Do Tweets Matter for Shareholders? An Empirical Analysis

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We identify the 215 members of the S&P 500 that operate corporate Twitter accounts. We find that both the number of daily tweets and the number of months a firm tweets is positively correlated with excess returns. These results indicate that tweeting is associated with positive returns to shareholders, and that tweeting and experience tweeting together can positively influence market activity.

INTRODUCTION

Twitter is a social networking website that enables firms (and individuals) to share information via tweets. Tweets are short, condensed messages less than 140 characters in length. Many companies are taking advantage of the easy and free communication line that Twitter offers. Twitter enables managers to communicate directly with investors and promote their companies. During our study period (2010-2011), 215 S&P 500 firms operate a company Twitter account. These corporate Twitter accounts are dedicated to sharing news regarding the company; examples include earnings information, dividend information, and annual reports. Previous research focuses on the relation between the internet, attention, and financial markets. For example, Da, Engelberg, and Gao (2011) find an increase in internet search frequency translates to an increase in stock prices. Fang and Peress (2009) show that low media coverage leads to higher returns. Tetlock (2007, 2011) documents the relation between news coverage and stock returns, and establishes a relation between returns and media pessimism and news staleness.

Our study is unique in that we do not focus on internet media coverage. Instead, we study the corporate twitter accounts of S&P 500 firms. Firms maintain their own corporate Twitter accounts, as opposed to relying on the news media to provide coverage or information about the firm. Additionally, we

focus on corporate Twitter activity as opposed to individual tweets. Our goal is to determine if corporate social media activity positively relates to shareholder value and market activity. Establishing the link between social media and shareholder value provides valuable insight into why firms spend time and money on social media initiatives; if the end goal of the corporation is to increase shareholder wealth, then social media use should have a positive relation with firm value.

First, we find a positive correlation between firm excess return and Twitter membership. We also find that share turnover increases following Twitter membership. After establishing the relation between

Twitter membership and excess return (share turnover), we focus on firm Twitter activity and its relation to both excess return and share turnover. Overall, we find a positive relation between tweeting activity and excess return. We also show that the relation between Twitter membership and excess return is temporary. After firms are Twitter members for more than 24 months, the relation between Twitter membership and excess return becomes insignificant. Lastly, we study Twitter activity and its relation to share turnover. We find that tweeting activity combined with months on Twitter positively influences share turnover, indicating there could be a learning curve to Twitter usage.

RELATED LITERATURE

Financial information is readily available in today's trading environment, thanks in part to the availability of news coverage and the internet. Research documents that the internet is not only a valuable source of information for traders, but also a valuable resource for traders. Online investment and firm information is available twenty-four hours a day. Wysocki (1999) is one of the first to establish a relation between the internet and financial markets. Wysocki finds that internet postings forecast next day trading volume and next day abnormal stock returns. Tumarkin and Whitelaw (2001), however, show that internet stock messages do not predict industry adjusted returns or abnormal trading volume. Das and Chen (2007) study both internet messages and the message content. They show that internet messages quickly reflect the information in the market, but that this information does not forecast stock returns.

Previous research also establishes a relation between stock prices and media coverage. Da, Engelberg, and Gao (2011) use the Google Search Volume Index (SVI) as a measure of stock attention. They find that an increase in Google SVI leads to an increase in stock prices over a two week period. However, the stock price increase is followed by a price reversal before year-end. Fang and Peress (2009) study the level of media coverage among firms. They find that firms with low media coverage earn higher returns than firms with high media coverage.

Other studies provide evidence related to media coverage and stock returns. Tetlock (2007) focuses on media coverage in *The Wall Street Journal* and the pessimism of the coverage. Overall, Tetlock (2007) documents that pessimistic media coverage predicts falling stock prices, and also shows both high and low pessimism predict increased trading volume. Tetlock (2011) focuses on news staleness and stock returns.[1] Overall, Tetlock finds that stale news negatively predicts the following week's stock returns.

Research also finds that social interaction plays a role in investor behavior. Shive (2010) develops a model of the determinants of trading and shows that social influence is a predictor of investor trading in high volume stocks. Dufflo and Saez (2002) detail that employee interactions with one another partially determine their decisions to enroll in employer retirement plans. In addition, Hong, Kubik, and Stein (2004) develop a model that utilizes two types of investors: social and non-social investors. The model predicts that social investors will participate more in the stock market. Some also claim that tentative investors are more likely to invest when their beliefs align with other investors' beliefs (Antweiler and Frank, 2004).

While the above mentioned research studies the value of the internet and media attention in today's financial markets, none of the previously mentioned work focuses specifically on social media activity. There are studies that focus on Twitter and its relation to financial markets, but the majority of these works study the overall sentiment of individual tweets. Bollen, Mao, and Zeng (2010) use daily closing values of the Dow Jones Industrial Average Index to show that the mood, or sentiment, of the public affects the DJIA. The authors use the Google Profile of Mood States to analyze the textual content of tweets and find that the DJIA prediction accuracy can be improved by using three specific public mood measurements: sure, vital, and happy.

