

Evaluating a News-Aware Quantitative Trader: The Effect of Momentum and Contrarian Stock Selection Strategies

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Abstract

We study the coupling of basic quantitative portfolio selection strategies with a financial news article prediction system, AZFinText. By varying the degrees of portfolio formation time, we found that a hybrid system using both quantitative strategy and a full set of financial news articles, performed the best. With a 1-week portfolio formation period we achieved a 20.79% trading return using a Momentum strategy and a 4.54% return using a Contrarian strategy over a five-week holding period. It was also found that trader overreaction to these events led AZFinText to capitalize on these short-term surges in price.

Keywords: Knowledge management, prediction from textual documents, quantitative funds

1. Introduction

Predicting activity in the stock market has always had a certain appeal to researchers. While numerous attempts have been made, the difficulty has always centered on the behaviors of human traders within this socially constructed system. With behavioral parameters not fully defined and constantly changing, making accurate predictions in this environment has been difficult. To further create confusion, there are two diametrically opposed philosophies of stock market research; fundamental and technical analysis techniques (Technical Analysis, 2005). While fundamental analysis leverages the security's relative data, ratios and earnings, technical analysis utilizes charts and modeling techniques based on historical trading volume and pricing. The main issue between them becomes *Can the market be timed or not?*

Information technology and the desire for information are constantly changing the way brokerage houses and securities analysts are approaching securities trading (Baldwin and Rice, 1997). With the advent of cheaper processing and knowledge acquisition techniques, the roles of computers in stock prediction has increased dramatically, where they have become mostly automated versions of existing fundamental and/or technical strategies. Their goal is to achieve better returns than their human counterparts by removing the elements of emotions and biases from trading (Jelveh, 2006). The downside of these systems is that they lack intuition and context where they continue buying battered stocks even after unfavorable news events, such as losing a costly court battle. These systems instead rely on news events being translated to numeric data before appropriate decisions can be made. This problem introduces serious lag-time into decisions and in some cases, trades must be overridden by human analysts.

The motivation of this paper is the following. We plan to build and test a hybrid quantitative system that incorporates both traditional quantitative trading strategies and a financial news article prediction piece. We plan to test various quantitative strategies and couple them with a financial news article prediction engine to find an optimal trading system.

This paper is arranged as follows. Section 2 provides an overview of literature concerning Stock Market prediction, textual representations and quantitative portfolio building techniques. Sections 3 and 4 describe our proposed approaches and the AZFinText system respectively. Section 5 provides an overview of our experimental design. Section 6 details our experimental findings and discusses their impact on stock market prediction. Section 7 delivers our conclusions and a brief discourse on future research directions.

2. Literature Review

Within stock market research, there have been two theories that have had a significant impact on predicting security prices; Efficient Market Hypothesis (EMH) and Random Walk Theory. In Fama's EMH, the price of a security is a reflection of complete market information and whenever a change in financial outlook occurs, the market instantly adjusts the price of the security to reflect this new information (Fama, 1964). Within EMH the amount of information can be varied to encompass three distinct levels; the weak form, the semi-strong and the strong form. In weak EMH, only historical data is embedded within the current price. The semi-strong form goes a bit farther by incorporating historical and current public information into its prices. The strong form includes historical, current public information and private information, such as

Insider Trading. From this theory, it was believed that markets behaved efficiently and that instantaneous price corrections would make prediction models useless.

Random Walk Theory is similar to the Semi-Strong EMH model where all information is contained within the current price and is worthless for future prediction. This theory is slightly different in its approach by insisting that short-term price movements are indistinguishable from random activities (Malkiel, 1973). This random activity produces unpredictable prices and makes it impossible to consistently outperform the market.

