Std Tenure* is the standard deviation of the tenure of all independent directors sitting on the board. *Average Age* is the average age of board members. *Board Size* is the number of directors. *Connections* is the average number of boards the board members serve on (including the firm observation). *Chair CEO* is an indicator variable that equals to one when the CEO also serves as board chair, zero otherwise. *Market cap* is the market value of equity. *Book value* is the book value of equity. *Book-to-market* is book value of equity divided by the market value of equity. *RET* are the one-month ahead buy and hold security returns from CRSP. *DGTW RET* are one-month ahead abnormal returns calculated as the monthly buy and hold security returns from CRSP minus the value-weighted average buy and hold return on securities with the same size (market capitalization, 3 groups), Book/Market (3 groups) and 11-month momentum (3 groups). *StdRet* is the standard deviation of daily stock returns during the prior calendar year. *Firm Age* (years) is the number of years since the firm is first listed in CRSP database. *Sales* are 12-month sales for a company. *SegNum* is the number of business segments. *Intangibles* are total intangible assets divided by lagged total assets. *Leverage* is long-term and short-term debt divided by lagged total assets. *ROA* is operating income before depreciation over the prior four quarters divided by lagged total asset. *R&D* is research and development expenditures from the prior four quarters divided by sales from the prior four quarters. *Sales Growth1* is the growth in the most recent four quarters of sales over the previous four quarters. *Sales Growth3* is growth of the most recent four quarters of sales over the corresponding period three years ago. *Fluidity* is the fluidity score obtained from the online data (http://cwis.usc.edu/projects/industrydata/industryconcen.htm) provided by Hoberg and Phillips. *Market-to-book* is market value of equity divided by book value of equity. The Correlation column reports correlation between board tenure and other variables. ***, **,* denote significance at 1%, 5% and 10% level.

Panel A: Descriptive statistics

	N	Mean	Median	Std Dev	p25	p75	Correlation
Board Characteristics							
Tenure (years)	638,717	6.65	6.00	3.89	3.83	8.83	
Med Tenure (years)	638,717	5.95	5.00	4.14	3.00	8.00	0.8676***
Std Tenure (years)	638,717	4.94	4.32	3.31	2.50	6.73	0.7763***
Average Age (years)	638,717	58.55	58.86	6.21	55.20	62.14	0.4681***
Board Size	638,717	7.00	7.00	2.86	5.00	9.00	0.1838***
Connections	638,717	2.80	1.80	0.78	1.33	2.44	-0.0973***
Chair CEO	638,717	0.36	0.00	0.48	0.00	1.00	0.0651***
Firm Characteristics							
Market cap	638,717	5911.50	805.02	21551.44	290.64	2953.73	0.0634***
Book value	638,717	2666.34	392.85	10737.63	139.53	1329.40	0.0939***
Book-to-market	638,717	0.54	0.48	1.72	0.27	0.72	0.0652***
RET	638,717	0.01	0.01	0.14	-0.05	0.06	0.0207***
DGTW RET	638,717	0.00	0.00	0.13	-0.05	0.05	0.0221***
StdRet	638,717	0.03	0.02	0.02	0.02	0.03	-0.1962***
Firm Age (years)	638,717	45.72	28.00	42.42	15.00	67.00	0.3422***
Sales	584,353	4467.86	657.95	18075.20	193.82	2379.10	0.0788***
SegNum	501,810	2.61	2.00	1.83	1.00	4.00	0.1063***
Intangibles	558,489	0.76	0.85	0.24	0.63	0.95	0.0025
Leverage	584,353	0.25	0.19	0.19	0.04	0.37	-0.0334***
ROA*t*	638,717	0.09	0.10	0.17	0.04	0.16	0.0657***
ROA*t-1*	638,717	0.09	0.10	0.17	0.04	0.16	0.0687***
Growth Proxies							
R&D	584,353	0.06	0.00	0.18	0.00	0.03	-0.1159***
Sales Growth1	616,007	0.13	0.09	0.25	0.00	0.22	-0.1347***
Sales Growth3	616,007	0.56	0.31	0.77	0.05	0.83	-0.2061***
Fluidity	475,358	7.33	6.60	3.94	4.49	9.37	-0.1578***
Market-to-Book	638,717	6.30	2.15	3.12	1.38	3.67	-0.0572***

Panel B: Correlations for Growth Proxies

	R&D	Sales Growth1	Sales Growth3	Fluidity	Market-to-Book
R&D	1				
Sales Growth1	0.0882***	1			
Sales Growth3	0.1121***	0.6031***	1		
Fluidity	0.2105***	0.1038***	0.1487***	1	
Market-to-Book	0.2664***	0.2357***	0.2138***	-0.0181***	1