Logunov and Panchenko (2011) use a ratio of the positive and negative words used in tweets to study the impact of social media on the market. They find that the overall sentiment contained in tweets is correlated with the return on financial indices. Sprenger, Tumasjan, Sandner, and Welpe (2013) show that the bullishness of tweets is associated with abnormal stock returns, and that Twitter message volume predicts next day trading volume. Sprenger and Welpe (2011a) examine the sentiment of tweets and the market reaction to company specific news events. The results, not surprisingly, indicate that positive news often leaks into stock prices prior to the announcement day. Lastly, Sprenger and Welpe (2011b) study the comovement of stocks to see if relatedness in an online forum influences how stocks move together in the market. They show that the news based measure explains stock returns as well as the SIC code used to group industries.

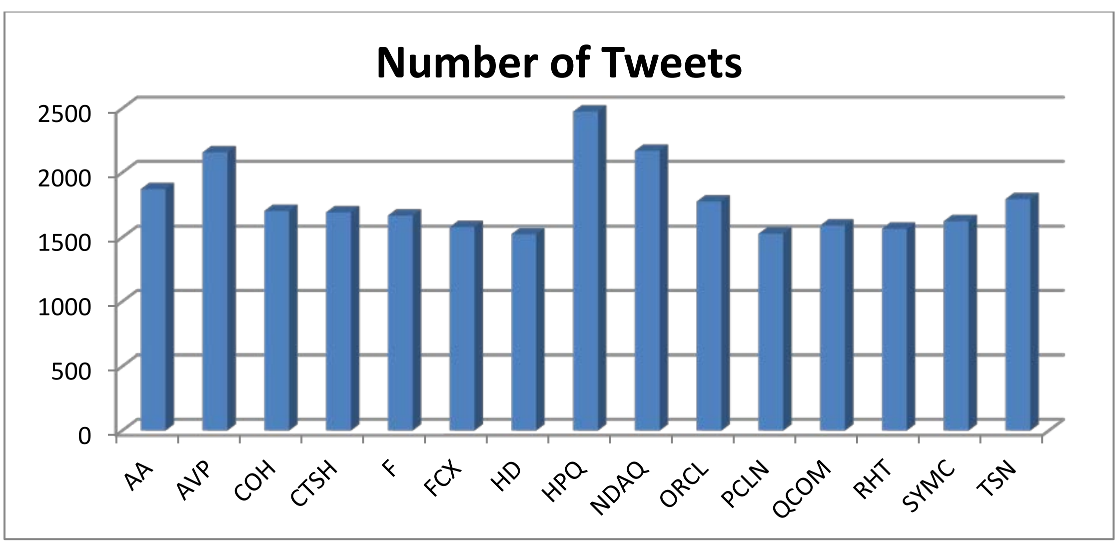
Prior literature regarding Twitter and the financial markets focuses on investor sentiment/mood predictors and the number of times a firm is mentioned (identified via the hashtag symbol, #) by individual Twitter account users. Our study differs from prior literature in a distinct way. We select our sample based on corporate Twitter accounts, not the number of times a firm is mentioned in the microblog atmosphere. We identify members of the S&P 500 that actively engage in social media via Twitter. Identifying corporate tweeting eliminates some of the noise in Twitter posts and allows us to focus on firms providing the investor with relevant company information, as opposed to an individual's opinion or belief.

DATA AND SAMPLE SELECTION

We collect each firm's tweets (excluding retweets) from January 1, 2010, to December 31, 2011. We utilize Twitter's API to collect the tweets. Our sample consists of firms included in the S&P 500 as of January 1, 2010. The initial sample of firms with Twitter accounts includes 250 firms. To be included in the final sample, the firm must have a company specific news account. Our final sample includes 215 firms. We obtain the following variables from the CRSP daily security files: stock price, volume, stock return (excluding dividends), shares outstanding, SIC code, and the equal weighted market return (excluding dividends). We also obtain the three Fama-French factors (1992, 1993) and the momentum factor (Carhart, 1997) from CRSP. We obtain dividend announcement dates and earnings announcement dates from CRSP and Compustat. The final sample consists of 38,275 observations from the twenty four month sample.