Studying the decisions of traders and the micro-effects of trading behavior on the scale of a market exchange is extremely difficult. However, to obviate this difficulty and test the impact of fundamental and technical trading strategies, LeBaron created an artificial stock market with simulated traders which can be dissected to inspect individual trading decisions (LeBaron, Arthur et al., 1999). He introduced new pieces of information into the market and adjusted the amount of time between when an individual trader would receive information and act upon it. It was found that traders with longer waiting times would form fundamental strategies (latching onto company performance data) while those that waited less time developed technical strategies (such as timing trades). This study had a more important contribution because it discovered a lag existed between the time that information was introduced to when the market would correct itself to equilibrium. This apparent delay in market behavior helped to dispel the instantaneous correction notions of EMH and lent support to the idea that the stock market could be forecast in short durations following the introduction of new information. Subsequent research into how long this short duration of time is, led to the discovery of a twenty minute window of opportunity

before and after a financial news article is released (Gidofalvi, 2001). Within this window, weak prediction of the direction of a stock price was found to be possible.

2.1 Financial News Articles

The introduction of new information into the market happens all the time. While rumors, eavesdropping and scandals can all move security prices, financial news articles are a more stable and generally a more trustworthy source, which has prompted some to declare news to be another form of commodity (Mowshowitz, 1992) that can have differing values (Raban and Rafaeli, 2006). However, the exact relationship between financial news articles and stock price movement is complex. While the information contained in financial news articles can have a visible impact on a security's price (Wuthrich, Cho et al., 1998; Lavrenko, Schmill et al., 2000a; Gidofalvi, 2001; Mittermayer, 2004), sudden price movements can still occur from large unexpected trades (Camerer and Weigelt, 1991).

The first challenge of textual financial prediction is to process the large amounts of textual information that exist for securities. This material includes required reports such as periodic SEC filings, press releases and financial news articles reporting both unexpected events and routine news. These documents can be automatically parsed using Natural Language Processing (NLP) techniques and can identify the specific article terms most likely to cause dramatic share price changes. This method can take advantage of arbitrage opportunities faster than human counterparts by repeatedly forecasting price fluctuations and executing immediate trades.

Obtaining timely financial documents from Web sources is a critical step. Luckily there are a variety of financial news aggregation sites that provide such services. One of which is Comtex

which offers real-time financial news in a subscription format. Another source is PRNewsWire which offers free real-time and subscription-based services. By contrast, Yahoo Finance is a compilation of 45 different news sources including the Associated Press, Financial Times and PRNewsWire among others. This source provides a variety of perspectives and timely news stories regarding financial markets.

2.2 Textual Representation

Once we have gathered the financial news articles, we must ultimately represent their important features in some machine-friendly form. One technique is to use a Bag of Words approach which has been extensively used in textual financial research (Lavrenko, Schmill et al., 2000a; Gidofalvi, 2001). This process involves removing the meaningless stopwords such as conjunctions and declaratives from the text and using what remains as the textual representation. While this method has been popular, it suffers from noise issues associated with seldom-used terms as well as problems of scalability where immense computational power is required for large datasets. An improved representational system which addresses a majority of these shortcomings is Noun Phrases. This representation retains only the nouns and noun phrases within a document and has been found to adequately represent the important article concepts (Tolle and Chen, 2000). As a consequence, this technique uses fewer terms and can handle article scaling better than Bag of Words. A third representational technique is Named Entities, which is an extension of Noun Phrases. It functions by selecting the proper nouns of an article that fall within well-defined categories. This process uses a semantic lexical hierarchy (Sekine and Nobata, 2004) as well as a syntactic/semantic tagging process (McDonald, Chen et al., 2005)

to assign candidate terms to categories. Selected categorical definitions are prescribed by the Message Understanding Conference (MUC-7) Information Retrieval task and they encompass the entities of date, location, money, organization, percentage, person and time. This method allows for better generalization of previously unseen terms. It also does not possess the scalability problems associated with a semantics-only approach. A fourth representational technique is Proper Nouns which functions as an intermediary between Noun Phrases and Named Entities. This representation is a subset of Noun Phrases which selects specific nouns and is also a superset of Named Entities, but without the constraint of pre-defined categories. This representation removes the ambiguity associated with those particular proper nouns that could be represented by more than one named entity category or fall outside one of the seven defined Named Entity categories. In a comparison study using these four representational techniques, it was found that Proper Noun representation was more effective in symbolizing financial news articles (Schumaker and Chen, 2006).

