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Does Chatting Really Help? Tweet Analytics and Analyst Forecast Dispersion

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Abstract:

Financial analysts use tweet analytics to prepare their forecasts, yet little information that describes how they do so exists. To address this gap, we scrutinize the associative relationships between tweets about a company's service and the dispersion of analyst forecasts about the same company's financial performance. We developed three sets of hypotheses. We extracted tweets related to airlines from the Twitter data from Archive Team and analyst forecast data from Institutional Brokers' Estimate System Academic. We obtained airline-related tweets from nearly 200,000 individual Twitter users about 10 airlines during a 55-month study period and ran multiple regressions to test the associations between tweet characteristics and forecast dispersion. Our results suggest that, when more posters generate more tweets about a company's service, analysts make less dispersed forecasts. In addition, negative (or non-verified) tweets reduce forecast dispersion to a greater extent than positive (or verified) tweets do. Theoretically, this paper confirms that Twitter can be a useful data source to provide analysts with additional information to prepare their forecasts. Practically, our findings provide empirical evidence about how Twitter data is associated with analyst forecast dispersion. We encourage stakeholders (such as analysts from small firms and individual investors) to extract data from Twitter as a supplement to market information when analyzing data.

Keywords: Social Media, Twitter, Sentiment Analysis, Analyst Forecast Dispersion.

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1 Introduction

Prior studies have revealed that discussions on social media about a company's services[1] reflect individuals' concerns about the services and help stakeholders make strategic decisions. However, only marketers and managers comprise the "stakeholders" in these studies. For instance, Zhang (2015) examined how companies leverage social media to communicate with consumers and influence their information-disclosure decisions, and Schniederjans, Cao, and Schniederjans (2013) suggested using social media to enhance corporate image. Cheng, Sun, Hu, and Zeng (2011) proposed a framework to control the volume of traffic for micro-blogging Web users to subsequently influence their information-seeking behavior. Unlike these prior studies, which have focused on consumers and Web users, we examine another group of stakeholders—financial analysts (hereafter simply "analysts")—to examine how discussions about a company's service extracted from social media are associated with analysts' ability to make less dispersed forecasts about the same company's financial performance. Among the various forms of social media, we focus on Twitter. Specifically, we examine which tweet characteristics are associated with analyst forecast dispersion.

Although companies provide financial statements to the public, information asymmetry still exists, which leads to stock market imperfection (Lambert, Leuz, & Verrecchia, 2012). As an information intermediary in financial markets, analysts prepare forecasts for companies to help the public better estimate companies' value. In preparing forecasts, analysts actively seek alternative information sources to reduce information asymmetry. In the past, they relied on offline information, such as product investigation reports and expert reviews (Tellis & Johnson, 2007). However, with the growth of social media, consumers have begun to increasingly share their opinions about products online (Godes & Mayzlin, 2004). Unlike product investigation reports and expert reviews, online discussions about a company's products represent consumers' first-hand feedback. Thus, these discussions will likely provide more reliable and timely information source than investigation reports and expert reviews to help analysts predict a company's future sales performance. Twitter (2016) has highlighted that "[f]inancial analysts, traders and market professionals globally are increasingly using Twitter to stay abreast of the market and make critical decisions". To respond to this technology trend, we explore the association between tweet characteristics and analyst forecasts in this study.

We extend prior research in two ways. First, we associate the characteristics of Twitter data with analyst forecast dispersion—a core quality of analyst forecasts (Gu & Wu, 2003). Prior research has often used stock prices as the predictor of interest. For example, Luo, Homburg, and Wieseke (2010) examined how the number of complaints about airline services submitted to the United States Department of Transportation related to long-term effects on stock prices. Luo and Homburg (2008) estimated a company's optimal market value and found that the gap between its market value and optimal market value increased with the number of consumer complaints. Tirunillai and Tellis (2012) examined whether and how consumer complaints on blogs affect stock returns. They found that these complaints exert a strong negative effect on abnormal stock returns with a short severe effect and long wear-out effect. In our study, we consider individuals' discussions in relation to a company's service as an information-sharing process and analysts as information users. Extending the prior research, we examine the value that sharing this information to analysts creates for reducing information asymmetry in financial markets (as reflected by reduced dispersion in analysts' forecasts).

Second, we examine the differential effects that tweet valence and source verification have on forecast dispersion. The literature in online consumer reviews has devoted greater attention to negative reviews. It has found negative reviews to damage product brands (Lee & Cranage, 2014), reduce the likelihood that consumers will purchase (Jansen, Zhang, Sobel, & Chowdury, 2009), and, consequently, decrease a company's sales performance and future earnings (Chevalier & Mayzlin, 2006). A company cannot as easily change the effects that negative reviews create compared to the effects that positive reviews create (Pantano & Corvello, 2013). Extending this prior research, our study considers the valence of tweets and examines the differential effects that positive and negative tweets have on the dispersion of analyst forecasts. In addition, given the two types of Twitter accounts (verified and non-verified) and tweet valence, we examine how source verification is associated with analyst forecast dispersion.

This study constitutes one of the first to scrutinize the associative relationships between tweets regarding a company's service and analysts' ability to make less dispersed forecasts about the company's financial

[1] In this paper, we use the term "services" to refer to both services and merchandise.

performance. To do so, we drew on the literature on information asymmetry. Information asymmetry describes a situation in which one party holds more information than the other and the lack of information constrains the latter party from making effective decisions. In addition to the amount of information, we theorized about how information valence and source verification are associated with forecast dispersion and developed three sets of hypotheses.

In this study, we adopted an archival research method. We extracted tweets from Twitter about major airlines in North America and obtained the financial data of these airlines from Institutional Brokers' Estimate System Academic (I/B/E/S Academic) on Wharton Research Data Services (WRDS). Correspondingly, we calculated the numbers of positive and negative tweets for each airline in each month. With a combined dataset of the Twitter data and analyst forecast data, we ran multiple regressions to associate tweet characteristics with analyst forecast dispersion.

Our study contributes to theory and practice in several ways. Theoretically, given that prior research has often focused on individuals' behavior (e.g., Ellison, Vitak, Gray, & Lampe, 2014; Ryan & Xenos, 2011) and communication between companies and customers (e.g., Schniederjans et al., 2013; Zhang, 2015) on social media, our study extends the boundary for using social media (Twitter, in our case) by examining the applicability of social media data to analyst forecasts. Practically, through empirical tests, we identified associations between tweet characteristics and analyst forecast dispersion. Given that analysts at major financial institutions actively use tweet analytics to prepare forecasts (Greenfield, 2016) but keep their techniques confidential, our findings provide analysts in small firms and individual investors with ideas on how to extract information from Twitter data as a supplement to market information when making financial-related decisions.

2 Literature Review

2.1 Information Asymmetry in Financial Markets and Analyst Forecasts

As we state above, information asymmetry describes a situation in which one party holds more information than the other and the lack of information constrains the latter party from making effective decisions. In financial markets, as insiders, a company's managers hold more information about the company's earnings and financial performance than outsiders (e.g., analysts). Countries such as China and the United States have mandatory disclosure systems—that is, listed companies must release audited financial reports periodically. In addition, corporate managers, as corporate insiders, can voluntarily issue earnings guidance (management forecasts). These disclosure systems can help reduce information asymmetry and improve the efficiency of resource allocation in the capital market (Healy & Palepu, 2001). However, even with these disclosure systems in place, analysts cannot solely rely on management forecasts or company disclosures to prepare their own forecasts because they may contain biases and/or may not provide complete information.

For instance, the accounting literature has established that managers have incentives to manipulate accounting numbers on the mandated financial reports to achieve certain objectives (e.g., Dechow, Sloan & Sweeney, 1996; Rogers & Stocken, 2005). At times, managers manipulate key accounting numbers in financial reports in their favored directions for their own job security and/or performance bonuses. At other times, they may manipulate reports due to pressure to meet market expectations, to avoid reporting a loss, and/or to surpass the previous year's earnings (Healy & Palepu, 2001). Managers typically manipulate such reports via accounting tricks (such as suppressing the depreciation rate), yet some desperate managers may even manipulate data through deliberately engaging in real but counterproductive activities (such as exercising planned overproduction) (Roychowdhury, 2006).

In addition, companies that suffer a decline in earnings attract exceptionally dispersed management earnings forecasts (Jelic, Saadouni, & Briston, 1998). Managers' opportunism and fear of litigation affects their accrual-related forecast bias in range forecasts (Xu, 2010). In other words, management earnings forecasts constitute the aggregate outcome of certain parameters, such as the various accounting treatments, estimates, and assumptions that managers make, and analysts cannot observe these parameters as easily as managers can.

As a result, even with both mandatory and voluntary disclosures in place, analysts hold less information than managers, which restricts their ability to reliably predict company earnings. This information asymmetry also makes it more difficult for individual financial analysts to reach consensus about a company's future performance and, thus, results in high dispersion among analysts' earnings forecasts.

