SOCIAL MEDIA INFLUENCE ON FIRMS' MARKET PERFORMANCE: THROUGH THE LENS OF EXPERTS' OPINION AND WISDOM OF THE CROWD

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Drawing on social influence theory, I examine the dynamics of social media impact in influencing *firm market performance* in the context of financial analyst recommendations. I show that *consistency* between multiple social influences as a process of frame alignment guides investor behavior. Through an event study, using social media data collected on Twitter consisting of S&P 500 firms from 2010 to 2015, I find that consistency between social media sentiment and analyst recommendations is significantly associated with firm market performance. In addition, a *positivity bias* of social media valance and social media sentiment polarity moderate consistency's influence on firm market performance. I conclude by discussing the need for integrating consistency and positivity bias effects of social media into the evaluation of social media influence. This study demonstrates that combining analyst expert opinions and the wisdom of the crowd provides a more nuanced view of social media influence on firm market performance.

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PREFACE

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1. INTRODUCTION

"We are like islands in the sea, separate on the surface but connected in the deep."
- William James, American philosopher and psychologist

Social media, as an important component of the social world, has penetrated every aspect of life and business during the past decade (Kaplan & Haenlein, 2010). Under the social media guidelines formulated by the U.S. Securities and Exchange Commission (SEC, 2013), firms have increasingly adopted social media platforms as important outlets to disclose information, in attempts to influence stakeholders such as market observers as well as collecting their information.[1] With a high degree of social interactivity, social media affects firms' sales revenues (Stephen & Galak, 2012), enables collective innovation through engaging consumer crowds (Kozinets et al., 2010), and energizes dynamic stakeholder activity (Kim & Youm, 2014). Moreover, a firm's engagement with individuals on social media impacts its reputation and attractiveness to investors (Cade, 2016).

Research has recognized the relevance of social media to firm market performance since investors are motivated to seek social media information to assess first-hand customer information to overcome information asymmetry (Luo, Zhang & Duan, 2013). People are increasingly relying on the digitized, aggregated opinions of others to make decisions (Muchnik, Aral & Taylor, 2013). Given the enormous traffic on social media and the noise it generates, the need for proper filtering

[1] As of 2015, among the Fortune 500 companies, 82% have corporate Facebook pages, and 79% have official Twitter accounts (Barnes & Lescault, 2016).

and analyzing social media information becomes pivotal (Kietzmann et al., 2011). An increasing body of social media research across disciplines has focused on examining the relationship between social media sentiment and firm market performance (i.e. Bollen & Mao, 2011; Zhang, Fuehres & Gloor, 2011; Baik et al., 2015). Despite the growing interest in social media research, most research studied social media impact in isolation and failed to account for information complexity when examining social media effects. Particularly from an investors' perspective, we know surprisingly little about how investors utilize social media information, combine it with information from other channels, and make investment decisions that influence firm market performance.

The focus of this study is to explore the effect of the interplay between social media and other market information on a firm's market performance. In contrast to existing social media studies that emphasize examining the isolated impact of social media, this work investigates how social media information influences firm market performance by its interaction with financial analyst recommendations. Specifically, this paper addresses three research questions: In the event of analyst recommendation announcements: (1) what is the effect of sentiment consistency between social media and analyst recommendation on firm market performance; (2) what is the moderating effect of positive/negative sentiment on the consistency effect on firm market performance; (3) what is the moderating effect of sentiment polarity on the consistency effect on firm market performance?

Social media information, characterized by user-generated content, has been viewed as "collaborative knowledge" (Niederer & Dijck, 2010). Compared with traditional information venues initiated by the firms, user-generated content has the advantage in matching customers with their preferences (Chen & Xia, 2008). As a "word-of-mouth" channel, social media enables investors to effectively scrutinize customer satisfaction and timely update their prospects for a firm's future performance (Anderson, Fornell & Mazvancheryl, 2004). Social media sentiment representing peer opinions is playing a greater role in the financial market because more and more investors resort to social media for investment advice (Cogent Research 2008). Specifically, sentiment captures the wisdom of the crowds, enabling investors with a timely update on firms' future prospects (Luo, Zhang & Duan, 2013). Facilitating multi-directional interactions among users and providing instant feedbacks, sentiments on social media serve as a reflection of "wisdom of the crowd" (Chen et al., 2014).

Drawing from social influence theory, social media sentiment can be conceptualized as the collective emotions expressed by the users of a social media platform toward a focal firm's stock and can serve as the *wisdom of the crowd;* while analyst recommendations, an analyst's expression of whether to buy, hold or sell a stock, serves as an *expert opinion*. Investors with the goal of accuracy are motivated to correctly interpret and react to incoming information from multiple information sources (Gialdini & Goldstein, 2004). Investors compare expert opinions with the wisdom of the crowd, and this comparison mechanism adopted by investors for information processing reveals the unique value of social media as an important informational and normative reference in influencing firm market performance. To infer a deeper understanding of the role of conformity on investor behavior, this work further investigates the moderating effect of positive and negative valence (i.e., emotional strength) of social media sentiment and the effect of polarity on sentiment consistency. This study proposes that a positivity bias exists in social media's influence on firm market performance, and sentiment consistency is most valuable when social media sentiment is highly polarized.

This work aims to make several contributions to existing work in this domain. First, by introducing the comparison mechanism through sentiment consistency, social influence theory is extended to incorporate how multiple influences interact to jointly affect investor behavior and thus impact firm market performance. Through theorizing on multiple social influences on investors and expounding the composite effect of expert opinion and the wisdom of the crowds on investors, this study advances our understanding of how investors' behaviors lead to firms' market performance. Few studies exist to investigate multiple social influences and even less research explore the interactions between influences. I propose that analyst recommendations provide rational advice for guiding investment decisions, while the collective social media sentiment provides an indicative social norm with value judgments to investors. Incorporating both factors provides a more holistic view of stock market reaction that combines rationality (Simon, 1978) with "subjective validity" (Festinger, 1950).

Second, examining social media's impact in the event of analyst recommendation announcements, this study distinguishes the stand-alone effect of social media with effects originating from other market information. It demonstrates that even when other important market information is considered, a social media effect is still significant. It elicits the answer to the social media value question: whether social media information is noise, repetition of existing information, or new information. Additionally, previous research regarding social media sentiment on firms' stock market performance has produced mixed results. Das & Chen (2007) found that although social media sentiment is associated with a stock market index, sentiment has no impact on an individual firms' stock. Although social media sentiment being found to be a significant predictor of firms' future market performance (i.e. Bollen & Mao, 2011; Zhang, Fuehres & Gloor, 2011; Baik et al., 2015), without controlling for concurrent market information makes these results untenable. Controlling for the confounding information from major firm announcements and integrating information from financial analyst recommendations, this study restores a realistic picture of social media's effect on firm market performance.

Third, examining the moderation effect of valence, this study investigates the positivity bias that exists in certain conditions, in order to reconcile the seeming conflict between the literature in Psychology on positivity bias (Heider, 1976; Karlsson, Loewenstein & Seppi, 2009; Mezulis et al., 2004) and asymmetric preference toward negative information in Economics (Kahneman & Tversky, 1979).

Fourth, by incorporating social media sentiment into a firm level analysis, this study empowers a micro-level explanation of firm market performance. In recent years, rather than relying purely on a market efficiency mechanism, management research on firms' market value benefits from exploring prevailing logic in the social construction of market value (Zajac and Westphal, 2004). Factors such as emotion and moods have been identified as important social contexts that exert influence on investors (Hirshleifer & Shumway, 2003). Investigating the multiple social influences on investors, this study reveals that a firm's market value is also influenced by social logic and the degree of the interaction between social influences. It adds information richness to a firm's value creation from an investor's perspective. Thus this paper provides a good example of how individual-level factors impact an organization (Fellin, Foss & Ployhart, 2015).

Practically, it is important for firms to understand the mechanism of social media's influence on investors that leads to firm performance. Without considering concurrent market information, social media influence on firm performance may be over or underestimated. To better allocate resources and develop effective strategic initiatives that manage various stakeholder dynamics, it is essential to assess social media's relative effect size.

The following sections discuss the theoretical foundations linking the two types of social influence toward investors: social media sentiment and analyst stock recommendations. Hypotheses will be developed to build support for their interplay depicting how consistency between social media sentiment and analyst recommendation affect firms market performance, demonstrate how positive/negative valence of social media sentiment moderates the consistency effect differently, and examine how polarity of social media sentiment moderates the consistency effect.

2. THEORY AND HYPOTHESES DEVELOPMENT

2.1 Theory

Building on social influence literature, I discuss the theoretical foundations linking two types of social influence toward investors: analyst stock recommendations and social media sentiment. Then, I develop my hypotheses that build support for their interplay depicting how consistency between analyst recommendations and social media sentiment affect firm market performance. Additionally, I explore how positive/negative valence of social media sentiment moderates the consistency effect differently and how the polarity of sentiments on social media moderates the consistency effect.

The theoretical model is depicted in Figure 1.

Insert Figure 1 here

Social influence involves the processes where people directly or indirectly influence the thoughts, feelings, and actions of others (Moscovici, 1976; Turner, 1991). During the social information process, people use information on values, norms, expectations, and behavior outcomes gathered in their social environment to guide behavior (Salancik & Pfeffer, 1978). The structural theory of social influence also suggests that people's attitudes and behavior can change endogenously through the influence of others (Friedkin, 1998). Such influence can be generated from power, prestige, authority, material resources, and information (Turner, 1991: p82). Influences can be either a real or imagined pressure to change one's behavior, attitudes or beliefs (Alcock, Carment, & Sadava, 1991). Researchers often manipulated social influence as the prior knowledge towards others' opinions and choices (Pitesa & Thau, 2013).

Socially dependent individuals are subject to informational and normative influences whereby people accept information from others as trustworthy evidence of objective and subjective validity (Deutsch & Gerard, 1955; Festinger, 1950). Investors are socially dependent such that they are subjected to dual pressures: informational influence, where they seek for evidence about objective reality, and from normative influence, where they comply with the expectations of others and they are concerned with the consequences of actions (Turner, 1991). Both informational and normative influences reflect investors' social dependence on others. Therefore, underlying social influences toward investors is crucial in explaining investor behaviors and sequentially leads to a better understanding of firm market performance. I propose that based on the context of evaluating firm market performance, investors are subjected to two major influences: the "experts" and the "crowd."

On the one hand, investors refer to analysts' stock recommendations as "expert opinion" to make trading decisions that affect market prices (Ramnath, Rock & Shane, 2008). Financial analysts act as intermediaries between firm and investors to help reduce information asymmetry between the firm and investors (Luo, Homburg, & Wieseke, 2010). Analyst recommendations play an important role as the expert opinion in the capital market for investors since these opinions provide investors with relevant firm and industry information (Franco et al, 2015). Analyst recommendations are reflections of analysts' belief about a firm's intrinsic stock value relative to its current market price (Francis & Soffer, 1997; Jegadeesh et al., 2004). Analyst activities increase the speed of information dissemination such that greater analyst coverage triggers faster price adjustments (Hong, Lim & Stein, 2000). Analyst opinions expressed through periodic stock recommendations have a significant impact on stock price changes (Barber, Lehavy & Trueman, 2010; Loh & Stulz, 2011). These recommendations are widely spread among various types of investors (Barber et al., 2001). An abundance of previous work indicates that analyst stock recommendations affect stock prices (e.g. Givoly & Lakonishok, 1979; Lys & Sohn, 1990; Francis & Soffer, 1997). Specifically, analyst recommendations exert a substantial effect on influencing trading behavior and, in turn, influence firms' stock market valuation (Womack, 1996; Loh and Mian, 2006; Ryan & Taffler, 2006). Market reactions are positively correlated with analyst stock recommendations especially when capital markets are highly efficient (Ramnath, Rock & Shane, 2008). Thus, I conceptualize analyst recommendations as expert opinions that contain specialized knowledge.

On the other hand, investors utilize social media sentiment as "wisdom of the crowd" to facilitate the stock price discovery process. "Wisdom of the crowds" conjectures that a group's average is typically more closely aligned with a true value compared to individual estimates and it is arguably even better than the estimates by experts (Surowiecki, 2004). The wisdom of the crowds has been adopted in various decision-making scenarios as a "vicarious form of wisdom" (Schijven & Hitt, 2012) such as investment evaluation (Schijven & Hitt, 2012) and belief revision (Mannes, 2009).

Social media sentiment, as aggregated user-generated content, provides information, influence, and social support (Butler, 2001). Socially constructed sentiment reveals the crowd's opinions, indicates social trends, and is thus meaningful in predicting stock returns (Chen et al., 2014). Specifically, social media sentiment indicates a set of beliefs about cash flows and investment risks that are not necessarily justified by the facts at hand (Joseph, Wintoki & Zhang, 2011). Recent studies propose that sentiment on social media reflects less biased information based on more credible Word-of-Mouth (WoM) sources and thus allows investors to timely update their prospects toward the firm (Luo et al., 2013; Schweidel & Moe, 2014). Capturing the collective mood on social media becomes crucial in predicting stock market movement (Bollen & Mao, 2011; Zhang, Fuehres & Gloor, 2011).

Additionally, social media sentiment reinforces the informational and normative influence on investors. First, social media sentiment enables investors to obtain the opinions of others, and this information advantage can further lead to higher investment profit (Dvořák, 2005). Bloomberg, one of the primary financial information service providers, started to integrate real-time Twitter feeds into its terminals beginning in 2013 (Bloomberg, 2013). Social media sentiment captures the wisdom of the crowd, providing investors with timely updates on firms' prospects (Luo, Zhang & Duan, 2013). Second, investors can access information from different reference groups via social media platforms (Cade, 2016) and facilitate interactive communications among stakeholders (Kim & Youm, 2014). Stakeholders, including stockholders, pay high attention to firms' social media activities (Romero et al., 2011). These activities not only contain rich information about the firm but also indicate stakeholders' preferences. The timely manner of social media sentiment also adds additional value to investors in that social media sentiment, especially from Twitter, is viewed as a real-time survey (Openshaw, 2013). Therefore, I conceptualize that social media sentiment serves as "wisdom of the crowd" for investors.

Compared with the rational choice model, social influence model reverberates the role of social influence of people's choice-making. It indicates that people are retrospectively rational and subjectively rational (Fulk, Schmitz & Steinfield, 1990). In other words, people can be efficiency-motivated with the goal of attaining accuracy (Turner, 1991). Hence, in a dynamic social situation, seeking "an accurate perception of reality" serves as an important motivation for people who desire to respond appropriately (Gialdini & Goldstein, 2004). I theorize that investors adopt the comparison mechanism that they contrast influence from multiple sources to facilitate their decision induction. In other words, investors try to seek consistency through comparison.

Strategy researchers espouse consistency as a necessary condition for firm survival (e.g. Lamberg et al., 2009). Information consistency signals the legitimacy of firm actions, validates motives, and heightens consumer confidence (Schuler & Cording, 2006). Social psychologists view consistency as a highly potent weapon of social influence (Cialdini, 1987). The desire of being consistent within one's attitudes, beliefs, and actions is a central motivator of personal behavior (Festinger, 1957; Heider, 1946), and demonstrating consistent behaviors with referent others serves as a principle of social proof (Festinger, 1954; Cialdini & Goldstein, 2004). Social cognition research suggests two routes of persuasion that people choose: either employing formal information process or adhering to social heuristics through consistency, depending on the uncertainty of the situation and the availability of reference information (Rao, Greve & Davis, 2001). More recently, researchers embrace the impact of multiple social influences. Friedkin (2006) proposed that social influence is a structural process of leveraging and integrating conflicting influences from different sources in opinion formation. Mollick & Nanda (2015) compared the funding decisions on theater projects between crowdfunding and expert funding and found although there is a significant agreement between the two sources in investment preference, where crowdfunding is more willing to fund in situations of disagreement which lowered the incidence of "false negatives."

Researchers found that investors adhere to both financial analysts with informed opinions (Lieberman & Asaba, 2006) and listen to public opinions as a "vicarious form of wisdom" (Schijven & Hitt, 2012). Both financial analysts who are respected as expert opinion leaders and social media sentiment that is more socially connected to the local community (Lococak et al., 2001; Iyengar, Van den Bulte & Valente, 2011) are considered as important influencers. Third parties play an important role in shaping market patterns through recommendations and endorsements (Zuckerman, 1999). However, past research on investor behavior has been focused on a sole nominal group such as financial analysts, investors, etc. In stock market transactions, investors who are socialized through observation, interaction, and imitation are subject to various types of social influence. An understanding of the social influence of consistency is important because it focuses our attention on the different sources and types of benefits that are available to investors and thus stock market reaction. Understanding the different sources and types of benefits that are available through these two information channels provides an opportunity for investors to compare information, choose beliefs, and make better investment decisions. Following this logic, I propose that "consistency" is instrumental in specifying the relationship between the two types of social influences and firm market performance.

2.2 Hypotheses

2.2.1 Sentiment Consistency and Firm Market Performance

In this study, consistency takes the meaning of sentiment conformity between analyst recommendation and social media sentiment—whether a firm receives conforming positive, neutral or negative opinions. Diverging from traditional consistency concepts that emphasize social proof, I theorize that sentiment consistency integrates both formal information processing and social heuristics. On the one hand, because of comparing two information sources from financial analysts and social media channel, consistency indicates a systematic validation process from available information channels. Being consistent enhances the accuracy of evaluating a firm's prospects. On the other hand, consistency also symbolizes social proof that through observing the attitudes of others, people make references on the legitimacy of the issues through heuristic processing. Therefore, I frame them as information validation versus social comparison aspects of consistency. There are two parts to my logic.