Simply assigning one representational mechanism is not sufficient to address the scalability issues associated with large datasets. A common solution to this problem is to introduce a term frequency threshold (Joachims, 1998). This method uses a term frequency cut-off to represent article terms that appear more frequently. This technique has the dual effect of eliminating noise from lesser used terms and reducing the number of features that need to be represented. Following this line of research, machine learning algorithms are unable to process raw article terms and require an additional layer of representation. A popular method is to represent the terms in binary where the term is either present or not in a given article (Joachims, 1998). This

solution leads to sparse matrices where the number of represented terms throughout the dataset will greatly outnumber the terms used in an individual article.

Once financial news articles are represented, computers can then begin the task of identifying patterns of predictable behavior. One accepted method, Support Vector Regression (SVR), is a regression equivalent of Support Vector Machines (SVM) but without the aspect of classification (Vapnik, 1995). Like SVM, SVR attempts to minimize its fitting error while maximizing its goal function by fitting a regression estimate through a multi-dimensional hyperplane. This method is also well-suited to handling textual input as binary representations and has been used in similar financial news studies (Tay and Cao, 2001; Schumaker and Chen, 2006).

2.3 Quantitative Portfolio Building

There are a variety of considerations and techniques involved in building a quantitative portfolio. In Figure 1, we illustrate a taxonomy of the major portfolio-building considerations partially based on the works of Torre and Rudd (Torre and Rudd, 2004).

Figure 1

From this taxonomy, there are several investment considerations that can be used to filter the number of stocks to choose from. These considerations could involve Social Responsibility, such as the energy consumption or environmental practices of companies, diversification issues where balancing portfolios in a mix of sectors may be a goal or asset liquidity where a high degree of liquidity in investments is needed to manage cash flow or seizing upon opportunities.

Once the filters have been applied, there are some factors to consider; investment risk, the effect of taxes, and growth and value stock selection approaches.

Risk is the dimension of investment that focuses on the risk tolerance of the Investor. This is usually a factor of age and/or investment goals, where low risk can provide a steady income and high risk can lead to high payoffs or losses. Taxes involve the tax consequences of investments and can sometimes play a role in asset selection. The choices between sheltered and non-sheltered investments and the effects of estate and capital gains taxes can all be a factor in stock selection.

While Risk level and Tax consequences are important factors in portfolio building, Growth and Value form two major criterion for stock selection (Fama and French, 1998). Growth looks for above-average returns and a reasonable profit. Stocks under the Growth factor will generally have Earning Per Share (EPS) of greater than 20%. On the other hand, Value looks for out of favor stocks that are currently being ignored by the market. These stocks have low Price to Earnings (P/E), low price to book and sometimes high dividends to attract buyers. Most literature seeks to define distinct differences between Growth and Value, however, stock guru Warren Buffet believes that no such distinction exists (Buffet, 1992).

Both Growth and Value have differing stock selection strategies. One of the more common approaches is the Securities Market Line (SML) approach which seeks to balance portfolio risk and return through a mathematical process of stock selection. A variety of techniques have used the SML approach and differ mainly in the exact mathematics used or external factors evaluated.

These strategies include Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT).

In MPT, assets are priced by balancing the potential risk and return of adding one more stock to an existing portfolio (Markowitz, 1952). CAPM prices assets by discounting future cash flows (Sharpe, 1964) and APT prices assets by a function of risk and macro-economic factors (Ross, 1976). APT further requires perfect competition which may not be an ideal choice for real-world application.

