

Why Social Media Matters: The Use of Twitter in Portfolio Strategies

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ABSTRACT

In previous works ([8], [12]), it has already been showed that Twitter and social media in general give an interesting additional predictive power to the models that take them into account. However, the contribution of social media is relatively small on a daily basis, because of the speed and the increasing efficiency of the stock markets. It has been decided then to deal with intraday prices to test whether micro-blogging data may actually be used to implement high-frequency forecasting models. It has been constructed an indicator to earn some insights on the Nasdaq-100's future movements. Once again, the results are very encouraging: the use of social media data increases the predictive power for general stock market index such as the Nasdaq, and becomes thus an essential building block for any pricing model.

Keywords

micro-blogging, sentiment analysis, forecasting, Twitter, index.

1. INTRODUCTION

Nowadays, the two main characteristics for any financial market or stock exchange are the enormous volumes traded, and the increasing speed of the order submitted and/or filled. Big data techniques and models from one hand, and computers and financial algorithms from the other hand, are changing the way we approach the markets and the tools we use. They are also breaking down the barriers regarding both the type and the amount of the data we can use to feed our models, so that interesting insights can be earned by a variety of different sources.

The majority of this information is quantitative and easy identifiable, such as prices, volumes, volatilities, and so on so forth. On the other hand though, it is quite cumbersome to find a way to quantify measures such as the market or investors sentiment. An extensive literature exists on both theoretical models and empirical applications that study how to embed this factor into a forecasting model and portfolio strategies: back in the first half of the century, Fisher and Statman ([18]) dealt with the interaction of investors' sentiment and tactical allocation, while only with Baker and Wurgler few years later ([4], [5]) a better comprehension has been achieved regarding how to incorporate behavioral biases and thus the market sentiment into the stocks selection process. Furthermore, Da et al. (2012) proposed in a first place how to quantify the investors demand using search frequency in Google for a five-year sample of Russell 3000 stocks, and afterwards ([15]) daily Internet search volume to construct a new index able to assess the investors' sentiment. Tetlock et al. ([32], [33]) proposed some analysis in which different financial languages in the financial news affect differently the stock returns. The impact of the negative news is thus larger for the stories concerning the fundamentals, and

negative firm-specific words have a greater forecasting power on low firm earnings - to which the prices shortly underreact. Many other different works have been written about market sentiment and the investors' perceptions, but only recently the field has experienced a turning point, i.e., when social media became part of the equation in formulating a more efficient trading model ([3]). The applications for social networks have been indeed manifold: epidemics and disease spread ([13]), movie revenues ([23]) or commercial sales forecasting ([11]), presidential elections ([34]), music albums release ([17]), and financial decision making ([25], [28]). Furthermore, it is also true that different kind of sources have been analyzed for this last purpose, e.g. financial news ([30], [20]), blogs ([16]), web search queries ([9]), stock message boards ([2], [19]), and security analyst recommendations ([6]).

Bollen et al. (2011) – and in a series of other works ([8], [21]) – have first deepened how Twitter could be used to forecast the Dow-Jones Index using a spectrum of different human emotions, and similar applications have been analyzed then by Mittal and Goel ([24]), Zhang [35] and Brown [10]. In a most recent paper, Mao et al. ([22]), exploited tweets predicting power in order to understand the international financial markets trend for several countries, including the United States, United Kingdom, and Canada. At the same time, Agarwal et al. (2011) and Ruiz et al. (2012) studied the existing correlation between micro-blogging data and financial time series. Then, Oh and Sheng ([26]) created a model for irrational investor sentiment, Oliveira et al. ([27]) assessed a positive effect of the Twitter volume on robust forecasting, and finally Sprenger et al. ([31]) proved how abnormal stock returns and message volume are associated to an increment in the posting volumes. Hence, differently from any other work before, this one is going to focus on the use of tweets about few stocks in order to predict the trend of a market index. The structure of the work will be as follows: first, the data will be presented and described. Then, some new indicator-tracking variables will be built and then different forecasting models will be tested, to finally assess the differences from the autoregressive benchmark model. In the section 3 some empirical results will be showed, to conclude then in section 4.