First, dual social influence from analysts and social media trigger an information validation process for investors. Social influence theory proposes that people are motivated to seek consistency under the desire of forming an accurate view of reality and act correctly (Turner, 1991). From an investor's perspective, it is essential to complete a thorough information search to make an informed choice because restricted information processing is prone to hastily contrived solutions using few alternatives (Eisenhardt & Zbaracki, 1992; Janis & Mann, 1977). To better understand a firm's stock market performance requires an exploration of the interaction between different types of information (Goldstein & Yang, 2015). Kittur et al., (2007)'s study shed light on this direction. By counting the total edits made by administrators vs. the crowd on Wikipedia, they found that the role of administrators was more important at the early growth stage of Wikipedia, while the balance shifted towards crowd contributors once the business matured. I propose that since social media influence is different from analyst recommendation influence in nature, these two influences have a substitution effect rather than a complementary effect which I explain below.

Investors rely on social media sentiment to validate the reliability of analyst recommendations. On the one hand, it is important to identify the limitations and contingencies of expert opinions. Looking at the expert's views in influencing box offices, Reinstein and Snyder (2005) pointed out that the strength of expert influence is contingent on factors such as movie release scope (narrow versus wide). Perceiving the importance of social influence from analyst recommendations, top management teams often adopt verbal impression management tactics toward analysts to enhance the legitimacy of a firm's policy and strategy initiatives (Westphal and

Graebner, 2010). Firms receiving downgraded recommendations from analysts may exert retaliation measures such as limiting analysts' access to management-provided information (Chen & Matsumoto, 2006) and rendering fewer favors (Westphal & Clement, 2008). These actions severely harm the perceived reliability of analyst recommendation among investors. On the other hand, differing information processing mechanisms between the influence of experts and crowds make it possible for social media sentiment to play a validation role. Although crowd judgment relies on the incremental contribution from each actor, the aggregated outcome from many individuals provides more valuable information (Mollick & Nanda, 2015). In other words, in contrast to expert opinion, each individual opinion included in crowd wisdom does not need to be efficient that reflects and incorporates all relevant information. Social media sentiment indicates the collective perception toward the firm. Siggelkow (2002) calls special attention to the interaction effect between complements, suggesting misperceptions on the interaction of complementary activities can be very costly to decision makers.

Understanding the information validation process is important in assessing investors' market reaction. Influence is generated from the quality of information (Botterger, 1984). An individual's sensemaking is strongly influenced by social interactions (Smart & Sycara, 2013). Social cognitive theory indicates that people acquire knowledge within the context of social interactions, experiences, and outside media influence (Bandura, 1986). Communication is a central component in sensemaking processes where people are collectively influenced by each other (Weick, Sutcliffe, & Obstfeld, 2005). Recent social media studies demonstrate that social media platforms facilitate communication among a diverse group of stakeholders (Kim & Youm, 2014). Social media sentiment adds new social dimensions to traditional information channels (Kaplan & Haenlein, 2010); social media platforms are more transparent, and investors are getting more diverse opinions from viewing and traversing social media content (Kane et al., 2014). The quality of crowd wisdom collected from social media platforms is improved with more interactions among diverse groups.

Second, consistency emphasizes the role of social consensus in shaping an actor's decision making (Cialdini, 1987; Cialdini, 1993). As a response to uncertainty in decision making, following the heuristics of social proof provides validation for individual actors (Cyert & March, 1963). Actors will consider an action as appropriate if they find social proof that their action is consistent with others (Cialdini, 1993). Researchers found that through social comparison with referent others actors validate the correctness of their opinions and decisions (Festinger, 1954). Additionally, actors value the consistency with others' behaviors as a way of avoiding mistakes (Rao, Greve & Davis, 2001). In the context of stock market reaction, based on the social proof framework, I suggest that investors elect to conform to a norm when they find consistency between the two types of social influence. The social proof principle becomes especially strong when investors can find consistent opinions from different sources. On the contrary, inconsistency between reference groups will confuse investors and trigger doubts in their beliefs.

Consistency provides a benchmark for a shared framework of multiple references that exerts normative pressure on investors. Investors can access the shared framework of the reference groups and interpret it as subjective validity. Besides enhancing the observability of social media information, investors can use references from informal social interactions among users and infer a collective response. Starting from an opposite view, some investors utilize a contrarian strategy based on collective Twitter sentiment if the sentiment seems too bullish (Openshaw, 2013). Convergence in behavior is a result of sharing similar information, facing similar action alternatives and payoffs (Bikhchandani, Hirshleifer, & Welch, 1998). An "informational cascade" occurs when individuals observe others' prior behavior and decide to follow to pursue optimal results, disregarding their own information (Bikhchandani et al., 1992). Another example of how investors seek information references is exhibited by herding behavior in the stock market. Herding can either be rational because it reveals private information about a firm's fundamentals (Hirshleifer et al., 1994; Wermers, 1999) or irrational caused by the delayed reaction of investors to the information about past returns and past earnings (Chan, Jegadeesh & Lakonishok, 1996). Thus, investors resort to consistency not only to obtain a quality indication (Hirshleifer, 1995), but also to maintain competitive parity (Lieberman & Asaba, 2006). Bartov et al., (2016) discovered that small firms with weaker information environments are subject to higher relevance to social media information.

To summarize, as the logic of referring to multiple social influences, consistency provides higher reliability than relying on herding rationality. Seeking consistency allows investors to be less reliant on a single information source and less dependent on traditional social and institutional constraints. Exploring the role of consistency in social influence provides an opportunity to restore a more realistic and complex explanation of investors' market reaction. Formulated with a simulation model, Fang et al., (2014) discovered that organizational members' propensity to distort information is subject to social influence. Social influence from a unified source often generates a strong imitation or herding effect that can be harmful to the performance outcome. Westphal and Clement (2008) also raised their concern that given the importance of analyst recommendation in influencing investor behavior, firms may deliberately manipulate the relationship with analysts and reduce the objectivity of analyst reports, which will ultimately lead to negative consequences in the financial market. Therefore, consistency between analyst recommendation and social media sentiment is important in improving investment decisions. Thus, this leads to the proposal that the consistency between two types of social influence will have a positive impact on firm market performance.

Baseline Hypothesis 1: Financial analyst recommendations are positively associated with firm market performance.

Baseline Hypothesis 2: Social media sentiment is positively associated with firm market performance.

Hypothesis 1: In the event of analyst recommendation announcements, sentiment consistency between analyst recommendations and social media sentiment is positively associated with firm market performance.

2.2.2 Positivity Bias of Social Media Sentiment Influence

While investors are under the dual social influences from expert opinion and wisdom of the crowd and thus seek consistency, they are likely to react differently to a different valence of social media sentiments. It is because ex-ante to forming consistency, investors are subject to the influence of others based on their prior knowledge on others' behavior (Pitesa & Thau, 2013). With the progressive popularity of information dissemination on social media platform, investors are increasingly liable to social media influences that are continuous and penetrating toward their social interactive activities. For decades, although researchers have explored investors' overreactions toward positive and negative information, we know surprisingly little about the magnitude of such effect when comparing positive with negative information. Researchers discovered that investors overreact to negative information in good times and underreact to good news in bad times (Veronesi, 1999). Since the state of good or bad times is a lasting underlying framework for investors, the phenomenon of "momentum" and "reversal" can be respectively attributed to the underreaction or overreaction toward good or bad information (Baur, Dimpfl & Jung, 2012). The state of good or bad times is especially pertinent to social media sentiment because investors are connected to an unceasing flow of social media sentiment that likely leaves an imprint on them. Therefore, to understand how positive or negative sentiment impacts investors in responding to consistency, I propose an affect-as-information logic (Schwarz, 1990: 529); the valence of social media sentiment acts as an important moderator for the consistency effect.

Prior studies indicate that investors may overreact to both good and bad news while underestimating regular news such as firm's earning announcements (Barberis, Shleifer & Vishny, 1998). Compared with traditional media, Green et al., (2014) documented that good news receives more coverage on Internet-based news outlets. On the contrary, research on social influence strategies discovered that negative valence could improve the quality and effectiveness of persuasive messages (Forgas, 2007). In the context of social influence on firm market performance, it is important to investigate whether and how such bias exists under the dual effects of expert opinion and wisdom of the crowd. Research on heuristics suggests that reliance on social proof may lead to overvaluation of the information and bring biases to the decision (Rao, Greve & Davis, 2001). Knowing what conditions that consistency conforms or reduces such bias will enhance our understanding of the impact of social media through the lens of multiple social influences. Therefore, by investigating how positive and negative valence of social media sentiment moderates the consistency effect on firm market performance, this study aims to uncover a positivity bias myth under multiple social influences.

Although prior research supports the existence of both positive and negative bias in investor reactions, I argue that a positivity bias is more likely to occur in moderating consistency effect. First, investors are subject to powerful subconscious bias toward positive sentiment. Social cognition research has demonstrated the presence of positivity bias in human cognition, where people make more internal, stable and global attributions for positive events than for negative events (Mezulis et al., 2004). For example, as one type of positivity bias, self-serving attributional bias predicts that people are more likely to attribute positive events to themselves while ascribing bad events to other causes (Heider, 1976). The Pollyanna principle describes the state that pleasantness predominates; that people process positive information more accurately than negative information (Matlin & Stang, 1978). Following the elevated influence from electric word-of-mouth, such concerns extend to the management field, suggesting that wisdom of the crowd and its feedback effect on individuals appears to be skewed on customer online rating systems (Flanagin et al., 2014). Through a large-scale randomized experiment on a social news aggregation website, scientists discovered that prior ratings created significant bias in influencing people's own rating behavior, and positive and negative social influences created asymmetric herding effects in exhibiting natural up-vote tendency (Muchnik et al., 2013).

Second, investors conceivably pay unequal attention toward positive or negative social media sentiment. Asymmetric preferences exist when people make decisions under uncertainty. Prospect theory indicates that people exhibit loss-aversion preferences, by evaluating negative outcome potentials more detrimental than gains in positive scenario (Kahneman & Tversky, 1979). On the other hand, Karlsson, Loewenstein, and Seppi (2009) proposed that an ostrich effect exists where people avoid acquiring negative information under the hedonic impact of information on utility. Specifically, they demonstrated that people have selective attention in that they receive preliminary but incomplete information and then decide whether to acquire and attend to definitive information. Derived from this selective exposure hypothesis (Caplin, 2003; Karlsson et al., 2009), if investors are surrounded by strong negative sentiment on social media, even when analysts issue the similar negative opinion, such consistency will generate less impact on investor behavior because they tend to ignore such consistency.

Additionally, the magnitude of investor reaction toward consistency can also be ascribed to various contingencies. Lee, Hutton, and Shu (2015) discovered that releasing negative information on social media during product recalls can attenuate the negative price reaction. Pan, Altshuler & Pentland (2012) report evidence suggesting that the having access to peer behavior will influence individuals to overreact in stock trading activities and such peer influence especially is stronger when market uncertainty is high. Rennekamp (2012) found that more readable firm information disclosures could cause investors to overreact to information, especially for less sophisticated investors. Given the concise information format on Twitter, the fluency in reading such information is likely to increase investors' belief in the accuracy of such information. Researchers discovered that most investors perform moderate-to-low information gathering strategies because they are constrained by limited attention (Barber & Odean, 2008), and they are only sensitive to visible and accessible information (Loibl & Hira, 2009). Exposed to social media sentiment, the tendency for investors to conduct new searches is decreased. The reduction effect is stronger when social media sentiment is more salient. Social psychologists discovered that the magnitude of an anchoring effect is mediated by the perceived plausibility of the anchors (Mussweiler & Strack, 2000). Hence, when social media sentiment is more positive, it boosts the confidence level of investors that investors are likely to weigh consistency as more important. Thus, I hypothesize that social valence of social media sentiment moderates the relationship between consistency effect and firm market performance that:

Hypothesis 2: In the event of analyst recommendation announcements, a positive valence of social media sentiment has a stronger moderation effect than a negative valence of social media sentiment on the relationship between consistency and firm market performance.

2.2.3 Emotion Amplification by Polarity of Social Media Sentiment

Social influence researchers define group polarization as the tendency to strengthen the prevailing response within a group (Turner, 1991: 49). Past research has focused on the antecedents of polarization. One stream of the research suggests that when people are mediated by persuasive argumentation, they adopt social comparison to deal with remote processes that may lead to polarization (Sanders & Baron, 1977). Mechanisms of social comparison that involve opinion maintenance and persuasive arguments that involve opinion change can be complementary (Sanders & Baron, 1977). However, another stream of research argues that social comparison processes have little direct effect on polarization (Burnstein & Vinokur, 1977).

Social influence is relatively remote on explaining polarization because polarization is more of a dynamic process of cognitive rehearsal and verbal commitment where social context may not always be present (Myers & Lamm, 1976). The heart of the disagreement lies in whether social context can generate sufficient motivation to trigger a change of attitude. This study does not join the debate on whether the social context is important in shaping polarization of opinions, but rather provide a new perspective to enrich the understanding of social comparison effect on polarization. Based on the context of investors under multiple types of social influences, I contend that one type of social influence can moderate the polarization effect produced by another type of social influence. Specifically, when encountered with polarized social media sentiments, it is difficult for investors to infer unified information from the wisdom of the crowd. Thus, expert opinion exerts influence on investors' prospects by playing an arbiter role. By way of explanation, under a high sentiment polarity situation, investors will positively respond to the consistency between expert opinion and social media sentiment.

First, under a highly polarized situation, consistency triggers a higher social context motivating investors to follow the same opinion. Social media platforms create an ecosystem for stakeholders, enabling a more interactive relationship among stakeholder groups (Hanna, Rohm & Crittenden, 2011; Larson & Watson, 2011). High polarity indicates that there is no dominant logic. As stakeholder theory predicts, stakeholders are likely to express different emotions on social media that demonstrates conflicting sentiments. Prior social psychology experiments indicate that polarization causes an increase in risk taking behaviors (Myers and Bishop, 1970). Simultaneously, in a polarized opinion climate, people may refrain from participating in publicly observable activities to reduce pressures such as potential scrutiny and criticism by others who hold different opinions (Hayes, Scheufele & Huge, 2006). High polarity adds uncertainty to investors that when crowd opinions on social media are polarized, it creates confusion and deters investors from acting, making them less confident about the firm's prospects. Therefore, I argue that a social comparison effect for consistency is strongest when the need for self-related information is particularly salient. Thus, when social media sentiment is polarized, consistency-seeking increases.

Second, under a polarized situation, consistency presents a persuasive argument for investors who may be confused by information polarity. In situations when mixed sentiments dominate a social media platform, analyst opinions catalyze investor reactions. In recent studies, Gennaioli et al., (2015) argued that there is a tipping point for overreacting to bad news when the accumulation of bad news leads to changes of underlying beliefs. Observing some bad news intermixed with good news does not change the investor's mind unless it reaches a tipping point. Following the same pattern, analyst opinions are likely to be the last straw that breaks the camel's back.

Third, polarized opinion is most likely related with high salience, where it attracts a higher level of investor's attention that they will increasingly appreciate the value of consistency. People will engage in active information processing when their own goal is threatened (Scott & Lane, 2000). I conjecture that social media activities are the most salient when positive sentiment and negative sentiment are both intense. On the one hand, when there are heated discussions on social media platforms, investors will likely pay more attention to the issue in discussion. They are more aware of the opposing opinion and take negative information more seriously. On the other hand, investors will allocate higher weight to analyst recommendation under polarized social media sentiment. Thus, they are more willing to adhere to the consistency rule. To summarize, when both positive and negative social media sentiments are strong, intensive debate occurs, and the role of consistency is enhanced. Thus, I hypothesize that:

Hypothesis 3a: In the event of analyst recommendation announcements, the polarity of social media sentiment is positively associated with social media activity salience.

Hypothesis 3b: In the event of analyst recommendation announcements, the polarity of social media sentiment positively moderates the relationship between consistency and firm market performance.

3. METHOD

3.1 Data and Sample

The empirical analysis is based on data gathered from six sources: *I/B/E/S, CRSP, Compustat, Thomson Reuter*, *Stocktwits*, and *PsychSignal*. My sample consists of firms in the *S&P 500* index. I chose *S&P 500* companies to test my hypotheses for several reasons. First, the percentage of companies with Twitter accounts in the *S&P 500* is very high. At the end of 2014, nearly 80% of *S&P* firms had an official Twitter account. Second, the *S&P 500* index allows us to examine the impact of social media across different industries. Through this approach, I was able to examine the industry variances of social media impact on investors' market reactions. Finally, since *S&P 500* firms offer more liquidity to the market and constitute a high percentage of market capitalization of the overall market, analysts provide stock recommendations and earnings estimates of *S&P 500* firms on a more frequent basis. In contrast, analysts may not provide stock recommendations or do not update their recommendations for entrepreneurial and small firms. Therefore, to examine the interaction effect between user sentiment and analyst recommendation on investors, the *S&P 500* index is more appropriate. I collected the *S&P 500* index constituents list from the Compustat database 2010 to 2015 and identified 646 companies. I excluded finance and insurance industries (NAICS: 52) because financial institutions are a different type of firms that require separate studies (Claessens et al., 2002).