There are other selection strategies that do not use the SML approach. These include Growth at a Reasonable Price (GARP), Intrinsic Value and Momentum/Contrarian strategies. GARP was pioneered by Peter Lynch and balances Growth and Value investment goals. In this strategy, securities are selected based on good growth (e.g., $EPS > 20\%$) and are not overpriced (e.g., $P/E < EPS$ growth rates). Intrinsic Value, which was pioneered by Warren Buffet, is a fundamental analysis of stocks. This strategy uses the fundamentals of a stock to derive an 'intrinsic value.' Stock selection then encompasses buying stocks that have an intrinsic value lower than their current market price. In Momentum/Contrarian strategies, stocks are selected based upon recent returns, with the expectation that past winning stocks will continue to win and that past losers will continue to lose. This strategy is easy to implement, has been widely studied and is susceptible to movement from financial news articles.

In the Momentum/Contrarian strategies, there is a portfolio formation period of f where returns are analyzed and stocks are selected, and a holding period h where the stocks are generating their returns. The first step involves analyzing the stock returns within period f . Step

two is a rank ordering of these returns. Then finally selecting the top fraction of stocks for period h is a Momentum strategy while selecting the bottom fraction of stocks is a Contrarian approach. From prior literature, it was found that past winning stocks will continue to outperform in intermediate-term horizons of 3-12 months (Jegadeesh and Titman, 1993), while past losing stocks will turn-around and outperform in short-term horizons of weeks or months (Jegadeesh, 1990; Lehmann, 1990) and longer-term horizons of 3-5 years (De Bondt and Thaler, 1985; De Bondt and Thaler, 1987).

In order to implement these strategies, a determination of the length of the formation period and the exact threshold of stocks to use, must be determined. In selecting the period of f , there have been several implementations. One of which is to assign $f = h - 1$ (Gervais, Kaniel et al., 2001), or make period f and h equivalent (Conrad and Kaul, 1998), or even assign f to be a series of values less than or equal to h (Kang, Liu et al., 2002), where the latter implementation provides a more robust model of strategies.

As for determining the top/bottom fractional cutoff for portfolio selection, there have also been several different instantiations. One is to assign the cutoff at 10% of stocks (Chan, Jegadeesh et al., 1996), or the more typically used 20% threshold (Lo and MacKinlay, 1990; Jegadeesh and Titman, 1993; Kang, Liu et al., 2002), and even 33% of stocks (Chan, 2003).

While Momentum and Contrarian strategies are generally linked to price, there are several approaches other than price. The first of which is earnings, where the momentum of earnings surprises can have an effect on current estimates (Chan, Jegadeesh et al., 1996). Second, in using a dividend contrarian strategy, Asness found a strong relation between dividend yield and

the contrarian returns (Asness, 1997). Rouwenhorst studied the effects of market capitalization and found that larger companies were more prone to Momentum because of their market exposure (Rouwenhorst, 1998). In terms of Volume, Gervais et. al., found that stocks with unusually high or low trading volumes outperform those with normal trading volumes (Gervais, Kaniel et al., 2001). However, using price returns is the most common usage of these strategies.

The reason behind the success of Momentum and Contrarian strategies is mainly because of investor's under or overreaction to news events. Investors tend to overweight recent information (overreaction) and underweight past information (underreaction) (De Bondt and Thaler, 1985). This overreaction was found to be a result of price shocks which cause excess trading volume and volatility (Chan and Franklin, 2003). Underreaction is when investors do not react quickly enough to a news event (Forner and Marhuenda, 2003). However, the reaction times are generally measured in terms of weeks, months and years following a news event in which price drift is evident and not in terms of minutes following a news release.

From this study of prior research, we identified several gaps which we plan to investigate. While Momentum and Contrarian strategies are well-understood in horizons of weeks or longer, short-term linkage to news event releases has not been studied. Will investors overreact to news events within the minutes following the release of a news article? We can indirectly measure this by applying basic quantitative strategies to an existing financial news prediction system and predict where the stock should be according to the news article terms.

3. Research Questions

From these gaps, we have formulated several research questions. The first of which is:

- What is the effect of combining Quantitative strategies with a financial news article prediction system?