Table 2
Impact of Board Tenure on Contemporaneous Firm Market Value

The table reports regression results of contemporaneous market-to-book on director, firm, and board characteristics. The regression specification is as follows:

$$Market/\ Book_{it} \quad = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it}$$

In all regression iterations the dependent variable is contemporaneous market-to-book ratio. *Tenure* is the average of the tenure of all independent directors sitting on the board. An individual director's tenure is calculated as the year of annual meeting minus the start year of directorship minus any breaks in the service of directorship. *Firm Age* (years) is the number of years since the firm is first listed in CRSP database. *Sales* are 12-month sales for a company. *SegNum* is the number of business segments. *Intangibles* are total intangible assets divided by lagged total assets. *Leverage* is long-term and short-term debt divided by lagged total assets. *R&D* is research and development expenditures from the prior four quarters divided by sales from the prior four quarters. *ROA* is operating income before depreciation over the prior four quarters divided by lagged total asset. *StdRet* is the standard deviation of daily stock returns during the prior calendar year. *Average Age* is the average age of board members. *Board Size* is the number of directors. *Connections* is the average number of boards the board members serve on (including the firm observation). *Chair CEO* is an indicator variable that equals to one when the CEO also serves as board chair, zero otherwise. *Stand* denotes that for regression purposes a variable was normalized using the Blom function which transforms a variable to a normal distribution with a range between plus and minus three. In Panel B we chose to show only the coefficients on *Log* (*Tenure)* and Log $(Tenure)^2$ with all other controls suppressed. In Panel B the t-statistic for the average coefficient is computed using the Fama and Macbeth methodology. Fama and French's 48 industry definitions are used for the industry fixed effects. The T-statistics are in parentheses and statistically significant terms are bolded. ***, **,* denote significance at 1%, 5% and 10% level.

Panel A: Panel regression

	Dependent Variable = Contemporaneous Market/ Book Ratio (stand.)			
	1	2	3	4
Log (Tenure)	-0.0042	0.3105***	0.2217***	0.1307***
	(-0.43)	**(6.89)**	**(5.24)**	**(2.60)**
Log $(\text{Tenure})^2$		-0.0877***	-0.0751***	-0.0439***
		(-7.16)	**(-6.51)**	**(-3.21)**
Log (Firm Age)			-0.0006	0.0022
			(-0.09)	(0.28)
Log (Sales)			-0.0449***	-0.0813***
			(-12.71)	**(-19.21)**
Log (SegNum)			-0.0557***	-0.0465***
			(-4.77)	**(-3.65)**
Intangibles (stand.)			0.0323***	0.0236***
			(4.13)	**(2.73)**
Leverage (stand.)			0.0709***	0.0654***
			(12.76)	**(10.65)**
R&D (stand.)			0.3130***	0.2838***
			(33.46)	**(27.92)**
ROA_t (stand.)			0.4127***	0.4226***
			(46.12)	**(43.44)**
ROA_{t-1} (stand.)			-0.0529***	-0.0516***
			(-6.02)	**(-5.39)**
StdRet (stand.)			-0.0155**	-0.0164**
			(-2.48)	**(-2.39)**
Log (Average Age)				-0.3991***
				(-5.43)
Log (Board Size)				0.1325***
				(6.58)
Log (Connections)				0.4143***
				(16.42)
Chair CEO				0.0376***
				(3.56)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	34,583	34,583	34,583	34,583