The timeframe for this study is 2010-2015. According to Pew Research Center surveys (Perrin, 2015), the social media adoption rate for internet users had a steady growth from 60% in 2010 to 76% in 2015. This growth excludes the potential confounding effect coming from the social media adoption trend itself. I use Twitter data in my study for capturing user sentiment on social media. Twitter is the most popular social media platform used by investors, making it an ideal platform for understanding the information flow on a social media platform. Bloomberg provides a social media feed that is at a comparable level with other news sources including *Bloomberg News, News Wire, Research, Web Sources, and References*. Inside the social media feed, Bloomberg provides *Twitter* and *Weibo* live feeds, and *Twitter* is the only US social media platform. Strong practitioner evidence suggests that investors are using *Twitter* information in making investment decisions. In addition, as the communication style of *Twitter* is heavily text-based and the texts are limited to 140 characters or less, it provides concise verbal expression in user comments. Prior literature suggested that *Twitter* communication is more direct and less symbolic (Fischer & Reuber, 2014). It allows large-scale sentiment analysis using machine learning techniques. Companies such as *Stocktwits* have built entire networks on the *Twitter* platform, populated with several hundred thousand traders. My analysis is constructed as panel data following analysts' recommendation announcements. The total scanned messages included in social media sentiment calculations were: 503,885 from *Stocktwits*, 1,204,399 from *Twitter* without retweets, and 1,486,008 from *Twitter* with retweets. The final datasets matched with analyst recommendations consists of 25,901 firm-date observations for *Stocktwit*s, 26,086 for *Twitter*, and 26,137 for *Twitter* with retweets. Examples of original tweets are demonstrated in Table 1.

Insert Table 1 here

3.2 Measures

3.2.1 Dependent variable

Firm market performance

To investigate firm market performance to the announcement of analyst stock recommendations, I calculate the Standardized Cumulative Abnormal Returns (SCARs). SCAR is a widely-adopted measure to reflect short-run market reaction toward analyst stock recommendations in the accounting, finance and management literature (Loh & Stulz, 2011; Firth et al., 2013; Brown et al., 2014). It reflects the informativeness that investors perceive toward analyst reports (Frankel, Kothari & Weber, 2006). Stock returns are calculated in Eventus. Specifically, for each recommendation announcement in the sample, I use trading days -246 through -42 relative to the analyst recommendation event date, as the estimation period and regression of the daily returns for the stock on the market return for this period. Previous empirical evidence strongly suggests that market prices react slowly to information contained in analyst recommendation (i.e. Barber et al, 2001; Brav & Lehavy, 2003; Stickel, 1995). Therefore, I adopt a one-day event window starting from the issuance date [0]. For recommendations released after market close (4:00 pm. Eastern time), the following trading day is taken as day 0 instead of the announcement day. Daily Abnormal Return (AR) is obtained by comparing the difference between the actual daily return in the event window and the predicted daily return based on the market model abnormal return. Returns for sell recommendations are multiplied by -1.

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt})$$

where R_{it} is the rate of return on the share price of firm i on day t, R_{mt} is the rate of return on a market portfolio of stocks on day t, α is the intercept term, β is the systematic risk of stock i, and ε_{it} is the error term, with $E(\varepsilon_{it})=0$.

Following McWilliams and Siegel (1997) and other researchers' suggestion for event study empirical operationalization, I calculated the SCAR using the equation below derived from *Eventus* database.

$$SAR_{it} = \mathrm{AR}_{it}/SD_{it}$$

with

$$\mathrm{SD}_{it} = \{S_i^2 \times [1 + 1/T(R_{mt} - R_m)^2/\sum_{t=1}^{T}(R_{mt} - R_m)^2]\}^{0.5}$$

where S_i^2 is the residual variance from the market model as computed for firm i, R_m is the mean return on the market portfolio calculated during the estimation period, and T is the number of days in the estimation period.

$$\mathrm{SCAR}_i = \sum_{t=T1}^{T2} \mathrm{SAR}_{it}/(T2 - T1 + 1)^{1/2}$$

I calculate the SCAR over a 1-day window, and I use other event windows to perform robustness checks to verify the results.

Social Media Activity Salience

Salience is frequently researched in the context of understanding firm responsiveness to stakeholder concerns (Bundy, Shrophire & Buchholtz, 2013; Desai, 2014). *Social Media Activity Salience* is measured as the total number of tweets on *Stocktwits*.

3.2.2 Independent variables

Analyst Stock Recommendation

To gauge analyst stock recommendation, I measure new (and reiterated) analyst stock recommendations made by the analysts following the focal firm (Francis & Soffer, 1997; Womack, 1996). This measure is operationalized as the individual analyst stock recommendation in the Institutional Brokers' Estimate System (I/B/E/S) database. The I/B/E/S database records analyst investment recommendations on a five-point Likert scale with 1=strong buy, 2=buy, 3=hold, 4=underperform, 5=sell. Consistent with prior studies (Luo et al., 2010; Ioannou and Serafeim, 2010), I invert this scale with the higher value indicating a more favorable recommendation. In my construct, *recommendation*, 5=strong buy, 4=buy, 3=hold, 2=underperform, and 1=sell. Analyst stock recommendation is a widely-used measure in finance and accounting literature (Howe, Unlu & Yan 2009). In general, the more favorable the recommendation, the more positive the opinion toward a firm's future performance (Ramnath, Rock & Shane, 2008), and positive recommendation also indicates positive investor beliefs (Benner & Ranganathan, 2013). I adopt the I/B/E/S detail files to avoid a timing inconsistency problem in the aggregated recommendation file (Brown, 1993). Additionally, because my primary focus is on understanding stock market reactions toward analyst recommendations, rather than on trading strategies, it is appropriate to use individual analysts' recommendations as the unit of observation. Finally, since many analysts announce recommendations after stock market work-hour (4:00 PM), I adjust the date of the announcement date with +1 day for after-hour recommendation announcements.

Valence of Social Media Sentiment

To collect tweets related to a specific firm, I adopt the cashtag ("$") + ticker symbol criteria in screening process (e.g. $GM for General Motors Inc., or $AAPL for Apple Inc.). Using cashtag plus ticker symbols ensures that the tweets are specifically related to a firm's financial performance and valuation (Bartov, Faurel & Mohanram, 2015). To test the sentiment sensitivity, I obtained the social media sentiment data on three related yet different databases: *Stocktwits*, *Twitter*, and *Twitter* with retweets, and tested the model on three databases. For testing the model, *Stocktwits* data are used primarily because *Stocktwits* data is applied to the most stringent filter to ensure that all tweets are closely related to stock trading topics.

I adopt the measure of valence of social media sentiment created by *PsychSignal*. *PsychSignal*[2] is a leading provider of real time Trader Mood, data, analytics and indices for financial institutions and investment professionals. *PsychSignal* data has been utilized by pioneering social media sentiment research increasingly (i.e. Hochreiter, 2015; Zheludev, 2015). The daily social media sentiment for each firm is calculated following five steps: 1. Ingest social media firehoses and eliminate non-financial data; 2. Identify and categorize by firm security; 3. Analyze mood via language analysis; 4. Aggregate mood scores and quantify sentiment; 5. Output sentiment data via an API. *Positive Valence* and *Negative Valence* are obtained directly as the value of bullish intensity score and bearish intensity score, ranging from (0, 4) for each variable. A value of 0 indicates a low level of valence and a value of 4 indicates a high level of valence.

Social Media Sentiment

Social Media Sentiment is calculated on a daily basis, and it is a categorical score. It takes the value of "-1" when *Positive Valence of SM Sentiment - Negative Valence of SM Sentiment < 0;* it takes the value of "0" when *Positive Valence of SM Sentiment - Negative Valence of SM Sentiment = 0*; and it takes the value of "1" when *Positive Valence of SM Sentiment - Negative Valence of SM Sentiment > 0*.

Sentiment Consistency

To compare sentiments between analyst recommendation and social media sentiment, I match the timing of the *Social Media Sentiment* with *Recommendation* announcement date. Since

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[2] http://www.psychsignal.com/

investors are not only be influenced by the same-day social media sentiment but also by accumulated sentiment from previous days, I chose several event windows to create aggregated social media sentiment around analyst recommendation announcement dates. These windows are: (0), (-1,0), (-3, 0) and (-7,0). The window of (-3,0) is reported as the main results, other results are reported in the robustness check.

I compute *Consistency* as sentiment conformity between analyst recommendation and social media sentiment. Consistency takes the value "1" if these two sentiments are both positive, negative or neutral. The value is "0" if the sentiments are inconsistent.

Sentiment Polarity

Like Stieglitz and Dang-Xuan's approach (2013), I compute *Sentiment Polarity* as the sum value between positive valence of social media sentiment and negative valence of social media. The value of polarity ranges from 0 to 8, with 0 indicating no polarity and 8 with extremely polarized sentiments.

$$Sentiment\ Polarity = Positive\ Valence\ of\ SM\ Sentiment + Negative\ Valence\ of\ SM\ Sentiment$$

3.2.3 Control variables

For an event study that investigates the causal relationship within an event window, it is extremely important to rule out confounding events that could result in spurious evidence for the proposed relationship. For example, both stock market reaction, social media sentiment, and analyst recommendation will likely be influenced by firms' quarterly earnings report announcements, thus without controlling quarterly earnings announcement effects, the result will be unreliable. Previous studies on analyst recommendations didn't address this issue sufficiently. Very few papers addressed the confounding event issue. Loh and Stulz (2011) deleted all recommendations around earning announcement and management forecasts dates. Li et al., (2015) are the first to systematically consider the confounding events and control for preceding corporate events collected from various news channels. Similar to their approach, I also identify all the confounding events and control for them.

Ivkovic and Jegadeesh (2004) indicated that a higher frequency of recommendation revisions occurred on the earning announcement date and the following several days. Therefore, to partition the market reaction effect contributing to the earning announcement date, I collected firms' quarterly earnings announcement dates from the COMPUSTAT Fundamental Quarterly database. I constructed *QE Announcement* as a dummy variable that takes the value of "1" if an analyst recommendation announces within seven days of a firm's quarterly earnings announcement date. Since merger and acquisition (M&A) activities are one of the significant events that will trigger a stock market reaction (i.e. Andrade, Mitchell & Stafford, 2001), I constructed *M&A Acquirer* and *M&A Target* taking the value of "1" if an analyst recommendation is released within five days after a M&A announcement. M&A announcement date is collected from Thomson Reuters SDC database. The Securities and Exchange Commission (SEC) has mandated new disclosure requirements in Form 8-K since 2004. Under the new requirements, firm needs to report promptly any material information that would impact investors. Therefore, an 8-K file contains comprehensive information including earnings, guidance, dividends, management, and related messages. I collected all firm-specific 8-K file announcement dates from the SEC Edgar database and constructed *8k Info Announcement* as a dummy value that takes the value of "1" if analyst recommendation is announced on the same day with 8k file filing date. Although management guidance announcements are included in an 8-K file, it is important to consider the direct effect of management communications. Therefore, I collected management guidance data from I/B/E/S and constructed *Management Guidance* as a dummy value that takes a value of "1" if an analyst recommendation is announced on the same day with management guidance.

Traditional media is an important alternative information channel for investors that may influence their decision making. However, very few social media studies consider the alternative information channel effect (Luo et al., 2013; Stenphen & Galak, 2012). *Media Sentiment* is collected from PsychSignal. This data is calculated with the Python programming language based on more than 20 sources such as Wall Street Journal, CNBC, Forbes, Business Insider, and Yahoo Finance. It ranges from -6 (extremely negative) to 6 (extremely positive).

Since I am investigating the interplay of influences from analyst recommendations and social media sentiment on investor market reactions, I control for factors that may affect the direction of a stock market reaction as well as the magnitude of that reaction. For industry characteristics, studies by Boni and Womack (2006) argued that industry returns precede industry-aggregated analyst upgrades and downgrades. Following their approach, I constructed *industry recommendation* to account for an industry average recommendation based on first two digits of SIC code.

I construct several firm-level controls to account for cross-sectional differences in abnormal returns. Prior studies indicated that smaller firms had earned higher returns than larger firms (Reinganum, 1981; Banz, 1981), but larger firms may have higher firm performance (Skaggs & Youndt, 2004). Therefore, I suspect that stock market reaction toward smaller firms on the same recommendation score may be more volatile than toward bigger firms. Thus, I control *size* as the natural logarithm of a firm's total assets at the end of its most recent fiscal quarter (Gleason & Lee, 2003). Prior literature tried to partition the pure analyst recommendation effect from the effect of a firm's price and earnings momentum, where the past winners received the most favorable recommendations (Jegadeesh et al., 2004). In the same spirit, researchers (Brown, Wei & Wermers, 2014) acknowledged the strong predictive power of prior returns toward future stock market reactions. Therefore, I control for *EPS* measured as earnings per share from the previous quarter. To measure the propensity of firms to spend on social media expenditures, I measure *SGA Ratio* as the quarterly selling and general and administrative expenses excluding research and development expenditures divided by quarterly sales (Ball et al., 2015). Prior studies indicated that analysts react differently to value-oriented or growth-oriented firms (Benner & Ranganathan, 2013). Therefore, I control for *firm type* difference with the lag of Tobin's Q from the last quarter (La Porta et al., 2002). I construct *stock volatility* measuring the intraday volatility as the difference between the high and low stock prices for the day divided by the average of the open and closing price (Das & Chen, 2007). I also calculate *stock volume* as the logarithm of the monthly stock trading volume.

I adopt several controls at the analyst recommendation level. Previous research indicates that analyst coverage may affect stock recommendation and firm value since analysts are more likely to follow large and profitable firms with better quality information (Lang & Lundholm, 1996; Barron, Byard & Kim, 2002). Therefore, I control *analyst coverage* as the number of analysts providing stock recommendations for the firm. Possessed with good reputations, star analysts have a larger impact on the financial market by making a high magnitude of stock market responses following their announcements (Stickel, 1995). Star analysts with superior skills bring higher values to investors by earning higher alphas on their recommendations (Fang & Yasuda, 2014). Therefore, I control for *star analysts*. A star analyst list is consolidated from analyst awards list from Thomson Reuter and analyst rankings from Institutional Investor magazine. Afterward, the list is matched with IBES analyst recommendations based on broker institutions and analyst name. Star analyst takes “1” if the analyst name is shown in the ranking in the same year with analyst recommendation announcement. Studies indicated that analysts might be influenced by other analysts (Chen et al., 2014). To rule out the herding behavior impact among analyst recommendations, I control for the *mean recommendation* value of analyst recommendation (reversely coded) and the *standard deviation* of analyst recommendations from the prior month in each analyst recommendation event. *Multiple recommendation* takes “1” if multiple recommendation announcements occur on the same day. Li et al., (2015) discovered that after-hour analyst recommendations carry different information than regular hour ones. Therefore, *Off-hour recommendation* takes “1”, if the recommendation is announced after 4 pm.

Bloomberg is added as a time control because the integration of social media feed into Bloomberg’s system creates a direct way for investors to access social media information. Data after April 4, 2012 takes value “1”, otherwise “0”. Each *year* is entered as a time control since the growing trend of Twitter may exert different influences on investors in evaluating the interaction between analyst recommendation and user sentiment on social media.

3.2.4 Estimation Method

To accommodate the unbalanced longitudinal data structure, I use the SAS GLM procedure of multiple regression to perform the estimation using the method of least squares. GLM is a flexible generalization of OLS that allows for a response variable that has error distribution models other than a normal distribution. Prior studies indicated that GLM provides the most appropriate estimation for panel data (Villalonga, 2004; Cheng, Ioannou & Serafeim, 2014). The results of a Hausman test (*Prob*>chi^2=0.0007) indicates a large and significant difference in coefficients of random effects and fixed effects. Since the GLM procedure controls for unmeasured, stable characteristics of firms, it introduces a firm fixed effect to further control for firm differences in analyst stock recommendations and firm market performance. The average VIF is 2.34 (Max:6.58, Min:1.02), which is lower than the threshold level 10 for the presence of multicollinearity (Chatterjee, Hadi, & Price, 2000). To avoid extreme values that might result from unusual circumstances, I excluded influential observations according to Cook's Distance cutoff criterion. This eliminated 1,168 observations, approximately 3.4% of the total sample.

I used the following models to examine the effect of sentiment consistency on market value created in analyst recommendation announcements, the moderating effects of positive and negative valence on consistency and the moderating effect of sentiment polarity on consistency.

$$
\begin{aligned}
SCAR_{(0,0)mnt} = \beta_0 &+ \beta_1 Recommendation_{mnt} + \beta_2 Social\ Media\ Sentiment_{mnt} \\
&+ \beta_3 Consistency_{mnt} + \beta_4 Positive\ Valence_{mnt} + \beta_5 Negative\ Valence_{mnt} \\
&+ \beta_6 Positive\ Valence * Consistency_{mnt} \\
&+ \beta_7 Negative\ Valence * Consistency_{mnt} \\
&+ \sum_{i=20}^{20} \beta_i Other\ Controls_{mnt} + y_t + \varepsilon_{mnt}
\end{aligned}
$$

$$
\begin{aligned}
SCAR_{(0,0)mnt} = \beta_0 &+ \beta_1 \mathrm{Recommendation}_{mnt} + \beta_2 Social\ Media\ Sentiment_{mnt} \\
&+ \beta_3 Consistency_{mnt} + \beta_4 Sentiment\ Polarity_{mnt} \\
&+ \beta_5 Sentiment\ Polarity * Consistency_{mnt} \\
&+ \sum_{i=20}^{20} \beta_i Other\ Controls_{mnt} + y_t + \varepsilon_{mnt}
\end{aligned}
$$

$SCAR_{(0,0)mnt}$ is the 1-day standardized cumulative abnormal return for the time window [0,0] for analyst recommendation announcements. The subscripts, *m*, *n* and *t* stand for firm *m*, announcement *n* and time *t*. As discussed above, the vector of controls included analyst, social media, firm, industry, stock level controls at time *t* for firm m in announcement *n*. y_t is used to account for unobserved year effects and ε_{mnt} is the error term.