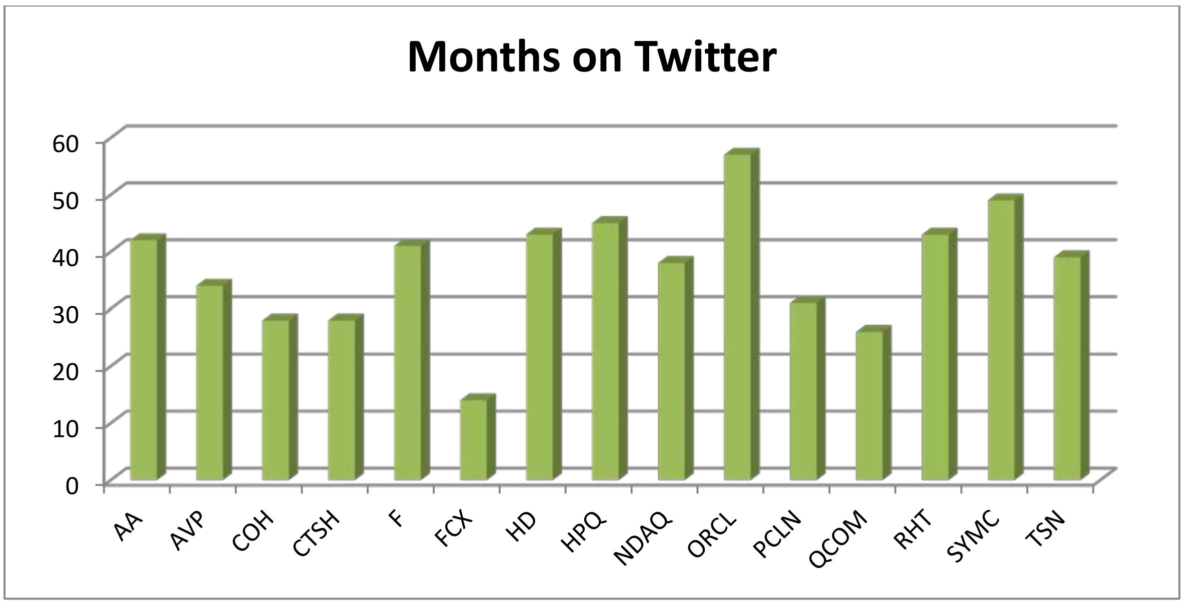
We first highlight the overall Twitter activity of the firms in our sample. Figure 1 shows the total number of tweets each of the top fifteen tweeters distributes from January 2010 to December 2011. Hewlett Packard utilizes Twitter the most during our sample period. NASDAQ and Avon also tweet heavily during the sample. The top fifteen tweeters send between 1,524 tweets and 2,474 tweets from January 2010 until December 2011.[2]

FIGURE 1
TWEETING ACTIVITY FOR THE 15 MOST ACTIVE (TWITTER) FIRMS



To further highlight our sample, we focus on the length of Twitter membership in Figure 2. We again show the 15 most active firms. A firm's Twitter experience is calculated using the number of months from the time the firm joins Twitter until the end of the sample in December 2011. Oracle is a Twitter member the longest of the most active firms, utilizing the social networking site for about 57 months. Hewlett Packard and Alcoa are also long-time tweeters, engaging in Twitter for 45 and 42 months, respectively. Freeport McMoRan Copper and Gold is the newest Twitter member (out of the most active firms), with a membership of 14 months.

FIGURE 2
LENGTH OF TWITTER MEMBERSHIP FOR THE 15 MOST ACTIVE (TWITTER) FIRMS



We provide variable descriptions in Appendix A. Table 1 provides summary statistics for the full sample. We divide the sample into low tweeting firms (less than three daily tweets), medium tweeting firms (between four and nine daily tweets), and high tweeting firms (greater than ten daily tweets). On average, firms tweet about 2.7 times per day. The "low tweeting" group tweets about two times per day, while the "high tweeting" group tweets over 15 times each day. It appears that the "high tweeters" have a slightly larger market value than the "low tweeting" group.[3]

TABLE 1
SAMPLE SUMMARY STATISTICS

Table 1 contains summary statistics for the sample. Panel A is for the full sample of observations from January 2010 through December 2011. Panel B includes firms that tweet less than three times per day, and Panel C includes firms that tweet between four and nine times per day. Panel D includes firms that tweet more than ten times per day. Market value is the daily average stock price times the daily shares outstanding. Volume is the daily number of shares traded. Share turnover is the daily shares traded divided by the shares outstanding. Return volatility is the standard deviation of the daily returns. The tweets variable is the number of daily tweets for each firm, and months on Twitter is the time a firm is a Twitter member, in months. Excess return is calculated as the stock's return minus the risk free rate.

