The Viability of StockTwits and Google Trends to Predict the Stock Market

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Introduction

Investors are always looking to gain an edge on the rest of the market. Traditional market theory tells us trying to predict future stock market movements is a wasted effort. The earliest forms of this concept focuses primarily on the random walk hypothesis, which asserts that stock market prices are random and day-to-day price movements are independent of one another. Fama expanded upon this theory, developing what is now commonly referred to as the Efficient-Market Hypothesis (EMH). The EMH states that it is impossible to 'beat the market' as market efficiency ensures that all security prices always 'fully reflect' all available information [1]. In short, an investor cannot reasonably expect to consistently beat the stock market through superior stock selections and market timing.

The expansion of the Internet in the past decade has given researchers new avenues to explore the art of prediction. First, online forums and blogs allowed individuals to share thoughts, opinions and information with one another on any imaginable subject. Dhar and Chang examined the predictive ability of Internet chatter from user-generated content on blogs and forums and its impact on music album sales [2]. Their research concluded that that online chatter is predictive of album sales during the first two weeks following the album release and the week preceding the album release. Mishne and Glance took a similar approach with movies and found correlation between references to movies in weblog posts—both before and after their release—and the movies' financial success [3]. The growth in size and popularity of social media sites like Facebook and Twitter gave researchers investigating the science of prediction another source of data. Asur and Huberman examined tweets from the site Twitter and made predictions about the financial success of various movies [4]. Using only tweets that preceded the release of a movie, they found a strong correlation between the amount of attention a movie is given and its future financial success. While this research doesn't pertain specifically to the stock market, their conclusions remain important as they show the predictive ability of blogs and social media.

The rapid expansion of social media in the past few years has changed the way people communicate information, ideas and opinions to one another. Twitter in particular has become a popular website, allowing its 500 million members to send an average of 340 million tweets daily, all of which contain 140 characters or less [5] [6]. In recent years stock market investors have increasingly turned to Twitter as an investment tool. Twitter's appeal as an investment tool lies in the users ability to relay company information, investment ideas and market sentiment in a short, concise manner. Nowadays, investors turn to the website StockTwits to share information. Developed in 2008, StockTwits boasts 300,000 investors, market professionals and public companies that use the site to share ideas and information about the market and individual stocks [7]. StockTwits is an investor focused platform like Twitter which operates in a similar manner. Users share short messages about a particular stock or index applying a $ symbol before the ticker symbol which allows StockTwits to organize streams of information about a particular stock or index.[1] StockTwits allows for a significant amount of information to be aggregated in one place, researchers have begun to examine the relationship between social media websites and the stock market.

[1] Ex.) $AAPL earnings tomorrow. Expecting a miss due to low Iphone sales and high expectations.

Bollen et al. (2010) used Twitter as a means to aggregate public sentiment and then test the correlation between the collective mood of Twitter and the movements of the Dow Jones Industrial Average over time [8]. Their research concluded that 86.7% of the time there was a positive correlation between public sentiment and the upward/downward movement of the Dow Jones. This conclusion, while significant, strays from the goals of our research. Unlike Bollen et al., we will focus only on StockTwits messages that pertain to specific stocks or stock market indices. Additionally, we will not utilize Twitter as a whole, but will focus solely on messages sent through StockTwits.

Sprenger and Welpe went into further detail with their research, analyzing the volume of stock related StockTwits messages and their impact on next day price movements [9]. Their research concluded that the sentiment of messages (i.e. bullish or bearish) associated with abnormal stock returns and next day trading volume. Our research will investigate whether a high volume of messages is a leading or lagging indicator of stock market returns.

This research will aim to further understand if StockTwits messages are leading or lagging indicators of stock market returns. Unlike Bollen et al., we will not focus on the entire Twitter user base when collecting data, but will focus specifically on messages collected from StockTwits.com. Our research will be similar to that of Sprenger and Welpe, but we will only examine individual stocks. More formally, we will aggregate data relating to a particular company using StockTwits “Cashtag” handle system (which tags company stocks by using the dollar sign, $, along with the company stock symbol) and Google Trends index and then test the significance of the StockTwits and Google Trends betas in explaining daily stock returns. If the

StockTwits and Google Trends betas are significant we will test if they are a significant leading or lagging predictor of daily stock returns.

Literature Review

In recent years, researchers have in increasingly looked towards sentiment analysis as a tool for making predictions. The evolution of the “Web 2.0” in the early 2000’s allowed researchers easy access to large amounts of data on online blogs and forums. Dhar and Chang [2] examined the usefulness of user-generated content consisting of data from blogs and forums to examine its predictive capability of music album sales. Mishne and Glance [3], using a similar tactic, applied their results to the box office performances of various movies. With the evolution of social networking, Asur and Huberman [4] used Twitter messages to once again examine the relationship between community chatter and the financial performance of movies. In all three above cases, the research concluded that there was a positive relation to online “chatter” and the financial performance of albums or movies.