4. RESULTS

4.1 Descriptive Statistics

Table 1 presents the number of observations, mean, standard deviation, maximum value, minimum value and correlations among the variables under study. It shows that the average cumulative abnormal returns of S&P 500 firms in analyst recommendation announcement events are slightly higher than 0, i.e., the mean is 0.007. The mean value for analyst recommendation is slightly positive 3.530 (3 as neutral) with a standard deviation of 0.898. The mean value for social media sentiment is slightly positive 0.360 (0 as neutral) with a standard deviation of 0.843. The mean value for sentiment consistency is 0.425 with a standard deviation of 0.494. The mean value for positive valence of social media sentiment is 1.012 with a standard deviation of 0.765. The mean value for negative valence of social media sentiment is 0.586 with a standard deviation of 0.699. The mean value for the polarity of social media sentiment is 1.598 with a standard deviation of 1.094. Table 1 shows that analyst recommendation, social media sentiments, consistency, positive valence, polarity are all positive and significantly associated with the cumulative abnormal returns ($p<0.05$). These correlations are consistent with what the hypotheses suggest.

Insert Table 2 here

4.2 Regression Analysis

Table 2 summarizes the empirical results of GLM analyses for the Baseline Hypotheses, Hypothesis 1, Hypothesis 2 and Hypothesis 3b. Model 1 is the base model with all the control variables. Model 2 examines the baseline hypotheses of the independent effects of analyst recommendation and social media sentiment. Model 3 examines the effect of sentiment consistency. Model 4 and Model 5 examine the moderating effects of valence and polarity of social media sentiment. Table 3 summarizes the result for Hypothesis 3a.

Insert Table 3 here

Insert Table 4 here

Model 1 is the base model with only control variables. Variables of multiple analyst recommendations, star analyst, social media activity salience, firm size, firm type, EPS, SGA ratio, stock volatility, average industry recommendation change, M&A announcement as the target, QE accouchement are consistently significant across the models, indicating that controlling for these variables provides a conservative test.

Model 2 tests the baseline hypotheses on whether analyst recommendation announcements and social media sentiment are positively associated with firm market performance. As shown in Model 2, analyst recommendation is positively associated with firm market performance (γ=0.092, ρ<0.0001), replicating prior findings of research on financial analyst recommendations (Li et al., 2015). Social media sentiment is positively associated with firm market performance (γ=0.182, ρ<0.0001), consistent with recent studies on social media sentiment (i.e. Luo, Zhang & Duan, 2013). In the context of big data analysis, researchers suggest that R squared provides better knowledge on the patterns of the relationship (George, Hass & Pentland, 2014). This step accounts for 1.4% additional variance in a firm's stock market performance over the first step with only controls (overall R^2=0.030). Baseline hypotheses are thus supported.

I tested Hypothesis 1, proposing that sentiment consistency between analyst recommendation and social media sentiments has a positive influence on firm market performance.

As shown in Model 3, sentiment consistency is significantly positively related to firm market performance (γ=0.336, ρ<0.0001). Adding consistency to the model explains an additional 1.5% of the variance in firm market performance. The overall R^2=0.058 indicates consistency is an important predictor. These results provide support for Hypothesis 1.

Hypothesis 2 states that there is a positivity bias of positive valence on moderating sentiment consistency. To test the effect size of positive valence vs. negative valence, I created two interaction terms between positive valence and consistency, and between negative valence and consistency. In model 4, both interaction terms (positive social media valence with consistency; negative social media valence with consistency) are significant (γ=0.505, ρ<0.0001; γ=-0.160, ρ<0.0001). Since positive valence and negative valence use the same scale, the comparison between the regression coefficient of positive social media valence (γ=0.602) and that of negative social media valence (γ=-0.150) indicates the slope of positive valence is much higher than the slope of negative valence. This result shows that positivity bias exists on positive social media valence. I then perform a simple slope analysis (Aiken & West, 1991) to examine whether the slopes of positive valence are significantly different from zero and those of negative valence. Results indicate that the simple slope of positive valence is significantly positive (t=27.18, ρ<0.0001).

To better illustrate the effect predicted by Hypothesis 2, I plotted simple slope significance for positive valence and negative valence. As indicated in Table 4, we see that the slopes of consistency are only positively significant at the mean and mean plus one standard deviation of positive valence, suggesting a certain level of positive valence need to be reached to boost the consistency effect. The simple slope of negative valence is also significantly different from zero (t=-8.09, ρ<0.0001). The addition of positive valence, negative valence, and their interaction term accounts for additional 2.6% of the variance of SCAR (overall R^2=0.096) compared with Model 3. As shown in Table 5, the slopes of consistency are significant at mean and mean plus one standard deviation, suggesting negative valence will have a negative moderating effect on consistency conditional on the degree of negative valence. Comparing the estimates of the slopes across positive and negative valence, we can see a larger effect size on positive valence except for one minus one standard deviation of valence. Visualization can be seen in Figures 2 and 3. Combined, these results provide partial support for Hypothesis 2. It means a positivity bias exists when positive valence is above the mean but not below the mean.

Insert Table 5, 6 and Figure 2, 3, 4, 5 here

In testing Hypothesis 3a, Model 6 shows controlling for social media sentiment (γ=-7.899, ρ<0.0001), the polarity of social media sentiment is significantly positively related to social media activity salience (γ=17.760, ρ<0.0001). It indicates when social media users hold polarized sentiments, there are more intensive social media activities. Thus, Hypothesis 3a is supported.

Finally, I test Hypothesis 3b, stipulating that polarity of social media sentiment has a positive moderating influence on the relationship between consistency and firm market performance. As shown in Model 5, the interaction term between the polarity of social media sentiment and sentiment consistency is significantly positive (γ=0.218, ρ<0.0001), indicating that the positive relation between consistency and firm market performance becomes stronger when polarity is high than when it is low. I performed a simple slope analysis to examine whether the slope is significantly different from zero. Results indicated that the simple slope was significantly positive (t=15.15, ρ<0.0001). The addition of polarity and its interaction term accounts for additional 1% variance of SCAR (overall R^2=0.068) compared with Model 3. The slopes of consistency are significant at three levels, indicating polarity is positively moderating consistency. The visualization of the interaction effect including the confidence interval estimation is shown in Figure 4. These results provide support for Hypothesis 3b.

Insert Table 7 and Figure 6 here

4.3 Robustness Checks and Supplementary Analysis

The endogeneity issue should be addressed when an independent variable is correlated with a nonrandom error term and thus leads to a biased estimate (Semadeni, Withers & Certo, 2014). Specifically, there could be an unobserved variable simultaneously influencing analyst recommendation and social media sentiment. To address such concern, first, I include confounding events controls in the model. Thus, information released by firms that can cause analyst recommendation and social media sentiment move in the same direction has been controlled. Second, to address the endogeneity concern, I create several lag variables including lag of Tobin's Q, EPS, etc. to control for a firm's endogenous characteristics.

Additionally, since it is possible that at the event of analyst recommendation announcement, there is no active social media sentiment. Therefore, I tested whether there is a significant difference between having social media sentiment and no social media sentiment in firm market performance. Among a total sample of 36,893 announcements, 27,411 are having social media sentiment with $SCAR_{mean\_with\_sentiment}$=-0.012, and 9,482 announcements are without social media sentiment with $SCAR_{mean\_no\_sentiment}$=0.007. Using the T-Test procedure, the $P\text{-}Value_{\text{Scatterthwaite}}$=0.251 means there is no significant difference between the mean in these two samples. To further address endogeneity, I conducted propensity-score matching to estimate the robust effect of sentiment consistency (in Appendix B).

Various robustness check methods have been employed to ensure the results reliabilities. First, I adopt multiple event windows on key variables to test the sensitivity of the proposed effects. For the dependent variable SCAR, besides the event window of (0,0), I adopted several different event windows (0,1) and (0,3) to check whether the results still hold and whether effect size changes following different event windows. All tests showed the same results: the effect size diminishes following the extension of event window, indicating information has been assimilated consistent with a market efficiency hypothesis. For social media sentiment, besides the (-3,0) window I used in the main models, I tested additional event windows of (0,0) and (-7,0). All the hypothesized results are the same and the sentiment in the aggregated (-7,0) window has the largest effect size. I utilize three datasets to test the theoretical model, including *Stocktwits*, *Twitter* without retweets, and *Twitter* with retweets. Results are consistent with the hypotheses.

Due to the data available for Media Sentiment starting from October 2012, I include *Media Sentiment* in robust check models only. Despite that media sentiment has a significant positive relationship with SCAR, the overall model result on hypothesized variables do not change with the inclusion of media sentiment. To further test the model fit, regression residual is plotted against fitted value of SCAR. The normal distribution of residuals indicates an appropriate model fit. Robustness checks results are in Appendix A.

5. DISCUSSION

5.1 Discussion

To date, research on social media has emphasized the individual influence on firm performance. My study complements this work by examining the interaction effect of social media sentiment and developing a theoretical framework of social media influence through the lens of expert opinion and wisdom of the crowd. First, the consistency effect between expert opinion and wisdom of the crowd extends past research, which has only demonstrated an individual effect. By illustrating why the consistency effect matters to investors, I enrich the understanding toward investor reaction leading to firm market performance. In this sense, my work is an important complement to extend social media research on its impact on firm market performance. Second, my study addresses the lack of theoretical framework germane to many of the social media studies. Through the use of social influence theory, which recognizes consistency as a function of comparing multiple social influences, the positivity bias moderating consistency effect, and the catalyst role of analysts in polarized sentiment situation, I provide a more feasible explanation on how social media influences firm market performance.

The existence of positivity bias calls for the attention to the pitfall of social media sentiment. It may boost the overconfidence of investors if they receive positive confirmation. Therefore, as a next step, exploring the relationship between firm market performance and accounting performance is relevant to verify whether social media influence works as a mechanism to deviate firm market performance from accounting performance.

Additionally, my findings indicate that analyst recommendations still play a very important role in firm market performance even in the context of social media prevalence. This paper joins the debate on whether the opinion of financial analysts still has value (i.e. Altınkılıç and Hansen, 2009; Barber et al., 2010). Based on the results, even controlling for social media sentiment, analyst recommendations still have a significant role in predicting firm market performance. The persistent negative effect of quarterly earning and 8-k announcements on firm market performance indicates that analyst recommendations immediately after these announcements are most likely to convey negative information. Furthermore, the result of polarity in a moderating consistency effect reveals a new catalyst role of analysts. The polarity effect demonstrates that under the situation of polarized social sentiments, expert opinions become crucial in determining the final result. Therefore, under the context of prevailing social media information, we need to reconsider financial analysts more as arbiters rather than new information providers.

5.2 Limitations and Future Directions

First, even though I included a large sample of S&P 500 firms, I recognize that the use of S&P 500 firms may potentially limit the generalizability of my findings toward small firms, especially young firms. Because financial analysts tend to cover firms in a larger size, including small firms in the sample may result in missing observations in the interaction. Future research should replicate this study using small firms through identifying other measures of expert opinion. Second, another limitation of my study is that the findings may subject to contingencies. Management scholars have demonstrated increasing interest in investigating the contingencies of influence – outcome relationships. Among these efforts, Afuah and Tucci (2012) made an important theoretical contribution by delineating the boundary conditions of efficient and effective crowdsourcing.

Future research could incorporate various contingency factors to learn more about variations in influence. For example, I tested investor reactions in this study. However, different types of investors may have different preferences in choosing information channels and thus has a systematic difference. Future research should explore the diverse shareholding structure of firms to distinguish blockholders from individual investors to get a more refined understanding of social media influence on firm market performance. Third, knowing that social media sentiment plays a crucial role in guiding investors' prospects, firms may proactively utilize social media tools to influence the perception of stakeholders including investors, customers, suppliers, and even alliance partners. Future research should investigate firms' specific use of social media in achieving this goal. Fourth, to capture social media users' sentiment specifically related to a firm's stock, I used the cashtag "$" sign plus ticker symbol as the key term to identify social media sentiment related to a specific firm. Using "$ticker" is an established protocol when mentioning a firm's stock, and it is also consistent with Psychsignal's sentiment analysis algorithm. Alternatively, future research can explore hashtag plus ticker symbol if researchers can conduct careful information scrutiny to rule out noises involved in hashtags.

5.3 Conclusion

Current social media research has mainly focused on the independent impact of social media in organizational contexts, often neglecting its interplay with influences from other types of concurrent information. From an investor's perspective, this study utilizes social influence theory to conceptualize the theoretical link between expert opinion and wisdom of the crowd on firm market performance. Demonstrating the positivity bias of investors in conforming to consistency and analysts' new role as arbiters in polarized opinion situations, I call for the importance of integrating behavioral sociology logic into the examination of social media influence. Thus, the theory and findings presented in this paper not only refine the social influence theory on adopting the lens of multiple influences but also underscore the importance of aligning social media information into firm performance evaluations. More research is needed to further unravel how firms can leverage the social media influence and enhance their market performance.

Table 1. Examples of Original Stocktwits Tweets

[1] "Morgan Stanley Downgrades ADT ($ADT) to Underweight http://stks.co/e1Trl"

[2] "ADT Corp downgraded by Morgan Stanley to underweight. http://stks.co/c1Tl5 $ADT"

[3] "#gapdown $SNDK $TSN $AAL $MU $RIO $ADT $TIF $APC http://stks.co/t1GbZ #daytrading #stockmarket #stocks #finance #gaps #gaptrading #market"

[4] "Top Analyst Upgrades and Downgrades: $ADT, $AA, $CHK, $GOOG, $KRFT, $ONDK, $WIN and More http://stks.co/s1GIA"

[5] "$VRNG To date Vringo has settled ADT, Tyco, Belkin, and now D-Link and has yet to disclose any compensation, nor terms."

[6] "NADT Affiliate: Nicholas Medina Commodity Update: http://stks.co/g1XnJ #commodity"

[7] "Street #downgrades: $EIX $JNPR $MS $ARUN $CPST $AOL $UIL $DHR $ADT $WR $PF $THS $EVTC $ALU $GOOG $MS $NPSP $ONDK $DF $TOL"

[8] "Street #downgrades: $JOY $ADT $ARUN $SEM $NWE $TER $EC $BBG $MKC $TW $WNR $KRFT $MDLZ $K $GOV $EVTC $DLR $HUBG $CAG $CPB $OII $WMGI $DPM"

[9] "@HAIRY Agreed, D-link , ADT ,TYCO, Belkin , Microsoft , settlements / license agreements , $938 + million due , Injunctions in place ZTE"

[10] "As $L and $ADTN trades neared stops on low volume this morning, we decided to live dangerously and hold them http://stks.co/g1Xoe"

[11] "Top Analyst Upgrades and Downgrades: ADT, Alcoa, Chesapeake, Google, Kraft, On Deck, Windstream and More - $AA http://stks.co/r1GgR"

[12] "$UBA: New Insider Transaction on UBA by\nChairman URSTADT CHARLES J:\nhttp://stks.co/d1Ttb"

[13] "Downgrades 1/12 $ONDK, $SEM, $GOV, $MDC, $NPSP, $WNR, $BBG, $WR, $ADT, $DPM, $NWE, $DHI, $VAC, $PF, $EVTC, $HUBG, $THS http://stks.co/b1Tz5"

[14] "Scan results - Fell Below 50 DMA today: $TIF $BITA $MSI $SEM $THC $DG $ALLY $TER $QDEL $ADT ... http://stks.co/a1U0s"