Time-scarce investors rely on financial analysts' research when making investment decisions; thus, high forecast dispersion creates confusion and uncertainty for investors. The finance literature has used forecast dispersion to indicate the extent to which financial analysts "disagree" in their predictions about financial markets (Athanassakos & Kalimipalli, 2003; Donelson & Resutek, 2015). It also serves as a proxy to indicate market uncertainty and the quality of the information environment (Güntay & Hackbarth, 2010; Zhang, 2006). In general, a strong information environment leads to consistent analyst forecasts and, consequently, low forecast dispersion.

To reduce information asymmetry, analysts collect data from public and private information sources, in addition to company disclosures, when preparing their forecasts. News media represents a major information source for analysts to predict a company's earnings. Pollock and Rindova (2003) studied 255 initial public offering (IPO) cases and found that the amount of public information that news media released influenced investors' behavior. From the perspective of information cascades, Pollock, Rindova, and Maggitti (2008) demonstrated the process by which investors shape their understanding about an IPO's value based on public information. Bushee, Core, Guay, and Hamm (2010) empirically demonstrated that news media information represents an important factor that affects the stock market because it rapidly spreads information and reduces information asymmetry.

2.2 Using Internet and Social Media Data to Make Predictions

Recent research has shifted the focus from news media to the Internet—digital mass media. One line of research in finance (not in the context of analyst forecasting) has focused on Internet searches and examines the relationship between the number of Internet searches and stock performance. Da, Engelberg, and Gao (2011) used a sample of Russell 3000 stocks from 2004 to 2008 and found that the search volume index (SVI) from Google correlated with investor attention to IPO stocks. Continuing this line of research, Luo, Zhang, Zhang, and Aspara (2014) found that information posted on blogs and online consumer ratings exerted a stronger effect on firm equity values than the SVI. Preis, Moat, and Stanley (2013) introduced a method to use Google SVI to develop trading strategies and identified online precursors for stock market moves. They used this method to identify 98 search terms of varying financial relevance and found that an increase in search volume for financial terms would likely precede large drops in stock markets. Interestingly, "debt" followed by "color" represented the most indicative search terms to predict the downward trend of the stock market (Preis et al., 2013). Moat et al. (2013) used Wikipedia articles to predict the movements of stock markets. They found a relationship between a large increase in the number of readings of Wikipedia articles about financial topics and subsequent large moves in stock markets. In general, recent research has considered the Internet a more effective information source than news media to predict the stock market (e.g., Goh, Heng, & Lin, 2013; Gu, Konana, Raghunathan, & Chen, 2014; Tirunillai & Tellis, 2012).

Social media emerged with Web 2.0. Unlike news media and Internet searches, social media gives everyone the same opportunity to speak and share information. This trait renders social media invincible in information creation and communication (Kwak, Lee, Park, & Moon, 2010), and motivates companies to increasingly advocate for social media to transform business processes to create a strong link between consumers and companies and enhance organizational performance (Luo, Zhang, & Duan, 2013). In the crisis-management context, Leong, Pan, Ractham, and Kaewkitipong (2015) conducted a case study on flooding in Thailand to investigate how social media could empower individuals to communicate. They studied three attributes of the empowerment process (structural, psychological, and resource empowerment) that attained collective participation, shared identification, and collaborative control in the community. Miranda, Young, and Yetgin (2016) identified societal opportunities that social media creates and examined the dynamics of information sharing among individuals. In particular, they examined how, and to what extent, social media were emancipatory (i.e., permitted individuals to participate in public discourse and surface diverse perspectives) versus hegemonic (i.e., contributed to ideological control by a few). Gu et al. (2014) examined information sharing among investors in social media and found that investors have the propensity to exhibit homophily (versus heterophily)—that is, to seek interactions with others who have a similar status and values. Oh, Eom, and Rao (2015) explored the role of Twitter in social change during the 2011 Egyptian Revolution and found that hashtags effectively funneled online users' attention to the Egyptian Revolution and helped them share situational information, which led to a collective sense-making phenomenon. Luo et al. (2013) used computer products as the study context and collected data about firms and their products via Lexis/Nexis blogs to predict firm equity value. They confirmed that social media metrics have a substantially stronger predictive relationship with firm equity value and a shorter wear-in time than conventional online behavioral metrics (Google searches and Web traffic).

Among the various forms of social media, Twitter represents one of the most popular. Prior research, such as Asur and Huberman's (2010) widely cited study, has used tweets as a surrogate to predict a company's future earnings. These authors counted the number of tweets related to targeted movies on Twitter and constructed a linear regression model to predict movies' box-office revenues before their release. Their prediction proved much more accurate than the Hollywood Stock Exchange Index. Moreover, researchers from Indiana University used Twitter data to examine the association between collective mood that tweets and stock market performance reflected (Bollen, Mao, & Zeng, 2011). They collected around nine million public tweets in an 11-month period and classified the collected tweets into mood categories. They then compared their data with the Dow Jones Industrial Average (DJIA) through Granger causality analysis under a self-organizing fuzzy neural network. They found that the collective mood on Twitter could predict the daily up and down changes in the closing values of the DJIA with high accuracy (i.e., 86.7%).

Extending this line of research, we examine how tweets about a company's service on Twitter are associated with analyst forecast dispersion. We used Twitter as the context for our study for four reasons. First, several financial institutions have begun actively exploring Twitter posts to make financial predictions. For instance, Bloomberg has integrated company-based tweet sentiment (as indicating market preference) and tweet-generation velocity (as indicating volatility) into its stock market analytics. Other examples of financial institutions that have adopted tweet analytics include PsychSignal, iSentium, and Social Market Analytics (Twitter, 2016). The two Twitter hoaxes disseminated in late January, 2013, provide further evidence that financial institutions have begun to devote great attention to posts on Twitter in their decision making. To elaborate, after tweets that suggested Audience was being investigated for fraud, its stock prices fell more than 25 percent and 300,000 shares changed hands within an hour. Similarly, Sarepta Therapeutics shares plummeted 9.9 percent in a matter of seconds after Twitter users alleged that the company had acted improperly. More than 700,000 shares changed hands during the minute in which the stock suffered its steep decline. These examples provide some evidence that financial institutions extract information from Twitter to facilitate their decision making. Given that we examine financial institutions' earnings forecasts, Twitter represents an appropriate data source.

We also chose to extract information from Twitter due to its high popularity. By the end of 2017, Twitter had nearly 330 million users and attracted nearly 350,000 posts per minute. In addition, unlike Facebook and Instagram, which users typically use to communicate with their friends and acquaintances, Twitter allows users to disseminate news to a wider population. Twitter users stay updated about events in a real-time news feed. Further, Twitter has two account types: verified and non-verified. Twitter gives verified status to accounts for highly sought-after celebrities and public figures to verify their identity. Due to the distinction between these two account types, we could study whether tweets that verified accounts generated exerted a similar effect on reducing information asymmetry as tweets that non-verified accounts generated.

3 Hypotheses Development

In this section, we present three hypotheses to associate tweet characteristics with analyst forecast dispersion. The first hypothesis examines the direct effect that the quantity of information extracted from tweets has on analyst forecast dispersion. We used two variables to operationalize the quantity of information—the number of tweets and the number of distinct posters who submitted the related tweets. The second hypothesis compares the effect of tweet valence (positive versus negative tweets) on analyst forecast dispersion. The third hypothesis compares the effect that source verification (verified versus non-verified tweets) has on analyst forecast dispersion.

3.1 Direct Effects of Number of Tweets and Number of Posters

The notion that a party cannot make effective decisions because it has incomplete information and, thus, that any additional information that reduces this information asymmetry can enhance decision quality underpins information symmetry. In analyst forecasting, although companies provide management reports (Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012; Healy & Palepu, 2001), as we discuss in Section 2, managers may intentionally not disclose insider trading or may be overconfident in estimating earnings and, consequently, provide biased information (Hilary & Hsu, 2011), which leads to information asymmetry between company insiders and analysts. With limited information, analysts cannot precisely predict a company's financial performance and, subsequently, provide dispersed forecasts (Godes & Mayzlin, 2004; Tellis & Johnson, 2007; Wong & Zhang, 2014). To reduce forecast dispersion, analysts should seek additional information to narrow information asymmetry. Consumer discussions about a company's service represent a source of additional information for analysts. In this paper, we argue that tweets about a company's service provide additional information for analysts about service quality, which relates to future sales. We used two proxies to operationalize the extent of additional information extracted from tweets: 1) the number of tweets and 2) the number of distinct posters who submitted the related tweets.