During the dot-com bubble of the late 1990’s, online blogs and message boards focused on stock market information and speculation became popular. Wysocki’s 1998 paper tested whether variation in message posting volume is just noise or if it is related to the underlying characteristics of a firm and stock market activity [10]. Wysocki’s research was significant in that it found a high level of correlation between messages posted after regular stock market hours (i.e. between 4:00 p.m. and 9:00 a.m. the following trading day) and the following trading day’s volume and returns.

Tumarkin and Whitellaw, using methods similar to Wysocki, focused their research using chatter only from the once popular website RagingBull.com [11]. Unlike previous research, they concluded that the message board activity of RagingBull.com did not have any predictive capabilities but did, however, show correlation between message volume and next day trading volume.

Antweiler and Frank examined 1.5 million messages focused on 45 companies that were posted on Yahoo! Finance and RagingBull.com [12]. Their research concluded that stock market messages help to predict market volatility and that while economically small; stock market message boards do affect stock market returns in a statistically significant manner.

Das and Chen added to previous research by developing a formal sentiment analysis tool and applying it to stock market message boards [13]. When applied to individual stocks they found no significant correlation between sentiment and stock price movements. They acknowledge this in their research and attribute it to the large amount of noise in stock market message boards as well as the lack of market power that many investors participating in online message boards have.

Previous research has primarily used online message boards as a mean to aggregate investor sentiment. Recent research has taken advantage of the emergence of social media and applied this towards financial markets. Bollen et al. [8] aggregated "tweets" from Twitter as a whole, choosing not to focus stock market specific "tweets," and examined the "mood" states of Twitter users and corresponding stock market movements. Signaling six different mood types that would reflect the mood of an individual (Calm, Alert, Sure, Vital, Kind and Happy), the research of Bollen et al. showed the collective "mood" of Twitter users successfully predicted the upward and downward movement of the stock market 86.7% of the time.

Sprenger and Welpe [9] used a more direct approach to examine the relation between Twitter messages and stock market movement by filtering out all non-market related "tweets." The did this by using messages only pulled from StockTwits.com. Using the S&P 100 as the market index for analysis, their research suggests that public sentiment conveyed through StockTwits.com aligns itself with the movement of the S&P 100 and is positively related to the volume of trading.

The quality of the information of Twitter has also been researched. Twitter allows people to "re-tweet" (or re-share) previous tweets and to follow others, naturally isolating and emphasizing accurate information and eliminating poor information. Evangelopoulos et al. found that Twitter is actually a leading indicator of stock performance, rather than a lagging indicator [14].

Methodology

To prove the significance of StockTwits and Google Trends, we will use a linear model to predict daily stock returns. The StockTwits data is comprised of a daily Bear index and a daily Bull index. StockTwits collects sentiment from users who tag their messages either “bullish” or “bearish”, messages not tagged are assumed “neutral”. The index is simply the number of messages relating to a particular stock each day. The Google Trend data is an index of specific search terms relating to a particular company.

Our first model will include three estimators, the Bear index, the Bull index, and the Google Trend index. If these estimators prove to be statistically significant, we will create a Cross-Correlation function to determine if one of the estimators is a good leading predictor of stock returns.

Data Collection

The StockTwits index has automatically been labeled either a Bearish or Bullish message. For sample size purposes, we compiled three months of messages, starting on January 1,2013 and ending on March 31, 2013. With over 19,000 messages, the law of large numbers should crowd out uninformed, inaccurate messages.

The Google Trends data was compiled and aggregated directly from the Google Trend website. Our index includes search terms relating to a particular company, like the company name and company products and services.

Our data will be focusing on four companies, Apple, Google, Microsoft, and Facebook. We hope to model the fast movement in technology stocks with a fast estimator, like StockTwits and Google Trends.

Model

For our first model, we will be using a linear model in R to predict stock returns. The LM function in R uses a least squares parameterization:

$$\begin{matrix} \min \\ S \\ s.t.: \beta \end{matrix} \quad S = \sum_{i=1}^{N} r_i^2$$

$$r_i = y_i - f(x_i, \beta)$$

If the betas are statistically significant, we will create a new model with the lagged data, depending on the Cross-Correlation function, which shows significant correlation in lagged data. If the lagged beta coefficients are statistically significant, then the betas will be leading predictors of stock returns.