Panel B: Annual Cross-Sectional Regressions

	Log (Tenure)			Log (Tenure)^2		
Year	2	3	4	2	3	4
1996	-0.3097	-0.1733	-0.1976	0.0399	-0.0064	0.0084
	(-0.98)	(-0.57)	(-0.65)	(0.47)	(-0.08)	(0.10)
1997	-0.0710	-0.1894	-0.1738	-0.0054	0.0276	0.0287
	(-0.23)	(-0.66)	(-0.60)	(-0.06)	(0.36)	(0.36)
1998	0.3218	0.2266	0.1380	-0.1224*	-0.0891	-0.0492
	(1.35)	(1.02)	(0.62)	**(-1.84)**	(-1.43)	(-0.77)
1999	0.2431	-0.0603	-0.1411	-0.0905	-0.0050	0.0263
	(0.95)	(-0.26)	(-0.61)	(-1.29)	(-0.08)	(0.41)
2000	0.5279**	0.4178**	0.3518	-0.1591**	-0.1135*	-0.0873
	(2.20)	**(1.85)**	(1.55)	**(-2.46)**	**(-1.86)**	(-1.42)
2001	0.6047***	0.3347	0.3085	-0.1759***	-0.1083*	-0.0905
	(2.69)	(1.62)	(1.49)	**(-2.84)**	**(-1.90)**	(-1.58)
2002	0.5970***	0.3358*	0.2920	-0.1514***	-0.0947*	-0.0778
	(3.04)	**(1.86)**	(1.62)	**(-2.76)**	**(-1.87)**	(-1.53)
2003	0.6810***	0.3581*	0.2242	-0.1598***	-0.0998*	-0.0482
	(3.25)	**(1.90)**	(1.19)	**(-2.77)**	**(-1.91)**	(-0.91)
2004	0.5143***	0.4096**	0.2783	-0.1608***	-0.1313***	-0.0806*
	(2.83)	**(2.37)**	(1.60)	**(-3.22)**	**(-2.76)**	**(-1.67)**
2005	0.7230***	0.5413***	0.4142**	-0.2015***	-0.1681***	-0.1176**
	(3.36)	**(2.67)**	**(2.03)**	**(-3.48)**	**(-3.07)**	**(-2.12)**
2006	0.7655***	0.7355***	0.5979***	-0.2281***	-0.2274***	-0.1779***
	(3.76)	**(3.80)**	**(3.07)**	**(-4.19)**	**(-4.38)**	**(-3.39)**
2007	0.5472***	0.4501**	0.3696*	-0.1627***	-0.1479***	-0.1083**
	(2.60)	**(2.26)**	**(1.85)**	**(-2.91)**	**(-2.78)**	**(-2.02)**
2008	0.5976***	0.4669**	0.3745*	-0.1657***	-0.1448***	-0.1001*
	(2.65)	**(2.20)**	**(1.76)**	**(-2.78)**	**(-2.59)**	**(-1.77)**
2009	0.6358**	0.4563**	0.3255	-0.1471**	-0.1205**	-0.0659
	(2.54)	**(2.02)**	(1.42)	**(-2.28)**	**(-2.07)**	(-1.11)
2010	0.5184**	0.3343	0.1125	-0.1418**	-0.1094*	-0.0343
	(1.98)	(1.36)	(0.46)	**(-2.13)**	**(-1.75)**	(-0.55)
2011	1.3888***	1.1230***	0.9823***	-0.3282***	-0.2798***	-0.2292***
	(5.08)	**(4.40)**	**(3.82)**	**(-4.81)**	**(-4.39)**	**(-3.56)**
2012	0.9143***	0.7846***	0.6836***	-0.2093***	-0.1974***	-0.1618***
	(3.53)	**(3.28)**	**(2.82)**	**(-3.21)**	**(-3.28)**	**(-2.64)**
2013	1.1246***	1.1072***	0.9663***	-0.2550***	-0.2721***	-0.2210***
	(4.18)	**(4.40)**	**(3.82)**	**(-3.80)**	**(-4.32)**	**(-3.47)**
2014	1.2334*	0.6786	0.3594	-0.3340*	-0.2048	-0.0925
	(1.70)	(0.97)	(0.51)	**(-1.90)**	(-1.20)	(-0.54)
2015	0.1956	0.1790	-0.0079	-0.0283	-0.0295	0.0323
	(0.81)	(0.80)	(-0.03)	(-0.46)	(-0.52)	(0.55)
2016	2.1484**	0.9977	0.5117	-0.5272**	-0.3012	-0.1844
	(2.15)	(1.11)	(0.56)	**(-2.25)**	(-1.43)	(-0.86)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	Yes	No	Yes	Yes
Board Controls	No	No	Yes	No	No	Yes
N	34,583	34,583	34,583	34,583	34,583	34,583

Table 3
Impact of Board Tenure on the Next Year Firm Market Value

The table reports regression results of forward market-to-book on director, firm, and board characteristics. The regression specification is as follows:

$$Market/\ Book_{it+1} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it}\ .$$

In all regression iterations the dependent variable is the next-year market-to-book ratio. In all regressions we also control for current year market-to-book. *Tenure* is the average of the tenure of all independent directors sitting on the board. An individual director's tenure is calculated as the year of annual meeting minus the start year of directorship minus any breaks in the service of directorship. *Firm Age* (years) is the number of years since the firm is first listed in CRSP database. *Sales* are 12-month sales for a company. *SegNum* is the number of business segments. *Intangibles* are total intangible assets divided by lagged total assets. *Leverage* is long-term and short-term debt divided by lagged total assets. *R&D* is research and development expenditures from the prior four quarters divided by sales from the prior four quarters. *ROA* is operating income before depreciation over the prior four quarters divided by lagged total asset. *StdRet* is the standard deviation of daily stock returns during the prior calendar year. *Average Age* is the average age of board members. *Board Size* is the number of directors. *Connections* is the average number of boards the board members serve on (including the firm observation). *Chair CEO* is an indicator variable that equals to one when the CEO also serves as board chair, zero otherwise *Stand* denotes that for regression purposes a variable was normalized using the Blom function which transforms a variable to a normal distribution with a range between plus and minus three. Industry fixed effect is at Fama French's 48 industries classification. The T-statistics are in parentheses and statistically significant terms are bolded. ***, **,* denote significance at 1%, 5% and 10% level.