While we know from the literature that both Quantitative and financial news article systems provide superior price predictions, combining the two would provide additional insight into AZFinText's predictive mechanism.

As a follow-up to this question, we also ask:

- Should a combined system use all financial news articles or only the articles of companies selected by the Quantitative strategy?

4. System Design

In order to properly evaluate our research questions, we designed the AZFinText system.

Figure 2 illustrates the AZFinText system design.

Figure 2

From the AZFinText system design in Figure 2, there are several major components to describe in detail. The first component is Numerical Data which gathers stock price data in one minute increments from a commercially available stock price database. The second component is Textual Analysis. This component gathers financial news articles from Yahoo Finance and represents them by their proper nouns. This module further limits extracted features to three or more occurrences in any document, which cuts down the noise from rarely used terms (Joachims, 1998).

Once this data has been gathered, AZFinText makes its predictions on each financial news article. From prior empirical testing, we found that including the proper noun representations and the stock price at the time the news article was released, provided AZFinText with superior

predictive performance compared to other textual representations and different pieces of price information (Schumaker and Chen, 2006).

Within the Model Building stage of AZFinText, we partitioned the data gathered in order to best answer our research questions. In the cases of the Quantitative strategies, this involved buying or shorting those stocks within the quantitative portfolio; Momentum and Contrarian.

For the machine learning algorithm we chose to implement the SVR Sequential Minimal Optimization (Platt, 1999) function through Weka (Witten and Eibe, 2005). This function allows for discrete numeric prediction instead of classification. We selected a linear kernel and ten-fold cross validation. A similar prediction method was employed in the forecasting of futures contracts (Tay and Cao, 2001).

AZFinText is then trained on the data and issues price predictions for each financial news article encountered. Evaluations are then made regarding the effect of stock returns in terms of the quantitative models generated.

5. Experimental Design

For our experiment, we selected a consecutive period of time to serve as our experimental baseline. We selected a five-week research period of Oct. 26, 2005 to Nov. 28, 2005, which incorporates twenty-three trading days. The five-week period of study was selected because it gathered a comparable number of articles in comparison to prior studies: 6,602 for Mittermayer (Mittermayer, 2004) and 5,500 for Gidofalvi (Gidofalvi, 2001). We also observe that the five-week period chosen did not have unusual market conditions and would be a good testbed for our evaluation. In order to identify companies with more financial news, we further limited the

scope of activity to focus on companies listed in the S&P 500 as of Oct. 3, 2005. Articles gathered during this period were restricted to occur between the hours of 10:30am and 3:40pm. While trading starts at 9:30am, we felt it important to reduce the impact of overnight news on stock prices and selected a period of one-hour to allow prices to adjust. The 3:40pm cut-off for news articles was selected to disallow any +20 minute stock predictions to occur after market hours. A further constraint was introduced to reduce the effects of confounding variables, where two articles on the same company cannot exist within twenty minutes of each other or both will be discarded. The above processes had filtered the 9,211 candidate news articles gathered during this period to 2,809, where the majority of discarded articles occurred outside of market hours. Similarly, 10,259,042 per-minute stock quotations, 302 analyst recommendations and 3,937 insider transactions were gathered during this period. This large testbed of time-tagged articles and fine-grain stock quotations allow us to perform our evaluation systematically.

For our quantitative portfolio, we followed the work of Kang et. al., and used our study period of Oct. 26 to Nov. 28 as our holding period h (Kang, Liu et al., 2002). Immediately preceding this period is the portfolio formation period f , where stock price returns are rank ordered and the top quintile of stocks becomes the Momentum portfolio while the bottom quintile of stocks becomes the Contrarian portfolio. The length of f is varied in 1 week increments up to 5 weeks in order to increase the model's robustness.

To answer our first research question on finding the most profitable strategy in terms of quantitative portfolios and financial news prediction, we created four models to test, as shown in Figure 3.

