PREDICTING AND EXAMINING LINKS BETWEEN IPO HYPE, MANAGERIAL EXPECTATIONS, AND FIRM OUTCOMES

by

KIP KIEFER

B.A., United States Air Force Academy, l996

M.A., University of Arizona, 2003

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirement for the degree of

Doctor of Philosophy

Department of Business

2013

PREDICTING AND EXAMINING LINKS BETWEEN IPO HYPE, MANAGERIAL EXPECTATIONS, AND FIRM OUTCOMES

This thesis entitled:
Predicting and Examining Links Between IPO Hype,
Managerial Expectations, and Firm Outcomes
written by Kip Kiefer
has been approved for the Department of Business

____
Mathew L. A. Hayward (Chair)

____
Russell Cropanzano

____
Bret R. Fund

Date____________________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

DECLARATION OF INTEREST: The author reports no conflicts of interest. The author alone is responsible for the content and writing of the paper.

DISCLAIMER CLAUSE: The views expressed in this article are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the U.S. Government.

Kip Kiefer (Ph.D., Management, Organizations, Strategy and Entrepreneurship)

Predicting and Examining Links Between IPO Hype, Managerial Expectations, and Firm Outcomes

Thesis directed by Associate Professor Mathew L. A. Hayward

ABSTRACT

Hype is a powerful force and it clearly influences people's behavior (Chen, Melessa, & Zhang, 2012; Kothari, Li, & Short, 2009; Lang & Lundholm, 1996). Understanding and being able to identify hype is important, but more important is understanding how hype influences behavior. This dissertation examines the links between media hype and managerial expectations and firm outcomes. The paper begins with a conceptual framework that provides a model for understanding the information environment and how differential relationships between media hype and managerial behavior exist. Key aspects of the model are the sources and timing of hype, particularly a concept called a trigger event. Next, the dissertation suggests a new taxonomy for exploring media hype based on sources of hype to include Community Hype (online traffic), Own Hype (firm-generated press releases), Market Hype (major news periodicals), and Expert Hype (Wall Street analyst reports). Following the presentation of the new taxonomy of hype, a predictive model of the relationship between media hype and managerial behavior is presented and then empirically tested. The sample includes 126 US IPOs from 2007-2011 and longitudinal data is gathered over a two-year period surrounding the

IPO event. Measures of over-confidence are develop theoretically and include 1) the allowance of negative earnings surprise events to occur and 2) failure of managers to prudently sell-off a portion of their equity at the expiration of the lock-up period. Hypotheses examine whether or not measures of over-confidence occur, how often they occur, and by how much they occur. Results indicate that managers are influenced by media hype in that they exhibit actions reflecting overconfidence when the media hype generated about the firm surrounding its IPO is volumous, salient with respect to the focal firm and relatively positive in nature. Curiously, results reveal that media's influence is not the same at all times and that it impacts managerial expectations and firm outcomes differently for different types of hype at different times.

DEDICATION

This dissertation is dedicated to all of those who supported me through the entire PhD program. It was a demanding road; beginning with my return to the classroom as a student after a six-year hiatus, to two grueling years of coursework, to preparing for, taking, and passing the comprehensive exam, to the challenges of formulating a topic and developing it enough to pass the dissertation proposal defense, to collecting the requisite data, analyzing it, and writing and rewriting and rewriting my dissertation.

In particular, this dissertation is dedicated to my family. First, and foremost, to my loving wife, Dominique, without whose care and support I never would have been able to complete the tasks listed above. Next, to my daughter Kylie and my sons Kaden and Keagan who took my long days and time away from the family in-stride and always made me feel loved and wanted whenever I was around. Third, to my parents, my siblings, and their families, who have always made me believe I could achieve anything I set my mind to. Finally, to my in-laws, who never doubted, although they probably should have, that I would finish and supported me all the way through the program. Thank you everyone!

ACKOWLEDGEMENTS

Several people provided essential assistance in helping me complete this dissertation and the PhD program overall. First, I wish to acknowledge the assistance and guidance of my Dissertation Committee Chair Professor Mathew Hayward. I thank him for his intellectual stimulation and support throughout the dissertation. He has become a strong mentor and, more importantly, a good friend during the writing of this dissertation. To the other members of my committee, Professors Russell Cropanzano, Markus Fitza, Bill Forster, and Bret Fund, thank you for all of your insightful comments and support throughout the process. Furthermore, thank you to the faculty and staff at the Leeds School of Business who warmly embraced me during my time here, and helped me expand my thinking and achieve my academic goal. Completion of this dissertation is a testament to the dedication of my committee members and the Leeds family of academic professionals.

I'd also like to thank Erna Blanche Imperatore of the University of Southern California, Timothy Pollock of Penn State University, Justin Martin of The Ohio State University, Oliver Chang of Creighton University, and Alan Singsaas of Tristan Technologies for sharing their wisdom and knowledge with me. They all influenced this work, making it better than it would have become without their input. Furthermore, I thank the United States Air Force and the United States Air Force Academy Department of Management, which competitively selected me to matriculate into a PhD program and then sponsored the pursuit of my degree.

Next, I must thank a number of students and peers who assisted me in the significant data collection and content analysis efforts involved in this project: Cassie, Catherine, Dominique, Jocelyn, Kelsey, Lena, Mari, and Vicki. These young scholars spent a significant amount of time, collecting, coding, and rating content for over 6,000 media articles from a variety of sources. These tasks were challenging and daunting and I am forever indebted to their willingness to participate and their focused expertise.

Furthermore, I would like to thank my fellow classmates. Their support was a pivotal part of my success in the program. They pushed me to challenge and test myself and to go further than I would have on my own. In particular, I'd like to thank Richard Hunt, a good friend of mine, who read my dissertation, on more than one occasion, and provide extensive and valuable feedback to help me shape and mend my ideas into a piece that I am very proud of.

CONTENTS

TABLES

FIGURES

CHAPTER 1: INTRODUCTION

On Friday, May 18, 2012 Facebook founder, chairman and CEO Mark Zuckerberg, rang the opening bell of the Nasdaq stock market (Nikolla, 2012). This opened a day of trading that included one of the most hyped stock market events in history—the Initial Public Offering (IPO) for the popular social networking site Facebook Inc. However, the event failed to live up to the hype and after jumping 18% in early trading, its gains quickly evaporated and by the end of the day it finished at $38.23, barely above its $38 offering price (Nikolla, 2012).

For months leading up to the Facebook IPO, numerous mass media news outlets and analysts provided their insights and opinions on the likely successful launch of the firm in the public domain. A general consensus had developed that Facebook's IPO would generate one of the largest principal amounts in history, and that investors would have an opportunity to reap the benefits of early ownership. However, the first day started strong and finished weak and the weeks following the IPO have not shown much of a recovery. Two months after Facebook's IPO, it traded at a depressed $30.27 per share, down 21% from its issue price and by the end of the third month of trading, the share price was a dismal $19.05, down 50% from its issue price (Yahoo Finance, 2012).

With all of the precautions in place as part of valuing a firm during IPO preparation, how is it possible that the initial share price at the issue date could be so far off its market value after such a short period of time? In this dissertation, I explore the role of media hype in influencing manager's expectations. These expectations are translated into managers' behaviors in response to the media hype. These behaviors are manifested in non-rational and/or less than optimal actions and inactions by firms and their executives.

1.1 Purpose of Study

My research question is: **What effect does media hype have on managerial expectations and firm outcomes?** The general hypothesis is that the greater the media hype surrounding a firm's IPO the more influence it will have on managerial decision making with regarding to firm expectations. This influence is recognized by an increase in managers exhibiting over-confidence on behalf of the firm and in their personal lives.

Hype is clearly a powerful force and it clearly influences people's behavior (Chen, Melessa, & Zhang, 2012; Kothari, Li, & Short, 2009; Lang & Lundholm, 1996). Understanding and being able to identify hype in itself is important, but more important is understanding how hype influences behavior. This dissertation evaluates the relationship between hype and manager's actions by exploring the following question: Is there a relationship between media hype and managers expectations and firm outcomes? Furthermore, beyond exploring whether or not there is a relationship between media hype and behavior, this dissertation explores how the sources and timing of hype effects this relationship.

Most investors are informed about potential investment opportunities through the media (Shiller, 2000). This fact is notably relevant when it comes to

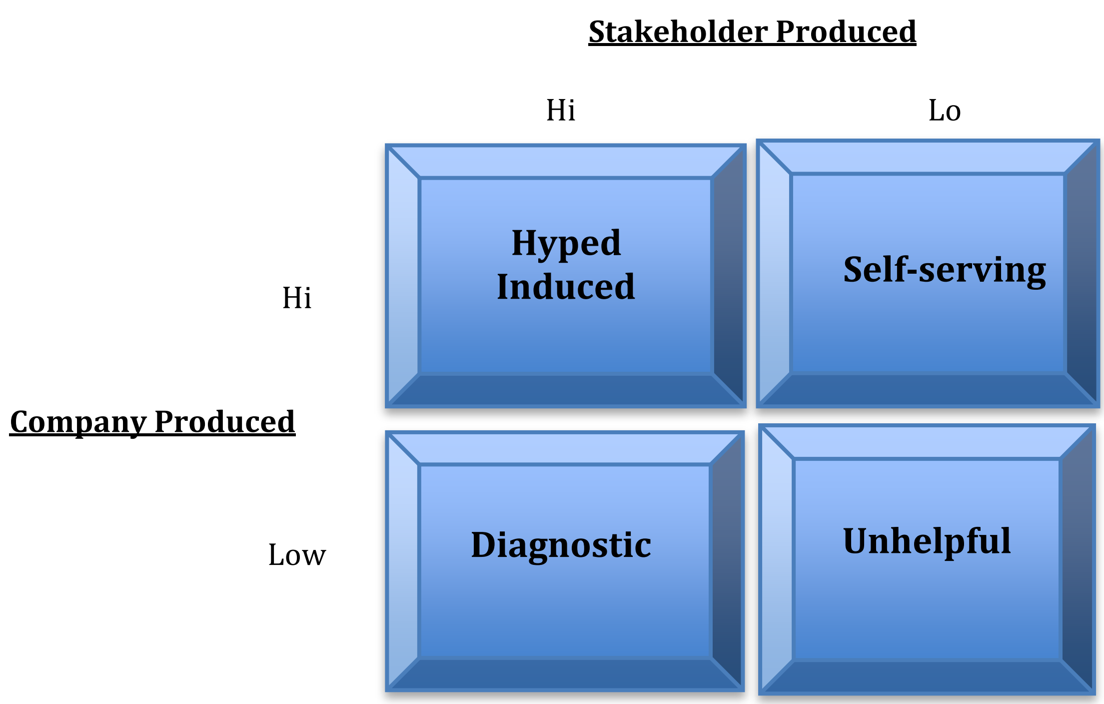
Initial Public Offerings (IPOs) since the vast majority of investors find information via the media and not in person during firm road shows or through conversations with Wall Street analysts (Bhattacharya et. al., 2011;). Certainly, many investors seek consult from investment professionals and brokers who gain their information from brokerage houses, who get their information from Wall Street analysts and other types of media hype. Therefore, there are obvious reasons to assume that the media has an effect on investors' perception of investment opportunities and whether, ultimately, they invest in one firm or another (Lambert, Leuz, and Verrecchia, 2012). Furthermore, the hype generated surrounding an IPO is intense and can have a significant influence on firm and managerial actions and behavior. Despite these insights, most studies of the impact of media deal with the agenda-setting, framing, and priming effects of issues in the news (McLeod, Kosicki, & McLeod, 2002; Scheufele, 2000; Weaver, McCombs, and Shaw, 2004), and fail to consider adequately the effects of how firms are presented. The focus of past research is all the more surprising in light of the very careful attention paid to questions regarding the influence of earnings forecasts and other signals sent to the market by various forms of media. This dissertation fills this research gap by proposing a new taxonomy of media hype and examining the specific effects of media hype on behaviors manifested in managerial actions.

1.1.1 Contributions

Generally, this dissertation extends research on media hype by examining the effects of media hype on actions by firm executives. Specifically, it predicts and then explores many unspecified and unexplained effects of media hype on top managers in entrepreneurial firms by focusing on specific behavioral effects derived from media hype surrounding a firm's IPO. In performing this assessment, this dissertation contributes to management theory in three notable ways.

First, this dissertation provides a new theoretical perspective on the effects of media hype on managerial expectations and behavior. In the conceptual portion of the dissertation I characterize the nature of an organizations' information environment by describing how it is shaped by the information disseminated by the

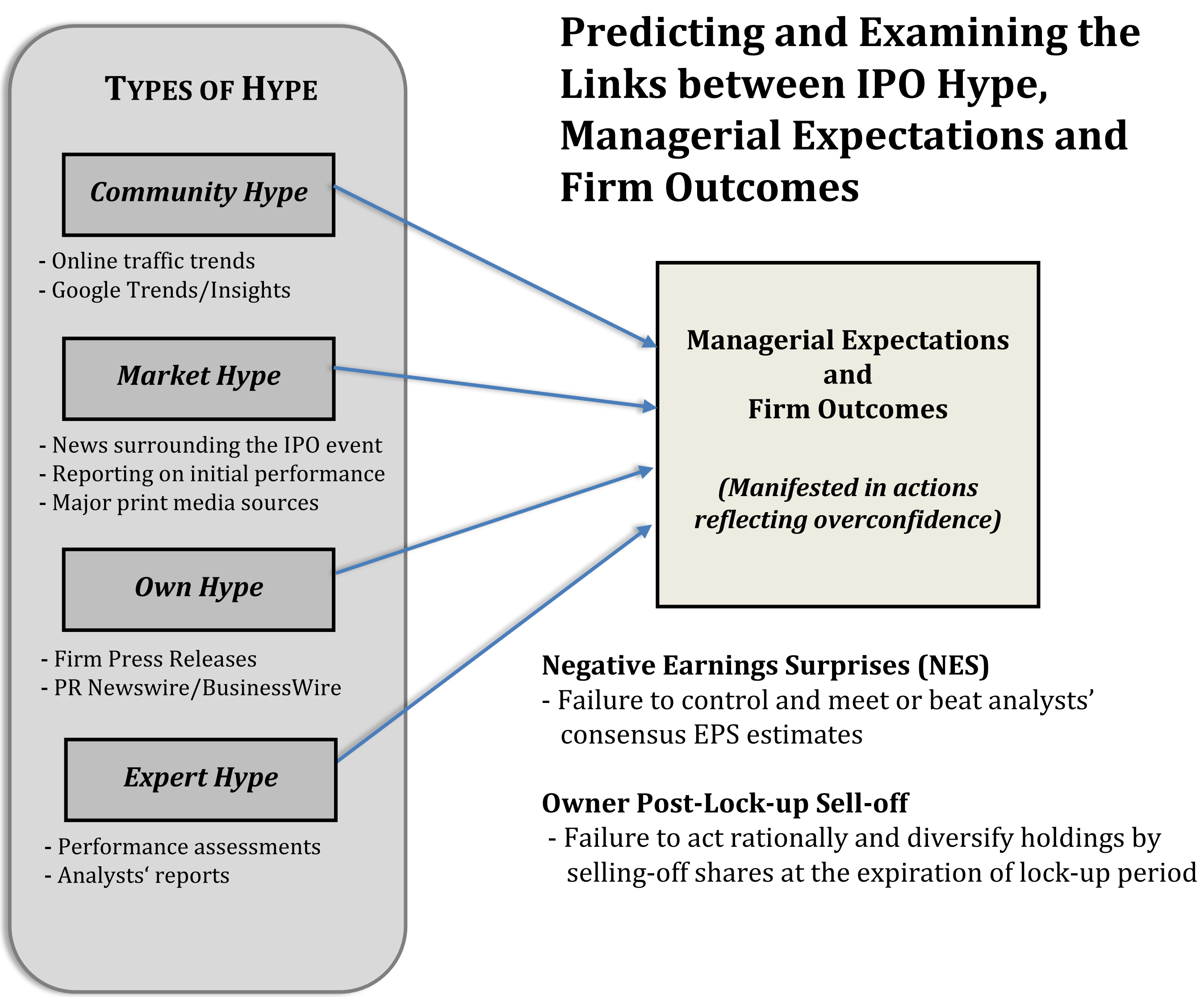
FIGURE 1.1: MODEL OF THE INFORMATION ENVIRONMENT SURROUNDING A TRIGGER EVENT



firm and by its stakeholders. In particular, I propose a link between intensity; direction (i.e. induced by the firm or induced by its stakeholders); nature and tenor of information to executives' judgment. Ultimately, this conceptual framework presents a new model of media hype by examining the differential effects of different sources of media. Specifically, I propose a model for exploring the informational environment and the differential effects of media as shown in Figure 1.1. As the model suggests, different sources and amounts of media will result in different information environments in which managers make their decisions.

Second, this dissertation aims to extend what we know about the effects of hype on managers' behavior by introducing a new taxonomy of considering and exploring the influence of media hype. The categorization system presented in the empirical portion of the dissertation, based on sources of hype, is a new and unique way to explore differences in media hype and their specific and consolidated effects on manager's expectations and firm outcomes. No other management article has made distinctions regarding the sources of media and tested whether these different sources truly have distinct and different influences on manager decisions and behaviors. Furthermore, I link this new taxonomy of media hype to managers' expectations and firm outcomes as manifested in managerial behaviors. Specifically, as the predictive model introduced in Figure 1.2 below indicates, media hype influences managerial behavior such that the more media hype a firm and its executives received the more likely the managers are to exhibit overconfidence in their actions.

FIGURE 1.2: PREDICTIVE MODEL



Third, this dissertation further contributes to theory regarding the effects of media hype by filling a gap in prior literature. Previous literature (Pollock & Rindova, 2003; Cen, 2008; Nam et al., 2008; Kothari et al., 2009) has many limitations and fails to provide a long enough analysis of the effects of media because they tend to focus on short-term events, a smaller volume of articles and specific types of media data instead of being more inclusive in their studies. Furthermore, they use stringent industry and time constraints and focus on a small breadth of media data in their samples limiting their generalizability. On the other hand, this dissertation provides a more comprehensive exploration of the effects of media hype by employing an extensive data set consisting of a large sample of media data through a very comprehensive article collection process evaluating the effects of media hype across a primary trigger event—the IPO—consisting of several sub-events, across multiple years, and across multiple industries. The sample is based on a two-year media data collection, one year prior and one year following a firm's IPO issue date, that provides a unique analysis of the true and complete affects of media hype on firm actor's behavior surrounding a specific event, namely its IPO.

1.2 Defining Media Hype

Hype means different things to different people. Often, media hype is examined superficially when scholars examine issues that cause media hype. In these cases, the focus tends to be on the causes of hype and not on the hype itself or its influence on people's behavior. For example, Dearing and Rogers (1996) focus on the issues that provoke media hype. Others view media hype as journalistic generated stories that gain attention. For instance, Kepplinger (1994: 230) views hype as stories "that seem to be the result of oscillating processes within the journalistic production, making coverage more an echo of previous coverage than a mirror of events." Following this perspective, hype can be seen as journalist-generated news stories than special or unique events that drive attention. Another definition of hype takes a more negatively slanted perspective by calling it coverage that creates false impressions where events accumulate around problems where they become more urgent (Kepplinger and Habermeier, 1995: 389).

However, in the hype literature, Vasterman (2005) is, to my knowledge, one of the only scholars explicitly interested in the concept of media hype and its influence on behavior, and thus is my point of departure. According to Vasterman (2005), media hype originates based on a non-daily, atypical or unusual event that triggers increased media attention. The collective media set their focus on this specific topic or event and then enlarge it. By doing so, the topic or event evokes all kinds of social responses, which will in turn become news as well, further stimulating a wave of news. This definition indicates a more active perspective of media hype than other scholars, by reflecting hypes' ability to influence behavior and begin to take on a life of its own.

Informed by this prior literature, I define hype as ***extraordinary media coverage about a firm associated with a particular event***. In the case of this dissertation, the event is the IPO and media includes press articles, community interest, expert analysis, and self-generated releases. This definition helps me distinguish between everyday news reporting and media hype by examining the effect of intense amounts of media coverage surrounding a single issue—the IPO. Empowered by this definition, I investigate how hype relates to firms' and its executives' subsequent behavior.

1.3 Scope of the Study and Boundary Conditions

Media hype associated with IPOs is nothing new. An IPO opens new opportunities to firms and their representatives (investment banks and their clients) and to the investment community at large. The opportunity to *get in at the ground level* is so attractive that it often leads to lofty visions of profitability. These lofty visions are hard for any firm, even one as established, popular and large as Facebook, to possibly achieve. The newness associated with an IPO sets the stage for the media to share their insights and trigger hype surrounding a firm's entrance into the marketplace.

This dissertation focuses on the larger and more recent IPOs. It does so purposely because the effects of hype are likely to be greater for firms with larger principal amounts due to the fact that those tend to generate more attention from the general media and Wall Street analysts, as well as the investing community at large. Furthermore, examining more recent (the past five years) IPOs was also done purposefully in an effort to leverage the increased access and intensity of media hype by firms, by analysts and in the general community. The increasing role of media in society is clear and understanding its effects is critical for managers in the future. Consequently, assertions made in this dissertation are focused on discussions surrounding media hype's effect on larger principal amount and more recent IPOs. Attempting to extend the findings beyond this may result in faulty assertions or conclusions.

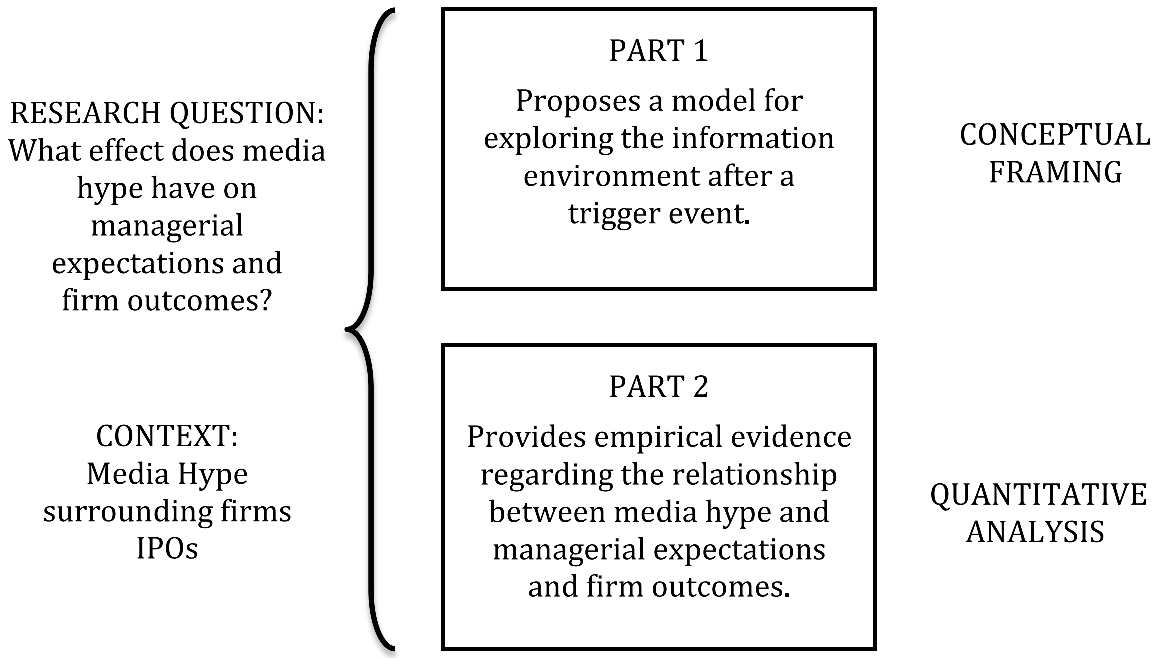
Finally, this dissertation examines firms by applying the lens of top management teams and their agency-oriented actions and behavior on behalf of their firms , Hambrick, Cho and Chen, 1996; Wiersema and Bantel, 1992; Smith et al., 1994; Finkelstein and Hambrick, 1990). Therefore, the level of analysis is based on the effect of firm-specific articles and their effects on managerial expectations and firm outcomes as reflected in managerial action and behavior.

To better ground this study, I consider information surrounding a material company event—the announcement and execution of a firm's IPO—an event for which public sense making is equivocal or not necessarily positive or negative in tone (Weick, 1979). Another boundary condition is that judgment in this dissertation refers specifically to the 'over estimation' perspective of over-confidence as reflected in executives' exaggerated beliefs in the prospects of their organizations, manifested in their management of projections about firm earnings and witnessed by their failure to diversify personal wealth away from their organizations when they have the opportunity (Moore and Healy, 2007). I chose this judgment because, arguably, overconfidence (and especially this manifestation of it) is perhaps the most pervasive and patent bias found in the literature on judgment in decision making (Pollock and Rindova, 2003).

1.4 Arrangement of the Thesis

In the next chapter, I discuss some of the relevant literature associated with the topics covered in this dissertation. I begin by exploring prior literature regarding the information environment and then present literature on hype, primarily from communications, and discuss its effect on human behavior. Following this, I explore literature regarding the influence of hype in society and in the economy. Finally, I provide the basis for a theoretical proposal predicting the differential effects of media in the information environment based on the sources and strengths of hype. Following this theoretical framing and literature review, in Chapter Three, I initiate the exploration of the relationship between media hype and managerial expectations and firm outcomes empirically. I describe the predictive model and begin by discussing the context for the dissertation—the IPO. Then I define the different elements of the model and develop testable hypotheses. Next, in Chapter Four, I describe the methodology for this dissertation. Included in the methodological section is an explanation of the sampling procedure, the data collection processes, the protocols followed in assessing, categorizing, and/or coding of the media data, the measures, and the analysis tools. Chapter Five reports the results and findings of the empirical analysis. Chapter Six provides a discussion section that explores what we learned from the findings along with the project's limitations, future research considerations, and final concluding thoughts.

FIGURE 1.3: DISSERTATION PROCESS OVERVIEW



CHAPTER 2: CONCEPTUAL FRAMING

2.1 Judgment, Decision Making, and the Information Environment

Literature on judgment in decision making tends to assume that the information environment facing decision makers is somehow 'exogenous' or 'given' and that they tend to make decisions under varying levels of certainty using the information available (Tversky and Kahneman, 1973; Simon, 1947; Knight, 1921). Furthermore, literature also presumes that the amount of information available is often something decision makers cannot readily influence (Knight, 1921). For example, weather professionals appear to be strong judges of the future. This, of course, is due to the fact that they can rely on past weather patterns as good guides to predict future weather and they receive prompt and free feedback on their judgments. By contrast, stock brokers face a less diagnostic informational environment because, inter alia, it is difficult to establish whether the efficacy of their judgment reflects luck or skill. Therefore, their judgments may not improve or become better calibrated over time.

Mindful of these factors, I adopt a social information perspective to inform a theoretical research question of this dissertation: How does the nature of the information environment that organizations, their representatives and their stakeholders enact influence the judgments that their executives make? The social information processing perspective states that one can learn most about behavior (and judgment) by studying the informational and social environment within which that behavior occurs and to which it adapts (Salancik and Pfeffer, 1978).

2.1.1 Reasons to Believe that the Information Environment Affects Judgment

It isn't hard sell to the claim that the amount and nature of the information available influences peoples' decision making and judgment. There are numerous examples of how the nature of the information environment or changes to the information environment lead to certain decisions (Brau, Carter, Christophe & Key, 2004; Pepitone, 2012). For example, Heflin, Subramanyam, and Zhang (2003) discuss the information environment by exploring the impact of a law enacted on October 23, 2000 by the SEC called Regulation Fair Disclosure (FD). FD prohibits firms from privately disclosing value- relevant information to select securities markets professionals without simultaneously disclosing the same information to the public. The researchers examined whether Regulation FD's prohibition of selective disclosure impairs the flow of financial information to the capital markets prior to earnings announcements. After implementation of FD, they found that rather than impairing the information flow in the information environment, it actually improved informational efficiency of stock prices prior to earnings announcements, as evidenced by smaller deviations between pre- and post-announcement stock prices. Furthermore, there was no reliable evidence of change in analysts' earnings forecast errors or dispersion and that there was a substantial increase in the volume of firms' *voluntarily* releasing forward- looking and earnings- related disclosures (Heflin, Subramanyam, and Zhang, 2003).

Other literature proposes that a stakeholder's information environment relates to the properties of their actions. For instance, in Barron, Kim, Lim and Stevens (1998), focusing on the properties of expert analysts' information environment, find that uncertainty and consensus can be measured by combining forecast dispersion, error in the mean forecast, and the number of forecasts. They also show that the quality of common and private information available to the analysts can be measured using these same observable variables (Barron et al., 1998). Similarly, Frankel and Li (2004) examines how financial statement informativeness, analyst following, and news relate to the information asymmetry between insiders and outsiders. Corporations' timely disclosures of value relevant information and information collection by outsiders reduce information asymmetry, limiting insiders' ability to trade profitably on private information. Use the profitability and intensity of insider trades as a proxy for information asymmetry, they find that increased analyst following is associated with reduced profitability of insider trades and reduced insider purchases (Frankel and Li, 2004).

2.1.2 Why Media Affects Executives' Judgments

Some attribution theorists suggest that the more that others provide an individual with attributional accounts (Hewstone and Jaspers, 1982), the more likely it is that the individual will adopt the view expressed by the others.

By extension, the organization as well as its leaders and stakeholders become less likely to attribute outcomes to their situation, as they receive more accounts that raise the salience of the organization (Kiesler, Nisbett, and Zanna, 1969; Pryor and Kriss, 1977; Krull, 2001). The more the celebrity organization interacts with others who also accept her celebrity, the more likely that those constituents will accept the celebrity attribution as true (Weiner, 1986; Hayward et al., 2004).

Perspectives on social information processing (Festinger, 1957; Pollock, Whitbred, and Contractor, 2000; Pfeffer and Salancik, 1978) also suggest that individuals rely on the perceptions and actions of others to infer their own attitudes and beliefs. Thus, as the organization becomes more aware of its newsworthiness, the attributions underlying their celebrity become more available to the CEO as an explanation for firm performance (Hayward, et al., 2004). In addition, the more frequently individuals are exposed to information, the more likely they are to rate this information as true (Hawkins and Hoch, 1992). Thus, the greater the media that the organization attracts, the more difficult it is for organizational members to reject the notion that the organization is celebrated. Or, as Eric Schmidt, the celebrity CEO, of Google puts it, 'It's very easy to confuse the company with yourself and let your ego go out of control' (Wall Street Journal Europe, 1997). Celebrated organizations have reason and incentive to embrace their celebrity status because of the financial rewards that come from being high profile, including higher compensation for its executives (Rosen, 1981; Rindova, et al., 2006).

These arguments suggest that the celebrity organization is unlikely to ignore or reject the celebrity that the media bestows on them (Sinha, et al., 2012). A more likely scenario is that the celebrity organization will cultivate and internalize celebrity, thereby asserting greater control over her firm and increasing the likelihood that she will receive richer compensation packages (Hayward, et al., 2004). As CEO celebrity galvanizes this perceived cause-and-effect relationship, it increases the CEO's efficacy in the minds of stakeholders (Pfeffer, 1981; Weick and Daft, 1983). CEO celebrity status can also help organizational leaders garner the resources needed to implement their plans by increasing the commitment of employees, customers, suppliers, and other members of the firm's task environment to the CEOs' present and proposed actions (Pfeffer and Salancik, 1978). As a result, over time, such celebrity may not only enhance the reputation, legitimacy and credibility of the firm but it may also increase the CEO's actual impact on the current and future performance of the firm. Thus, the greater a CEO's celebrity, the more likely a firm's stakeholders are to (a) make similar attributions regarding the CEO's responsibility for past performance, and (b) positively evaluate and respond to CEO actions (Hayward et al., 2004).

Furthermore, firm executives are chartered to act as agents for their firms' making decisions that are in the best interest of their firms. Ideally, this decision making process occurs independent of internal and external forces. If so, then why would stakeholder opinion affect executives' judgment? Senior executives recognize that public opinion shapes their own judgment. Daniel Vasella, formerly CEO of Novartis, observed:

> "… a pattern of celebration leading to belief, leading to distortion … You are idolized by the outside world, and there is a natural tendency to believe that what is written is true. It isn't though—no CEO is as good (or as bad) as the media makes him or her out to be. Nevertheless many come to believe their own press. Then it becomes difficult, if not impossible, to change the course you and your company are on … You must make the targets—must keep delivering record results at whatever cost to continue the celebration."
> (*Fortune*, 2002:112)

The notion that stakeholder opinion affects executives' judgment also features strongly in studies of impression management and media effects**.**
In fact, managers are incentivized to control the information environment such that sometimes it is in their best interest to withhold even positive information about the firm (Botosan and Stanford, 2005). In an effort to manage expert analyst perceptions, some firms readily withhold positive firm results in order to control performance expectations. In fact, firms are more prone to protect and withhold positive performance data from analysts to keep analysts from overreacting to the information and potentially leading them to unrealistic or unobtainable expectations (Botosan and Stanford, 2005). This impression management tactic of course has a deleterious effect on the completeness and transparency of the information environment. Although firm's prefer to be assessed by informed

analysts, they are careful to control the potential overreaction by analysts when both highly positive and negative information becomes available.

2.2 Managing in Ever-Changing Information Environments

Firms tend to desire a level of performance and firm outcomes that places the firm in a future state that is better than what they are currently in and reflects the growth and strength of the firm going forward. Aiming for this goal, firm managers strive to arrange their resources and manage information strategically so that their chances of arriving at a desired "future" state are improved (Ference and Thurman, 2009). However, as previously illustrated, firm's actions are influenced by the information environment. The information that is available, or unavailable, influences the options and alternatives available to managers in making decisions (Simon, 1997). Performance planning and managing begins by conceiving of a desired future state of affairs and then analyzing every choice from a list of alternative actions to select an optimal or, better said, the best solution under uncertainty (Ference and Thurman, 2009). However, since most decisions are *bounded* rationally and made with less than perfect information (Simon, 1997; Knight, 1921), we are at the mercy of the information environment when developing alternatives and selecting a final action (Ference and Thurman, 2009).

Furthermore, our decisions should consider various and dynamic sources of information. There are numerous stakeholders involved in every phase of a firm's activities and all of their information environments are different and constantly changing. When seeking to manage this dynamic information environment, managers seek to control as much of the playing field as possible, because basing their understanding, analyses, and decisions on a single snapshot of information, frozen in time, likely will lead to less than optimal information control and decision making (Kepplinger and Habermeier, 1995). In short, a desired firm future is based on decisions and actions that take place over time, influencing, and being influenced by, a variety of stakeholders in which the initial attributes, forecasts and constraints are constantly changing.

Effective managerial decision making involves a cycle of generating ideas, testing them, discarding some, and exploring the future that is likely and promising (Ference and Thurman, 2009). All of these steps require information and the information environment shapes the type, amount and source of information available to firm decision makers. Managers seek flexibility to handle the unknown which lurks just beyond their ability to forecast (Tversky and Kahneman, 1973). An essential skill of managers is being an excellent diagnostician. First, this is the ability to ask the right questions in the right order and to listen carefully to the answers. Then the manager must be able to integrate their knowledge, experience, and insight to make optimal decisions. Faced with uncertainty, investing professionals work hard to learn ways to gain more diagnostic information in order to make better judgments (Knight, 1921). Diagnostic information, as in the weather professional example, provides greater insight and is based on more historical precedence than other types of information. Doctors undertake more extensive tests to increase the likelihood of appropriately diagnosing a medical condition; investigators assemble more forensic evidence to solve a crime; auditors extensively review documentation and interview audit clients' customers and suppliers to establish a clearer picture of the firm's financial health, and so on.

Typically, managers' diagnostic approach is composed of a set of heuristics that provide them with the ability to reduce the seemingly overwhelming complexity of the organization, external factors, and the information environment to a workable model through a series of carefully chosen and sequenced questions. Depending on the answers to these questions, and to the further probing that the answer to each question suggests, managers are able to form hypotheses, assess probabilities, and make decisions. Therefore, I propose that without effective diagnostic information, managers' decision making capabilities are compromised.

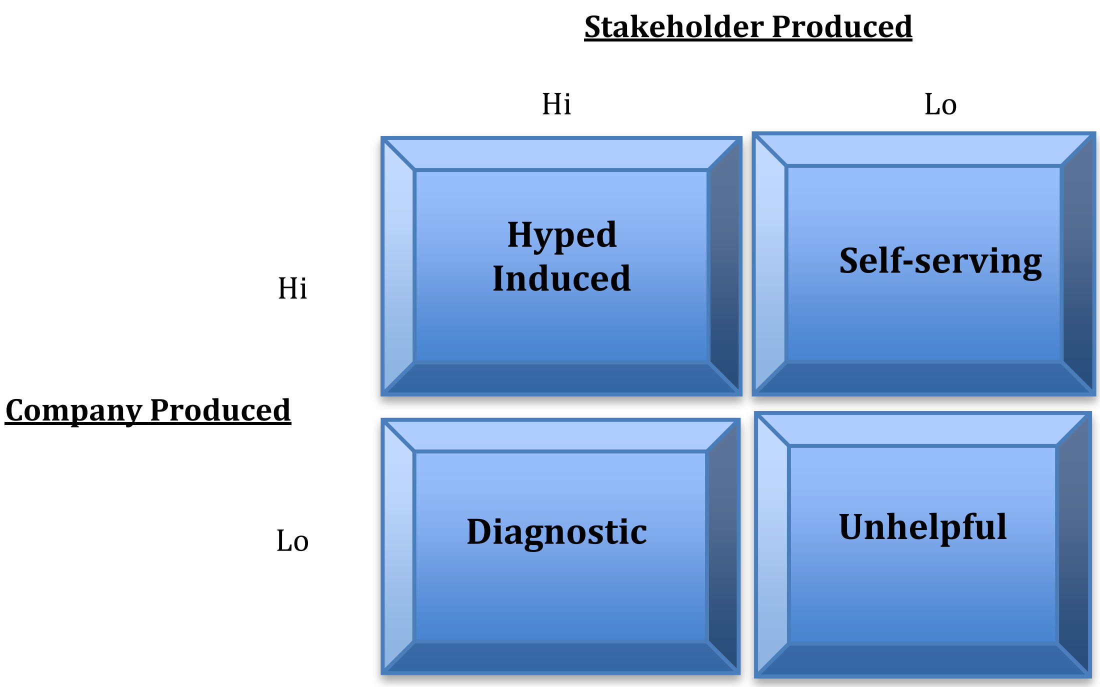
One danger of all of the diagnostic efforts is that the data collection and tests may be performed to confirm pre-existing biases, rendering decision makers more confident in a pre-existing judgment even if it is erroneous. Another is that experts and their organizations can create or enact the information environment which shapes their judgment increasing the likelihood that they will judge with potentially less complete and more distorted information. Goffman (1959) emphasized that we incessantly and dramaturgically 'perform roles' such that our judgment can only be assessed relative to the expectations established by that role or caricature, not to an objective standard of 'calibrated judgment' or even 'authentic and rational' thinking. Examining the information environment with organization as the level of analysis, Elsbach (1994:12) defines organizational perception management as actions "that are designed and carried out by organizational spokespersons to influence audiences' perceptions of the organization," a definition akin to how the psychology literature treats individual perception management (Schlenker, 1980; Tedeschi, 1981; Tedeschi and Reiss, 1984). Amongst those actions are verbal accounts which describe and explain organizational behavior and intention; and in some cases these accounts can shape the agenda of public discourse about the organization. The prospect is that organizations and their representatives are heavily influenced by the accounts which they themselves produce. Put differently, they can believe or be influenced by their potentially self-serving representations, prognostications and press.

2.3 Modeling the Effect of the Information Environment on Judgment

In this dissertation, I propose that the information environment is in part made up of various sources of information provided by two distinct categories of stakeholders. Internally, the managers and employees maintain, manage, provide a good portion of the information available about the firm, its operations and its performance. This internal firm information is controlled by the managers who decide which information to share with external stakeholders and what information to withhold. Since much of the information maintained by the firm is not as interpretable by external stakeholders, managers employ impression management principals in determining what information to disseminate, at what time and which to hold in an effort to maintain control of the information environment such that false interpretations do not ensue and that the firm can manage sentiments the results from the information they provide (Elsbach, 1994). Externally, stakeholders learn information both from the firm and from other parties in the market. Information is dispensed by a variety of sources at a variety of time with a variety amount of accuracy. However, the independent nature of the information often lends more credibility than firm-spun information (Kepplinger and Habermeier, 1995). As with our weatherperson example, the goal of external stakeholders is to gather the requisite amount of viable and reliable data from which to make assessments of the firms short and long-term viability. The more data they can collect, both in volume and reliability, the better able they are to make diagnostic-driven decisions (Ference and Thurman, 2009).

Therefore, a typically complex information environment can, coarsely, be considered in terms of the information that organizations generate about themselves and that which is generated by stakeholders (e.g., journalists, analysts, investors, general public search). Consider on one axis of a 2X2 matrix, that organizations can produce high or low levels of self-generated information depending on their public relations intentions. On the other axis is high or low levels of stakeholder produced information about the organization. Conjure the case where the level of self-generated information is low and autonomously produced information is high, such that external observers provide more diagnostic information about the organization. Unburdened by internal perspectives or biases, it would seem as though external objective assessments may provide the best diagnostic information about a firm. Diametrically opposite is the case where the public information about the firm is substantially self-generated, such that firms

FIGURE 2.1: RESTATING A MODEL OF THE INFORMATION ENVIRONMENT SURROUNDING A TRIGGER EVENT



enact their own information environment in a manner which is presumably positive and salutary towards themselves. Here, we would imagine that organizational executives would exercise the most skewed over-confident judgment (Hayward, Rindova and Pollock, 2004). Interesting cases arise in which high levels of self-generated information induces a considerable amount of stakeholder attention as well. In these instances, high levels of hype are induced clouding the information environment which may lead to over-confidence by executives. Also, by way of contrast, there are cases in which there is limited public information emanating from the organization or its stakeholders, such that judgment may not be readily affected by this 'information environment'.