First, we discuss the number of tweets. Tweets related to a company's service inform analysts about service quality and future purchasing behavior. Prior studies (Bughin, Doogan, & Vetvik, 2010; Mansi, Maxwell, & Miller, 2011) have found that online consumers' comments about a company's service constitute a primary consideration factor that explains 20 to 50 percent of their and others' purchase decisions, particularly for first-time buyers or with expensive services. Therefore, tweets represent useful pieces of information to help analysts estimate the popularity of a company's service and the company's potential market share. With more tweets, analysts gain a more complete picture of consumer preferences and future purchasing behavior, which helps them make more precise forecasts and, thereby, results in less dispersed forecasts. Therefore, we hypothesize the following:

> **H1a:** The number of tweets related to a company's service is negatively associated with forecast dispersion.

Second, we discuss the number of distinct posters tweeting about a company's service. According to the statistics that Twitter provided on 31 July, 2016, it had 100 million (out of 313 million) daily active users, yet 44 percent of registered users had never posted a tweet. Thus, Twitter users vary in their activity level. We anticipate that, when more individual poster submit tweets, the amount of additional information available to analysts increases, and, subsequently, analyst forecasts become less dispersed. To elaborate, we predict that 10 posts from one person has a weaker effect on reducing information asymmetry than 10 posts from more than one person because a large group of information providers voicing their opinions enables information receivers (analysts in our case) to assess opinion consistence (Koriat, Adiv, & Schwarz, 2016), which is associated with opinion confidence (Orive, 1988). Specific to our research context, when more individuals voice their opinions about a company's service on Twitter, analysts can better estimate the proportion of individuals who are satisfied or dissatisfied and, subsequently, can make a less dispersed judgment about the company's future earnings. Thus, we anticipate the number of distinct Twitter posters to be associated with reduced analyst forecast dispersion. As such, we hypothesize the following:

> **H1b:** The number of distinct posters submitting tweets related to a company's service is negatively associated with forecast dispersion.

3.2 Differential Effects of Positive versus Negative Tweets

The marketing literature suggests that individuals value negative consumer reviews more than positive reviews (Chen & Lurie, 2013; Lim & Chung, 2011; Mourdoukoutas & Siomkos, 2010), for three reasons. First, individuals are more sensitive to losses than to gains (Kahneman & Tversky, 1979); thus, they devote more attention to information relating to potential losses than to information relating to potential gains. Hence, individuals devote more attention to negative tweets than positive tweets during their decision making. Second, the two types of tweets differ in causal attributions (Chen & Lurie, 2013). To elaborate, individuals tend to attribute positive tweets to the reviewer's personal experience but negative tweets tend to service quality. Thus, individuals find negative tweets more informative and diagnostic than positive tweets. Third, Twitter involves a certain degree of "deception". Companies may arrange fake user accounts to post positive tweets regarding their company's service (Elder, 2013); thus, consumers rely less on positive tweets to make a purchase decision. Taken together, since consumers rely more on negative tweets when making a purchase decision, negative tweets have a stronger and more predictable effect on consumer decision making than positive tweets. As a result, negative tweets offer more additional information to analysts in making less dispersed forecasts than positive tweets. Hence, we hypothesize the following:

> **H2:** Negative tweets exert a stronger effect on reducing forecast dispersion than positive tweets do.

3.3 Differential Effect of Tweets from Verified and Non-verified Accounts

Verification refers to the process in which one establishes the validity of a person's identity (Castillo, Mendoza, & Poblete, 2011). Twitter grants verified accounts only a small group of individuals. According to Twitter policy, the company seeks potential verified users in government, politics, religion, journalism, media, sports, business, or key interest areas. Twitter invites only important individuals who are outstanding in their professional fields to open verified accounts. Notably, verification differs from authentication (i.e., the act of comparing a person's identity with a database of authorized users through a username and password combination when logging into a system). On Twitter, everyone can register an account. With a registered account, all users must provide a username and password to undergo the authentication process before they can post tweets. However, in creating a general Twitter account, users do not need to undergo any verification process.

We anticipate that tweets from verified accounts will exert a more significant effect on reducing analysts' forecast dispersion than tweets from non-verified accounts for two reasons. First, verified accounts are associated with higher source credibility than non-verified accounts; thus, individuals are more likely to view tweets from verified accounts more seriously than tweets from non-verified accounts because, before creating a verified account, Twitter has checked the applicant's identity. Further, the individuals who hold verified accounts are often well known or famous (Castillo et al., 2011; Hentschel & Counts, 2011; Lian, Liu, Zhang, Cheng, & Xiong, 2012) and, subsequently, tend to cautiously post their opinions on Twitter. Thus, they will be less likely to present an objectively untrue statement on this open platform. In contrast, anonymous and/or less well-known individuals who have a lower level of responsibility for their behavior on Twitter own non-verified accounts. Further, merchants may arrange fake user accounts to post tweets favorable to company services, and computer programs operate some non-verified Twitter accounts (Elder, 2013). Hence, non-verified accounts have less source credibility lower than verified accounts. Prior research reveals that individuals are more likely to be persuaded when the source presents as credible (Petty, Cacioppo, & Goldman, 1981; Sussman & Siegal, 2003; Zhang & Paxson, 2011). On the Internet, source credibility plays an even more important role in people's judgments than in offline media (Gefen, Karahanna, & Straub, 2003; Rieh, 2002; Xiao & Benbasat, 2007). Thus, owing to their high source credibility, tweets from verified accounts are more influential than those from non-verified accounts.

Second, tweets from verified accounts spread more easily than do tweets from non-verified accounts because verified accounts have more followers (Castillo et al., 2011). In July, 2016, verified accounts had around 13,000 followers on average compared with 208 for non-verified accounts. As such, tweets that verified accounts post gain more attention from Twitter users than tweets that non-verified accounts post (Yang & Leskovec, 2010). Taken together, tweets from verified accounts are more influential and more easily spread to other users; therefore, analysts are likely to find greater consistency in the effects that tweets from verified accounts have on predicting a company's future sales. As such, we hypothesize the following:

> **H3:** Tweets from verified accounts exert a stronger effect on reducing forecast dispersion than tweets from non-verified accounts do.

4 Data Sources

4.1 Context of the Study

At the time we conducted this research in 2016, more than 100 certificated passenger airlines operated in the United States. We selected the top 10 airlines in North America in terms of enplaned passengers, fleet size, and number of destinations: Alaska Airlines, Allegiant Travel, American Airlines, Delta Air Lines, Hawaiian Airline, JetBlue Airway, Southwest Airlines, Spirit Airlines, United Airlines, and Virgin America. These airlines held 4,010 aircrafts, carried around 808 million flight passengers (90% of the total passengers that all airlines carried) and contributed 23,000 daily departures (86% of the total departures from all airlines) to reach 1,538 destinations in North America (69% of total destinations) (Gara, 2017).

4.2 Data on Analyst Forecasts and Airline Financials

We used forecast dispersion as our dependent variable. We obtained the analyst forecast data from Thomson Reuters's I/B/E/S Academic through WRDS access. This database contains over 230 industry-specific key performance indicators across 12 industries. It provides monthly data on analyst forecasts for each of the listed firms in North America. The monthly data include analyst forecast median, standard deviation, and number of analysts following a given firm[2]. Regarding control variables, we extracted airlines' quarterly financial data from Standard & Poor's Compustat Capital IQ database through WRDS, which contains quarterly financial statement data that firms release.

4.3 Twitter Data

We downloaded the Twitter data from Archive Team—an open-resource organization that offers historical Twitter raw data. This website provided sets of Twitter data for the period from January, 2012, to November, 2016. These data contained one percent of tweets randomly extracted from Twitter in the specified period (Morstatter Pfeffer, & Liu, 2014)[3]. The data from April, 2012, January, 2014, January, 2015, and February, 2015, were corrupted. As a result, the available data contained 55 months of Twitter activity. We used several procedural steps to extract and process relevant tweets about the targeted airlines,.

4.3.1 Data Extraction and Cleaning

We identified all tweets related to the airlines of interest. The tweet line contained all information about the tweet, including the tweeter's ID, the tweet's time and date, and the number of followers that the tweeter had. The final dataset contained 245,495 tweets from 198,712 distinct Twitter users with regard to 10 airlines during the 55-month study period. We then extracted all the hashtags from the airline tweets, which amounted to nearly 35,000 hashtags. These hashtags highlighted tweeters' discussion topics, such as #delayed and #flyunited.

The dataset we obtained from Archive Team had two limitations. First, it contained corrupted data. As such, Twitter data retrieved from Archive Team did not contain data for April, 2012, January, 2014, January, 2015, and February, 2015. We used tweets for the three months prior to these missing months to calculate an average and used this average to replace the missing values[4]. Moreover, the data for some months were incomplete. For example, while December, 2012, had 31 days, the data contained tweets for only 27 days. Similarly, June, 2013, only contained 28 days, July, 2014, only contained 27 days, and April, 2015, only contained 25 days. Thus, we standardized our variables of interest into a tweets-per-day basis.