2. DATA AND METHODOLOGY

Since the aim was to analyze the Nasdaq-100's behavior, three of the major technology stocks belonging to the index have been taken into account, i.e., Apple, Google, and Facebook. The reason why is quite intuitive: hundred companies compose the index, but clearly not every company has the same weight on the bundle. Hence, selecting ex-ante the biggest ones, it has been reduced the model complexity and the number of features to be taken care of. In other words, this prior could be considered to have the same function of a "qualitative" principal component analysis, which allows us to

shrink the model and allocate a greater explanatory power to firms that are more meaningful to the index. First of all, the data for the intraday prices for the Nasdaq-100 have been obtained through Bloomberg. It has been collected therefore a dataset for the period that goes from September 24th to November 21st 2014, and it was possible to gather almost 88,000 tweets for Apple, 43,600 for Facebook, and slightly less than 32,000 for Google. There are indeed many ways to gather this kind of dataset, e.g. through APIs or similar, but it

has been used instead a data provider called DataSift because it was able to supply a scoring algorithm for the tweets' content. Figures 1 – 3 display indeed the overall tweets volume for each stock (blue bars), and the sentiment means for the daily tweets (black lines). The black lines are indeed built so that the lowest value represents the average for the negative tweets, while the highest extreme is the mean for the positive ones, and the small dashes the overall daily averages.

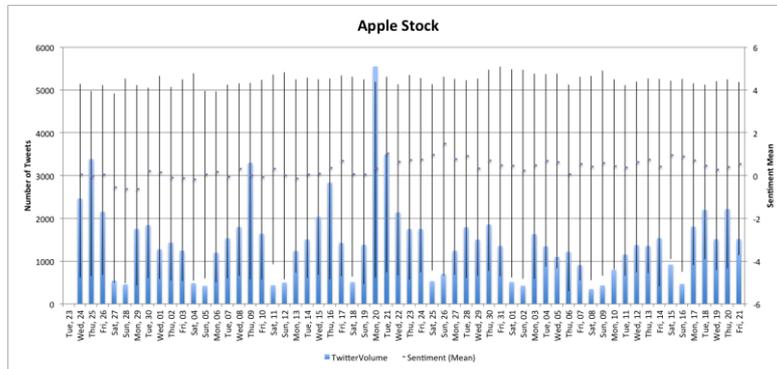


Figure 1. Twitter Volume, Mean of positive sentiment, Mean Negative sentiment and Daily sentiment mean for Apple.

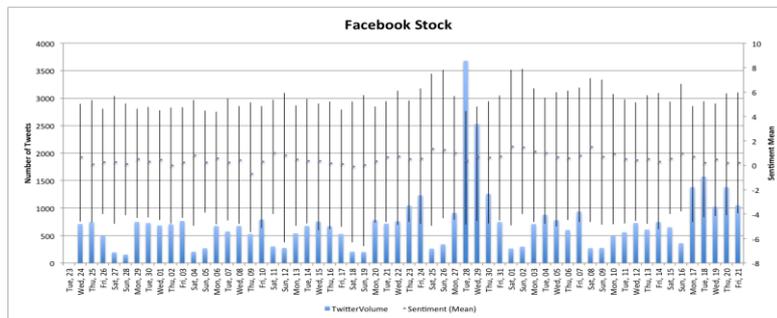


Figure 2: Twitter Volume, Mean of positive sentiment, Mean Negative sentiment and Daily sentiment mean for Facebook.

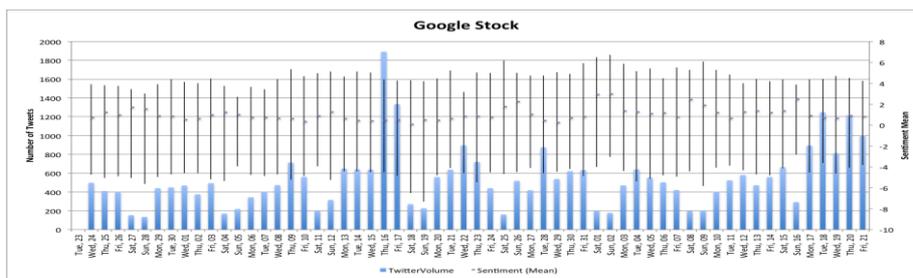


Figure 3: Twitter Volume, Mean of positive sentiment, Mean Negative sentiment and Daily sentiment mean for Google.

In addition, DataSift provides a wide spectrum of information, such as the gender, location, time, username, and much more. For the preliminary analysis, many of them were actually meaningless, but additional studies may be implemented using this information. Further noise comes directly from the tweets text, which are often irrelevant for the study. Hence, it has been decided to consider only the tweets in which some extent of financial knowledge was observed, i.e., only the tweets in which appeared the stock's ticker. Every tweet that was not in English has been eliminated during this first step, since taking into account other languages was not relevant to the study per

se – and because they represented a small portion of the dataset as well.