2.4 Foundational Literature from Communications on Media Hype

Sometimes news media suddenly generates surprisingly high news waves on one specific story. For weeks that topic dominates newspapers, evening newscasts and other the public forums. This media hype occurs on a regular basis and attracts much media and community attention, but there is very little knowledge about them (Kepplinger, 1994). When a key event triggers the media, the production of news shifts into high gear, with more and more reporters hunting for 'newer' news to report on the story, gaining momentum day by day (Vasterman, 2005). Each day offers new scoops, disclosures and developments: even the most trivial details can become the most important news fact of that day (Kovach and Rosenstiel, 1999). Consequently, the news seems to develop a life of its own, creating huge news waves on one specific story or topic. In quick succession, events accumulate and create an impression that a particular situation suddenly deserves our undivided attention (Wien and Elmelund-Praestekaer, 2009). For instance, past literature has observed this process in cases where one person, such as a CEO, can garner celebrity status and become the target of intensive media attention and scrutiny (Hayward, Rindova and Pollock, 2004; Rindova, Pollock and Hayward, 2006; Sinha, Inkson, and Barker, 2012).

There is something different about news that becomes media hype, compared to other big stories, such as those on wars and natural disasters (Vasterman, 2005). There is an apparent mismatch between these media hype events and the real world that the media is supposed to cover (Boorstin, 1963). Writing about pseudo-events, Daniel Boorstin (1963:40), says confusion exists between the object and the subject, because the media constantly seems to switch from one role to the other. He continues to explain that there is ambiguity about covering versus creating news and about cause versus impact of news. In short, he proposes questions of whether the event is important news, or has it become important news because the media made it important? Furthermore, he asks whether the hype is real or does media hype create a new reality? (Boorstin, 1963)

Even though media hype seems to be quite common in modern journalism, little academic work has been conducted exploring the concept (Wien and Elmelund-Praestekaer, 2009). Other related concepts such as 'media scandal' (Lull and Hinerman, 1997; Thompson, 2000) and 'moral panic' (Thompson, 1998; Welch, Price, and Ynakey, 2002) are explored far more often. The term 'media hype' is often used when referencing self-inflating media coverage, but the concept has limited exposure in scientific literature, mainly because it often entails value judgments (Kepplinger and Habermeier, 1995). However, by not limiting our investigations into media hype to examples like 'exaggeration' and 'distortion' and by focusing on the processes and effects of amplification and magnification during these media-generated news waves, the concept can become a valuable tool for news-related research.

2.4.1 Trigger Events

In order to describe and understand media hype, one must know how and when the hype begins. Vasterman (2005:513) argues that media hype begins with a 'key-event'. Cobb and Elder, (1972) referred to this concept as a 'trigger event' denoting the beginning of something and implying that the event starting the media hype is a critically important part. Furthermore, news making is a social construction (i.e. Baumgartner and Jones, 1993), which means that a trigger event is likely, but not necessarily, an actual event in the real world. It could be a pseudo-event: an event constructed by the media or other actors in order to set the hype agenda. Although I concur with Vasterman (2005:514) when he states that news is what media sources consider newsworthy and that news making thereby is highly self-referential, I am also convinced that trigger events have some particular qualities to them that make them interesting and newsworthy. The introduction of a private firm to the public market is a big economic event and acts as a strong trigger in the media.

To my knowledge, very little work has been done on what happens after the trigger event has sparked media attention. According to Vasterman (2005), the media coverage is at its most intense some days after the trigger event and then it slowly fades. Consequently, one would expect the graphic image of a media hype to look like a series of waves of declining intensity. Such a prediction is noted, but not formally discussed, by Jorgensen and Rasmussen (2001: 62). However, hype might, and often time does, regain some of its intensity through follow-up stories (Vasterman, 2005:514). We need not look any further than Facebook's IPO as a prime example of how questions regarding improprieties and poor stock performance have given it a second traction in the media well beyond the first three months after the IPO trigger.

For this dissertation, I explore the IPO as a trigger event. I investigate media hype throughout the entire IPO process by collecting and exploring the effects of media hype for one year prior and one year following the IPO issue date. Included in this two-year period are four sub-events involved in an IPO that contribute to increases in media hype. The first sub-event occurs approximately one year prior to the IPO when the firm formally files with the SEC to announce its intentions and request permission to conduct an IPO. The second sub-event is the actual issuance of shares during the IPO. The third sub-event occurs six months following the IPO issue date when the IPO lock-up period expires. The fourth sub-event occurs one year following the IPO issue date when the firm releases its first annual earnings report. These four sub-events are foundational elements contributing to the IPO's role as a trigger event that generates media hype.

2.5 The Social Influence of Media Hype

Past literature has found an indelible connection between hype and behavior. Newspapers are a major source of information (Johnson, 1998; Jordan, 1993) and hype generated by mass media can manifest itself in behavioral responses (Fiske, 1994). Dearing and Rogers (1996:91) argue that in order for an issue to provoke media hype it should be able to generate strong emotions. Similarly, Vasterman (2005:516) argues that media hype creates a 'spiral of social amplification' that has the ability to transform a single case into general social problems and mobilize social outcry. Combining these two observations, one might argue that in order for a subject area to be a 'Petri dish' for media hype it must be a subject of concern and/or interest for many members of society (Wien and Elmelund-Praestekaer, 2009). This was certainly the case in the media coverage of senseless street violence in the Los Angeles riots (i.e., Rodney King) and in the coverage of AIDS in the US (Rogers et al., 1991). It is also the case with IPOs because it engages the excitement and opportunities that accompany the release of previously privately held shares.

Accordingly, in Vasterman's (2005) theoretical framework of media hype, media actively influences the social world. Prior research notes that sudden changes in media coverage of public events influences peoples' awareness, understanding and behavior. Media hype research has also been used to identify trends. In 1982, John Naisbitt published his popular Megatrends, based on content analysis in the US media. For example, after President Reagan's diagnosis of skin cancer the number of skin-cancer-related papers increased sharply during 1985 and 1988 (Heneghan, Hazan, Halpern, & Oliveria, 2007). Similarly, news media has been identified as a powerful tool for skin cancer prevention and detection education, ultimately decreasing the incidence of skin cancer (Liu, Liu, Xiao, Cai and Xu, 2010).

Therefore, not only does media hype influence what information is viewed as most important at a given moment, but it also plays a key role in society. By making images and information available to individuals located in distant locales, media shapes and influences the course of events, and creates events that would not have existed in their absence (Thompson, 1995:117). As a source of social influence, media has become the source of many decisions and behavioral actions (Fiske, 1994).

Furthermore, media attention is considered such an important societal tool. It is the primary way to share information about the world around us and more importantly about how people act in that world. For instance, Gurun and Butler (2012) found that local media reports about local people and companies, tend to use fewer negative words compared to the same media reporting about nonlocal companies even though there is certainly plenty of negative discussion points to be reported locally as well. They submit that one reason for this positively slanted artificial hype is that the same people and firms they are reporting on are the primary source of local media advertising expenditures. In other words, media hype influences behavior with regard to support. When support is high and positive, advertising expenditures are high. These findings show that news content varies systematically with the characteristics and conflicts of interest of the source and since media does influence behaviors in society, this conflict of interest that generates certain type of hype guides societal behavior.

Past journal articles examine the effects of hype in business related topics such as consumer habits and opinions. Other research examines the effect of hype in sports examining the effect on team performance, referee decisions, and players' compensation. Additional research exists in the medical field exploring the propagation of certain medicines, medical procedures, and medical technological exploration and innovation. In the next section, I explore how media hype has influenced economic-specific decisions and behaviors.

2.6 Evidence that Media Hype Influences the Economy

With regard to market influence, the predominance of work regarding hype is exploring whether the hype was or was not warranted. For instance, some have examined how to take hype out of the equation with regard to IPOs (Mullaney, 2000), others have described ways to uncover the reality behind the hype (Clark and Neill, 2001), and even others develop means for identifying the important information inside the hype (Hanley and Hoberg, 2010). However, there are numerous examples where media has been shown to influence economic actions and outcomes. Stocks experience strong drifts after bad news (Chan, 2003), and media coverage helps explain stock market returns (Fang and Peress, 2009; Dougal, Engelberg, García and Parsons, 2012) and acquisition premiums (Hayward and Hambrick, 1997). Furthermore, studies have shown how stale news, if widely publicized, can increase short-term returns (Huberman and Regev, 2001) and that public reports from firms that are given to the media are often put right back out as new investigative news information (Ohl, et al., 1995).

Merton (1987) established the attention hypothesis that states news releases with no economic content, which draw the attention of market participants to a firm, can produce an increase in the value of that firm. For instance, Huberman and Regev (2001), shows how a feature story in the New York Times caused the stock price of Entremed to increase four times overnight despite the fact that all of the facts reported in this new news story had been previously reported in scientific journals. Furthermore, Ahern and Sosyura (2011) illustrate how media coverage has a significant effect on stock trading and returns and that even stale news, if widely publicized, can dramatically raise short-term returns and influence prices of large and widely followed stocks in the S&P 500. They found that bidders in stock mergers originate substantially more news stories after the start of merger negotiations, but before the public announcement in an effort to generate short-lived run-up in bidders' stock prices precisely during the period when the stock-exchange ratio is determined. This leads to a lower takeover price. In short, Merton’s attention hypothesis and these articles provide strong evidence that firms manage their media through news releases precisely when they would benefit the most from a temporary price increase (Ahern and Sosyura, 2011; Huberman and Regev, 2001; Merton, 1987). Furthermore, abnormal positive local media attention has been shown to strongly relate to firm equity values and this effect is strongest for small firms, firms held predominantly by individual investors, and firms with illiquid or highly volatile stock, low analyst following, or high dispersion of analyst forecasts (Gurun and Butler, 2012).

Specifically, regarding media effects surrounding IPOs, Liu, Sherman and Zhang (2009a and 2009b) discovered that media coverage is positively related to

IPO returns, analyst coverage & institutional ownership. Again these results seem to relate to genuine (vs. temporary) investor demand as in Merton's (1987) attention hypothesis (i.e., investors only buy securities of firms they are aware of). Other studies show how media hype fosters a market for the firm's shares (Ho et al., 2001), drives up the offer price (Cliff and Denis, 2004), and increases IPO underpricing (DuCharme, Rajgopal and Sefcik, 2001). Adams, Thornton and Hall (2008) discuss how media hype surrounding the IPO drives an over-reaction bias in anticipation of the new offering and usually causes investors to over react. Ljungqvist and Wilhelm (2003) state that there is a range of behavioral biases that exist in equity markets in general and IPO pricing in particular. Moreover, Battacharya et al, (2011) shows how media coverage for all IPOs is more intense following the Internet boom (and bust) than prior to Internet IPOs. They express how the media hyped bad news post-bubble, but that this hype was somewhat discounted by the market. This dissertation seeks to extend this IPO media-oriented research to explore the specific effects of hype on managers' expectations and firm outcomes.

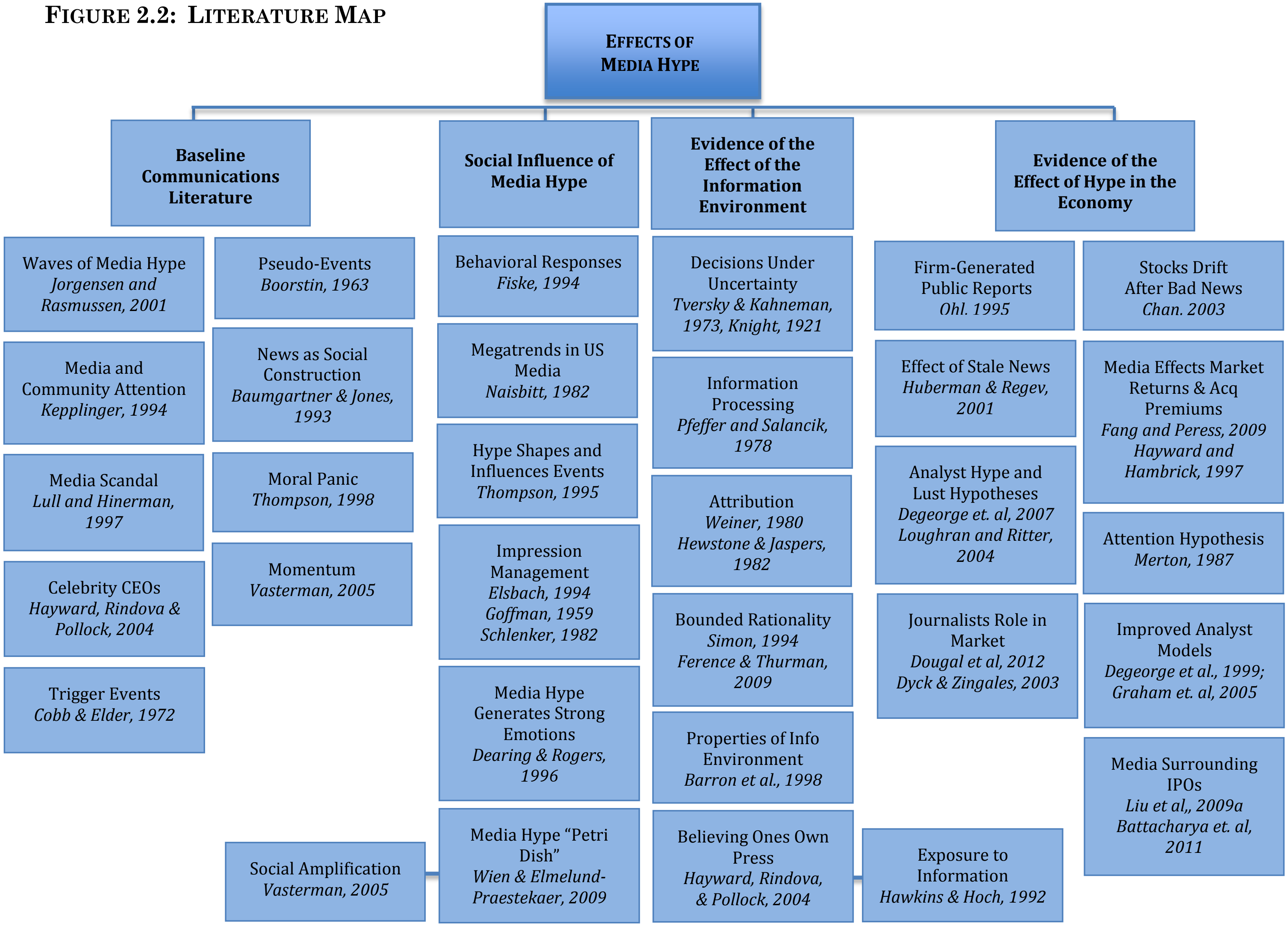
Similarly, Degeorge, Derrien, and Womack (2007) discuss a concept they call the "analyst hype" hypothesis, where issuers and investment banks are in a quid pro quo relationship that extends beyond the obvious direct costs of an IPO. That is, a tacit agreement exists where issuers are willing to pay the higher direct and indirect costs to underwriters to bookbuild for the IPO in exchange for increased and more favorable research coverage because analyst coverage is important to them. Degeorge et al. (2007) accordingly found that affiliated analysts were more likely to provide positive recommendations post-IPO after a poor performance, a practice known as 'giving the firm a booster shot.' Consequently, when an investment bank underwrites a firm's IPO, it implicitly commits to providing favorable coverage to them in the aftermarket. Moreover, Loughran and Ritter (2004) proposed and found evidence to support their "analyst lust" hypothesis, which argues that issuers' perceived importance of analyst coverage increased in the 1990s, and led to an over-inflated importance placed on analysts' perspectives.

Moreover other studies show how journalists play a key role in market movement and actions. For example, Dougal et al. (2012) specifies that even though specific journalists are strongly and consistently associated with certain kinds of spin, the market fails to adjust for this known hype. They argue that the market should learn and anticipate this type of hype, but that it does not seem to. In fact, they were able to identify that some journalists have strong effects and their writing had a causal effect on aggregate market outcomes. Dyck and Zingales (2003) further show how some journalists tend to spin information along similar lines in similar contexts without regard to new or different information. Furthermore, as analysts improve their modeling techniques and offer better opinions, investors appear to be relying more on their advice in making their investment decisions (Degeorge et al., 1999; Graham et. al, 2004). Added to this is the finding that there has been a temporal increase in media attention paid to analyst forecasts over the past decade (Brown and Caylor, 2005).

2.7 Summary

Generally speaking, chapter two provides the conceptual framework for this dissertation and establishes a baseline understanding of the influence of media on judgment and decisions making that will be explored empirically in the chapters to come. This chapter began by discussing the information environment and the influence of media and other attributions on executive's judgment and decision making. The discussion on the information environment culminated in a theoretical model for considering how the information environment is shaped by the sources of information. Next, I discussed the foundational communications literature regarding media hype and explored hypes influence in society and the economy. Figure 2.2 presents a literature map of the topics discussed in this chapter. Although the theoretical framing has been set in this chapter, chapters three and four continue to explore past theoretical and empirical literature related to the topics of media hype, actions reflecting overconfidence, content analysis, variable development and other research from management, finance, accounting and communication literatures.

FIGURE 2.2: LITERATURE MAP



CHAPTER 3: PREDICTIVE MODEL AND HYPOTHESES

The general premise of this dissertation is to explore the relationship between media hype and managerial expectations and firm outcomes. I test this relationship by examining how media hype surrounding the IPO period influences subsequent managerial behavior and subsequent firm performance. The predictive model (restated in Figure 3.2 below) begins with four main sources of media hype. The four general sources of hype include 1) community hype, 2) event hype, 3) own hype, and 4) expert hype. The model proposes that media hype influences managers' expectations and firm outcomes by examining the relationship between hype and founders/CEOs actions and firm performance. Specifically, I examine the relationship between hype and actions by CEOs/founders that reflect overconfidence. Namely, the model predicts that founders/CEOs will exhibit over-confidence in their actions with regard to the firm and in their personal lives. With respect to the firm, the model predicts that media will influence managers such that the firm will *allow* earnings surprises to occur at quarterly EPS reporting periods. With respect to the managers, the model predicts that hype will influence managerial expectations such that they will fall victim to the hype and make less than optimal decision regarding selling off their firm holdings after the IPO lock up period expires. Their actions, which are not inline with conventional financial theory and decision-making, reflect overconfidence.

The following sections provide background and details regarding each of the different parts of the model. First, I provide a basic background and understanding regarding Initial Public Offerings (IPOs), the framework and context for this project. Second, I describe the new proposed taxonomy of hype by describing the four different types of hype identified in the model, explaining who generates it and why they generate it. Third, I discuss the subsequent managerial actions resulting from media hype that reflect overconfidence. Along the way, I present a series of hypotheses for subsequent testing.

3.1 Project Context: Initial Public Offerings

3.1.1 What is an IPO?

An Initial Public Offering (IPO) is a public offering of a firm's stock. The primary reason that a company conducts an IPO is to raise cash and gain access to capital markets. Usually when a firm issues an IPO, they are seeking to raise lots of cash. For example, when Google conducted its IPO in 2004, it sold approximately 20 million shares of stock at $85 per share. Consequently, Google raised about $1.7 billion dollars. More recently, in March, 2012, Facebook conducted an IPO at $38 per share to raise the company's value to $104 billion dollars, an opening day record (Watson, 2012).

There are many different reasons why businesses need money. With the funds generated from their IPOs, companies can invest in new projects or infrastructure, pay down their debt or spend the money in many other business related projects. For instance, if someone started a moderately successful small company and were interested in expanding their operations nationally or globally, they may seek funds through an IPO.

3.1.2 The IPO Process

The U.S. Securities and Exchange Commission (SEC) regulates the IPO registration process consisting of three phases:

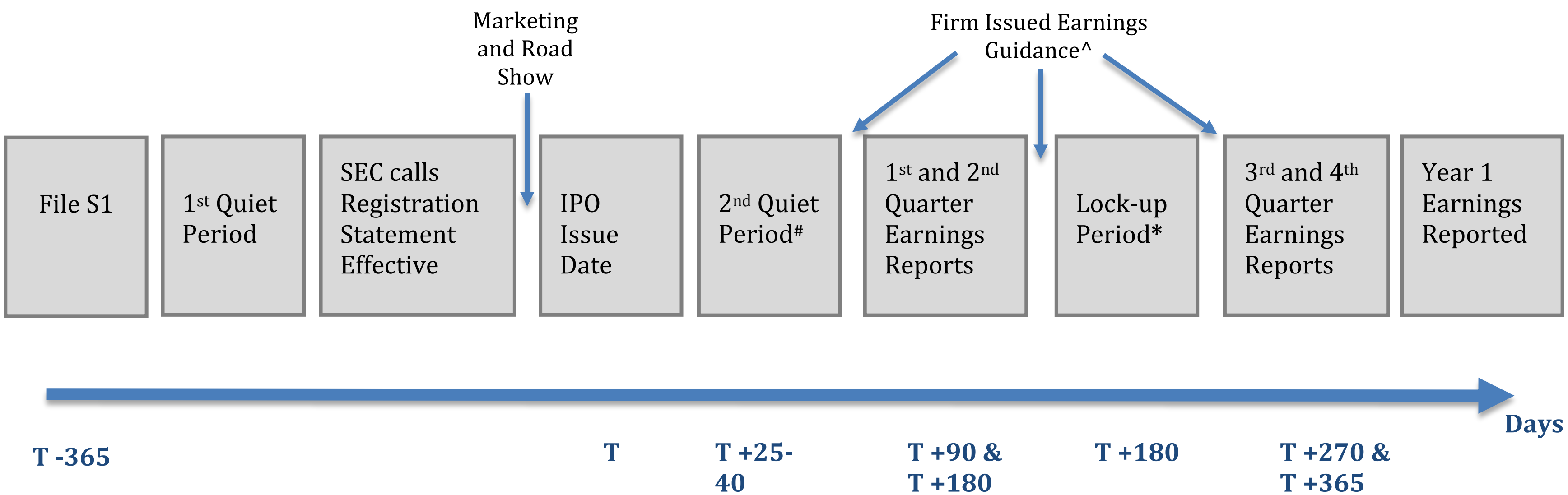
1) pre-registration period, when a firm begins planning to going public,
2) registration period, when the firm requests approval to offer its stock to the public, and
3) post-effective period, when the SEC grants a company permission to offer its shares to the public and the firm distributes its stock (Husick & Arrington, 1998; Pollock and Rindova, 2003).

Practitioner literature on IPOs (e.g., Gutterman, 1991; Husick & Arrington, 1998) suggests that firms begin planning for their initial public offerings about a year before they actually file with the SEC and are especially likely to engage in activities that will result in media exposure during this time (Pollock & Rindova, 2003). By beginning media collection one year prior to the IPO issue date and concluding one year after the IPO issue date, articles were collected in all three phases of the IPO process and, consequently, I can make strong assertions regarding the effects of media hype on managerial expectations and firm outcomes surrounding the entire IPO. Pre-IPO hype sets the foundation for media attention and the post-IPO hype either confirms or refutes previous opinions.

Figure 3.1 provides a description of the IPO process timeline. First, firms obtain SEC approval through submission of an S-1 document. Next, they seek shareholder approval. Prior to the IPO, the company is a private company and has private investors. Those investors have to agree via a vote on whether or not to issue an IPO. Following private shareholder approval, the firm selects an exchange to trade on, files for an IPO, and hires investment banks to underwrite the deal. Working with their underwriters, companies begin to evaluate their market value based on a number of variables and metrics to try to determine an appropriate share price and reasonable expectations for performance once it goes public. Next, along with the firm, the investment bank begins to raise investor interest for the IPO through the use of the road show, in which the company makes presentations to large investors and investment banks to sell large blocks of stock at the IPO price. One might have assumed that, on the day of the IPO, that shares are offered directly to the general public; however, in most cases they are not. Large investors and investment banks buy big blocks of stock after conversations with the company and its underwriting investment banks. In fact, on the morning of the IPO, money from big investors flows to the IPO firm, and then the big investors start selling their shares on the public exchange. Practically all of the trading that occurs on the stock market after the IPO is between investors; the company gets none of that money directly.

After the IPO there are a number of additional important timeframes. First, is the quiet period. The quiet period typically lasts between 25 and 40 days

Figure 3.1: IPO Process and Timeline



Notes:

^ Firms, individually, chose whether or not to issue earnings guidance to analysts and the market. Firms that release guidance, often do to manage the expectations of analysts and market stakeholders with respect to firm performance.

The 2nd quiet period, typically 25 to 40 days after the IPO issue date, is a time during which the firm is prohibited from releasing any new firm performance-oriented information. Only business that existed prior to the quiet period may be discussed.

* The Lock-up Period is a time during which firm officers (insiders including firm managers and members of the Board of Directors) may not sell their shares. This is typically 180 days after to the IPO issue date.

and it is the time "extended from the time a company files a registration statement with the SEC until SEC staff declared the registration statement effective. During that period, the federal securities laws limit what information a company and related parties can release to the public." (SEC Website, 2012) Essentially this is a "cool off" period and time in which a company making an IPO must be silent about its activities, so as not to inflate the value of the stock artificially. During the quiet period, a publicly-listed company cannot make any announcements about anything that could cause a normal investor to change their position on the company's stock. Normally, that means the company does not discuss any of the following: 1) New deals or wins signed in that current quarter (although announcements about previously-sold implementations going live are allowed, but must be explicitly described as such), 2) Management changes, 3) Progress against company goals, 4) Major product or service announcements, and 5) Major partnership announcements (SEC Website, 2012).

Another important milestone occurs, typically, 180 days following the IPO issue date. On this date the lock-up period expires. The lock up period is a predetermined amount of time following an initial public offering during which employees and close associates of the company, often referred to as insiders who are given or bought shares at or prior to the IPO, are not allowed to sell those shares. The main purpose of this restrictive period is to avoid a "fire sale" of the firm's stock by members of the board of directors, managers and other insiders directly following or even on the first day of the IPO. The general premise is that insiders of the firm's stock should be focused on developing a long-term firm strategy and not be using the IPO as a "get rich quick" exit strategy, leaving only a shell of a firm behind for investors.

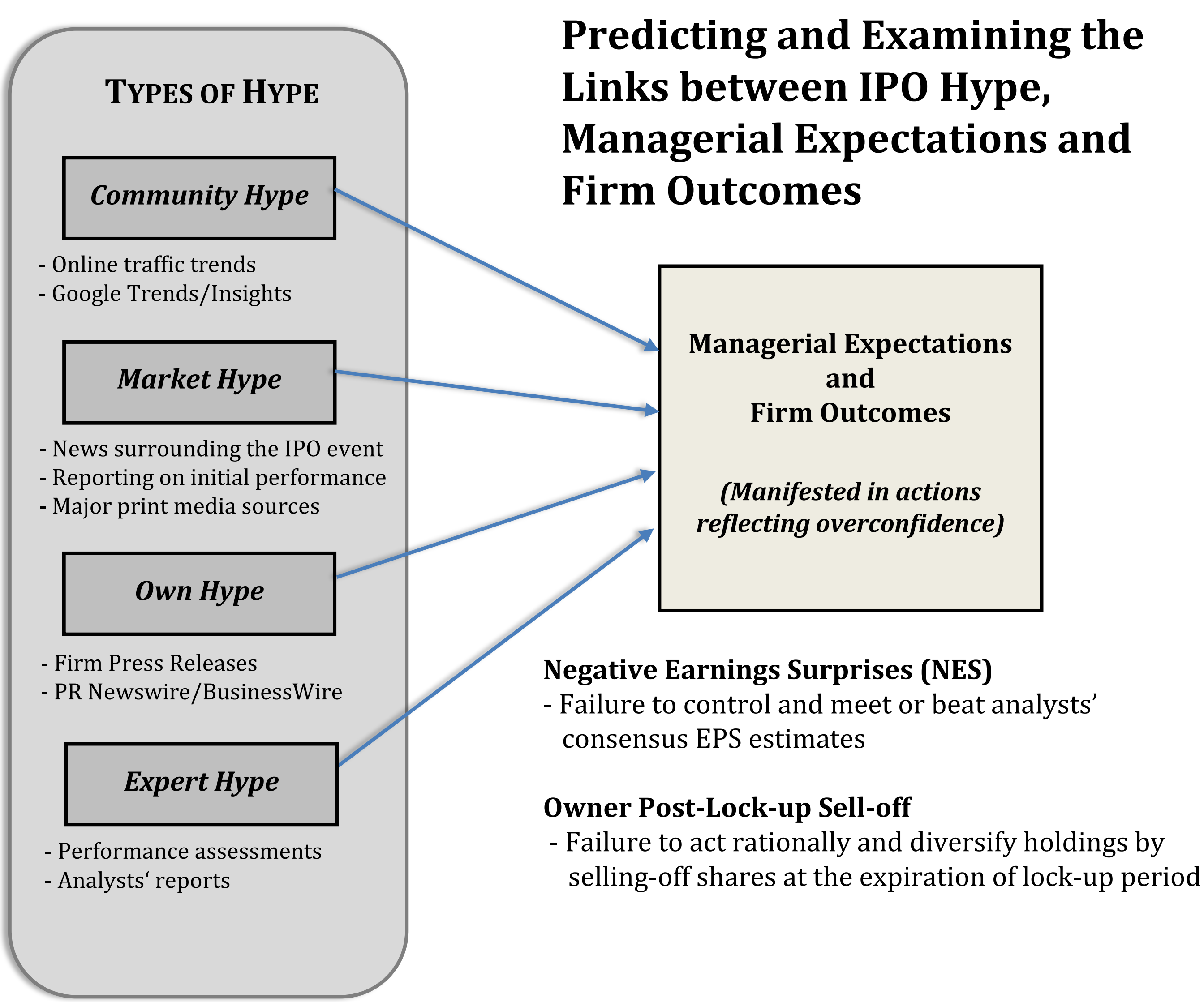
3.2 Types of Media Hype

When firm owners and/or managers decide to explore an exit or growth strategy by way of an IPO, they set into motion a detailed examination of the firm. This examination is often unlike any experienced by the firm previously and is especially unique for small, nascent, privately owned ventures. The increased scrutiny, brings with it media attention from four distinct sources, namely 1) the community, 2) the event itself, 3) self-generated press, and 4) experts. Some media hype is sourced through the world-wide-web, others come from mass media such as newspapers, some are derived from internal firm sources, and some come from expert analyst reports. The following sections provide more details regarding the new taxonomy for media hype proposed in this study.

3.2.1 Community Hype

Community hype refers to online activity with respect to the firm by examining the search traffic timing and volume surrounding the IPO. The world wide web has changed the way information is disseminated and shared. Information travels further and faster than it ever has in history. The fingertip access to information changes the ways in which firms manage their information and deal with asymmetric information. However, readily accessible information

Figure 3.2 Restating the Predictive Model



presents challenges for firms regarding the way they must manage the various stakeholders that influence the firm. The shear speed and volume at which online information is exchanged makes community hype a critical consideration in this dissertation. The 24-hour global nature of community hype makes it a potential powerful player in influencing behavior. In short, this dissertation hypothesizes that online activity influences firms' outcomes, either directly or indirectly.

3.2.2 Market Hype

Event hype includes mass media articles about the firm. It includes news related to the firm's performance, products and services, and in the context of an IPO, it will often discuss elements associated with the firm's road show or other IPO enhancing efforts by the firm. Furthermore, event hype often includes expert analysis and predictions, journalist opinions, and competing firm and industry information to support its claims or predictions. The public fascination for IPOs is so great that all highly circulated major periodicals include business sections that will dedicate large amounts of coverage and print space to the more popular, typically larger, offering deals. As the trigger event gets closer the intensity in both volume and tenor tend to increase such that investors thirsting for IPO related information could quickly find their fix in a nationally circulated major periodical.

3.2.3 Own Hype

Own hype is a measure of firm-driven media and includes press releases by the firm. It includes information regarding performance reports, new product or service launches, fundraising efforts, and other firm related pertinent information.

Oftentimes, firms use own hype as a way to release data to analyst and other investors that gauge the performance of the firm in a way that helps present their firm in the best light. This is particularly important for unique firms where traditional financial metrics fail to identify the best elements of the firm. In these instances, firms may choose to relate their performance in their press releases using other performance metrics that reflect favorable performance. For instance, many young technology firms have great ideas, but they have not yet begun to generate much, if any, revenue streams for their product or service. In this instance, a young technology start up may decide to present performance metrics such as new customer accounts, speed of processing, or some other technological advancement measurement of performance. Of course, in these circumstances, valuing a firm that files for an IPO is more difficult when uniquely built entrepreneurial venture tries to bet their price based on unproven and untested firm-specific metrics, making it hard to compare it with other firms or to fully understand the financial implications of the metrics the firm uses to measure performance. In essence, own hype is the firm's way to send signals to the market regarding their firm in an attempt to manage expectations and impressions of analysts, investors, and customers. Because it is firm generated news, it tends to be skewed to the positive side of the firm's actions.

3.2.4 Expert Hype

While Degeorge et al. (2007) discussed a concept they called "analyst hype hypothesis," where a quid pro quo is established between investment banks and IPO firms, this idea is vastly different from the concept I refer to here as expert hype. Expert hype is media generated by Wall Street analysts via analysts' reports. Traditionally, analysts use fundamental analysis principles, but technical chart analysis and tactical evaluation of the market environment are also routine. Often at the end of the assessment of analyzed securities, an analyst provides a rating recommending that investors buy, sell, or hold the security. These recommendations are important to firms because they have been shown to correlate with firms' stock price movements. Analysts obtain information by studying public records and filings by the company, as well as by participating in public conference calls where they can ask direct questions to the management. Additional information can be also received in small group or one-on-one meetings with senior members of management teams. However, in many markets, such information gathering became difficult and potentially illegal due to legislative changes brought upon by corporate scandals in the early 2000s. Because analysts typically use firm-provided data and make recommendations based on interactions with firms' management, it is clear that firm manager have a strong influence on the impressions of analysts.

Different from community, own, and event hype, expert hype typically begins just before the IPO, or more often just after the IPO, when data about the firm is public and analyst have an opportunity to better make assessments of the firm's earning potential. Therefore, since it is often so limited, hype preceding an IPO is not the critical element of expert hype. Expert hype likely plays a greater role in post-IPO decisions made by firm founder and CEOs. Prior to the IPO, hype is found via the Internet, through self-generated newswires and through sometimes less-than-professional mass media authors. When a firm begins to be evaluated by Wall Street experts who historically drive market value, the influence of expert hype is likely to be significant. If a firm is codified positively in the writings of Wall Street experts, it likely drives the founder/CEO into a greater overconfident position. If on the other hand the experts do not endorse the firm, founders and CEOs may be compelled by overconfidence to prove the experts wrong by taking risks and acting in ways that stretch the firm's capabilities.

3.3 Managerial Expectations and Firm Outcomes

This project explores how media hype influences managerial expectations and firm outcomes. In particular, the model predicts that media hype will influence managerial decision-making and behaviors such that high amounts of media hype will lead to greater exhibitions of overconfidence. Specifically, the model analyzes the relationship between the amount, salience, and tone of Pre- and Post-IPO hype and actions by managers on behalf of their firm and in their personal financial portfolios.

3.3.1 Actions Reflecting Overconfidence

Overconfidence influences behavior (Koellinger, Minniti, and Schade, 2007). Prior literature discuss how overconfident actors make excessive new market entries (Camerer and Lovallo, 1999), overestimate the likelihood of new venture success (Hayward and Shepherd, 2004), develop riskier products (Simon and Houghton, 2003), and pay higher acquisition premiums (Hayward and Hambrick, 1997). Overconfidence refers to the exaggerated sense that one can predict or produce a desired future outcome (Camerer and Lovallo, 1999; Griffin and Tversky, 1992, Koellinger et al., 2007).

In this dissertation, overconfidence is examined in two ways. First, overconfidence is the confidence that individuals express in their judgments relative to the accuracy of those judgments (Klayman et al., 1999). Overconfidence exists when the ex ante expected accuracy of judgments exceeds their ex post accuracy (Hayward, Rindova, & Pollock, 2004). For instance, sometimes firms' managers exhibit overconfidence when managing analysts' perceptions of their firms' performance such that they allow analysts consensus estimates to exceed firm performance capabilities. Second, overconfidence exists when managers overestimate their own ability relative to others (often referred to as the 'better-than-average' effect) (Moore and Kim 2003; Camerer and Lovallo, 1999). For example, the better-than-average effect manifests itself in the actions of firm managers when they maintain unrealistically positive images of themselves relative to others and rate themselves above the average with regard to selling-off their shares at the expiration of the lock-up period (Alicke, Klotz, Breitenbecher, Yurak, & Vredenburg, 1995; Eiser, Pahl, & Prins, 2001).

The model proposes two key dependent variables to examine the relationship of media hype and overconfidence in Founder-CEOs and Professional Manager-CEOs and their personal and professional lives. The first measure of overconfidence analyzes differences between analyst consensus estimates and actual quarterly reported earnings (Hsuan-Chi, Fauverb, Hsuc and Shenc, 2003). Discrepancies between these two are referred to as earnings surprises, and when the firm underperforms analyst estimates, it is considered a Negative Earnings Surprise. The second measure of overconfidence examines sell-off trading activity of firm CEOs at the expiration of the lock-up period. The following sections discuss these measures and describe the basis, relationship and logic associated with these dependent variables.

3.3.1.1 Negative Earnings Surprises (NES)

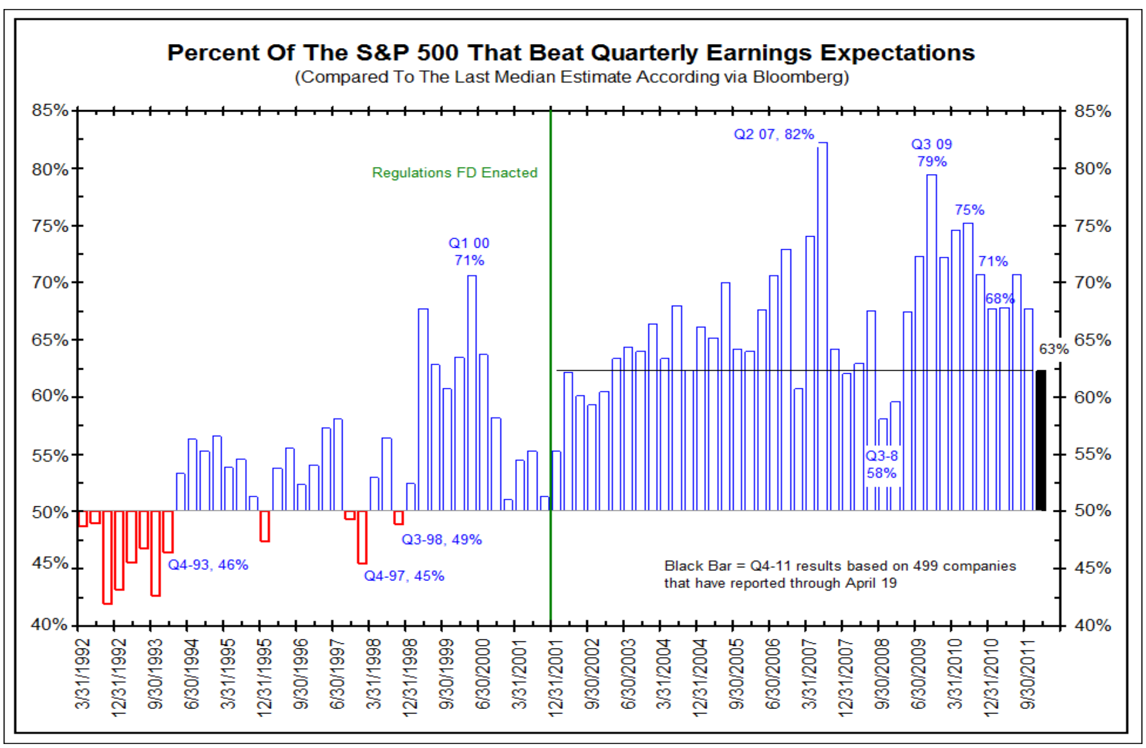
In the absence of historical data, which is typically associated with IPO firms, it is difficult to assess how well existing revenue streams will hold up if macro economic conditions become less favorable. In other words, for many entrepreneurial firms, there is little or practically no prior financial data making it more difficult to make a judgment on whether current earnings represent a flash in the pan or are sustainable. For instance, the lack of data from prior years makes it more difficult to analyze how earnings would change, if the company changes its pricing policy or faces new competition. Therefore, although not blindly (analysts can assess likely future firm performance based on a firm's S-1 and other available information, although much of it is firm-generated) it is prudent for analysts of these new firms to heavily rely on firm offered information in making their earnings per share estimates. Consequently, many newly IPO'ed firms have a great deal of influence on analysts' EPS consensus estimates, at least in the short-term following their IPO, while the firm establishes a history of financial performance for analysts to begin making more independent assessments.

Impact of Negative Earnings Surprises

Meeting or beating analysts' forecasts of earnings is a notion well entrenched in today's corporate culture. From corporate boards' deliberations to financial press reporting and Internet chats, emphasis is placed on whether the company meets its earnings forecasts (Bartov, Givoly and Hayn, 2000). Over the past ten-year the historical average of firms beating analyst consensus estimates is 62% (The Big Picture Website, 2012). If we extend success to include firms that meet or beat (MoB) earnings estimates, the percentage of MoB is over 75%. Furthermore, evidence shows that after controlling for the overall earnings performance in the quarter, firms that manage to meet or beat their earnings expectations enjoy an average quarterly return that is higher by almost 3% than their peers that fail to do so (Bartov, Givoly and Hayn, 2000).

Therefore, there is an intense incentive to meet or beat analysts' estimates (MBE) (Graham, Harvey and Rajgopal, 2005). If a company fails to meet its earnings, the price of its stock almost certainly will fall, stockholders will be upset, and managers may lose their jobs (Dechow, Richardson and Tuna, 2003). The comparison of analysts' earnings estimates to actual earnings is one of the most closely watched rituals in the financial world (Degeorge et al., 1999). To miss an estimate by as little as a penny a share invites trouble. Consequently, many corporate managers deal with this quarterly ritual with a ritual of their own. In fact, Recognizing the significance of meeting or beating analysts' consensus estimates, firms' managers' try to steer analysts toward a number the corporation can in fact meet or beat (Graham et al., 2005; Hsuan-Chi et al., 2003). Sometimes they do this by providing management's own earnings estimates via earnings

FIGURE 3.3: PERCENTAGE OF FIRM BEATS OF QUARTERLY EARNINGS EXPECTATIONS



Source: The Big Picture

guidance; sometimes they do it by providing a few key tidbits of useful financial information. Additionally, once analysts reach a consensus estimate, management can make minor (hopefully) legal accounting adjustments to ensure they meet or beat that number (Wiedman, 1996). For example, managers can boost profits by changing the estimates they use of how long certain equipment or infrastructure they own will last, thereby reducing the allowance for depreciation (Dechow et al., 2003).