Figure 3

From this figure, the first model utilizes quantitative strategies by themselves, by measuring the returns of Momentum and Contrarian portfolios during the holding period under differing formation periods. In this model, trading returns are simply the percentage difference between the stock at the beginning and end of period h .

Our second and third models are hybrid systems incorporating both quantitative strategy and financial news prediction. In these models, AZFinText is limited to performing trades on only those companies within the Momentum or Contrarian portfolios. These models differ from one another on the scope of financial news articles available for system training. Model two, or 'Full Article,' uses all financial news articles regardless of whether they are in the quantitative portfolio. Model three, or 'Restricted Article,' limits AZFinText to only those financial news articles within the portfolio. This differentiation can help determine the value of using financial news articles from peer organizations as a prediction tool.

The fourth model is the financial news prediction system, AZFinText, by itself. This model is free to trade on all of the S&P500 stocks and uses all financial news articles at its disposal.

Prior research has also shown that grouping companies based on their industry sectors leads to better results. One such grouping classification system is the Global Industrial Classification System (GICS) which was developed by Morgan Stanley. This classification system was found to be superior to other systems (Bhojraj, Lee et al., 2003) and is also best able to describe analysts' areas of expertise (Boni and Womack, 2004). This method will be repeated on our

models using AZFinText, where articles are trained within each GICS Sector and then aggregated together to determine trading returns.

While computing the trading returns of a quantitative-only strategy is straight-forward, for the models incorporating AZFinText we utilize a modified version of Lavrenko's Trading Engine (Lavrenko, Schmill et al., 2000a) that examines the percentage return of the stock. When a stock demonstrates an expected movement exceeding 1%, then \$1,000 worth of that stock is then either bought or shorted and then disposed of after twenty minutes. This modified version differs from Lavrenko's original design in regards to the dollar amount of stock bought. We further assume zero transaction costs, consistent with Lavrenko.

An example of our system's operation is shown in Figure 4.

Figure 4

The first part of operation is to extract financial news articles. The entire corpus of news articles are represented by its Proper Nouns in binary as to whether or not that particular Proper Noun feature is present in the article and then stored within the database. Concurrently, stock quotations gathered on a per minute basis and are similarly stored. Analyst Recommendations and Insider Transactions are also captured and stored. To build a model, we first pair together the representational Proper Nouns and stock quotation at the time the article was released, for each financial news article. Then, depending upon the particular model that is tested, data is aggregated and passed to our machine learning component for training and testing. Stock price predictions are then made for each financial news article and passed along to the evaluation instruments.

In the example above, AZFinText derived a prediction price of \$15.945 which is greater than 1% of the stock price at the time the article was released, \$15.65. Our trading engine makes a trade and disposes of it in twenty minutes time, for a trade return of \$23.64 or 2.36%.

6. Experimental Results

To answer our first research question of *What is the effect of combining Quantitative strategies with a financial news article prediction system*, we tested four models of varying levels of quantitative and financial news prediction as well as different portfolio formation periods. The results of the Momentum strategies are presented in Table 1 and Contrarian is in Table 2.

Table 1

In Table 1, we are measuring the trading returns of each strategy. As a note to readers, the n's for each strategy reflect the number of trading returns, which in the case of 'Strategy Alone' is also the number of companies in the portfolio. For the remaining three models, n-values are still a measure of the number of trading returns performed, but on a news article-basis. Since we are ultimately evaluating the number of trading returns, whether they are company or article-based, we feel that these values are comparable and can be evaluated.

The first thing to notice is that the 'Full Article' AZFinText hybrid outperformed the Momentum strategy alone in all five portfolio formation periods (20.79% to -5.54%, etc.), with p-values < 0.05. While the Momentum strategies by themselves are successful in the 3-12 month horizon, they are not successful by themselves in the short-term, five week period of our study, as evidenced by the negative trading returns for each of the five portfolio formation periods.

The second item of interest, is that ‘Full Article’ AZFinText outperformed ‘Restricted Article’ AZFinText for all five portfolio formation periods (20.79% to 0.33%, etc.), p-values < 0.05. It would appear that AZFinText needs a breadth of articles from peer companies not in its portfolio, to make better predictions.