Table 2. Descriptive statistics and correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	SCAR(0,0)	1													
2	Recommendation [b]	0.109	1												
3	Social Media Sentiment [b]	0.130	0.041	1											
4	Consistency [b]	0.187	0.116	0.324	1										
5	Positive Valence	0.109	0.033	0.512	0.137	1									
6	Negative Valence	-0.088	-0.038	-0.514	-0.231	0.114	1								
7	Sentiment Polarity	0.020	-0.001	0.030	-0.051	0.773	0.719	1							
8	SM Activity Salience [c]	0.026	-0.010	-0.024	-0.022	0.452	0.499	0.635	1						
9	Mean Recommendation	0.057	0.185	0.065	0.115	0.047	-0.046	0.003	-0.017	1					
10	SD. Recommendation	-0.014	-0.030	-0.019	-0.022	0.023	0.045	0.044	0.007	-0.061	1				
11	Analyst Coverage	-0.012	0.019	-0.014	-0.016	0.131	0.183	0.209	0.306	0.118	0.090	1			
12	Multiple Recommendation [b]	-0.036	-0.017	-0.005	0.017	0.041	0.058	0.066	0.096	-0.009	0.006	0.051	1		
13	Off-hour Recommendation [b]	0.011	0.008	0.017	0.006	-0.012	-0.028	-0.026	-0.026	0.021	-0.011	-0.003	-0.025	1	
14	Star Analyst [b]	-0.007	-0.003	0.007	-0.002	0.009	0.006	0.010	0.021	0.006	-0.026	-0.009	0.096	-0.020	1
15	Size [c]	0.006	0.040	0.024	0.007	0.080	0.074	0.104	0.190	0.163	-0.091	0.217	-0.012	-0.005	0.003
16	Firm Type	-0.009	0.021	0.004	0.002	0.097	0.122	0.146	0.210	0.120	0.087	0.122	-0.002	0.040	0.000
17	EPS	-0.017	0.025	-0.008	-0.000	0.053	0.063	0.077	0.155	0.143	-0.041	0.046	-0.014	-0.002	0.010
18	SGA Ratio	0.006	-0.007	0.004	-0.011	0.031	0.040	0.047	0.052	0.002	0.075	0.073	-0.002	0.014	0.001
19	Stock Volume [c]	0.011	0.012	-0.001	-0.035	0.147	0.201	0.231	0.315	0.071	0.071	0.429	0.047	-0.018	-0.018
20	Stock Volatility	-0.008	-0.003	-0.042	-0.023	0.050	0.125	0.114	0.130	-0.038	0.035	0.048	0.056	-0.022	-0.010
21	Avg. Industry Change	0.117	0.249	0.035	0.096	0.035	-0.024	0.009	0.000	0.012	-0.003	-0.002	-0.020	-0.005	-0.002
22	MA Announcement Target [b]	0.008	0.004	0.003	-0.008	0.018	0.022	0.027	0.046	0.007	-0.007	-0.007	0.014	-0.009	-0.004
23	MA Announcement Acquirer [b]	-0.001	0.014	0.021	0.006	0.040	0.019	0.040	0.064	0.034	-0.004	0.024	0.004	-0.008	-0.002
24	QE Announcement [b]	-0.022	-0.030	-0.001	-0.042	0.055	0.078	0.088	0.183	-0.028	-0.008	-0.054	0.125	-0.060	0.015
25	8K Info Announcement [b]	-0.019	-0.004	0.019	-0.009	0.014	0.010	0.017	0.070	-0.019	-0.006	-0.015	0.025	-0.036	-0.005
26	Management Guidance [b]	-0.003	-0.007	0.014	-0.007	0.004	0.008	0.008	0.041	-0.017	0.004	0.005	-0.012	-0.019	-0.018
27	Media Sentiment	0.022	0.015	0.007	0.002	-0.034	-0.067	-0.065	-0.090	0.003	0.039	-0.043	-0.004	-0.003	0.003
28	Bloomberg [b]	-0.026	-0.021	0.015	0.027	0.103	0.121	0.150	0.321	-0.095	-0.170	-0.057	-0.031	0.006	0.035
	Number of Observations	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949
	Mean	0.007	3.530	0.360	0.425	1.012	0.586	1.598	0.586	3.672	0.841	23.975	0.054	0.267	0.225
	Std. Dev.	1.028	0.898	0.843	0.494	0.765	0.699	1.094	0.508	0.358	0.144	8.616	0.226	0.442	0.418
	Min	-3.720	1	-1	0	0	0	0	0	2.08	0	1	0	0	0
	Max	3.894	5	1	1	3.38	4	5.88	3.647	5	1.47	57	1	1	1

a. In this correlation table, n=25,901 except for running the correlation with media sentiment (n=12,084)
b. Categorical Variables
c. Logarithm
Correlation>0.02 are significant at 5%

Table 2. Descriptive statistics and correlations (continued)

	Variables	15	16	17	18	19	20	21	22	23	24	25	26	27	28
15	Size [c]	1													
16	Firm Type	-0.409	1												
17	EPS	0.135	0.156	1											
18	SGA Ratio	-0.259	0.264	-0.022	1										
19	Stock Volume [c]	0.531	-0.173	-0.192	-0.043	1									
20	Stock Volatility	-0.161	0.002	-0.127	-0.006	0.205	1								
21	Avg. Industry Change	0.003	0.002	0.000	0.000	0.003	-0.005	1							
22	MA Announcement Target [b]	0.002	0.001	0.019	0.007	0.014	0.020	-0.002	1						
23	MA Announcement Acquirer [b]	0.083	-0.004	0.022	0.027	0.070	-0.015	-0.006	0.363	1					
24	QE Announcement [b]	-0.026	-0.026	-0.004	-0.010	-0.015	0.035	-0.020	0.048	0.024	1				
25	8K Info Announcement [b]	0.015	-0.029	-0.008	-0.017	0.018	0.011	-0.006	0.021	0.047	0.176	1			
26	Management Guidance [b]	-0.001	0.003	0.001	0.009	0.005	-0.002	-0.005	-0.002	0.003	0.151	0.267	1		
27	Media Sentiment	-0.009	-0.020	-0.001	0.004	-0.040	-0.056	0.002	-0.017	-0.028	-0.026	-0.007	0.000	1	
28	Bloomberg [b]	0.059	0.008	0.027	-0.021	-0.176	-0.125	0.007	-0.010	-0.005	-0.034	-0.009	-0.015	-	1
	Number of Observations	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	25,949	12,084	25,949
	Mean	4.133	2.108	2.909	0.161	5.871	0.111	0.002	0.008	0.034	0.173	0.065	0.012	1.336	0.662
	Std. Dev.	0.495	1.333	4.144	0.148	0.443	0.087	0.451	0.088	0.182	0.378	0.247	0.109	2.784	0.473
	Min	2.740	0.618	-37.890	-2.014	4.463	0.005	-4	0	0	0	0	0	-3	0
	Max	5.891	13.711	45.840	2.053	7.355	4.033	4	1	1	1	1	1	6	1

a. In this correlation table, n=25,901 except for running the correlation with media sentiment (n=12,084)
b. Categorical Variables
c. Logarithm
Correlation>0.02 are significant at 5%
Correlation between Bloomberg and Media Sentiment cannot be calculated because the availability date of Media Sentiment is very close to Bloomberg date.

Table 3. Results of Generalized Linear Model Regression on SCAR (0,0)

Variables	**Model 1 CV only**	**Model 2 Baseline**	**Model 3 Hypothesis 1**	**Model 4 Hypothesis 2**	**Model 5 Hypothesis 3b**
Control Variable					
Mean Recommendation	.185(.019)***	.124(.019)***	.086(.019)***	.002(.019)	.065(.019)***
SD. Recommendation	-.131(.045)**	-.116(.045)**	-.116(.044)**	-.092(.044)*	-.145(.044)**
Analyst Coverage	-.004(.000)***	-.004(.000)***	-.004(.000)***	-.003(.000)***	-.004(.000)***
Multiple Recommendation	-.161(.028)***	-.158(.028)***	-.179(.028)***	-.202(.027)***	-.193(.028)***
Off-hour Recommendation	.021(.014)	.016(.014)	.017(.014)	.020(.014)	.018(.014)
Star Analyst	-.007(.015)	-.007(.015)	-.004(.015)	-.004(.015)	-.006(.015)
SM Activity Salience	.220(.018)***	.214(.018)***	.220(.017)***	.276(.020)***	.220(.020)***
Size	-.036(.020)+	-.040(.020)*	-.039(.019)*	-.035(.019)+	-.042(.019)*
Firm Type	-.032(.006)***	-.032(.006)***	-.031(.006)***	-.024(.006)***	-.030(.006)***
EPS	-.010(.002)***	-.009(.002)***	-.009(.002)***	-.008(.002)***	-.008(.002)***
SGA Ratio	.043(.045)	.039(.045)	.050(.045)	.040(.044)	.037(.044)
Stock Volume	-.056(.023)*	.054(.022)*	.041(.022)+	.027(.022)	-.042(.022)+
Stock Volatility	-.324(.080)***	-.276(.079)***	-.286(.079)***	-.251(.077)**	-.274(.078)***
Avg. Industry Change	.261(.014)***	.211(.014)***	.189(.014)***	.153(.014)***	.182(.014)***
MA Announcement Target	.088(.077)	.096(.076)	.109(.075)	.113(.074)	.122(.075)
MA Announcement Acquirer	-.041(.037)	-.057(.037)	-.061(.037)+	-.062(.036)+	-.062(.036)+
QE Announcement	-.097(.018)***	-.092(.018)***	-.078(.018)***	-.068(.017)***	-.076(.018)***
8K Info Announcement	-.084(.027)**	-.095(.027)***	-.091(.026)***	-.088(.026)***	-.089(.026)***
Management Guidance	.029(.060)	-.031(.060)	-.025(.059)	-.037(.058)	.034(.059)
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.084(.033)**	.101(.032)**	.090(.032)**	.083(.032)**	.087(.032)**
Independent Variables					
Recommendation		**.083(.007)*** **	.071(.007)***	.051(.007)***	.065(.007)***
Social Media Sentiment		**.147(.007)*** **	.091(.008)***	.035(.012)**	.071(.008)***
Consistency			**.304(.013)*** **	.099(.022)***	.002(.022)
Positive Valence				-.137(.014)***	
Negative Valence				-.070(.015)***	
Sentiment Polarity					-.079(.009)***
Interaction Effects					
Positive Valence*Consistency				**.463(.017)*** **	
Negative Valence*Consistency				**-.167(.021)*** **	
Sentiment Polarity*Consistency					**.201(.012)*** **
Number of Observations	25,901	25,901	25,901	25,901	25,901
F-Value	29.65***	47.54***	65.18***	85.83***	71.49***
R^2	.028	.047	.066	.096	.077

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 4. Results of Generalized Linear Model Regression on Social Media Activity Salience

Variable	Model 6 Hypothesis 3a
Control Variable	
Social Media Sentiment	0.003 (.003)
Independent Variable	
Sentiment Polarity	**0.295(.002)*****
Number of Observations	25,901
F-Value	8757.13***
R^2	.403

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 5. Simple slope significance with positive valence

Estimates					
Label	Estimate	Standard Error	DF	t Value	Pr > |t|
consistency slope, positive valence=mean-sd	0.01489	0.01969	25868	0.76	0.4496
consistency slope, positive valence=mean	0.3691	0.01638	25868	22.54	<.0001
consistency slope, positive valence=mean+sd	0.7234	0.02210	25868	32.73	<.0001

Table 6. Simple slope significance with negative valence

Estimates					
Label	Estimate	Standard Error	DF	t Value	Pr > |t|
consistency slope, negative valence=mean-sd	-0.08050	0.02303	25868	-3.50	0.0005
consistency slope, negative valence=mean	-0.1971	0.02253	25868	-8.75	<.0001
consistency slope, negative valence=mean+sd	-0.3137	0.03001	25868	-10.46	<.0001

Table 7. Simple slope significance with sentiment polarity

Estimates					
Label	Estimate	Standard Error	DF	t Value	Pr > |t|
consistency slope, polarity=mean-sd	0.1037	0.01772	25870	5.85	<.0001
consistency slope, polarity=mean	0.3237	0.01339	25870	24.17	<.0001
consistency slope, polarity=mean+sd	0.5438	0.01923	25870	28.28	<.0001

Figure 1. Theoretical Frameworks

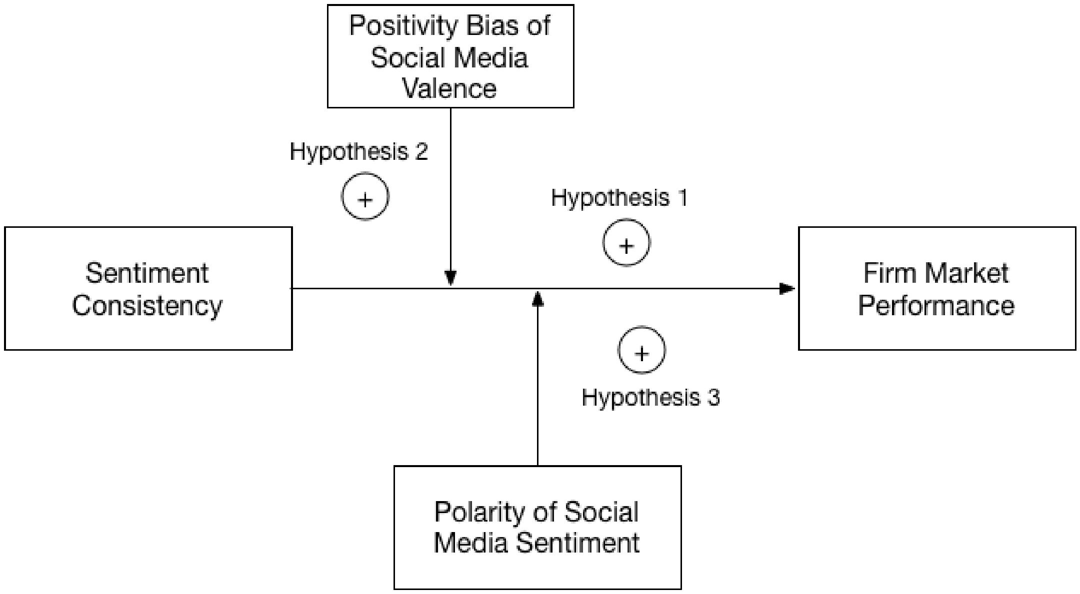
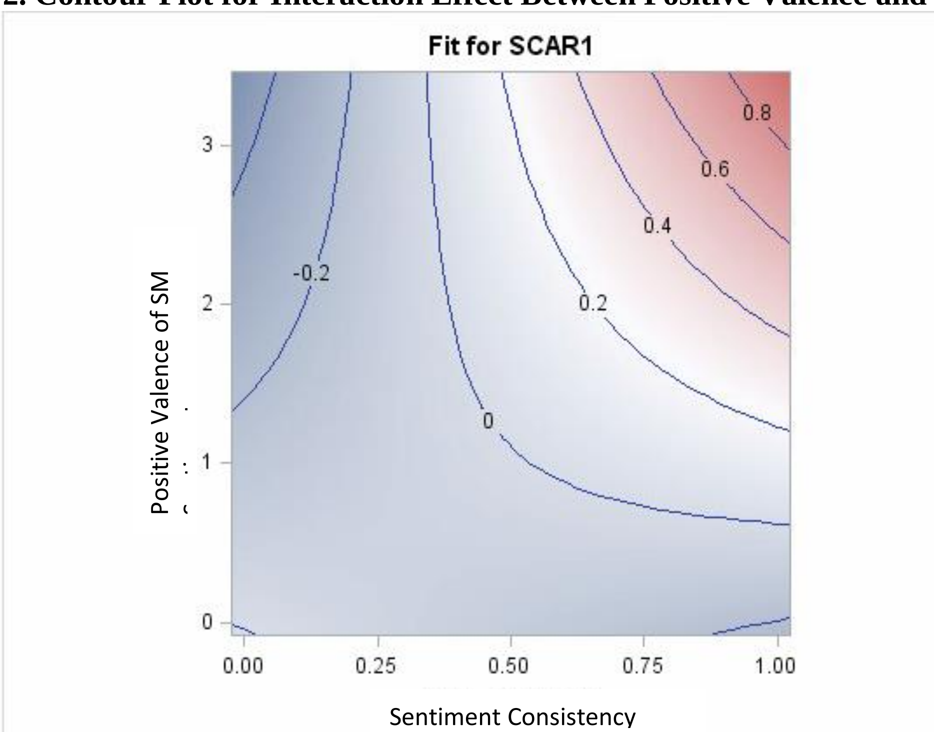


Figure 2. Contour Plot for Interaction Effect Between Positive Valence and Consistency



Fit computed at recommendation=3.53 sentiment=0.36 negative valence=0.586

Figure 3. Contour Plot for Interaction Effect Between Negative Valence and Consistency