Second, we had to carefully handle tweets for airlines that merged with other airlines or that other airlines acquired during our study period. AirTran Airways was purchased by Southwest Airlines in 2010, American Airlines merged with US Airways in 2013, and Continental Airlines merged with United Airlines in 2012. These airlines retained the name of the latter airline in each pair. Considering that individuals might use the old names AirTran Airways and Continental Airline in tweets and the merger of United Airlines and Southwest Airlines finished before 2012, we included the tweets for AirTran Airways and Continental Airlines for Southwest Airlines and United Airlines, respectively. For American Airlines, since its merger with US Airways finished in December, 2013, and a new airline was founded after that, we did not include any tweets about American Airlines and US Airways before December 2013 in the selected data and counted all tweets for US Airways after December, 2013, as being for American Airlines.

4.3.2 Content Analysis and Sentiment Analysis

We underwent two major computational steps—content analysis and sentiment analysis—to extract and code the tweets. Content analysis systematically evaluates texts to interpret and code textual material. On Twitter, people connect and discuss many topics. Generally, people use the @ sign to state usernames in tweets, such as @USAirways, to mention an entity in tweets, and to link tweets to their profiles. They use hashtags (#) to specify discussion topics. When one applies content analysis to process tweets, it extracts

[2] If an analyst makes earnings forecast revisions within a month, in I/B/E/S Academic records only the most recent earnings forecast. Therefore, analysts who submitted numerous forecast revisions did not bias our results.

[3] The "Twitter Streaming Application Programming Interface (API)" policy allows anyone to download at most one percent of all Twitter activities by providing some parameters. Although Twitter has not published the way in which its APIs sample the data, prior research (e.g., Morstatter et al., 2014) has examined the extent of randomness of tweet extraction. These previous researchers completed statistical tests and empirically demonstrated that "overall the tweets that come through the sample API are a representative sample of the true activity on Twitter" (Morstatter et al., 2014, p. 556).

[4] To address concerns over potential measurement errors arising from seasonality in tweeting activities, we imputed the missing data with the predicted values from regression models that regressed each tweet variable on year and month indicators for each firm. Our results and inferences remained the same.

relevant tweets based on the @ sign. To extract tweets related to the focal airlines, our Python programs used the following list: @Airtran, @AlaskaAir, @AllegiantTravel, @AmericanAir, @Continental, @Delta, @HawaiianAir, @JetBlue, @SouthwestAir, @SpiritAirlines, @USAirways, @United, @VirginAmerica, and @VirginAtlantic. The Python programs also extracted tweets that considered the full titles of airlines without the @ sign.

We then inputted our tweets for sentiment analysis. Sentiment analysis refers to the process in which one identifies and categorizes opinions expressed in a piece of text to determine whether the person's attitude towards a subject matter is positive, neutral, or negative. This classification relies on a set of keywords and a machine-learning algorithm. In our study, we used a cloud machine-learning package—Aylien—to conduct sentiment analysis. We chose Aylien because it sees wide use in natural language engineering (Dale, 2015) and represents one of the best opinion-mining packages (Batista et al., 2015). Aylien uses deep learning and natural language-processing algorithms to parse text. It can handle complex structures, such as comparative sentences, negation, transferred negation, and double negation. Aylien assigns tweets into positive, neutral, and negative (for tweet valence). In addition, it provides a confidence score for each tweet assignment (a number between 0 and 1 to indicate the strength of the sentiment expressed in the tweet).

In the main analysis (see Section 5), we included all tweets in the regression models. Since one can question Aylien's accuracy, we conducted a robustness test. Specifically, we re-ran regression models using only tweets with a polarity confidence of 0.5 or above and again using tweets with a polarity confidence of 0.8 or above. We present the results of the robustness test in Section 5.2.4. We found that the results held. Indeed, when we only used positive and negative tweets with high polarity confidence, the magnitude of coefficients of tweet-related variables on forecast dispersion became larger. That is, when we included only strongly positive/negative tweets in the analysis, the effect of tweets on forecast dispersion became more salient.

4.4 Data on Media and Other Information Sources

We identified and counted the number of news articles from traditional media, Web-based media, and Internet blogs that related to each airline in the Factiva database to control for the effect of traditional and Web-based media on forecast dispersion. We also downloaded flight delay statistics from the Bureau of Transportation Statistics by the Department of Transportation. Moreover, we collected Skytrax's World Airline Awards data from their website. Finally, we sourced management earnings guidance data from Zacks Investment Research database through WRDS.

5 Data Analysis

5.1 Descriptive Statistics

Table A1 in Appendix A displays the descriptive statistics and correlations of all variables we employed in the regression models. Appendix B displays detailed definitions of our variables of interest. Appendix C gives tweet examples.

5.2 Regression Models

The airline industry is a cyclical business (Pearce, 2012). Moreover, individuals often make travel plans in advance and rely on online information to detail their plans (Pan & Fesenmaier, 2006). Therefore, tweets do not have an immediate effect on company finances; thus, a time lag should occur between the time tweets appear and analyst forecasting. Goh et al. (2013) set a time lag in their regression model to examine the relationship between product reviews on social media and consumer behavior. Inspired by their work, we set a one-month time lag between the month in which tweets appeared and the month in which analysts issued their forecasts. We used the Twitter data in the m^{th} month (e.g., January, 2010) to predict the dispersion of the forecast issued in the $(m + 1)^{th}$ month (e.g., February, 2010). As such, we used a one-month time lag between the independent variables (tweet characteristics) and the dependent variable (forecast dispersion).

The three sets of hypotheses contained the same dependent variable—analyst forecast dispersion (*Disp*). We followed the finance literature (e.g., Hilary & Hsu, 2013; Hughes, Liu, & Su, 2008) to measure forecast dispersion as the standard deviation of analysts' earnings per share forecasts deflated by the stock price of airline *i* at the beginning of the current fiscal quarter. The four independent variables were highly correlated. To avoid multicollinearity, we ran four ordinary least squares (OLS) regressions. All OLS regressions contained the same set of control variables, though we included the number of neutral tweets to test H2 in the third regression.

We included four sets of control variables. First, we controlled for basic firm characteristics, such as firm size (*lnSize*), financial leverage (*Leverage*), and a firm's growth prospect (*MB*). Prior studies have found that large firms generally have a better information environment because they tend to disclose information more frequently and have more stable earnings than smaller firms (Barron, Kim, Lim, & Stevens, 1998; Lang & Lundholm, 1996). Firms with a higher level of debt are inherently riskier and, subsequently, less predictable (Barth, Kasznik, & McNichols, 2001). Researchers have previously used market-to-book as a proxy for growth prospect to control for the difference in difficulty of valuing high- versus low-growth firms (Dechow & Sloan, 1997).

Second, we controlled for the effect of firm performance on forecast dispersion. Prior studies have found that well-performing firms tend to disclose more information while poor-performing firms tend to do the opposite (Kothari, Shu, & Wysocki, 2009), which could affect analyst forecasts (Hwang, Jan, & Basu, 1996). We controlled for the effect of firm performance on analyst forecasting by including returns volatility (*ROA_sd*) and a loss indicator (*Loss*).

Third, we controlled for forecast characteristics, such as forecast horizon (*Horizon*) and the number of analysts following (*Ana_num*), that we knew to be related to forecast outcomes. Forecasts issued closer to the earning announcement often incorporate up-to-date information since a firm has a richer information environment when more analysts cover it (Healy & Palepu, 2001).

Fourth, we controlled for information disclosed on several important and publicly available information sources, other than Twitter, to which analysts likely devoted their attention. In particular, airline managers, as corporate insiders, might voluntarily issue earnings guidance to the market (*Management_forecast*) and substantiate their views on an airline's prospects. Journalists of traditional media (*Trad_media*) and Web-based media (*Web_media*) might publish articles that reveal significant information about an airline. In addition, the United States Department of Transport regularly publishes updates on flight performance data, including delays, diversions, and cancellations, which reveal negative information on customer satisfaction (*Flight_dissatisfaction*). Likewise, Skytrax gives out its widely recognized World Airlines Awards (*Awards*) to airlines that provide outstanding services each year. These awards signal positive information on customer satisfaction.

5.2.1 Empirical Results for H1—Number of Tweets and Number of Posters

H1a posits that the number of tweets related to a company's service is negatively associated with forecast dispersion. To test H1a, we regressed analyst forecast dispersion on the number of tweets related to a given airline's service. The tweets column in Table 1 presents the results. The adjusted R-squared was 0.601. The standardized coefficient of the number of classified tweets on analyst forecast dispersion was significant ($\beta = -1.169$, $t = -1.767$, $p < 0.05$). The negative sign of the coefficient indicated that forecast dispersion reduced with the number of tweets. Hence, we found support for H1a.