	Market Value	Stock Price	Volume	Share Turnover	Return Volatility	Number of Daily Tweets	Months on Twitter	Excess Return
				Panel A: Full Sample				
Mean	29,699,661	$46.85	8,848,863	13.96	0.0163	2.65	21.25	0.0007
Median	11,499,743	$37.49	3,944,600	9.99	0.0143	2.00	20.00	0.0006
N	43,949	43,949	43,949	43,949	43,949	43,949	43,949	43,949
				Panel B: Low Tweeters (less than three tweets per day)				
Mean	28,183,096	$47.05	8,511,315	13.81	0.0162	1.59	21.11	0.0006
Median	11,161,100	$37.92	3,781,500	9.89	0.0143	1.00	20.00	0.0006
N	35,037	35,037	35,037	35,037	35,037	35,037	35,037	35,037
				Panel C: Middle Tweeters (between 4 and 9 tweets per day)				
Mean	36,026,229	$46.73	9,892,253	14.47	0.0166	5.33	21.69	0.0007
Median	12,467,679	$36.37	4,627,100	10.32	0.0147	5.00	21.00	0.0006
N	7,699	7,699	7,699	7,699	7,699	7,699	7,699	7,699
				Panel D: High Tweeters (more than 10 tweets per day)				
Mean	33,349,839	$41.63	11,969,057	15.14	0.0169	16.46	22.29	0.0003
Median	14,418,252	$35.55	5,938,900	10.80	0.0151	13.00	23.00	0.0009
N	1,213	1,213	1,213	1,213	1,213	1,213	1,213	1,213

RESULTS

We first examine if a firm choosing to join Twitter influences returns. While previous research studies media coverage of stocks (Da, Engelberg, and Gao, 2011; Fang and Peress, 2009), Twitter is unique in that it allows a firm to self-promote (via the firm's corporate Twitter account). Our variable of interest in the first two sets of regressions (Tables 2 and 3) is a dummy variable equal to one if the firm is a Twitter member and zero otherwise. Da, Engelberg, and Gao (2011) find that increased attention leads to higher stock prices, while Fang and Peress (2009) show that low media coverage translates to higher returns. Based on the previous findings regarding media and the internet, Twitter membership may have either a positive or a negative relation with return.

We estimate Fama-MacBeth (1973) style regressions for excess return. We control for factors shown to influence returns, including liquidity, firm size, day of the week /time of year effects, dividend announcements, and earnings announcements. The functional form of the regression model is as follows[4]:

$$\begin{aligned}\text{Excess Return}_{i,t} &= \beta_0 + \beta_1 \text{Firm Size}_{i,t} + \beta_2 \text{Log(Volume)}_{i,t} + \beta_3 \sigma_{\text{returns}_{i,t}} \\ &+ \beta_4 \text{Twitter}_{\text{Member}_{\text{DV}_{i,t}}} + \beta_5 \text{HML}_{i,t} + \beta_6 \text{Momentum}_{i,t} + \beta_7 \text{Day of the Week}_{\text{DV}_t} \\ &+ \beta_8 \text{Dividend}_{\text{DV}_{i,t}} + \beta_9 \text{Earnings}_{\text{DV}_{i,t}} + \beta_{10} \text{January}_{\text{DV}_t} + \varepsilon_{i,t}\end{aligned} \tag{1}$$

Previous research documents a relation between media coverage and trading volume. We expect share turnover to increase after a firm joins Twitter because Twitter membership/activity should increase investor awareness and attention for the firm. Specifically, Tetlock (2007) shows that media coverage (regardless of content) predicts an increase in trading volume. We estimate share turnover regressions to determine if trading activity responds to a firm joining Twitter. The functional form of our regression model is as follows:

$$\begin{aligned}\text{Share Turnover}_{i,t} &= \beta_0 + \beta_1 \text{Firm Size}_{i,t} + \beta_2 \text{Log(Stock Price)}_{i,t} \\ &+ \beta_3 \text{Twitter}_{\text{Member}_{\text{DV}_{i,t}}} + \beta_4 \sigma_{\text{returns}_{i,t}} + \beta_5 \text{Momentum}_{i,t} + \beta_6 \text{Day of the Week}_{\text{DV}_t} \\ &+ \beta_7 \text{Dividend}_{\text{DV}_{i,t}} + \beta_8 \text{Earnings}_{\text{DV}_t} + \varepsilon_{i,t}\end{aligned} \tag{2}$$

Table 2 provides the initial results supporting Twitter membership. The variable of interest is the Twitter member dummy variable. The dummy variable coefficients indicate a positive relation between Twitter membership and firm excess return. The magnitude of the coefficient ranges from 0.007% to 0.011% on a daily basis. The positive relation between Twitter activity and excess return remains after controlling for firm and time fixed effects, the Fama-French factors, day of the week influences, earnings dates, dividend dates, and the January effect.[5]