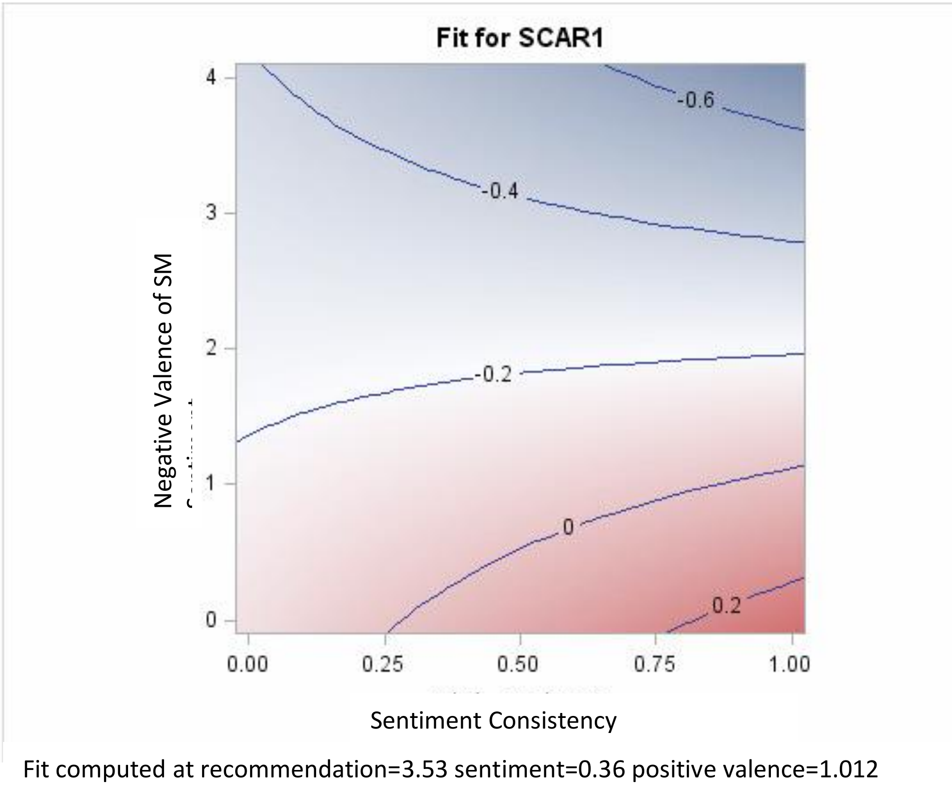


Figure 4. Visualization of Positive Valence of SM Sentiment Slopes

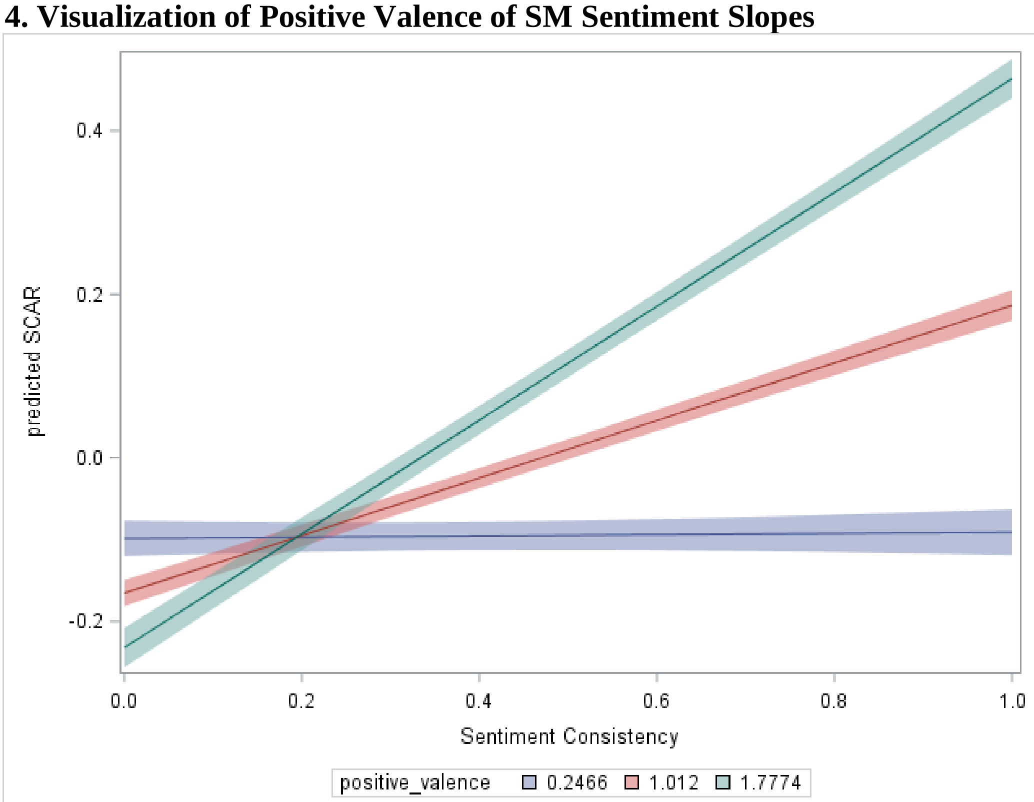


Figure 5. Visualization of Negative Valence of SM Sentiment Slopes

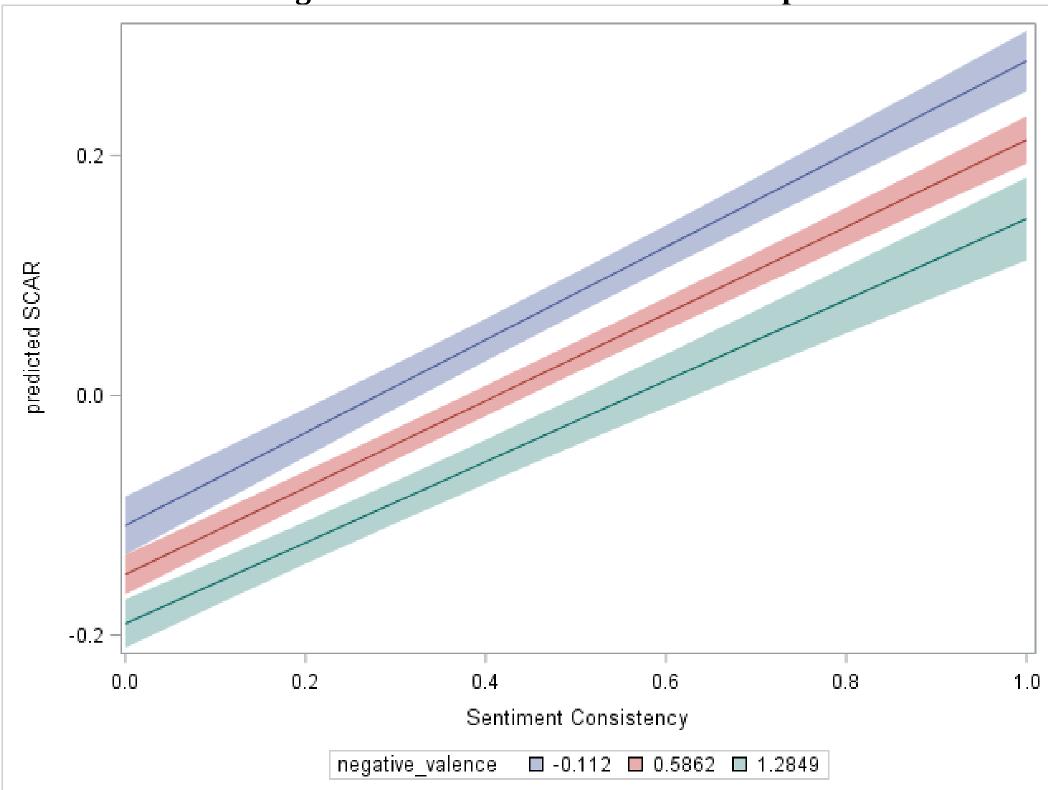


Figure 6. Visualization of Polarity Slopes

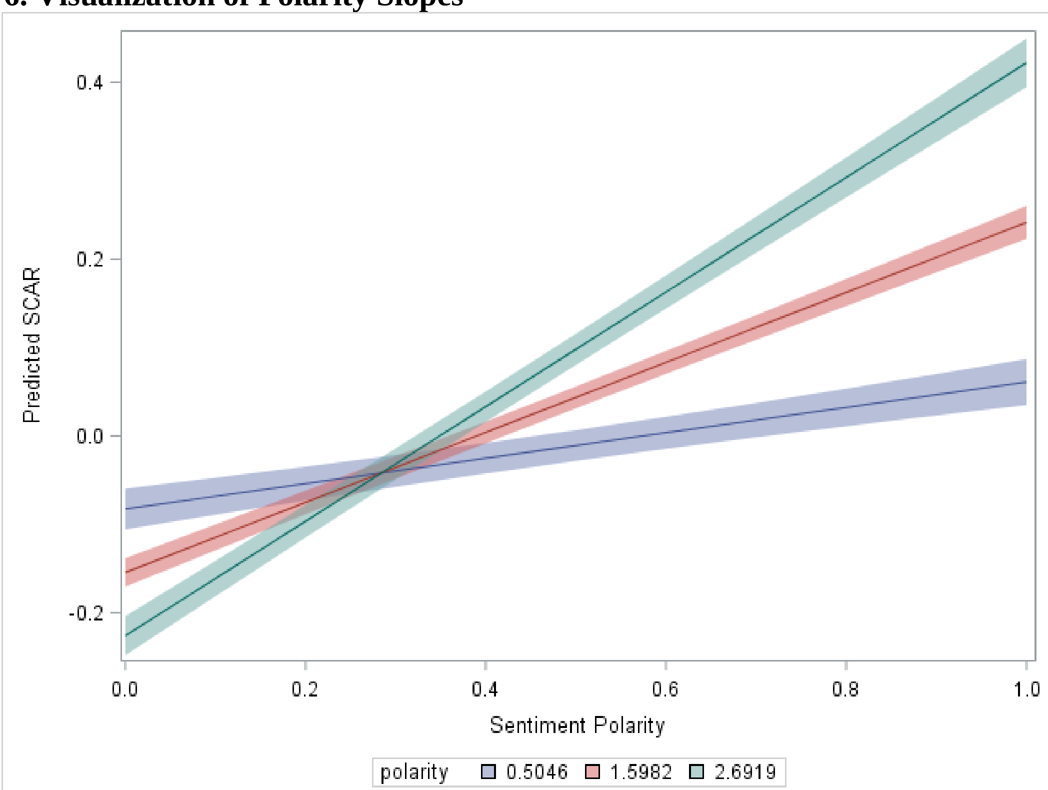
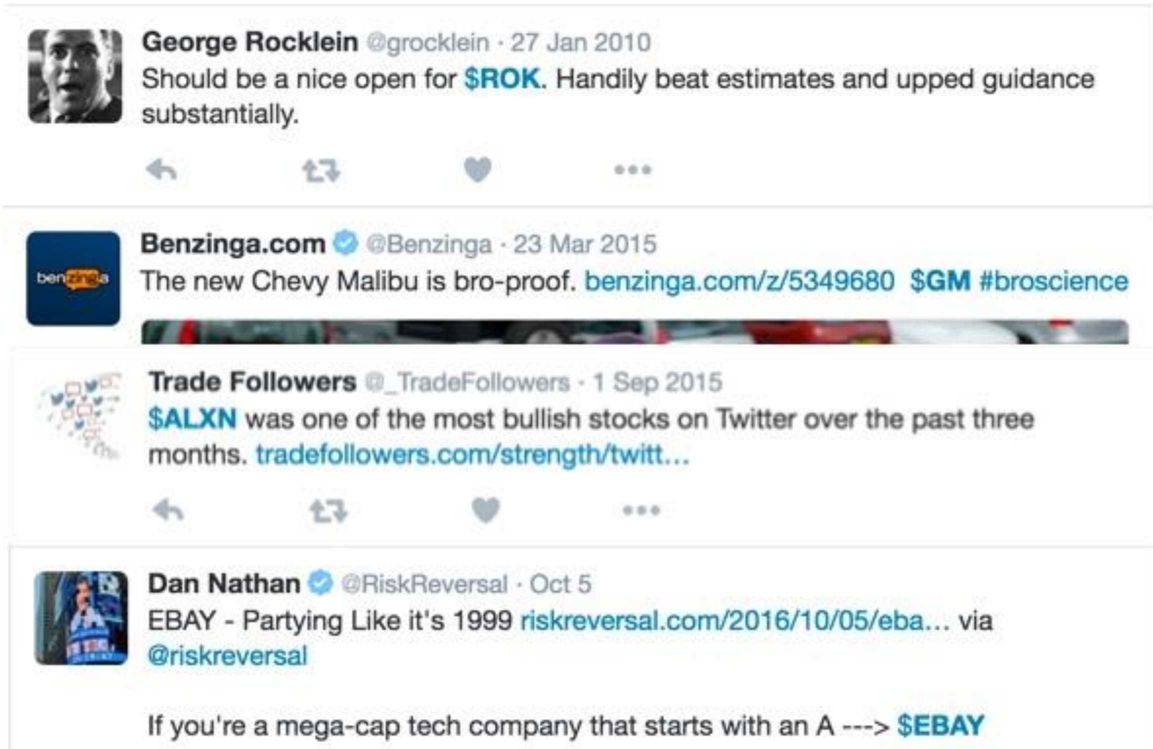


Figure 7. Examples of Tweets' Sentiment

Tweets with Positive Sentiment



Tweets with Negative Sentiment

APPENDIX A

ROBUSTNESS CHECKS RESULTS

Table 8. TTEST Procedure on SCAR(0,0) between with/without Social Media Sentiment

The SAS System

The TTEST Procedure

Variable: SCAR1 (Standardized CAR (0,0))

No_sentiment	N	Mean	Std Dev	Std Err	Minimum	Maximum
0	27411	-0.0124	2.0793	0.0126	-26.7788	53.6952
1	9482	0.00731	1.1401	0.0117	-11.5601	15.5948
Diff (1-2)		-0.0197	1.8832	0.0224		

No_sentiment	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev		95% UMPU CL Std Dev	
0		-0.0124	-0.0370	0.0122	2.0793	2.0621	2.0969	2.0620	2.0969
1		0.00731	-0.0156	0.0303	1.1401	1.1241	1.1565	1.1240	1.1565
Diff (1-2)	Pooled	-0.0197	-0.0637	0.0243	1.8832	1.8697	1.8969	1.8697	1.8969
Diff (1-2)	Satterthwaite	-0.0197	-0.0534	0.0140					

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	36891	-0.88	0.3800
Satterthwaite	Unequal	30079	-1.15	0.2513
Cochran	Unequal	.	-1.15	0.2513

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	27410	9481	3.33	<.0001

Table 9. Robustness Test Results on SCAR with event window (0,1)

Variables	Model 1 CV only	Model 2 Baseline	Model 3 Hypothesis 1	Model 4 Hypothesis 2	Model 5 Hypothesis 3b
Control Variable					
Mean Recommendation	.142(.017)***	.091(.017)***	.060(.017)***	.007(.017)	.047(.017)**
SD. Recommendation	-.105(.042)**	-.090(.042)**	-.089(.041)*	-.061(.041)	-.106(.041)**
Analyst Coverage	-.003(.001)***	-.003(.001)***	-.003(.001)***	-.003(.001)***	-.003(.000)***
Multiple Recommendation	-.089(.026)***	-.087(.026)***	-.107(.026)***	-.123(.025)***	-.118(.025)***
Off-hour Recommendation	.009(.013)	.004(.013)	.005(.013)	.007(.013)	.005(.013)
Star Analyst	.027(.014)*	.027(.014)*	.030(.014)*	.030(.014)*	.029(.014)*
SM Activity Salience	.145(.016)***	.140(.016)***	.143(.016)***	.198(.019)***	.148(.019)***
Size	-.034(.019)+	-.038(.018)*	-.037(.018)*	-.034(.018)+	-.039(.018)*
Firm Type	-.033(.005)***	-.033(.005)***	-.032(.005)***	-.027(.005)***	-.032(.005)***
EPS	-.007(.002)***	-.006(.002)***	-.006(.002)***	-.004(.002)***	-.005(.002)**
SGA Ratio	.023(.041)	.023(.041)	.032(.041)	.027(.040)	.027(.041)
Stock Volume	.010(.021)	.009(.021)	.002(.021)	.014(.021)	.001(.021)
Stock Volatility	-.327(.082)***	-.288(.081)***	-.289(.081)***	-.269(.080)***	-.278(.080)***
Avg. Industry Change	.232(.013)***	.189(.013)***	.172(.013)***	.141(.013)***	.167(.013)***
MA Announcement Target	.037(.072)	.046(.071)	.054(.071)	.054(.070)	.064(.070)
MA Announcement Acquirer	-.041(.034)	-.053(.034)	-.056(.034)	-.056(.033)+	-.055(.034)
QE Announcement	-.065(.016)***	-.042(.016)**	-.049(.016)**	-.039(.016)**	-.047(.016)**
8K Info Announcement	.022(.025)	.031(.025)	.022(.024)	.023(.024)	.025(.024)
Management Guidance	-.025(.061)	-.016(.060)	-.022(.060)	-.019(.059)	-.020(.059)
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.132(.030)***	.147(.030)***	.138(.030)***	.130(.030)***	.136(.030)***
Independent Variables					
Recommendation		**.071(.007)*****	.062(.007)***	.046(.007)***	.058(.007)***
Social Media Sentiment		**.117(.007)*****	.072(.007)***	.025(.011)*	.059(.007)***
Consistency			**.246(.012)*****	-.039(.021)+	.047(.021)*
Positive Valence				-.102(.013)***	
Negative Valence				-.052(.014)***	
SM Sentiment Polarity					-.055(.008)***
Interaction Effects					
Positive Valence*Consistency				**.352(.016)*****	
Negative Valence*Consistency				**-.178(.019)*****	
Polarity*Consistency					**.131(.011)*****
Number of Observations	25,909	25,909	25,909	25,909	25,909
F-Value	21.12***	38.00***	51.13***	64.90***	52.89***
R^2	.020	.038	.052	.074	.057

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 10. Robustness Test Results on SCAR with event window (0,3)