It is well known that managers have some flexibility when preparing and reporting earnings; therefore, when a firm misses a quarterly or annual earnings estimate it is often construed as a sign of trouble. This signal is often interpreted as a big problem for the firm's future outlook because it means the firm doesn't even have enough *slack* to manage its earnings to meet or beat known analyst expectations (Graham et al., 2005). The impact of this signal can be pretty dramatic, and is likely to be reflected in its stock price (Dechow et al., 2003).

Dechow et al. (2003) shows that avoiding negative earnings surprises is extremely important for firms. They explain that managers' wealth (e.g., stock holdings, option holdings, and job security) are closely tied to their firms' stock price such that managers focus their attention intently on avoiding negative earnings surprises. Consequently, managers place a high priority on avoiding negative earnings surprises (Lee, 2007; Degeorge et al., 1999). Furthermore, investors recognize that analysts have become more accurate in estimating earnings and have shifted their focus away from penalizing earnings decreases to penalizing a firm's inability to meet analysts earnings estimates (Brown and Caylor, 2005; Graham et al., 2005; Wiedman, 1996). Consequently, the investor community now places a higher regard on how the firm does with regard to analyst expectations as a predictor of future performance than it does on whether or not the earnings per share is trending upward or downward (Fried and Givoly, 1982; Brown et al., 1987).

Given the importance of MBE as a performance benchmark and the consequences of failing to meet this benchmark, it is not surprising that top corporate executives place such a strong emphasis on MBE (Lee, 2007). Almost any and all efforts are made to control analyst perspectives with regard to analysts' opinions and earning estimates because of the grave consequences. Consequently, over the past decade, numerous studies suggest that meeting or beating analysts' expectations has become increasingly common (e.g., Brown 2001; Matsumoto 2002; Brown and Caylor 2005).

Failing to adequately manage analyst expectations is a sign of overconfidence because by allowing analyst to have a picture that you could not achieve, you set the firm up for a grave consequence in its stock price. This makes shareholders angry and may lead to the management team being replaced. Only an overconfident manager would allow analyst expectations to run so wild as to make them unobtainable for the firm, either by its normal activity or by a mild massaging of the books. For instance, when Apple failed to meet analyst expectations in July 2012, David Rolfe, chief investment officer at Wedgewood Partners Inc., stated that the results were "big miss" after two previous blowout quarters. "We became too confident, in our expectations, that Apple had literally a perfect pulse on end demand throughout the globe... and quite simply, that wasn't the case this quarter," Rolfe said (Shields, 2012). This clearly exhibits the role overconfidence plays in analyst expectations. It is the firm's management job to manage those expectations such that they are achievable. Allowing anything else to happen shows overconfidence on behalf of the firm managers.

Management must manage the expectations of the analyst so to avoid negative earnings surprises (Bartov, Givoly and Hayn, 2000). These are so rare that when they happen they are met with significant consequences (Barefield and Comiskey, 1975). Knowing this, and everyone knowing that the firm does have some ability to massage the books some to avoid negative earnings surprises, it really should not happen at all (Brown and Rozeff, 1978); however they do. The thesis in this paper is that firms that have higher levels of hype will allow this anomaly to occur more often than firms that have lesser levels of hype. This occurs because the hype influences the manager's behavior such that they act in an overconfident manner in dealing with analyst and meet or beating analyst consensus expectations. Therefore, I offer the following predictions to answer the questions: 1) Do firms miss? 2) How often do they miss? and 3) By how much do they miss?

Hypothesis 1a: *Media hype influences managers to act over confidently as manifested by an increase in hype being associated with a greater likelihood that a firm will experience at least one NES.*

Hypothesis 1b: *Media hype influences managers to act over confidently as manifested by an increase in hype being associated with a greater likelihood that a firm will experience a NES in a given quarter.*

Hypothesis 2: *Media hype influences managers to act over confidently as reflected by increasing media hype related to an increase in the number of NES misses per firm.*

Hypothesis 3: *Media hype influences managers to act over confidently as exhibited by increasing media hype related to higher NES value misses.*

3.3.1.2 Owner Sell-off Activity After the Lock-up Period

The second measure of overconfidence is owner sell-off activity following the IPO lock-up period. This measure of overconfidence builds upon previous literature in corporate finance on the optimal timing of option exercises for under-diversified, risk-averse executives (Carpenter, 1998; Hall and Murphy, 2002). Unlike outside investors, firm founders and CEOs cannot trade their options or hedge the risk by short-selling stock of the company. In addition, their human capital and reputations are intimately linked to the firm's performance. Therefore, a founder or CEO is likely to be overexposed to their firm's idiosyncratic risk and, in most cases, should not hold options on company stock until expiration.

Similarly, firm executives should seek to diversify their personal investment portfolio as soon as possible. As the lock-up period expires, founders and CEOs should seek to diversify their personal financial portfolio risk from the over-emphasized commitment to the firm by selling large portions of their shares (Brau et al., 2004). Although the optimal plan for selling-off shares at the lock-up expiration depends on individual factors such as wealth, degree of risk-aversion and other forms of diversification, any risk-averse founder or CEO should sell-off all (or nearly all) of the shares that they can at the expiration of the lock-up period, given a sufficient stock price. Failing to do so exhibits over-confidence (Malmendier and Tate, 2005a). It does so by flouting sound financial advice regarding financial diversification. Therefore, when managers fail to sell their holdings at the expiration of the lock-up period, a rational financial decision, I infer that they are overconfident about their ability to keep the company's stock price rising and they want to profit from expected stock increases by holding the shares. However, extent literature has found that among founders and CEOs who hold their shares past the lock-up period, the average executive does not make a profit (Malmendier and Tate, 2005b; Brau et al., 2004).

Furthermore, typically, when early investors first get a chance to sell their shares in a newly public company, a stock typically falls as owners flood the market with "new" shares as they pare back their holdings and cash out some of their employment equity. This influx of new shares to the market raises concerns based on the laws of supply and demand believing it will cause the stock price to plummet. However, some recent highly regarded and heavily media-attended lock up expirations are challenging this perspective. For instance, stock of Yelp, a social media firm, soared after the lock up period expired. On the firm's lock up expiration date, the stock price rose 22.51 percent to close at $22.37. To date, this was the largest one-day gain since the company went public in March 2012 (Rusli, 2012). Likewise, Facebook's lock-up period was followed closely by media which predicted doomsday-like results, but in reality, the firm's stock also experienced one of its largest gains in its brief and maligned history (Krantz, 2012). Despite expectations that Facebook's share price would fall because more than 850 million additional shares in the company were being freed up for sale, on the day of Facebook's lockup expiration its share price shot up more than 7 percent (Ortutay, 2012).

Therefore, ultimately, the key argument surrounding owner sell-off at the expiration of the lock-up period is about diversification. Simply stated, rational actors will diversify their risks if and when they can. Therefore, when managers reach the expiration of the lock-up period, they should diversify their risks by selling-off available holdings of their firm and transfer the proceeds to other investments to diversify their portfolios and spread out their risk. Lack of actions following a well-established strategy of diversification is indicative of over-confident behavior. Therefore, I offer the following predictions to answer the following questions: 1) Do firm managers fail to sell-off at the expiration of the lock-up period? and 2) By how much do firm managers fail to sell-off their shares?

Hypothesis 4: *Media hype relates to post-lock-up CEO sell-off activity such that as media hype increases, the likelihood that managers will sell-off their shares at the expiration of the lock-up period decreases.*

Hypothesis 5: *Market hype relates to post-lock-up CEO sell-off activity such that as media hype increases, the amount of sell-off activity by managers at the expiration of the lock-up period decreases.*

CHAPTER 4: METHODOLOGY AND MEASURES

4.1 Data Collection and Sample Procedures

Following procedures performed in prior literature, this quantitative study collects and analyzes a number of different variables. Most notable of the data collection and variable development is the content analysis of media data. This data and the variables measured from it help create the empirical predictive models used to test the previously established hypotheses. The sampling process, data collection, and variable building are a significant part of this study. Over 600 man-hours went into formulating the sample parameters, collecting the various types of data from a variety of sources, conducting content analysis, and formulating the different variables. These features of this study are described and discussed in the next sections of the thesis.

4.1.1 A-priori Statistical Power Assessment

A critical issue in designing any study is determining whether there is adequate statistical power (Tabachnick and Fidell, 2007). To verify that the sample size adequately affords enough statistical power, I conducted an a-priori power analysis. Judd et al. (2009) indicates that "too many researchers fail to ask "what if" power questions before they collect their data." The consequence of this is that their study has virtually no chance of rejecting the null hypothesis, even if the ideas and theory that motivated the research is correct.

A Type I error is the probability of erroneously rejecting the null hypothesis, while a Type II error is the probability of erroneously failing to reject the null hypothesis (Judd et al., 2009). Statistical power = 1 – β, where β is the rate of Type II errors. Power is calculated as:

$$\text{Power} = (ES \cdot \alpha \cdot \sqrt{n}) / \sigma \qquad \textit{Equation 1}$$

where ES is the effect size, α is the Type I error rate, n is the sample size, and σ is the population standard deviation.

I apply Cohen's (1960, 1988) and Rossi's (1990) recommendations that power should be 0.8 (or 80%) or greater. With respect to effect size, I employed Cohen's (1988) f^2 principles. The f^2 effect size measure for multiple regression is defined as:

$$f^2 = R^2 / 1- R^2 \qquad \textit{Equation 2}$$

where R^2 is the squared multiple correlation.

In their meta-analysis examining power and effect sizes in entrepreneurship research, Connelly et al. (2010) observed average reported effect sizes of 0.28 (standard deviation [SD] = .01). Likewise, Nam et al. (2008) in their piece regarding information disclosure and IPO firm performance reported using 0.2 effect sizes in their calculations. Typically, these values reflect high-medium to large effect sizes as defined by Cohen (1977 and 1988). Conservatively, I apply the average of these values in my analysis, by instituting a 0.24 effect size value in my a-prior power calculations (Nam et al., 2008; Cohen, 1977). Instituting this conservative measure helps develop a strong, defensible baseline for my findings (Aguinis et al., 2005).

Table 4.1 indicates the required sample size for a multiple regression study, given a desired statistical power, the anticipated effect size, the number of predictors in the model, and the desired probability level. Consequently, the project sample of 126 firms, sufficiently meets statistical power conventions for 24 predictor variables, at p=0.05, with a conservative effect size of 0.24 and 80% power.

TABLE 4.1: A-PRIORI STATISTICAL POWER ASSESSMENT

Desired statistical power:	0.80	(In accordance with Cohen, 1960 & Rossi, 1990.)
Anticipated effect size (f^2):	0.24	(In accordance with Nam et al., 2008 & Connelly et al., 2000.)
Total number of predictors:	24	(Not including the regression constant.)
Probability level:	0.05	(Also known as the p-value or type I error rate. By convention, this value should be 0.05 in order to claim 95% statistical significance.)
Minimum required sample size:	**114**	

4.1.2 Data Sources

There are a number of different data collected in the preparation of this dissertation. The variety of data sources rendered a very complicated and long data collection period, but the resulting data set is unique and comprehensive. Media and other variables were collected from several primary sources and supplemented, as necessary, by extensive database and Internet searches.

Focusing first on the main independent variables, all independent variables were collected by searching media for a two-year period surrounding the IPO issue date (one year prior and one year following) for each firm. Community hype data was collected via Google Insights searches regarding the Google traffic averages for each firm for the two-year period surrounding the IPO. Own hype was collected through Proquest database by gathering every article that referred to the focal IPO firm in both PR Newswire and BusinessWire. Event hype articles were collected from the United States' four most circulated newspapers in the Wall Street Journal, USA Today, New York Times and Los Angeles Times. A list of the top 10 US periodicals by circulation is provided in Appendix M. Expert hype was collected via searches in Thomson One database for each firm for analyst reports for each firm.

Shifting to the collection of the dependent variables, negative earnings surprises were gathered through searches on the SEC website, Thomson Reuters' Earnings.com, Hoovers Online and supplemented by data included in Compustat. Founder-CEO and Professional-CEO sell-off activity data was collected via Wharton Research Data System (WRDS) database, supplemented by searches in the Emergent and SEC Edgar databases.

Control variables were collected via a number of research databases. For instance, names of Founders and CEOs at the time of the IPO were identified via Edgars Pro and VentureXpert. Gender was determined via Internet searches for each CEO and founder. Lock-up period durations, lock-up period expirations, quiet period durations, and quiet period expirations were gathered through the Edgar Pro and VentureXpert databases and through the SEC website. General firm-level IPO data (such as firm name at time of issue date, issue date, IPO share price, number of shares offered, number of employees at time of IPO, firm industry affiliation, principal deal amount, etc.) were collected via Compustat and supplemented by Edgars Pro and VentureXpert databases and the SEC website when necessary. Some firms change names over time; therefore, database and Internet searches were used to confirm all firm data was appropriate for the firms in the sample. Missing data was found via detailed searches in Hoovers Online, Edgars Pro, Compustat, the SEC website, other databases and general Internet searches.

4.1.3 Sample Selection Criteria

There have been 9,457 IPOs in the United States from 1970-2011 (SEC Website; SDC Compustat). A series of filters were applied to reduce this number to a more manageable and revealing group of IPOs for studying the relationship between media hype and managerial expectations and firm outcomes. In particular, this study examines the relationship between media hype surrounding a firm's IPO and actions/behaviors by firm founders and CEOs. Therefore, a more recent set of IPOs, those more likely to have been influenced by the media boom of the past decade, are the focus of this dissertation. The sample selection criteria and procedures follow previously published literature on IPOs (most notably work conducted by James Ritter, 1991).

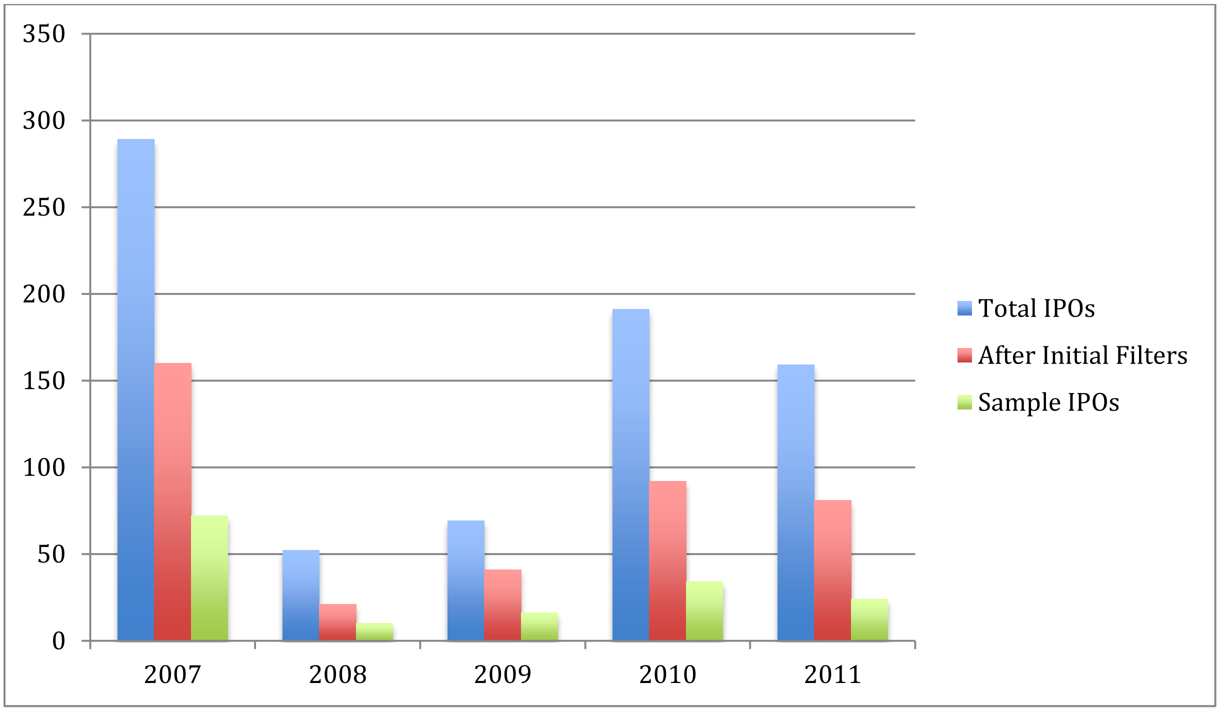
Although some data exists for IPOs from 1970-2011, for reasons of meaningfulness of the firms included in the sample, data availability, and the intensity of the data collection procedures, the sample was restricted to cover a recent five-year period running from 2007 to 2011. 395 operating companies went public in the U.S. from 2007-2011, after applying a series of *initial filters* common in IPO research (listed below). Higher volume figures have been reported previously (a population of 760 counting all offerings), but typically included in this higher number are companies that were already traded in other countries and/or were eliminated via application of the initial filters. Namely, initial filters include the exclusion of American Depositary Receipts (ADRs), limited partnerships and limited liability companies, closed-end funds, Real Estate Investment Trusts (REITs), special purpose acquisition companies (SPACs), trusts and other unit offers, and penny stocks (Ritter & Zhang, 2007; Ritter, 1991; Loughran & Ritter, 2002). Some of the IPOs are excluded from the 760 count for more than one reason.

Furthermore, *additional filters* were applied limiting the inclusion of IPOs to specific US-based exchanges including AMEX, NYSE and NASDAQ and deals that had principal amounts of $80M or greater. This "deal size" filter was applied to focus the study on a sample that consisted of firms that were most likely to receive media attention and, therefore, most susceptible to media hype. Applying these additional filters helps this study focus on firms most likely to receive media attention and highlights the effects of media coverage on managers' expectations and firm outcomes. Therefore, simply stated, the final sample consists of 126 U.S. IPOs from 2007-2011 (5 year period) eliminating companies based on a series of initial filters that are regularly applied in extent literature and additional filters that focused on specific U.S. exchanges and large IPO deals with principal amounts of $80M or greater.

Figure 4.1 provides a comparison of the population of IPOs over the five-year period with a sample after application of the initial filters and with the final sample after the additional filters were applied. Additionally, the sample filtering process and other information regarding the sample is provided in Tables B.1-B.2 in Appendix B. The final sample contains 16% of the total IPOs conducted during the five-year period; however, the final sample encompasses a much larger portion of the population (31%) after the application of the initial filters. During an initial review, the sample appears to be representative of the population. This is based on the per year inclusion of IPOs in the sample which closely resembles the per year proportion for all IPOs in the population and also closely resembles the sample of IPOs after the initial filters were applied. Table 4.1 provides a comparison of the total number of IPOs that took place per year and the corresponding proportion of the IPOs for each of the five years, compared to the number of firms in the initial and additional filtered samples per year and the corresponding proportion of IPOs per year in the samples. A macroeconomic control variable is included to account for not only yearly, but quarterly IPO market effects.

Furthermore, an analysis of the industry mix (a key control variable) of the firms in the population of IPOs over the five-year period revealed that the industry mix of the population closely mirrors that of the initial and additional filtered samples (see Appendix B, Table B.2). The consistency that exists between the population of IPOs to the initial filtered IPO (following typical literature

FIGURE 4.1: NUMBER OF IPOS IN THE POPULATION VERSUS THE STUDY SAMPLE



conventions) with the additionally filtered final sample lends credence to the claim that the final sample is representative of the population of IPOs from 2007-2011.

4.1.4 Media Collection Procedures

The project required that all articles and data for a two-year period (one year on each side of the firm IPO issue date), for all 126 firms be gathered. Every effort was made to find an automated way to collect the articles and data for each type of hype; however, no such automated system exists. Therefore, in accordance with prior literature (Sandelowski & Barroso, 2007; McKibbon, Wilczynski, & Haynes, 2006; Wong, Wilczynski, & Haynes, 2006; Wong, Wilcynski, & Haynes, 2004), a search strategy customized for the specific databases used was developed in collaboration with an experienced librarian to ensure a systematic and exhaustive search. Detailed descriptions of the manual media collection procedures are provided in Appendix A.

The primary investigator (myself) and three undergraduate students searched for articles and data related to each firm through ProQuest Central and Thomson One databases. This team performed searches using the firm name as the keyword(s) and searched for firm data and articles in the United States most circulated newspapers, in BusinessWire and PR Newswire releases, and in official analysts' reports. The team collected every article that mentioned the firm in any of the following: the title, the abstract, or the text of every article in the different media types. In accordance with prior literature, advertisements, editorial articles, legal notices, and letters were excluded (Liu, Liu, Xiao, Cai, and Xu; 2010).

Articles in each of the different media types were collected for four different time periods. Specifically, articles were collected for each firm for six-month time blocks surrounding the firm's IPO issue date. Articles in each media type were gathered for 1) 7-12 months prior to the IPO issue date, 2) 0-6 months prior to the IPO issue date, 3) 0-6 months after the IPO issue date, and 4) 7-12 months after the IPO issue date. Furthermore, in an effort to capture as much firm information as possible, the team conducted subsequent searchers for each firm using shortened, expanded and abbreviated versions of the firm's names as key words. For instance, Zipcar Inc. was searched using "Zipcar", "Zipcar Inc.", and "ZIP" (Zipcar's ticker). Therefore, the team is relatively confident that it succeeded in capturing nearly every article that referenced the focal firm over the two-year period. At a minimum, the procedures applies helped the team capture the most pertinent articles for each firm for each time period.

This data collection effort and the subsequent content analysis task constituted a significant effort by the lead researcher and his assistants. Well over 600 man-hours were employed in collecting and content analyzing the data for each firm, for each time period, for all of the different types of media. Research assistants were paid for their participation; therefore, although a larger sample was desired, the cost in time and money made it unfeasible.

4.1.5 Conducting Content Analysis

Content analysis is "a systematic, replicable technique for compressing many words of text into fewer content categories based on explicit rules of coding" (Stemler, 2001). Even as early as Lasswell (1949), the core questions of content analysis were formulated including, "Who says what, to whom, why, to what extent and with what effect?" Recently, Neuendorf (2002:10) offered a definition of content analysis by describing it as a "quantitative analysis of messages that relies on the scientific method (including attention to objectivity, inter-subjectivity, a priori design, reliability, validity, generalizability, replicability, and hypothesis testing) and is not limited as to the types of variables that may be measured or the context in which the messages are created or presented."

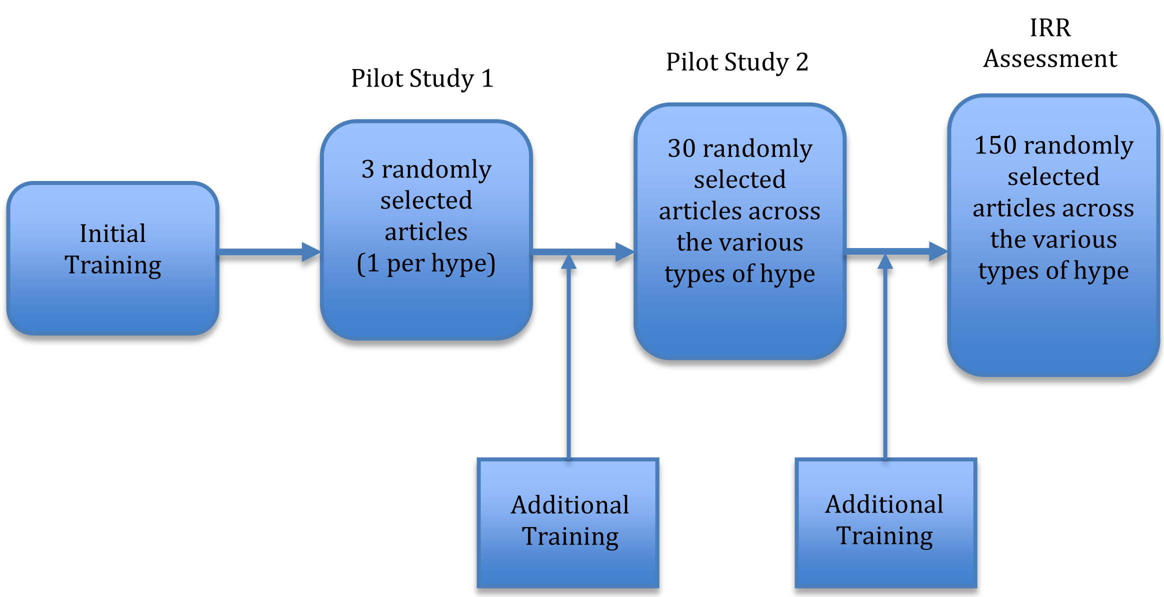
There are a number of quantitative strengths that result from conducting content analysis-based research. First, content analysis research is a non-obtrusive, non-reactive measurement technique. The messages already exist and are separate from the communicators and the receivers. Therefore, armed with a strong theoretical framework, the researcher can draw conclusions from content analysis without having to gain access to the communicators, who may be unwilling or unable to be examined directly (Riffe, Lacy, & Fico, 1998). Further, Kerlinger (1973) observed that the studies that use content analysis were able to explore different and new questions by asking unique questions regarding not just the communicators, but of the communications as well. Another strength of content analysis projects is that they can explore longitudinal questions because of the use of the archival nature of the data, much of which outlives the communicators, their audiences, the memory of any of the participants, or the events described in the communication. Moreover, content analysis procedures allow researchers to reduce the numbers of large amounts of information and data into quantitative measures that otherwise would be logistically impossible for close qualitative analysis. When properly operationalized and measured, despite the process of reduction, meaningful distinctions among the data still exist (Lombard et al., 2003).

The primary method for media content analysis for this dissertation was manual analysis. In the following sections, I introduce this project's content analysis by describing the training program, the pilot studies, and the protocol. Next, I present information regarding the reliability of the content analysis assessments made for this dissertation as expressed in a series of inter-rater reliability checks. Additional details regarding the content analysis procedures can be found in Appendices D through L.

4.1.5.1 Content Analysis Training and Assessment Process

Fortunately, the team of coders selected to participate in this project had extensive prior experience coding articles. They had all participated in prior research projects where they performed qualitative assessments and content analysis of media articles. The multi-step training, pilot studies and inter-rater reliability (IRR) process is depicted in Figure 4.2.

FIGURE 4.2: CONTENT ANALYSIS TRAINING, PILOT STUDIES AND INTER-RATING RELIABILITY (IRR) ASSESSMENT PROCESS



For this project, with an experienced team of raters, coder training focused on potential nuisances the coders may face while working on this project that they might not have faced in the past. Coders were forthcoming with sharing their past experience to help modify the initial drafts of the Content Analysis Protocol and help all coders get on the same page with regard to coding the articles. All five raters participated in the initial training, both pilot studies and the large subsample IRR assessment to verify consistency of understanding, interpretation and rating. For each step in the process, coders were asked to code the articles without external inputs (Lombard et al., 2003). Also, for each of the pilot studies and the large-scale subsample IRR assessment, articles were randomly selected and stemmed across the three different types of print media hype included in the project (Own, Event, and Expert). In addition to coding the articles based on the Content Analysis Protocol, team members were asked to track the speed of their performance and to list any questions and/or concerns that they ran into while working on the tasks.

During each phase of the training, coders identified some areas of confusion and requested clarification regarding the protocol. Adjustments were made to accommodate to resolve any confusion and to address unexpected and unanticipated issues. In each case the protocol was revised to address these issues so that all coders felt sufficiently satisfied that any confusion and that questions were answered. Furthermore, following each phase of the training process, intermediate inter-rater reliability scores were calculated to verify the effectiveness of the training and the Content Analysis Protocol.

The training process began with two face-to-face meetings followed by a series of very detailed and informative e-mail exchanges in which all coders were copied on all transactions. Following initial training, which focused on project-specific nuisances, all coders were asked to conduct three article assessments on a randomly selected group of articles (one from each type of content analyzed hype) as part of the first pilot study. The goal was to identify issues and find any problems associated with biases or confusion with the initial Content Analysis Protocol. Following the assessments, an initial inter-rater assessment was conducted yielding high Krippendorff's alphas ranging from 0.90-0.95 for the 5 different coding categories. Although this high score was encouraging, the use of any IRR index with such a small sample of articles should be considered cosmetic at best. Issues with regard to the five content analyzed variables were discussed as a group and a few suggestions to improve the assessment tool were incorporated into a subsequent version of the protocol. Namely, category distinctions were made clearer and, when appropriate, less distinct categories were collapsed to make coding more meaningful and more efficient.

After the Content Analysis Protocol was revised to reflect what was learned from the first pilot study, a larger second pilot study was conducted. In the second pilot study each coder was asked to code a new set of 30 randomly selected articles across the three types of hype using the updated Content Analysis Protocol (Lacy and Riffe, 1996). A second set of Krippendorff's alphas based on the new codings for the second pilot study revealed consistent, strong inter-rater reliability scores ranging from 0.87-0.91 for the five different coding categories. Also, any remaining questions were addressed as a group and resolved to clarify any remaining issues that existed. Another protocol revision commenced, with very limited changes, in preparation for the large, subsample IRR check. Details regarding the inter-rater reliability check for the third, large subsample are provided in section 4.2.6 below.

4.1.5.2 Content Analysis Protocol

In recognition of the complexity involved in coding, conducting content analysis and performing qualitative assessments for such a diverse and multifarious sample of media data a team of experienced researchers and research assistants were used. The research team consisted of one experienced researcher and five experienced research assistants. The researcher and research assistants have over 1,000 combined hours and an average of over 12 months of content analysis experience.

In addition to basic data collected regarding the articles such as the date of the article, article counts per firm, article counts per time period, words per article and article sources, each article was read and coded in five different areas. The first rating determined the general topic of the article. Next, every article was assessed based on the general level of analysis of the article with respect to the focal firm. Third, each article was analyzed for the relative importance and relevance that the target firm played in the article. Finally, the tone of each article was assessed based on two questions targeted at whether the article was 1) positive with regard to the focal firm and 2) if the article was negative with regard to the focal firm. This two-part tone coding scheme establishes a simple and consistent coding methodology and allows me to calculate an overall positive or negative sentiment of the article with respect to the focal firm.

Rating 1. Article Topic

Although every article was identified as a particular type of hype (own, event or expert) during the collection process based on the source of the media, articles discuss a plethora of different topics relevant to different aspects of the firm's activities. Because of this each article was categorized based on the general topic of the article by the content analysis team. In developing this categorization scheme, I heeded the advice of Krippendorff (1970b) regarding variables with a large number of categories. He warns against creating variables with a large number of categories within a variable (e.g., a twenty-six category scheme for coding the variable "news topic"), especially categories that require subjective assessments, because variables with large numbers of categories create logistical problems. Generally, the more specific and encompassing your variables are the more granular the data you are able to examine empirically. However, Krippendorff argues that some researchers create subsets or consolidated categories that improve their inter-rater reliability and create simpler variables often without sacrificing the information necessary for the variables to identify interesting and unique findings. Consequently, Krippendorff recommends considering the tradeoff between the logistical problems versus the potential impact of such "micro" measured variables. Following this advice, and recognizing the shear magnitude of different topics in the media, I created a topic categorization scheme, based on prior literature, that consolidates smaller media topics into larger grouping categories of similar topic areas.

Existing literature provides broad categories identified in media releases based on an assessment of words associated with six broad categories of the business environment. For instance, some research has used strategy, operations, human resources, and a mix of a few others to build a classification scheme (Kothari, Li, & Short, 2009; Riloff, 1993). In addition to existing literature, a random sample of 200 articles from this study's sample were selected for analysis to identify the most common/consistent themes that arose in the articles pertinent to this study. Combining past literature categorization standards with what was learned from the sample of articles in this topic pilot study, a list of general topics were determined that appropriately reduced smaller topics into larger consolidated topics that reflect similar article topic areas. After a few iterations, a core group of seven categories remained. The seven categories used for coding the topic for each article is provided in Table D.1 in Appendix D. Although this list is not exhaustive, since media can focus on any topic relevant to a firm, it is based on prior literature and a preliminary sample study, and therefore is quite comprehensive for the types of topics explored in the media regarding the firms in this study's sample. In fact, less than 1% of all of the articles were coded as “other” meaning that they did not fall into any of the other six categories. For more details regarding how article topic was assessed, see Appendix D.

Rating 2. Article Level of Analysis (LoA)

Next, each rater identified the level of analysis for each article. It is hypothesized that media hype related to different levels of analysis will have different types of influences on Founder/CEOs, Professional CEOs and their firms. Although there are many taxonomies with regard to unit of analysis, I used a similar scheme as developed by Babbie (1998). For each article, raters wee asked to indicate all of the following three levels that applied in each article with respect to the focal firm: 1) individual-level, 2) firm/organization-level, and 3) inter-organization-level. Individual-level articles are articles that discuss specific members of the management team or board of directors of the focal firm. A mere quote from an officer of the firm did not trigger a ‘1’ score, but discussion regarding new hire, ascension within the ranks of the firm or other person-specific portions of the article with respect to members of the focal firm were coded as ‘1’. The most common rating is firm-level and designated by a ‘2’ by the raters for this category. Most of the articles (approximately 60%) were regarding firm-specific topics dealing with firm performance. Finally, if the article discussed inter-firm topics, such as mergers, acquisitions, cooperative agreements, or other industry-based topics with regard to the firm, then the coders rated this rating as a ‘3’. Table D.2 in Appendix D provides more information regarding article coding for level of analysis.

Rating 3. Article Salience

Next, experienced coders read each article and subjectively rated them based on the relative role the focal firm played in the article. Weaver (1996) discusses the importance of salience. He indicates that issues can be ranked on how much coverage they receive and the role of the issue in the coverage. This is particularly important in contexts where people have choices such as when people have several political candidates to choose from or when there are a number of stocks for investors to choose between (Semetko and Schoenbach, 1994). Sometimes the choices do not differ significantly in their ideology, their stance on issues, or their performance. Therefore, the relative visibility of a firm compared to others is very important when studying the effect of media on behavior (Weaver, 1996). Therefore, Weaver argues that not only does the amount of attention and tone an issue receive matter, but also the salience of those messages plays a critical roe in shaping behavior.

Article salience was assessed as a content analysis variable primarily because of the search criteria and methodology for articles. Since articles were merely examined or any inclusion of the company name in the title, abstract or text of an article, there are many cases for which an article was identified for a firm, but that the firm was not the focal part of the article. For example, it was not uncommon for an article to be allocated to a firm, but the firm was merely ancillary to the focus of the article. Specifically, many articles spoke about one firm, but in the text merely mentioned other firms within the same or similar industry or geography. The general hypothesis is that the more salient the coverage, the more influence it will have on founder/CEO behavior.

Based on past communication literature, I hypothesize that these ancillary mentions of the target firm in these articles will not have much, if any, influence on decisions or behavior of Founder/CEOs or Professional CEOs. I hypothesize that the larger the role the firm plays in the article, the more salient the message is to the firm, the more likely it is to have an affect on behavior. Therefore, if much of the media surrounding a firm's IPO is ancillary to the firm, meaning that it is more about other firms or events, then the media is not likely to have much of an effect on behavior. If however, the media scrutiny with regard to a firm is truly focused on the firm, behavioral responses are likely to manifest themselves.

Article salience was determined by applying an ordinal scale regarding whether the target firm was the only firm mentioned in the article, a major point of emphasis in the article, shared the emphasis of the article with another firm, was clearly mentioned, but the focus was on another firm(s), or whether the focal firm was a on the periphery of the article. A rating scale from 1 to 5 corresponding the descriptions above were developed (see Figure D.3 in Appendix D**)**.

Ratings 4 and 5. Article Tone

Consistent across most research involving media data are assessments of the tone of the article to the subject of interest (Hayward & Hambrick, 1997; Tetlock et al., 2008; Pollock and Rindova, 2003; Schulz, 1994; Walgrave & de Swert, 2004) because tone is known to influence behavior. Coders assessed article tone based on two variables. First, codes were asked to subjectively assess the articles focusing on the references in the article to the focal firm for whether the article was positive or not positive with respect to eh focal firm. Next coders were asked to review the article and assess whether the article was negative or not negative with respect to the focal firm. Therefore, there were four possible outcomes for each firm with regard to tone. Articles could be rated as 1) positive and not negative, 2) not positive and negative, both not positive and not negative or 4) positive and negative. Articles that were coded as not positive and not negative and positive and negative were considered neutral articles. More details regarding rating of tone or each article can be found in Table D.4 in Appendix D.

4.1.6 Inter-rater Reliability Check

Inter-rater reliability (IRR), inter-rater agreement, or concordance is the degree of agreement among raters. It helps evaluate how much homogeneity, or consensus, there is in the ratings across different coders/raters (Cohen, 1960). It is useful in refining and ensuring that tools used by human coders are appropriate for measuring a particular variable (Krippendorff, 2004). If various raters do not agree, either the tool is defective or the raters need to be re-trained. Different raters may disagree about assessments of the same article because of variations in the procedures, differences in how material in media articles is presented or because of the way the coder interprets the material in the article (Gwet, 2012).

In this dissertation, coders were asked to make consistent and accurate ratings of media articles with respect to focal firms. Each rater was asked to act much like a computer by reducing the effects of bias by controlling their emotions and external factors while rating. Ratings of articles should not depend on external factors outside the specific assessment (Page & Petersen, 1995). However, I also asked the raters to go beyond a computer's capabilities and act as independent assessors by requiring them to make subjective assessments of vernacular used by articles across a variety of news media (Saal, Downey, & Lahey, 1980). Consequently, to ensure consistency and accuracy of ratings across the different content analysis coders, a competent IRR check was necessary.

There are a number of statistics that can be used to determine inter-rater reliability. Different statistics are appropriate for different types of measurement. Some alternatives include joint-probability of agreement, Cohen's kappa, Fleiss' kappa, inter-rater correlation, concordance correlation coefficient and intra-class correlation (Cohen, 1960; Fleiss, 1971; Krippendorff, 2004; Shrout & Fleiss, 1979). Most notably from the list above with regard to this project is Krippendorff's alpha. Krippendorf's alpha (Krippendorff, 1970a; Hayes & Krippendorff, 2007) is a versatile, general statistical measure for assessing the agreement between multiple raters while creating or measuring a variable. Alpha found its origins in content analysis where text is categorized by trained coders into analyzable terms and in observational studies where unstructured events are recorded for subsequent analysis. It is widely applicable wherever two or more methods of generating data and/or multiple coders are applied to the same set of items so that the resulting data can be trusted to represent something real. Perhaps the greatest advantage to using Krippendorff's alpha is that is applies to any number of observers (not just two), any number of categories, any type of measurement (nominal, ordinal, interval, ratio, and more), incomplete or missing data, and large and small sample sizes alike (it does not requiring a minimum number of units) (Gwet, 2012; Krippendorff, 2004; Hayes & Krippendorff, 2007). Due to the appropriateness of its application with regard to the assessment made in this dissertation and the advantages that it offers over other reliability assessment indexes, Krippendorff's alpha is the primary index used in this dissertation to evaluate inter-rater reliability.

Many researchers believe that, ideally, two or more raters should review all units of investigation. Then comprehensive inter-rater assessments based on inter-rater agreement statistics for the entire sample can be conducted. However, do to the large number of media articles being assessed for this dissertation, it is unrealistic to have two or more coders assess every article. Both the financial and time costs associated with double (or greater) review of every article is significantly cost prohibitive. Consequently, I sought a reasonable alternative to full-sample inter-rater reliability assessments. Fortunately, prior research exists to help determine an adequate subsample size for evaluating IRR. The following section describes the statistics involve in making this determination.

4.1.6.1 Calculating Subsample Size for the Inter-Rater Reliability Check

There is no consensus on the right amount of data to assess inter-rater reliability. Past literature has frequently used a 10% random sample, but other proportions are used as well (see Neuendorf, 2002; Riffe, Lacy, & Fico, 1998). For instance, some reliability samples have been selected haphazardly or based on convenience (e.g., the first 50 items) (Lacy & Riffe, 1996). Other scholars have used even less scientific standards for determining appropriate subsample sizes for IRR analyses. Weber (1985:23), for instance, recommended that the best test of clarity of category definitions is to code "a small sample of the text." Similarly, Stempel (1981:128) recommended a minimum standard of "three passages to be coded by all coders." Moreover, Kaid and Wadsworth (1989) suggest that when a large sample is involved, "a subsample of 5-7 percent of the total is probably sufficient for assessing reliability." To help resolve the inconsistency of conventions, Riffe, Lacy, & Fico (1998) examined the question of how many content units are needed to achieve a given confidence level for agreement. Their calculations indicate that sometimes subsamples of even less than 1%, especially for large data sets where conducting IRR checks of 10% of the total sample is less than ideal (i.e., too costly or too time consuming), can be conducted without sacrificing accuracy or consistency.

To face the content analysis challenges associated with large data sets, this study focuses on resolving the question of intercoder reliability by examining it as a potential sampling issue. Riffe et al. (1998) suggests using content analysis samples that have reliability estimates representing the population. Following prior literature, we can consider the entire sample of 6,835 articles as the "population" of codeable articles from which I can select a particular number of articles to act as a representative, random subsample (Riffe et al., 1998). Therefore, if agreement is found in the subsample, we know, with an acceptable level of confidence, that this is representative of the pattern that would occur if all articles in the sample were coded by all coders.

Using probability sampling as a measure of representativeness, Riffe et al. (1998) estimated simple random sample sizes for reliability checks. Calculating sampling error for reliability tests is possible using probability sampling, but few content analyses address this point (Triola, 2004). Using the formulas identified by Riffe et al. (1998) and Triola (2004), I established a subsample size with confidence intervals so that minimal acceptable reliability figures have been achieved. For instance, by setting a standard of 80% or greater reliability to meet acceptability conventions (Krippendorff, 2005; Lombard et al., 2002; Lacy & Riffe, 1996), I must generate a subsample that has a confident interval that does not dip below 0.80. If the confidence interval extends below 0.80, I cannot conclude that the "true" reliability of the full sample equals or exceeds the minimal acceptable level. The focus is on a one-tailed confidence interval because the acceptable reliability is not affected by whether the population agreement exceeds 5% on the positive side, because acceptance is based on a minimum standard, which would fall on the negative side of the interval only.

Therefore, based on prior literature, I estimated a population level of agreement 85% (Neuendorf, 2002; Lacy & Riffe, 1996; Riffe et al., 1998). Furthermore, I applied a standard desired level of certainty by using the traditional p = .05 level and a .05 confidence interval. By achieving 85% or greater in agreement in my subsample reliability check and applying a confidence interval of 5%, I ensure that agreement falls at or above 80% and since the random subsample is representative of the sample, I can infer a population level of agreement at or above 0.80 if all coders were to code all of the articles in the sample. In fact, Schutz (1952)[1], studying chance agreement, previously identified 83% as an appropriate estimated population level of agreement so that the "remainder level of agreement would exceed 80%". I conservatively estimated 85% based on my 5% confidence interval. The formula and calculations applied are provided below.

