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Incorporating Social Velocity in the Value-Momentum Model

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Abstract

Fama-French's Three-Factor Model stands as one of the overarching financial models in investing. This model details the risk and return attributed to stocks, based on capitalization, book value, and market return. Since then, a number of financial theorists have proposed amendments to the model, finding other factors with correlation to stock returns. One in particular was momentum, proposed by Mark Carhart to enhance the model further. From this Four-Factor Model, the question remains whether or not more factors can be added to better explain excess return.

The goal of this study is to find a correlation between Social Velocity ranking and stock returns over a trading day. If the correlation is statistically significant, this could prove to be an added factor in a new, more telling five-factor model. Using the Bloomberg Social Velocity Monitor, a one-month study was conducted, with the price and Social Velocity recorded for the top 30 equities in the monitor each trading day. Once these were recorded, a final price was found at either the end of the trading day or the end of the next trading day, depending one when the original data was collected.

Our study found statistical significance in correlation between Social Velocity ranking and stock return. In using a regression model, we were able to conclude that sentiment toward a company can in fact affect a stock price over a trading day. In turn, this factor could indeed be a plausible addition to the model.

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I. Introduction

Throughout the history of market returns and pricing, researchers, mathematicians, and financial analysts alike have worked to uncover market trends and patterns. These researchers have created a wide array of different algorithms and models to better understand characteristics of market conditions, portfolios, and equities. Those algorithms and models that stay true to an ever-changing market have become the crux of many analyst and investor investment strategies and philosophies. Explicitly, some seek to better understand what company or equity qualities drive risk and return, two critical factors in investment decision-making. One of these models is the Fama-French Three-Factor Model.

The Fama-French Three-Factor Model has been widely accepted as the center of return and risk attribution when performing financial analysis. Another model, the Carhart Four-Factor Model, added momentum to the Three-Factor model to create a more intrepid attribution, and further detail the market and portfolio variables. The question remains, is this model comprehensive enough?

Following the likes of Cliff Asness and Mark Carhart, the goal of this study was to find correlation between a known variable and stock return. The variable in question is called Social Velocity, a term used to define the sentiment a company or equity has in the greater community. Before the likes of social media and data mining, this variable was much more difficult to study and quantify. With a technological revolution in data collection and global communication, this variable can be more widely understood. The characteristic has remaining an anomaly to the financial industry, and a more in depth approach to applying this factor to the Carhart Four-Factor Model could yield significant developments on understanding driving variables behind returns and risk.[1] Furthermore, the ability to find correlation between return and this variable can create the possibility for this to be utilized as an investment strategy. If there is significance is outperforming the market by investing based on Social Velocity, this factor could be a profitable and alpha-yielding strategy for investors.

[1] Klein, Spencer L. "Evidence to Support the Four-Factor Pricing Model from the Canadian Stock Market." CFA Digest 35, no. 1 (2005): 37-38. doi:10.2469/dig.v35.n1.1616.

II. History, Literature, & Related Works

In understanding Social Velocity, it is important to recognize the history of how financial analysis has been conducted using similar methodologies in the past. A very common bottom-up method of due diligence in reviewing the value of a particular company is customer research. Asset managers with a focal point on individual securities and specific companies have long used this methodology in finding valuable prospects for their portfolios. Social Velocity expands upon previous held notions of customer value creating stock value, by expanding the study of specific customers to a universal population's sentiment of the company in question. While this screening process is not necessarily new, as it is similar to that of customer studies and research, the results produced are.