Results/Analysis

		Coefficient Estimate	Std. Error	t-Value	P-Value
Apple	(Intercept)	0.0386600	0.035730	1.082	0.283900
	Bear	**-0.0004485**	**0.000083**	**-5.406**	**0.000001**
	Bull	**0.0001279**	**0.000044**	**2.894**	**0.005410**
	Google Index	-0.0006734	0.000767	-0.878	0.383690

	R-squared:	34.33%			
	F-statistic:	**9.759**	**P-value:**	**0.000028**	
Facebook	(Intercept)	0.3241618	0.174820	1.854	0.069000
	Bear	-0.0004924	0.000375	-1.312	0.194800
	Bull	0.0002395	0.000150	1.602	0.114700
	Google Index	-0.0035892	0.001926	-1.864	0.067600

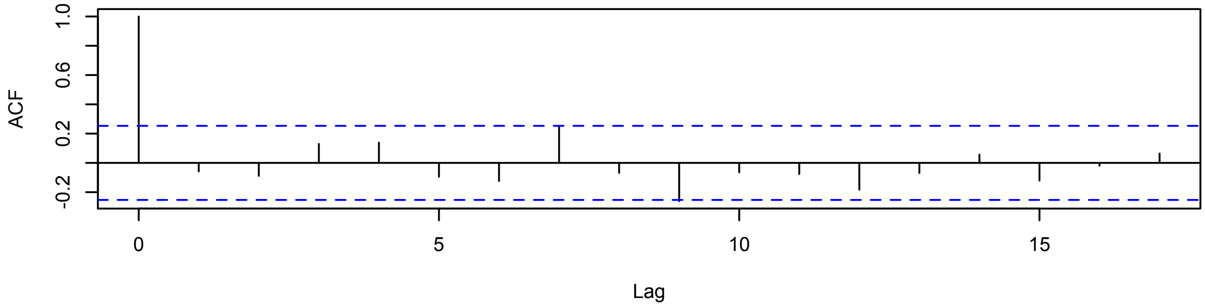
	R-squared:	8.56%			
	F-statistic:	1.748	P-value:	0.168000	
Google	(Intercept)	-0.1286272	0.088892	-1.447	0.153500
	Bear	**-0.0004158**	**0.000190**	**-2.188**	**0.032900**
	Bull	**0.0007549**	**0.000131**	**5.746**	**0.000000**
	Google Index	0.0012790	0.000932	1.373	0.175300

	R-squared:	42.17%			
	F-statistic:	**13.610**	**P-value:**	**0.000001**	
Microsoft	(Intercept)	0.0329365	0.0374552	0.879	0.383000
	Bear	**-0.0011688**	**0.0005481**	**-2.132**	**0.037400**
	Bull	**0.0011777**	**0.0004443**	**2.651**	**0.010400**
	Google Index	-0.0006885	0.0007532	-0.914	0.364600

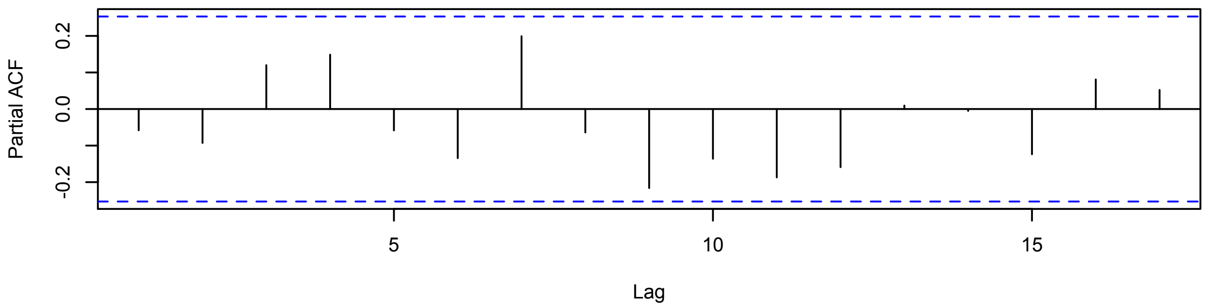
	R-squared:	11.23%			
	F-statistic:	2.360	P-value:	0.081160	

**Bold Indicates Statistical Significance at 5%

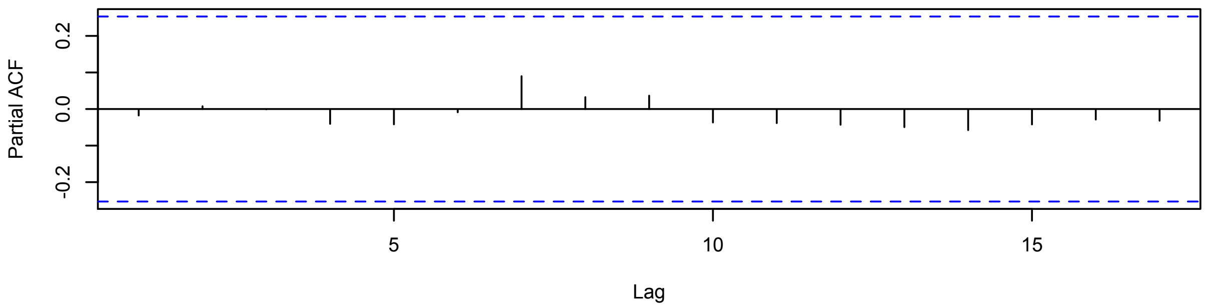
As the table shows in bold, the Bear and Bull StockTwits index was significant in predicting stock returns for Apple, Google, and Microsoft. To draw inference from these three models, autocorrelation and heteroskedasticity must not exist in the model. Below are autocorrelation, partial autocorrelation plots, and heteroskedasticity plots that will show significant lags (lags beyond the blue-dotted line):



