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Scares and Stocks: Evidence from Twitter Sentiments During Covid-19

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(Work in Progress)

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ABSTRACT

This paper examines the investor reaction of firm-specific pessimistic sentiment extracted from Twitter messages during the pandemic period due to the Covid-19. We find that Twitter sentiment predicts stock returns without subsequent reversals. This finding is consistent with the view that tweets provide information not already reflected in stock prices during the pandemic period. We investigate possible sources of return predictability with a Twitter sentiment. The results show that Twitter's pessimistic sentiment towards the Covid-19 provides new information about the investor. This information explains about one-third of the predictive ability of Twitter sentiment for stock returns. Our findings shed new light on the predictive value of social media content for stock returns.

Keywords: Investor sentiments, Covid-19, Twitter.

"Whenever you consider the economic implications of stock prices, you want to remember three rules. First, the stock market is not the economy. Second, the stock market is not the economy. Third, the stock market is not the economy (…). The relationship between stock performance – largely driven by the oscillation between greed and fear – and real economic growth has always been somewhere between loose and nonexistent".

——Paul Krugman (2020)

INTRODUCTION

By February of 2020, the coronavirus 2019 (COVID-19) pandemic had set in motion a worldwide disruption in economic activity, causing the falling S&P 500 stock market index to react to news of the disease by losing 33.7% of its value in one month. As the world suffered from the worst economic crisis since the Great Depression (Baldwin and Weder di Mauro 2020a, 2020b, Bénassy-Quéré and Weder di Mauro 2020, Coibon et al. 2020), the reaction of stock markets raises serious concerns. Since the beginning of the crisis, stock prices seem to be running wild. They first ignored the pandemic, then panicked when Europe became its epicenter. Now, they are behaving as if the millions of people infected, the 400,000 deaths and the containment of half the world's population will have no economic impact after all.

LITERATURE REVIEW

Emerging literature subsequently explored the impact of the COVID-19 pandemic on equity markets (e.g., Cox et al., 2020; Baker et al., 2019; Gormsen and Koijen, 2020) and the debt markets (e.g., Haddad et al. 2020). However, the causal impact of COVID-19 on investor sentiments has not been formally examined and understood. Barclay (2019)'s report shows that people feel stressed and anxious when faced with financial and investment terminology, compared to neutral words. For instance, investment terms were shown to be particularly stressful, with 'stockbroker,' 'asset management,' and 'investment risk' evoking the slowest response times and therefore being the most likely to provoke anxiety. This effect is most pronounced for those who already self-report as being financially anxious, with this cohort of participants taking the longest to respond. An important question is whether investors' fears on the diseases really have an impact on the investment behavior in stock markets. It remains unclear whether investors' sentiments increase or decrease the investment performance for purchasing or selling a stock, particularly in different markets with the opposite attitudes towards the pandemic COVID-19 (e.g., USA and China).

The aim of this paper is to provide insights into the investors' sentiments and the informational role of social media and enhance our understanding of how social media can best be employed as part of an investment strategy. Bollen et al. (2011) provide evidence that the public mood extracted from Twitter predicts daily aggregate stock returns. However, we still know little about the information content of firm-specific Twitter sentiment, especially when investors' scare raised from such a pandemic COVID-19. Our study attempts to shed new light on this issue.

IDENTIFICATION STRATEGY

We use Bloomberg's firm-specific Twitter sentiment calculated using tweets from the overall Twitter and StockTwits that Bloomberg classifies as being about a given company. Bloomberg uses supervised machine learning algorithms that, for example, identify financial tweets about Apple, determine if the particular tweet is positive, negative, or neutral, and assign it a confidence score. A firm's daily Twitter sentiment is derived from its story-level sentiment and associated confidence scores in the last 24 hours. The sentiment values are released every morning before the stock market's open during the pandemic COVID-19. Using Bloomberg's Twitter sentiment data allows us to contribute to the literature on the informational content of Twitter messages without doing a daunting and potentially subjective analysis of tweet content. This makes it feasible to examine the predictive content of Twitter sentiment for a large number of individual firms over a long sample period. In addition, using Bloomberg's Twitter sentiment makes our study replicable and transparent.

Bloomberg uses a suite of supervised machine learning methods for social media sentiment analysis. First, Bloomberg lets human experts manually process a large set of tweets. Experts examine the language in a given tweet about a company to determine if the tweet is positive, negative, or neutral. The labeling is based on the question, "If an investor having a long position in the security mentioned were to read this news or tweet, would he/she be bullish, bearish, or neutral on his/her holdings?" Bloomberg then feeds the manually classified tweets into machine-learning models that are trained to mimic language experts in analyzing textual information.

Bloomberg computes firm-level daily Twitter sentiment scares using the confidence-weighted average of the past 24 hours' story-level sentiment scores as follows:

$$Scares_{i,t} = \frac{\sum_{k\in P(i,T)} S_i^k C_i^k}{N_{i,T}}, \qquad T \in [t-24h, t] \tag{1}$$

To investigate the impact of Twitter sentiment scares on stock returns, we use daily cross-sectional regressions similar to those in Fama and MacBeth (1973). Specifically, we first run cross-sectional regressions for each day and then report the time-series averages of the daily coefficient estimates and the corresponding t-statistics. The t-statistics are robust to heteroskedasticity and autocorrelation. Tetlock (2011) uses a similar method to investigate the impact of firm-specific news on stock returns. The regression specification is:

$$Return_{i,t} = a + bScares_{i,t-1} + \sum_{k=1}^{5} c_k Return_{i,t-k} + Controls_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $Return_{i,t}$ is the holding period return of stock *i* from market open on day *t* to the open on the next trading day. $Scares_{i,t-1}$ is the Twitter sentiment scares of stock *i* on day *t –1* during the Covid-19 period. As discussed above, $Scares_{i,t-1}$ measures the sentiment between day *t-1* and day *t* during the pandemic COVID-19. The coefficient of $Scares_{i,t-1}$ is our main parameter of interest.