H1b posits that the number of distinct posters submitting tweets related to a company's service is negatively associated with forecast dispersion. To test H1b, we regressed analyst forecast dispersion on the number of posters who submitted tweets related to a given airline's service. The posters column in Table 1 presents the results. The adjusted R-squared was 0.602. The standardized coefficient of the number of posters on analyst forecast dispersion was significant ($\beta = -0.121$, $t = -1.795$, $p < 0.05$). The negative sign of the coefficient indicated that forecast dispersion reduced with the number of posters who submitted tweets about the related airline's service. Hence, we found support for H1b. Taking H1a and H1b together, we empirically found that the quantity of information that tweets generated (as operationalized by the number of tweets and number of posters) was negatively associated with analyst forecast dispersion.

Table 1. Regression of Effects of Number of Tweets and Number of Posters on Forecast Dispersion

Dependent variable: Disp	Tweets	Posters
Tweets	-0.1169** (-1.767)	
Posters		-0.1212** (-1.795)
lnSize	-0.7924*** (-4.396)	-0.7109*** (-3.791)
MB	-0.0292 (-0.581)	-0.0331 (-0.646)
Leverage	0.0273 (0.469)	0.0370 (0.622)
Loss	0.2598*** (7.530)	0.2452** (6.777)
ROA_sd	-0.1031** (-2.178)	-0.0970** (-1.974)
Ana_num	-0.2728*** (-2.699)	-0.2531*** (-2.648)
Horizon	-0.1091*** (-3.454)	-0.1038*** (-3.183)
Trad_media	0.0000 (0.000)	-0.0089 (-0.120)
Web_media	0.1671*** (3.504)	0.1717*** (3.515)
Flight_dissatisfaction	0.0032 (0.075)	0.0227 (0.512)
Management_forecast	0.0239 (0.771)	0.0234 (0.725)
Awards	0.1003 (1.534)	0.0885 (1.341)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	465	465
Adjusted R-squared	0.6014	0.6016

Key: t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. One-sided p-values reported for the independent variables tweets and posters. We define variables in Appendix B.

5.2.2 Empirical Results for H2—Number of Positive and Negative Tweets

H2 posts that negative tweets exert a stronger effect on reducing forecast dispersion than positive tweets do. To test H2, we regressed analyst forecast dispersion on the numbers of positive and negative tweets that revealed a given airline's service. Table 3 presents the results. The combined column in Table 2 shows the regression result that included both positive and negative tweets as independent variables.

The adjusted R-squared was 0.604. The standardized coefficient of positive tweets on analyst forecast dispersion was non-significant (β = 0.026, t = 0.364, p > 0.1), while the standardized coefficient of negative tweets was significant (β = –0.234, t = –2.598, p < 0.01). This result indicates that negative tweets exerted a stronger effect on reducing analyst forecast dispersion than positive tweets did. One may note that the numbers of positive, neutral, and negative tweets had high correlations, which could have led to high multicollinearity. To ease this concern, we computed a tweet sentiment score[5] (*Net_negative*—the

[5] Our tweet sentiment score is defined consistently with the news sentiment score of Bhattacharya, Galpin, Ray, and Yu (2009). The results are qualitatively the same if we also included the number of tweets (*Tweets*) as a control variable.

signed difference between the number of negative tweets and the number of positive tweets) and re-ran the regression analysis. The significant and negative coefficient of *Net_negative* in the sentiment score column in Table 2 presents a consistent inference. Hence, we found support for H2.

Table 2. Regression of Relative Effects of Positive and Negative Tweets on Forecast Dispersion

Dependent variable: Disp	Positive	Neutral	Negative	Combined	Sentiment score
Positive	-0.0568 (-1.001)			0.0260 (0.364)	
Neutral		-0.0218 (-0.439)		0.0592 (0.987)	
Negative			-0.1719*** (-2.540)	-0.2337*** (-2.598)	
Net_negative					-0.1670*** (-2.609)
lnSize	-0.7840*** (-4.339)	-0.7821*** (-4.321)	-0.8207*** (-4.557)	-0.8432*** (-4.651)	-0.8274*** (-4.591)
MB	-0.0229 (-0.452)	-0.0264 (-0.522)	-0.0339 (-0.676)	-0.0370 (-0.731)	-0.0373 (-0.742)
Leverage	0.0324 (0.556)	0.0337 (0.577)	0.0288 (0.498)	0.0352 (0.606)	0.0303 (0.525)
Loss	0.2627*** (7.603)	0.2651*** (7.687)	0.2546*** (7.381)	0.2530*** (7.320)	0.2548*** (7.393)
ROA_sd	-0.1128** (-2.400)	-0.1160** (-2.463)	-0.0970** (-2.060)	-0.1002** (-2.123)	-0.0977** (-2.081)
Ana_num	-0.2897*** (-2.877)	-0.2893*** (-2.859)	-0.2638*** (-2.619)	-0.2662*** (-2.637)	-0.2616*** (-2.597)
Horizon	-0.1083*** (-3.420)	-0.1088*** (-3.433)	-0.1096*** (-3.483)	-0.1099*** (-3.491)	-0.1100*** (-3.499)
Trad_media	0.0009 (0.012)	0.0018 (0.024)	-0.0029 (-0.040)	-0.0048 (-0.064)	-0.0032 (-0.043)
Web_media	0.1680*** (3.487)	0.1625*** (3.397)	0.1658*** (3.496)	0.1608*** (3.349)	0.1619*** (3.417)
Flight_dissatisfaction	0.0081 (0.188)	0.0049 (0.113)	0.0076 (0.177)	0.0134 (0.308)	0.0070 (0.164)
Management_forecast	0.0226 (0.728)	0.0232 (0.744)	0.0236 (0.765)	0.0228 (0.738)	0.0238 (0.772)
Awards	0.1005 (1.521)	0.1070 (1.621)	0.1102 (1.699)	0.1260 (1.890)	0.1173* (1.808)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	465	465	465	465	465
Adjusted R-squared	0.5995	0.5987	0.6044	0.6038	0.6047

Key: t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. One-sided p-values reported for the independent variables positive, neutral, and negative. We define variables in Appendix B.

5.2.3 Empirical Results for H3—Numbers of Tweets from Verified and Non-verified Accounts

Finally, H3 posits that tweets from verified accounts exert a stronger effect on reducing forecast dispersion than tweets from non-verified accounts do. To test H3, we regressed analyst forecast dispersion on the numbers of verified and non-verified tweets that revealed a given airline's service. Table 3 presents the results. The combined column in Table 3 shows the regression results that included both the numbers of verified and non-verified tweets as independent variables. The adjusted R-squared was 0.600. Both standardized coefficients of verified tweets ($\beta = -0.033$, $t = -0.680$, $p > 0.1$) and non-verified tweets ($\beta = -0.089$, $t = -1.161$, $p > 0.1$) on analyst forecast dispersion were non-significant. The high variance inflation factors indicated that multicollinearity caused this result—the correlation between the number of verified tweets and number of non-verified tweets was very high ($\rho = 0.753$). To probe into this issue, we ran two regressions to separately test the effects of verified and non-verified tweets on forecast dispersion. The verified and non-verified columns in Table 3 show that verified tweets had a marginally significant effect on forecast dispersion ($\beta = -0.061$, $t = -1.472$, $p < 0.1$) and non-verified tweets had a significant effect on forecast dispersion ($\beta = -0.116$, $t = -1.748$, $p < 0.05$). We then tested if the coefficient of verified tweets in the verified column was statistically smaller than the coefficient of non-verified tweets in the non-verified column following Clogg, Petkova and Haritou (1995). The test results confirmed that the difference in coefficient estimates between tweets from verified and non-verified accounts was not statistically significant (difference = 0.0545; $Z = 0.696$; $p = 0.743$). Thus, we found that tweets from verified accounts did not exert a stronger effect on reducing analyst forecast dispersion than tweets from non-verified accounts. Hence, we did not find support for H3.

Table 3. Regression of Relative Effects of Verified and Non-verified Tweets on Forecast Dispersion

Dependent variable: Disp	Verified	Non_verified	Combined
Verified	-0.0614* (-1.472)		-0.0329 (-0.680)
Non_verified		-0.1159** (-1.748)	-0.0893 (-1.161)
lnSize	-0.8038*** (-4.444)	-0.7918 (-4.392)	-0.8001*** (-4.425)
MB	-0.0330 (-0.653)	-0.0290 (-0.576)	-0.0321 (-0.634)
Leverage	0.0329 (0.568)	0.0274 (0.470)	0.0276 (0.474)
Loss	0.2609*** (7.556)	0.2600*** (7.534)	0.2588*** (7.486)
ROA_sd	-0.1133** (-2.429)	-0.1032** (-2.181)	-0.1038** (-2.191)
Ana_num	-0.2882*** (-2.866)	-0.2729*** (-2.700)	-0.2748*** (-2.716)
Horizon	-0.1113*** (-3.516)	-0.1090*** (-3.451)	-0.1103*** (-3.484)
Trad_media	-0.0127 (-0.170)	0.0006 (0.008)	-0.0069 (-0.092)
Web_media	0.1605*** (3.370)	0.1672*** (3.505)	0.1655*** (3.461)
Flight_dissatisfaction	0.0054 (0.126)	0.0033 (0.076)	0.0032 (0.075)
Management_forecast	0.0234 (0.755)	0.0239 (0.770)	0.0240 (0.773)
Awards	0.1136* (1.743)	0.1001 (1.531)	0.1040 (1.583)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	465	465	465
Adjusted R-squared	0.6005	0.6013	0.6008

Key: t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. One-sided p-values reported for the independent variables verified and non_verified. We define variables in Appendix B.