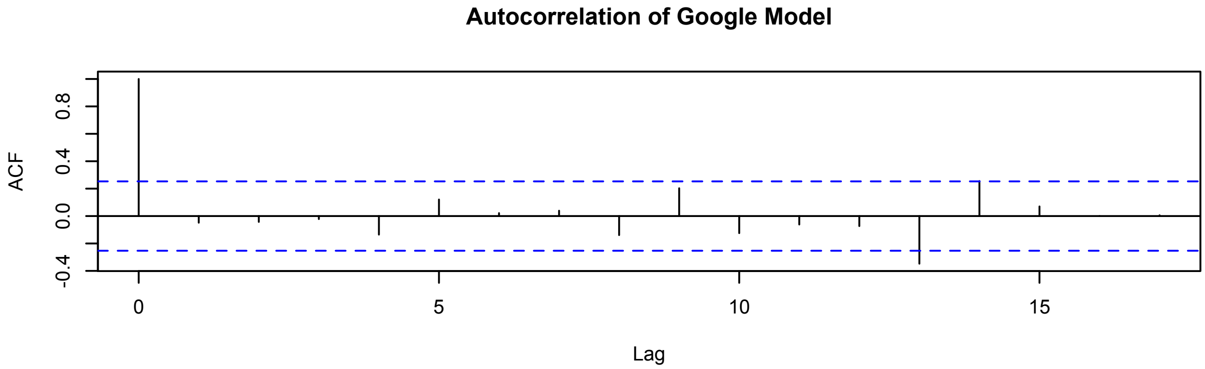
Autocorrelation of Apple Model

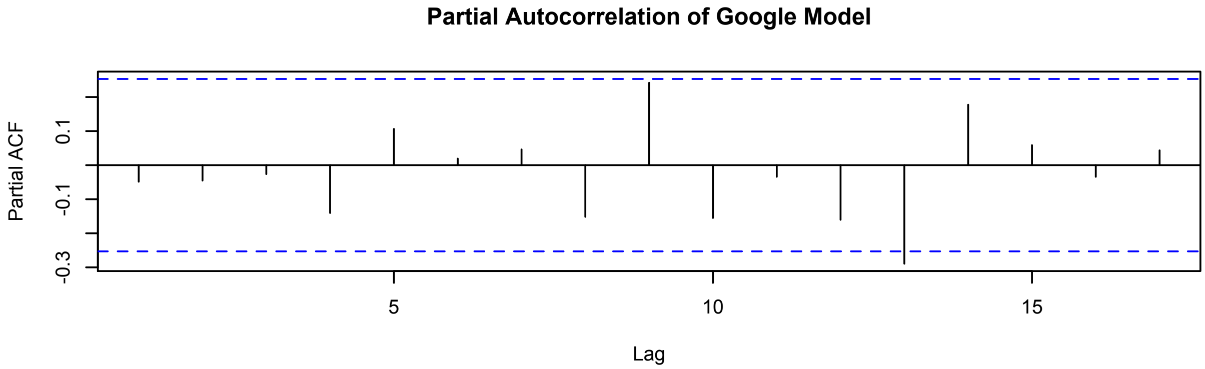


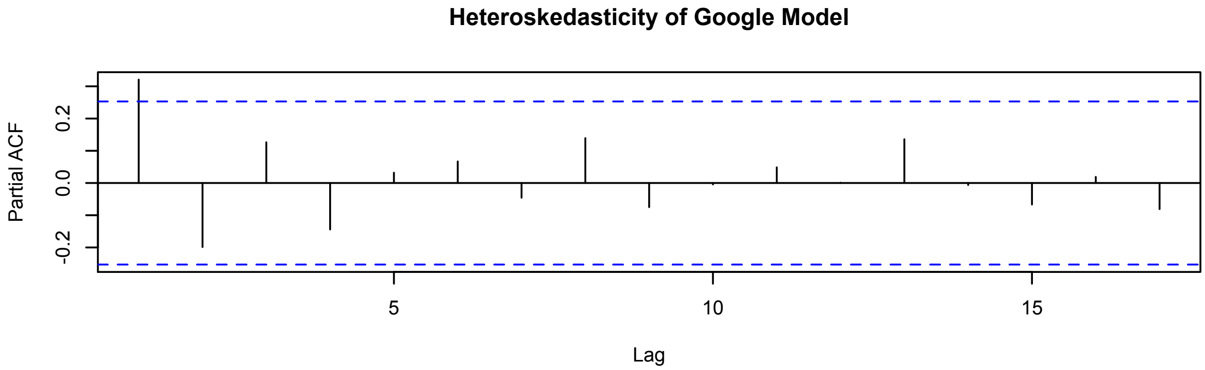
Partial Autocorrelation of Apple Model

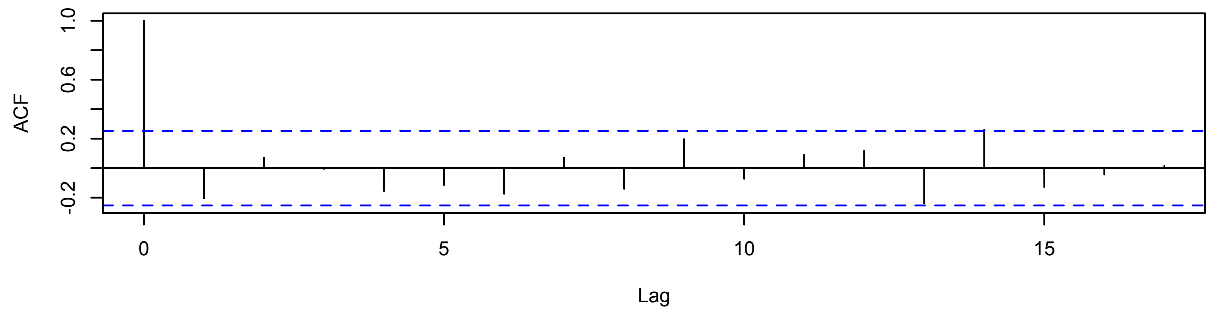


Heteroskedasticity of Apple Model

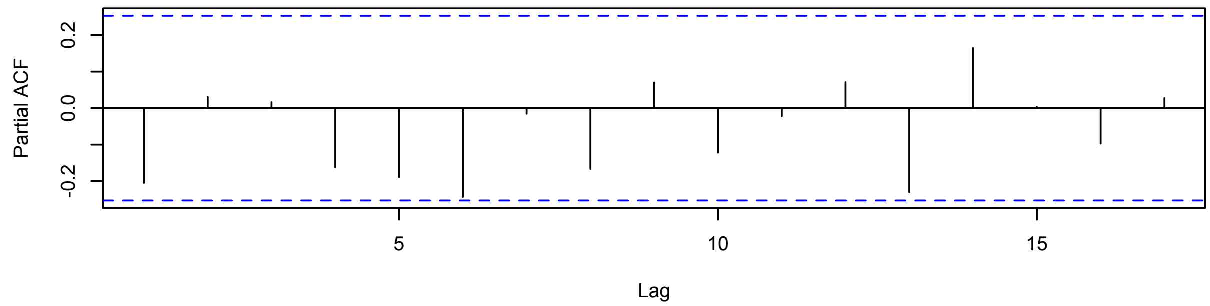

Autocorrelation of Google Model
ACF
-0.4
0.0
0.4
0.8
0
5
10
15
Lag


Partial Autocorrelation of Google Model
Partial ACF
-0.3
-0.1
0.1
5
10
15
Lag

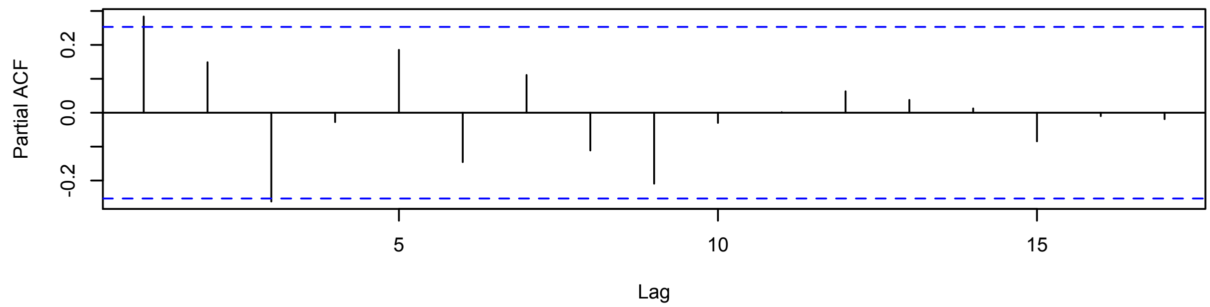

Heteroskedasticity of Google Model
Partial ACF
-0.2