A. *The Long-Term Stock Market Valuation of Customer Satisfaction*

To find a precedent for correlation between customer sentiment, we reviewed an article published by the American Marketing Association, in which consumer sentiment was reviewed as a potential valuation methodology. The art of this study is in the structure, as customer satisfaction was tracked in tandem with price of 151 unique, different firms over a ten-year period. The process included using the ASCI, an index measuring the quality of company production and/or services in the US, based on 0-100 scale.[2]

From their results, the study concluded that stocks of firms that had high levels and positive changes in customer satisfaction outperformed those with low levels and/or negative changes in

[2] Aksoy, Lerzan, Bruce Cooil, Christopher Groening, Timothy L. Keiningham, and Atakan Yalçın. "The Long-Term Stock Market Valuation of Customer Satisfaction." Journal of Marketing 72, no. 4 (2008): 105-22. doi:10.1509/jmkg.72.4.105.

customer satisfaction, as well as the S&P500 Index. Furthermore, the stock market was found to have undervalued positive satisfaction initially, but adjusted in the long-term. In turn, it is appropriate to say there is precedent for studying the effects and correlation of Social Velocity on equity return.[3]

B. *Twitter Sentiment Analysis*

Understanding Social Velocity begins with understanding sentiment analysis. "Twitterscrapers," the tools used to analyze beds of tweets, have become a popular way to understand and mine opinions or user emotion. A study conducted at the Nation Institute of Technology Calicut sought to study the effects of different heuristics for training networks to analyze tweets in a more comprehensive manner. While classifications like positive, negative, and neutral are commonplace, the authors of this study detail and introduce training data for better subjective and objective classifications. The data and process shows how those who look to interpret and obtain user data on Twitter classify and segments their findings. Attaching emotions and sentiments to the content of tweet could be relatively difficult when reviewing tens of thousands of tweets through a single network.[4] The level of intricacy in understanding the finer details of the user behind the tweets incorporates understanding their care for spelling, their vocabulary and common words or phrases, as well as current news and geopolitical landscape driving tones and emotions presented in the texts. From this, it can be better understood how sentiment can be applied to how consumers and the public feel toward a company, its operations, and/or financial performance.

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[3] Aksoy, Lerzan, Bruce Cooil, Christopher Groening, Timothy L. Keiningham, and Atakan Yalçın. "The Long-Term Stock Market Valuation of Customer Satisfaction." Journal of Marketing 72, no. 4 (2008): 105-22. doi:10.1509/jmkg.72.4.105.

[4] Jose, Anthony K., Bhatia, Nipun, and Krishna, Sarah S. "Twitter Sentiment Analysis" National Institute of Technology at Calicut (2010): Kerala – 673601

C. *Stock Prediction Using Twitter Sentiment Analysis*

Social Velocity, as it is used in this study, was derived by Bloomberg's Social Velocity Monitor. This tool was developed in 2013 as a way to integrate the raw data and potential of the Twitterverse with the analytics and statistical models of Bloomberg. While this tool was in development, the engineers and developers behind the product sought to test this on an individual equity. The equity in question was Regeneron, a pharmaceuticals company that had created a stir on Twitter—and after tracking, the stock rose over $20, roughly 11%, over the course of three days.[5]

A study done by Arpit Goel and Anshul Mittal of Stanford University encompassed much of what the Bloomberg Social Velocity Monitor exhibits. In fact, they review whether they could accurately predict DJIA values based on Twitter data. They recorded public sentiment through recording and grading tweets based on their content. They were subdivided in four categories: calm, happy, alert, and kind. These categories helped define the daily public sentiment, and stated buys on days when public sentiment was calm and/or happy, and sells on days when the sentiment alert. They were able to predict the DJIA's performance with 75.56% accuracy using correlations crossing both data sets.[6] The question remains, while this accuracy was truly impressive in predicting total market movements, how does this same public sentiment affect individual equities and companies?

[5] "Trending on Twitter: Social Sentiment Analytics | Bloomberg L.P." Bloomberg.com. February 20, 2014. Accessed February 07, 2018. https://www.bloomberg.com/company/announcements/trending-on-twitter-social-sentiment-analytics/.