Using a normal curve, I identified that a one-tailed Z-score associated with a .05 confidence level is 1.64. Based on this, I identified the baseline formula for determining confidence intervals:

Confidence Interval = Z • SE *Equation 3*

Adjusting the equation to find the standard error, we solve the following:

SE = Confidence Interval / Z *Equation 4*

SE = .05 / 1.64 = .03

[1] Chance agreements can lead content analysts to overestimate the extent of coder agreement due to the precision of the coding instrument. Schutz sought to control for this effect, but just because chance can affect reliability does not mean that it does. Schutz notes that chance agreement cannot be eliminated or even controlled, its effect can only be acknowledged and compensated for.

As demonstrated above, by applying a confidence interval of 5% and a Z-value reflecting probability of 95% (p-value = .05), I calculate a standard error of .03 (Triola, 2004, p. 307). This standard error can then be use to determine a sample size that has a sampling error equal to or less than 5% for the assumed population level of agreement meaning that the .80 agreement standard is assured to be met. To solve for the necessary subsample size, I applied a finite population adjustment to the equation for standard error of proportions. This equation is:

$$SE = \sqrt{[(P \cdot Q) / (n-1)]} \cdot \sqrt{[(N-n) / (N-1)]} \qquad \textit{Equation 5}$$

Removing the radicals and applying the distributive property, the formula becomes:

$$n = [(N-1)(SE)^2 + P \cdot Q \cdot N] / [(N-1)(SE)^2 + P \cdot Q] \qquad \textit{Equation 6}$$

Where N = the population size (number of articles),
SE = .03 (for a .05 confidence interval and a p-value of .05),
P = estimated percentage of agreement in population,
Q = (1-P), and
n = the sample size (Lacy & Riffe, 1996:967).

I entered appropriate values to determine how large of a random subsample I need to achieve a minimum 80% reliability agreement, with approximately 6,835 articles and an estimated true agreement level of 85%. Thus, PQ = .85 (.15) or .1275. I instituted a confidence interval of .05, and the resulting SE at p = .05 confidence level is .03, squared to .0009. So with values entered, Equation 4 now looks like:

$$n = [(6834)(.0009) + .1275(6835)] / [(6834)(.0009) + (.1275)]$$

$$= 877.61 / 6.28$$

$$= 139.77$$

In summary, I used accepted conventions from past literature regarding content analysis to calculate a viable subsample size for checking inter-rater agreement for a large dataset. Applying the 'Round-Off Rule' (Triloa, 2004:308), conducting IRR assessments on a subsample of 138 articles or greater provides a sufficient assessment or inter-rater consistency and reliability. Therefore, I chose to conduct my IRR calculations on a conservative number of articles using a slightly larger subsample of 150 randomly selected articles.

4.1.6.2 Evaluating IRR Assessments

Reliability is a necessary (although not sufficient) criterion for validity; however, without it, all results and conclusions in the research project may justifiably be doubted or even considered meaningless (Lombard et al., 2002). Generally speaking, coefficients of .90 or greater are nearly always acceptable, .80 or greater is acceptable in most situations, and .70 are appropriate in exploratory studies for some indices (Kroppendorff, 2005; Lombard et al., 2003). Higher criteria should be used for indices known to be liberal (i.e., percent agreement) and lower criteria can be used for indices known to be more conservative (such as Cohen's kappa and Krippendorff's alpha). As previously discussed, the most appropriate and most widely used index in this dissertation is Krippendorff's alpha. I selected a conservative .80 as my acceptance level (Lombard et al., 2002, 2003; Krippendorff, 1978, 2004; Lacy & Riffe, 1996).

Although partial to Krippendorff's alpha for this project, the preferred approach is to calculate and report two (or more) indices (Lombard et al., 2003). Therefore, as a sensitivity check for IRR, I calculate and report several IRR index scores. Perhaps the most popular IRR index is Cohen's kappa; however, I primarily use Fleiss' kappa as a robustness check for inter-rater reliability assessments because while Cohen's kappa only works for two raters, Fleiss' kappa works for any number of raters. It is interpreted as expressing the extent to which the observed amount of agreement among raters exceeds what would be expected if all raters made their ratings completely randomly (Fleiss, 1971). Moreover, in a prudent effort to confirm consistently high IRR scores, rather than calculate one overall IRR measure for all assessments combined, I calculated IRR assessments for each individual content analysis measure. Appendix F thru J provides a minimum of two indexes per variable and shows consistently high (kappa > 0.85) IRR ratings for each variable.

All IRR index scores were calculated using ReCal 0.1 and NIWA's statistical calculators. ReCal 0.1 is an online intercoder reliability calculator for 2 or more coders developed by Deen Freelon of the Department of Communication at the University of Washington. ReCal 0.1 calculates several indices including percent agreement, average pairwise percent agreement (for 3+ coders), Scott's Pi, Cohen's Kappa, Fleiss' Kappa, and Krippendorff's Alpha (Freelon, 2010). Lin's Concordance, another statistical measure used to evaluate IRR based on ordinal variables, was collected via an online statistical calculator through NIWA's website. NIWA is a research and consultancy company out of New Zealand, with a global reputation as experts in water and atmospheric research.

4.2 Measures

In the following sections the dependent, independent (predictor) and control variables included in the analyses used to test the aforementioned hypotheses are described and discussed.

4.2.1 Dependent Variables

NEGATIVE EARNINGS SURPRISE (NES)

Negative Earnings Surprises are evaluated using four separate measures. Each measure helps answer a specific question. Generally speaking, the four NES variables allow us to learn 1) whether the firm experienced a NES in the year and per quarter following the IPO issue date, 2) how many NES events the firm experienced during the year following the IPO issue date, and 3) by how much firms missed their consensus earnings expectations.

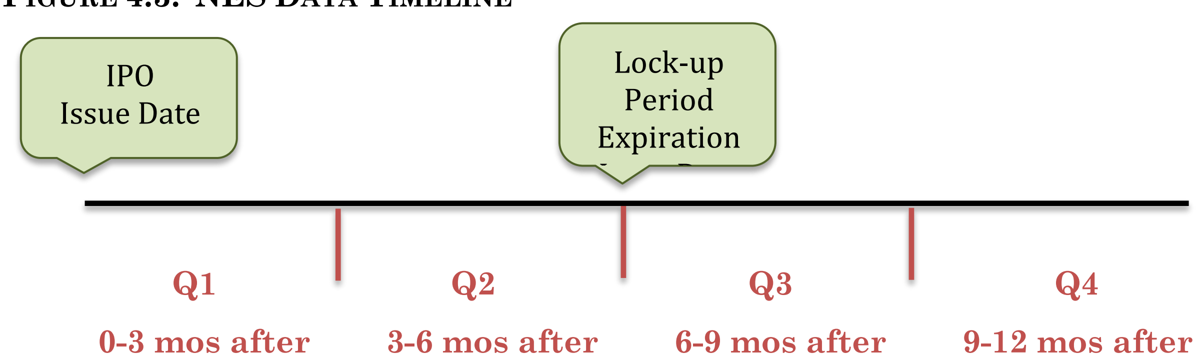
1) **NES_YN** is a dichotomous variable that assesses whether or not the firm experienced any NES events in the four quarters following the IPO issue date. It indicates '1' when a firm experiences a negative earnings surprise during any of the four quarters following the IPO issue date and '0' otherwise.
2) **Q'X'_MoB** is similar to NES_YN in that it is a dichotomous variable that assesses whether or not the firm experienced an NES event, but in this

variable it assesses NES events one quarter at a time. It indicates ‘1’ when a firm experiences a negative earnings surprise during a given quarter following the IPO issue date and ‘0’ otherwise.

3) **<u>NES_Misses</u>** measures the number of times the firm experienced an NES over the year following the IPO by providing a count of NES events with values of 0, 1, 2, 3, 4, where ‘0’ indicates no NES events and ‘4’ indicates that the firm experienced an NES in each of the four quarters in the year following the IPO issue date.

4) **<u>Q’X’_NES_10_Winsor</u>** measures by how much the firm missed its analyst consensus earnings estimates. For instance, if a firm’s analyst consensus estimate was $0.20/share and the actual EPS was $0.18/share, the variable reads -0.02. Likewise, if the firm beats its analyst consensus estimate, it will read as a positive value. For instance, if a firm’s consensus estimate was $0.20/share and the firm earns $0.24 per share, the firm’s resultant score is 0.04. This variable is 10% Winsorize (Hasings, Mosteller, Tukey, and Winsor, 1947…discussed in more detail in Chapter 5) to help address outlier issues.

FIGURE 4.3: NES DATA TIMELINE



Q = Firm EPS Reporting Quarter

Some of the NES variables are based on consolidated data and others are based on quarterly data. Figure 4.4 provides a graphic description of the time aspect of NES data.

SELL-OFF ACTIVITY

Sell-Off Activity is evaluated using two measures. Each measure helps answer a specific question. Generally speaking, the two sell-off activity variables allows us to examine 1) whether or not managers/CEOs sold any shares at the lock-up period expiration, and 2) how much they sold.

1) **SellOff_YN** is a dichotomous variable that indicates whether or not a firm's CEO sold any shares within two weeks of the expiration of the lock up period. For each firms' CEO, '1' indicates that the manager made a sale and '0' otherwise. I selected a two-week collection period to make a fair assessment of stock transactions by CEOs that coincide with the lock-up expiration. A two week period is a better assessment of lock-up expiration transaction activity than to assume that if managers do not sell shares on the specified lock-up expiration date that they are acting over-confidently. This slightly conservative approach allows me to be more confident that I captured any and all transactions associated with the lock-up expiration period, even those that were slightly delayed.

2) **<u>%_SellOff</u>** measures the percent of the CEO stock holdings the CEO sold at the expiration of the lock-up period. Stock holding is the amount the CEO held at the IPO issue date. For example, if a firm's CEO owns 100,000 shares at the IPO issue date and then sells 10,000 shares at the expiration of the lock-up period, they, and by extension their firm, receives a %_SellOff score of .10. Again, I employed a two-week collection period to account for slightly delayed, but likely associated sale transactions.

To test the operationalization of this variable I collected a sub-sample of 25 firms (20% of the total sample) and evaluated any restrictions placed on firm managers beyond the SECs Rule 144. Only two firms (8%) had additional selling restrictions and in both instances the restrictions allowed for the managers to sell over 80% of their holdings. Furthermore, in both of these cases, managers sold off less than the amount they were able to sell. Therefore, with only a few exceptions and those exceptions were not large deviations from the norm, firm managers could sell all of their holdings at the expiration of the lock-up period.

4.2.2 Independent Variables

The data collection effort for this dissertation was immense and resulted in a plethora of variables. However, the goal is to parsimoniously present the data and test previously stated hypotheses with meaningful and useful variables. To provide more stable and parsimonious measures of media hype, composites were formed using averages and unit-weighted z statistics (from here forward will be referred to as z-scores) of the content analysis and other pertinent media data (Judd et al, 2009). This process is described in the following sections.

COMMUNITY HYPE: Community hype is distinct from the other measures of hype. Based on the nature of the data, community hype is calculated differently. It is measured based on Google Trends traffic data (search volume index (SVI) provided by Google Inc.). Search volume indexes are correlated but different from existing proxies and capture the attention in a more timely fashion by measuring the real time changes in attention of potential consumers and investors (Marks, 2012). Google Trends tracks online users traffic activity and captures investor attention (Da, Engelber and Gao, 2011) using the world's largest internet service provider data by offering a relative search activity for each firm in the sample. Specifically, it shows how often a particular search-term is entered relative to the total search-volume. The horizontal axis of the main graph represents time (starting from 2004), and the vertical is how often a term is searched for relative to the total number of searches, globally. By examining longitudinal search data and traffic patterns with regard to each firm in the sample, I assess the relative importance of the firm in the online community during the time period surrounding the IPO.

Findings, published in the journal Scientific Reports, suggest there may be a link between online behavior and real-world economic indicators (Preis, Moat, Stanley and Bishop, 2012). The authors of this study examined Google search queries made by Internet users in 45 different countries in 2010 and calculated the ratio of the volume of searches for the coming year ('2011') to the volume of searches for the previous year ('2009'), which they call the 'future orientation index'. They compared the future orientation index to the per capita GDP of each country and found a strong tendency for countries in which Google users enquire more about the future to exhibit a higher GDP (Preis et al., 2012). The results hint that there may potentially be a relationship between the economic success of a country and the information-seeking behavior of its citizens online (Preis et al., 2012; Johnston, 2012). Furthermore, increases in Google Trends SVI have been used to predict higher stock prices over two weeks prior to price reversals (Da, Engelber and Gao, 2011). Research has shown that searches increase by 20% the week of a firm's IPO and that search volume contributes to large first day return and long run underperformance of IPOs.

Therefore in accordance with past literature, community hype is calculated by taking the average search traffic score for each firm for the two-year period surrounding the IPO from the Google Insights database. This score is then divided by the number of month of collection to establish an average Internet search volume score per firm. The final value is a comparable composite score for each firm's community hype.

COMPOSITE HYPE SCORES: As previously discussed, a series of variables were collected for each firm from each article for event, own and expert hypes. Each article was assessed for seven different variables. The first two variables are nominal, count variables collected during content analysis. Five of the variables were collected via content analysis coding for each article with respect to the focal firm. The following paragraphs provide a description of all of the different measures collected for each article including count-oriented and content analysis-generated variables. A description of the different media assessment measures used to develop Composite Hype variables for own hype, event hype and expert hype are also described below. The composite measure highlights the influence of attention, visibility, relevance and tone of media articles on firms' outcomes and managers' expectations.

ARTICLE TOPIC: Article Topic is a nominal variable that assesses the general topic of the article with respect to the focal firm. It ignores other topics in the article that relate to other firms. Generally, coders identified a single main topic for the focal firm for each article, but for a few articles (<5%) coders inputted more than one topic category indicating that there was more than one main topic in the article with regard to the focal firm. Each firm's average topic score is converted to a z-score and then added to each firm's per hype composite score (i.e., Own $_{\text{Z-Topic, Firm X}}$).

ARTICLE LEVEL OF ANALYSIS: Article Level of Analysis is a nominal variable that examines the levels of analysis are discussed in each article with respect to the focal firm. This variable was rated such that all of the levels that are discussed in the article with respect to the focal firm should be identified. However, various levels discussed in the article, but not with respect to the focal firm were ignored. In 98% of the articles, one level with respect to the focal firm was identified. Each firm's average level of analysis is converted to a z-score and then added to each firm's per hype composite score (i.e., Market $_{\text{Z-LoA, Firm X}}$).

NUMBER OF ARTICLES: Number of articles is a measure of the number of articles in each type of hype for each firm for the entire two-year period. The final score of this variable is based on the total number of articles in each type of hype for each firm. Each firm's number is converted to a z-score and then added to each firm's per hype composite score (i.e., Own $_{\text{Z-\# of articles, Firm X}}$).

ARTICLE LENGTH: Article length is a measure of the average number of words per article per firm for the entire two year period. The final score of this variable is based on the Average article length in each type of hype for each firm. Each firm's number is converted to a z-score and then added to each firm's per hype composite score (i.e., Market $_{\text{Z-Avg Length, Firm X}}$).

PAGE LENGTH: For Expert Hype only, Page Length is a measure that reflects the average number of pages of analysts' reports per firm for the two year period. Each firm's page length average is converted to a z-score and then added to each of the firm's expert hype composite score (i.e., Expert $_{\text{Z-Page Length, Firm X}}$).

Expert hype is slightly different than the other types of hype because the focus was on the analysts' reports' executive summaries, rather than the entire article. Although these are of various lengths and do provide some variance, a better measure of the length of the attention is gained by adding one additional variable to the composite. For expert hype the composite score also includes the Z-score of the average number of pages per report per firm.

ARTICLE SALIENCE: Article Salience is measured based on the relative role that the firm played in each article. This is measured on a five point ordinal scale where '5' represents that an article's sole focus is the focal firm and '1' which indicates that the firm is "barely mentioned." All five categories and their descriptions are provided in Appendix X. Each firm's average salience score is converted to a z-score and then added to each firm's per hype composite score (i.e., $\text{Own}_{\text{Z-Salience, Firm X}}$).

ARTICLE TONE1 AND TONE2: Article Tone1 measures whether an article was positive or not positive with respect to the focal firm. Tone1 is a dichotomous variable where '1' indicates that the article is positive with respect to the focal firm and a '0' indicates that the article was not positive with respect to the focal firm. Assessments ignored other firms or events in the article when evaluating the tone of the article. Tone2 is also a dichotomous variable and measures whether the article was negative or not negative with respect to the focal firm. Again, assessments ignored other firms or events in the article. Tone2 indicates '1' when an article is negative with respect to the focal firm and '0' when the article is not negative with respect to the focal firm. Therefore, when scores of '0' are indicated for both Tone1 and Tone2, the article was considered neutral article. In the few cases (<5%) where the article was rated '1' for both Tone1 and Tone2, the article was also rated neutral (Lamertz & Baum, 1998).

To operationalize the media-provided attributes into a firm-specific 'Tone' variable for each type of hype I calculated the Janis-Fader coefficient of imbalance (Janis & Fader, 1965; Deephouse, 2000; Pollock & Rindova, 2003). This measure was calculated using the following formula:

$$\text{Tenor} = \begin{cases} (P^2 - PN)/V^2 & \text{if } P > N; \\ 0 & \text{if } P = N, \text{ and} \\ (PN - N^2)/V^2 & \text{if } N > P) \end{cases} \qquad \textit{Equation 7}$$

where P is the number of positive articles about a firm, N is the number of negative articles about it, and V is the total volume of articles about it, including articles that are neutral in tenor.

The variable range is -1 to +1, where -1 equals "all negative coverage" and +1 equals "all positive coverage" (Pollock & Rindova, 2003). To allow for nonlinear transformations of this measure, I multiplied this score by 100. Consistent with prior research (Deephouse, 2000) and as described previously, each article was content analyzed as positive or not positive, negative or not negative, and those assessments revealed articles that were subsequently coded neutral. These assessments were based on the articles discussion regarding the focal firm by a group of trained, experienced coders who showed high inter-rater agreement with

Krippendorf's alphas greater than .85 (IRR discussion provided in section 4.2.6 above). Each firm's Janis-Fader coefficient of imbalance is converted to a z-score and then added to each firm's hype composite score for each type of hype (i.e., Expert $_{\text{Z-tone, Firm X}}$).

CALCULATING COMPOSITE HYPE SCORES

Researchers in social sciences often have a large number of variables; however, science aims for parsimonious explanations of the world. Therefore, I developed a principled approach to dealing with the multiplicities that arise in this dissertation. A common approach to deal with the challenge of large sets of variables is to combine the measures into a single (or a few) measure(s) that evaluate similar things into composites. In the following paragraphs I describe the method instituted in establishing composite measures for the different types of media hype. In this instance, I collected a number of variables regarding the amount, type and tone of media articles with respect to focal firms. Because of concerns regarding parsimony and meaningful descriptive variables, it may be more appropriate and useful to form one or more composites versus using all of the different individual variables in the regression analysis. Once verified for their similarity, these composites can then be used in subsequent analyses (Borgen and Barnett, 1987).

The first step was deciding the appropriate variables to be included in forming the different composites. Anglim and Waters (2007) recommends that three major sources of information should be considered when choosing which variables should be grouped together to form composites: (1) data, (2) aims, and (3) theory. First, they explain that in social sciences, all else being equal, it makes more sense to combine variables that are correlated with each other than to sacrifice statistical power by inputting several variables into your test equations that are measuring the same construct. Data that are highly correlated (e.g., r greater than 0.5 for most social science research) suggest that the subset is measuring something in common.

Second, Anglim and Waters (2007) suggests that researchers consider the purpose of forming composites with respect to the planned analyses. For example, since in this instance we are interested in testing the effect of media hype (as a whole) on managerial expectations and firm outcomes, having a general measure of hype for each type is sufficient for testing its effect. Had we been more interested in how the parts that make up the different types of hype predicted behavior or if there were specific theoretical elements for each of the pieces of hype that were to be tested, than a fine grained split of the construct hype would have been more appropriate.

Third, theory and past research may have suggested that the tests should be grouped in particular way; however, that is not the case in this instance. Being that this project is the first of its kind, there limited theoretical foundations regarding the development of composite measures for different types of hype. In short, recognizing the clear trade-offs between complexity and parsimony, it was appropriate in this dissertation to combine similar measures into one measure of hype for three of the four categories of hype (Anglim and Waters, 2007).

The next step is to determine how to form the composite measures. Following previous literature (Tabachnick & Fiddel, 1996) variables were weighted to create a linear composite of the component variables. The first variable included in the component is the total number of articles found in each type of hype for each firm. The second variable is the average length of the article. The third through sixth variables were the five assessments made for each firm for each article during content analysis. The principal components analysis indicated a strong correlation between these six variables such that one component score adequately addresses three of the different types of hype (event, own, and expert...community hype is determined differently). A simple procedure would be to calculate the composite score by simply adding the different variables together such that:

$$\text{Hype Composite} = \#\text{ of Articles} + \text{Avg Length of Articles} + \text{Avg Article Salience} + \text{Avg Article Tone1} + \text{Avg Article Tone2}$$

Equation 8

However, there are a number of problems with such a technique. First, these variables are measured using several different metrics. Therefore, the result is that the measures with larger standard deviations will be weighted more in the composite even if its impact is no stronger than the other measures. Allowing the weighting of the variables to be arbitrarily applied (particularly if driven by metrics) leads to erroneous conclusions (Hair et al, 2006). Consequently, it is generally better to weight all of the tests equally, unless there is some theoretical support for weighing the variables in a particular way (Tabachnick & Fiddel, 1996). Therefore, a common procedure is to convert the raw test scores to z-scores[2], and then add-up the z-scores. To convert each raw score to a z-score I applied the following formula:

$$Z = (\text{score} - \mu) / SD \qquad \textit{Equation 9}$$

Where Z is the z-score, score is the observed or assessed variables value (or average value when appropriate), μ is the mean, and SD is the standard deviation.

Z-scores were determined using a common mean and standard deviation to standardize the variables despite the different times of the different articles in the data set. For instance, in the case of Article Salience for Event Hype the formula converts to the following:

$$\text{Z-Salience}_{\text{Event Hype, Firm X}} = (\text{Firm Avg Article Salience} - M) / SD$$

Equation 10

Where 'M' is the mean and 'SD' is the standard deviation of all salience scores for event hype for the entire sample.

Finally, our refined composite hype measure is computed using z-scores and the more appropriate formula:

[2] When the population standard deviation is not known and the population is assumed to be normal, the most appropriate distribution to use is the t-distribution with n-1 degrees of freedom. However, as the sample size increases, the t-distribution converges such that the z-distribution is the same as the t-distribution. For instance, when n=121 (df=120), $t_{0.05}$=1.98 and $z_{0.05}$=1.96. The convergence only increases as the sample size increases such that the two distributions are practically identical. Therefore, it is appropriate to use the z-distribution in this instance (Aczel, 1989).

$$\text{HYPE}_{\text{(event or own), Firm X}} = Z_{\text{\# of Articles}} + Z_{\text{Article Length}} + Z_{\text{Salience}} + Z_{\text{Tone}}$$

Equation 11

$$\text{HYPE}_{\text{(expert), Firm X}} = Z_{\text{\# of Articles}} + Z_{\text{Summary Length}} + Z_{\text{Page Length}} + Z_{\text{Salience}} + Z_{\text{Tone}}$$

Equation 12

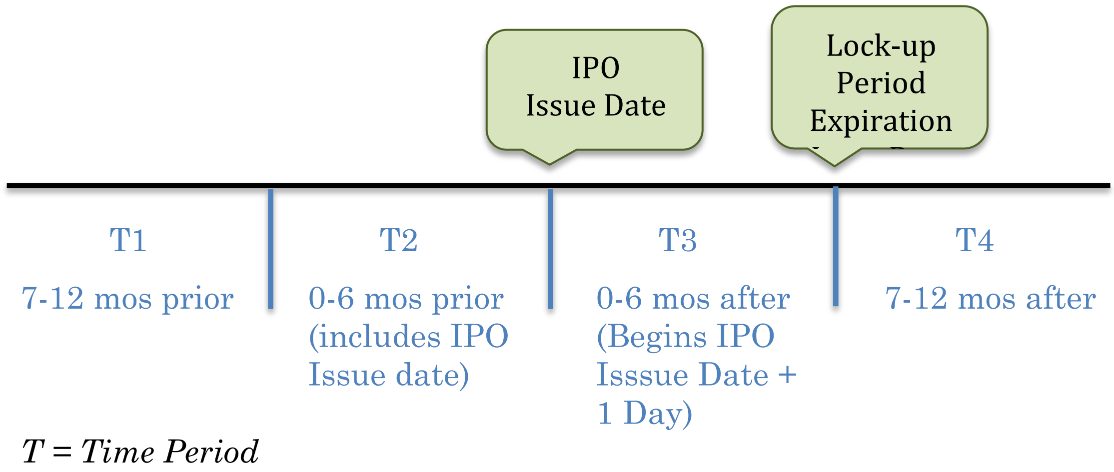
Fortunately, in all of the variables above, higher scores reflect higher values; therefore, there is no need to adjust any of the values above due to concerns over reverse testing (i.e., tests where lower scores reflect better or greater levels of performance). The composite scores for each of the three different types of hype (event, own and expert…community hype is determined differently, see below) can be used in subsequent regression analyses as predictors. The chief benefit is that the complexity of the data has been simplified and is better able to present a more parsimonious explanation (Ackerman & Cianciolo, 2000) regarding the relationship between media and firm outcomes and manager expectations.

Furthermore, in addition of one single composite hype score for each type of hype for each firm, more granular data was obtained by for each type of hype, by calculating composite hype scores for each firm for four time periods (i.e., Expert_T4). The time periods are described in Figure 4.4 below.

4.2.3 Control Variables

A number of control variables are included to properly account for potential firm-level and macro-level differences. Firm-specific controls pertaining to industry, deal size, firm age, firm size, whether or not the firm has a Founder-CEO

FIGURE 4.4: DATA COLLECTION AND COMPOSITE HYPE SCORE TIMELINE



or a Professional Manager-CEO are important factors for IPO firms and are incorporated in the models. Likewise, macro-economic factors are potentially significant determinants of the influence of hype and IPOs are particularly susceptible to macro-economic fluctuations, including market risks, changes in investing habits, and general economic growth. Additionally, the critical role of the lead underwriters and venture capitalist support in any IPO led to an underwriter reputation and VC backing values to be included as controls during model assessments. The following sections define and describe these measures.

INDUSTRY: An industry control variable was included, to account for any potential systematic differences that may exist between companies in different industries for both the independent and dependent variables. Some industries lend themselves more to media attention and, consequently, are more susceptible to media hype.

First, industry is measured based on industry membership for each firm by determining the SIC code of each firm. Then, based on prior literature, a categorization process coverts the SIC codes into tech and non-tech categories (Kile and Philips, 2009; Stough et al., 2000).[3] Therefore, the final variable is a dichotomous variable, based on industry membership, coding each firm as '1' indicating the firm is in a tech-oriented industry or '0' indicating that it is in a non-tech-oriented industry.

DEAL SIZE: Deal size focuses on the principal amount of an offer. The principal amount sends signals to the market about the relative quality and stability of an offer (Ibbotson & Ritter, 1995). Furthermore, the larger the deal the more hype is created. Therefore, the principal amount of a deal is a critical factor in determining the influence of hype on behavior. Principal Amount is measured as the total number of shares offered during an IPO multiplied by the offering price. This variable is logged to reduce the effect of extreme values.

FIRM SIZE: Firm size is measured based on the total number of employees at the time of the IPO. In general, there tends to be more information available about larger firms than for smaller firms. Therefore, concerns regarding asymmetric information are generally less for larger firms than for smaller firms.

---

[3] Additionally, the Center for Innovative Technology in Virginia developed a definition of high technology and separated it into sub-sectors according to SIC codes.

This variable was then logged to reduce the effects of extreme values on the analysis. No firms had zero employees, therefore, no adjustment factor was necessary prior to logging.

FIRM TOTAL ASSETS: Firm Total Assets indicates the firm's assets at the issue date. The units are dollars. This is a common firm-oriented control variable to help manage firm effects on the regression analysis.

UNDERWRITER REPUTATION: A critical element of the IPO is the investment bank that underwrites the offer. The hiring firm and the investing community charge underwriters to provide external independent assessments of the firm and set a fair price for the firms stock in the market. Underwriter reputation helped control for signaling effects and the resources that high status underwriters bring to bear when they take a company public (Carter & Manaster, 1990). The underwriter reputation measure is based on work performed by Loughran and Ritter (2002). Loughran and Ritter score each investment bank on these series of variables on a scale from 1 to 9. The final score for each firm in this dissertation is the average of the 10 year aggregate average score by Loughran and Ritter from 2000-2009 for each underwriting firm identified as a "lead underwriter" for each focal firm in the SEC Edgar website. For example, if a firm has three lead underwriters identified in the SEC Edgar database, IB1, IB2, IB3, and their average reputation scores over the 10 year period according to Loughran and Ritter are 7, 8, and 9 respectively, the focal firm will receive an '8' for its underwriter reputation score (underwriter rep = ((7+8+9)/3)).

VC BACKING: VC Backing (short for venture capital backed firms) reflects whether or not the firm has received venture capitalist support. This variable is a dichotomous variable where '1' indicates that the IPO firm received VC financing prior to its IPO and '0' reflects no VC involvement.

CHANGE IN GDP: Since the sample includes articles and IPOs that took place over a five-year period, a macro-economic control variable is instituted to eliminate the macro-economic variability from one year to the next. This macro-economic control variable is measured quarterly, so it also controls for within-year variances, since particular industries, and the IPO market in general, can go in and out of favor in less than a year (Pollock and Rindova, 2003).

As a measure of market activity, economic growth and macro-economic conditions, the Gross Domestic Product (GDP) is unparalleled (Samuelson and Nordhaus, 1985). Therefore, for this dissertation, the macro-economic conditions are measured as the GDP increase from one quarter to the next. For example, the value for a firm that has an IPO issue date in January, February and March 2007 is based on the change in GDP from the 4^{th} quarter of 2006 (2.7%).

TABLE 4.2: QUARTERLY CHANGES IN GDP

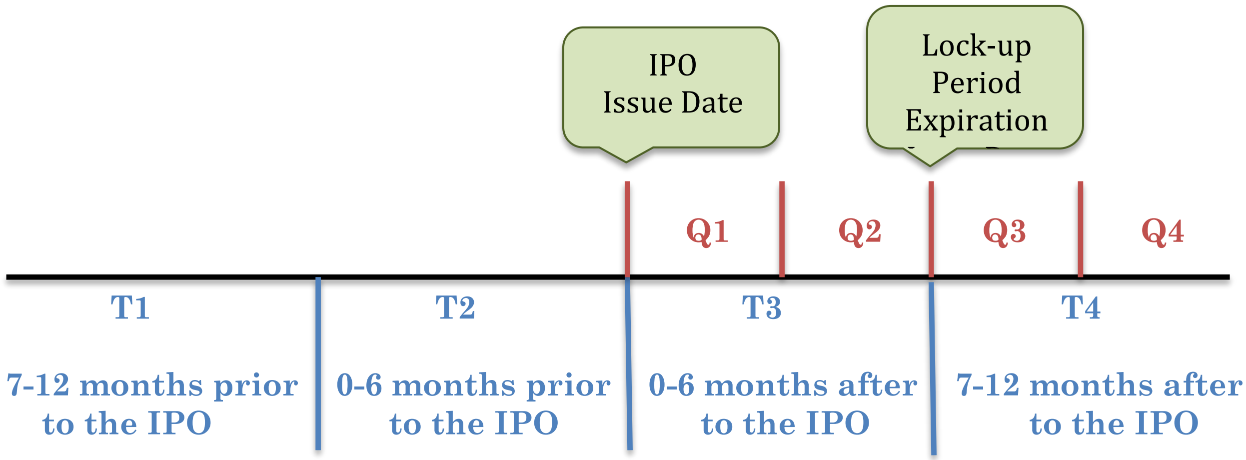
Firm IPO Issue Date	GDP Quarter	GDP Quarterly % Growth Rate
Jan, Feb, Mar 2007	4th Qtr 2006	2.7
Apr, May, Jun 2007	1st Qtr 2007	0.5
Jul, Aug, Sep 2007	2nd Qtr 2007	3.6
Oct, Nov, Dec 2007	3rd Qtr 2007	3.0
Jan, Feb, Mar 2008	4th Qtr 2007	1.9
Apr, May, Jun 2008	1st Qtr 2008	-1.8
Jul, Aug, Sep 2008	2nd Qtr 2008	1.3
Oct, Nov, Dec 2008	3rd Qtr 2008	-3.7
Jan, Feb, Mar 2009	4th Qtr 2008	-8.9
Apr, May, Jun 2009	1st Qtr 2009	-5.3
Jul, Aug, Sep 2009	2nd Qtr 2009	-0.03
Oct, Nov, Dec 2009	3rd Qtr 2009	1.4
Jan, Feb, Mar 2010	4th Qtr 2009	4.0
Apr, May, Jun 2010	1st Qtr 2010	2.3
Jul, Aug, Sep 2010	2nd Qtr 2010	2.2
Oct, Nov, Dec 2010	3rd Qtr 2010	2.6
Jan, Feb, Mar 2011	4th Qtr 2010	2.4
Apr, May, Jun 2011	1st Qtr 2011	0.1
Jul, Aug, Sep 2011	2nd Qtr 2011	2.5
Oct, Nov, Dec 2011	3rd Qtr 2011	1.3

* *Values obtained from the New York Times US Economy Webpage (2012)*

4.2.4 Review of the Time element of the Variables

Figure 4.5 is intended to clarify and avoid potential confusion regarding the different time elements for the different variables by mapping the different time-oriented variable on one another. Simply stated, the different hype measures are collected during four time periods, two prior to and two following the IPO issue date. Negative earnings surprises are all collected after the IPO issue date over the four EPS reporting quarters following the IPO issue date.

FIGURE 4.5: TIME ASPECTS OF THE DATA



T = Time period…refers to the collection time periods for the media data
Q = Reporting Quarter…refers to the collection periods for the negative earnings surprise data

4.3 Methods of Analysis and Model Specifications

I test the aforementioned hypotheses by estimating two types of models for the six dependent variables, four types for EPS and two for owner sell-off after the lock-up period expiration. For each regression, I began by running a regression model including explanatory control variables such as industry, Δ in GDP, principal amount, underwriter reputation, VC backing, firm size, total assets. The second set of regression models adds the independent variables evaluating the effect of the four types of media hype.

Two types of empirical analysis methods are instituted in evaluating the models. The first method utilizes logistic regression to assess the probability of an outcome in relation to a set of hypothesized predictors. For instance, logistic regression is used to test the set of predictors related to the dichotomous relationship between hype and negative earnings surprises. The basic structure of the Logistic Regression Model is represented by:

$$
\begin{aligned}
NES\_YN = {} & \beta_0 + \beta_1 CON(\text{industry}) + \beta_2 CON(\text{deal size}) + \beta_3 CON(\text{total assets}) \\
& + \beta_4 CON(\text{firm size}) + \beta_5 CON(\text{underwriter rep}) + \beta_6 CON(\text{VC backing}) \\
& + \beta_7 CON(\Delta \text{ in GDP}) + B_{8\text{-}12} COMM\_T1\text{-}4 + \beta_{13\text{-}16} MARKET\_T1\text{-}4 + \\
& + \beta_{17\text{-}20} OWN\_T1\text{-}4 + \beta_{21\text{-}22} EXPERT\_T3\text{-}4 + \varepsilon_i
\end{aligned}
$$

The second method involves a series of comparisons using an OLS regression models to test for the best fitting relationship between media hype and managerial expectations and firm outcomes. For example, the generalized OLS Model is represented by:

$$
\begin{aligned}
\%\_SellOff = {} & \beta_0 + \beta_1 CON(\text{industry}) + \beta_2 CON(\text{deal size}) + + \beta_3 CON(\text{total assets}) \\
& + \beta_4 CON(\text{firm size}) + \beta_5 CON(\text{underwriter rep}) + \beta_6 CON(\text{VC backing}) \\
& + \beta_7 CON(\Delta \text{ in GDP}) + B_{8\text{-}12} COMM\_T1\text{-}4 + \beta_{13\text{-}16} MARKET\_T1\text{-}4 + \\
& + \beta_{17\text{-}20} OWN\_T1\text{-}4 + \beta_{21\text{-}22} EXPERT\_T3\text{-}4 + \varepsilon_i
\end{aligned}
$$

where β_0 is the intercept, β_1 is the regression coefficient for the industry control variable, β_2 is the regression coefficient for the deal size control variable (referring to the IPO principal amount), β_3 is the regression coefficient for the control variable measuring the total assets, β_4 is the regression coefficient for the control variable measuring the size of the firm, β_5 is the regression coefficient for the underwriter reputation control variable, β_6 is the regression coefficient for the VC backing control variable, β_7 is the regression coefficient for the macroeconomic control variable, and $\beta_{8\text{-}12,}$ $\beta_{13\text{-}16,}$ $\beta_{17\text{-}20,}$ $\beta_{21\text{-}22}$ are the regression coefficients for Community, Market, Own, and Expert Hype variables, respectively, and ε is the normally distributed random error term (Aguinis et al., 2005; Cohen, Cohen, West, & Aiken, 2003; Zedeck, 1971).

4.4 Preparing the Data for Analysis

Prior to running descriptive statistics, correlations, and regression analyses, I examined the data to 1) ensure that the data does not violate any of the three assumptions for running regression analysis (normality, linearity and homoscedasticity), 2) address concerns associated with missing data and 3) deal with outliers. As part of these assessments, I also examined the data to identify and calculated the appropriate variable transformations. The sections below briefly describe these efforts.

4.4.1 Assessing Normality, Linearity and Homoscedasticity

The assumption of normality refers to all of the predictor variables being normally distributed (Tabachnick and Fidell, 2007). When this assumption is met, the residuals of the analysis are normally distributed and independent. In probability theory the central limit theory states that, given certain conditions, the mean of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed (Rice, 1995). Beyond this simple probability statistical theorem, there are several methods for assessing whether data are normally distributed or not. The measures of normality fall into two broad categories: statistical and graphical (see Table 4.3).

TABLE 4.3: METHODS FOR EVALUATING NORMALITY

STATISTICAL	GRAPHICAL
◆ Kolmogorov-Smirnov Test	◆ Quantile-Quantile (Q-Q) Probability Plots
◆ Shapiro-Wilks Test	◆ Histograms
◆ Skewness Statistic	◆ Cumulative Frequency (P-P) Plots
◆ Kurtosis Statistic	

Typically, statistical tests generate more accurate information regarding normality. However, the Kolmogorov-Smirnov test is not particularly sensitive to outliers and is best for data sets under 50 cases. Similarly, the Shapiro-Wilks test does not work particularly well if several values in the data set are the same (Tabachnick and Fidell, 2007). Therefore, for this dissertation, the primary screening of continuous variables for normality was conducted by evaluating the skewness and kurtosis statistics and conducting visual assessments of the graphical measures listed above (Cohen and Cohen, 1983; Tabachnick and Fidell, 2007). Findings indicate that all variables are relatively normally distributed or were transformed to meet the assumption of normality.

The assumption of linearity is that there is a straight line relationship between the variables. Linearity is important for many reasons, one of which is the usefulness of Pearson's correlations (*r*) since it only captures the linear relationships among variables. Linearity was assessed via inspection of bivariate scatterplots. "Oval-shaped" plots helped to confirm linearity of the data (Tabachnick and Fidell, 2007).

Homoscedasticity is related to normality in that when multivariate normality is met, the relationships between variables is homoscedastic (Tabachnick and Fidell, 2007). In assessing homoscedasticity of the variables, bivariate scatter plots were assessed. During graphical assessment, a perfectly homoscedastic variable would possess a bivariate scatter plot that is roughly the same width all over with some bugling in the middle (football-shaped) (Tabachnick and Fidell, 2007). The variables in this dissertation met the assumption of homoscedasticity.

4.4.2 Managing Missing Observations

Consistent with practically all research, there were some firms for which some of the data was not collectable. For this dissertation, great strides were made to keep as much of the sample and data as possible. However, there were a few firms that met the multistage criteria selection process described in the sampling section of chapter four, but I was not able to collect all of the pieces of data required to keep the firm in the sample. Most notable were firms whose earnings per share data were unobtainable from the various sources used to collect firms' analysts consensus and actual performance data. Since this data provides the foundation fro a critically important dependent variable, the lack of data made these firms a potential bias hazard for most impute, estimate or substitute technique.

Experts have not reached a consensus regarding the percentage of missing data that becomes problematic (Schlomer, Bauman and Card, 2008). Schafer (1999) recommends a 5% cutoff. Alternatively, Bennett (2001) suggests that more than

10% of data is missing may lead to biased statistical analyses. Others have used 20% (e.g., Peng et al., 2006). Fortunately, the number of firms missing data is relatively low at 5% (7/133). Therefore, deleting these firms meets all of the aforementioned cut-off criteria.

However, short of blindly following the prior literature “cut offs” listed above, I examine two other considerations help determine whether a certain amount of missing data (also referred to as missingness) is problematic. The first is whether the resultant data set has adequate statistical power to detect the effects of interest. In this case, the loss of 7 firm’s worth of data does not drop the overall data set below the previously calculated necessary number of observations to possess adequate statistical power. The second consideration is the pattern of missingness. The pattern of missingness speaks to the potential biasing impact on the data analyses. In this instance, data is missing at random and any technique to try and impute or substitute estimated values (such as mean substitution, multiple imputation (Acock, 2005) or pattern-matching imputation (Roth, 1994) introduces potential bias. In summary, the amount of missing data is well below prior literature cut offs and a cursory review of the data indicates that the missing data is consistent with the data remaining in the data set. Consequently, although there is a preference to apply nonstochastic imputation, stochastic imputation or other modern imputation procedures which aim to retain the maximum amount data to support maximum statistical power, listwise deletion of this small, inconsequential portion of the sample is prudent.

4.4.3 Dealing with Outliers

The distribution of many statistics can be heavily influenced by outliers. Generally, the two most popular methods for dealing with outliers is trimming and winsorising (Tukey, 1962). Trimming is basically identifying cases with outlying data and eliminating them from the data set. This is often a less desirable solution for two main reasons. First, when data sets are small, eliminating cases reduces statistical power and hinders the likelihood of finding an effect. Second, eliminating cases may also eliminate other values from the cases that could positively contribute to the overall regression analysis (Dixon, 1960).