0.0
0.2
5
10
15
Lag



Autocorrelation of Microsoft Model



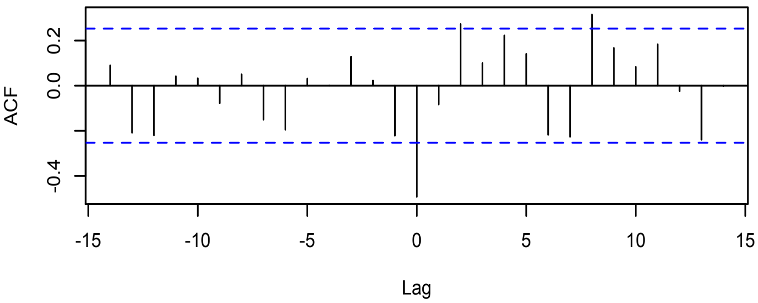
Partial Autocorrelation of Microsoft Model

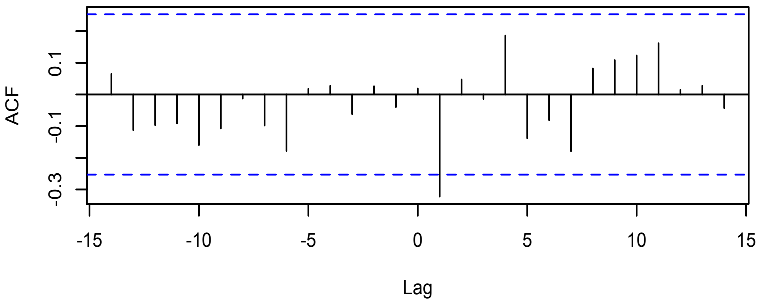


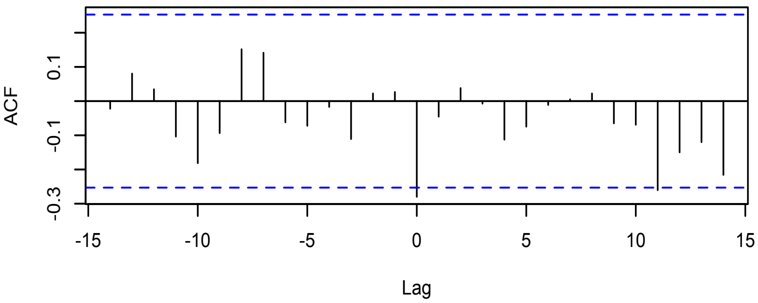
Heteroskedasticity of Microsoft Model

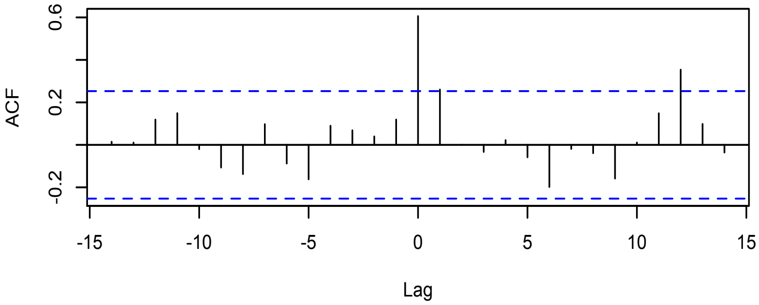
Aside from the significant spurious lag in the heteroskedastic plot for the Microsoft model, all three models show no signs of significant autocorrelation or heteroskedasticity. The assumptions of independence of residuals (lack of autocorrelation) and constant variance (homoscedasticity) are crucial to the significance of the betas. Without these assumptions, there's the chance that the betas are underemphasized or overemphasize in significance. Because our model fulfills these assumptions, we are confident our model's significance is authentic.

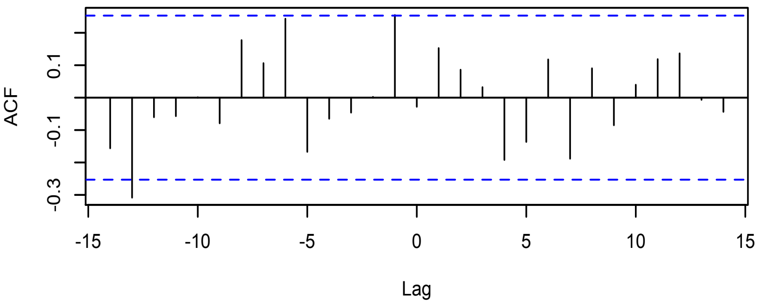
To get an idea of the leading or lagging performance, a cross-correlation function between the stock’s returns and the bear and bull index are below. Lags beyond the dotted-blue line are significantly correlated:

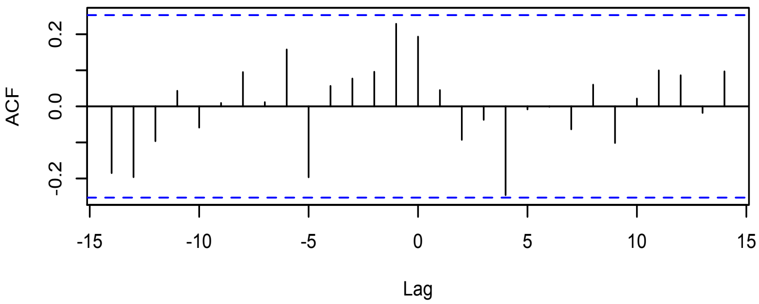

Cross-Correlation between Apple Returns and Bear Index


Cross-Correlation between Apple Returns and Bull Index

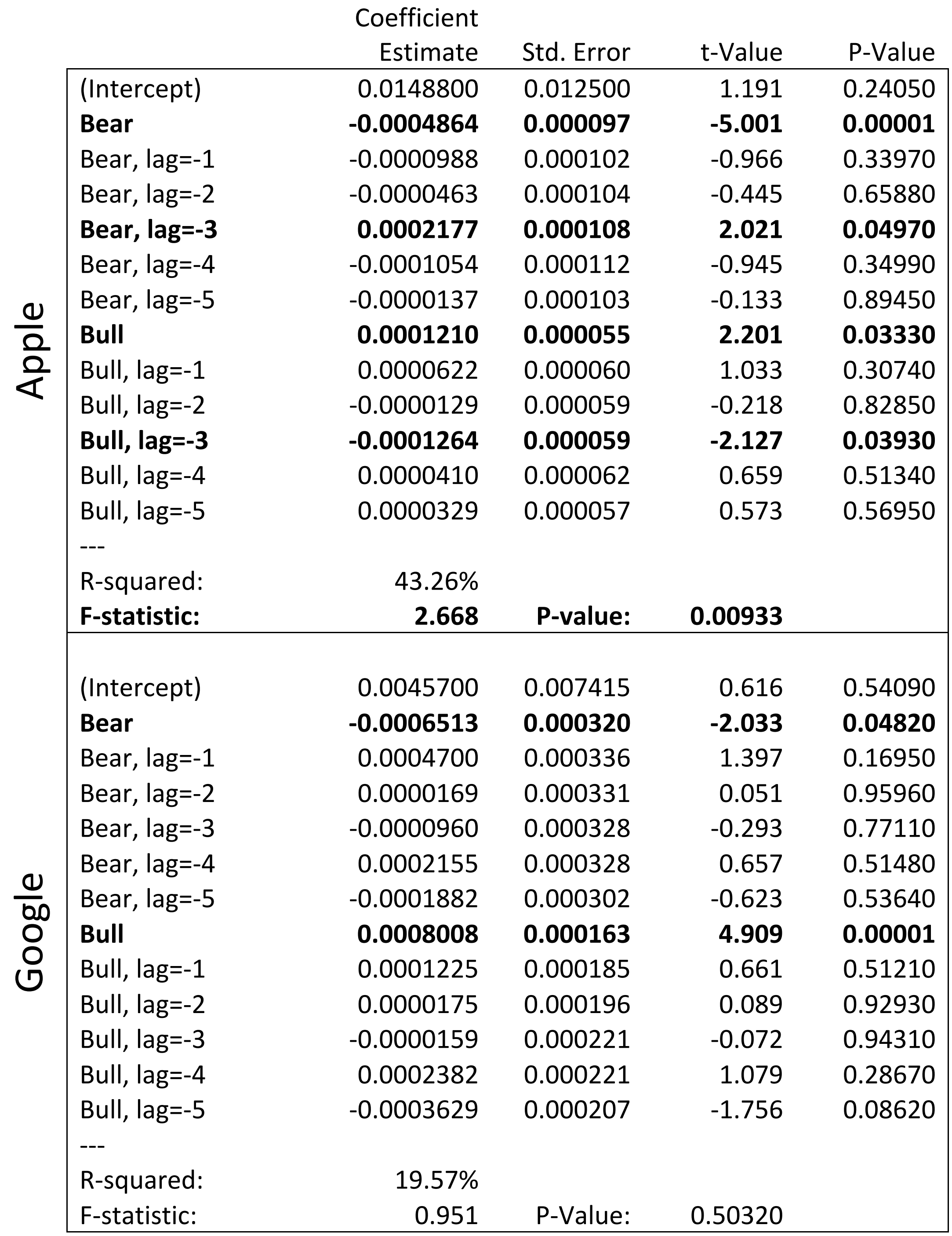

Cross-Correlation between Google Returns and Bear Index


Cross-Correlation between Google Returns and Bull Index


Cross-Correlation between Microsoft Returns and Bear Index


Cross-Correlation between Microsoft Returns and Bull Index

Most of the significant lags are around lag zero or greater, meaning a there are significant lagging predictors or stock returns. However, there are some significant leading predictors once modeled.