[6] Anshul Mittal, Arpit Goel. "Stock Prediction Using Twitter Sentiment Analysis." Stanford (2011): http://cs229.stanford.edu/proj2011/GoelMittal-StockMarketPredictionUsingTwitterSentimentAnalysis.pdf.

D. *Sentiment Analysis of Twitter Data for Predicting Stock Market Movements*

While the previous literature correlated public sentiment to total market movement, does the same correlation occur when reviewing individual equities? A study completed at the Indian Institute of Technology sought to uncover whether you could predict a stock's price change with a sentiment analysis tool. In this study, they found a strong correlation exists between the changes in stock price and public opinions and emotions expressed in tweets. This study used up-to-date information to predict stock price, rather than historical prices.[7] Furthermore, knowing that historical pricing has been largely refuted by the financial community as a viable option in developing pricing models, this study extrapolates on current information, providing a deeper dive into an expanded view of Efficient Market theory, a theory tested by this very factor.

This study furthered the basis of my topic. If there is a definitive correlation between public sentiment and stock price change, furthering this study using a more comprehensive tool, Social Velocity, allows for a more intrepid review of the utility of the possible new factor. In structuring the study around Social Velocity, the evidence supplied in this article is critical in understanding how these prices fluctuate with sentiment. There is, however, a deviation in the study proposed and this article: this test of correlation between the two factors is proposed as a way to lay the groundwork as a factor furthering the Carhart Four Factor Model. This correlation could prove to be statistically significant, and if so, the development of this factor would need to be in the likes of that set forth in the Fama-French Three Factor Model.

[7] Pagolu, Venkata Sasank, Kamal Nayan Reddy, Ganapati Panda, and Babita Majhi. "Sentiment Analysis of Twitter Data for Predicting Stock Market Movements." 2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES), 2016. doi:10.1109/scopes.2016.7955659.

E. *Multifactor Explanations of Asset Pricing Anomalies*

Fama-French published this article in 1996, finding that asset pricing has correlations to three definitive factors: value, market return, and capitalization. After development of the CAPM many years before, this new model better detailed anomalies in return and risk, but not perfectly.[8] While, theoretically, it is impossible to attribute all risk and return associated with a portfolio or equity, however there may be more undiscovered factors.

When reviewing the three factors in Fama-French's study, the portfolio composition becomes an important characteristic for further research on factors. The model is as such:

$$\mathbf{Ri{-}Rf{=}\alpha i{+}bi(RM{-}Rf){+}siSMB{+}hiHML{+}\varepsilon i}$$[9]

The **SMB** factor represents the difference between the return on a portfolio of small cap equities and the return on a portfolio of large cap equities. The **HML** factor represents the difference between the return on a portfolio of high book-to-market stocks, or value stocks, and low book-to-market stocks, or growth stocks.[10] In turn, developing another factor would likely entail creating portfolios of equities with the highest and lowest Social Velocity, and finding the subsequent difference.

[8] Fama, Eugene F., and Kenneth R. French. "Multifactor Explanations of Asset Pricing Anomalies." The Journal of Finance 51, no. 1 (1996): 55-84. doi:10.1111/j.1540-6261.1996.tb05202.x.
[9] Fama, Eugene F., and Kenneth R. French. "Multifactor Explanations of Asset Pricing Anomalies." The Journal of Finance 51, no. 1 (1996): 55-84. doi:10.1111/j.1540-6261.1996.tb05202.x.
[10] Fama, Eugene F., and Kenneth R. French. "Multifactor Explanations of Asset Pricing Anomalies." The Journal of Finance 51, no. 1 (1996): 55-84. doi:10.1111/j.1540-6261.1996.tb05202.x.

III. Hypothesis

After reviewing the history and literature of social sentiment in investing and factor modeling, there is evidence to suggest Social Velocity could be another factor in the Four-Factor model. For the purposes of this study, the correlation between Social Velocity ranking and return over the course of a trading day is being measured. Thus, our hypothesis is that there is statistical significance in the correlation between Social Velocity ranking and return.