Alternatively, I chose to Winsorize some of the variables containing outlying values. Contrary to trimming, where extreme values are discarded, Winsorizing keeps the cases which contain outliers and replaces extreme values by percentile values (a "trimmed" minimum and maximum) (Hasings, Mosteller, Tukey and Winsor, 1947). Simply stated, Winsorising transforms variables by limiting the effects of extreme values to reduce the effect of spurious outliers by adjusting the outlier data to confirm more with a normal distribution (Griffith, 2006). Furthermore, Winsorizing data is common in literature and appropriately applied when extreme values, like those experienced in this dissertation, are exaggerated versions of true values (Angrist and Krueger, 2000).[4] In this dissertation, I instituted a 10% Winsorisation for the negative earnings surprise variables by

[4] As Angrist and Krueger (2000) explain, "…winsorizing the data is desirable if the extreme values are exaggerated versions of the true values, but the true values still lie in the tails. Truncating or trimming the sample is more desirable if the extremes are mistakes that bear no resemblance to the true values." (p. 1349)

setting all high outlier data (those above the 90^{th} percentile) to the 90^{th} percentile value and the low outlier data (those values below the 10^{th} percentile value) to the 10^{th} percentile value.

4.4.4 Variable Transformations

Variables differ in the extent to which they diverge from a normal distribution (Tabachnick and Fidell, 2007). As Tabachnick and Fidell (2007) noted, sometimes, researchers must try several transformations before they find the most useful one. For the purposes of this dissertation, and in accordance with prior literature, when a variable's distribution differs moderately from normal, a square root transformation was tried first. If this transformation does not sufficiently manage the distribution concern, or if the distribution differed substantially from normal, a log transformation was applied. Variables receiving square root and log transformations was identified in the variable section of chapter four above.

CHAPTER 5: ANALYSES, RESULTS AND FINDINGS

5.1 Descriptive Statistics and Correlations

Appendix M provides a summary and description of each variable, Appendix N presents descriptive statistics and Appendix O delivers the correlation matrix. The 126 firm sample consists of 42% hi-tech and 58% non-hi tech firms, focuses on larger IPO's which on average have a principal amount of $498M, and are spread across five years running from 2007 through 2011. The median firm total assets at their IPO for the sample is $134M and the median firm age reflects a slightly more mature data set for entrepreneurial analysis at 6.5 years. 69 firms (55%) were VC backed and 61 firms (48%) had CEOs at the time of their IPO offering that were also the firm's founder (including those who were members of a team of founders).

With regard to negative earnings surprises, 81 firms (64%) in the sample failed to meet or beat (MoB) analyst consensus estimates at least once over the four quarters following their IPO. On average, across the entire sample, firms missed analyst consensus 1.16 times out of four quarters. However, when focused only on firms that missed analysts' consensus at least once (81 of 126 firms), the average number of misses per firm is 1.90 misses per firm for the four quarters. Although the means for the raw miss values per quarter are not significantly different from one another, we do see a trend where firms raw miss values got worse over time from the first to the fourth quarter.

TABLE 5.1: EPS/NES STATISTICS PER QUARTER

	Average EPS Performance Raw Value	Standard Deviation EPS Performance RAW Values	Number of Misses	Miss Rate
1st Quarter	0.002	0.121	36	29%
2nd Quarter	0.008	0.011	31	25%
3rd Quarter	-0.018	0.172	41	33%
4th Quarter	-0.009	0.099	45	36%
Total			153	30%

Furthermore, the firms in the sample experienced 153 total negative earnings surprises over the four quarters (504 quarters) for a MoB rate (inverse of the Miss Rate presented in Table 5.2) of 70%. This MoB rate falls in line with prior literature (Loughran and Ritter, 2002). Also, Table 5.4 provides the number of firms who failed to MB analysts' earnings estimates 0, 1, 2, 3, and 4 times. Finally, Table 5.5 indicates, for those firms that did miss in each quarter, the high, low and average raw miss per firm.

TABLE 5.2: NUMBER OF QUARTERLY NES MISSES PER FIRM

# of Misses	Number of Firms	Percentage of Total Firms
0	45	35.7%
1	33	26.2%
2	32	25.5%
3	8	6.3%
4	8	6.3%
Total	126	100%

With regard to sell-off activity, 60 of the 126 (48%) firm CEOs sold at least a portion of their stock at the expiration of the lock-up period. On average, these firm

CEO's sold 20% of their holdings. Interestingly, 58 of 126 (46%) CEOs also acquired firm stock at the expiration of the lock-up period for an average of 12% of their holdings. However, it is important to note that these actions are not mutually exclusive since some firm managers (24 of 126, 19%) both bought and sold shares at the expiration of the lock-up period. Finally, 31 (25%) firm CEOs took no action at the expiration of the lock-up period.

TABLE 5.3: AVERAGE RAW MISS PER QUARTER FOR FIRMS WITH NES EVENTS

	Number of Misses	Average Raw Miss	Raw Miss Standard Deviation	Highest Miss	Lowest Miss
1st Quarter	36	0.11	0.15	0.65	0.01
2nd Quarter	31	0.10	0.15	0.71	0.01
3rd Quarter	41	0.14	0.24	1.09	0.01
4th Quarter	45	0.08	0.13	0.61	0.01
Total	153				

Shifting focus to the correlation matrix, low correlations between all of the variables (no *r* greater than .650) reduces concerns associated with multicollinearity. Additionally, the low correlations between the four types of hype (*r* never above .377) provides strong support for the paper's claim of presenting a new taxonomy for considering hype. Low correlations between these various hypes indicates that there are four distinct types of hype based on the sources of hype. In fact, the correlations between the different time periods of the same hype, although higher than any other variables correlations, are not as high as expected meaning that not only are the different hypes distinctive, but the different time periods even within the same type of hype are relatively distinctive. Therefore, we can infer that the hypes' relationship with the measures of overconfidence presented in this dissertation are different based not only on the source of hype, but also on the timing of the hype. For convenience, Appendix P presents a table that provides the key dependent and independent correlations.

5.2 Regression Results and Hypothesis Testing

In an effort to test the hypotheses proposed in chapter three, I ran a series of regression tests to evaluate different predictive models. The results of these tests are provided below. A summary table of all of the models and their findings is provided in Appendix O. More detailed examination of the results and a discussion of their meanings are provided in Chapter 6.

5.2.1 Evaluating Goodness-of-Fit

For all regression models, it is important to assess the goodness-of-fit for the overall model. Doing so evaluates the predictability of the independent variables as a group in predicting the dependent variable. In ordinary least square (OLS) regressions we use the R-Squared value to express the amount of variance in the dependent variable explained by the predictors in the model. For instance, if the R-Squared is .371, as it is in Model 10 below, we infer that the model explains 37% of the variance in fourth quarter NES results (i.e., Q4_NES_10_Winsor).

However, with logistic regression, we cannot interpret model fit the same way. For logistic regression the most straightforward measure of goodness-of-fit is to compare how accurately the model predicts the dependent variable against the extent to which the proposed model is better able to predict the dependent variable than a model without any of the independent variables. In the case of Model 1 below, the predictive model increases the predictability versus the constant only model by 17% (from 52% to 69%). Although there is not set limit for assessing goodness-of-fit, this is a fairly large improvement over the null, constant only model. Additionally, for logistic regression there are *pseudo r-squared* values, but they must be interpreted slightly different than the OLS regression R-squared values. For instance, the Cox & Snell R-squared value of .233 in Model 1 tells us something similar to what R-squared tells us in OLS regression regarding the proportion of variance accounted for in the dependent variable based on the predictive power of the independent variables in the model. However, it should never be interpreted exactly as one would interpret R-squared in OLS regression. Similarly, the Nagelkerke R-square statistic also purporting to tell us something along the lines of an OLS R-squared, but is not directly comparable to it. These are a valid assessment tools, but contrary to OLS R-squared values, pseudo R-squared values in logistic regressions merely approximation something similar to R-squared. Furthermore, some of the pseudo measures used in logistic regression are not scaled from 0 to 1 as in R-squared values.[5] Overall, high values are better than low values, since higher values suggests that your model fits increasingly well.[6]

---

[5] The Nagelkerke R-squared will always be less than the Cox & Snell R-square, since the Nagelkerke R-squared is an adjustment of the Cox & Snell, for which the maximum value it can attain is equal to 1.0. The maximum value for the Cox & Snell is 0.75.

[6] Cohen, Cohen, West & Aiken (2003) refer to these statistics as "Multiple R-squared Analogs" to emphasize that they are not equivalent to the R-squared in OLS regression. As they describe, ". . . we caution that all these indices are not goodness-of-fit indices in the sense of "proportion of

5.2.2 Predictive Model Testing

It is important to understand the relationship between the variables, performance and the measures of over-confidence. For instance, for logistic regression models testing the likelihood of an NES event, an increase in NES is a reflection of a higher likelihood that the firm will miss its EPS consensus estimate. Therefore, positive coefficients reflect higher likelihood of an NES event and greater over-confidence. For OLS regression testing the number of NES events, higher NES_Miss values is associated with more EPS consensus analysts misses and worse performance. Therefore, as NES_Miss increases this indicates more misses and poorer performance by the firm. Consequently a positive coefficient is associated with more misses which reflects greater over-confidence. For OLS regressions testing NES, a decrease in NES infers a decrease in EPS performance relative to the firm's consensus analyst estimates. Therefore, decreases in NES, reflected by negative coefficients, are associated with higher levels of over-confidence. For logistic regressions of the sell-off variable, reductions in the dichotomous sell-off yes or no variable, where 1 indicates that the firm manager acted prudently in selling of a portion of their shares at the expiration of the lock-up period and 0 indicates that the CEO failed to sell-off any portion of their stock, represents less likelihood that a CEO will sell-off any of their holdings at the expiration of the lock-up period. Therefore, negative coefficients reflect a decrease in the likelihood that a firm CEO sold their shares at the lock-up expiration and is associated with more over-

---

variance accounted for, in contrast to R-squared in OLS regression" (p. 503). For further details on this issue, see Cohen et al., pp. 502-504.

confidence. Similarly, a decrease in sell-off percentage variable reflects less sell-off percentage sold at the expiration of the lock-up period and indicates a greater amount of over-confidence.

Model 1 in Table 5.4 presents the results of a logistic regression testing Hypothesis 1a which predicts that media hype will influence managers to act over confidently as manifested by an increase in hype being associated with a greater likelihood that a firm will experience at least one NES. Generally, results support Hypothesis 1a that hype does in fact influence over-confidence as manifested in likelihood for a firm to experience an NES event at least once in the four quarters following the IPO. Although not every hype and every time period significantly relates to NES performance, many of the different sources of hype over different time periods do, in fact, significantly influence firm NES misses. For instance, Model 1 indicates that own hype in period 1 is a significant predictor of the likelihood of a firm experiencing at least one NES event in the four quarters following the IPO. As own hype increases so does the likelihood of an NES event and, consequently, a greater likelihood of over-confidence ($\beta=0.225$, Wald(1, N=126)=4.589, $p=0.032$). Community hype in periods 2 and 4 marginally and significantly influences NES outcomes, respectively. However, these influences move in opposite directions. For instance, as community hype in period 2 increases, the likelihood that the firm will experience an NES increases reflecting a higher level of over confidence ($\beta=0.033$, Wald(1, N=126)=3.552, $p=0.059$). However,

TABLE 5.4: RESULTS OF LOGISTIC REGRESSION ANALYSIS PREDICTING THE LIKELIHOOD OF ANY NES (NES_YN)

Model 1: NES Y/N

Variable	β	s,e,	Sig.
Constant	.483	1.000	.629
Industry(1)	.530	.608	.384
Change_in_GDP	-.088	.113	.433
Deal_Size_10_Winsor	.006 **	.003	.038 **
Firm_Size_10_Winsor	-.001 **	.000	.033 **
Total_Assets_10_Winsor	.000	.000	.579
Underwriter_Rep	-.126	.107	.237
VC_Backing(1)	.287	.638	.652
Comm_T1	-.006	.018	.722
Comm_T2	.033	.018	.059 *
Comm_T3	.037	.027	.171
Comm_T4	-.054	.028	.050 **
Market_T1	-.079	.110	.474
Market_T2	-.186	.122	.127
Market_T3	-.108	.118	.360
Market_T4	.164	.097	.091 *
Own_T1	.225	.105	.032 **
Own_T2	-.030	.126	.813
Own_T3	-.218	.150	.147
Own_T4	.078	.108	.471
Expert_T3	-.460	.153	.003 ***
Expert_T4	.218	.131	.095 *
Cox-Snell R^2	.249		
Nagelkerke R^2	.342		
Classification Table Change	.135		
Omnibus Model Test	.022 **		
n	126		

*** p < .10, ** p < .05, *** p < .01**

community hype in period 4 indicates that as community hype in period 4 increases, the likelihood that the firm will experience at least one NES miss decreases reflecting a lower level of over confidence (β=-0.054, Wald(1, N=126)=3.677, p=0.055). We notice a similar unusual phenomena for expert hype whereas expert hype in period 3 increases, the likelihood of the firm suffering at least one NES decreases reflecting a lower likelihood of over confidence (β=-0.460, Wald(1, N=126)=8.975, p=0.003). However, when expert hype in period 4 increases, although only marginally significant, the likelihood of a firm experiencing an NES increases and so does their likelihood to act over confidently (β=0.218, Wald(1, N=126)=2.785, p=0.095).

Models 2 thru 5 in Tables 5.5a and 5.5b are logistic regression results that test Hypothesis 1b regarding the per quarter likelihood of an NES event as a result of the influence of media hype. Hypothesis 1b is partially support. Models 2 and 5, representing tests of the 1st and 4th quarter NES performance indicated significant models; however, models 3 and 4 which tested the likelihood of an NES in quarters 2 and 3 failed to produce significant models. In Model 2, we observe significant findings for the influence of market hype in periods 1 and 2, but again the direction of the influence is in different directions for the two periods. Period 1 market hype influences the likelihood of an NES in the 1st quarter such that as market hype increases, the likelihood of an NES in the 1st quarter increases reflecting a higher likelihood of over-confidence (β=0.266, Wald(1, N=126)=5.243, p=0.022). However, market hype in period 3 has a relationship with 1st quarter NES such that as market hype in period 2 increases, the likelihood that an NES will occur in the 1st quarter decreases reflecting a lower likelihood of over confidence (β=-0.311, Wald(1, N=126)=5.662, p=0.017). Model 5 in Table 5.5b partially supports Hypothesis 1b based on the influence of own hype in time period 1 and expert hype in time period 3 on the likelihood of a 4th quarter NES event. Both of these specific hypes are significant predictors. As own hype in period 1 increases, the likelihood of an NES event in the 4th quarter increases, reflecting an increase in over-confidence (β=0.236, Wald(1, N=126)=4.498, p=0.034). However, expert hype in time period 3 appears to time period 3 appears to suppress a manager's over-confidence because as expert hype in time period 3 increases, the likelihood of an NES in the 4th quarter decreases (β=-0.329, Wald(1, N=126)=4.545, p=0.033).

TABLE 5.5A: RESULTS OF LOGISTIC REGRESSION ANALYSIS PREDICTING THE LIKELIHOOD OF A 1ST AND 2ND QUARTER NES (Q1_MOB AND Q2_MOB)

	Model 2: 1st Quarter NES Y/N			Model 3: 2nd Quarter NES Y/N		
Variable	**β**	**s,e,**	**Sig.**	**β**	**s,e,**	**Sig.**
(Constant)	-.719	.880	.414	-2.542	1.081	.019
Industry	-.364	.570	.523	.912	.646	.158
Change_in_GDP	-.079	.119	.504	.096	.157	.542
Deal_Size_10_Winsor	**.007 *****	.003	**.009 *****	.000	.003	.977
Firm_Size_10_Winsor	**-.001 ***	.000	**.065 ***	**-.001 ***	.001	**.071 ***
Total_Assets_10_Winsor	.000	.000	.127	.000	.000	.951
Underwriter_Rep	-.135	.095	.155	.007	.099	.940
VC_Backing	-.201	.598	.736	-.247	.703	.725
Comm_T1	.005	.015	.760	-.025	.017	.133
Comm_T2	.015	.013	.248	.015	.015	.311
Market_T1	**.266 ****	.116	**.022 ****	-.075	.130	.565
Market_T2	**-.311 ****	.131	**.017 ****	-.005	.131	.970
Own_T1	.099	.098	.314	.057	.105	.591
Own_T2	-.128	.095	.179	.023	.133	.863
Q1_MoB				**.893 ***	.535	**.095 ***
Comm_T3				**.030 ***	.017	**.076 ***
Market_T3				.051	.120	.670
Own_T3				.143	.139	.304
Expert_T3				-.044	.114	.697
Cox-Snell R^2	.155			.179		
Nagelkerke R^2	.222			.267		
Classification Table Change	.078			.079		
Omnibus Model Test	**.068 ***			.127		
n	126			126		

*** p < .10, ** p < .05, *** p < .01**

TABLE 5.5B: RESULTS OF LOGISTIC REGRESSION ANALYSIS PREDICTING THE LIKELIHOOD OF A 3RD AND 4TH QUARTER NES ***(Q3_MOB AND Q4_MOB)***

Variable	Model 4: 3rdst Quarter NES Y/N β	s,e,	Sig.	Model 5: 4th Quarter NES Y/N β	s,e,	Sig.
(Constant)	-.900	.941	.339	-1.744	1.041	.094
Industry(1)	.623	.602	.301	-.393	.659	.551
Change_in_GDP	-.070	.114	.539	-.110	.129	.395
Deal_Size_10_Winsor	.004	.003	.112	.005 *	.003	.060 *
Firm_Size_10_Winsor	.000	.000	.790	-.001 **	.000	.042 **
Total_Assets_10_Winsor	.000	.000	.395	.000	.000	.716
Underwriter_Rep	-.153	.097	.113	.022	.103	.830
VC_Backing(1)	-.185	.615	.764	.537	.660	.416
Comm_T1	.000	.017	.981	-.004	.019	.838
Comm_T2	-.003	.014	.805	-.005	.015	.749
Comm_T3	-.012	.015	.435	-.006	.022	.788
Market_T1	.030	.121	.803	-.078	.124	.530
Market_T2	-.171	.131	.191	-.220	.146	.133
Market_T3	.067	.111	.543	-.083	.125	.508
Own_T1	.012	.095	.900	.236 **	.112	.034 **
Own_T2	.019	.123	.877	.053	.129	.682
Own_T3	-.248	.161	.124	-.117	.172	.498
Expert_T3	-.093	.113	.411	-.329 **	.154	.033 **
Q1_MoB	.092	.513	.858	1.200 **	.543	.027 **
Q2_MoB	1.667 ***	.542	.002 ***	1.215 **	.582	.037 **
Q3_MoB				.340	.520	.513
Comm_T4				-.005	.022	.811
Market_T4				.140	.098	.154
Own_T4				-.062	.114	.584
Expert_T4				.175	.137	.203
Cox-Snell R^2	.182			.281		
Nagelkerke R^2	.254			.386		
Classification Table Change	.040			.119		
Omnibus Model Test	.151			.014 **		
n	126			126		

* $p < .10$, ** $p < .05$, *** $p < .01$

Model 6 in Table 5.6 is an OLS regression that presents both unstandardized and standardized regression coefficients. This model tests Hypothesis 2 regarding the relationship between the different hypes over the different time periods and the number of total NES misses over the four quarters following the IPO. Hypothesis 2 is supported. Again, we notice opposing coefficients within the same hype across different time periods. For instance, although only marginally significant, community hype in time periods 3 and 4 are significant predictors of the number of NES events a firm experiences. However, while community hype during period 3 has a positive relationship, such that as community hype increases, the incident of NES events increases reflecting a greater amount of over confidence occurs ($\beta=0.017$, $t(104)=1.786$, $p=0.077$), for community hype in period 4 the opposite occurs such that as community hype in period 4 increases, the incident of NES events decreases reflecting a lesser amount of over confidence ($\beta=-0.017$, $t(104)=-1.742$, $p=0.084$). A similar phenomena exists for market hype where as market hype in period 2 increases, NES events decreases, and overconfidence decreases ($\beta=-0.146$, $t(104)=-2.634$, $p=0.010$). But as market hype composite score in period 4 increases, NES events increases ($\beta=0.081$, $t(104)= 1.854$, $p=0.067$). The increase in NES events is associated with market hype period 4 reflects higher levels of over-confidence. Contrary to what was revealed during logistic regression expert hype is not a significant predictor of number of NES occurrences, but own hype in period 1 is significant of number of misses such that as own hype in period 1 increases, the number of total NES events per firm increases, reflecting higher levels of over-confidence ($\beta=0.074$, $t(108)=1.658$, $p=0.010$).

Models 7 thru 10 in Tables 5.7a and 5.7b are OLS regressions that present both unstandardized and standardized regression coefficients for the OLS regressions testing Hypothesis 3. Hypothesis 3 tests the relationship between media hype and the amount of NES miss in raw performance and predicts that

TABLE 5.6: RESULTS OF REGRESSION ANALYSIS PREDICTING NUMBER OF NEGATIVE EARNINGS SURPRISES PER FIRM FOR THE FOUR QUARTERS FOLLOWING THE IPO ISSUE DATE *(NES_MISS)*

	Model 6: NES Misses		
	Unstandardized		Standardized
Variable	**β**	**s,e,**	**β**
(Constant)	1.437	.479	
Industry	-.279	.272	-.117
Change_in_GDP	-.041	.055	-.075
Deal_Size_10_Winsor	**.003 *****	.001	.355
Firm_Size_10_Winsor	**.001 *****	.000	-.316
Total_Assets_10_Winsor	-2.296E-010	.000	-.103
Underwriter_Rep	-.063	.047	-.128
VC_Backing	.041	.283	.017
Comm_T1	-.002	.008	-.027
Comm_T2	.005	.007	.086
Comm_T3	**.017 ***	.010	.285
Comm_T4	**-.017 ***	.010	-.263
Market_T1	.014	.051	.033
Market_T2	**-.146 *****	.055	-.344
Market_T3	-.007	.055	-.015
Market_T4	**.081 ***	.044	.202
Own_T1	**.074 ***	.046	.201
Own_T2	-.025	.057	-.063
Own_T3	-.030	.064	-.061
Own_T4	.033	.048	.076
Expert_T3	-.076	.063	-.133
Expert_T4	.054	.058	.104
R^2	.248		
Adjusted R^2	.096		
Model Sig	**.049 ****		
n	126		

*** p < .10, ** p < .05, *** p < .01**

Note: NES_Miss reflects number of times the firm failed to MoB analyst consensus EPS Estimates over the four quarters following the IPO Issue Date

increases in media hype will be associated with an increase in the amount of the NES misses. This hypothesis is partially supported. Similar to the unusual phenomena experienced with the logistic quarter by quarter yes or no NES assessment in models 3 thru 6, Models 7 and 10 which correspond with the tests of NES miss values for the 1st and 4th quarters reveals that the set of predictors are significant, while the set of predictors for Models 8 and 9 that tests NES miss values for the 2nd and 3rd quarters are not a set of significant predictors. In the 1st quarter (Model 7) we notice that market hype in two time periods have significant predictive power. And again, the results are opposing from one period to the next within the same type of hype. For example, market hype in time period 1 is a significant predictor (β=-0.004, t(112)=-1.977, p=0.050), such that as the market hype composite score in time period 1 increases, NES performance decreases. This

TABLE 5.7A: RESULTS OF REGRESSION ANALYSIS PREDICTING 1ST AND 2ND QUARTER NES *(Q1_NES_10_WINSOR AND Q2_NES_10_WINSOR)*

	Model 7: 1st Quarter NES			Model 8: 2nd Quarter NES		
	Unstandard		Standard	Unstandard		Standard
Variable	**β**	**s,e,**	**β**	**β**	**s,e,**	**β**
(Constant)	.021	.019		.014	.017	
Industry	-.014	.011	-.133	.006	.010	.068
Change_in_GDP	.001	.002	.057	-.002	.002	-.091
Deal_Size_10_Winsor	**.001 *****	.000	-.449	6.392E-005	.000	.211
Firm_Size_10_Winsor	8.118E-006	.000	.145	2.506E-006	.000	.059
Total_Assets_10_Winsor	**3.231E-011 *****	.000	.327	5.609E-013	.000	.006
Underwriter_Rep	.003	.002	.137	-.001	.002	-.058
VC_Backing	-.003	.012	-.033	.002	.010	.026
Comm_T1	.000	.000	-.085	**.001 ****	.000	.231
Comm_T2	.000	.000	-.050	-9.213E-005	.000	-.048
Market_T1	**-.004 ****	.002	-.215	.000	.002	-.023
Market_T2	**.007 *****	.002	.353	.001	.002	.047
Own_T1	-.001	.002	-.055	.000	.002	.013
Own_T2	.002	.002	.127	.000	.002	.018
Q1_NES_10_Winsor				.077	.079	.101
Comm_T3				**-.001 ****	.000	-.254
Market_T3				-.002	.002	-.143
Own_T3				-.002	.002	-.127
Expert_T3				.000	.002	-.021
R^2	.195			.150		
Adjusted R^2	.102			.007		
Model Sig	**.020 ****			.212		
N	126			126		

*** p < .10, ** p < .05, *** p < .01**

decrease in NES performance reflects over-confidence. However, when market hype in time period 2 increases, the NES miss value increases (β=0.007, t(112)=2.998, p=0.003), which reflects better firm performance with regard to meeting analysts consensus estimates and indicates a decreases in over-confidence. Likewise, in

TABLE 5.7B: RESULTS OF REGRESSION ANALYSIS PREDICTING 3RD AND 4TH QUARTER NES *(Q3_NES_10_WINSOR AND Q4_NES_10_WINSOR)*

	Model 9: 3rd Quarter NES			Model 10: 4th Quarter NES		
	Unstandard		Standard	Unstandard		Standard
Variable	**β**	**s.e.**	**β**	**β**	**s.e.**	**β**
(Constant)	-.022	.018		-.006	.012	
Industry	.015	.011	.169	.001	.007	.012
Change_in_GDP	.001	.002	.037	.002	.001	.113
Deal_Size_10_Winsor	-5.060E-005	.000	-.149	-2.002E-005	.000	-.082
Firm_Size_10_Winsor	7.822E-006	.000	.163	4.020E-006	.000	.117
Total_Assets_10_Winsor	-1.138E-011	.000	-.134	-4.549E-012	.000	-.074
Underwriter_Rep	.003	.002	.139	-.001	.001	-.060
VC_Backing	-.010	.011	-.107	.014 *	.007	.211
Comm_T1	2.273E-006	.000	.001	.000	.000	.091
Comm_T2	1.596E-005	.000	.007	2.260E-006	.000	.001
Comm_T3	.000	.000	.090	.000	.000	-.115
Market_T1	.001	.002	.088	.001	.001	.070
Market_T2	.001	.002	.088	.002	.001	.143
Market_T3	-.002	.002	-.095	.001	.001	.110
Own_T1	-.002	.002	-.151	-.003 **	.001	-.299
Own_T2	.000	.002	-.023	.000	.001	-.027
Own_T3	.002	.002	.100	.000	.002	-.034
Expert_T3	.001	.002	.068	.004 ***	.002	.288
Q1_NES_10_Winsor	.023	.087	.027	.043	.059	.069
Q2_NES_10_Winsor	.362 ***	.106	.323	.193 ***	.073	.240
Q3_NES_10_Winsor				.162 ***	.064	.226
Comm_T4				.000	.000	.064
Market_T4				-.001	.001	-.080
Own_T4				.001	.001	.117
Expert_T4				-.002 *	.001	-.171
R^2	.170			.371		
Adjusted R^2	.050			.221		
Model Sig	.195			.001 ***		
n	126			126		

* p < .10, ** p < .05, *** p < .01

Model 10 examining 4th quarter NES raw performance, two of the types of hype are significant predictors. For instance, as own hype in time period 1 increases, NES decrease indicating poorer firm EPS performance and greater over-confidence (β=-0.003, t(101)=-2.554, p=0.012). Then again we experience diametrically opposing influence on NES by expert hype. For instance, expert hype in period 3 has a positive coefficient which indicates that as the expert hype period 3 composite score increases, EPS performance by the firm increases, reflecting less over-confidence (β=0.004, t(101)=2.769, p=0.007). However, expert hype in period 4 has the opposite effect of relating to decreasing firm EPS performance and increasing over-confidence (β=-0.002, t(101)=-1.658, p=0.100).

Model 11 in Table 5.8 presents the results of a logistic regression testing Hypothesis 4, which predicts that media hype influences managers to act over confidently as manifested by an increase in hype being associated with a greater likelihood that a firm's manager will fail to sell-off any of the their holdings at the expiration of the lock-up period. Hypothesis 4 is partially supported. Although only two of the four types of hype are significant predictors, results do show that a relationship exists between our measures of hype and sell-off activity. Both market and own hype influence sell-off activity. Own hype in time period 1 influences manager's sell-off at the expiration at the lock-up period such that as the own hype composite score in period 1 increases, sell-off activity also increases, reflecting lower over-confident activity (β=0.208, Wald(1, N=126)=4.667, p=0.031). In the case of market hype during periods 2 and 3, we saw diametrically opposite affects. A

TABLE 5.8: RESULTS OF LOGISTIC REGRESSION ANALYSIS PREDICTING LIKELIHOOD TO SELL-OFF AT THE LOCK-UP EXPIRATION *(SELLOFF_YN)*

Model 11: Sell-Off Y/N

Variable	β	s,e,	Sig.
Constant	-.002	.915	.998
Industry(1)	.749	.559	.180
Change_in_GDP	-.049	.108	.650
Deal_Size_10_Winsor	.002	.003	.538
Firm_Size_10_Winsor	**.001 ****	.000	**.038 ****
Total_Assets_10_Winsor	**.000 ***	.000	**.057 ***
Underwriter_Rep	-.055	.095	.563
VC_Backing(1)	**-1.294 ****	.575	**.025 ****
Comm_T1	-.022	.016	.177
Comm_T2	.008	.014	.564
Comm_T3	.010	.014	.470
Market_T1	.007	.102	.942
Market_T2	**-.215 ***	.123	**.079 ***
Market_T3	**.204 ****	.105	**.050 ****
Own_T1	**.208 ****	.097	**.031 ****
Own_T2	.004	.114	.974
Own_T3	.039	.123	.750
Expert_T3	.029	.101	.775
Cox-Snell R^2	.233		
Nagelkerke R^2	.311		
Classification Table Change	.166		
Omnibus Model Test	**.010 *****		
n	126		

*** p < .10, ** p < .05, *** p < .01**

decrease in Market Hype in period 2 is associated with a decrease in the likelihood of sell-off meaning that managers are acting more over confident (β=-0.215, Wald(1, N=126)=3.089, p=0.079). However, when market hype in period 3 increases, the likelihood that a manager will sell shares at the expiration of the lock-up period increases, reflecting lower levels of over confidence (β=0.204, Wald(1, N=126)=3.877, p=0.050).

Model 12 in Table 5.9 provides unstandardized and standardized regression coefficients for the OLS regressions testing Hypothesis 5 which states that an increase in media hype will result in manager's selling less at the expiration of the lock-up period reflecting higher levels of over confidence. Results partially support Hypothesis 5. Although Own, Expert and Comm hype do not have a significant relationship with manager sell-off percentage, market hype is a significant predictor. When market hype increases, as it does for market period 3, sell-off percentage rises and the manager reflects less over confidence (β=0.032, t(108)=3.699, p=0.000).

TABLE 5.9: RESULTS OF REGRESSION ANALYSIS PREDICTING PERCENT SELL-OFF (%_SellOff)

	Model 12: % Sell-Off		
	Unstandardized		Standardized
Variable	**β**	**s,e,**	**β**
(Constant)	.133	.079	
Industry	.035	.046	.085
Change_in_GDP	-.002	.009	-.016
Deal_Size_10_Winsor	-7.724E-005	.000	-.050
Firm_Size_10_Winsor	**7.327E-005 *** **	.000	.337
Total_Assets_10_Winsor	-4.205E-011	.000	-.110
Underwriter_Rep	-.003	.008	-.035
VC_Backing	**-.099 ** **	.048	-.242
Comm_T1	.002	.001	.151
Comm_T2	-.001	.001	-.090
Comm_T3	9.052E-005	.001	.009
Market_T1	.005	.009	.061
Market_T2	**-.028 *** **	.009	-.387
Market_T3	**.032 *** **	.009	.420
Own_T1	.005	.008	.083
Own_T2	.006	.010	.090
Own_T3	-.005	.011	-.063
Expert_T3	.009	.009	.089
R^2	.230		
Adjusted R^2	.109		
Model Sig	**.026 ** **		
n	126		

*** p < .10, ** p < .05, *** p < .01**

However, when the market hype composite score for period 2 decreases, managers sell-off less percentage of their shares and exhibit higher amounts of over-confidence (β=-0.028, t(108)=-2.988, p=0.003).

5.2.3 Post-Regression Inspections and Robustness Checks

Since several of the variables in the regression models were not normally distributed, even after transformations and prior to running the regression, I evaluated the post-regression distribution of the residuals for normality and all of the regression residuals are normally distributed. Furthermore, I checked for homoscedasticity by reviewing the unstandardized and standardized regression residuals with the predicted values via scatter plots. Patterns in the scatter plots are consistent with meeting the assumption of homoscedasticity. In addition to these data-driven robustness checks, I performed a number of pre- and post-analysis robustness checks. The following list provides details for each of the robustness tests:

1) Because systematic differences could exist between companies in different industries for both the independent and dependent variables, I controlled for the potential effects by regression five dummy variables representing membership in the following categories: manufacturing, finance, retail, service, bio and other technology (including software) firms (Pollock and Rindova, 2003). The results reflected no discernable differences from those reported above.

2) Additionally, since particular industries, and the IPO market in general, can go in and out of favor from one year to the next or even in less than a year, I also ran regressions using dummy variables for year and fiscal quarter of the IPO to control for year and within-year variances. Results reflect no discernable differences from those presented previously. My suspicion is that GDP change sufficiently acts as a macroeconomic and IPO fiscal quarter control simultaneously such that there is no value added in including an IPO year or quarter variable.
3) All of the regressions run in the analyses above were also run using consolidated hype values, one per firm, per hype. These consolidate hype scores measure the average hype per firm across the four time periods. This less granular data revealed less significant results, but no discernable contradictory findings were observed.
4) In addition to running the regressions using the 10% Winsorized data, I also calculated the variables for and ran the regression analyses using raw NES performance and 5% Winsorized data. Although not as clean as the 10% Winsorized data (as revealed by a more normal distribution than that of the 5% Winsorized and raw NES performance data) the 5% Winsorized and raw data results are consistent with those previously reported. However, these alternative variables for NES performance reveal less normally distributed residual histograms and Normal P-P plots. Therefore, similar to findings presented by Angrist and Krueger (2000) where winsorizing variables with

large outliers (such as employer and employee wage data) improved correlations and regression outcomes, I present the more normally distributed residual producing 10% Winsorized data results.

5) In another sensitivity check, I explored whether binning the NES data changes the results. The first step in running this sensitivity check was recoding the Q1-4_NES_10_Winsor variables into NES variables based on a relative miss in a set of categorical variables. I took all of the raw NES scores for each quarter and placed them into 10 bins looking for natural breaks and based on relative strength with regard to the rest of the NES values per quarter. This assessment was done subjectively by two researchers independently. Cohen's kappa of 0.90 indicates "near-perfect inter-rater reliability" (Landis and Koch, 1977).[7] Armed with these relative-strength binned variables, I ran the same regressions listed previously for Q1_NES_Bin thru Q4_NES_Bin. As expected, the results were consistent with those presented above.

6) I also analyzed whether two weeks of sell-off data is an appropriate amount of time for post-lock-up period sell-off consideration. As a robustness check, I analyzed the data using one week's worth of post-lock-up sell-off data and found, although less significant, similar results as when the data is analyzed using two weeks worth of sell-off data.

[7] Landis and Koch, 1977 establish a categorization of Cohen kappa values such that < 0 indicates no agreement, 0–.20 indicates slight agreement, .21–.40 reflects fair agreement, .41–.60 indicates moderate agreement, .61–.80 reflects substantial agreement, and .81–1 signifies almost perfect agreement. However, it is important to note that these values are based on the authors' personal opinions and not on empirical evidence. In fact, Gwet (2010) noted that arbitrary guidelines like the ones proposed by Landis and Koch may be more harmful then they are helpful. Yet despite the lack of empirical evidence, these values are readily accepted in literature and Cohen's kappa values greater than .85 is nearly always considered strong.

7) I considered the potential concerns regarding endogeneity and selection bias by running the regressions including an instrument variable for endogeneity and employing Heckman's two-stage correction for any potential selection bias. No discernible differences in the results were noticed. Since the results were not different, I eliminated those variables from the results reported here to present more parsimonious predictive models and to mitigate potential concerns regarding degrees of freedom and statistical power (Heckman, 1979).

8) In order to see if the effects of hype are cumulative, I also ran the regressions listed above using aggregated hype scores by adding the various different time periods within the same hype together, appropriate for the time period involved in the regressions for the different dependent variables' analyses. The les granular variables consistently generated less significant results.

9) Additionally, I ran a number of regressions to examine potential differences that may arise in the relationship between media hype and manager's expectations and firm outcomes by aggregating the hypes prior to the IPO issue date and after the IPO. Specifically, I aggregated the hype scores for time periods 1 and 2 and 3 and 4 and ran regressions on the NES and the Sell-off variables to see if the results changed. Again, no discernable new findings arose. In fact, in the sensitivity checks listed above, R-squared values and goodness-of-fit statistics dropped. The goodness-of fit measures dropped below statistically significant levels indicating the group of predictors was no longer a significant predictor of NES performance nor post-lock-up sell-off activity. Not

surprisingly, it appears that more granular data provides a better picture of the influence of media on managerial expectations and firm outcomes when compared to aggregated data.

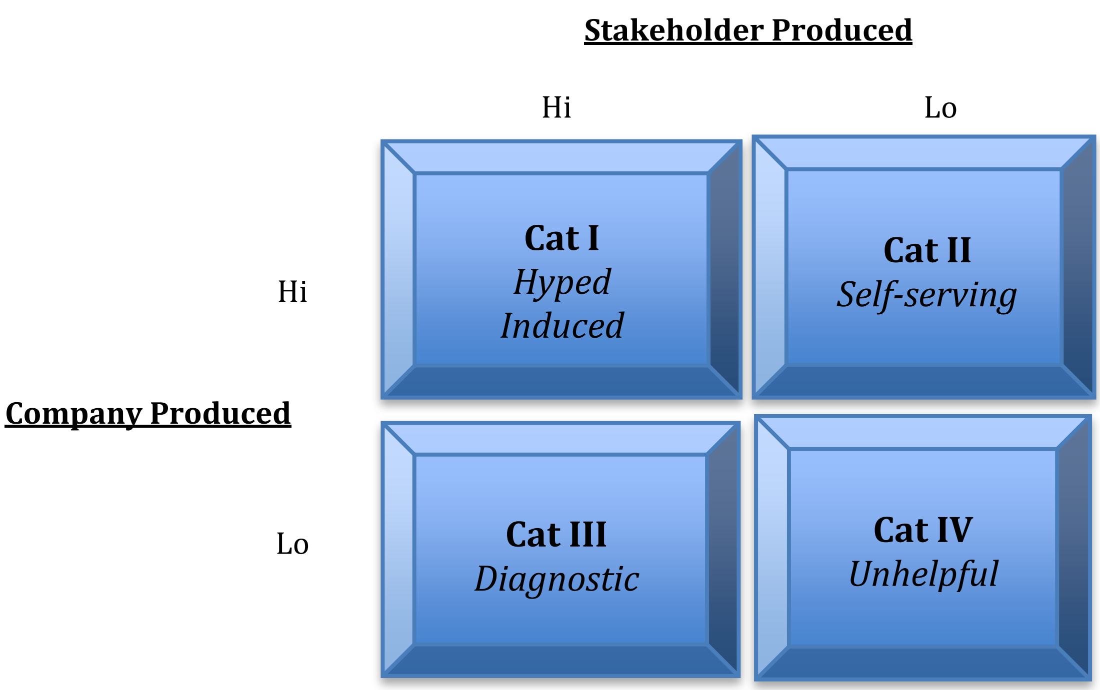
CHAPTER 6: DISCUSSION

The importance of findings are determined by connecting the realized relationships with the problems that underlie the research question and topic. Rather than focusing on how much the findings are disseminated in future management literature, researchers should seek to use empirical findings to extend theory, answer long-standing phenomenally-driven questions, and raise new and provocative questions for future researchers to explore. Certainly powerful statistical procedures can demonstrate the presence of variable relationships either through descriptive statistics of a population or inferential statistics when using a targeted or randomly selected sample. The associations among the variables found in the previous chapter vary in strength and statistics are available that summarize the degree of these relationships. However, a relationship can be statistically strong, but have little importance for scholarship or society. For example, as Lacy and Riffe (2005) point out, a strong relationship exits between bad weather and the amount of television watching. People tend to watch more television during the winter than in the summer. But is this an important finding? Television networks and marketing and advertising firms may believe so, but social scientists may not feel so. Therefore, with these thoughts in mind, in the following sections I consciously connect the findings with theory surrounding this area of study. I identify what we learned, explain why it matters and discuss limitations and future opportunities that exist with respect to this stream of research.

6.1 Evaluating the Model of the Information Environment Surrounding a Trigger Event

Returning to our model of the Information Environment following a trigger event, we now can assess the number of firms that fall into each of the different categories. Below is a restatement of the model presented both Chapters 2 and 3 with a numerical categorization system. For instance, firms that had both high levels of stakeholder produced media and company produced media are members of Category I (see Figure 6.1).