	Dependent Variable = Forward Market/ Book (stand.)			
	1	2	3	4
Log (Tenure)	0.0729***	0.2459***	0.2031***	0.1731***
	(10.94)	**(8.11)**	**(6.72)**	**(4.82)**
Log $(\text{Tenure})^2$		-0.0482***	-0.0416***	-0.0348***
		(-5.85)	**(-5.04)**	**(-3.57)**
Market/Book (stand.)	0.7941***	0.7933***	0.7844***	0.7818***
	(219.14)	**(218.87)**	**(203.48)**	**(183.37)**
Log (Firm Age)			0.0179***	0.0133**
			(3.53)	**(2.36)**
Log (Sales)			0.0254***	0.0147***
			(9.99)	**(4.84)**
Log (SegNum)			-0.0257**	-0.0224**
			(-3.08)	**(-2.46)**
Intangibles (stand.)			-0.0199***	-0.0216***
			(-3.54)	**(-3.50)**
Leverage (stand.)			0.0010	0.0032
			(0.26)	(0.72)
R&D (stand.)			0.0687***	0.0624***
			(10.08)	**(8.34)**
ROA*t* (stand.)			-0.0219***	-0.0255***
			(-3.33)	**(-3.55)**
ROA*t-1* (stand.)			0.0485***	0.0516***
			(7.72)	**(7.55)**
StdRet (stand.)			-0.0252	-0.0223***
			(-5.60)	**(-4.54)**
Log (Average Age)				0.0066
				(0.13)
Log (Board Size)				0.0294**
				(2.04)
Log (Connections)				0.1321***
				(7.29)
Chair CEO				-0.0064
				(-0.86)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	34,082	34,082	34,082	34,082

Table 4

Impact of Growth Options on the Value Relevance of Board Tenure: Market Valuation Evidence

The table below reports regression results where the dependent variable is contemporaneous market-to-book ratio. In each column we report results of the following specification that includes one of our four proxies for firm growth:

$$Market/\,Book_{it} \;=\beta_1 Tenure_{it}\;+\;\beta_2 Tenure_{it}^2+Tenure_{it}^2\times Growth\;Proxy+Growth\;Proxy\;Dummy \\ +\;Board\;Controls_{it}+\;Firm\;Controls_{it}+\;\epsilon_{it}$$

We use four proxies for firm growth: (i) *R&D*, which is an indicator variable equal to one if the firm's ratio of research and development expenses to sales is over the 75th percentile value for all firms for that year. (ii) *SalesGrowth1*, which is an indicator variable equal to one if the firm's sales growth in the most recent four quarters over the previous four quarters is above the median value of other firms for the year. (iii) *SalesGrowth3*, which is an indicator variable equal to one if the firm's sales growth of the most recent four quarters over the corresponding period three years ago is above the median value of other firms for the year. (iv) *Fluidity* is an indicator variable equal to one if firm's *Fluidity* score is above the median value of other firms for the year. *Fluidity* is the fluidity score obtained from the online data (http://cwis.usc.edu/projects/industrydata/industryconcen.htm) provided by Hoberg and Phillips. All board and firm control variables are as defined in Table 2. In the interest of conciseness, we report only the results on the key independent variables. Panel A reports the results of panel regression. Industry fixed effect is at Fama French's 48 industries classification. The T-statistics are in parentheses and statistically significant terms are bolded. Panel B reports the results of Fama-MacBeth style regressions. Panel B reports average coefficients from 21 annual cross-sectional regressions. The averages are time-series means with t-statistics (in parentheses) corresponding to the standard error of the mean; statistically significant terms are bolded. *N* denotes the average number of cross-sectional observations. ***, **,* denote significance at 1%, 5% and 10% level.