TABLE 2
TWITTER INITIATION, EXCESS RETURN

Table 2 provides excess return regressions for Twitter membership initiation. The dependent variable is excess return. Market value is the daily average stock price times the daily shares outstanding. Volume is the number of shares traded daily. Share turnover is the daily shares traded divided by the shares outstanding. The standard deviation of returns is the standard deviation of the daily returns. The Twitter Member DV is equal to one if the firm is a Twitter member on that trading day and zero otherwise. Excess return is calculated as the stock's return minus the risk free rate. HML and SMB are the Fama-French factors, and momentum is Carhart's momentum factor. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and * respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.069	0.076	0.098	0.077	0.076	0.076
	(0.99)	(1.10)	(0.94)	(0.84)	(0.86)	(0.86)
Log(Mkt_Val)						0.046***
						(3.99)
Log(Vol)	-0.002*	-0.009*	-0.008*	-0.006	-0.008	-0.022
	(1.99)	(1.89)	(1.82)	(1.45)	(1.36)	(1.75)
$\sigma_{Returns}$	0.098	0.099	0.066	0.099	0.141	0.141
	(1.45)	(1.24)	(1.23)	(1.45)	(1.65)	(0.52)
Twitter_Member_DV	0.007***	0.007***	0.008***	0.009***	0.010***	0.011***
	(3.78)	(4.12)	(4.00)	(4.20)	(7.23)	(7.98)
SMB	-0.730***	-0.435***	-0.789***	-0.730***	-0.730***	
	(-24.42)	(-22.47)	(-27.43)	(-23.52)	(-24.38)	
HML	-0.047*	-0.033*	-0.091*	-0.070*	-0.048	
	(-1.89)	(-1.76)	(-1.99)	(-1.88)	(-0.98)	
Momentum	-0.126***	-0.117***	-0.123***	-0.105***		
	(-5.62)	(-5.57)	(-5.57)	(-5.47)		
R-squared	0.080	0.078	0.077	0.066	0.054	0.021
Firm Fixed Effects	Yes	Yes	Yes	No	No	No
Time Fixed Effects	Yes	Yes	Yes	No	No	No

In Table 3, we document a positive relation between Twitter membership and share turnover. Initiating tweeting positively influences share turnover across all six regression models. The magnitude of the coefficient indicates that share turnover increases roughly 15% to 30% after firms begin tweeting. The increase in turnover is consistent with expectations, given previous media research documents a positive relation between media coverage and trading activity (Tetlock, 2007).

TABLE 3
TWITTER INITIATION, SHARE TURNOVER

Table 3 provides share turnover regressions for Twitter membership initiation. Market value is the daily average stock price times the daily shares outstanding. Share turnover is the daily shares traded divided by the shares outstanding. The standard deviation of returns is simply the standard deviation of the daily returns. The Twitter Member DV is equal to one if the firm is a Twitter member on that trading day, and zero otherwise. Momentum is Carhart's momentum factor. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and * respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	89.901***	91.450***	110.989***	111.000***	112.789***	115.889***
	(33.45)	(33.88)	(48.40)	(47.14)	(49.11)	(34.55)
Log(Mkt_Val)	-8.901***	-8.432***	-10.334***	-11.305***	-11.337***	-11.235***
	(-25.01)	(-23.44)	(-31.11)	(-34.16)	(-33.12)	(-23.23)
Log(Stock_Price)	-3.999***	-4.800***	-15.123***	-17.989***	-15.666***	-15.840***
	(-8.01)	(-7.89)	(-21.00)	(-23.72)	(-19.99)	(-19.87)
Twitter_Member_DV	150.898***	178.838***	220.781***	278.915***	301.906***	303.844***
	(5.67)	(6.00)	(7.66)	(8.12)	(8.15)	(8.41)
$\sigma_{\mathrm{Returns}}$	300.891***	243.010***	175.379***	173.510***	179.162***	165.999***
	(9.23)	(8.32)	(4.98)	(5.99)	(6.00)	(5.99)
Momentum	-33.789***	-33.560***	-34.001***	-33.789***		
	(-5.55)	(-4.56)	(-3.35)	(-3.34)		
R-squared	0.560	0.556	0.500	0.495	0.490	0.435
Firm Fixed Effects	Yes	Yes	No	No	No	No
Time Fixed Effects	Yes	Yes	No	No	No	No

In Tables 2 and 3, we document a positive relation between Twitter membership and excess return (turnover). Next, we focus on the number of daily tweets and its relation to excess return. We use a contemporaneous estimate of the number of tweets in our regression estimates, but we also replicate the results using a lagged number of tweets. The results are quantitatively similar using both contemporaneous and lagged tweet measures. The number of times a firm tweets each day may have either a positive or negative relation with the firm's excess return. Da Engelberg, and Gao (2011) find that increased attention leads to higher stock prices, while Fang and Peress (2009) document an advantage to low media coverage. Given that Twitter may increase the attention given to a firm, the (expected) relation between the daily number of tweets and excess return is ambiguous. We estimate the following excess return regression model[6]:

$$\begin{aligned}\text{Excess Return}_{i,t} &= \beta_0 + \beta_1\text{Firm Size}_{i,t} + \beta_2\text{Log(Volume)}_{i,t} + \beta_3\sigma_{\text{returns}_{i,t}} \\ &+\beta_4\text{Tweets}_{i,t} + \beta_5\text{Twitter}_{12_{\text{Month}_{\text{DV}\,i,t}}} + \beta_6\text{Twitter}_{24_{\text{Month}_{\text{DV}\,i,t}}} + \beta_7\text{Twitter}_{36_{\text{Month}_{\text{DV}_{i,t}}}} \\ &+\beta_8\text{HML}_{i,t} + \beta_9\text{Momentum}_{i,t} + \beta_{10}\text{Day of the Week}_{\text{DV}_t} + \beta_{11}\text{Dividend}_{\text{DV}_{i,t}} \\ &+\beta_{12}\text{Earnings}_{\text{DV}_{i,t}} + \beta_{13}\text{January}_{\text{DV}_t} + \varepsilon_{i,t}\end{aligned} \quad (3)$$

The excess return regression results are located in Table 4. Our two main variables of interest are the number of daily firm tweets and a series of dummy variables indicating the length of time a firm is a Twitter member. The number of daily tweets has a consistent relation with excess return. The magnitude of the coefficients for the number of daily tweets ranges from 0.010% to 0.004%. Tweeting's positive impact remains even after controlling for days of the week, earnings announcement dates, dividend dates, and the January effect.[7]

We document a positive relation between Twitter activity and excess return in Table 4. However, it is possible that the positive relation is a function of how long firms are (or have been) Twitter users. We control for whether a firm is a Twitter member for less than 12 months, between 12 and 24 months, and between 24 and 36 months. Models 1, 2, and 3 are the most robust models and provide the main results for the Time spent on Twitter. Overall, we find that Twitter membership significantly increases the excess return for up to 24 months. Twitter membership is insignificant for firms with more than 24 months on

TABLE 4
TWITTER ACTIVITY, EXCESS RETURN

Table 4 provides excess return regressions. Market value is the daily average stock price times the daily shares outstanding. Volume is the number of daily shares traded. Share turnover is the daily shares traded divided by the shares outstanding. The standard deviation of returns is the standard deviation of the daily returns. Tweets is the number of daily tweets a firm distributes. The Twitter 12 month DV is equal to one if the firm is a Twitter member twelve months or less. The Twitter 24 Month DV is equal to one if the firm is a Twitter member between 12 and 24 months. The Twitter 36 Month DV is equal to one if the firm is a Twitter greater between 24 and 36 months. Excess return is calculated as the stock's return minus the risk free rate. HML and SMB are the Fama-French factors, and momentum is Carhart's momentum factor. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and * respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.004	0.004	0.004	0.007	0.006	0.006
	(0.49)	(0.50)	(0.51)	(0.84)	(0.76)	(0.76)
Log(Mkt_Val)						0.056***
						(2.99)
Log(Vol)	-0.002***	-0.002*	-0.002*	-0.002	-0.002	-0.002
	(1.81)	(1.94)	(1.92)	(1.58)	(1.55)	(1.55)
$\sigma_{Returns}$	0.082	0.078	0.078	0.086	0.101	0.101
	(1.22)	(1.17)	(1.17)	(1.31)	(1.52)	(1.52)
Tweets	0.004***	0.006***	0.007***	0.008***	0.008***	0.010***
	(3.88)	(4.12)	(4.50)	(5.68)	(5.73)	(7.73)
Twitter_12_Month DV	0.003***	0.004***	0.007***	0.007***	0.007***	
	(2.72)	(2.87)	(3.01)	(3.91)	(4.88)	
Twitter_24_MonthDV	0.003***	0.003***	0.004***	0.005***	0.006***	
	(2.50)	(2.75)	(3.33)	(3.12)	(3.00)	
Twitter_36_MonthDV	0.002	0.001	0.002	0.003	0.003*	
	(1.11)	(1.09)	(1.64)	(1.66)	(1.98)	
SMB	-0.610***	-0.609***	-0.609***	-0.610***	-0.610***	
	(-22.42)	(-22.42)	(-22.43)	(-22.52)	(-22.38)	
HML	-0.060*	-0.061*	-0.061*	-0.060*	-0.028	
	(-1.91)	(-1.94)	(-1.93)	(-1.90)	(-0.88)	
Momentum	-0.106***	-0.105***	-0.105***	-0.102***		
	(-4.62)	(-4.57)	(-4.57)	(-4.47)		
R-squared	0.083	0.079	0.078	0.075	0.061	0.031
Firm Fixed Effects	Yes	Yes	Yes	No	No	No
Time Fixed Effects	Yes	Yes	Yes	No	No	No

Twitter. So while we document a positive relation between excess return and Twitter activity, the effect does not last forever. In fact, it appears (based on the results in Table 4), that firms only experience increased excess returns for the first 24 months of membership.