IV. Methodology

To test our hypothesis, we began by collecting data on daily Social Velocity rankings and equity prices daily over the course of February 2018. Through the month, and based on the data collected, we found twelve trading days of viable data for return-rank comparison. The data was then extrapolated into two segments: that which was collected before 12pm, and that which was collected after 12pm. This collection segmentation influenced the pricing at "day end" as final price was recorded at two different times, depending on the time of the Social Velocity data collection. If the data was collected prior to 12pm, the prices of the recorded equities were recorded intraday at day end. If the data was collected after 12pm, the prices were then recorded at the end of the next day.

Due to some erroneous reporting in the Bloomberg Social Velocity Monitor, the data had to be reviewed and scrubbed. Common errors found when reviewing the data portrayed in the monitor were foreign exchange discrepancies, mispricing, and erroneous share classes. At one point in this study, the Social Velocity Monitor only showed equities and prices from the Frankfurt exchange, and another error occurred when finding the differing prices of certain securities. This created a need for a scrupulous review of the data utilized in this study, as the discrepancies could have caused further error in return calculations.

Once this data was collected, market return over the same period was recorded. To account for the totality of market return, the Russell3000 Index (^RUA) was used as the comparable index. This index was chosen as it was the most comprehensive index of publicly traded equities, accounting for 98% of all US incorporated equity securities, and the Bloomberg Social Velocity Monitor was objective of market capitalization, meaning the equities with the highest Social

Velocity may not have been captured by the S&P500 (^GSPC) the DJIA (^DJI), or any other index.

After recording the return of the market and the equities on the Bloomberg Social Velocity Monitor, the excess return was measured. The returns were then funneled into a regression model, using the excess as the dependent variable, and market return and Social Velocity ranking as the independent variables. This allowed us to test the statistical significance of return being attributed to Social Velocity ranking. The data was then condensed, and a regression ran on the collective of all 12 days of recorded data.

V. Results & Data

In reviewing the outcomes of this study, it is important to note that there were two types of results. First, running a regression model to find statistical significance was the most important result, as it laid the foundation and framework for further research and development in creating an additional factor to the standard factor models. Next, there a number of return attributes resulting from assuming the snapshots are portfolio holdings. The combination of these two results help better detail the significance and efficacy of Social Velocity as both a financial theory and investment strategy.