Given this result, we explored whether the two independent variables in H2 and H3 (i.e., tweet sentiment and verification) interacted to affect forecast dispersion. To probe into this issue, we subclassified verified and non-verified tweets according to tweet sentiment and ran a regression to test the interaction between tweet sentiment and verification. Table 4 shows the results. We found an interaction between tweet sentiment and verification. Specifically, for verified accounts, positive tweets exerted a stronger impact on analyst forecast dispersion than negative tweets did (β = –0.065 for positive verified tweets, and β = –0.022 for negative verified tweets). For non-verified accounts, negative tweets exerted a stronger impact on analyst forecast dispersion than positive tweets did (β = –0.103 for positive non-verified tweets, and β = –0.239 for negative non-verified tweets).

Table 4. Regression of Interactions between Tweet Sentiment and Verified / Non-verified Tweets on Forecast Dispersion

Dependent variable: Disp	Verified	Non_verified	Combined
Verified_positive	-0.0713*** (-2.176)		-0.0653** (-1.961)
Verified_neutral	-0.0102 (-0.263)		-0.0163 (-0.378)
Verified_negative	-0.0644* (-1.493)		-0.0223 (-0.448)
Non_verified_positive		0.0959 (1.497)	0.1026 (1.576)
Non_verified_neutral		0.0746 (1.163)	0.0716 (1.007)
Non_verified_negative		-0.2934*** (-3.247)	-0.2385*** (-2.288)
lnSize	-0.8331*** (-4.559)	-0.8761*** (-4.766)	-0.8869*** (-4.827)
MB	-0.0212 (-0.418)	-0.0137 (-0.264)	-0.0271 (-0.518)
Leverage	0.0409 (0.705)	0.0471 (0.803)	0.0439 (0.745)
Loss	0.2396*** (6.762)	0.2362*** (6.648)	0.2330*** (6.557)
ROA_sd	-0.1106** (-2.379)	-0.0808* (-1.719)	-0.0907* (-1.877)
Ana_num	-0.2141** (-2.152)	-0.2261** (-2.277)	-0.2154** (-2.171)
Horizon	-0.1146*** (-3.600)	-0.1068*** (-3.361)	-0.1100*** (-3.461)
Trad_media	-0.0212 (-0.283)	-0.0538 (-0.711)	-0.0503 (-0.656)
Web_media	0.1729*** (3.600)	0.1662*** (3.425)	0.1619*** (3.323)
Flight_dissatisfaction	-0.0096 (-0.222)	0.0113 (0.257)	0.0104 (0.236)
Management_forecast	0.0112 (0.356)	0.0143 (0.457)	0.0153 (0.489)
Awards	0.1293** (1.966)	0.1471** (2.234)	0.1444** (2.177)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	465	465	465
Adjusted R-squared	0.5891	0.5912	0.5924
Key: t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. One-sided p-values reported for the independent variables verified and non_verified. We define variables in Appendix B.			

5.2.4 Robustness Test

At times, the tweets contained vague and weak sentiments, which could affect the results due to inaccurate sentiment classifications and, subsequently, inaccurate positive and negative tweet classifications. As such, during the sentiment analysis, Aylien also outputted a polarity confidence (i.e., a number between 0 and 1 for each tweet that indicated the strength of the sentiment that the tweet expressed). Scores closer to 1 indicated a higher confidence in the classified sentiment. We conducted robustness tests by running the four regression models using only tweets with a polarity confidence of 0.50 or above. We then ran the four regression models using only tweets with a polarity confidence of 0.80 or above. In both robustness tests, the results held. We report the results in Appendix D.

6 Discussion

6.1 Key Findings

In this study, we drew on the information asymmetry literature and investigated how individuals' discussions about airline services on Twitter can reduce the information asymmetry gap for analysts and whether analysts prepare less dispersed forecasts. We examined the associations between four tweet characteristics and analyst forecast dispersion. Table 5 summarizes our findings.

Table 5. Summary of Findings

Hypotheses	Results
H1a: The number of tweets related to a company's service is negatively associated with forecast dispersion.	Supported
H1b: The number of distinct posters submitting tweets related to a company's service is negatively associated with forecast dispersion.	Supported
H2: Negative tweets exert a stronger effect on reducing forecast dispersion than positive tweets do.	Supported
H3: Tweets from verified accounts exert a stronger effect on reducing forecast dispersion than tweets from non-verified accounts do.	Not supported

Our study led to three major findings. First, a higher number of individuals offering tweets about a company's service increases the information available to analysts, which results in a reduction in forecast dispersion. Specifically, our study suggests that the topics individuals discuss on Twitter provide additional information to inform analysts about the quality of a company's products (airline service quality, in our case), which has implications for people's future purchase behavior. We developed the first set of hypotheses (H1a and H1b) to explore this association. H1a posits that a greater number of tweets on Twitter will decrease analyst forecast dispersion. Aligned with our prediction, more tweets reduced the information asymmetry gap for analysts, and analysts generated less dispersed forecasts. In addition to the number of tweets, we used the number of posters to approximate the amount of information extracted from Twitter. Similar to what H1b posits, the number of posters sending tweets regarding airlines' services was negatively associated with analyst forecast dispersion. Combining the results for H1a and H1b, a reduction in information asymmetry depends on the volume of discussions and number of individual users speaking on Twitter.

Second, similar to what H2 posits, we found negative opinions about airline services posted on Twitter to be associated with less dispersed forecasts than positive opinions were even after we controlled for the effects of flight delays and cancellations, as the United States Department of Transportation has reported. This finding implies that negative tweets have a much more substantial effect on reducing forecast dispersion than positive tweets do.

Third, contrary to H3, tweets from verified accounts did not give more information to help analysts make a less dispersed forecast than tweets from non-verified accounts did. 3. One possible explanation for this outcome concerns the fact that our dataset contained 2,101 verified accounts and that airline announcements comprised more than half of the tweets that these accounts generated. Intuitively, these company users do not represent passengers buying air tickets; thus, their tweets would prove less useful for predicting an airline's future earnings. In addition, even if widespread, these tweets do not help analysts acquire new information on the airlines. As a result, we found that verified tweets did not exert a stronger effect on forecast dispersion than non-verified tweets did.

6.2 Theoretical Contributions

Our study contributes to the literature in two ways. First, it extends the scope of research on social media data by shifting the focus from making predictions about individual behavior to making predictions about business problems in professional services. A large body of prior studies has examined how to stimulate individual consumer behaviors by using social media. Researchers have investigated the antecedents influencing a user to post, re-tweet, or respond to a tweet. For instance, Ellison et al. (2014) surveyed Facebook users and found that individuals tended to maintain their relationship with others and bridge social capital while using Facebook. Nadkarni and Hofmann (2012) used Facebook as the study context to examine why Facebook users share posts and comment on others' posts. Ryan and Xenos (2011) focused on Facebook users' personality traits and found that users with extraverted and narcissistic personalities were more likely to post messages than users with conscientious and socially lonely personalities. These prior studies often considered traits, perceptions, and user behaviors as the variables of interest. Extending this prior research, we investigated how to use the information obtained from Twitter to predict an accounting variable—analyst forecast dispersion. Analysts' judgments are bounded by guidelines in their profession and are supposed to be highly rational. Thus, integrating the information extracted from Twitter in analysts' forecasts is a high-cost, high-involvement business activity. However, our empirical results indicate statistically significant associations between tweet characteristics and analyst forecast dispersion. This finding implies that, to some extent, analysts consider tweets when making forecasts. Given that analysts keep their analytic techniques confidential, our study provides open information that demonstrates associations between Twitter data and analysts' judgments. It opens up an avenue for researchers to use Twitter data to make predictions related to business problems in professional services.

Second, our study contributes to research on analyst forecasting. We do not know about any previous research that has theorized about how Twitter data is associated with the quality of analysts' forecasts. Adding to prior research, our study suggests that Twitter provides an additional information source that analysts can use to reduce the information asymmetry in financial markets. In our research context, social media causes communication among the public (air travelers, in our case) to be visible to analysts. Social networks enable analysts to improve their knowledge of public opinions about an airline, how far or how quickly these opinions spread to other people, and even whether or how the airline responds to the public. When this communication becomes transparent to analysts, information asymmetry reduces, which improves analysts' judgment. For instance, among the public, some individuals hold verified accounts, while some hold non-verified accounts. Holding a different account type may correspond to individuals of different social status. The results in Table 4 show that positive tweets from verified accounts and negative tweets from non-verified accounts have strong associations with forecast dispersion. Transparent communication enables analysts to conduct more interesting analyses. Our study integrates two research areas—social media and analyst forecasting—and the rationale developed in this study about the ways social media data reduce information asymmetry echoes the theory of communication.