Panel A: Panel Regression

	Dependent Variable = Contemporaneous Market to Book (stand.)			
	Growth Option Proxy =			
	R&D	Sales Growth1	Sales Growth3	Fluidity
Growth × Log (Tenure)^2	-0.0205***	-0.0201***	-0.0022	-0.0119**
	(-3.31)	**(-3.87)**	(-0.41)	**(-2.13)**
Log (Tenure)	0.1424***	0.1306***	0.1470***	0.1354***
	(2.96)	**(2.77)**	**(3.08)**	**(2.81)**
Log (Tenure)^2	-0.0393***	-0.0336***	-0.0447***	-0.0382***
	(-3.01)	**(-2.59)**	**(-3.42)**	**(-2.91)**
Growth Option Proxy	0.0749**	0.4245***	0.2396***	0.0771***
	(2.09)	**(18.05)**	**(10.01)**	**(3.08)**
Firm Controls	Yes	Yes	Yes	Yes
Board Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	34,583	34,583	34,583	34,583

Panel B: Fama-MacBeth Regression

	Dependent Variable = Contemporaneous Market to Book (stand.)			
	Growth Option Proxy =			
	R&D	Sales Growth1	Sales Growth3	Fluidity
Growth × Log (Tenure)^2	-0.0192***	-0.0216***	-0.0027	-0.0072
	(-3.53)	**(-2.94)**	(-0.35)	(-1.08)
Log (Tenure)	0.1809**	0.1652**	0.1993***	0.1754**
	(2.49)	**(2.54)**	**(2.84)**	**(2.42)**
Log (Tenure)^2	-0.0569***	-0.0490***	-0.0654***	-0.0570***
	(-3.28)	**(-3.25)**	**(-3.85)**	**(-3.38)**
Growth Option Proxy	-0.654	0.4461***	0.2771***	0.0572
	(0.71)	**(11.98)**	**(6.06)**	(1.56)
Firm Controls	Yes	Yes	Yes	Yes
Board Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,646	1,646	1,646	1,646

Table 5
Abnormal Stocks Returns to Portfolios Sorted by Board Tenure

The first two columns presents average monthly excess returns (*X_RET*) and characteristic adjusted returns (*DGTW_RET*) for quintiles and deciles of portfolios formed based on *Tenure*. *X_RET* are monthly buy and hold security returns from CRSP in excess of the value-weighted market portfolio. *DGTW_RET* are characteristic-adjusted returns calculated as the monthly buy and hold security returns from CRSP minus the value-weighted average buy and hold return on securities with the same size (market capitalization, 3 groups), Book/Market (3 groups) and 11-month momentum (3 groups). The remaining columns show the results of Fama-French regressions for quintiles and deciles of portfolios formed based on *Tenure*. The regressions have the following specification:

$$Rp_t - Rf_t = FF\_RET + b \cdot [Rm_t - Rf_t] + s \cdot SMB_t + h \cdot HML_t + u \cdot UMD_t + e_t$$

Dependent variables are portfolio returns, Rp_t, in excess of the one-month Treasury bill rate, Rf_t, observed at the beginning of the month. The intercept denotes the risk adjusted return, *FF_RET*. Each month we form equal-weighted portfolios of all sample firms based the length of directors' tenure (*Tenure*). The three Fama-French factors are zero investment portfolios representing the excess return of the market, *Rm-Rf*; the difference between a portfolio of ''small'' stocks and ''big'' stocks, *SMB*; and the difference between a portfolio of ''high'' book-to-market stocks and ''low'' book-to-market stocks, *HML*. The fourth factor, *UMD*, is the difference between a portfolio of stocks with high past one-year returns and a portfolio of stocks with low past one-year returns. The number of monthly cross-sectional regressions is denoted by *N* and *t*-statistics are in parentheses; statistically significant terms are bolded.