We focus on the relation between Twitter activity and share turnover in Table 5. We estimate the following turnover regression. All variables are estimated contemporaneously.[8]

$$\begin{aligned}
&\text{Share Turnover}_{i,t} = \beta_0 + \beta_1 \text{Firm Size}_{i,t} + \beta_2 \text{Log(Stock Price)}_{i,t} + \beta_3 \sigma_{\text{returns}_{i,t}} \qquad (4)\\
&+\beta_4 \text{Momentum}_{i,t} + \beta_5 \text{Tweets}_{i,t} + \beta_6 \text{Twitter}_{12_{\text{Month}_{\text{DV}}}{}_{i,t}} + \beta_7 \text{Twitter}_{24_{\text{Month}_{\text{DV}}}{}_{i,t}}\\
&+\beta_8 \text{Twitter}_{36_{\text{Month}_{\text{DV}}}{}_{i,t}} + \beta_9 \text{Tweets}_{i,t} * \text{Twitter}_{12_{\text{Month}_{\text{DV}}}{}_{i,t}}\\
&+\beta_{10} \text{Tweets}_{i,t} * \text{Twitter}_{24_{\text{Month}_{\text{DV}}}{}_{i,t}} + \beta_{11} \text{Tweets}_{i,t} * \text{Twitter}_{36_{\text{Month}_{\text{DV}}}{}_{i,t}}\\
&+\beta_{12} \text{Day of the Week}_{\text{DV}_t} + \beta_{16} \text{Dividend}_{\text{DV}_{i,t}} + \beta_{17} \text{Earnings}_{\text{DV}_{i,t}} + \varepsilon_{i,t}
\end{aligned}$$

A firm can utilize Twitter to increase the attention it receives on the internet or in the media. If tweeting increases investor awareness of a firm, then we expect the number of daily tweets to have a positive relation with turnover. However, contrary to our expectations, we find a negative relation between the number of daily tweets and stock turnover. Specifically, we find that tweeting activity results in roughly a 4% reduction in stock turnover. Based on the negative relation between tweeting and share turnover, it does not appear that Twitter increases investor attention.

However, it is possible that Twitter usage has a learning curve. A unique feature of Twitter is the constraint placed on message length. Users are restricted to sending messages of 140 characters or less. Users can send unlimited messages throughout the day as long as each message is less than 140 characters. Due to the limitations placed on message length, there is an inherent learning curve to using Twitter effectively. Because of this learning curve, we believe that the number of daily tweets and the time spent on twitter combined can provide valuable information. To see the combined impact of the number of tweets and the time on Twitter, we add an interaction variable to the turnover regression. We interact the number of tweets with the 12, 24, and 36 month Twitter membership variables. As a firm becomes more effective at sharing information via Twitter, its share turnover should increase as a result of increased investor attention.

TABLE 5
TWITTER ACTIVITY, STOCK TURNOVER

Table 5 provides stock turnover regressions. Market value is the daily average stock price times the daily shares outstanding. Volume is the number of daily shares traded. Share turnover is the daily shares traded divided by the shares outstanding. The standard deviation of returns is the standard deviation of the daily returns. Tweets is the number of daily tweets a firm distributes. The Twitter 12 month DV is equal to one if the firm is a Twitter member twelve months or less. The Twitter 24 Month DV is equal to one if the firm is a Twitter member between 12 and 24 months. The Twitter 36 Month DV is equal to one if the firm is a Twitter member between 24 and 36 months. The Tweets*Twitter Months DV variables are the interaction terms. Momentum is Carhart's momentum factor. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and * respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	88.531***	88.139***	110.902***	110.687***	110.600***	109.732***
	(31.02)	(30.42)	(47.29)	(47.14)	(47.13)	(47.55)
Log(Mkt_Val)	-9.300***	-9.245***	-10.307***	-10.305***	-10.304***	-10.217***
	(-25.53)	(-24.96)	(-34.19)	(-34.16)	(-34.13)	(-34.25)
Log(Stock_Price)	-4.665***	-4.722***	-15.528***	-15.538***	-15.541***	-15.550***
	(-7.90)	(-7.77)	(-21.86)	(-21.82)	(-21.91)	(-21.86)
$\sigma_{Returns}$	234.693***	240.559***	173.344***	173.001***	178.738***	177.516***
	(8.51)	(8.65)	(5.84)	(5.83)	(6.04)	(6.00)
Momentum	-32.384***	-33.114***	-34.939***	-36.133***	-36.133***	
	(-4.14)	(-4.21)	(-3.77)	(-3.95)	(-3.95)	
Tweets	-0.049***	-0.047***	-0.047***	-0.060***	-0.071***	
	(-3.23)	(-4.74)	(-3.74)	(-6.00)	(-6.54)	
Twitter_12_MonthDV	0.039***	0.045***	0.051***	0.051***	0.053***	
	(3.43)	(3.14)	(3.74)	(4.01)	(3.33)	
Twitter_24_MonthDV	0.089***	0.087***	0.099***	0.010***	0.010***	
	(4.89)	(4.99)	(5.01)	(5.55)	(5.25)	
Twitter_36_MonthDV	0.056***	0.066***	0.078***	0.067***	0.089***	
	(3.33)	(3.45)	(3.99)	(3.98)	(5.98)	
Tweets*Twitter_12_MonthDV	0.007**	0.008***	0.008***	0.007***		
	(2.25)	(2.99)	(2.99)	(3.45)		
Tweets*Twitter_24_MonthDV	0.008**	0.009***	0.010***	0.011***		
	(2.12)	(2.56)	(3.87)	(4.12)		
Tweets*Twitter_36_MonthDV	0.009***	0.089***	0.078***	0.890***		
	(3.11)	(4.21)	(5.43)	(4.23)		
R-squared	0.651	0.644	0.516	0.516	0.515	0.514
Firm Fixed Effects	Yes	Yes	No	No	No	No
Time Fixed Effects	Yes	Yes	No	No	No	No