Variables	Model 1 CV only	Model 2 Baseline	Model 3 Hypothesis 1	Model 4 Hypothesis 2	Model 5 Hypothesis 3b
Control Variable					
Mean Recommendation	.088(.016)***	.052(.016)***	.030(.016)+	.019(.017)	.034(.019)+
SD. Recommendation	-.090(.039)*	-.079(.039)*	-.079(.039)*	-.051(.039)	-.099(.046)*
Analyst Coverage	-.002(.001)*	-.002(.001)**	-.002(.001)**	-.002(.001)**	-.002(.000)*
Multiple Recommendation	-.030(.024)	-.028(.024)	-.042(.024)+	-.055(.024)*	-.096(.027)**
Off-hour Recommendation	.002(.013)	.004(.012)	.004(.012)	.002(.012)	.013(.015)
Star Analyst	.012(.013)	.013(.013)	.015(.013)	-.016(.013)	-.009(.015)
SM Activity Salience	.093(.015)***	.089(.015)***	.091(.015)***	.135(.018)***	.000(.000)**
Size	-.052(.017)**	-.054(.017)**	-.053(.017)**	-.052(.017)**	-.073(.021)***
Firm Type	-.038(.005)***	-.038(.005)***	-.037(.005)***	-.034(.005)***	-.048(.006)***
EPS	-.004(.002)*	-.004(.002)*	-.003(.002)*	-.002(.002)	-.003(.002)
SGA Ratio	.047(.039)	.049(.039)	.054(.039)	.049(.039)	.047(.016)**
Stock Volume	.026(.020)	.028(.020)	.036(.020)+	.043(.020)*	.067(.023)**
Stock Volatility	-.404(.076)***	-.385(.076)***	-.382(.076)***	-.367(.075)***	-.441(.088)***
Avg. Industry Change	.180(.012)***	.148(.012)***	.135(.012)***	.114(.012)***	.151(.014)***
MA Announcement Target	.034(.066)	.033(.065)	.022(.065)	.016(.065)	.156(.072)***
MA Announcement Acquirer	-.006(.033)	-.014(.032)	-.016(.032)	-.017(.032)	-.017(.037)
QE Announcement	-.019(.015)	-.015(.015)	-.007(.015)	-.000(.015)	-.035(.017)
8K Info Announcement	-.024(.023)	-.029(.023)	-.024(.026)	-.024(.022)	-.011(.026)
Management Guidance	-.060(.053)	-.056(.053)	-.054(.052)	-.049(.052)	-.305(.055)***
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.108(.026)***	.115(.028)***	.110(.028)***	.102(.028)***	.155(.033)***
Independent Variables					
Recommendation		**.055(.006)*** **	.048(.006)***	.037(.006)***	.046(.006)***
Social Media Sentiment		**.074(.006)*** **	.041(.006)***	.026(.011)*	.033(.007)***
Consistency			**.177(.012)*** **	-.019(.019)	.048(.020)*
Positive Valence				-.096(.013)***	
Negative Valence				-.011(.014)	
SM Sentiment Polarity					-.040(.008)***
Interaction Effects					
Positive Valence*Consistency				**.259(.015)*** **	
Negative Valence*Consistency				**-.154(.018)*** **	
Polarity*Consistency					**.085(.010)*** **
Number of Observations	25,913	25,913	25,913	25,913	25,913
F-Value	19.32***	25.70***	33.07***	40.15***	33.23***
R^2	.018	.026	.035	.047	.037

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 11. Robustness Test Results on SCAR (0,0) with SM Sentiment Window (0,0)

Variables	**Model 1** **CV only**	**Model 2** **Baseline**	**Model 3** **Hypothesis 1**	**Model 4** **Hypothesis 2**	**Model 5** **Hypothesis 3b**
Control Variable					
Mean Recommendation	.209(.021)***	.114(.021)***	.106(.021)***	.008(.021)	.086(.021)***
SD. Recommendation	-.180(.052)***	-.148(.050)**	-.152(.050)**	-.137(.049)**	-.189(.050)***
Analyst Coverage	-.006(.001)***	-.005(.001)***	-.005(.001)***	-.004(.001)***	-.005(.001)***
Multiple Recommendation	-.169(.032)***	-.162(.031)***	-.166(.030)***	-.188(.030)***	-.178(.030)***
Off-hour Recommendation	.019(.016)	.011(.016)	.012(.016)	.022(.016)	.019(.016)
Star Analyst	-.004(.017)	-.002(.017)	-.001(.017)	-.004(.016)	-.000(.016)
SM Activity Salience	.282(.018)***	.285(.017)***	.287(.017)***	.296(.019)***	.262(.019)***
Size	-.067(.023)**	-.065(.022)**	-.063(.022)**	-.059(.021)**	-.063(.022)**
Firm Type	-.046(.006)***	-.040(.006)***	-.039(.006)***	-.034(.006)***	-.039(.006)***
EPS	-.014(.002)***	-.012(.002)***	-.012(.002)***	-.010(.002)***	-.011(.002)***
SGA Ratio	.004(.051)	.011(.049)	.020(.049)	.027(.048)	.021(.049)
Stock Volume	-.106(.026)***	-.092(.025)***	-.084(.025)***	-.059(.024)*	-.083(.025)***
Stock Volatility	-.430(.098)***	-.313(.094)***	-.305(.094)**	-.297(.092)**	-.310(.094)***
Avg. Industry Change	.276(.016)***	.197(.016)***	.192(.016)***	.137(.016)***	.180(.016)***
MA Announcement Target	.032(.087)	.036(.084)	.041(.084)	.047(.082)	.046(.083)
MA Announcement Acquirer	-.001(.042)	-.017(.041)	-.016(.041)	-.019(.040)	-.015(.041)
QE Announcement	-.073(.020)***	-.053(.019)**	-.046(.019)*	-.031(.019)+	-.040(.019)*
8K Info Announcement	-.101(.030)***	-.100(.029)***	-.099(.029)***	-.097(.028)***	-.098(.029)***
Management Guidance	-.002(.064)	-.003(.062)	-.009(.062)	.042(.061)	.030(.062)
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.046(.039)	.066(.038)	.059(.031)	.054(.037)	.053(.037)
Independent Variables					
Recommendation		**.079(.008)*** **	.076(.008)***	.050(.008)***	.070(.008)***
Social Media Sentiment		**.317(.008)*** **	.284(.009)***	.091(.016)***	.251(.009)***
Consistency			**.156(.015)*** **	-.234(.023)***	-.098(.023)***
Positive Valence				-.037(.012)**	
Negative Valence				-.108(.013)***	
SM Sentiment Polarity					-.044(.007)***
Interaction Effects					
Positive Valence*Consistency				**.371(.014)*** **	
Negative Valence*Consistency				**-.111(.016)*** **	
Polarity*Consistency					**.144(.010)*** **
Number of Observations	21,580	21,580	21,580	21,580	21,580
F-Value	32.53***	89.88***	90.95***	113.04***	92.88***
R^2	.036	.101	.106	.144	.115

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 12. Robustness Test Results on SCAR (0,0) with SM Sentiment Window (-7,0)

Variables	**Model 1 CV only**	**Model 2 Baseline**	**Model 3 Hypothesis 1**	**Model 4 Hypothesis 2**	**Model 5 Hypothesis 3b**
Control Variable					
Mean Recommendation	.185(.018)***	.137(.018)***	.070(.018)***	.007(.018)	.055(.018)**
SD. Recommendation	-.140(.043)**	-.136(.043)**	-.130(.042)**	-.101(.042)*	-.142(.042)***
Analyst Coverage	-.003(.001)***	-.003(.001)***	-.003(.001)***	-.003(.001)***	-.003(.001)***
Multiple Recommendation	-.126(.027)***	-.126(.027)***	-.155(.027)***	-.176(.027)***	-.165(.027)***
Off-hour Recommendation	.024(.014)+	.022(.014)	.024(.013)+	.027(.013)*	.026(.013)+
Star Analyst	-.003(.015)	-.001(.014)	-.002(.014)	-.002(.014)	-.000(.014)
SM Activity Salience	.174(.019)***	.171(.019)***	.174(.018)***	.241(.022)***	.171(.022)***
Size	-.037(.019)+	-.044(.019)*	-.040(.019)*	-.040(.018)*	-.041(.018)*
Firm Type	-.027(.006)***	-.027(.006)***	-.027(.006)***	-.023(.006)***	-.027(.006)***
EPS	-.009(.002)***	-.009(.002)***	-.008(.002)***	-.008(.002)***	-.008(.002)***
SGA Ratio	.033(.043)	.033(.043)	.049(.043)	.041(.042)	.047(.042)
Stock Volume	.043(.022)*	.040(.022)+	.032(.022)	.022(.021)	.031(.021)
Stock Volatility	-.253(.075)***	-.246(.075)**	-.242(.074)**	-.238(.073)**	-.242(.074)**
Avg. Industry Change	.245(.013)***	.200(.014)***	.164(.014)***	.135(.013)***	.158(.014)***
MA Announcement Target	.082(.076)	.092(.076)	.114(.074)	.106(.074)	.121(.074)
MA Announcement Acquirer	-.030(.036)	-.039(.036)	-.046(.036)	-.045(.035)	-.047(.035)
QE Announcement	-.092(.017)***	-.090(.017)***	-.076(.017)***	-.076(.017)***	-.076(.017)***
8K Info Announcement	-.056(.026)*	-.059(.026)*	-.056(.025)*	-.053(.025)*	-.051(.025)*
Management Guidance	.054(.058)	.053(.058)	.058(.057)	.067(.056)	.060(.057)
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.083(.031)**	.091(.031)**	.078(.030)*	.076(.030)*	.077(.030)*
Independent Variables					
Recommendation		**.085(.007)*** **	.067(.007)***	.053(.007)***	.063(.007)***
Social Media Sentiment		**.078(.007)*** **	.011(.008)	-.000 (.011)	-.001(.008)
Consistency			**.373(.013)*** **	-.027(.023)	.087(.022)***
Positive Valence				-.174(.016)***	
Negative Valence				-.027(.017)	
SM Sentiment Polarity					-.074(.010)***
Interaction Effects					
Positive Valence*Consistency				**.499(.020)*** **	
Negative Valence*Consistency				**-.218(.024)*** **	
Polarity*Consistency					**.198(.013)*** **
Number of Observations	27,708	27,708	27,708	27,708	27,708
F-Value	27.46***	35.62***	65.17***	80.50***	69.16***
R^2	.024	.034	.062	.085	.070

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 13. Robustness Test Results on SM Activity Salience with Sentiment Window (0,0)

Variable	Model 6 Hypothesis 3a
Control Variable	
Social Media Sentiment	.003(.004)
Independent Variable	
SM Sentiment Polarity	**.225(.002)*** **
Number of Observations	22,026
F-Value	5748.87***
R^2	.343

Table 14. Robustness Test Results on SM Activity Salience with Sentiment Window (-7,0)

Variable	Model 6 Hypothesis 3a
Control Variable	
Social Media Sentiment	.010(.003)***
Independent Variable	
SM Sentiment Polarity	**.340(.002)*** **
Number of Observations	28,320
F-Value	11132.6***
R^2	.440

Table 15. Robustness Test Results on SCAR (0,0) with Twitter without Retweets

Variables	**Model 1 CV only**	**Model 2 Baseline**	**Model 3 Hypothesis 1**	**Model 4 Hypothesis 2**	**Model 5 Hypothesis 3b**
Control Variable					
Mean Recommendation	.206(.018)***	.153(.019)***	.074(.018)***	.014(.018)	.067(.018)***
SD. Recommendation	-.150(.045)***	-.137(.045)***	-.134(.044)**	-.098(.043)*	-.131(.044)**
Analyst Coverage	-.004(.001)***	-.004(.001)***	-.004(.001)***	-.004(.001)***	-.004(.001)***
Multiple Recommendation	-.124(.029)***	-.124(.029)***	-.165(.029)***	-.170(.028)***	-.170(.029)***
Off-hour Recommendation	.002(.014)	-.001(.014)	.005(.014)	.010(.014)	.006(.014)
Star Analyst	.002(.015)	.002(.015)	.002(.015)	.005(.015)	-.003(.015)
SM Activity Salience	.258(.018)***	.249(.018)***	.246(.018)***	.275(.021)***	.252(.021)***
Size	-.079(.020)***	-.084(.020)***	-.078(.020)***	-.074(.020)***	-.076(.020)***
Firm Type	-.033(.006)***	-.030(.006)***	-.026(.006)***	-.023(.006)***	-.026(.006)***
EPS	-.010(.002)***	-.009(.002)***	-.008(.002)***	-.007(.002)***	-.008(.002)***
SGA Ratio	-.024(.046)	-.011(.046)	-.001(.045)	-.008(.044)	-.001(.045)
Stock Volume	-.078(.023)***	-.067(.023)**	-.054(.022)*	-.042(.022)+	-.056(.023)*
Stock Volatility	-.362(.078)***	-.305(.078)***	-.297(.076)***	-.290(.075)***	-.278(.076)***
Avg. Industry Change	.261(.014)***	.218(.014)***	.178(.014)***	.152(.014)***	.175(.014)***
MA Announcement Target	-.022(.081)	.013(.080)	.002(.079)	.008(.078)	.006(.079)
MA Announcement Acquirer	-.020(.038)	-.037(.038)	-.043(.037)	-.044(.037)	-.047(.037)
QE Announcement	-.118(.019)***	-.112(.019)***	-.095(.018)***	-.086(.018)***	-.094(.018)***
8K Info Announcement	-.084(.028)**	-.084(.027)**	-.080(.027)**	-.084(.027)**	-.081(.027)**
Management Guidance	.046(.062)	-.042(.061)	-.068(.060)	-.064(.060)	-.067(.060)
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.070(.030)*	.080(.030)**	.074(.029)*	.069(.029)*	.074(.029)*
Independent Variables					
Recommendation		**.075(.007)*** **	.055(.007)***	.043(.007)***	.054(.007)***
Social Media Sentiment		**.128(.007)*** **	.051(.008)***	.031(.011)**	.042(.008)***
Consistency			**.415(.014)*** **	-.063(.026)*	.221(.024)***
Positive Valence				-.118(.017)***	
Negative Valence				-.001(.023)	
SM Sentiment Polarity					-.046(.009)***
Interaction Effects					
Positive Valence*Consistency				**.440(.021)*** **	
Negative Valence*Consistency				**-.273(.023)*** **	
Polarity*Consistency					**.108(.011)*** **
Number of Observations	26,086	26,086	26,086	26,086	26,086
F-Value	33.27***	46.77***	80.01***	88.34***	77.96***
R^2	.031	.047	.080	.099	.084

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 16. Robustness Test Results on SCAR (0,0) with Twitter with Retweets

Variables	Model 1 CV only	Model 2 Baseline	Model 3 Hypothesis 1	Model 4 Hypothesis 2	Model 5 Hypothesis 3b
Control Variable					
Mean Recommendation	.202(.018)***	.146(.018)***	.066(.018)***	.007(.018)	.061(.018)***
SD. Recommendation	-.155(.045)***	-.144(.045)**	-.140(.044)**	-.104(.043)**	-.138(.044)**
Analyst Coverage	-.004(.001)***	-.004(.001)***	-.004(.001)***	-.004(.001)***	-.004(.001)***
Multiple Recommendation	-.127(.029)***	-.124(.029)***	-.165(.029)***	-.171(.028)***	-.170(.029)***
Off-hour Recommendation	.006(.014)	.003(.014)	.009(.014)	.013(.014)	.009(.014)
Star Analyst	-.001(.015)	-.001(.015)	-.001(.015)	-.002(.015)	.001(.015)
SM Activity Salience	.234(.017)***	.228(.017)***	.224(.017)***	.250(.020)***	.228(.020)***
Size	-.078(.020)***	-.083(.020)***	-.076(.020)***	-.072(.020)***	-.074(.020)***
Firm Type	-.031(.006)***	-.028(.006)***	-.024(.006)***	-.021(.006)***	-.024(.006)***
EPS	-.009(.002)***	-.008(.002)***	-.007(.002)***	-.006(.002)***	-.007(.002)***
SGA Ratio	-.030(.046)	.016(.045)	.006(.045)	.013(.044)	.004(.045)
Stock Volume	-.068(.023)**	.056(.023)*	.044(.023)*	.031(.022)	.045(.023)*
Stock Volatility	-.367(.078)***	-.309(.078)***	-.302(.076)***	-.299(.076)***	-.286(.076)***
Avg. Industry Change	.257(.014)***	.211(.014)***	.171(.014)***	.146(.014)***	.169(.014)***
MA Announcement Target	-.010(.081)	.006(.081)	.011(.079)	.006(.079)	.020(.079)
MA Announcement Acquirer	-.019(.046)	-.036(.038)	-.042(.037)	-.043(.037)	-.046(.037)
QE Announcement	-.030(.038)	-.101(.018)***	-.085(.018)***	-.076(.018)***	-.084(.018)***
8K Info Announcement	-.084(.028)***	-.085(.027)**	-.082(.027)**	-.085(.027)**	-.083(.027)**
Management Guidance	-.043(.062)	-.038(.061)	-.062(.060)	-.058(.059)	-.061(.060)
Year Effects	Included	Included	Included	Included	Included
Bloomberg	.071(.030)*	.082(.030)**	.076(.029)**	.070(.029)*	.075(.029)*
Independent Variables					
Recommendation		**.081(.007)*****	.063(.007)***	.051(.007)***	.062(.007)***
Social Media Sentiment		**.125(.007)*****	.049(.007)***	.028(.011)*	.041(.008)***
Consistency			**.413(.014)*****	.074(.026)**	.234(.024)***
Positive Valence				-.112(.017)***	
Negative Valence				.002(.018)	
SM Sentiment Polarity					-.041(.009)***
Interaction Effects					
Positive Valence*Consistency				**.431(.021)*****	
Negative Valence*Consistency				**-.278(.023)*****	
Polarity*Consistency					**.099(.011)*****
Number of Observations	26,137	26,137	26,137	26,137	26,137
F-Value	31.84***	45.73***	78.68***	86.64***	76.21***
R^2	.030	.046	.078	.097	.082

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Table 17. Robustness Test Results on SM Activity Salience with Twitter without Retweets

Variable	**Model 6** **Hypothesis 3a**
Control Variable	
Social Media Sentiment	.018(.003)***
Independent Variable	
SM Sentiment Polarity	**.353(.002)*** **
Number of Observations	26,199
F-Value	14438.1***
R^2	.524

Table 18. Robustness Test Results on SM Activity Salience with Twitter with Retweets