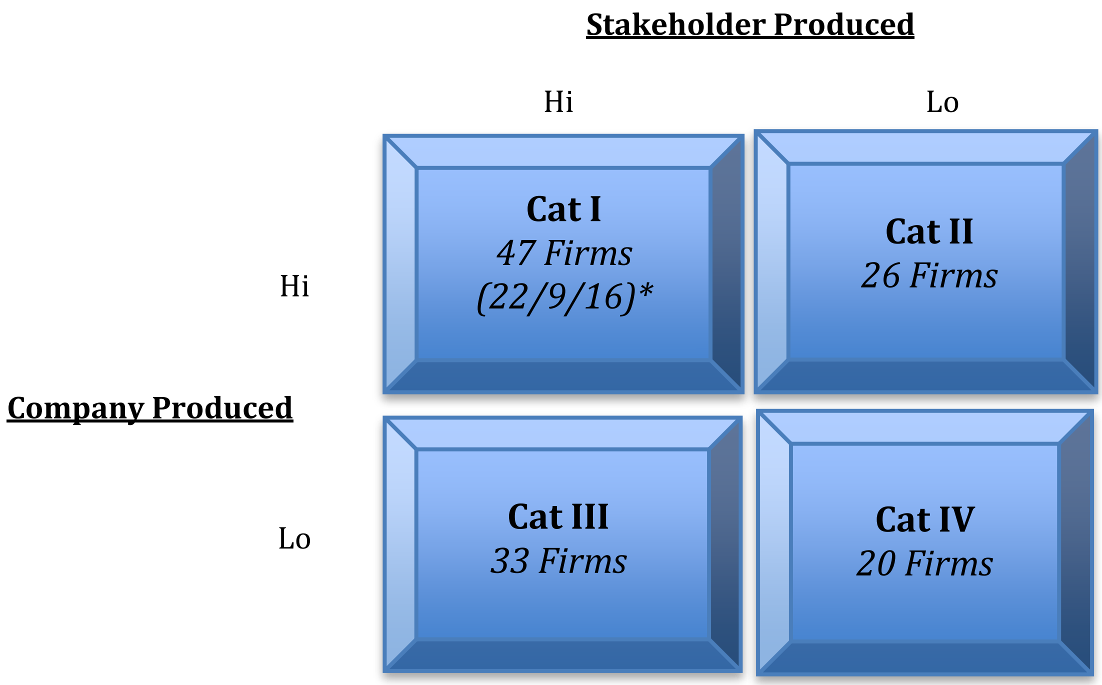
FIGURE 6.1: RESTATING THE MODEL OF THE INFORMATION ENVIRONMENT SURROUNDING A TRIGGER EVENT



The procedures for identifying the amount of firm hype and placing the firms into different categories consisted of three steps. First, I examined the consolidated media hype scores for each of the four types of hype and identified two levels of stakeholder hype. The first level, labeled as "High Hype", includes firms whose consolidated hype (a single hype score per type of hype across all four time periods) was one or more standard deviation away from the mean. The second level, labeled as "Very High Hype" includes firms with consolidated media hype scores in each type of hype that was two or more standard deviations away from the mean. Step two examined the number of consolidated hypes that exceeded 1 standard deviation from the mean. For company produced evaluations only one type of hype, Own Hype scores were assessed. Therefore, if the score was greater than one standard deviation above the mean or more than two standard deviations above the mean, the firms would be rated as a high hype firm and very high hype firm, respectively. For stakeholder produced hype, I considered consolidated scores for Market Hype, Community Hype and Expert Hype. If any two of the three were greater than one standard deviation above the mean or two standard deviations above the mean the firm was coded as high hype and very high hype for the firm's stakeholder produced assessment, respectively. The number of firms that fell into each category based on this process described above is depicted for each level of hype (high and very high) in Figures 6.2 and 6.3 below, respectively.

Interestingly, the number of firms that are in each category for high hype (one standard deviation above the mean) and very high hype (two standard deviations above the mean) is quite different. In the high hype examination, we notice a relatively equal split of firms into the four different categories. 47 firms fall

FIGURE 6.2: FIRM DISTRIBUTION IN THE MODEL OF THE INFORMATION ENVIRONMENT SURROUNDING A TRIGGER EVENT - ***HIGH HYPE***

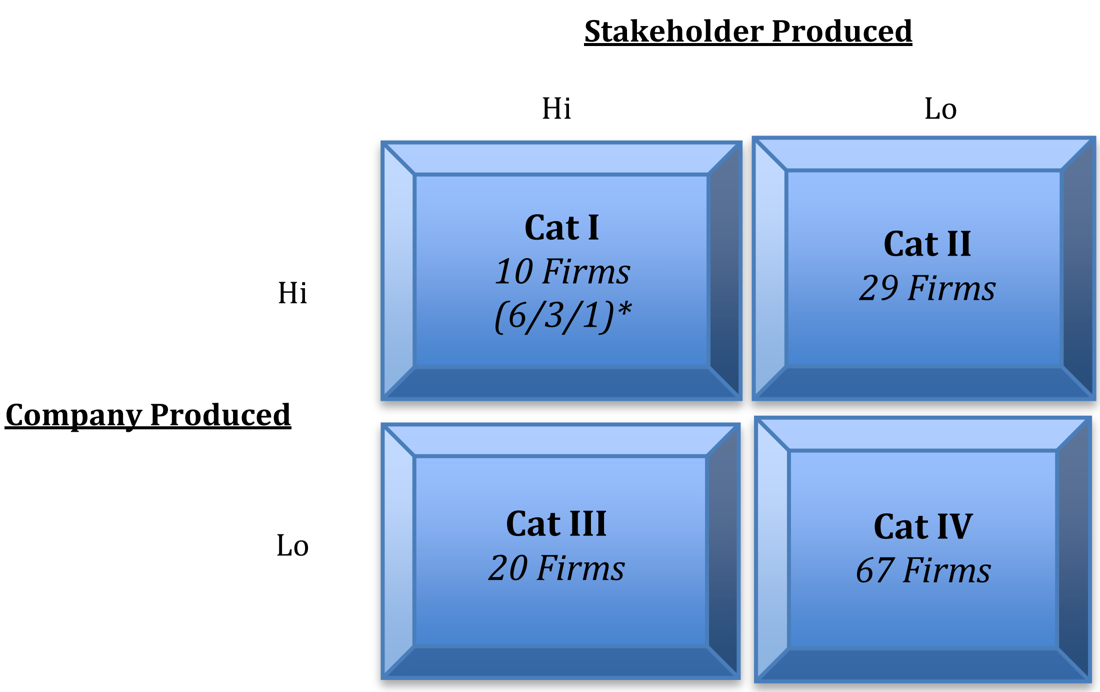


* Values indicate number of firms that reflect over confidence in both NES events and sell-off activity, firms that reflect over confidence in one of the two measures, and firms that do not reflect over confidence in either of the two areas.

into category I reflecting a high volume (37%) of hype induced firms relative to the other categories. Meanwhile, Category IV, labeled unhelpful, contains a mere 20 firms (16%). Generally speaking, firms fall more commonly into categories I and III reflecting a higher concentration of firms that receive high volumes of stakeholder produced (externally produced) hype (64%).

Our examination of the model of the information environment surrounding a trigger event reveals that a relatively large subset of the firms in the sample (47 firms – 37%) fall into category I reflecting a high hype induced information environment. This means that a lot of firms receive high levels of media attention surrounding their IPOs from both internal and external sources. If the information environment for a given firm has a high amount of stakeholder and company produced media hype, it may influence managers' behaviors. As the predictive model testing the influence of media hype revealed, media hype does in fact influence manager's expectations and firm outcomes such that they take actions reflecting higher levels of over-confidence. Therefore, since a lot of firms exist in a high hype induced information environment and since, generally speaking, media hype does lead to less than optimal decisions by firm managers, firm managers

FIGURE 6.3: FIRM DISTRIBUTION IN THE MODEL OF THE INFORMATION ENVIRONMENT SURROUNDING A TRIGGER EVENT – *VERY HIGH HYPE*



* Values indicate number of firms that reflect over confidence in both NES events and sell-off activity, firms that reflect over confidence in one of the two measures, and firms that do not reflect over confidence in either of the two areas.

should be cognizant of the potential deleterious effects media hype may have on their behavior and decision making and adjust for such influences.

Conversely, when focusing on very high levels of hype, termed here as "very high hype" results of the categorization process are quite different. When focusing on vey high levels of hype, only 10 firms (8%) fall into category I reflecting very high hype by both the stakeholders and the company. While category IV, reflecting low hype by both the stakeholders and the company, contains 67 firms (53%). Very high hyped companies based on stakeholder produced media (categories I and III) contains only 30 firms (24%). Slightly more common then high stakeholder generated hype (categories I and III) are very highly hyped firms based on company produced hype (categories I and II) accounts for 39 firms (31%).

6.2 Assessing the Predictive Model for the Influence of Media Hype

As reported in the descriptive statistics section above, 64% of the firms in the sample fail to meet or beat analyst consensus estimates at least once in the four quarters following their IPO. These firms on average tended to miss more often in the third and four quarters than in the first two quarters. This reflects one of a few alternative explanations. First, firms garner a decent infusion of funds as a result of the IPO and are well-positioned to meet expectations early after the IPO issue date. Another explanation is that the information environment is clouded with asymmetric information for a period of time as a firm enters the marketplace and this forces analysts to rely more on company provided information such that less diagnostic information is available. Since the analyst rely on firm-provided data, the firm is better able to manage the analysts' expectations to EPS estimates that are very achievable by the firm. As more information about the firm becomes available, analysts begin to make more independent assessments and are less controlled by the firm's own information and guidance. As such, analysts begin to push the firm by extending their assessment models outside of a firm-generated only information environment to one that allows analysts to make better diagnostic assessments with more and varied information. As such the firm loses some control over analysts' expectations and subsequently they are not able to MoB expectations at the same level as when they were nearly the only stakeholder with reliable information. An alternative explanation is that successful performance with regard to EPS in the first two quarters leads to an increase in managerial hubris that drives managers to lose some level of control over analyst expectations, as reflected in lesser MoB rates in the third and fourth quarter compared to what was experienced in the first two quarters following the IPO issue date. This alternative explanation was the focus of the examination in this dissertation. The following paragraphs explore and discus some of the more interesting and unexpected results observed.

One especially interesting finding is how the different quarterly EPS models rendered different goodness-of-fit scores. The data reveals that sufficiency of the models appears to move with an unclear pattern. For instance, all of the EPS models share a common unexpected trend. Models associated with 1st and 4th

quarter EPS results were significant. However, models associated with 2^{nd} and 3^{rd} quarter EPS results failed to be significant. This varying level of significance in the overall models was unexpected. In short, I expected consistency in model fit across the different quarters such that all or none of the quarters would reveal significant model fits. When this was not the case, I initially suspected that perhaps the dependent variables were distinctive for the 1^{st} and 4^{th} periods versus the 2^{nd} and 3^{rd} periods. However, examination of the means and standard deviations of the variables shows little or no differences across all four time periods. Then I suspected that the independent variables, specifically the measures of hype, especially across the different time periods, was significantly different and was driving the varying results. However, again an examination of the means and standard deviations of the different hype periods yielded little variability. The control variables are static and, therefore, do not lend any potential solution to explain the apparent lack of consistent goodness-of-fit results. Therefore, although interesting, I was perplexed with how to interpret what these different goodness-of-fit results mean.

One potential explanation for these unusual results is that the events surrounding the different hype time periods are distinctive from one another. For instance, the 2^{nd} and 3^{rd} hype time periods surround the actual IPO trigger event while the 1^{st} and 4^{th} time periods are temporally less connected with this trigger event. Perhaps the nature of the hype and its potential influence on behavior during period 2 and 3 are significantly different from hype time periods 1 and 4. In short, perhaps it is the case that firm-level influences are different from one period to the next. Another potential solution focuses on the concept we are trying to test—over-confidence. For instance, managers may be differentially influenced by media attention during different quarters. It may be that most managers are very sensitive to meeting or beating 1st quarter EPS consensus estimates since 1) they feel they have a lot of control over analysts' perceptions and 2) they know the penalty for missing the first EPS consensus after the IPO is harsh. Once they reach this milestone they may switch their focus to other aspects of the firms activities for the next two quarters. To be clear, I am not contradicting previous literature regarding the importance of MoB analysts' expectations for each quarter, but rather considering that perhaps the salience of MoB EPS estimates is less in the 2nd and 3rd quarters than in the 1st and 4th quarters. Why is there a rejuvenation of significance in the fourth quarter? As the firm moves to the 4th quarter, firm managers renew their interest in ESP reporting, but not because of the 4th quarter release, but rather because of the corresponding annual report. In short, I submit that the 1st quarter EPS results set the stage for the company and are critical from a manager's perspective for getting off on the right foot and the annual report that corresponds with the 4th quarter increases the managers attention regarding EPS and this renewed focus is what increases the relationship between the predictor and dependent variables during the 1st and 4th quarters.

Another interesting finding is that, based on the results, it appears the relationship between expert and market hype and the measures of over confidence are stronger than for community and own hype. Initially surprising, own hype shows the weakest relationship with the measures of over-confidence. On the surface this may appear that the results presented here flout prior literature regarding managers believing their own press (Hayward, Rindova and Pollock, 2004); however, we are reminded that studies that examined this managerial phenomena focused on firm an CEO-focused press that was generated by what is categorized in this dissertation as market hype, not own hype. So rather than contradict believing one's own press literature, my findings support this line of reasoning since consistently the most influential of all of the types of hype was market hype. Surprisingly though, the small amount of significant results pertaining to own hype is perplexing since it makes it seem as though firm press releases practically occur in a vacuum or outside of the manager's consciousness.

Another interesting finding is how the same type of hype predicting the same quarterly NES value will act in opposite directions with practically the same significance level. For example, in Model 7 predicting Q1 NES performance, we observe that market hype 1 has a negative coefficient value and market hype 2 has a positive coefficient. Simply finding opposing coefficients for different time periods for the same type of hype is mildly surprising since we would expect a relatively consistent hype score over the four periods. However, it is not unfounded theoretically that hypes at different time period would relate to the same quarterly NES differently. In fact, we may expect the media influence pre and post IPO would be distinctively different based on the type, nature and amount of media hype.

Also, as the firm moves from the pre-IPO period to the post-IPO period, the information environment likely changes drastically. It is quite likely that the pre-IPO information environment is one that is company-managed and driven, such that it confounds the *believing their own press* concern leading to lower EPS performance and a greater level of over-confidence. However, following the IPO the information environment swiftly changes as more information about the firm is made public and the market learns about the firms ability (or inability) to meet market expectations. Therefore, the increasingly stakeholder influenced information environment that persists following the IPO suppresses the CEO's control over the media and its deleterious effects n their expectations and subsequent firm outcomes.

What makes this finding particularly interesting is that two different market hype scores that both take place prior to the IPO issue date would swap in direction from negative to positive at nearly the same effect size. When I performed an analysis of the means and standard deviation of the Independent variables, no significant differences were uncovered. Likewise, as discussed previously, the means and standard deviations of the NES variables are not significantly different from one another across the different quarters.

Despite this obtuse result, there are a few potential explanations. Most probable is that the salience of the media to the manager's consciousness is greatest as they closer to the IP trigger event. Therefore, media is likely to have a greater influence on their behavior during the second hype time period which leads into the

IPO issue date than the earlier first hype period media hype. Furthermore, the change in coefficient from negative to positive may e the result of a reduction of concerns over asymmetric information. As the firm works through its book-building exercise and road show as part of preparing for the IPO both the firm and external stakeholders learn a lot about the firm. Therefore, potential early hesitation and concern about the firm immediately following its announcement to go with an IPO is suppressed as the firm manager and other stakeholders gain more information and become more comfortable about the firm's entrance into the marketplace.

Interestingly, we see the same pattern with respect to the post-lock-up period sell-off regression. In Models 11 thru 14 we see Market 2 has a negative and marginally or fully significant coefficient and then Market 3 has a positive and significant coefficient. In this case the values are not changing from time period 1 to time period 2 within the same type of hype, but this may make sense. For example in the case of regression of Q1 NES, the dependent variable began at the end of the second hype period, after the period one and period two alternating positive, negative coefficients. In the case of the sell-off regressions, the sell-off period begins at the end of the third hype period. Therefore, the patter we observed in Q1 NES of two previous hype periods within the same hype having opposing coefficients is repeated in sell-off where again two periods in a row of the same hype have opposing coefficients. Therefore, since in the Q1 NES example I argue that the IPO issue date is the trigger event that raises the salience and the influence on managerial expectations and firm outcomes, in the case of sell-off as a dependent variable the lock-up expiration may be acting as a salient trigger event that influences the effects of media on managerial behavior.

6.3 Project Limitations

Extensive data collection and content analysis of media data occurred in the preparation of this dissertation. This data collection and rating effort took over 600 man hours by a team of researchers under the watchful eye of five PhDs and made up of two PhD students and five research assistants. Despite this team's tremendous efforts to fill in all of the gaps in the secondary data explored in this dissertation, some information just could not be found. As a result some firms that otherwise would have been included in the sample were unable to be included. All efforts were made to limit exposure to omitted data and omitted variable biases, to include a series of robustness checks, but some potential valuable information was unfortunately unobtainable.

One potential issue for this paper is the fact that not all of the variables are in lock-step with regard to time. This forces the analysis to consider cross time elements in the various regressions. Since media hype is fluid this is not a critically important issue, but it does confound the analysis and interpretation of the findings. Although not any more meaningful than the timing aspects of the variables as presented in this paper, if the times did overlap perfectly, it might make the analysis a bit cleaner.

Market hype media data was collected from the top four circulated US newspapers and this is likely a solid representation of news media data, particularly media associated with IPOs. This selection does potentially neglect the San Jose/San Francisco CA, Washington DC and Chicago, IL areas (other cities with highly circulated newspapers and that play large roles in the economy). However, considering the intensity of the data collection efforts involved in this dissertation, collecting more articles from other US newspapers was not realistic. Also, collecting articles from PR Newswire and BusinessWire, as well as Analyst Reports certainly includes stakeholders from these and other investment active areas of the country.

Additionally, although this project is focused on new, nascent firms that have evolved enough to go public, but are still finding their way in the marketplace, there are some large firms, such as Visa and General Motors, in the sample with vast resources and experience that may, even despite outlier transformations, influencing the results. In particular, these larger established firms likely have vast experience advantages over the rest of the sample. As such, if going public requires learning, it is likely their learning curve is steeper than their counterparts. In short, these larger organizations join the market place with a very different information environment than their younger, smaller counterparts and these discrepancies may be influencing the behavior responses. Furthermore, younger firms are less likely to have been in the public's eye previously, so when they come to their IPO and their principal values are so high, as were all of the firms in this sample, they are less equipped to handle the deleterious effects that associated with media hype influence. Moreover, if a firm is smaller and younger, the effects of media hype may be even greater. One way to address these issues is to include other variables that can account for these differences, even beyond the variables selected for this project, such as firm age and managerial experience; however, degrees of freedom and power considerations must be taken into account.

6.4 Future Research Opportunities

A plethora of potential research opportunities exists to extend the work presented here. Rather than identify future opportunities as a list of correcting the limitations listed above, I provide a series of research extensions that can be explored to further our understanding of the phenomena discussed in this dissertation. For instance, future studies could explore the relationships and links between the different types of hype. It is quite possible that there are relationships between own and market hype and that these relationships effect managerial behavior, firm outcomes or some other set of dependent variables. Understanding the relationship between the different sources of hype will make managers more aware of the influence of media attention on their subsequent behavior.

Another potential area of study is to examine the influence of media topics and level of analysis on managers' behavior. In studying these aspects the media hype, we may learn that more important than the salience and tenor of media hype is the topic and level of analysis of the articles. Perhaps articles that focus on financial performance carry much more weight than those that include information about managerial changes or improvements to operations. Similarly, maybe managers and stakeholders become relatively immune to and or unsurprised by regularly scheduled financial reporting, such as quarterly reports, but are greatly influenced by the topic of the articles or the level of focus of the article. In exploring these elements of the media hype, we can learn whether individual focused articles do truly expose CEO celebrity (Hayward et al., 2004) behavioral responses and whether stakeholders are truly more interested in performance or operation-oriented media pieces (Rindova, et al., 2006).

Furthermore, future research could explore actions by other firm inside stock holders. It is quite possible that different members of management, the Board of Directors, institutional owners and other stakeholders may be differentially influenced by media hype. Understanding this influence better can help managers and stakeholders predict future firm outcomes and managerial behaviors.

Another extension of the work presented here is to explore how change in EPS performance and sell-off over time is related to media hype. Perhaps firm performance and/or personal financial decision making is enhanced or degraded as a reflection of increases or decreases in media hype. A longitudinal examination of the data might expose a relationship where media hype increases over-confidence. Alternatively, perhaps when firms experience an increase in media hype it exposes the media as artificial and reduces its deleterious effects on managerial expectations and firm outcomes.

6.5 Conclusion

On 10 December 2012, Facebook's stock was a paltry $27/share (still 30% below its opening day high), yet many wall street pundits were claiming that Facebook is a success. Their claim is based on their opinions that Facebook has weathered the storm and the worst is behind the firm. They claim they see growth on the horizon and strong expansion opportunities into the mobile market. This is all well and good and may turn out to be accurate; however, it seems odd that despite failing to regain the price set at its IPO and simply meeting, but not significantly exceeding its first two EPS consensus estimate, Facebook is being declared a winner. Could it be that Facebook's IPO, one of the largest ever, was such a large trigger event that it could sustain such discrepant perspectives and maintain such obtuse hype even nine months after the IPO debacle?

In order to understand media hype as a management phenomenon, we have to begin with its trigger event. A trigger event sparks the attention of several media at the same time and allows for the intense coverage of the same news story or event. The trigger event has some quite distinct characteristics to it: 1) it meets all the traditional news values; 2) it taps into an issue that is able to promote debate as it can be seen from several points of view; and 3) it can be related to existing stereotypes and prejudices in order to present a simple and striking image of a complex problem. Empirical evidence presented here suggests that media hype surrounding a trigger event can influence managerial expectations and firm outcomes such that managers may be influenced by media hype such that they exhibit actions that reflect over-confidence. In this piece, we explore media hype over a two year span surrounding a trigger event. This time span allows for a particular sequence of different actors to participate, starting with a variety of stakeholders debating and assimilating the available information and ending with expert analysis. This sequence repeats itself a couple of times during the media hype before media attention fades away. Little prior literature has exposed both the leading and post-trigger event media hype to gather a better understanding of the lead-up and repercussions of media exposure.

One question that remains is whether the results presented here are generalizable to other contexts. I believe that the model of media hypes presented here can be applied in other countries with a similar media structure.[8] At a minimum, I expect this model to be applicable in most nations with a robust stock market and a relatively strong media circuit (e.g., UK, Germany, Japan). However, it is likely that unique social forces will lead to varying differential effects of media hype on managerial behavior. Issue-wise, I propose that this media hype model is transferable to other contexts where trigger events may influence behavior. In other words, I see no reason why the model could not apply to coverage of other subject areas, but I leave it up to future research to test this proposition. Hence, it is clear that still more empirical analysis of media hype is needed in order to shed light on the phenomenon and be able to identify various types and models of media hype influence.

[8] Hallin and Mancini (2004) provide a distinction on different media models. In this case, I am referring to other countries with a democratic corporatist media model.

REFERENCES

Ackerman, P. L. & Cianciolo, A. T. (2000). Cognitive, perceptual-speed, and psychomotor determinants of individual differences during skill acquisition. Journal of Experimental Psychology Applied, 6(4), 259-290.

Acock, A. C. (2005). Working with missing values. Journal of Marriage and Family, 67, 1012–1028.

Aczel, Amir D. (1989). Complete Business Statistics. Homewood, IL: Irwin.

Adams, Michael, Thornton, Barry & Hall, George. (2008). IPO Pricing Phenomena: Empirical Evidence Of Behavioral Biases, Journal of Business & Economics Research, 6(4), 67-74.

Aguinis, H., Beaty, J. C., Boik, R. J. & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. Journal of Applied Psychology, 90, 94-107.

Ahern, K. R. & Sosyura, D. (2011). Who writes the news? Corporate press releases during merger negotiations. Journal of Finance.

Alicke, M. D., Klotz, M. L., Breitenbecher, D. L., Yurak, T. J., et al., (1995). 'Personal contact, individuation, and the better-than-average effect', Journal of Personality and Social Psychology, 68, 804–25.

Anglim, J. & Waters, L. (2007). Practical tips on how to conduct a sophisticated online psychological experiment. In 43rd APS Annual Conference, 23-27 September 2008. Hobart, Tasmania, Australia.

Angrist, Joshua D. & Krueger, Alan B. (2000). "Empirical Strategies in Labor Economics," in Orley Ashenfelter and David Card (Eds.) Handbook of Labor Economics, Vol 3A (Elsevier Science).

Babbie, E. (1998). The practice of social research. (8th ed.). Westford, MA: Wadsworth.

Barefield, R. M. & Comiskey, E. E. (1975). The accuracy of analysts' forecasts of earnings per share. Journal of Business Research, 3(3), 241-252.

Barron, Orie E., Kim, Oliver, Lim, Steve C. & Stevens, Douglas E. (1998). Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment. The Accounting Review, 73(4), 421-433.

Bartov, E., Givoly, D. & Hayn, C. (2002). The rewards to meeting or beating earnings expectations. Journal of Accounting and Economics, 33(2), 173-204.

Baumgartner, Frank R. & Jones, Bryan D. (1993). Agendas and Instability in American Politics. Chicago: University of Chicago Press.

Bennett, D. A. (2001). How can I deal with missing data in my study? Australian and New Zealand Journal of Public Health, 25, 464–469.

Bhattacharya, N., Ecker, F., Olsson, P. M. & Schipper, K. (2011). Direct and mediated associations among earnings quality, information asymmetry, and the cost of equity. The Accounting Review, 87(2), 449-482.

Boorstin, D. (1963). The Image, or What Happened to the American Dream. New York: Atheneum.

Borgen, F. H. & Barnett, D. C. (1987). Applying cluster analysis in counseling psychology research. Journal of Counseling Psychology, 34(4), 456-468.

Botosan, C. A. & Stanford, M. (2005). Managers' Motives to Withhold Segment Disclosures and the Effect of SFAS No. 131 on Analysts' Information Environment. The Accounting Review, 80(3), 751-772.

Brau, James C., Carter, David A., Christophe, Stephen E. & Key, Stephen E. (2004). Market reaction to the expiration of IPO lockup provisions, Managerial Finance, 30(1), 75 – 91.

Brown, L. D. (2001). “A Temporal Analysis of Earnings Surprises: Profits versus Losses.” Journal of Accounting Research, 39, 221-241.

Brown, L. D. & Caylor, M. L. (2005). A temporal analysis of quarterly earnings thresholds: Propensities and valuation consequences. The Accounting Review, 80(2), 423-440.

Brown, L. D. & Rozeff, M. S. (1978). The superiority of analyst forecasts as measures of earnings expectations: Evidence from earnings. Journal of Finance 33 (1), 1-16.

Brown, L. D., Richardson, G. D. & Schwager, S. J. (1987). An information interpretation of financial analyst superiority in forecasting earnings. Journal of Accounting Research 25 (1), 49-67.

Camerer, C. & Lovallo, D. (1999). ‘Overconfidence and excess entry: an experimental approach’, American Economic Review, 89(1), 306–18.

Carpenter, J. (1998). The exercise and valuation of executive stock options. Journal of Financial Economics, 48, 127-158.

Carter, R. B. & Manaster, S. (1990). Initial public offerings and underwriter reputation. Journal of Finance, 65, 1045–1067.

Cen, Ling. (2008). Information, Market Sentiment and Corporate Finance
The Role of Investors’ Attention. Doctoral Dissertation, The Hong Kong University of Science and Technology.

Chan, W. S. (2003). Stock price reaction to news and no-news: Drift and reversal after headlines. Journal of Financial Economics, 70(2), 223-260.

Chen, Qi, Melessa, Sam & Zhang, Ning. (2012). The Effects of Aggregate Demand for Meeting Earnings Expectations on Managerial Behavior, American Accounting Association Conference.

Clark, Peter J. & Neill, Stephen. (2001). Net Value: Valuing Dot-Com Companies—Uncovering the Reality Behind the Hype. New York, NY: American Management Association.

Cliff, M. T. & Denis, D. J. (2004). Do initial public offering firms purchase analyst coverage with underpricing?. The Journal of Finance, 59(6), 2871-2901.

Cobb, R. W. & Elder, C. D. (1972). Individual Orientations in the Study of Political Symbolism. Social Science Quarterly, 53(1), 79-90.

Cohen, J. (1960). "A coefficient for agreement for nominal scales" in Education and Psychological Measurement, 20, 37–46.

Cohen, J. (1977). Statistical power analysis for the behavioral sciences (revised edition). New York: Academic Press.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd edition). Hillsdale, NJ: Erlbaum.

Cohen, J. & Cohen. P. (1983). Applied multiple regression/correlation analysis for the behavioral sciences. L. Erlbaum Associates: Hillsdale, N.J.

Cohen, J., Cohen, P., West, S. G. & Aiken, L. S. (2003). Applied multiple regression/correlation analysis for the behavioral sciences (3rd ed.). Mahwah, NJ: Erlbaum.

Connelly, Brian L., Ireland, R. D., Reutzel, Christopher R. & Coombs, Joseph E. (2010). The Power and Effects of Entrepreneurship Research. Entrepreneurship Research and Practice, 34(1), 131-149.

Da, Z., Engelberg, J. & Gao, P. (2011). In search of attention. The Journal of Finance, 66(5), 1461-1499.

Dearing, J. W. & Rogers, E. (1996). Agenda-setting (Vol. 6). SAGE Publications, Incorporated.

Dechow, P. M., Richardson, S. A., & Tuna, I. (2003). Why are earnings kinky? An examination of the earnings management explanation. Review of Accounting Studies, 8(2-3), 355-384.

Deephouse, D. L. (2000). Media reputation as a strategic resource: An integration of mass communication and resource based theories. Journal of Management, 26, 1091–1112.

Degeorge François, Derrien, François & Womack, Kent L. (2007). Analyst Hype in IPOs: Explaining the Popularity of Bookbuilding, Review of Financial Studies, 20(4), 1021-1058.

Degeorge, F., Patel, J. & Zeckhauser. R. (1999). Earnings management to exceed thresholds, Journal of Business, 72, 1-33.

Dixon, W. J. (1960). Simplified Estimation from Censored Normal Samples, The Annals of Mathematical Statistics, 31, 385–391.

Dougal, C., Engelberg, J., García, D. & Parsons, C. A. (2012). Journalists and the stock market. Review of Financial Studies, 25(3), 639-679.

DuCharme, Larry, Rajgopal, Shivaram & Sefcik, Stephan E., (2001). Lowballing for 'Pop': The Case of Internet IPO Underpricing. SSRN Working Paper Series.

Dyck, A., & Zingales, L. (2003). The media and asset prices. Unpublished http://www. nber. org/~ confer/2003/si2003/papers/cf/dyck. pdf.

Eiser, J. R., Pahl, S., & Prins, Y. R. (2001). Optimism, pessimism, and the direction of self–other comparisons. Journal of Experimental Social Psychology, 37(1), 77-84.

Elsbach, K. D. (1994). Managing organizational legitimacy in the California cattle industry: The construction and effectiveness of verbal accounts. Administrative Science Quarterly, 39, 57–88.

Fang, L., & Peress, J. (2009). Media Coverage and the Cross‐section of Stock Returns. The Journal of Finance, 64(5), 2023-2052.

Ference, T. P., & Thurman, P. W. (2009). MBA Fundamentals Strategy. Kaplan Test Prep.

Festinger L. (1957). A Theory of Cognitive Dissonance. Stanford University Press: Palo Alto, CA.

Finkelstein, Sydney & Hambrick, Donald C. (1990). Top-Management-Team Tenure and Organizational Outcomes: The Moderating Role of Managerial Discretion. Administrative Science Quarterly. 35(3), 484-503.

Fiske, J. (1994). Media Matters: Everyday Culture and Political Change. Minneapolis: University of Minnesota Press.

Fleiss, J. L. (1971). "Measuring nominal scale agreement among many raters." Psychological Bulletin, 76(5), 378–382.

Fortune. 2002. Temptation is all around us. December 2, 109–116.

Frankel, Richard & Li, Xu. (2004). Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders, Journal of Accounting and Economics, 37(2), 229‑259.

Freelon, Deen G. (2010). ReCal: Intercoder Reliability Calculation as a Web Service. International Journal of Internet Science, 5(1), 20-33.

Fried, D., & Givoly, D. (1982). Financial analysts' forecasts of earnings: A better surrogate for market expectations. Journal of Accounting and Economics, 4(2), 85-107.

Goffman, E. (1959). The Presentation of Self in Everyday Life, New York : Anchor Books.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. Journal of accounting and economics, 40(1), 3-73.

Griffin, D. W. & Tversky A. (1992). The weighing of evidence and the determinants of confidence. Cognitive Psychology 24, 411–435.

Griffith, Daniel A. (2006). Assessing Spatial Dependence in Count Data: Winsorized and Spatial Filter Specification Alternatives to the Auto-Poisson Model. Geographical Analysis, 38(2), 160–179.

Gurun, Umit G. & Butler, Alexander W. (2012). Don't Believe the Hype: Local Media Slant, Local Advertising, and Firm Value. Journal of Finance, 67(2), 561-598.

Gutterman, A. (1991). Marketing the initial public offering: Strategic planning analysis—Part II. Securities Regulation Law Journal, 18, 422–432.

Gwet, K. L. (2010). "Handbook of Inter-Rater Reliability, Second Edition, Gaithersburg: Advanced Analytics, LLC.

Gwet, K. L. (2012). Handbook of Inter-Rater Reliability, Third Edition, Gaithersburg: Advanced Analytics, LLC.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate Data Analysis (6th ed). New York: Macmillion Publishing Company.

Hall, B. & Murphy, K. J. (2002). 'Stock options for undiversified executives', Journal of Accounting and Economics, 33, 3–42.

Hallin, D. C., & Mancini, P. (2004). Comparing media systems: Three models of media and politics. Cambridge University Press.

Hambrick, Donald C., Cho, Theresa Seung & Chen, Ming-Jer. (1996). The Influence of Top Management Team Heterogeneity on Firms' Competitive Moves. Administrative Science Quarterly, 41(4): 659-684.

Hanley, Kathleen Weiss & Hoberg, Gerard. (2010). The Information Content of IPO Prospectuses, Review of Financial Studies. 23(7), 2821-2864.

Hasings, C., Mosteller, F., Tukey, J.W. & Winsor, C.P. (1947). Low moments for small samples: a comparative study of order statistics, Annals of Mathematical Statistics, 18, 413–426.

Hawkins S.A. & Hoch S.J. (1992). Low-investment learning: memory without evaluation. Journal of Consumer Research 19, 212–225.

Hayes, A. F. & Krippendorff, K. (2007). Answering the call for a standard reliability measure for coding data. Communication Methods and Measures, 1, 77-89.

Hayward, M. L. A. & Hambrick, D. C. (1997). Explaining the Premiums Paid for Large Acquisitions: Evidence of CEO Hubris, Administrative Science Quarterly, 42(1), 103-127.

Hayward, M. L. A., Rindova, V. P. & Pollock, T. G. (2004). Believing one's own press: the causes and consequences of CEO celebrity. Strategic Management Journal, 25(7), 637–653.

Heckman, J. (1979). "Sample selection bias as a specification error". Econometrica 47(1), 153–61.

Heflin, Frank, Subramanyam, K. R. & Zhang, Yuan. (2003). Regulation FD and the Financial Information Environment: Early Evidence. The Accounting Review, 78(1), 1-37.

Heneghan, M. K., Hazan, C., Halpern, A. C. & Oliveria, S. A. (2007). Skin cancer coverage in a national newspaper: A teachable moment. Journal of Cancer Education, 22, 99–104.

Hewstone, M. & Jaspers, J. (1982). Explanations for racial discrimination: The effect of group discussion on intergroup attribution. European Journal of Social Psychology, 12, 1–16.

Ho, Beauty, Taher, Maya, Lee, Robert & Fargher, Neil L. (2001). Market Sentiment, Media Hype and The Underpricing Of Initial Public Offerings: The Case Of Australian Technology IPOs. SSRN Working Paper Series.

Hsuan-Chi Chena, Fauverb, Larry, Hsuc, Yu & Shenc, Yang-Pin. (2003). Do IPO Earnings and Revenue Surprises Surprise Investors? Working Paper.

Huberman, G. & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. The Journal of Finance, 56(1), 387-396.

Husick, G. C. & Arrington, J. M. (1998). The initial public offering: A practical guide for executives. New York: Bowne & Co.

Ibbotson, R. G. & Ritter, J. R. (1995). Initial public offerings. In R. Jarrow et al. (Eds.), Handbook in operations research and management science: 993– 1016. London: Elsevier Sciences B.V.

Janis, I. L. & Fader, R. (1965). The coefficient of imbalance. In H. Lasswell, N. Leites, & Associates (Eds.), Language of politics: 153–169. Cambridge, MA: MIT Press.

Johnson, T. (1998). Shattuck lecture—Medicine and the media. New England Journal of Medicine, 325, 87–92.

Johnston, Casey. (2012). "Google Trends reveals clues about the mentality of richer nations". Ars Technica. April 6, 2012.

Jordan, D. L. (1993). Newspaper effects on policy preferences. Public Opinion Quarterly, 57, 191–204.

Jorgensen, J. & Rasmussen, T. M. (2001). 'Mediestorme', In Mie Femo Nielsen (ed.) Profil of Offentlighed. Roskilde Samfundslitteratur, 59-89.

Judd, Charles M., McClelland, Gary H., & Ryan, Carey S. (2009). Data Analysis. Routledge.

Kaid, L. L. & A. J. Wadsworth. (1989). Content Analysis. In P. Emmert and L. L. Baker, editors. Measurement of communication behavior: 197–215. Longman, White Plains, New York.

Kepplinger, H. M. (1994). 'Publizistische Konflikte. Begriffe, Ans¨atze, Ergebnisse',: 214–33 in F. Neidhardt (ed.) ¨ Offentlichkeit, ¨ Offentliche Meinung, Soziale Bewegungen. Opladen: Westdeutscher Verlag.

Kepplinger, H. M. & Habermeier. J. (1995). 'The Impact of Key Events on the Representation of Reality', European Journal of Communication 10(3), 271–390.

Kerlinger, F. N. & Lee, H. B. (1973). Foundations of behavioral research.

Kiesler, C. A., Nesbett, R. E. & Zanna, M. P. (1969). On inferring one's beliefs from one's behavior. Journal of Personality and Social Psychology, 11, 321-327.

Kile, C. O. & Phillips, M. E. (2009). Using Industry Classification Codes to Sample High-Technology Firms: Analysis and Recommendations. Journal of Accounting, Auditing & Finance, 24(1), 35-58.

Klayman, J, Soll, JB, Gonzalez-Vallejo, C. & Barlas, S. (1999). Overconfidence: it depends on how, what and whom you ask. Organizational Behavior and Human Decision Process 79, 216–247.

Knight, F. H. (1921). Risk, uncertainty and profit. New York: Hart, Schaffner and Marx.

Koellinger, Philipp, Minniti, Maria & Schade, Christian. (2007). "I think I can, I think I can": Overconfidence and entrepreneurial behavior. Journal of Economic Psychology. 28(4), 502-527.

Kothari, S., Li, X., & Short, J. (2009). The Effect of Disclosures by Management, Analysts, and Financial Press on the Equity Cost of Capital: A Study Using Content Analysis, The Accounting Review.

Kovach, B. & Rosenstiel, T. (1999). Warp Speed. America in the Age of Mixed Media. New York: The Century Foundation Press.

Krantz, Matt. (2012). Facebook at risk as lock-up expiration looms. USA TODAY, October 26, 2012.

Krippendorff, K. (1970a). Estimating the reliability, systematic error, and random error of interval data. Educational and Psychological Measurement, 30 (1),61-70.

Krippendorff, K. (1970b). Bivariate agreement coefficients for reliability data. In E. R. Borgatta & G. W. Bohrnstedt (Eds.), Sociological methodology: 139-150. San Francisco, CA: Jossey Bass.

Krippendorff, K. (1978). Reliability of binary attribute data. Biometrics, 34, 142-144.

Krippendorff, K. (2004). Content analysis: An introduction to its methodology. Second Edition. Thousand Oaks, CA: Sage.

Krull, D. S. (2001). On partitioning the fundamental attribution error: dispositionalism and the correspondence bias. In Cognitive Social Psychology: The Princeton Symposium on the Legacy and Future of Social Cognition, Moskowitz GB (ed): 211 – 227. Erlbaum: Mahwah, NJ.

Lacy, S. & Riffe, D. (1996). Sampling Error and Selecting Intercoder Reliability Samples for Nominal Content Categories. Journalism & Mass Communication Quarterly, 73(4), 963-973.

Lambert, R. A., Leuz, C. & Verrecchia, R. E. (2012). Information asymmetry, information precision, and the cost of capital. Review of Finance, 16(1), 1-29.

Lamertz, K. & Baum, J. (1998). The legitimacy of organizational downsizing in Canada: An analysis of explanatory media accounts. Canadian Journal of Administrative Sciences, 15, 93–107.

Landis, J.R. & Koch, G.G. (1977). "The measurement of observer agreement for categorical data". Biometrics 33(1), 159–174.

Lang, Mark H. & Lundholm, Russell J. (1996). Corporate Disclosure Policy an Analyst Behavior, The Accounting Review, 71(4), 467-492.

Lasswell, H. D. (1949). The structure and function of communication in society. In W. Schramm (Ed.), Mass communications: 102–115. Urbana IL: University of Illinois Press.

Lee, Jimmy. (2007). Earnings Management to Just Meet Analysts' Forecast.

Lin, L. (1989). A concordance correlation coefficient to evaluate reproducibility. Biometrics 45, 255-268.

Lin, L. (2000). A note on the concordance correlation coefficient. Biometrics 56, 324-325.

Liu, L. X., Sherman, A. E. & Zhang, Y. (2009a). The role of the media in initial public offerings. DePaul University and Hong Kong University of Science & Technology Working Paper.

Liu, L. X., Sherman, A. E. & Zhang, Y. (2009b). Media coverage and IPO underpricing. In AFA 2009 San Francisco Meetings Paper.

Liu, Yu, Mingna Liu, Hai Xiao, Jianping Cai & Wanhai Xu. (2010). A Content Analysis of News Coverage of Skin Cancer in China Newspapers, Health Communication, 25, 647–649.

Ljungqvist, A. & Wilhelm, W. (2003). Hot markets, investor sentiment and IPO pricing, Journal of Finance, 58(2), 723-752.

Lombard, M., Snyder-Duch, J. & Bracken, C. C. (2002). Content analysis in mass communication research: An assessment and reporting of intercoder reliability. Human Communication Research, 28, 587-604.

Lombard, M., Snyder-Duch, J. & Bracken, C. C. (2003). Correction. Human Communication Research, 29, 469-472.

Loughran, T. & Ritter, J. (2002). Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? Review of Financial Studies, 15(2), 413-443.

Loughran, T. & Ritter, J. (2004). Why Has IPO Underpricing Changed Over Time? Financial Management, 33, 5-37.

Lull, J. & Hinerman, S. (eds). (1997). Media Scandals. Cambridge: Polity Press.