Third, ‘Full Article’ AZFinText steadily loses returns with additional portfolio formation time (20.79% to 14.53%, etc.), p-values < 0.05. This result most likely capitalizes on short-term investor overreaction to news articles while the company is still in the headlines and consequently in our portfolio. These results were not totally unexpected as Schiereck et. al. found similar decreasing returns with increasing portfolio formation time (Schiereck, DeBondt et al., 1999).

Fourth, in comparing ‘Full Article’ AZFinText to ‘AZFinText Alone,’ the hybrid system had better returns for portfolio formation periods of three weeks or less (20.79% to 8.50%, etc), p-values < 0.05. It seems that the incorporation of a Momentum strategy into AZFinText helped it to achieve higher returns than would be ordinarily possible.

We present the results of the Contrarian strategy in Table 2.

Table 2

From this table, the first thing to note is that Contrarian ‘Strategy Alone’ outperformed Momentum ‘Strategy Alone’ for all five portfolio formation periods. Prior studies noted that Contrarian strategies by themselves are successful in the short-term (weekly, monthly) and long-term (3-5 year) horizons. However, Contrarian’s best success of a 3.36% return was overshadowed by an overall market return of 5.62%.

Second, 'Full Article' AZFinText outperformed the Contrarian 'Strategy Alone' for all five formation periods (4.54% to 3.36%, etc.), p-values < 0.05. This result was similarly observed in Momentum strategies and would imply that the addition of financial news article prediction has helped the system achieve better returns.

Third, 'Full Article' again performed better than 'Restricted Article' for all five portfolio formation periods (4.54% to 0.37%, etc.), p-values < 0.05. Again it would appear that AZFinText needs a breadth of articles from companies not in its portfolio to make better predictions.

The Contrarian 'Full Article' AZFinText did not perform as well against 'AZFinText Alone' (4.54% to 8.50%), p-value < 0.05. While the 2, 4 and 5 week portfolio formation returns of 13.18%, 11.65% and 11.94% performed better than the 8.50% of 'AZFinText Alone,' there was no consistency in trading returns as a function of portfolio formation periods, as was observed in Momentum.

In both Momentum and Contrarian, 'Full Article' AZFinText performed the best. However, in comparing the two against one another, Momentum appeared stronger with sizably larger returns. This may be from capitalizing on investor overreaction to news on companies that have had recent success. Investors bid the stock price higher than it should be and AZFinText makes a profit on it.

7. Conclusions

From our investigations we found several valuable results. The first of which is that using a Momentum strategy coupled with 'Full Article' training of AZFinText led to the best trading

returns. While the ‘Contrarian Alone’ strategy outperformed the ‘Momentum Alone’ strategy in all five portfolio formation periods, coupling the financial news prediction system of AZFinText to Momentum led to better overall performance on our five-week dataset. Furthermore, the one-week portfolio formation time led to the best trading returns of 20.79% and most likely capitalizes on the short-term overreaction to news articles while the company is still in the headlines.

We would also suggest several future directions for this stream of research. The first of which is to investigate the linguistic weighting of trained article terms. Within the machine learning algorithm, certain article terms will be weighted higher than others, indicating their prominence in predicting future prices. Investigating the impact of the most important terms will provide insights into future tuning activities.

Second, an investigation into the type of financial news article being used would be essential. Perhaps certain classes of news articles such as acquisitions, changes in directorships, etc. may lead to trader sensitivity and further overreaction. Some article types may not provide additional predictive capacity and may be omitted from prediction activity.

Third, the roles of market exchanges and market capitalization on the predictive abilities of a financial news system is not known. Perhaps traders are more likely to pursue large-cap stocks on particular exchanges and open profit-taking opportunities on the lesser traded stocks. Analyzing these features may lead to better predictability and a better understanding of how a financial news article system beats the market.

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