		Coefficient Estimate	Std. Error	t-Value	P-Value
Apple	(Intercept)	0.0148800	0.012500	1.191	0.24050
	Bear	**-0.0004864**	**0.000097**	**-5.001**	**0.00001**
	Bear, lag=-1	-0.0000988	0.000102	-0.966	0.33970
	Bear, lag=-2	-0.0000463	0.000104	-0.445	0.65880
	Bear, lag=-3	**0.0002177**	**0.000108**	**2.021**	**0.04970**
	Bear, lag=-4	-0.0001054	0.000112	-0.945	0.34990
	Bear, lag=-5	-0.0000137	0.000103	-0.133	0.89450
	Bull	**0.0001210**	**0.000055**	**2.201**	**0.03330**
	Bull, lag=-1	0.0000622	0.000060	1.033	0.30740
	Bull, lag=-2	-0.0000129	0.000059	-0.218	0.82850
	Bull, lag=-3	**-0.0001264**	**0.000059**	**-2.127**	**0.03930**
	Bull, lag=-4	0.0000410	0.000062	0.659	0.51340
	Bull, lag=-5	0.0000329	0.000057	0.573	0.56950

	R-squared:	43.26%			
	F-statistic:	**2.668**	**P-value:**	**0.00933**	
Google	(Intercept)	0.0045700	0.007415	0.616	0.54090
	Bear	**-0.0006513**	**0.000320**	**-2.033**	**0.04820**
	Bear, lag=-1	0.0004700	0.000336	1.397	0.16950
	Bear, lag=-2	0.0000169	0.000331	0.051	0.95960
	Bear, lag=-3	-0.0000960	0.000328	-0.293	0.77110
	Bear, lag=-4	0.0002155	0.000328	0.657	0.51480
	Bear, lag=-5	-0.0001882	0.000302	-0.623	0.53640
	Bull	**0.0008008**	**0.000163**	**4.909**	**0.00001**
	Bull, lag=-1	0.0001225	0.000185	0.661	0.51210
	Bull, lag=-2	0.0000175	0.000196	0.089	0.92930
	Bull, lag=-3	-0.0000159	0.000221	-0.072	0.94310
	Bull, lag=-4	0.0002382	0.000221	1.079	0.28670
	Bull, lag=-5	-0.0003629	0.000207	-1.756	0.08620

	R-squared:	19.57%			
	F-statistic:	0.951	P-Value:	0.50320	

Microsoft

	Coefficient Estimate	Std. Error	t-Value	P-Value
(Intercept)	-0.0025431	0.003262	-0.780	0.44120
Bear	**-0.0016277**	**0.000627**	**-2.597**	**0.01390**
Bear, lag=-1	0.0004735	0.000761	0.622	0.53800
Bear, lag=-2	-0.0006245	0.000786	-0.795	0.43260
Bear, lag=-3	-0.0005225	0.000753	-0.694	0.49250
Bear, lag=-4	-0.0003256	0.000817	-0.399	0.69280
Bear, lag=-5	0.0002635	0.000757	0.348	0.73000
Bear, lag=-13	**-0.0009739**	**0.000468**	**-2.079**	**0.04540**
Bull	**0.0011619**	**0.000484**	**2.402**	**0.02210**
Bull, lag=-1	0.0003083	0.000703	0.439	0.66370
Bull, lag=-2	0.0002712	0.000694	0.391	0.69850
Bull, lag=-3	0.0001555	0.000680	0.229	0.82060
Bull, lag=-4	0.0009784	0.000696	1.406	0.16920
Bull, lag=-5	-0.0007898	0.000685	-1.153	0.25730

R-squared:	44.58%			
F-statistic:	**2.042**	**P-Value:**	**0.04863**	

**Bold Indicates Statistical Significance at 5%

The significant lagged indices indicate the previous day (or days, depending on the amount of lag) were significant in predicting the stock returns the day after. Significant lagged data is vital to profit opportunities in the financial market.

Conclusion

From our analysis, Google Trends data was not significant in predicting stock returns. But StockTwits data was significant in predicting Apple, Google, and Microsoft stock returns. When the data was lagged, the Bear and Bull indices were significant in predicting Apple and Microsoft stock returns. Because this data was lagged, StockTwits data is significant as a leading predictor of stock returns.

Because we only covered four companies, this isn't a foolproof investment tool. It was merely an investigation and exploration into using alternative information sources. However, StockTwits data can serve as a trust-worthy supplemental source of information to an investor.

Contributions

Erik Harnisch was responsible for the data mining, aggregation and modeling. Chris Loughlin was responsible for the research and analysis of previous economic work. Together we examined the results and formed our economic conclusions.

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