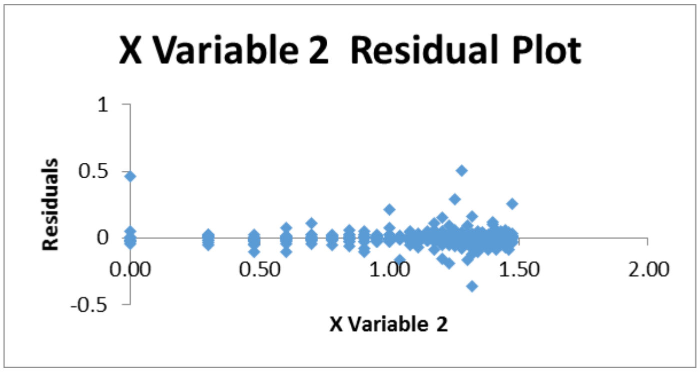
A. Statistical Significance in Modeling

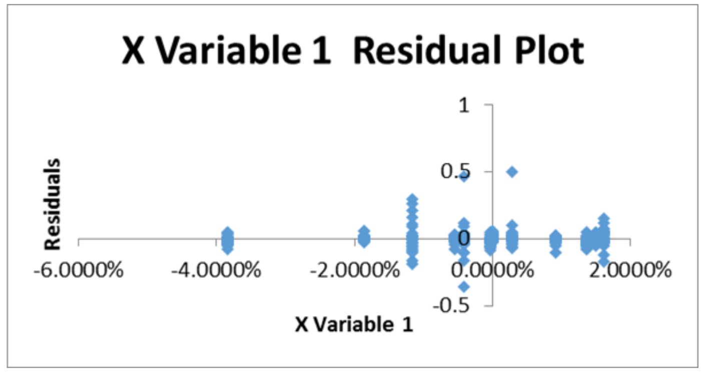
After collecting, reviewing, pooling, and analyzing the data, we found that there is statistical significance in the correlation between Social Velocity ranking and return. The regression model suggests that Social Velocity ranking better accounted for return than that of the Russell3000, our market variable. In fact, the difference was larger than expected. However, the important facet of the study is the following outcome:

a) Raw Statistical Data

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.018276955	0.010190985	1.793443502	0.073748293
Russell3000 Return	-0.154346045	0.215054609	-0.717706287	0.473407772
Social Velocity	-0.017425105	0.008931719	-1.950923964	0.051848075

b) Graphical Data





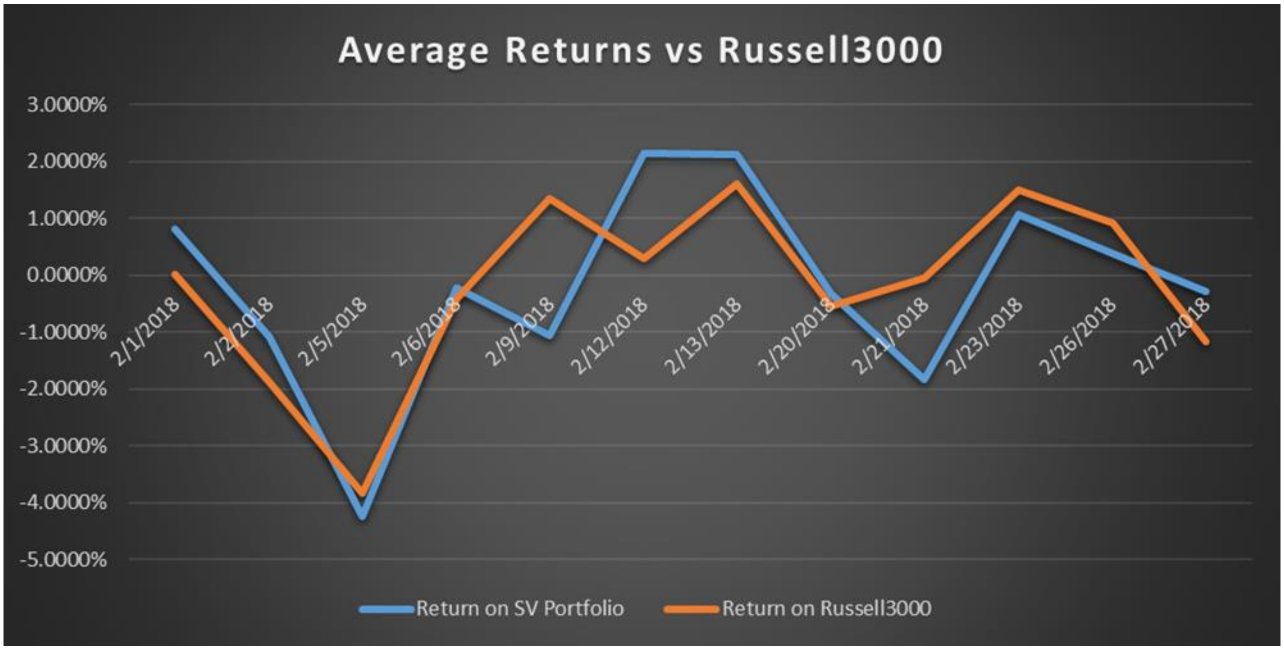
B. Portfolio Performance

While we found a correlation between return and Social Velocity, another question arose about the viability of using Social Velocity as an investment strategy. To review this question, the Social Velocity Monitor snapshots were treated as portfolio holdings, and collective return calculated. From this review, many other interesting characteristics and details arose. As such, these are the results found:

a) Portfolio Statistics

Statistics	SVs	R3K	Excess
Number of days positive	5	6	-
Number of days negative	7	6	-
Average return over recorded period	-0.2081%	-0.1803%	-0.0278%
Number of intra trade days positive	2	3	-
Number of intra trade days negative	4	3	-
Number of next trade days positive	4	4	-
Number of next trade days negative	2	2	-
Average intraday trade return	-0.9149%	-0.6607%	-0.2541%
Average next trade day return	0.4987%	0.3001%	0.1986%

b) Daily Return vs. Russell3000



The results found in simulating these snapshots a composition of the portfolio unveil interesting results. While the portfolio itself underperformed the market by 2.78bps, a more intrepid review reveals that there was clear outperformance in the subsect of snapshots taken after 12pm. The portfolio, on the other hand, significantly underperformed with the intraday snapshots.

VI. Limitations & Issues

In evaluating the problems and shortcomings of the study, we uncovered some possibilities for further progress. Firstly, we recognize the need for data uniformity. In this instance, there were a number of snapshots recorded at differing times of the day. This could have caused some slight discrepancies in the data, and total uniformity would have been more beneficial. This leads to our second recommendation, increasing the size of snapshots to encompass the total Bloomberg Social Velocity Monitor output, rather than the top 30. Furthermore, the length of the study was concise. To capture the full breadth of fiscal events, a full quarter, three months, would have produced more intrepid results. The three-month length would then encompass and exhibit most companies’ earnings, reporting, dividend declarations, and other typical fiscal events. This three-month study could also be parsed into multiple different studies across multiple years, capturing both bear and bull markets, to increase the accuracy of the findings and subsequent results.

To expand upon the study, it would have been wise to use multiple indices when measuring outperformance and study the statistical significance in each instance. If this study were to succeed after further evaluation, the next step would be creating the portfolio to measure the risk and return of the factor. Finally, testing this factor as an investing strategy, longing high Social Velocity equities and shorting low Social Velocity equities, could prove to have utility, especially if compared to other market strategies.

In turn, further studies on this financial phenomenon could yield significant changes to understanding security risk and return. The Fama-French Three Factor Model is a robust, tried and tested model that has been set apart from many financial theories as revolutionary. Developing upon the findings and implications found this model, creating and testing new factors could only further market efficiency and investors' understanding of risk-return attribution.

VII. Conclusion & Implications

In this study, we reviewed whether public perception of a company and/or equity could be correlated with the respective equity's return over the recorded period. Bloomberg's Social Velocity was used as the metric to measure the social sentiment. We found statistical significance in this correlation, showing there is a clear evidence of a correlation between the return and the Social Velocity ranking of an equity as it appears on the Bloomberg Social Velocity Monitor.

From this study and further research, the viability of Social Velocity as another factor in the Carhart Four-Factor Model has potential. To further this, developing a more robust study to prove correlation on a greater scale would allow this factor to become apparent in a new, more comprehensive model. While this study was statistically significant, developing a factor should come after further proof of correlation and more results from a long, more thorough study of Social Velocity and return.

This possible "Fifth-Factor" would entail longing those equities with high Social Velocity, and shorting those with low Social Velocity. Retrieving the risk-return profile from that factor and incorporating it into the equation would be one-step further in developing a more efficient and clear model. This new model could better attribute both risk and return, meaning this could allow for a better understanding of the current level of market efficiency and the pricing of specific equities

Furthermore, the returns based on Social Velocity could, in theory, be achieved by creating a portfolio on long equities with high Social Velocity, and short those with low Social

Velocity. This allows this factor to act as an investing strategy, much like those strategies involving investing in value or strong momentum equities.

VIII. Acknowledgements

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IX. Citations

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