Our work contributes to the small but growing literature in corporate finance about the impacts of the pandemic COVID-19 on investors' sentiments and stock markets. Our study will provide empirical evidence of a causal relationship between investors' sentiments and the volatility of stock markets performance. This study adds to the ongoing debate over whether and how public opinion through social media impacts capital markets. Due to the rapid development of textual analysis techniques, a growing literature attempts to directly measure investor sentiment by analyzing communications of those who are commenting on stocks. This study led some light on the technical use of textual analysis in behavioral finance.

SAMPLE

We analyze Twitter sentiment for the S&P 500 component stocks. We randomly select 29 stocks from the S&P 500 components. Bloomberg integrated Twitter fed into its platform in April 2013 and started releasing Twitter sentiment data in January 2021. Our sample period is from March 2020 to December 2020 and contains 213 trading days. In total, we have 6,177 stock-day observations and 5,592 non-missing observations of firm-specific Twitter sentiment.

PRELIMINARY RESULTS

In Table 1, we present summary statistics for our full sample. The panel shows that the average Scares measured by Twitter sentiment is -0.072, indicating that, on average, the content of tweets concerning members of the S&P 500 index is slightly negative. The mean raw return is about 0.1 basis points, consistent with the general upward trend in the stock market during our sample period. The mean values of positive tweets, negative tweets, volatility, and the bid-ask spread are 24.713, -28.648, 31.619, and 0.031, respectively. All variables show large variation. This suggests that negative tweets are associated with higher contemporaneous volume, volatility, spread, and firm size than positive tweets. This is consistent with the well-documented finding that bad news tends to have a larger effect on stock return volatility than does good news (e.g., Engle and Ng, 1993).

Table 1: Summary statictics.

Variable Name	Obs	Mean	SD	Min	Median	Max
Scares	5592	-0.072	0.069	-0.900	-0.049	-0.002
TwttrPubCnt	6177	507.777	958.440	3.000	136.000	17825.000
TwttrPosSentCnt	5820	24.713	59.228	1.000	9.000	1676.000
TwttrNegSentCnt	5592	-28.649	70.298	-3081.000	-9.000	-1.000

Volatility	6177	31.619	11.698	20.570	27.760	82.690
Raw Returns	6177	0.001	0.030	-0.238	0.001	0.243
ReturnontheSP500Index	6177	0.001	0.023	-0.120	0.003	0.094
Bid-ask_Spread	6177	0.031	0.023	0.005	0.024	0.333

Table 2 reports the regression estimates. As discussed above, the raw return is computed from the current day to the following day as a daily return. As seen in column 1, the coefficient estimate on $Scares_{i,t-1}$ is negative and but not significant. When we adjust the raw return by deducting the market return, the coefficient estimate on $Scares_{i,t-1}$ is negative and statistically significant, as seen in column 2. On average, the adjusted stock return over the next 24h for firms with the most negative Twitter sentiment (Scares = 1) is about 27.2 basis points higher than the return for firms with the most negative Twitter sentiment (Scares = −1).

Table 2: Main regressions on scares and stock returns.

	(1)	(2)
VARIABLES	Raw Return	Risk-adjusted Return
Scares$_{t-1}$	-0.0029	-0.0085**
	(-0.48)	(-2.05)
Volatility	-0.0007***	-0.0001***
	(-13.70)	(-4.54)
Bid_ask_Spread	0.2041***	0.1341***
	(8.25)	(8.06)
Size	0.0000	0.0000
	(0.10)	(0.71)
Constant	0.0161***	0.0009
	(12.39)	(0.98)
Observations	5,591	5,591
R-squared	0.033	0.012

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The predictive power of Twitter sentiment for individual stock returns may be explained by its information content. If Twitter sentiment contains useful fundamental information about stocks, its effect on returns should be permanent. Mao et al. (2015) find that the effect of market-wide Twitter sentiment on stock indices is permanent. On the other hand, if Twitter sentiment simply reflects the sentiment of uninformed traders, the impact of Twitter sentiment on stock returns should be reversed over the next few trading days. We test whether the negative influence of Twitter sentiment on returns is temporary or permanent by including four additional lags of Twitter sentiment in the model in Eq. (2). We run regressions for both raw returns and risk-adjusted returns. Table 3 shows that controlling for lags of Scares measured by Twitter sentiment has little effect on the predictive value of Twitter sentiment for stock returns.

Table 3: Main regressions on lagged scares and stock returns.

	(1)	(2)
VARIABLES	Raw Return	Risk-adjusted Return
Scares$_{t-1}$	-0.0074	-0.0057
	(-0.82)	(-0.94)
Scares$_{t-2}$	0.0006	-0.0028
	(0.07)	(-0.43)
Scares$_{t-3}$	-0.0062	0.0083
	(-0.65)	(1.28)
Scares$_{t-4}$	0.0156	0.0047
	(1.62)	(0.73)
Scares$_{t-5}$	-0.0182**	-0.0026
	(-2.06)	(-0.43)
Volatility	-0.0007***	-0.0002***
	(-12.09)	(-4.21)
Bid_ask_Spread	0.2023***	0.1388***
	(7.23)	(7.37)
Size	0.0000	0.0000

	(0.28)	(0.66)
Constant	0.0156***	0.0011
	(10.06)	(1.07)
Observations	4,470	4,470
R-squared	0.034	0.013

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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