			Fama-French Regressions					
	Average X_RET	Average DGTW _RET	Intercept (FF_RET)	Rm - Rf	SMB	HML	UMD	R^2/ N
Panel A: Tenure Quintile Portfolios								
1 (Low)	-0.13%	-0.26%	-0.27%	1.0703	0.5857	0.1386	-0.1638	0.9346
	(-0.77)	**(-2.55)**	**(-2.66)**	**(44.66)**	**(19.18)**	**(4.18)**	**(-8.14)**	246
2	0.09%	-0.03%	-0.07%	1.0379	0.5272	0.2618	-0.1122	0.9431
	(0.60)	(-0.37)	(-0.79)	**(49.84)**	**(19.87)**	**(9.10)**	**(-6.42)**	246
3	0.30%	0.17%	0.16%	0.9831	0.4736	0.3549	-0.0854	0.9389
	(2.20)	**(1.86)**	**(1.86)**	**(48.82)**	**(18.46)**	**(12.75)**	**(-5.05)**	246
4	0.32%	0.18%	0.19%	0.9388	0.4334	0.3901	-0.0736	0.9501
	(2.49)	**(1.95)**	**(2.65)**	**(54.77)**	**(19.85)**	**(16.47)**	**(-5.12)**	246
5 (High)	0.37%	0.23%	0.24%	0.8896	0.4554	0.4810	-0.0604	0.9426
	(2.64)	**(2.16)**	**(3.22)**	**(49.99)**	**(20.09)**	**(19.57)**	**(-4.04)**	246
High - Low	0.50%	0.49%	0.51%	-0.1808	-0.1303	0.3425	0.1034	0.5014
	(3.21)	**(4.00)**	**(4.46)**	**(-6.65)**	**(-3.76)**	**(9.12)**	**(4.53)**	246
Panel B: Tenure Decile Portfolios								
1 (Low)	-0.33%	-0.46%	-0.48%	1.0884	0.6085	0.1017	-0.1577	0.9192
	(-1.80)	**(-3.93)**	**(-4.13)**	**(39.70)**	**(17.42)**	**(2.69)**	**(-6.85)**	246
2	0.07%	-0.06%	-0.06%	1.0521	0.5646	0.1751	-0.1698	0.9220
	(0.42)	(-0.60)	(-0.53)	**(40.74)**	**(17.16)**	**(4.91)**	**(-7.83)**	246
3	0.04%	-0.08%	-0.12%	1.0574	0.5467	0.2416	-0.1202	0.9337
	(0.26)	(-0.81)	(-1.27)	**(45.66)**	**(18.53)**	**(7.55)**	**(-6.18)**	246
4	0.14%	0.02%	-0.01%	1.0183	0.5072	0.2831	-0.1037	0.9331
	(0.93)	(0.17)	(-0.14)	**(45.99)**	**(17.99)**	**(9.26)**	**(-5.58)**	246
5	0.20%	0.08%	0.05%	0.9924	0.4839	0.3548	-0.1008	0.9223
	(1.35)	(0.79)	(0.53)	**(42.59)**	**(16.30)**	**(11.02)**	**(-5.15)**	246
6	0.41%	0.26%	0.26%	0.9751	0.4621	0.3561	-0.0688	0.9367
	(2.99)	**(2.79)**	**(3.04)**	**(48.31)**	**(17.97)**	**(12.77)**	**(-4.06)**	246
7	0.32%	0.19%	0.19%	0.9424	0.4590	0.3731	-0.0723	0.9491
	(2.43)	**(1.97)**	**(2.52)**	**(53.83)**	**(20.58)**	**(15.43)**	**(-4.92)**	246
8	0.32%	0.17%	0.20%	0.9358	0.4069	0.4067	-0.0749	0.9342
	(2.44)	**(1.80)**	**(2.42)**	**(47.57)**	**(16.24)**	**(14.96)**	**(-4.54)**	246
9	0.37%	0.25%	0.24%	0.9017	0.4768	0.4430	-0.0741	0.9411
	(2.62)	**(2.22)**	**(3.13)**	**(48.97)**	**(20.33)**	**(17.42)**	**(-4.79)**	246
10	0.37%	0.21%	0.24%	0.8775	0.4338	0.5191	-0.0467	0.9237
	(2.52)	**(1.91)**	**(2.81)**	**(43.18)**	**(16.76)**	**(18.49)**	**(-2.74)**	246
High – Low	0.70%	0.66%	0.72%	-0.2109	-0.1747	0.4174	0.1110	0.4843
	(3.66)	**(4.40)**	**(5.02)**	**(-6.21)**	**(-4.04)**	**(8.90)**	**(3.89)**	246

Table 6

Fama-MacBeth Cross-Sectional Regressions of Monthly Stock Returns

The table reports regression results estimating variations of the following regression:

$$DGTW\_RET_{it+1} = \beta_1 Tenure_{it} + \beta_2 Tenure^2_{it} + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it}$$

In all regression iterations the dependent variable is the one-month ahead excess stock return – *DGTW_RET* (characteristic adjusted returns calculated as the monthly buy and hold security returns from CRSP minus the value-weighted average buy and hold return on securities with the same size (market capitalization, 3 groups), Book/Market (3 groups) and 11-month momentum (3 groups)). *Tenure* is the average of the tenure of independent directors sitting on the board. An individual director's tenure is calculated as the year of annual meeting minus the start year of directorship minus any breaks in the service of directorship. *Firm Age* (years) is the number of years since the firm is first listed in CRSP database. *SegNum* is the number of business segments. *Intangibles* are total intangible assets divided by lagged total assets. *Leverage* is long-term and short-term debt divided by lagged total assets. *R&D* is research and development expenditures from the prior four quarters divided by sales from the prior four quarters. *ROA* is operating income before depreciation over the prior four quarters divided by lagged total asset. *StdRet* is the standard deviation of daily stock returns during the prior calendar year. *Average Age* is the average age of board members. *Board Size* is the number of directors. *Connections* is the average number of boards the board members serve on (including the firm observation). *Chair CEO* is an indicator variable that equals to one when the CEO also serves as board chair, zero otherwise. *DGTW_RET* is winsorized at 99% and 1%. The table reports average coefficients from 251 monthly cross-sectional regressions. The averages are time-series means with t-statistics (in parentheses) computed using the standard error of the mean; statistically significant terms are bolded. *N* denotes the average number of cross-sectional observations. Industry fixed effect is at Fama French's 48 industries classification. ***, **,* denote significance at 1%, 5% and 10% level.