6.3 Practical Contributions

Our study contributes to practice in two ways. First, we inform practitioners, especially analysts, about the value of Twitter data in the finance domain. Individuals' tweets represent a source of information to reduce the dispersion of analyst forecasts. Twitter continues to expand at a rapid pace; however, unfortunately, most people see only the hedonic benefits that it brings to individual users. In our study, we show that Twitter also provides utilitarian benefits to companies (specifically, financial institutions in which analysts make earnings forecasts for companies). Data extracted from Twitter can help business professionals perform their jobs. In particular, we focused on analyst forecast dispersion. In finance, practitioners use forecast dispersion to study the effects that analyst beliefs have on company earnings and/or securities trading. They often interpret it as a measure of the degree of uncertainty and, thus, risk associated with a target company's future earnings or a target security (Gu & Wu, 2003). In our findings, the negative associations between tweet-related variables and forecast dispersion imply that examining tweets reduces the prediction uncertainty and risk associated with an airline's future earnings.

At present, it takes significant resources to process Twitter data. Thus, practitioners must develop computer programs and execute these programs on distributed computers to extract relevant information from tweets. Currently, only analysts in large firms have the technological resources to process the data. Our findings encourage analysts working in small firms to start exploring the value of Twitter data. When tools for tweet analytics become more readily available, more analysts can leverage these tools to make predictions regarding company finances, and analyst forecasts will likely become less dispersed, which is good news for both analysts and investors. In the near future, companies could foreseeably progressively create insightful and robust tweet analytics to monitor relevant activities on Twitter and extract insights from posters' conversations. We believe that tweet analytics will continue to gain popularity among financial institutions.

Second, after Bollen et al. (2011), hedge funds emerged to analyze tweets to determine where to invest. Many of these were successful. For instance, during the month that the $40 million Derwent Capital Markets fund operated, the reported return was 1.86 percent, which beat the overall market and the average hedge fund (Tweney, 2012). This success evidences that practitioners have realized the potential of using Twitter data to predict company finance; however, the development remains at an early stage. Previous researchers (e.g., Luo et al., 2013) have focused on how social media enhances prediction accuracy and conducted studies to scrutinize the predictive relationships between social media data and stock returns. Adding to the existing studies, our study broadens the application scope of Twitter data to the analyst forecasting domain and specifically focuses on forecast dispersion—that is, the consistency of a group of analysts' predictions. We conducted our study based on the rationale that individuals' tweets about the quality of a company's products represent useful pieces of information, and, when analysts collectively use this information to generate forecasts, their forecasts become less dispersed. We used airlines as the context for this study and found that the number of negative tweets and number of tweets from non-verified accounts were associated with reduced analyst forecast dispersion. Practitioners can apply these findings to companies in the consumer sector of the economy whereby individuals' tweets about a company's products reflect the company's future earnings. Examples of such companies include restaurants and automobiles. For instance, individuals' tweets about McDonald's, Toyota, or BMW could indicate to analysts the product's popularity, which would help their forecasts converge.

6.4 Limitations and Future Research

This paper has several limitations. First, we focused only on airlines. We chose to study airlines because, in 2016, the airline industry supported US$2.7 trillion (3.5 percent) of the world's gross domestic product (GDP) and US$1.5 trillion (5.4 percent) of the United States' GDP. Thus, the airline industry is important; however, unavoidably, the focus on one single industry reduces our findings' generalizability. Second, in our sample, the downloaded tweets represented one percent of all Twitter activities. As such, we did not analyze the hundreds of thousands of tweets related to airlines. In the future, when researchers can download all tweets, researchers will obtain much richer data and can build the entire social network. Researchers can then answer interesting research questions, such as how the speed of verified and non-verified tweets spreading throughout the network affect analyst forecast dispersion. Further, future research can study how companies' responses to individuals' online complaints may affect analyst forecast dispersion.

7 Conclusion

In this study, we scrutinize the associative relationships between the characteristics of tweets regarding a company's products and the dispersion of analyst forecasts about the company's financial performance. We drew on the literature on information asymmetry to suggest that tweets provide additional information to analysts to enable them to make less dispersed forecasts. We extracted tweets related to the service that the top 10 airlines in the United States provide. Our regression results indicate that analyst forecast dispersion decreased with the number of tweets and number of posters. In addition, we found negative tweets to more usefully reduce forecast dispersion than positive tweets. Theoretically, our study indicates that Twitter can be a useful data source to assist analysts to make decisions in relation to financial markets. Practically, given that analysts at major financial institutions actively use tweet analytics to prepare forecasts yet keep their techniques confidential, our findings provide analysts in small firms and individual investors with actionable guidelines on how to leverage Twitter data to predict company earnings.

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Appendix A

Table A1. Descriptive Statistics and Correlations

	Variable	Mean	Std. dev.	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
[1]	Disp	0.003	0.003	1.00									
[2]	Posters	3.320	4.376	-0.08	1.00								
[3]	Verified	0.052	0.090	-0.13	0.75	1.00							
[4]	Non_verified	3.148	4.343	-0.09	1.00	0.75	1.00						
[5]	Tweets	12.170	18.401	-0.09	0.96	0.70	0.96	1.00					
[6]	Positive	0.362	0.494	-0.08	0.91	0.63	0.91	0.91	1.00				
[7]	Negative	1.599	2.547	-0.08	0.97	0.75	0.97	0.92	0.87	1.00			
[8]	Neutral	1.240	1.588	-0.09	0.93	0.71	0.93	0.90	0.82	0.83	1.00		
[9]	Net_negative	1.238	2.131	-0.07	0.95	0.75	0.95	0.95	0.81	0.99	0.81	1.00	
[10]	lnSize	22.092	1.290	-0.28	0.65	0.51	0.66	0.60	0.63	0.65	0.59	0.63	1.00
[11]	MB	3.188	3.187	-0.27	0.37	0.19	0.37	0.40	0.38	0.36	0.33	0.34	0.40
[12]	Leverage	0.289	0.112	0.21	0.16	0.07	0.13	0.14	0.08	0.16	0.06	0.17	-0.34
[13]	Loss	0.084	0.277	0.51	-0.06	-0.11	-0.06	-0.08	-0.08	-0.06	-0.07	-0.05	-0.13
[14]	ROA_sd	0.011	0.011	0.03	0.30	0.25	0.31	0.34	0.24	0.32	0.27	0.32	0.19
[15]	Ana_num	12.701	3.626	-0.19	0.44	0.32	0.45	0.41	0.45	0.44	0.41	0.42	0.73
[16]	Horizon	-40.959	25.950	-0.12	0.04	-0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.04
[17]	Trad_media	135.886	112.796	0.08	0.69	0.45	0.70	0.65	0.69	0.68	0.62	0.66	0.72
[18]	Web_media	1.037	2.030	0.04	0.59	0.33	0.59	0.59	0.63	0.56	0.55	0.52	0.43
[19]	Flight_dissatisfaction	0.000	1.000	-0.11	0.26	0.18	0.25	0.22	0.26	0.26	0.19	0.25	0.35
[20]	Management_forecast	0.004	0.066	0.10	-0.04	-0.04	-0.04	-0.04	-0.05	-0.04	-0.02	-0.04	-0.09
[21]	Awards	2.120	1.808	-0.26	0.00	0.14	0.04	0.04	0.06	0.01	0.09	-0.00	0.25

Table A1. Descriptive Statistics and Correlations (cont.)