Regarding how the scoring system works, the underlying algorithm assesses how positive or negative is the text of certain tweet. For this work, the range of this rating oscillates between -20 and +20, even if particular topic/text requires sometimes a higher/lower evaluation. The figure 4 shows the daily volatility of the scores with respect to the stock volatility. The first ones are quite stable, while of course the stock variations are really volatile.

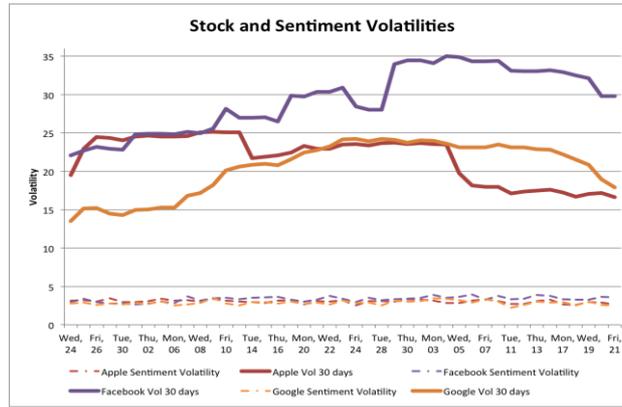


Figure 4: Stock volatility (lines) and sentiment score volatility (dashes) for Apple, Google and Facebook.

The following step was the construction of relevant variables for the empirical analysis. It has been indeed built a variable for the *sentiment mean*, taking the simple average for the tweets' scores on a minute basis; it was also computed the time volume moving average, and a sentiment moving average (SMMA), where both of them are five-minutes moving average; finally, two variables for tracking the Nasdaq-100 were created: the *sentiment index-tracking* (SIT) and the weighted *sentiment index-tracking* (SITw), respectively

$$SIT_t = \frac{SM_{Apple,t}TV_{Apple,t} + SM_{Google,t}TV_{Google,t} + SM_{Facebook,t}TV_{Facebook,t}}{3} \quad (1)$$

and

$$SITw_t = \frac{SM_{Apple,t}TV_{Apple,t} + SM_{Google,t}TV_{Google,t} + SM_{Facebook,t}TV_{Facebook,t}}{TV_{Apple,t} + TV_{Google,t} + TV_{Facebook,t}} \quad (2)$$

There have then created the equivalent moving average variables, i.e., *SITma* and *SITwma*.

Hence, two different set of regressions were run: the first one was the standard one, in which the dependent variable was always the Nasdaq value at a certain minute. The second block concerned instead the Nasdaq's variations, so in other words the *direction* or *trend* the index was assuming.

Afterwards, the first thing has been setting the benchmark model, i.e., a simple autoregressive model such as

$$M1: P_t = \alpha + \varphi P_{t-1} + \epsilon_t \quad (3)$$

Secondly, it has been tested whether the hypothesis of

Table 1: OLS regressions results for model 1-7. T-statistics in parenthesis, * p<0.1, ** p<0.05, *** p<0.01.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Price _t						
Price _{t-1}	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
	(11975.8)	(5787.1)	(4635.2)	(5790.2)	(5786.2)	(4653.3)	(4640.9)
Apple SM _{t-1}		0.03***					
		(2.68)					
Google SM _{t-1}		-0.007					
		(-0.72)					

grouping the three stocks was indeed useful, or if maybe each of them had a different impact on the Nasdaq price:

$$M2: P_t = \alpha + \varphi P_{t-1} + \beta_1 SM_{Apple} + \beta_2 SM_{Google} + \beta_3 SM_{Facebook} + \epsilon_t \quad (4)$$

For a robustness check, it was run the same model for the sentiment five-minutes moving averages:

$$M3: P_t = \alpha + \varphi P_{t-1} + \beta_1 SMMA_{Apple} + \beta_2 SMMA_{Google} + \beta_3 SMMA_{Facebook} + \epsilon_t \quad (5)$$

Finally, the other model embedding the simple sentiment index-tracking variables has been tested, i.e.,

$$M4: P_t = \alpha + \varphi P_{t-1} + \beta SIT_{t-1} + \epsilon_t \quad (6)$$

and then the same has been implemented for the weighted version, the moving average one, and finally the weighted moving average, respectively *M5*, *M6*, and *M7*.