	Dependent Variable = DGTW_RET			
	1	2	3	4
Log (Tenure)	0.0030***	0.0077***	0.0071***	0.0058**
	(4.71)	**(3.20)**	**(2.82)**	**(2.43)**
Log (Tenure)^2		-0.0013**	-0.0014**	-0.0010
		(-2.23)	**(-2.21)**	**(-1.61)**
Log (Firm Age)			-0.0005	-0.0006
			(-1.21)	(-1.34)
Log (SegNum)			0.0002	0.0003
			(0.29)	(0.38)
Intangibles (stand.)			-0.0006	-0.0004
			(-1.29)	(-0.69)
Leverage (stand.)			-0.0003	-0.0003
			(-0.75)	(-0.62)
R&D (stand.)			0.0004	0.0003
			(0.48)	(0.36)
ROA (stand.)			0.0019***	0.0026***
			(2.73)	**(2.92)**
ROA_{t-1} (stand.)			0.0004	0.0000
			(-0.59)	(0.05)
StdRet (stand.)			-0.0008	-0.0005
			(-1.07)	(-0.61)
Log (Average Age)				-0.0063
				(-1.58)
Log (Board Size)				0.0012
				(1.00)
Log (Connections)				0.0054***
				(4.06)
Chair CEO				-0.0004
				(-0.74)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620

Table 7
Impact of Growth Options on the Value Relevance of Board Tenure: Stock Return Evidence

The table below reports regression results where the dependent variable, *DGTW_RET*, is one month ahead characteristic adjusted returns calculated as the monthly buy and hold security returns from CRSP minus the value-weighted average buy and hold return on securities with the same size (market capitalization, 3 groups), Book/Market (3 groups) and 11-month momentum (3 groups). In each column we report results of the following specification that includes one of our five proxies for firm growth:

$$DGTW\_RET_{it+1} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Tenure_{it}^2 \times Growth\ Proxy + Growth\ Proxy\ Dummy + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it}$$

We use five proxies for firm growth: (i) *M/B* is an indicator variable equal to one if firm's market-to-book ratio is above the median value of other firms for the year. (ii) *R&D*, which is an indicator variable equal to one if the firm's ratio of research and development expenses to sales is over the 75th percentile value for all firms for that year. (iii) *SalesGrowth1*, which is an indicator variable equal to one if the firm's sales growth in the most recent four quarters over the previous four quarters is above the median value of other firms for the year. (iv) *SalesGrowth3*, which is an indicator variable equal to one if the firm's sales growth of the most recent four quarters over the corresponding period three years ago is above the median value of other firms for the year. (v) *Fluidity* is an indicator variable equal to one if firm's *Fluidity* score is above the median value of other firms for the year. *Fluidity* is the fluidity score obtained from the online data (http://cwis.usc.edu/projects/industrydata/industryconcen.htm) provided by Hoberg and Phillips. All other control variables are as defined in Table 6. In the interest of conciseness, we report only the results on the key independent variables. *DGTW_RET* is winsorized at 99% and 1%. The table reports average coefficients from 251 monthly cross-sectional regressions. The averages are time-series means with t-statistics (in parentheses) corresponding to the standard error of the mean; statistically significant terms are bolded. *N* denotes the average number of cross-sectional observations. Industry fixed effect is at Fama French's 48 industries classification. ***, **,* denote significance at 1%, 5% and 10% level.

	Dependent Variable = DGTW_RET				
	Growth Option Proxy =				
	M/B	R&D	Sales Growth1	Sales Growth3	Fluidity
Growth × Log (Tenure)^2	-0.0004*	-0.0002	0.0002	0.0004	0.0001
	(-1.70)	(-0.49)	(0.67)	(1.46)	(0.08)
Log (Tenure)	0.0058**	0.0056**	0.0060**	0.0055**	0.0059**
	(2.43)	**(2.34)**	**(2.49)**	**(2.30)**	**(2.44)**
Log (Tenure)^2	-0.0008	-0.0009	-0.0011*	-0.0011*	-0.0010
	(-1.25)	**(-1.46)**	**(-1.75)**	**(-1.75)**	(-1.52)
Growth Option Proxy	-0.0007	0.0014	-0.0016	-0.0024*	0.0013
	(-0.44)	(0.47)	(-1.15)	**(-1.76)**	(0.88)
Firm Controls	Yes	Yes	Yes	Yes	Yes
Board Controls	Yes	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620	1,620