Malmendier, U. & Tate, G. (2005a). Does overconfidence affect corporate investment? CEO overconfidence measures revisited. European Financial Management, 11(5), 649-659.

Malmendier, U. & Tate, G. (2005b). 'CEO overconfidence and corporate investment', Journal of Finance, 60(6).

Marks, Paul. (2012). "Online searches for future linked to economic success". New Scientist. Retrieved April 9, 2012.

Matsumoto, D. A. (2002). Management's incentives to avoid negative earnings surprises. The Accounting Review, 77(3), 483-514.

McKibbon A. K., Wilczynski N. L. and Haynes B. R. (2006). Developing optimal search strategies for retrieving qualitative studies in PSYCINFO. Evaluative Health Professional, 29, 440–54.

McLeod, D. M., Kosicki, G. M. & McLeod, J. M. (2002). Resurveying the boundaries of political communication effects. Media effects: Advances in theory and research, 2, 1-18.

Merton, Robert C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information, Journal of Finance, 42(3), 483-510.

Moore, D. A. & Healy, P. J. (2007). The trouble with overconfidence.

Moore, D. A. & Kim, T. G. (2003). 'Myopic social prediction and the solo comparison effect', Journal of Personality and Social Psychology, 85(6), 1121–35.

Mullaney, Timothy. (2000). How to Take Hype Out of IPOs. Business Week.

Nam, Daeil, Arthurs, Jonathan, Nielsen, Marsha, Mousa, Fariss & Liu, Kun. (2008). Information Disclosure and IPO Valuation: What Kinds of Information Matter and is More Information always Better? Frontiers in Entrepreneurship Research.

Neuendorf, K. A. (2002). The content analysis guidebook. Thousand Oaks, CA: Sage.

Nikolla, Zef. (2012). Associated Press. Facebook didn't make too many friends Friday.

Ohl, C. M., Pincus, J. D., Rimmer, T., & Harrison, D. (1995). Agenda building role of news releases in corporate takeovers. Public Relations Review, 21(2), 89-101.

Ortutay, Barbara. (2012). Associated Press. Facebook stock jumps even as lockup period expires. November 15, 2012.

Page, E. B, & Petersen, N. S. (1995). "The Computer Moves into Essay Grading: Updating the Ancient Test" in Phi Delta Kappan. 76 (7), 561–565.

Peng, C.-Y. J., Harwell, M., Liou, S.-M., & Ehman, L. H. (2006). Advances in missing data methods and implications for educational research. In S. Sawilowsky (Ed.), Real data analysis: 31–78. Greenwich, CT: Information Age.

Pepitone, Julianne. (2012). @CNNMoneyTech. Facebook: IPO debacle was Nasdaq's fault. June 15, 2012. http://money.cnn.com/2012/06/15/technology/facebook-ipo-lawsuit/index.htm]

Pfeffer J. (1981). Power in Organizations. Pittman: Boston, MA.

Pollock, T. G., & Rindova, V. P. (2003). Media Legitimation Effects in the Market for Initial Public Offerings. Academy of Management Journal, 46(5), 631-642.

Pollock, T. G., Whitbred, R. C., & Contractor, N. (2000). Social information processing and job characteristics: a test and integration of two theories with implications for job satisfaction. Human Communication Research, 26(2), 292-330.

Preis, Tobias, Moat, Helen Susannah, Stanley, H. Eugene & Bishop, Steven R. (2012). "Quantifying the Advantage of Looking Forward". Scientific Reports, 2, 350.

Pryor, J. B.; Kriss, M. (1977). The cognitive dynamics of salience in the attribution process. Journal of Personality and Social Psychology, 35(1), 49-55.

Rice, John. (1995). Mathematical Statistics and Data Analysis (Second ed.). Duxbury Press.

Riffe, Daniel, Lacy, Stephen & Fico, Frederick G. (1998), Analyzing Media Messages: Using Quantitative Content Analysis in Research. Lawrence Erlbaum Associates: London.

Riloff, E. (1993). Automatically Constructing a Dictionary for Information Extraction Tasks. In Proceedings of the Eleventh National Conference on Artificial Intelligence: 811-816. AAAI Press/The MIT Press: Boston, MA.

Rindova, V. P., Pollock, T. G. & Hayward, M. L. A. (2006). Celebrity Firms: The Social Construction of Market Popularity, Academy of Management Review, 31(1), 50-71.

Ritter, J. R. (1991). The long-run performance of initial public offerings. Journal of Finance, 46, 3–27.

Ritter, J. R. & Zhang, D. (2007). Affiliated mutual funds and the allocation of initial public offerings. Journal of Financial Economics, 86(2), 337-368.

Rogers, Everett, Dearing, James & Soonbum, Chang. (1991). 'AIDS in the 1980s: The agenda-Setting Process for a Public Issue', Journalism Monographs, 126.

Rosen S. (1981). The economics of superstars. American Economic Review, 71, 845–858.

Rossi, J. S. (1990). Statistical power of psychological research: What have we gained in 20 years?. Journal of Consulting and Clinical psychology, 58(5), 646.

Roth, P. L. (1994). Missing data: A conceptual review for applied psychologists. Personnel Psychology, 47, 537–570.

Rusli, Evelyn. (2012). Yelp Surges After Lockup Expires. New York Times, B3, August 30, 2012.

Saal, F.E., Downey, R.G. & Lahey, M.A. (1980). "Rating the Ratings: Assessing the Psychometric Quality of Rating Data" in Psychological Bulletin. 88 (2), 413–428.

Salancik, G. R. & Pfeffer, J. (1978). A social information processing approach to job attitudes and task design. Administrative Science Quarterly, 224-253.

Samuelson, P. and Nordhaus, W. (1985). Principles of Economics. New York, NY: McGraw-Hill.

Sandelowski, M. & Barroso, J. (2007). Handbook for synthesizing qualitative research. New York: Springer-Verlag.

Schafer, J. L. (1999). Multiple imputation: A primer. Statistical Methods in Medical Research, 8, 3–15.

Scheufele, D. A. (2000). Agenda-setting, priming, and framing revisited: Another look at cognitive effects of political communication. Mass Communication & Society, 3(2-3), 297-316.

Schlenker, B. R. (1980). Impression Management: The Self-Concept, Social Identity, and Interpersonal Relations. Monterey/California: Brooks/Cole.

Schlomer, Gabriel L., Bauman, Sheri & Card, Noel A. (2010). Best Practices for Missing Data Management in Counseling Psychology. Journal of Counseling Psychology, 57(1), 1-10.

Schultz, J. M. (1994). Stylistic reformulation: Theoretical premises and practical applications. Modern Language Journal,78, 169-178.

Schutz, William C. (1952). "Reliability, Ambiguity and Content Analysis," Psychological Review, 59, 119-29.

SEC Website. (2012). Security Exchange Commission Regulatory Actions. http://www.sec.gov/rules.shtml.

Semetko, H. A., & Schoenbach, K. (1994). Germany's "unity election": Voters and the media. Cresskill, NJ: Hampton Press.

Shields, Brian. (2012). Apple Earnings Fail to Meet Expectations. The Associate Press. July, 24 2012.

Shiller, Robert J. (2000). Irrational Exuberance, Princeton University Press: Princeton, New Jersey.

Shrout, P. & Fleiss, J. L. (1979). "Intraclass correlation: uses in assessing rater reliability" in Psychological Bulletin. 86(2), 420–428.

Simon, H. A. (1947). 1997. Administrative behavior.

Simon, M., & Houghton, S. M. (2003). The Relationship between Overconfidence and the Introduction of Risky Products: Evidence from a Field Study. Academy of Management Journal, 46(2), 139-149.

Sinha, Paresha N., Inkson, Kerr & Barker, James R. (2012). Committed to a failing strategy: Celebrity CEO, intermediaries, media and stakeholders in a co-created drama, Organization Studies, 33(2), 223-245.

Smith, Ken G., Smith, Ken A., Olian, Judy D. Sims, Jr., Henry P., O'Bannon, Douglas P. & Scully, Judith A. (1994). Top Management Team Demography and Process: The Role of Social Integration and Communication. Administrative Science Quarterly, 39(3), 412-438.

Stemler, S. (2001). An overview of content analysis. Practical assessment, research & evaluation, 7(17), 137-146.

Stempel, Guido H., III. (1981). “Content Analysis,” in Research Methods in Mass Communication, ed. Guido H. Stempel III & Bruce H. Westley, Englewood Cliffs, NJ: Prentice-Hall, Inc.

Stough R., Lall S. V. & Trice M. P. (2000). Infrastructure and technology in US metropolitan regions, International Regional Science Review (forthcoming).

Tabachnik, Barbara G. & Fidell, Linda S. (1996). Using Multivariate Statistics. Boston, MA: Pearson Education Inc.

Tabachnik, Barbara G. & Fidell, Linda S. (2007). Using Multivariate Statistics, 5th ed. Boston, MA: Pearson Education Inc.

Tedeschi, J. T. (1981). Impression management theory and social psychological research. Academic Pr.

Tedeschi, J. T. & Riess, M. (1984). Identities, the Phenomenal Self, and Laboratory Research, in: Tedeschi, James T. (Ed.): Impression Management Theory and Social Psychological Research, Academic Press, New York.

Tetlock, P. E., Mitchell, G. & Murray, T. L. (2008). The challenge of debiasing personnel decisions: Avoiding both under- and overcorrection. Industrial and Organizational Psychology, 1, 439-443.

The Big Picture Website. (2012). http://www.ritholtz.com/blog/2012/04/the-earnings-beat-rate-in-perspective/, Retrieved 2012.

Thompson, J.B. (1995). The Media and Modernity: A Social Theory of the Media. Stanford, CA: Stanford University Press.

Thompson, John. (2000). Political Scandal: Power and Visibility in the Media Age. Cambridge: Polity Press.

Thompson, Kenneth. (1998). Moral Panics. New York: Routledge.

Triola, Mario F. (2004). Elementary Statistics (9th edition). Boston, MA: Pearson.

Tukey, J. W. (1962). The Future of Data Analysis, The Annals of Mathematical Statistics, 33, 18.

Tversky, A. & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. Cognitive psychology, 5(2), 207-232.

Vasterman, Peter L. M. (2005). Media-Hype: Self-reinforcing News Waves, Journalistic standards and the Construction of Social Problems. European Jounral of Communication, 20, 508.

Walgrave, S. & Deswert, K. (2004). The making of the (issues of the) Vlaams Blok. The media and the success of the Belgian extreme-right party. Political Communication, 21, 479–500.

Wall Street Journal Europe. (1997). American CEOs gain a celebrity status, mixture of money power and mythology creates a cult of personality, Europe prefers real royalty. September 4, 1997, 1.

Watson, Bruce. (2012). "Facebook IPO Valuation Sets Record: Is It Really Worth $104 Billion?" Daily Finance, May 17, 2012.

Weaver, D., McCombs, M., & Shaw, D. L. (2004). Agenda-setting research: Issues, attributes, and influences. In L. L. Kaid (Ed.), Handbook of political communication research: 257–282. Mahwah, NJ: Erlbaum.

Weber, Robert Philip. (1985). Basic Content Analysis, 2d ed. Newbury Park, CA.: Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-075.

Weick, K. (1979). The Social Psychology of Organizing (2nd ed). Addison-Wesley: Reading, MA.

Weick, K. E. & Daft, R. L. (1983). The effectiveness of interpretation systems. In Organizational Effectiveness: A Comparison of Multiple Models, Cameron KS, Whetten DA (eds): 71–93. Academic Press: New York.

Weidman, C. (1996). The relevance of characteristics of the information environment in the selection of a proxy for the market's expectations for earnings: An extension of Brown, Richardson and Schwager [1987]. Journal of Accounting Research, 34, 313-324.

Weiner, B. (1986). An Attributional Theory of Motivation and Emotion. Springer: New York.

Welch, Michael, Price, Eric A. & Ynakey, Nana. (2002). 'Moral Panic Over Youth Violence: Wilding and the Manufacture of Menance in the Media', Youth and Society. 34(3), 3–30.

Wien, Charlotte & Elmelund-Praestekaer, Christian. (2009). An Anatomy of Media Hypes: Developing a Model for the Dynamics and structure of Intense Media Coverage of Single Issues, European Journal of Communication, 24(2), 183.

Wiersema, Margareth F. & Bantel, Karen A. (1992). Top Management Team Demography and Corporate strategic Change. Academy of Management Journal, 35(1), 91-121.

Wong S. S.-L., Wilcynski N. L. & Haynes B. (2004). Developing optimal search strategies for detecting clinically relevant qualitative studies in MEDLINE. MEDINFO, 311–314.

Wong, S. S.-L., Wilczynski N. L. & Haynes B. R. (2006). Optimal CINAHL search strategies for identifying therapy studies and review articles. J Nurs Scholar. 38, 194–199.

Yahoo Finance. (2012). Facebook CEO Mark Zuckerberg Rings NASDAQ Opening Bell. http://yahoo.com/facebook-ceo-mark-zuckerberg-rings-nasdaq-opening-bell-29339291.html.

Zedeck, Sheldon. (1971). “Problems with the use of ‘moderator’ variables.” Psychological Bulletin, 76(4), 295-310.

APPENDICIES

Appendix A: Media Collection Procedures

Step 1: VPN or go to CU to gain access to CU Libraries databases

Step 2: Login into the system
User name: Your User Name
Password: Your Password

Step 3: Go to the database
A] Search for CU Libraries
B] Select Libraries and Departments
C] Select Business Library
D] Select ProQuest Central

Step 4: Set up basic search settings
A] Select "select multiple databases"
B] Add checks to "ABI/INFORM Dateline" and "ProQuest Newspapers"
C] Click "Continue" at the top of the page
D] Confirm that it went through by seeing three databases selected near the top of the screen:
"ProQuest Newspapers, ABI/INFORM Dateline, ProQuest Central"

Step 5: Set up the search
A] Paste the following stream in the top block
((((pmid(12816)) OR (pmid(11947)) OR (pmid(7818)) OR (pmid(7631)) OR (pmid(7510)) OR (pmid(7683)))))
B] Add company name to the second block
C] Adjust date range using the "specific date range" option

Step 6: Hit enter and get a list of articles in that date range
A] Remember, now is a good time to add a bunch of spaces below the company name on both the "Business & PR News" sheet and the "Major News Outlets" sheet to prepare to add one article per line
B] Also, remember to put the firm number in the first column on each row

Step 7: Review the article and log it in when appropriate
A] Quickly skim the article to **make sure that the firm is not just a footnote in the article, but an important/major part of the article**
B] If the article is about the firm you are searching for, ***place the article info on the appropriate sheet*** (Businesswire and PR Newswire on the "Business & PR News" sheet and the other news periodicals on the "Major News Outlets" sheet)

C] Mark the following information

1) Mark the count column for the appropriate date range with a "1"
2) Add the source of the article
3) Add the date of the article
4) Paste the primary article text in the text column (you don't have to copy charts and graphs and stuff like that, just the basic article, but not just the abstract)

Step 8: Click the back button on your browsers and click the next article (repeat the article logging in process above)

Step 9: When you are done with that date range, move onto the next date range

Step 10: When you are done with a firm, use the search engine's back button to get back to the main page and then change to the second line to the next firm and update the date range and you're off again.

Appendix B: Sample Procedure and the Application of the sample Filters

The final sample was determined using a two-step sample procedure. Step one included the elimination of firms based on a set of initial filters common in past literature (see Ritter, 1991). Initial filters included the exclusion of Special Purpose Acquisition Companies (SPACs), closed-end funds, Real Estate Investment Trusts (REITs), unit offers (typically composed of a share plus a warrant to buy a share), limited partnerships, small best efforts offers, foreign companies issuing American Depositary Receipts (ADRs). Step two included the application of additional filters focused on identifying firms trading on primary U.S. exchanges and larger IPO deals. The later additional filter is based on theory based expectation that larger deals are more likely to experience and therefore are more likely to be influenced by media hype. Specifically, these additional filters included the exclusion of firms that were not promptly listed on the Amex, NYSE, or Nasdaq, and IPOs with principal amounts less than $80M.

Table B.1: IPOs per Year—Population vs After Initial Filters vs After Additional Filters

Year	Gross US IPOs*	% of Gross IPOs from 2007-201	Sample After Initial Filters Applied	% of IPOs After Initial Filters Applied from 2007-2011	Sample after Additional Filters Applied	% of IPOs After Additional Filters Applied from 2007-2011
2007	304	40%	160	41%	53	42%
2008	53	7%	21	6%	8	7%
2009	68	9%	41	10%	15	12%
2010	183	24%	92	23%	26	20%
2011	152	20%	81	20%	24	19%
Total	760	100%	395	100%	126	100%

* Gross and initial filter IPO data gathered through Internet searches through SDC Compustat database and Prof J. R. Titter's webpage.

Table B.2: IPOs per Year, per Industry—Population vs After Initial Filters vs After Additional Filters

Year	Industry	Gross US IPOs*	% of Gross IPOs from 2007-2011	Sample After Initial Filters Applied*	% of IPOs After Initial Filters Applied from 2007-2011	Sample After Additional Filters Applied	% of IPOs After Additional Filters Applied from 2007-2011
2007	Tech	178	(59%) *23%*	90	(56%) *23%*	29	(55%) *23%*
	Non-Tech	126	(41%) *17%*	70	(44%) *18%*	24	(45%) *19%*
2008	Tech	32	(60%) *4%*	14	(66%) *4%*	1	(13%) *1%*
	Non-Tech	21	(40%) *3%*	7	(34%) *2%*	7	(87%) *6%*
2009	Tech	42	(62%) *6%*	26	(63%) *7%*	7	(47%) *6%*
	Non-Tech	26	(38%) *3%*	15	(37%) *3%*	8	(53%) *6%*
2010	Tech	104	(57%) *14%*	51	(55%) *13%*	16	(61%) *12%*
	Non-Tech	79	(43%) *10%*	41	(45%) *10%*	10	(39%) *8%*
2011	Tech	95	(62%) *12%*	51	(63%) *13%*	13	(54%) *10%*
	Non-Tech	57	(38%) *8%*	30	(37%) *7%*	11	(46%) *9%*
Total		760	*100%*	395	*100%*	126	*100%*

* *Gross and initial filter IPO data gather through an Internet searches through SDC Compustat databse and Prof. J. R. Ritter's webpage.*

Note: In each percentage column, numbers in parentheses represent the percentage of tech versus non-tech firms per year while the italicized figures reflect the percentage of IPOs in each industry category, per year with respect to the entire population or sample.

Appendix C: Content Analysis Protocol

Articles are content analyzed in four different categories (Topic, Level of Analysis, Salience, and Tone) by the following procedures:

Step 1: Verify that the article actually has the firm name in the article. The best way to verify this is to quickly skim the article for the firm name (or use the "Find" function) to verify the firm is included in the text.

A] Tremendous effort and care was taken during the article collection period to provide a clean, comprehensive article list, but with over 4,000 articles I am sure a few rogue articles made it into the dataset accidentally. If a mistake occurred during article collection and you find an article that either does not have the focal firm name within the text or the article slipped through the collection filters because it includes a common word (such as "Visa", which is a company name, but also refers to an endorsement on a passport for the holder to enter, leave, or stay in a country), but the article has nothing to do with the focal firm, then indicate that the article is ***"not about the focal firm"*** in the notes section in the last column on the article line. Then move on to the next article.

B] If you find that the firm is simply mentioned once as a member of a list of other firms somewhere in the text, please input ***"list only"*** in the notes column at the end of the article row. However, continue to analyze the article's topic, level of analysis, salience and tone as best you can.

Step 3: Once you confirm the firm name is within the article text, read the article and rate it in the following four areas:

A] Article Topic: Determine the primary or general topic of the article. The list of topics below are based on guidance from past literature (Kothari, Li & Short, 2009; Riloff, 1993) and from what was learned during a pilot study of a sample of the articles. If one topic tends to dominate the article, then input that topic number in the appropriate cell. Dominating topics are those that account for greater than 50% of the article or account for more content of the article than any other topic. If, for instance, one topic accounts for over 50% of the article's content, then that topic is the dominant topic. In another example, if one topic accounts for 40% and two other topics account for 30% each, then the 40% topic is the dominant topic. If, however, one dominant focus topic cannot be clearly determined, then input the two or three topic areas that are of equal focus in the article in the appropriate cells in the spreadsheet with commas between the values. Notice that topics that are not captured by any of the defined/described categories (categories 1 through 6 below) should be placed in the "Other" category (category 7). For articles identified as "Other", please add a very brief general description of the article topic in the "Notes" column at the end of the article row.

Table C.1: Article Topics

Topics	Definition	Focus of Article
1	Firm Performance	- Financial reporting (i.e., quarterly reports, EPS guidance, etc.) - Forward looking financial statements - Firm investments (including information about the IPO, mergers and/or acquisitions, cooperative agreements, joint ventures, etc.)
2	Firm Operations	- Firm products or services - Customer service - Development and execution of firm strategy (including growth/expansion plans)
3	Firm Reputation	- Discussions regarding image, brand and other firm reputation building or assessments - Awards or other special recognition - Special event announcements (i.e., charity events, sponsored concerts or other events, a presentation by a firm representative, etc.)
4	Organizational Mgmt and Governance	- CEO activity (including succession news) - Other management activity - News regarding the Board of Directors
5	HRM	- Employee oriented information (i.e., hirings, firings, layoffs, etc.) - Building of organizational capital
6	External Issues	- Market risks and issues affecting the market, the industry, or the competitive landscape - Regulatory risks (i.e., announcement and impact of governmental regulation or litigation against the firm)
7	Other	- Topics not covered by any other category

B] Article Level of Analysis: Determine what level of analysis the article is discussing. Do this by identifying which of the following three levels are discussed with respect to the firm in the article. *Select all that apply.*

Table C.2: Article Level of Analysis

Rating	**Description**
1	Individual Level *(eg., about a CEO or other manager or individual)*
2	Firm or Organizational Level
3	Inter-Firm or Inter-Organizational Level *(eg.. actions between two or more firms such as a merger, acquisition, cooperative agreement, or industry level articles)*

C] Article Salience: Determine the relative role that the firm plays in the article. Code articles based on the following five-point scale.

Table C.3: Article Salience

Rating	Category Title	Description
5	Focal Firm Only	Focal firm is clearly the focus of the article. Practically no other firm is even mentioned in the article.
4	Focal Firm Focused	Focal firm is the key focus of the article, but other firms may be discussed within the article.
3	Shared Focused	Focal firm is an important part of the article, but the firm shares a good portion of the article with other firm(s) (i.e., announcement of an award, merger or acquisition, cooperative agreement, etc.).
2	Other Firm (or Event) Focused	Focal firm is identified in the article, but the article is focused on other firms or other events.
1	Barely Referenced	Article is focused other firms or events and only references the focal firm. Focal firm is mentioned as a member of a list with other firms. The article essentially has nothing significant to say specifically about the focal firm.

D] Article Tone: As a measure of article sentiment, determine the general tone of the article by making an assessment of the overall positive or negative tone of the article ***with respect to the focal firm***. Some articles will be about more than the focal firm. Remember to focus your assessment of the tone of the article based on the tone in reference to the focal firm only and not the tone of the article overall or the tone of the article with respect to other firms. Ratings will be based on two dichotomous questions (meaning questions with only two possible answers):

Table C.4: Rating Article Tone

Questions	**Responses**
1) Is the article sentiment **positive or not positive** with respect to the focal firm?	Enter '1' for Positive Enter '0' for Not Positive
2) Is the article sentiment **negative or not negative** with respect to the focal firm?	Enter '1' for Negative Enter '0' for Not Negative

NOTE: Neutral articles are those articles scored with two '0's or two '1's for the two questions above.

Step 4: You are coding a lot of articles and the spreadsheet may become difficult to read/see at times, so please double check your work. At the completion of each article coding, ensure all columns are filled in for the appropriate row for the article you just read and coded. Then move on to the next article.

Appendix D: Content Analysis Example for Own Hype (i.e., *articles from Businesswire and PR Newswire*)

SAMPLE ARTICLE: Verisk Analytics, Businesswire, 11 Mar 2010

Verisk Health, Inc., a global leader in healthcare data analytics and risk management, today announced several upgrades to its Explorer product line, including functionality that allows users to evaluate the impact of a member's lifestyle behaviors on an organization's overall healthcare and utilization costs. Explorer is one of several tools from Verisk Health that focuses on identifying, understanding, and taking action to improve an organization's exposure to healthcare risk. Specifically, Explorer is a suite of risk adjustment and predictive modeling solutions that enable organizations to analyze, predict, manage, and minimize healthcare risks and costs associated with Commercial, Medicare, and Medicaid populations.

"It's widely known that if you smoke, suffer from depression, or are overweight, there is an impact on your health. The latest release of Explorer shows how such lifestyle behaviors actually impact cost," said Nathan Gunn, MD, chief medical officer of Verisk Health. "From there, we can identify at a population level, the individuals who will most benefit from clinical intervention programs and make wellness and disease management programs more effective."

Verisk Health's Explorer is a web-native, application service provider (ASP) solution that enables healthcare organizations to leverage data to better manage their risk. Two new features available in this latest release include:

-- HRA Impact Report. The HRA Impact Report provides the impact of lifestyle behaviors on cost and utilization. For example, a customer can see the effect smoking has on their overall claim costs and utilization of services such as ER visits. This information is a critical data point for helping customers fine tune and measure the impact of behavior modification programs.

-- Medical Intelligence Report. The updated Medical Intelligence report features several new clinical sections, including a clinical disease fingerprint that reveals the relationship between the risk index and the care gap index. It then compares this to the norm and identifies where to focus to improve quality. It also displays areas of clinical quality performance and economic opportunity by identifying individuals who would benefit from case management, disease management, or wellness programs. The new report is an actionable roadmap that can help customers design and implement the most effective programs for their care community.

Please join us for a complimentary webinar on March 17th at 1 pm to learn more about Explorer and these latest enhancements. Registration is required. Please click here.

Verisk Health is an industry leader in the area of risk identification and data analytics with a comprehensive suite of products, including:
-- enterprise business intelligence solutions
-- risk adjustment and predictive modeling
-- HEDIS quality and reporting solutions
-- data aggregation, analytics, and benchmarking solutions
-- clinical, analytics, and technology consulting services

ARTICLE CODING:

Category	Rating	Rating Definition
Topic	2	Firm Operations
Level of Analysis	2	Firm Level
Salience	5	Focal Firm Only
Tone 1	1	Positive
Tone 2	0	Not Negative

Appendix E: Content Analysis Example for Event Hype
(i.e., articles in highly circulated US newspapers)

SAMPLE ARTICLE: Visa Inc, New York Times, 26 Feb 2008

Undaunted by recent turbulence in the financial markets, Visa Inc., the nation's biggest credit card network, said Monday that it would forge ahead with what would be the largest initial public stock offering in United States history. Visa plans to sell as much as $17.1 billion of stock in late March, following in the footsteps of its smaller rival, MasterCard, which went public in May 2006.

Visa and MasterCard are prospering as Americans increasingly flex plastic, rather than use cash, to pay for just about everything. The companies have not been hurt by the credit squeeze, because they do not actually make credit card loans; they merely process transactions for banks that do.

If all goes as planned, Visa's offering would generate a windfall for thousands of its so-called member banks, which own the company. The largest gains would go to many of the nation's biggest banks, which have been stung by losses stemming from mortgage-linked investments.

"Visa will be able to tell its story, even in an uncertain market, because its story is a good one," said David Robertson, publisher of The Nilson Report, a payment industry newsletter. "If investors think MasterCard is a good story, Visa looks like the same thing on a bigger scale."

Visa plans to sell 406 million Class A shares for $37 to $42 a share, with just over half going to the public and the rest to Visa's member banks.

The first $3 billion will be placed into a special account to cover outstanding antitrust and unfair-pricing claims brought by merchants. Visa will use some of the new money to streamline its operations, expand in fast-growing emerging markets and invest in new technology like systems that enable people to make card payments via cellphone. But the bulk of the capital will end up in the banks' coffers, from repurchasing stock from them. Visa's member banks can use the extra cash.

If Visa's shares are valued at a midpoint price of $39.50, JPMorgan Chase, the company's largest shareholder, would receive an estimated $1.1 billion for its stake. Bank of America would get about $545 million; National City would get about $380 million; and Citigroup, U.S. Bancorp and Wells Fargo can each expect around $240 million or more.

"The credit crunch is pretty cyclical; the prospects for Visa are very strong long-term," said Marc Abbey, the managing partner of First Annapolis, a consulting firm that works with many banks and payments companies. "I am sure it is convenient for them to have extraordinary gains at the same time they have extraordinary losses."

Since going public nearly two years ago, MasterCard shares have soared 408 percent, closing at $198.45 on Monday. It now has a market value of $26 billion.

MasterCard's successful I.P.O. prompted Visa to move forward with its own plans to go public. Since October 2006, Visa has reorganized its sprawling management structure, bringing together all of its global operations with the exception of those in Europe.

It has also hired Joseph W. Saunders, the former head of the Providian Financial Corporation, as its new chairman and chief executive, giving him a pay package worth $11.1 million in cash for 2007. Upon completion of the I.P.O., he is expected to receive an additional $11.5 million in stock and options, according to Equilar, a compensation research firm.

Visa transactions accounted for roughly 66 percent of all credit and debit card purchases in the United States in 2006, compared with about 26 percent for MasterCard, according to The Nilson Report data.

Growth in card transactions, the foundation of the companies' businesses, has historically held up well, even when the economy and consumer spending slows.

ARTICLE CODING:

Category	Rating	Rating Definition
Topic	1	Firm Performance
Level of Analysis	2	Firm Level
Salience	4	Focal Firm Focused
Tone 1	1	Positive
Tone 2	0	Not Negative

Appendix F: Content Analysis Example for Expert Hype
(i.e., executive summaries of analyst reports)

SAMPLE ARTICLE: Zynga, Sterne, Agee & Leach, Inc. (Bhatia), 13 Dec 2011

INITIATING COVERAGE ON ZYNGA WITH AN UNDERPERFORMRATING;
PT $7.00

Summary. Ahead of Zynga's (ZNGA) expected IPO pricing this week in a range of $8.50-$10.00 per share, we are initiating coverage with an Underperform rating and target price of $7, based on a healthy 11x EV to EBITDA (2012E) multiple, which is a 30% premium to its peer group. While we believe in the potential for social games, we think Zynga's growth is slowing even faster than what is obvious at first, its margins are under pressure, and free cash flow has been declining recently; thus we believe the implied valuation in the IPO is not justified.

The Bottom Line. Farmville, the company's flagship title which helped generate hyper-growth in the past, has peaked and the other titles are coming on line at a much slower pace. Cityville, currently Zynga's best title in terms of traffic, is tracking, by our estimates, 50% below Farmville at the same point in its history. Castleville (released 11/15), the new title in the "Ville" series, is averaging DAUs 50% below Cityville at the same point. The picture with Mafia Wars 2 (released in early October this year) appears quite dismal with DAUs having already declined to less than 1M from 28M reached 2 weeks after launch. This also implies, perhaps, that sequels in social gaming are not a guaranteed success. Zynga Poker, the company's oldest title, seems relatively stable but is also past its peak. For 2012, we expect two new Zynga titles on Facebook: Hidden Chronicles and Zynga Bingo. Also, we expect ZNGA to grow its mobile business and expand its overall reach internationally. All said, we expect bookings (a measure of cash-based revenue) growth to slow to 20% and 17% in 2012 and 2013, respectively, versus growth of 156% in 2010 and (estimated) 37% in 2011.

Other Bear Arguments. Another bear argument is that Zynga is overly dependent on the Facebook platform (94% of revenue is generated on Facebook). A slowdown or disruption in the growth of Facebook, or Facebook policy changes, will negatively impact Zynga (and it did in 2010). Bears also would argue that barriers to entry in social gaming aren't really that high. As an example, Electronic Arts (ERTS - $21.68 - Buy) recently saw its title The Sims Social climb to the #2 spot on Facebook within a few weeks of launch. Another bear argument is that there are only a very small number of actual payers that generate all of the revenue which makes Zynga more vulnerable if these players lose interest. In the TTM ending September 30, 2011, while there were 221M average monthly active users (MAUs), the actual unique payers totaled 7.7M or only 3.5%.

ARTICLE RATINGS:

Category	Rating	Rating Definition
Topic	1	Firm Performance
Level of Analysis	2	Firm Level
Salience	5	Focal Firm Only
Tone 1	0	Not Positive
Tone 2	1	Negative

Appendix G: Topic Inter-Rater Reliability Calculations

ReCal 0.1 Alpha for Nominal Data for 3+ Coders

N coders:	5
N cases:	150
N decisions:	750

Average Pairwise Percent Agreement

Average pairwise percent agr.	Pairwise pct. agr. cols 1 & 5	Pairwise pct. agr. cols 1 & 4	Pairwise pct. agr. cols 1 & 3	Pairwise pct. agr. cols 1 & 2	Pairwise pct. agr. cols 2 & 5	Pairwise pct. agr. cols 2 & 4	Pairwise pct. agr. cols 2 & 3	Pairwise pct. agr. cols 3 & 5	Pairwise pct. agr. cols 3 & 4	Pairwise pct. agr. cols 4 & 5
92.319%	87.681%	94.203%	93.478%	91.304%	87.681%	94.203%	96.377%	89.855%	96.377%	92.029%

Fleiss' Kappa

Fleiss' Kappa	Observed Agreement	Expected Agreement
0.868	0.923	0.417

Average Pairwise Cohen's Kappa

Average pairwise CK	Pairwise CK cols 1 & 5	Pairwise CK cols 1 & 4	Pairwise CK cols 1 & 3	Pairwise CK cols 1 & 2	Pairwise CK cols 2 & 5	Pairwise CK cols 2 & 4	Pairwise CK cols 2 & 3	Pairwise CK cols 3 & 5	Pairwise CK cols 3 & 4	Pairwise CK cols 4 & 5
0.869	0.79	0.9	0.885	0.849	0.794	0.901	0.937	0.828	0.937	0.867

Krippendorff's Alpha (nominal)

Krippendorff's Alpha	N Decisions	$\Sigma_c o_{cc}$***	$\Sigma_c n_c(n_c - 1)$***
0.869	690	637	197608

****These figures are drawn from Krippendorff (2007, case C.)*

Appendix H: Level Of Analysis Inter-Rater Reliability Calculations

ReCal 0.1 Alpha for Nominal Data for 3+ Coders

N coders:	5
N cases:	150
N decisions:	750

Average Pairwise Percent Agreement

Average pairwise percent agr.	Pairwise pct. agr. cols 1 & 5	Pairwise pct. agr. cols 1 & 4	Pairwise pct. agr. cols 1 & 3	Pairwise pct. agr. cols 1 & 2	Pairwise pct. agr. cols 2 & 5	Pairwise pct. agr. cols 2 & 4	Pairwise pct. agr. cols 2 & 3	Pairwise pct. agr. cols 3 & 5	Pairwise pct. agr. cols 3 & 4	Pairwise pct. agr. cols 4 & 5
92.754%	90.58%	90.58%	97.101%	94.203%	90.58%	92.029%	91.304%	93.478%	93.478%	94.203%

Fleiss' Kappa

Fleiss' Kappa	Observed Agreement	Expected Agreement
0.859	0.928	0.487

Average Pairwise Cohen's Kappa

Average pairwise CK	Pairwise CK cols 1 & 5	Pairwise CK cols 1 & 4	Pairwise CK Cols 1 & 3	Pairwise CK cols 1 & 2	Pairwise CK cols 2 & 5	Pairwise CK cols 2 & 4	Pairwise CK cols 2 & 3	Pairwise CK cols 3 & 5	Pairwise CK cols 3 & 4	Pairwise CK cols 4 & 5
0.859	0.816	0.819	0.943	0.884	0.815	0.846	0.829	0.874	0.875	0.889

Krippendorff's Alpha (nominal)

Krippendorff's Alpha	N Decisions	$\Sigma_c o_{cc}$***	$\Sigma_c n_c(n_c - 1)$***
0.859	690	640	230972

****These figures are drawn from Krippendorff (2007, case C.)*

Appendix I: Salience Inter-Rater Reliability Calculations

ReCal for Ordinal, Interval, and Ratio Data for 3+ Coders

N coders:	5
N cases:	150
N decisions:	750
Krippendorff's alpha (ordinal)	0.856

Derived from Krippendorff (2007)

Multiple measures of IRR are typically only necessary when a researcher is trying to justify a variable that fails a stricter coefficient. However, Krippendorff's alpha is sufficient in nearly all cases where it meets or exceeds the desired level. There are not many accepted alternatives for calculating non-nominal IRR. However, as a sensitivity check, I calculated Lin's Concordance using software available online.[9] The concordance correlation coefficient (Lin, 1989) assesses concordance in continuous data. It represents a breakthrough in assessing agreement between alternative methods for continuous data in that it avoids the shortcomings associated with alternative procedures (such as Pearson correlation coefficient r, paired t-tests, least squares analysis for slope and intercept, coefficient of variation, intraclass correlation coefficient, etc.). Furthermore, Lin's Concordance is robust on as few as 10 pairs of data (Lin 1989; Lin, 2000). Lin's Concordance is mathematically very similar to Krippendorff's alpha.

Lin's Concordance

Sample concordance correlation coefficient (ρc) = 0.8514
Lower one-sided 95% CL for ρc = 0.7891
Lower two-sided 95% CL for ρc = 0.7678
Upper one-sided 95% CL for ρc = 0.8747
Upper two-sided 95% CL for ρc = 0.8955

[9] An online calculator for calculating Lin's Concordance is located at http://www.niwa.co.nz/our-services/online-services/statistical-calculators/lins-concordance. This calculator was u
pdated in April 2012, incorporating more accurate confidence limits using the inverse hyperbolic tangent transformation (or Z-transformation) (Lin, 1989; 2000); however, calculated values of the Lin coefficient are unchanged.

Appendix J: Tone 1 (Positive) Inter-Rater Reliability Calculations

ReCal 0.1 Alpha for Nominal Data for 3+ Coders

N coders:	5
N cases:	150
N decisions:	750

Average Pairwise Percent Agreement

Average pairwise percent agr.	Pairwise pct. agr. cols 1 & 5	Pairwise pct. agr. cols 1 & 4	Pairwise pct. agr. cols 1 & 3	Pairwise pct. agr. cols 1 & 2	Pairwise pct. agr. cols 2 & 5	Pairwise pct. agr. cols 2 & 4	Pairwise pct. agr. cols 2 & 3	Pairwise pct. agr. cols 3 & 5	Pairwise pct. agr. cols 3 & 4	Pairwise pct. agr. cols 4 & 5
93.043%	89.13%	94.203%	94.928%	94.203%	93.478%	92.754%	96.377%	91.304%	90.58%	93.478%

Fleiss' Kappa

Fleiss' Kappa	Observed Agreement	Expected Agreement
0.864	0.93	0.49

Average Pairwise Cohen's Kappa

Average pairwise CK	Pairwise CK cols 1 & 5	Pairwise CK cols 1 & 4	Pairwise CK Cols 1 & 3	Pairwise CK cols 1 & 2	Pairwise CK cols 2 & 5	Pairwise CK cols 2 & 4	Pairwise CK cols 2 & 3	Pairwise CK cols 3 & 5	Pairwise CK cols 3 & 4	Pairwise CK cols 4 & 5
0.864	0.787	0.887	0.901	0.887	0.872	0.858	0.929	0.828	0.815	0.871

Krippendorff's Alpha (nominal)

Krippendorff's Alpha	N Decisions	$\Sigma_c o_{cc}$***	$\Sigma_c n_c(n_c - 1)$***
0.864	690	642	232658

****These figures are drawn from Krippendorff (2007, case C.)*

Appendix K: Tone 2 (Negative) Inter-Rater Reliability Calculations

ReCal 0.1 Alpha for Nominal Data for 3+ Coders

N coders:	5
N cases:	150
N decisions:	750

Average Pairwise Percent Agreement

Average pairwise percent agr.	Pairwise pct. agr. cols 1 & 5	Pairwise pct. agr. cols 1 & 4	Pairwise pct. agr. cols 1 & 3	Pairwise pct. agr. cols 1 & 2	Pairwise pct. agr. cols 2 & 5	Pairwise pct. agr. cols 2 & 4	Pairwise pct. agr. cols 2 & 3	Pairwise pct. agr. cols 3 & 5	Pairwise pct. agr. cols 3 & 4	Pairwise pct. agr. cols 4 & 5
97.971%	97.826%	97.826%	98.551%	98.551%	97.826%	97.826%	98.551%	97.826%	97.826%	97.101%

Fleiss' Kappa

Fleiss' Kappa	Observed Agreement	Expected Agreement
0.879	0.98	0.832

Average Pairwise Cohen's Kappa

Average pairwise CK	Pairwise CK cols 1 & 5	Pairwise CK cols 1 & 4	Pairwise CK cols 1 & 3	Pairwise CK cols 1 & 2	Pairwise CK cols 2 & 5	Pairwise CK cols 2 & 4	Pairwise CK cols 2 & 3	Pairwise CK cols 3 & 5	Pairwise CK cols 3 & 4	Pairwise CK cols 4 & 5
0.879	0.87	0.86	0.91	0.91	0.879	0.87	0.916	0.879	0.87	0.833

Krippendorff's Alpha (nominal)

Krippendorff's Alpha	N Decisions	$\Sigma_c o_{cc}$***	$\Sigma_c n_c(n_c - 1)$***
0.88	690	676	395348

****These figures are drawn from Krippendorff (2007, case C.)*

Appendix L: Top United States Newspapers by Circulation

List of the top 10 newspapers in the United States by daily circulation for the six-month period ended March 31, 2011.