In a perfectly symmetric way the same has been done using, instead of price variables, the direction (or trend) variable, i.e., a simple dummy variable that took value one if the ratio between the prices today and yesterday price was greater than one, zero otherwise (*M8 – M14*).

3. EMPIRICAL RESULTS

It has been used an ordinary least square regression for the models from one to seven, while the linear probability model has been used for the regressions *M8 – M14*. The results from the regressions are shown in Table 1 and Table 3, while Table 2 and 4 exhibit the root mean squared errors and the adjusted R² for all the models. These two tools can be used to compare the models at a glance.

Facebook SM _{t-1}		0.0040					
		(0.42)					
Apple SMMA _{t-1}			0.0178				
			(0.60)				
Google SMMA _{t-1}			-0.00828				
			(-0.31)				
Facebook SMMA _{t-1}			-0.00006				
			(-0.00)				
SIT _{t-1}				0.0123*			
				(1.90)			
SITw _{t-1}					0.0287*		
					(1.82)		
SITma _{t-1}						0.0180	
						(0.97)	
SITwma _{t-1}							0.0210
							(0.53)

Table 2: Adjusted R² and root mean square error for all the models.

Model	M1	M2	M3	M4	M5	M6	M7
Adj-R ²	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
RMSE	1.5641	1.3978	1.4401	1.3983	1.3984	1.4392	1.4394

Table 3: LPM regressions results for model 8-14. T-statistics in parenthesis, * p<0.1, ** p<0.05, *** p<0.01.

Model	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Trend _t						
Apple SM _{t-1}		0.008**					
		(1.98)					
Google SM _{t-1}		0.00083					
		(0.23)					
Facebook SM _{t-1}		0.00017					
		(0.05)					
Apple SMMA _{t-1}			0.00098				
			(0.10)				
Google SMMA _{t-1}			-0.0052				
			(-0.58)				
Facebook SMMA _{t-1}			0.004				
			(0.49)				
SIT _{t-1}				0.00414*			
				(1.83)			
SITw _{t-1}					0.00973*		
					(1.77)		
SITma _{t-1}						0.00137	

						(0.22)	
SITwma_{t-1}							0.00405
							(0.30)
Trend_{t-1}	0.117***	0.158***	0.155***	0.159***	0.159***	0.156***	0.156***
	(16.22)	(8.99)	(7.08)	(9.02)	(9.02)	(7.11)	(7.11)

Table 4: Adjusted R² and root mean square error for all the models.

Model	M8	M9	M10	M11	M12	M13	M14
Adj-R²	0.0135	0.0254	0.0227	0.0257	0.0256	0.0234	0.0234
RMSE	0.49459	0.48774	0.48862	0.48767	0.48769	0.48844	0.48843

Beginning from the price regressions, the models where the single stocks are taken into account (*M2 – M3*) seem to increase the accuracy of the forecasts with respect to the benchmark model, but unfortunately almost none of the results are statistically significant. On the other hand, the sentiment index-tracking variables give positive results: even if the moving averages are not significant as well, the simple *SIT* or the weighted one are significant and meaningful. Besides, Table 2 shows the improvement of using this model with respect to the benchmark. In particular, it turns out that the simplest one (*M4*), in which the easiest version of *SIT* has been used, is the one that performs the best.

The results from the second block of LPM regressions do not show any inconsistency with what just claimed above. The outcomes and considerations are perfectly symmetric, and once again the *SIT*-model seems to be the most explicative one, able to reduce the RMSE and anticipate to some extent the market trend.

4. CONCLUSIONS

Both the academic literature and the industry professionals are approaching social media as source of interesting insights. A strong hidden value is contained in this new information channel, and financial markets could exploit it as well. Even if the results are quite simple, specific to the technological sector, and still preliminary because of the limitless work that could be done about it, they give us many foods for thoughts. The high frequency nature of this new dataset is indeed able to capture some price variations for the Nasdaq-100 way better than basic forecasting models. To prove it, it was built a dataset for a two-months period using data from Twitter, and then it was created a synthetic way to track the general index about the Nasdaq through his three main companies, i.e. Apple, Google, and Facebook. Different analysis were run, and it was used a comparative augmented approach to evaluate their differences in performance. With respect to the simple autoregressive benchmarks, the explanatory power and the accuracy achieved by the sentiment-models are bigger, and this pushes us to create new models in which human judgment, sentiment and opinions play a role.

The study is only a first look on this immense field, and many more improvements could be done in future: different sector or regions, longer time series, event studies related to corporate or market events, or particular situations of the market cycle (crisis, expansion, etc.).

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