Table 8
Robustness Tests: Market-to-Book Evidence

The table reports regression results of contemporaneous market-to-book on director, firm, and board characteristics. Dependent variable is Market/ Book and is normalized using the Blom function which transforms a variable to a normal distribution with a range between plus and minus three. Unless otherwise stated, the regressions contain same set of control variables as in Table 2 Column 4. Panel A separates our sample in two ways: the earlier period (1996-2003) vs. later period (2004-2014) and large-cap stocks vs. small-cap stocks. Panel B1 uses median board tenure (*Med Tenure*) and its square in the regression as an alternative measure of board tenure, and it also tests the robustness of our results to the standard deviation of board tenure (*High Std Tenure* vs. *Low Std Tenure*). Panel B2 omits two groups of companies: column one excludes companies that are ranked into the decile one of average board tenure and column two excludes companies that are ranked into decile one or two of average board tenure. Panel C separates our sample in high and low board tenure stocks and omits squared tenure term in the regression to test the robustness of linear model use. In the interest of conciseness, we report only the results on the key independent variables. All other control variables are as defined in Table 2. Fama and French's 48 industry definitions are used for the industry fixed effects. The T-statistics are in parentheses and statistically significant terms are bolded. ***, **,* denote significance at 1%, 5% and 10% level.

Panel A: Sample Selection.

	1996-2003 period	2004-2014 period	Large-Cap	Small-Cap
Log (Tenure)	0.1003	0.4967***	0.2262***	0.3345***
	(1.21)	**(5.89)**	**(3.69)**	**(4.61)**
Log $(\text{Tenure})^2$	-0.0362*	-0.1263	-0.0489***	-0.1010
	(-2.04)	**(-6.63)**	**(-2.96)**	**(-5.20)**
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	8,024	23,226	16,296	14,957

Panel B1: Design of Board Tenure Measure.

	Median Tenure	High Std Tenure	Low Std Tenure
Log (Tenure)	0.1048***	0.2934	0.1215
	(3.20)	(1.42)	(1.56)
Log $(\text{Tenure})^2$	-0.0270***	-0.0901*	-0.0072
	(-2.81)	**(-2.00)**	(-0.29)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	31,253	16,044	15,209

Panel B2: Design of Board Tenure Measure.

	Excluding D1	Excluding D1-D2
Log (Tenure)	0.4199***	0.2527
	(3.83)	**(1.61)**
Log $(\text{Tenure})^2$	-0.1088***	-0.0740**
	(-4.15)	**(-2.08)**
Year FE	Yes	Yes
Industry FE	Yes	Yes
N	28,625	25,572

Panel C: Use of Linear Model.

	High Board Tenure	Low Board Tenure
Log (Tenure)	-0.2059***	0.1290***
	(-3.77)	**(6.88)**
Year FE	Yes	Yes
Industry FE	Yes	Yes
N	7,842	23,411

Table 9

Robustness Tests: Annual Stock Returns Evidence

The table reports regression results estimating variations of the following regression:

$$DGTW\_RET_{it+1} = \beta_1 Tenure_{it} + \beta_2 Tenure_{it}^2 + Board\ Controls_{it} + Firm\ Controls_{it} + \epsilon_{it}.$$

In all regression iterations the dependent variable is the one-year ahead excess stock return – *DGTW_RET* (characteristic adjusted returns calculated as the annual buy and hold security returns from CRSP minus the value-weighted average buy and hold return on securities with the same size (market capitalization, 3 groups), Book/Market (3 groups) and 11-month momentum (3 groups)). All independent variables are as defined in Table 6. In the interest of conciseness, we report only the results on the key independent variables. *DGTW_RET* is winsorized at 99% and 1%. The table reports average coefficients from 21 annual cross-sectional regressions. The averages are time-series means with t-statistics (in parentheses) corresponding to the standard error of the mean; statistically significant terms are bolded. *N* denotes the average number of cross-sectional observations. Industry fixed effect is at Fama French's 48 industries classification. ***, **,* denote significance at 1%, 5% and 10% level.

	Dependent Variable = $DGTW\_RET_{it+1}$			
	1	2	3	4
Log (Tenure)	0.0300***	0.1108***	0.0964***	0.0800**
	(2.92)	**(3.40)**	**(3.02)**	**(2.60)**
Log $(\text{Tenure})^2$		-0.0211***	-0.0180**	-0.0102
		(-2.77)	**(-2.53)**	**(-1.54)**
Firm Controls	No	No	Yes	Yes
Board Controls	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620