Rank	Newspaper	City, State	Daily Circulation	Sunday Circulation	Owner
1	The Wall Street Journal	New York, NY	2,117,796	1,994,121	Dow Jones News Corporation
2	USA Today	McLean, VA	1,829,099	N/A	Gannett Company
3	The New York Times	New York, NY	916,911	1,339,462	The New York Times Company
4	Los Angeles Times	Los Angeles, CA	605,243	948,889	Tribune Company
5	San Jose Mercury News	San Jose, CA	577,665	636,999	MediaNews Group
6	The Washington Post	Washington DC	550,821	852,861	The Washington Post Company
7	Daily News	New York, NY	530,924	584,658	Daily News, L.P.
8	New York Post	New York, NY	522,874	355,784	News Corporation
9	Chicago Tribune	Chicago, IL	437,205	780,601	Tribune Company
10	Chicago Sun Times	Chicago, IL	419,407	421,453	Sun-Times Media Group

* *These figures compiled by the Audit Bureau of Circulations.*

Appendix M: Distribution of Articles per Time Period per Hype
(FOR OWN, MARKET AND EXPERT HYPES)

Hype	T1	T2	T3	T4	Total
Own	**435**	**484**	**1119**	**972**	**3010**
Market	**179**	**293**	**378**	**226**	**1076**
Expert *	**N/A**	**N/A**	**1775**	**974**	**2749**
Total	**614**	**777**	**2972**	**2472**	**6835**

** Generally, analyst coverage, did not begin until after the firm's IPO.*

Appendix N: Summary of Variables

	Variable Name	Description
DVs		
	NES_YN	Dichotomous variable where '1' indicates the firm missed their EPS estimate at least once in the four quarters following the IPO an '0' otherwise
	Q1_MoB	Dichotomous variable where '1' indicates the firm missed their EPS estimate in the 1st quarter following the IPO an '0' otherwise
	Q2_MoB	Dichotomous variable where '1' indicates the firm missed their EPS estimate in the 2nd quarter following the IPO an '0' otherwise
	Q3_MoB	Dichotomous variable where '1' indicates the firm missed the: EPS estimate in the 3rd quarter following the IPO an '0' otherwise
	Q4_MoB	Dichotomous variable where '1' indicates the firm missed their EPS estimate in the 4th quarter following the IPO an '0' otherwise
	NES_Misses	Represents the number of EPS estimates missed by a firm in total over the four quarters after the IPO
	Q1_NES_10_Winsor	The difference between the firm's 1st quarter actual and estimated EPS value (Winsorized)
	Q2_NES_10_Winsor	The difference between the firm's 1st quarter actual and estimated EPS value (Winsorized)
	Q3_NES_10_Winsor	The difference between the firm's 1st quarter actual and estimated EPS value (Winsorized)
	Q4_NES_10_Winsor	The difference between the firm's 1st quarter actual and estimated EPS value (Winsorized)
	SellOff_YN	Dichotomous variable where '1' indicates the firm's CEO sold some of their shares at the expiration of the lock-up period and '0' otherwise
	%_SellOff	Percentage of shares held by the CEO that were sold at the expiration of the lock-up period.

	Variable Name	Description
IVs		
	Comm_T1	Community Hype Composite Score for Time Period 1 (7-12 months prior to the IPO)
	Comm_T2	Community Hype Composite Score for Time Period 2 (0-6 months prior to the IPO)
	Comm_T3	Community Hype Composite Score for Time Period 3 (0-6 months after to the IPO)
	Comm_T4	Community Hype Composite Score for Time Period 4 (7-12 months after to the IPO)
	Market_T1	Market Hype Composite Score for Time Period 1 (7-12 months prior to the IPO)
	Market_T2	Market Hype Composite Score for Time Period 2 (0-6 months prior to the IPO)
	Market_T3	Market Hype Composite Score for Time Period 3 (0-6 months after to the IPO)
	Market_T4	Market Hype Composite Score for Time Period 4 (7-12 months after to the IPO)
	Own_T1	Own Hype Composite Score for Time Period 1 (7-12 months prior to the IPO)
	Own_T2	Own Hype Composite Score for Time Period 2 (0-6 months prior to the IPO)
	Own_T3	Own Hype Composite Score for Time Period 3 (0-6 months after to the IPO)
	Own_T4	Own Hype Composite Score for Time Period 4 (7-12 months after to the IPO)
	Expert_T3	Expert Hype Composite Score for Time Period 3 (0-6 months after to the IPO)
	Expert_T4	Expert Hype Composite Score for Time Period 4 (7-12 months after to the IPO)

	Variable Name	Description
Controls		
	Industry	Dichotomous variable where ‘1’ indicates a high-tech firm and ‘0’ otherwise
	Change_in_GDP	Quarterly change in GDP in the quarter prior to the IPO
	Deal_Size_10_Winsor	Principal amount of the IPO (Winsorized)
	Firm_Size_10_Winsor	Number of firm employees at the time of the IPO (Winsorized)
	Total_Assets_10_Winsor	Firm total assets at the time of the IPO (Winsorized)
	Underwriter_Rep	Underwriter reputation score
	VC_Backing	Dichotomous variable where ‘1’ indicates that the firm had VC support and 0 otherwise

Appendix O: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
NES_YN	126	.0	1.0	.643	.4811
NES__Misses	126	.0	4.0	1.214	1.1839
Q1_MoB	126	0	1	.29	.454
Q2_MoB	126	0	1	.25	.432
Q3_MoB	126	0	1	.33	.470
Q4_MoB	126	0	1	.36	.481
Q1_NES_10_Winsor	126	-.08	.10	.0131	.05251
Q2_NES_10_Winsor	126	-.06	.08	.0137	.04013
Q3_NES_10_Winsor	126	-.09	.08	.0028	.04507
Q4_NES_10_Winsor	126	-.06	.05	-.0006	.03221
SellOff_YN	126	0	1	.48	.501
%_SellOff	126	.0000	1.0000	.096847	.2041176
Industry	126	.0	1.0	.421	.4956
Change_in_GDP	126	-8.90	4.00	1.4856	2.15006
Deal_Size_10_Winsor	126	87.45	500.00	201.3030	132.63548
Firm_Size_10_Winsor	126	12.0	2970.0	740.333	940.1992
Total_Assets_10_Winsor	126	16618000	1678000000	393127093.52	533627753.79
Underwriter_Rep	126	1.00	9.00	7.4180	2.39551
VC_Backing	126	.0	1.0	.548	.4997
Comm_T1	126	.0000	75.3000	15.113333	18.2122095
Comm_T2	126	.0000	100.0000	25.318571	20.9294823
Comm_T3	126	.0000	83.1200	28.411270	19.4740822
Comm_T4	126	.0000	77.1500	26.130794	18.5840211
Market_T1	126	-1.4257	11.4681	.000000	2.7350108
Market_T2	126	-2.3153	10.3940	.000000	2.7901510
Market_T3	126	-2.9105	9.4037	.000000	2.6526488
Market_T4	126	-1.8154	10.8114	.000000	2.9278884
Own_T1	126	-3.1876	8.1944	.000000	3.2308497
Own_T2	126	-3.9179	7.2320	.000000	2.9801320
Own_T3	126	-4.8399	10.5648	.000000	2.3974869
Own_T4	126	-3.6071	9.0000	.000000	2.7504647
Expert_T3	126	-5.0031	4.4387	.000000	2.0781263
Expert_T4	126	-6.7234	3.8792	.000000	2.2754184
Valid N (listwise)	126				

Appendix P: Pearson Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11
1 NES_YN	1	.768**	.471**	-.301**	.426**	-.254**	.518**	-.467**	.556**	-.488**	-.251**
Sig.		.000	.000	.001	.000	.004	.000	.000	.000	.000	.005
2 NES__Misses	.768**	1	.600**	-.407**	.678**	-.536**	.606**	-.570**	.693**	-.620**	-.200*
Sig.	.000		.000	.000	.000	.000	.000	.000	.000	.000	.025
3 Q1_MoB	.471**	.600**	1	-.783**	.210*	-.178*	.086	-.110	.262**	-.137	-.005
Sig.	.000	.000		.000	.018	.047	.340	.222	.003	.126	.955
4 Q1_NES_10_Winsor	-.301**	-.407**	-.783**	1	-.132	.141	-.005	.056	-.139	.106	-.017
Sig.	.001	.000	.000		.139	.114	.951	.535	.120	.239	.851
5 Q2_MoB	.426**	.678**	.210*	-.132	1	-.754**	.272**	-.282**	.305**	-.386**	-.065
Sig.	.000	.000	.018	.139		.000	.002	.001	.001	.000	.470
6 Q2_NES_10_Winsor	-.254**	-.536**	-.178*	.141	-.754**	1	-.264**	.298**	-.215*	.333**	.070
Sig.	.004	.000	.047	.114	.000		.003	.001	.016	.000	.436
7 Q3_MoB	.518**	.606**	.086	-.005	.272**	-.264**	1	-.779**	.189*	-.247**	-.255**
Sig.	.000	.000	.340	.951	.002	.003		.000	.034	.005	.004
8 Q3_NES_10_Winsor	-.467**	-.570**	-.110	.056	-.282**	.298**	-.779**	1	-.286**	.360**	.274**
Sig.	.000	.000	.222	.535	.001	.001	.000		.001	.000	.002
9 Q4_MoB	.556**	.693**	.262**	-.139	.305**	-.215*	.189*	-.286**	1	-.808**	-.180*
Sig.	.000	.000	.003	.120	.001	.016	.034	.001		.000	.044
10 Q4_NES_10_Winsor	-.488**	-.620**	-.137	.106	-.386**	.333**	-.247**	.360**	-.808**	1	.230**
Sig.	.000	.000	.126	.239	.000	.000	.005	.000	.000		.010

	1	2	3	4	5	6	7	8	9	10	11
11 SellOff_YN	-.251**	-.200*	-.005	-.017	-.065	.070	-.255**	.274**	-.180*	.230**	1
Sig.	.005	.025	.955	.851	.470	.436	.004	.002	.044	.010	
12 %_SellOff	-.208*	-.127	-.038	.052	-.042	.054	-.138	.212*	-.103	.116	.500**
Sig.	.020	.158	.674	.563	.642	.545	.123	.017	.250	.196	.000
13 Industry	-.002	-.059	.066	-.075	-.076	.005	-.180*	.098	.036	.055	.089
Sig.	.979	.509	.462	.404	.397	.956	.044	.276	.689	.542	.322
14 Change_in_GDP	.041	.051	-.003	.019	.085	-.126	-.012	-.029	.064	-.024	-.041
Sig.	.652	.569	.971	.829	.342	.158	.892	.748	.474	.787	.649
15 Deal_Size_10_Winsor	-.002	.054	.040	-.057	-.083	.166	.104	.007	.067	-.057	-.036
Sig.	.979	.549	.660	.528	.357	.063	.245	.940	.453	.529	.690
16 Firm_Size_10_Winsor	-.187*	-.237**	-.153	.142	-.262**	.192*	-.029	.127	-.176*	.111	.151
Sig.	.036	.007	.088	.113	.003	.031	.743	.156	.049	.216	.093
17 Total_Assets_10_Winsor	-.040	-.046	-.096	.161	-.130	.143	.073	-.006	.024	-.084	-.116
Sig.	.659	.612	.283	.071	.147	.110	.415	.946	.793	.347	.194
18 Underwriter_Rep	-.104	-.146	-.102	.108	-.066	.034	-.131	.148	-.074	.036	-.014
Sig.	.246	.104	.254	.230	.465	.710	.142	.099	.409	.693	.878
19 VC_Backing	-.045	-.092	.010	-.019	-.073	.045	-.117	-.001	-.055	.183*	.292**
Sig.	.616	.307	.911	.829	.416	.617	.190	.995	.543	.040	.001
20 Comm_T1	-.027	-.074	.040	-.052	-.051	.091	-.098	.123	-.077	.125	-.123
Sig.	.763	.412	.654	.561	.569	.312	.273	.170	.390	.162	.171

		1	2	3	4	5	6	7	8	9	10	11
21 Comm_T2		.096	-.016	.072	-.045	.079	-.038	-.097	.106	-.083	.107	-.025
	Sig.	.286	.861	.422	.617	.378	.670	.280	.237	.354	.235	.779
22 Comm_T3		.102	.125	.191*	-.235**	.176*	-.157	-.044	.072	.012	-.058	-.104
	Sig.	.255	.163	.032	.008	.049	.079	.623	.425	.895	.516	.248
23 Comm_T4		-.011	.000	.027	-.023	.062	-.015	-.037	.082	-.046	.023	.020
	Sig.	.903	.997	.760	.800	.491	.870	.678	.359	.609	.796	.825
24 Market_T1		-.085	-.041	.076	-.028	-.104	.030	-.034	.060	-.045	.045	.055
	Sig.	.342	.649	.400	.759	.245	.743	.706	.502	.615	.620	.540
25 Market_T2		-.132	-.180*	-.094	.141	-.107	.090	-.120	.069	-.142	.149	.051
	Sig.	.140	.043	.294	.116	.235	.317	.179	.443	.113	.096	.569
26 Market_T3		-.081	-.049	.004	.009	-.034	-.038	-.047	-.044	-.048	.062	.180*
	Sig.	.367	.583	.969	.919	.708	.676	.599	.628	.593	.487	.044
27 Market_T4		.021	.068	.003	.094	.066	-.078	.046	-.129	.059	.012	-.040
	Sig.	.812	.451	.971	.293	.464	.383	.607	.149	.509	.896	.656
28 Own_T1		.034	-.006	-.024	.078	-.026	.031	-.086	-.074	.118	-.132	.283**
	Sig.	.706	.951	.786	.388	.769	.731	.336	.412	.189	.141	.001
29 Own_T2		-.060	-.021	-.082	.095	.047	.004	-.088	-.037	.069	-.078	.159
	Sig.	.504	.813	.359	.292	.603	.964	.328	.679	.442	.388	.076
30 Own_T3		-.145	-.031	-.076	.031	.054	-.035	-.086	.007	.032	-.100	.057
	Sig.	.104	.732	.395	.726	.550	.694	.339	.939	.725	.263	.527

	1	2	3	4	5	6	7	8	9	10	11
31 Own_T4	.038	.096	.077	-.028	.088	-.116	.040	-.046	.045	-.055	-.042
Sig.	.669	.286	.391	.758	.327	.197	.656	.609	.618	.540	.641
32 Expert_T3	-.200*	-.045	.079	-.126	.008	-.040	-.054	.067	-.141	.180*	.000
Sig.	.025	.615	.379	.159	.930	.654	.551	.453	.116	.043	.997
33 Expert_T4	-.046	.017	.040	-.137	.055	-.087	-.037	.060	-.009	-.017	-.085
Sig.	.611	.849	.655	.126	.541	.333	.685	.506	.916	.850	.345

Note 1: Sample size is 126 for all variables
Note 2: All significance values are 2-tailed
Note 3: ** Correlation is significant at the 0.01 level
Note 4: * Correlation is significant at the 0.05 level

Pearson Correlations *(Continue)*

	12	13	14	15	16	17	18	19	20	21	22
1 NES_YN	-.208*	-.002	.041	-.002	-.187*	-.040	-.104	-.045	-.027	.096	.102
Sig.	.020	.979	.652	.979	.036	.659	.246	.616	.763	.286	.255
2 NES__Misses	-.127	-.059	.051	.054	-.237**	-.046	-.146	-.092	-.074	-.016	.125
Sig.	.158	.509	.569	.549	.007	.612	.104	.307	.412	.861	.163
3 Q1_MoB	-.038	.066	-.003	.040	-.153	-.096	-.102	.010	.040	.072	.191*
Sig.	.674	.462	.971	.660	.088	.283	.254	.911	.654	.422	.032
4 Q1_NES_10_Winsor	.052	-.075	.019	-.057	.142	.161	.108	-.019	-.052	-.045	-.235**
Sig.	.563	.404	.829	.528	.113	.071	.230	.829	.561	.617	.008
5 Q2_MoB	-.042	-.076	.085	-.083	-.262**	-.130	-.066	-.073	-.051	.079	.176*
Sig.	.642	.397	.342	.357	.003	.147	.465	.416	.569	.378	.049
6 Q2_NES_10_Winsor	.054	.005	-.126	.166	.192*	.143	.034	.045	.091	-.038	-.157
Sig.	.545	.956	.158	.063	.031	.110	.710	.617	.312	.670	.079
7 Q3_MoB	-.138	-.180*	-.012	.104	-.029	.073	-.131	-.117	-.098	-.097	-.044
Sig.	.123	.044	.892	.245	.743	.415	.142	.190	.273	.280	.623
8 Q3_NES_10_Winsor	.212*	.098	-.029	.007	.127	-.006	.148	-.001	.123	.106	.072
Sig.	.017	.276	.748	.940	.156	.946	.099	.995	.170	.237	.425
9 Q4_MoB	-.103	.036	.064	.067	-.176*	.024	-.074	-.055	-.077	-.083	.012
Sig.	.250	.689	.474	.453	.049	.793	.409	.543	.390	.354	.895
10 Q4_NES_10_Winsor	.116	.055	-.024	-.057	.111	-.084	.036	.183*	.125	.107	-.058
Sig.	.196	.542	.787	.529	.216	.347	.693	.040	.162	.235	.516

	12	13	14	15	16	17	18	19	20	21	22
11 SellOff_YN	.500**	.089	-.041	-.036	.151	-.116	-.014	.292**	-.123	-.025	-.104
Sig.	.000	.322	.649	.690	.093	.194	.878	.001	.171	.779	.248
12 %_SellOff	1	.026	-.032	.109	.245**	.112	.055	-.108	.041	-.040	-.005
Sig.		.776	.719	.226	.006	.213	.537	.230	.645	.654	.952
13 Industry	.026	1	-.038	-.115	-.016	-.044	-.015	.484**	.139	.248**	.138
Sig.	.776		.673	.200	.863	.627	.871	.000	.121	.005	.122
14 Change_in_GDP	-.032	-.038	1	-.150	-.191*	-.074	-.052	-.085	-.144	-.058	-.065
Sig.	.719	.673		.093	.033	.410	.566	.345	.107	.519	.471
15 Deal_Size_10_Winsor	.109	-.115	-.150	1	.514**	.646**	.187*	-.340**	-.016	-.105	.004
Sig.	.226	.200	.093		.000	.000	.036	.000	.862	.241	.968
16 Firm_Size_10_Winsor	.245**	-.016	-.191*	.514**	1	.523**	.225*	-.027	.003	-.008	-.147
Sig.	.006	.863	.033	.000		.000	.011	.763	.969	.929	.100
17 Total_Assets_10_Winsor	.112	-.044	-.074	.646**	.523**	1	.165	-.316**	.058	-.048	-.003
Sig.	.213	.627	.410	.000	.000		.065	.000	.521	.596	.975
18 Underwriter_Rep	.055	-.015	-.052	.187*	.225*	.165	1	.014	.230**	.135	.018
Sig.	.537	.871	.566	.036	.011	.065		.874	.010	.132	.844
19 VC_Backing	-.108	.484**	-.085	-.340**	-.027	-.316**	.014	1	.118	.150	-.113
Sig.	.230	.000	.345	.000	.763	.000	.874		.190	.094	.208
20 Comm_T1	.041	.139	-.144	-.016	.003	.058	.230**	.118	1	.558**	.522**
Sig.	.645	.121	.107	.862	.969	.521	.010	.190		.000	.000

	12	13	14	15	16	17	18	19	20	21	22
21 Comm_T2	-.040	.248**	-.058	-.105	-.008	-.048	.135	.150	.558**	1	.517**
Sig.	.654	.005	.519	.241	.929	.596	.132	.094	.000		.000
22 Comm_T3	-.005	.138	-.065	.004	-.147	-.003	.018	-.113	.522**	.517**	1
Sig.	.952	.122	.471	.968	.100	.975	.844	.208	.000	.000	
23 Comm_T4	.094	.042	-.039	-.028	-.107	-.023	-.008	-.074	.549**	.464**	.791**
Sig.	.295	.643	.666	.753	.234	.802	.933	.408	.000	.000	.000
24 Market_T1	.131	.145	.021	.419**	.334**	.337**	.117	-.039	-.011	-.019	-.017
Sig.	.142	.104	.813	.000	.000	.000	.192	.662	.902	.833	.853
25 Market_T2	.004	.272**	-.223*	.351**	.290**	.213*	.047	.109	.063	.093	-.034
Sig.	.968	.002	.012	.000	.001	.017	.600	.224	.482	.298	.709
26 Market_T3	.251**	.281**	-.175*	.201*	.154	.127	.067	.127	-.024	.004	-.097
Sig.	.005	.001	.050	.024	.085	.156	.455	.155	.793	.962	.281
27 Market_T4	.044	.235**	.062	.160	.185*	.181*	-.037	.131	-.024	.031	-.052
Sig.	.621	.008	.493	.073	.038	.042	.677	.145	.788	.728	.560
28 Own_T1	.109	.378**	.046	.065	.160	.128	.038	.286**	-.081	-.061	-.147
Sig.	.226	.000	.608	.469	.074	.155	.676	.001	.368	.496	.100
29 Own_T2	.072	.180*	.129	.206*	.088	.159	.056	.168	.038	.038	-.070
Sig.	.422	.043	.150	.021	.325	.075	.535	.060	.670	.669	.435
30 Own_T3	.072	.099	-.038	.327**	.154	.297**	.075	-.089	-.064	-.136	-.099
Sig.	.421	.269	.674	.000	.085	.001	.407	.322	.479	.129	.268

	12	13	14	15	16	17	18	19	20	21	22
31 Own_T4	.002	.053	.098	.319**	.123	.355**	.134	-.181*	-.136	-.030	.025
Sig.	.979	.559	.273	.000	.168	.000	.135	.043	.128	.738	.784
32 Expert_T3	.066	-.133	-.016	.033	.060	-.020	.035	-.081	-.027	.012	.056
Sig.	.464	.139	.860	.718	.507	.823	.697	.366	.765	.893	.534
33 Expert_T4	.098	-.045	.059	.109	.134	.108	.019	-.093	-.059	-.056	.071
Sig.	.276	.614	.509	.225	.134	.230	.832	.303	.514	.531	.432

Note 1: Sample size is 126 for all variables
Note 2: All significance values are 2-tailed
Note 3: ** Correlation is significant at the 0.01 level
Note 4: * Correlation is significant at the 0.05 level

Pearson Correlations *(Continue)*

	23	24	25	26	27	28	29	30	31	32	33
1 NES_YN	-.011	-.085	-.132	-.081	.021	.034	-.060	-.145	.038	-.200*	-.046
Sig.	.903	.342	.140	.367	.812	.706	.504	.104	.669	.025	.611
2 NES__Misses	.000	-.041	-.180*	-.049	.068	-.006	-.021	-.031	.096	-.045	.017
Sig.	.997	.649	.043	.583	.451	.951	.813	.732	.286	.615	.849
3 Q1_MoB	.027	.076	-.094	.004	.003	-.024	-.082	-.076	.077	.079	.040
Sig.	.760	.400	.294	.969	.971	.786	.359	.395	.391	.379	.655
4 Q1_NES_10_Winsor	-.023	-.028	.141	.009	.094	.078	.095	.031	-.028	-.126	-.137
Sig.	.800	.759	.116	.919	.293	.388	.292	.726	.758	.159	.126
5 Q2_MoB	.062	-.104	-.107	-.034	.066	-.026	.047	.054	.088	.008	.055
Sig.	.491	.245	.235	.708	.464	.769	.603	.550	.327	.930	.541
6 Q2_NES_10_Winsor	-.015	.030	.090	-.038	-.078	.031	.004	-.035	-.116	-.040	-.087
Sig.	.870	.743	.317	.676	.383	.731	.964	.694	.197	.654	.333
7 Q3_MoB	-.037	-.034	-.120	-.047	.046	-.086	-.088	-.086	.040	-.054	-.037
Sig.	.678	.706	.179	.599	.607	.336	.328	.339	.656	.551	.685
8 Q3_NES_10_Winsor	.082	.060	.069	-.044	-.129	-.074	-.037	.007	-.046	.067	.060
Sig.	.359	.502	.443	.628	.149	.412	.679	.939	.609	.453	.506
9 Q4_MoB	-.046	-.045	-.142	-.048	.059	.118	.069	.032	.045	-.141	-.009
Sig.	.609	.615	.113	.593	.509	.189	.442	.725	.618	.116	.916
10 Q4_NES_10_Winsor	.023	.045	.149	.062	.012	-.132	-.078	-.100	-.055	.180*	-.017
Sig.	.796	.620	.096	.487	.896	.141	.388	.263	.540	.043	.850

	23	24	25	26	27	28	29	30	31	32	33
11 SellOff_YN	.020	.055	.051	.180*	-.040	.283**	.159	.057	-.042	.000	-.085
Sig.	.825	.540	.569	.044	.656	.001	.076	.527	.641	.997	.345
12 %_SellOff	.094	.131	.004	.251**	.044	.109	.072	.072	.002	.066	.098
Sig.	.295	.142	.968	.005	.621	.226	.422	.421	.979	.464	.276
13 Industry	.042	.145	.272**	.281**	.235**	.378**	.180*	.099	.053	-.133	-.045
Sig.	.643	.104	.002	.001	.008	.000	.043	.269	.559	.139	.614
14 Change_in_GDP	-.039	.021	-.223*	-.175*	.062	.046	.129	-.038	.098	-.016	.059
Sig.	.666	.813	.012	.050	.493	.608	.150	.674	.273	.860	.509
15 Deal_Size_10_Winsor	-.028	.419**	.351**	.201*	.160	.065	.206*	.327**	.319**	.033	.109
Sig.	.753	.000	.000	.024	.073	.469	.021	.000	.000	.718	.225
16 Firm_Size_10_Winsor	-.107	.334**	.290**	.154	.185*	.160	.088	.154	.123	.060	.134
Sig.	.234	.000	.001	.085	.038	.074	.325	.085	.168	.507	.134
17 Total_Assets_10_Winsor	-.023	.337**	.213*	.127	.181*	.128	.159	.297**	.355**	-.020	.108
Sig.	.802	.000	.017	.156	.042	.155	.075	.001	.000	.823	.230
18 Underwriter_Rep	-.008	.117	.047	.067	-.037	.038	.056	.075	.134	.035	.019
Sig.	.933	.192	.600	.455	.677	.676	.535	.407	.135	.697	.832
19 VC_Backing	-.074	-.039	.109	.127	.131	.286**	.168	-.089	-.181*	-.081	-.093
Sig.	.408	.662	.224	.155	.145	.001	.060	.322	.043	.366	.303
20 Comm_T1	.549**	-.011	.063	-.024	-.024	-.081	.038	-.064	-.136	-.027	-.059
Sig.	.000	.902	.482	.793	.788	.368	.670	.479	.128	.765	.514

		23	24	25	26	27	28	29	30	31	32	33
21 Comm_T2		.464**	-.019	.093	.004	.031	-.061	.038	-.136	-.030	.012	-.056
	Sig.	.000	.833	.298	.962	.728	.496	.669	.129	.738	.893	.531
22 Comm_T3		.791**	-.017	-.034	-.097	-.052	-.147	-.070	-.099	.025	.056	.071
	Sig.	.000	.853	.709	.281	.560	.100	.435	.268	.784	.534	.432
23 Comm_T4		1	-.060	-.068	-.152	-.069	-.111	-.051	-.143	-.088	.021	-.022
	Sig.		.504	.448	.089	.443	.214	.567	.109	.328	.814	.808
24 Market_T1		-.060	1	.576**	.464**	.400**	.303**	.230**	.219*	.223*	-.066	.081
	Sig.	.504		.000	.000	.000	.001	.010	.014	.012	.460	.369
25 Market_T2		-.068	.576**	1	.618**	.416**	.377**	.268**	.236**	.217*	-.014	.012
	Sig.	.448	.000		.000	.000	.000	.002	.008	.015	.876	.891
26 Market_T3		-.152	.464**	.618**	1	.512**	.330**	.227*	.237**	.229**	-.093	-.038
	Sig.	.089	.000	.000		.000	.000	.011	.007	.010	.300	.676
27 Market_T4		-.069	.400**	.416**	.512**	1	.254**	.205*	.177*	.273**	.046	.011
	Sig.	.443	.000	.000	.000		.004	.021	.047	.002	.612	.906
28 Own_T1		-.111	.303**	.377**	.330**	.254**	1	.556**	.297**	.314**	-.081	-.101
	Sig.	.214	.001	.000	.000	.004		.000	.001	.000	.368	.261
29 Own_T2		-.051	.230**	.268**	.227*	.205*	.556**	1	.649**	.346**	-.040	-.046
	Sig.	.567	.010	.002	.011	.021	.000		.000	.000	.655	.613
30 Own_T3		-.143	.219*	.236**	.237**	.177*	.297**	.649**	1	.444**	-.029	-.004
	Sig.	.109	.014	.008	.007	.047	.001	.000		.000	.749	.967

	23	24	25	26	27	28	29	30	31	32	33
31 Own_T4	-.088	.223*	.217*	.229**	.273**	.314**	.346**	.444**	1	.109	.013
Sig.	.328	.012	.015	.010	.002	.000	.000	.000		.226	.883
32 Expert_T3	.021	-.066	-.014	-.093	.046	-.081	-.040	-.029	.109	1	.577**
Sig.	.814	.460	.876	.300	.612	.368	.655	.749	.226		.000
33 Expert_T4	-.022	.081	.012	-.038	.011	-.101	-.046	-.004	.013	.577**	1
Sig.	.808	.369	.891	.676	.906	.261	.613	.967	.883	.000	

Note 1: Sample size is 126 for all variables
Note 2: All significance values are 2-tailed
Note 3: ** Correlation is significant at the 0.01 level
Note 4: * Correlation is significant at the 0.05 level

Appendix Q: Key Dependent and Independent Pearson Correlations

Key Independent to Independent Pearson Correlations:

Variable 1	***Variable 2***	***Pearson Correlation***
Comm_T1	Comm_T2	.558 **
	Comm_T3	.522 **
	Comm_T4	.549 **
	Market_T1	-.011
	Market_T2	.063
	Market_T3	-.024
	Market_T4	-.024
	Own_T1	-.081
	Own_T2	.038
	Own_T3	-.064
	Own_T4	-.136
	Expert_T3	-.027
	Expert_T4	-.059
Comm_T2	Comm_T3	.517 **
	Comm_T4	.464 **
	Market_T1	-.019
	Market_T2	.093
	Market_T3	.004
	Market_T4	.031
	Own_T1	-.061
	Own_T2	.038
	Own_T3	-.136
	Own_T4	-.030
	Expert_T3	.012
	Expert_T4	-.056

Comm_T3	Comm_T4	.791 **
	Market_T1	-.017
	Market_T2	-.034
	Market_T3	-.097
	Market_T4	-.052
	Own_T1	-.147
	Own_T2	-.070
	Own_T3	-.099
	Own_T4	.025
	Expert_T3	.056
	Expert_T4	.071
Comm_T4	Market_T1	-.060
	Market_T2	-.068
	Market_T3	-.152
	Market_T4	-.069
	Own_T1	-.111
	Own_T2	-.051
	Own_T3	-.143
	Own_T4	-.088
	Expert_T3	.021
	Expert_T4	-.022
Market_T1	Market_T2	.576 **
	Market_T3	.464 **
	Market_T4	.400 **
	Own_T1	.303 **
	Own_T2	.230 **
	Own_T3	.219 *

	Own_T4	.223 *
	Expert_T3	-.066
	Expert_T4	.081
Market_T2	Market_T3	.618 **
	Market_T4	.416 **
	Own_T1	.377 **
	Own_T2	.268 **
	Own_T3	.236 **
	Own_T4	.217 *
	Expert_T3	-.014
	Expert_T4	.012
Market_T3	Market_T4	.512 **
	Own_T1	.330 **
	Own_T2	.227 *
	Own_T3	.237 **
	Own_T4	.229 **
	Expert_T3	-.093
	Expert_T4	-.038
Market_T4	Own_T1	.254 **
	Own_T2	.205 *
	Own_T3	.177 *
	Own_T4	.273 **
	Expert_T3	.046
	Expert_T4	.011
Own_T1	Own_T2	.556 **
	Own_T3	.297 **
	Own_T4	.314 **

	Expert_T3	-.081
	Expert_T4	-.101
Own_T2	Own_T3	.649 **
	Own_T4	.346 **
	Expert_T3	-.040
	Expert_T4	-.046
Own_T3	Own_T4	.444 **
	Expert_T3	-.029
	Expert_T4	-.004
Own_T4	Expert_T3	.109
	Expert_T4	.013
Expert_T3	Expert_T4	.577 **

Note 1: Sample size is 126 for all variables
Note 2: All significance values are 2-tailed
Note 3: ** Correlation is significant at the 0.01 level
Note 4: * Correlation is significant at the 0.05 level

Key Independent to Dependent Pearson Correlations:

Variable 1	***Variable 2***	***Pearson Correlation***
Comm_T1	NES_YN	-.027
	NES_Misses	-.072
	Q1_MoB	.040
	Q2_MoB	-.051
	Q3_MoB	-.098
	Q4_MoB	-.077
	Q1_NES_10_Winsor	-.052
	Q2_NES_10_Winsor	.091
	Q3_NES_10_Winsor	.123
	Q4_NES_10_Winsor	.125
	SellOff_YN	-.123
	%_SelOff	.041
Comm_T2	NES_YN	.096
	NES_Misses	-.016
	Q1_MoB	.072
	Q2_MoB	.079
	Q3_MoB	-.097
	Q4_MoB	-.083
	Q1_NES_10_Winsor	-.045
	Q2_NES_10_Winsor	-.038
	Q3_NES_10_Winsor	.106
	Q4_NES_10_Winsor	.107
	SellOff_YN	-.025
	%_SelOff	-.040
Comm_T3	NES_YN	.102
	NES_Misses	.125

	Q1_MoB	.191 *
	Q2_MoB	.176 *
	Q3_MoB	-.044
	Q4_MoB	.012
	Q1_NES_10_Winsor	-.235 **
	Q2_NES_10_Winsor	-.157
	Q3_NES_10_Winsor	.072
	Q4_NES_10_Winsor	-.058
	SellOff_YN	-.104
	%_SelOff	-.005
Comm_T4	NES_YN	-.011
	NES_Misses	.000
	Q1_MoB	.027
	Q2_MoB	.062
	Q3_MoB	-.037
	Q4_MoB	-.046
	Q1_NES_10_Winsor	-.023
	Q2_NES_10_Winsor	-.015
	Q3_NES_10_Winsor	.082
	Q4_NES_10_Winsor	.023
	SellOff_YN	.020
	%_SelOff	.094
Market_T1	NES_YN	-.085
	NES_Misses	-.041
	Q1_MoB	.076
	Q2_MoB	-.104
	Q3_MoB	-.034

	Q4_MoB	-.045
	Q1_NES_10_Winsor	-.028
	Q2_NES_10_Winsor	.030
	Q3_NES_10_Winsor	.060
	Q4_NES_10_Winsor	.045
	SellOff_YN	.055
	%_SelOff	.131
Market_T2	NES_YN	-.132
	NES_Misses	-.180 *
	Q1_MoB	-.094
	Q2_MoB	-.107
	Q3_MoB	-.120
	Q4_MoB	-.142
	Q1_NES_10_Winsor	.141
	Q2_NES_10_Winsor	.090
	Q3_NES_10_Winsor	.069
	Q4_NES_10_Winsor	.149
	SellOff_YN	.051
	%_SelOff	.004
Market_T3	NES_YN	-.081
	NES_Misses	-.049
	Q1_MoB	.004
	Q2_MoB	-.034
	Q3_MoB	-.047
	Q4_MoB	-.048
	Q1_NES_10_Winsor	.009
	Q2_NES_10_Winsor	-.038

	Q3_NES_10_Winsor	-.044
	Q4_NES_10_Winsor	.062
	SellOff_YN	.180 *
	%_SelOff	.251 **
Market_T4	NES_YN	.021
	NES_Misses	.068
	Q1_MoB	.003
	Q2_MoB	.066
	Q3_MoB	.046
	Q4_MoB	.059
	Q1_NES_10_Winsor	.094
	Q2_NES_10_Winsor	-.078
	Q3_NES_10_Winsor	-.129
	Q4_NES_10_Winsor	.012
	SellOff_YN	-.040
	%_SelOff	.044
Own_T1	NES_YN	.034
	NES_Misses	-.006
	Q1_MoB	-.024
	Q2_MoB	-.026
	Q3_MoB	-.086
	Q4_MoB	.118
	Q1_NES_10_Winsor	.078
	Q2_NES_10_Winsor	.031
	Q3_NES_10_Winsor	-.074
	Q4_NES_10_Winsor	-.132
	SellOff_YN	.238 **

	%_SelOff	.109
Own_T2	NES_YN	-.145
	NES_Misses	-.031
	Q1_MoB	-.076
	Q2_MoB	.054
	Q3_MoB	-.086
	Q4_MoB	.032
	Q1_NES_10_Winsor	.031
	Q2_NES_10_Winsor	-.035
	Q3_NES_10_Winsor	.007
	Q4_NES_10_Winsor	-.100
	SellOff_YN	.057
	%_SelOff	.072
Own_T3	NES_YN	.038
	NES_Misses	.096
	Q1_MoB	.077
	Q2_MoB	.088
	Q3_MoB	.040
	Q4_MoB	.045
	Q1_NES_10_Winsor	-.028
	Q2_NES_10_Winsor	-.116
	Q3_NES_10_Winsor	-.046
	Q4_NES_10_Winsor	-.055
	SellOff_YN	-.042
	%_SelOff	.002
Own_T4	NES_YN	.038
	NES_Misses	.096

	Q1_MoB	.077
	Q2_MoB	.088
	Q3_MoB	.040
	Q4_MoB	.045
	Q1_NES_10_Winsor	-.028
	Q2_NES_10_Winsor	-.116
	Q3_NES_10_Winsor	-.046
	Q4_NES_10_Winsor	-.055
	SellOff_YN	-.042
	%_SelOff	.002
Expert_T3	NES_YN	-.200 *
	NES_Misses	-.045
	Q1_MoB	.079
	Q2_MoB	.008
	Q3_MoB	-.054
	Q4_MoB	-.141
	Q1_NES_10_Winsor	-.126
	Q2_NES_10_Winsor	-.040
	Q3_NES_10_Winsor	.067
	Q4_NES_10_Winsor	.180 *
	SellOff_YN	.000
	%_SelOff	.066
Expert_T4	NES_YN	-.046
	NES_Misses	.017
	Q1_MoB	.040
	Q2_MoB	.055
	Q3_MoB	-.037

	Q4_MoB	-.009
	Q1_NES_10_Winsor	-.137
	Q2_NES_10_Winsor	-.087
	Q3_NES_10_Winsor	.060
	Q4_NES_10_Winsor	-.017
	SellOff_YN	-.085
	%_SelOff	.098

Note 1: Sample size is 126 for all variables
Note 2: All significance values are 2-tailed
Note 3: ** Correlation is significant at the 0.01 level
Note 4: * Correlation is significant at the 0.05 level

Appendix R: Summary of Regression Results

Model	Hypothesis Tested	Dependent Variable	Significance	Strength of Relationship	Direction of Relationship	Meaning of Relationship
1 Logistic Regression	Hypothesis 1a: Do firms misses EPS estimates in any of the 4 Quarters after the IPO	NES_YN	Omnibus Model Test	$p = .022$		
			Comm_T2	$p < .10$	Positive	Higher likelihood of Over Confidence
			Comm_T4	$p < .05$	Negative	Lower Likelihood of Over Confidence
			Market_T4	$p < .10$	Positive	Higher likelihood of Over Confidence
			Own_T1	$p < .05$	Positive	Higher likelihood of Over Confidence
			Expert_T3	$p < .01$	Negative	Lower likelihood of Over Confidence
			Expert_T4	$p < .10$	Positive	Higher likelihood of Over Confidence
2 Logistic Regression	Hypothesis 1b: Do firms miss EPS estimates in the 1st quarter after the IPO?	Q1_MoB	Omnibus Model Test	$p = .091$		
			Market_T1	$p < .05$	Positive	Higher likelihood of Over Confidence
			Market_T2	$p < .05$	Negative	Lower likelihood of Over Confidence
3 Logistic Regression	Hypothesis 1b: Do firms miss EPS estimates in the 2nd quarter after the IPO?	Q2_MoB	Omnibus Model Test	$p = .127$		
			Comm_T3	$p < .10$	Positive	Higher likelihood of Over Confidence

4 Logistic Regression	Hypothesis 1b: Do firms miss EPS estimates in the 3rd quarter after the IPO?	Q3_MoB	Omnibus Model Test	$p = .151$		
5 Logistic Regression	Hypothesis 1b: Do firms miss EPS estimates in the 4th quarter after the IPO?	Q4_MoB	Omnibus Model Test	$p = .014$		
			Own_T1	$p < .05$	Positive	Higher likelihood of Over Confidence
			Expert_T3	$p < .05$	Negative	Lower likelihood of Over Confidence
6 OLS Regression	Hypothesis 2: How often do firms miss EPS estimates in total over the four quarters after the IPO?	NES_Misses	Model Sig	$p = .049$		
			Comm_T3	$p < .10$	Positive	Higher likelihood of Over Confidence
			Comm_T4	$p < .10$	Negative	Lower likelihood of Over Confidence
			Market_T2	$p < .01$	Negative	Lower likelihood of Over Confidence
			Market_T4	$p < .10$	Positive	Higher likelihood of Over Confidence
			Own_T1	$p < .10$	Positive	Higher likelihood of Over Confidence
7 OLS Regression	Hypothesis 3: By how much firms miss in the 1st quarter after the IPO?	Q1_NES_10_Winsor	Model Sig	$p = .020$		
			Market_T1	$p < .05$	Negative	Higher likelihood of Over Confidence
			Market_T2	$p < .01$	Positive	Lower likelihood of Over Confidence

8 OLS Regression	Hypothesis 3: By how much firms miss in the 2nd quarter after the IPO?	Q2_NES_10_Winsor	Model Sig	p = .212		
			Comm_T1	p < .05	Positive	Lower likelihood of Over Confidence
			Comm_T3	p < .05	Negative	Higher likelihood of Over Confidence
9 OLS Regression	Hypothesis 3: By how much firms miss in the 3rd quarter after the IPO?	Q3_NES_10_Winsor	Model Sig	p = .195		
10 OLS Regression	Hypothesis 3: By how much firms miss in the 4th quarter after the IPO?	Q4_NES_10_Winsor	Model Sig	p = .001		
			Own_T1	p < .05	Negative	Higher likelihood of Over Confidence
			Expert_T3	p < .01	Positive	Lower likelihood of Over Confidence
			Expert_T4	p < .10	Negative	Higher likelihood of Over Confidence
11 Logistic Regression	Hypothesis 4: Do CEOs sell-off any of the holdings at the expiration of the lock-up period?	SellOff_YN	Omnibus Model Test	p = .010		
			Market_T2	p < .10	Negative	Lower likelihood of Over Confidence
			Market_T3	p < .05	Positive	Higher likelihood of Over Confidence
			Own_T1	p < .05	Positive	Higher likelihood of Over Confidence
12 OLS Regression	Hypothesis 5: How much of their holdings do CEOs sell-off at the expiration of the lock-up period?	%_SellOff	Model Sig	p = .026		
			Market_T2	p < .01	Negative	Higher level of Over Confidence
			Market_T3	p < .01	Positive	Lower level of Over Confidence