CONCLUSION

Previous research documents a relation between the internet (media coverage) and the stock market. For example, Wysocki (1999) shows that internet postings forecast next day trading volume and returns. Da, Engelberg, and Gao (2011) demonstrate that an increase in the Google SVI translates to an increase in firm stock price. Fang and Peress (2009) find that there is an advantage to low media coverage, and detail that firms with less media coverage tend to earn higher returns than firms with more media coverage. Tetlock (2007, 2011) shows that the market responds not only to stale news coverage but also to pessimistic news coverage.

We study the role of corporate social media activity in today's news environment. Specifically, we study the Twitter activity of 215 firms included in the S&P 500 that operate corporate Twitter accounts. Studying the corporate social media activity of firms is valuable because it sheds light on what influence (if any) that social media activity has on both returns and trading activity. We find that Twitter membership leads to both an increase in excess returns and an increase in share turnover. We also find a positive relation between Twitter activity and excess return, and show that Twitter activity combined with Twitter experience has a positive relation with share turnover. Overall, our results are valuable because they provide support for why firms engage in social media activity.

ENDNOTES

1. Tetlock (2011) defines news staleness as a particular news story's textual similarity to the previous 10 news stories.
2. While we are unable to collect the daily number of followers for each Twitter account, we do document the follower count (as of January 29, 2013) for the most active Tweeters in the sample. As of January 29, the most active accounts had followers ranging from 1,142 (Freeport McMoRan Copper and Gold) to 364,322 (Coach).
3. We also study the number of times firms tweet using earnings announcement and dividend announcement dates. For both earnings and dividends, we find that firms increase their tweeting activity leading up to the announcement.
4. We estimate the excess return regressions two alternative ways. First, we include market capitalization and the SML factor in all regression models. The results are quantitatively similar to the ones presented in the paper. We also estimate the regressions using beta instead of return volatility. The results are quantitatively similar.
5. All regression variables are estimated contemporaneously. We also replicate the results using a lagged Twitter membership dummy variable, and the results are quantitatively similar.
6. We estimate the excess return regressions two alternative ways. First, we include market capitalization and the SML factor in all regression models. The results are quantitatively similar to the ones presented in the paper. We also estimate the regressions using beta instead of return volatility. The results are quantitatively similar.
7. We do not report the coefficients for days of the week, earnings announcements, dividend announcements, and the January effect for brevity.
8. We also replicate the turnover regressions using lagged number of daily tweets, and the results are quantitatively similar.

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APPENDIX A
VARIABLE DESCRIPTIONS

Variable	Notation	Description
Excess Return		Daily return – Risk free rate
Market Value	Mkt_Val	Daily average stock price * daily shares outstanding
Volume	Vol	Number of daily shares traded
Standard Deviation of Returns	$\sigma_{returns}$	Standard deviation of daily return
Twitter Membership	Twitter_Member_DV	Dummy variable equal to one of the firm is a Twitter member
SMB	SMB	Fama-French small-minus-big factor
HML	HML	Fama-French high-minus-low factor
Momentum	Momentum	Carhart's momentum factor
Stock Price	Stock_Price	Average daily stock price
Tweets	Tweets	Daily number of tweets
Twitter 12 Month Membership	Twitter_12_Month DV	Dummy variable equal to one if the firm is a Twitter member less than 12 months
Twitter 24 Month Membership	Twitter_24_Month DV	Dummy variable equal to one if the firm is a Twitter member between 12 and 24 months
Twitter 36 Month Membership	Twitter_36_Month DV	Dummy variable equal to one if the firm is a Twitter member between 24 and 36 months