	Variable	Mean	Std. dev.	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]
[11]	MB	3.188	3.187	1.00										
[12]	Leverage	0.289	0.112	0.18	1.00									
[13]	Loss	0.084	0.277	-0.11	0.16	1.00								
[14]	ROA_sd	0.011	0.011	0.13	0.04	0.06	1.00							
[15]	Ana_num	12.701	3.626	0.31	-0.34	-0.14	0.09	1.00						
[16]	Horizon	-40.959	25.950	0.06	-0.04	0.00	0.02	0.11	1.00					
[17]	Trad_media	135.886	112.796	0.26	-0.07	0.04	0.24	0.61	0.13	1.00				
[18]	Web_media	1.037	2.030	0.37	0.08	0.00	0.13	0.38	0.10	0.61	1.00			
[19]	Flight_dissatisfaction	0.000	1.000	0.06	-0.01	-0.01	0.02	0.31	0.03	0.23	0.28	1.00		
[20]	Management_forecast	0.004	0.066	-0.06	0.04	0.22	-0.04	-0.13	0.05	-0.08	-0.03	0.02	1.00	
[21]	Awards	2.120	1.808	-0.11	-0.45	-0.22	0.15	0.30	0.02	0.12	-0.04	0.03	-0.08	1.00

Appendix B

Table B1. Variable Definitions

Variable	Definition	Source(s)
Dependent		
Disp	Earnings forecast dispersion, measured as the monthly standard deviation of analysts' forecasts for the earnings per share in the upcoming quarter, scaled by stock price at the beginning of the fiscal quarter.	I/B/E/S Academic
Independent		
Tweets	Daily average number of tweets posted about at least one service dimension of a particular airline, as classified by Aylien, one month before the forecast.	Archive Team, Aylien
Posters	Daily average number of distinct Twitter users who posted about the services of a particular airline one month before the forecast.	Archive Team, Aylien
Positive	Daily average number of positive tweets about the services of a particular airline, as classified by Aylien, one month before the forecast.	Archive Team, Aylien
Neutral	Daily average number of neutral tweets about the services of a particular airline, as classified by Aylien, one month before the forecast.	Archive Team, Aylien
Negative	Daily average number of negative tweets about the services of a particular airline one month before the forecast.	Archive Team, Aylien
Net_negative	The signed difference between the daily average number of negative and positive tweets about the services of a particular airline, as classified by Aylien, one month before the forecast (i.e., negative minus positive).	Archive Team, Aylien
Verified	Daily average number of classified tweets that a verified Twitter account posted about a particular airline one month before the forecast.	Archive Team, Aylien
Non_verified	Daily average number of classified tweets that a non-verified Twitter account posted about a particular airline one month before the forecast.	Archive Team, Aylien
Control		
lnSize	Natural logarithm of market capitalization	Compustat
MB	Book-to-market ratio represents a proxy for firm growth. Book-to-market ratio refers to the book value of equity over market value of equity.	Compustat
Leverage	Debt-to-asset ratio: the sum of long-term and short-term debts over total assets.	Compustat
Loss	Loss indicator that is equal to one when profit is negative but is otherwise equal to zero.	Compustat
ROA_sd	Returns volatility, measured as the standard deviation of return on asset ratios over the past four quarters, where the return of asset ratio refers to earnings before interest and tax (EBIT) over total assets.	Compustat
Ana_num	The number of analysts following the firm in the month.	I/B/E/S Academic
Horizon	The number of days from when the consensus forecast is made to when the actual earnings of interest is announced.	I/B/E/S Academic
Trad_media	The count of unique traditional-media mentions of the airline company in the month as compiled by the Factiva database.	Factiva
Web_media	The count of unique web-media mentions of the airline company in the month as compiled by the Factiva database.	Factiva

Table B1. Variable Definitions

Flight_dissatisfaction	The principal component of four on-time performance variables: 1) departure delays, 2) arrival delays, 3) flight cancellations and 4) flight diversions. The website of the U.S. Bureau of Transportation Statistics provides monthly airline on-time performance data (www.transtats.bts.gov).	U.S. Bureau of Transportation Statistics
Management_forecast	An indicator that is equal to one when the management issued earnings guidance in that quarter, but is otherwise equal to zero. We sourced this data from Zacks Investment Research database.	Zacks Investment Research
Awards	Number of Skytrax World Airline Awards that an airline earned in a year.	Skytrax World Airline Awards

Appendix C

Table C1. Variable Definitions

Classification	Examples
Positive tweets	This is my first time flying @JetBlue and I'm very impressed. Comfy seats, TV, good snacks and FREE WIFI. :) Will fly them when possible :) @united @Amber_Raynexxx This is great service. @AmericanAir The lovely ppl in the Admirals Club are assisting me. Thank you though :) I appreciate how much @Delta @DeltaAssist continue to prove how important my business is to them. @United Airlines Classic Italian Meatball Penne Pasta Is Good!
Neutral tweets	@DenisDoiron45 @AirCanada Travelling with them tomorrow for my honeymoon. Hope they don't lose my bride. Anybody ever flew @usairways??? Take a look at how @AmericanAir is evolving for a chance to win a first class trip. #newAmerican The start of my 1 year anniversary trip to NYC with wide (@ JetBlue Airways).
Negative tweets	@USAirways you cancel flights, then say online only option is to call. Then we call, and you say phone systems are overwhelmed. What gives! @AmericanAir - You guys suck. We booked our vacation 2 mos ago, had our seats all assigned, paid your fees, day before we're unassigned! **! "@TheEconomist: United Airlines cannot seem to get its computers to work properly and it has useless crappy staff @united I have been an extremely loyal customer and have earned close to 50,000 travelled miles. This was no way to treat a valued customer. Bravo to @AmericanAir for losing my bag. But there's more. They also have NO idea where it is. Going real casual for my @sxsw talÁ_

Appendix D

Table D1. Regression of Relative Effects of High-confidence Positive and Negative Tweets on Forecast Dispersion

Dependent variable: Disp	Positive50	Neutral50	Negative50	Combined	Positive80	Neutral80	Negative80	Combined
Positive50	0.0039 (0.064)			0.1565** (1.653)				
Neutral50		0.0079 (0.137)		0.0522 (0.717)				
Negative50			-0.1115** (-1.681)	-0.2719*** (-2.683)				
Positive80					0.0127 (0.220)			0.1518*** (1.984)
Neutral80						0.0068 (0.128)		0.0354 (0.597)
Negative80							-0.1574*** (-2.305)	-0.2911*** (-3.244)
lnSize	-0.7872*** (-4.283)	-0.7845*** (-4.237)	-0.8285*** (-4.495)	-0.8295*** (-4.487)	-0.7856*** (-4.278)	-0.7847*** (-4.238)	-0.8443*** (-4.592)	-0.8458*** (-4.587)
MB	-0.0115 (-0.218)	-0.0129 (-0.241)	0.0067 (0.129)	-0.0161 (-0.302)	-0.0130 (-0.250)	-0.0126 (-0.237)	0.0084 (0.163)	-0.0143 (-0.271)
Leverage	0.0482 (0.818)	0.0495 (0.829)	0.0344 (0.590)	0.0555 (0.932)	0.0499 (0.846)	0.0493 (0.828)	0.0317 (0.546)	0.0558 (0.940)
Loss	0.2519*** (7.097)	0.2523*** (7.086)	0.2426*** (6.797)	0.2399*** (6.721)	0.2522*** (7.112)	0.2522*** (7.091)	0.2390*** (6.712)	0.2367*** (6.656)
ROA_sd	-0.1035** (-2.191)	-0.1049** (-2.159)	-0.0887* (-1.880)	-0.1019** (-2.109)	-0.1048** (-2.218)	-0.1049** (-2.151)	-0.0808* (-1.709)	-0.0931* (-1.920)
Ana_num	-0.2252** (-2.251)	-0.2245** (-2.241)	-0.2254** (-2.260)	-0.2187** (-2.194)	-0.2249** (-2.248)	-0.2244** (-2.239)	-0.2296** (-2.308)	-0.2251** (-2.266)
Horizon	-0.1117*** (-3.485)	-0.1117*** (-3.486)	-0.1101*** (-3.447)	-0.1096*** (-3.438)	-0.1119*** (-3.491)	-0.1117*** (-3.485)	-0.1091*** (-3.422)	-0.1106*** (-3.482)
Trad_media	-0.0164 (-0.220)	-0.0177 (-0.241)	-0.0242 (-0.330)	-0.0101 (-0.134)	-0.0142 (-0.190)	-0.0176 (-0.240)	-0.0342 (-0.467)	-0.0171 (-0.229)
Web_media	0.1740*** (3.538)	0.1742*** (3.601)	0.1843*** (3.807)	0.1697*** (3.464)	0.1726*** (3.514)	0.1743*** (3.610)	0.1859*** (3.857)	0.1689*** (3.468)
Flight_ dissatisfaction	-0.0195 (-0.451)	-0.0192 (-0.441)	-0.0107 (-0.246)	0.0075 (0.169)	-0.0192 (-0.444)	-0.0191 (-0.438)	-0.0051 (-0.118)	0.0144 (0.324)
Management_ forecast	0.0074 (0.235)	0.0074 (0.234)	0.0094 (0.299)	0.0106 (0.336)	0.0075 (0.236)	0.0074 (0.234)	0.0095 (0.303)	0.0110 (0.352)
Awards	0.1275* (1.926)	0.1274* (1.938)	0.1203* (1.834)	0.1347** (2.044)	0.1288* (1.946)	0.1273* (1.936)	0.1212* (1.854)	0.1387** (2.112)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	465	465	465	465	465	465	465	465
Adjusted R-squared	0.5833	0.5833	0.5859	0.5881	0.5833	0.5833	0.5881	0.5911

Key: t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. One-sided p-values reported for the independent variable. Positive50 (80), neutral50 (80), and negative50 (80) refers to the number of tweets classified as positive, neutral, and negative with 50% (80%) confidence. We define the other variables in Appendix B.

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