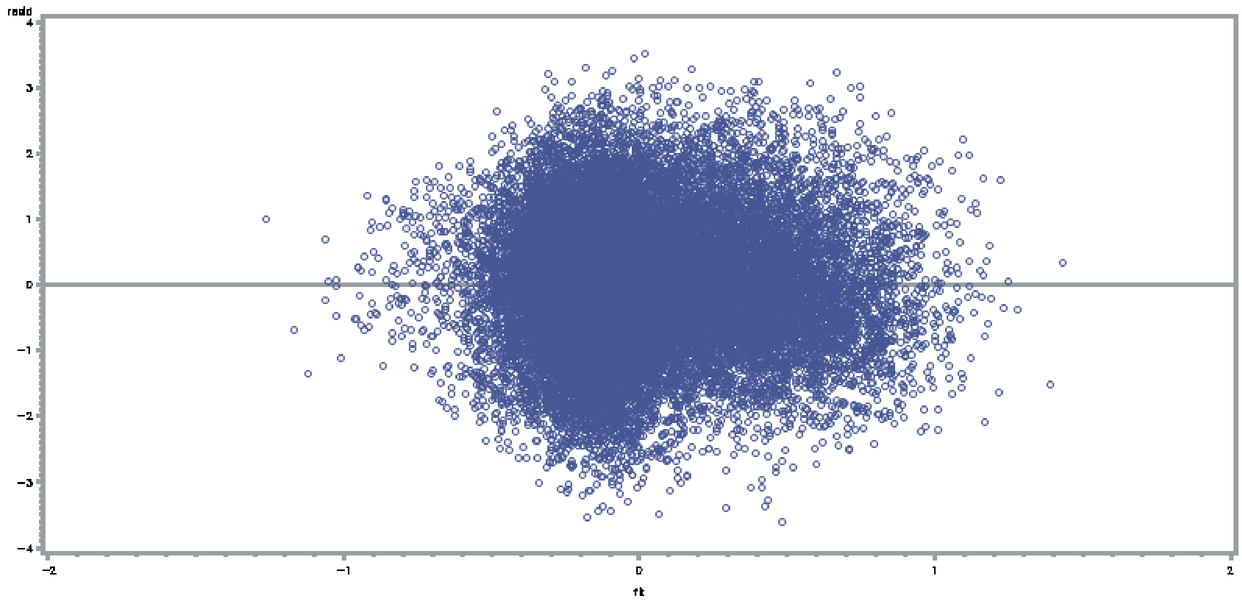
Variable	**Model 6** **Hypothesis 3a**
Control Variable	
Social Media Sentiment	.017(.003)***
Independent Variable	
SM Sentiment Polarity	**.363 (.002)*** **
Number of Observations	26,249
F-Value	14135.4***
R^2	.519

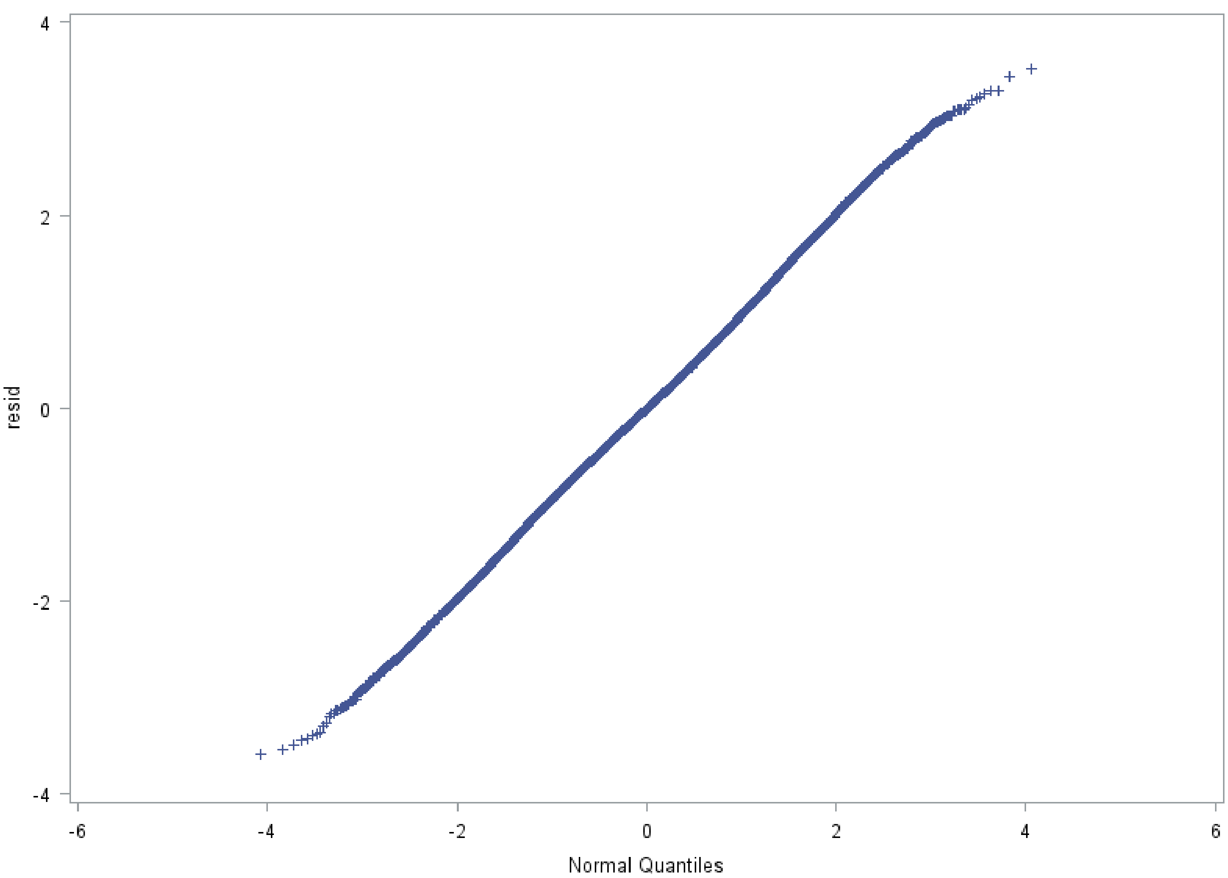
Table 19. Robustness Test Results on SCAR (0,0) including Media Sentiment

Variables	**Model 1 CV only**	**Model 2 Baseline**	**Model 3 Hypothesis 1**	**Model 4 Hypothesis 2**	**Model 5 Hypothesis 3b**
Control Variable					
Mean Recommendation	.190(.028)***	.102(.028)***	.041(.027)	.039(.028)	.033(.027)
SD. Recommendation	-.069(.068)	-.042(.067)	-.036(.066)	-.017(.065)	-.057(.066)
Analyst Coverage	-.005(.001)***	-.004(.001)**	-.004(.001)**	-.003(.001)**	-.004(.001)**
Multiple Recommendation	-.143(.046)**	-.137(.045)**	-.169(.045)***	-.189(.044)***	-.173(.044)***
Off-hour Recommendation	.039(.022)+	.023(.021)	.024(.021)	.035(.021)+	.026(.021)
Star Analyst	-.036(.022)	-.033(.022)	-.041(.022)	.041(.021)+	.037(.021)+
SM Activity Salience	.230(.025)***	.231(.025)***	.233(.025)***	.277(.029)***	.227(.029)***
Size	-.046(.031)	-.063(.030)*	-.062(.030)*	-.061(.030)*	-.066(.030)*
Firm Type	-.019(.010)*	-.020(.009)*	-.017(.009)+	-.017(.009)+	-.016(.009)+
EPS	-.012(.002)***	-.010(.002)***	-.009(.002)***	-.008(.002)***	-.009(.002)***
SGA Ratio	.044(.076)	.009(.076)	.009(.074)	.007(.073)	.009(.074)
Stock Volume	-.072(.037)+	-.068(.036)+	-.043(.036)	-.020(.035)	-.042(.036)
Stock Volatility	-.689(.147)***	-.649(.145)***	-.628(.143)***	-.589(.141)***	-.616(.143)***
Avg. Industry Change	.275(.020)***	.205(.021)***	.171(.020)***	.140(.020)***	.169(.020)***
MA Announcement Target	-.011(.120)	-.052(.118)	-.040(.116)	-.048(.115)	-.035(.116)
MA Announcement Acquirer	-.018(.056)	-.029(.055)	-.027(.054)	-.028(.054)	-.028(.054)
QE Announcement	-.053(.028)+	-.053(.028)+	-.036(.027)	-.027(.027)	-.035(.027)
8K Info Announcement	-.030(.042)	-.049(.042)	-.040(.041)	-.034(.041)	-.037(.041)
Management Guidance	.176(.103)+	.202(.102)*	.197(.100)*	.181(.099)+	.188(.100)+
Media Sentiment	.011(.003)***	.011(.003)**	.011(.003)***	.011(.003)***	.011(.003)**
Independent Variables					
Recommendation		**.102(.011)*** **	.085(.011)***	.064(.011)***	.080(.011)***
Social Media Sentiment		**.180(.011)*** **	.111(.011)***	.026(.017)	.099(.011)***
Consistency			**.392 (.020)*** **	.043(.036)	.164(.036)***
Positive Valence				-.059(.024)*	
Negative Valence				-.098(.025)***	
SM Sentiment Polarity					-.051(.014)***
Interaction Effects					
Positive Valence*Consistency				**.407(.028)*** **	
Negative Valence*Consistency				**-.199(.031)*** **	
Polarity*Consistency					**.135(.017)*** **
Number of Observations	12,011	12,011	12,011	12,011	12,011
F-Value	18.35***	33.51***	49.73***	55.95***	48.40***
R^2	.030	.058	.087	.112	.092

+ p<0.1, * p<0.05, **p<0.01, ***p<0.001

Figure 8. Plot of Regression Residual with Fitted SCAR(0,0)





APPENDIX B

PROPENSITY SCORE MATCHING

To further test the sentiment consistency effect on firms' market performance, I adopted the propensity score matching (PSM) technique to estimate the effect of sentiment consistency by accounting for covariates that predict receiving the sentiment consistency. PSM attempts to reduce the bias due to confounding variables that could be found in an estimate of the treatment effect obtained from simply comparing the outcomes among units that received the treatment versus those that did not (Rosenbaum & Rubin, 1983). PSM is a recent methodological development to control for endogeneity that enabled me to create a quasi-experimental setting (Imbens & Wooldrige, 2009). Specifically, it allows the creation of a control group consisting of firms that have nearly the same characteristics, receiving similar type of information during the recommendation events with same recommendation and social media sentiment scores but without sentiment consistency.

To implement propensity score matching, I estimate a Probit of SCAR during analyst recommendation announcement event and use fitted values from that model as estimates of the propensity score: $\Pr(SCAR_{\mathrm{i}}=1 — X_{ij})$, where X_{ij} includes all the observable characteristics of firms and concurrent information release. I used *teffects psmatch* procedure in Stata 14 to estimate treatment effect (sentiment consistency) from observational data by propensity-score matching. PSM imputes the missing potential SCAR for each event by using an average of the SCAR of similar event subjects that receive the other sentiment consistency level. Similarity between event firms is based on estimated treatment probabilities, known as propensity scores. The average treatment effect (ATE) is computed by taking the average of the difference between the observed and potential SCAR for each firm event.

The Z value of 14.89 (p<0.0001) indicates a significant effect of Sentiment Consistency controlling for all the other covariates. In the covariate summary, the mean of variance ratio is: 1.0038 close to 1, indicating a balanced matching. Finally, I obtained the overlap plot. The plot finds evidence of overlapping between treated and matched groups, which satisfies the common support condition.

B.1.1 Treatment-Effects Estimation

Treatment-effects estimation			Number of obs	=	25,901
Estimator	:	Propensity-score matching	Matches: requested	=	20
Outcome model	:	matching	min	=	20
Treatment model	:	probit	max	=	21

Scar1	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATE						
Consistency (1 vs 0)	.2476971	.0145122	17.07	0.000	.2192538	.2761404

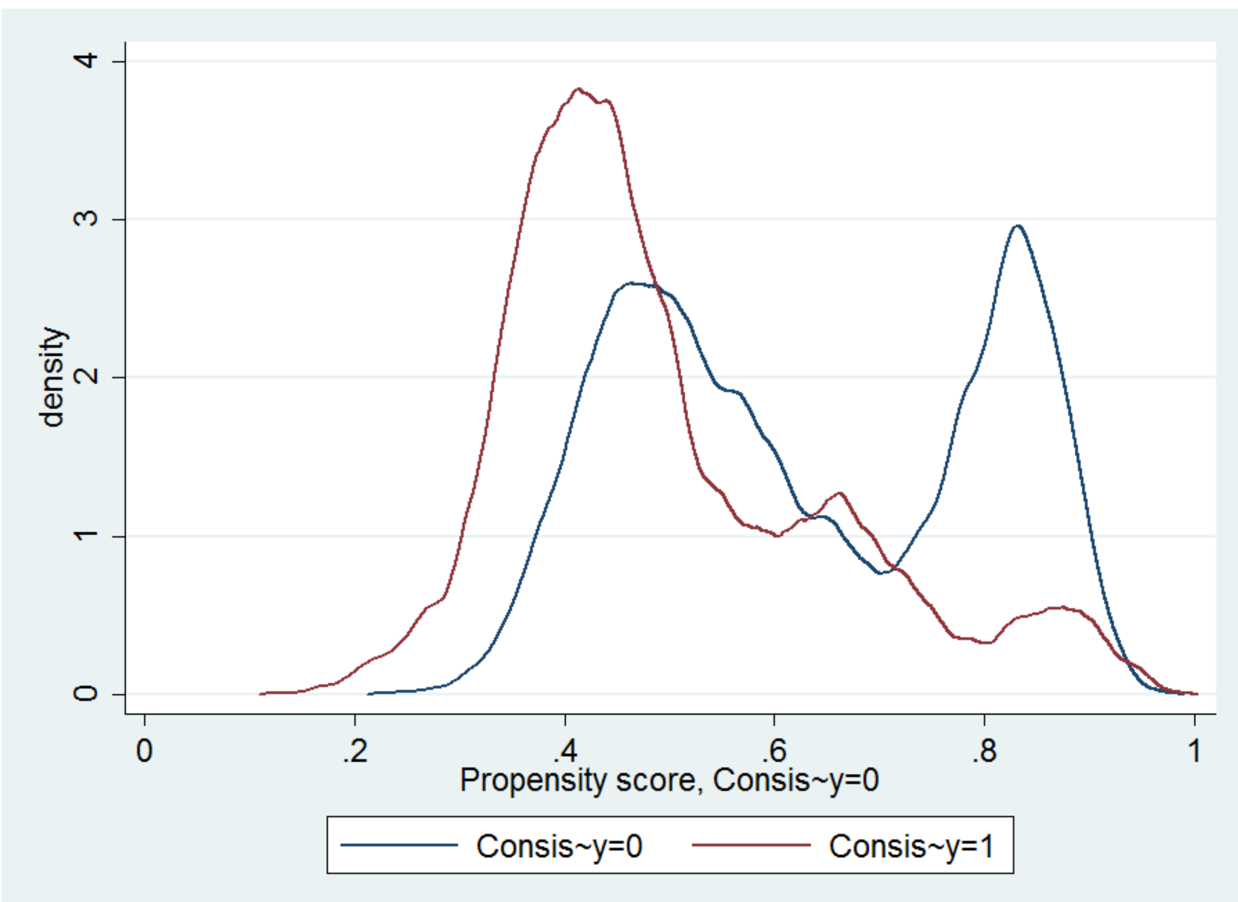
B.1.2 Covariate Balance Summary

		Raw	Matched
Number of obs	=	25,901	51,802
Treated obs	=	11,014	25,901
Control obs	=	14,887	25,901

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Recommendation	.236035	-.0593047	1.053649	1.011329
Social Media Sentiment	.7137081	.0569647	.4262508	.8320316
Mean Recommendation	.2351785	-.072318	.941343	1.038143
SD. Recommendation	-.0446292	.061018	.9617519	1.121281
Analyst Coverage	-.0319082	.0123971	1.014983	1.091027
Multiple Recommendation	.0336118	-.008821	1.140908	.9667966
Off-hour Recommendation	.0127711	-.0077951	1.013547	.9918035
Star Analyst	-.0036096	.0070975	.9952806	1.009389
SM Activity Salience	-.0447924	-.0055505	.8396659	.9840785
Size	.0137959	.0035753	.9481607	.9891935
Firm Type	.0044448	-.0168898	.9833955	.9270813
EPS	-.0004114	-.002548	.7581785	.8843738
SGA Ratio	-.0213643	.0319768	1.024164	.9260241
Stock Volume	-.0707848	.032959	1.011607	1.088498
Stock Volatility	-.0458747	-.0026299	1.157314	1.23963

Avg. Industry Change	.1936594	-.0386636	1.179601	.9488446
MA Announcement Target	-.0160853	.0031269	.8338121	1.035495
MA Announcement Acquirer	.0119739	.0100207	1.063129	1.052047
QE Announcement	-.0851784	.0272685	.8610274	1.048137
8K Info Announcement	-.0191694	.0070807	.9343089	1.025263
Management Guidance	-.013473	-.0012409	.8856492	.9890939
Y2011	-.0009179	.0070928	.9984102	1.01257
Y2012	-.0738442	.023319	.8823961	1.040048
Y2013	.0368322	-.0208471	1.056581	.9695109
Y2014	.0644996	-.0228397	1.113917	.9624429
Y2015	.0119625	-.003442	1.022762	.9933966
Bloomberg	.0555778	-.0311068	.9622554	1.021025

B.1.3 Teffects Overlap Graph



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