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Asset Allocation Strategies: Enhanced by Micro-Blog

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Abstract

The rapid rise of social media communication has touched upon all aspects of our social and commercial life. In particular, the rise of social media as the most preferred way of connecting people on-line has led to new models of information communication amongst the peers. Of these media Twitter has emerged as a particularly strong platform and in the financial domain tweets by market participants are of great interest and value. News in general, and commercial and financial news wires, in particular provide the market sentiment and in turn influence the asset price behaviour in the financial markets. In a comparable way micro-blogs of tweets generate sentiment and has an impact on market behaviour, that is , the price as well as the volatility of stock prices.

In our recent research [26] we have introduced news sentiment based filters such as News RSI (NRSI) and Derived RSI (DRSI), which restrict the choice of asset universe for trading. In this present study, we have extended the same approach to StockTwit s data. We use the filter approach of asset selection and restrict the available asset universe. We then apply our daily trading strategy using the Second Order Stochastic Dominance (SSD) as an asset allocation model. Our trading model is instantiated by two time series data, namely, (i) historical market price data and (ii) StockTwits sentiment (scores) data. Instead of NRSI we compute the Micro-blog RSI (MRSI) and using this a DRSI is computed. The resulting combined filter (DRSI) leads to an enhancement of the SSD based trading and asset allocation strategy. Empirical experimental results of constructing portfolios are reported for S&P 500 Index constituents.

1 Introduction and Background

1.1 Literature Review

The rapid rise of social media communication has impacted the social milieu; thus many aspects of our Political, Economic, Social and Technological social and commercial life are affected. In particular, the rise of social media as the most preferred way of connecting people on-line has led to new models of information communication amongst the peers. Of these media Twitter has emerged as a particularly strong platform and in the financial domain twits by market participants are of great interest and value. The provider of our Social media data, namely StockTwits is a financial social media platform for traders, investors, media, public companies, and investment professionals. Nowadays, with the rapid development of social media platforms, more and more financial market participants such as investors, analysts, traders, brokers and market makers prefer to communicate their respective perspectives about market as well as individual equities on social platforms. Our company

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and our quant analysts in an earlier study, [28] used news and StockTwits data to enhance momentum strategy. The authors reported improved portfolios with news and StockTwits. The maximum portfolio returns were doubled with the introduction of StockTwits data reported in that study. Further that report made a strict distinction of sentiments expressed on social platforms, such as Twitter and StockTwits, from news sentiment obtained via newswires . This is because the messages shared publicly between traders are more germane and insightful than published news. Returning to Stocktwits the supplier of our social media data, they are a leading communication platform founded in 2008 with more than one million registered users, serves as a financial trending tool for regular investors and traders to share their opinions and learn from others about the market and stocks. Just like Twitter, messages shared on it are restricted to no more than 140 (now 250) characters, including ideas, charts, links and other forms of data [18]. The company, founded in 2008, was initially built to utilise Twitter's application programming interface (API). It has since grown in to a standalone micro-blogging platform for social media for finance. It is 2M registered members and gets about 4M monthly messages. Users can create free accounts in StockTwits and share messages on stocks with cash tags to identify them (example $AAPL for Apple Inc.) But what makes it extremely unique and interesting for financial market participants is that this platform focuses specifically on the field of financial markets and investment. Thus, a huge database with less noise than that collected from a more common social network is available. Lastly, the biggest feature of this platform is that people can directly see the level of bullishness and bearishness of a stock any time and this sentiment data is available as a chart. Based on the convenience and novelty of the StockTwits database, researchers are intrigued to find out the value within this dataset. Yet, to date, work in this area is not in abundance. [17] applied microblogging data to find a more robust evaluation method to forecast the following stock market variables: volume of trading, profits and volatility. Choosing five large US companies (AAPL, AMZN, GS, GOOG and IBM) and one market index (SPX), they obtained two kinds of daily data, namely indicators for sentiment and the number of posts for each stock from June 2010 to November 2012. They explored several regression models but were unable to find a good predictive model that used sentiment indicators to predict the return and volatility. However, [29] found that public sentiment delivered via StockTwits is aligned with the movement of S&P 500 and is positively associated with trading volumes. [8] uses StockTwits data for 30 listed companies in Dow Jones Industrial Average from 2010 to 2014. He applied evolutionary optimization methods to construct optimal rule-based trading strategies. The result was that the portfolio built with evolutionary optimization techniques outperforms the classical Markowitz optimal portfolio with reduced risks. Micro-blogging platforms such as Twitter and Weibo encourage short messages that are restricted in length and utilise tags to highlight the main topics. In turn this increases the speed at which users can create posts, and consequently the volume of posts, often resulting in the first release of particular information, for example economic reports, earnings release and CEO departures. Obviously, this advantage in timing compared to classic newswires, is contributed to the fact that information does not have to be verified by multiple sources. Over the past few years, the amount of academic literature associated with sentiment analysis has increased dramatically. In particular, the study by Pear Analytics [9], Twitter conversations were analysed and classified to be 40% Pointless babble , 38% conversational and the rest is either self-promotion, spam, pass along, or news. There are few studies that explored the

StockTwits data, which is a micro-blogging platform exclusively dedicated to the stock market. [1] proposed a new intelligent trading support system based on sentiment prediction by combining text-mining techniques, feature selection and decision tree algorithms in an effort to analyze and extract semantic terms expressing a particular sentiment (sell, buy or hold) from StockTwits messages. They confirmed that StockTwits postings contain valuable information and lead trading activities in capital markets

1.2 Asset Allocation by Second Order Stochastic Dominance

Second order Stochastic Dominance (SSD) has a well recognised importance in portfolio selection, due to its connection to the theory of risk-averse investor behaviour and tail risk minimisation. Until recently, stochastic dominance models were considered intractable or at least very demanding from a computational point of view. Computationally tractable and scalable portfolio optimization models which apply the concept of SSD were proposed by [5], [22], [24] and [6]. These portfolio optimisation models assume that a benchmark, that is, a desirable "reference" distribution is available and a portfolio is constructed, whose return distribution dominates the reference distribution with respect to SSD. Index tracking models also assume that a reference distribution (that of a financial index) is available. A portfolio is then constructed, with the aim of replicating, or tracking, the financial index. Traditionally, this is done by minimising the tracking error, that is, the standard deviation of the differences between the portfolio and index returns. Other methods have been proposed (for a review of these methods, see for example [2] and [4]. Recently further logical extensions of the SSD Long only models to Long/Short models have been proposed and formulated as Mixed Integer Programming (MIPs) (please see [11]).

1.3 Micro Blog Sentiment and the Impact of Micro Blog Sentiment on Asset Return

Recently availability of High Performance computer systems has facilitated high frequency trading. Further the automated analysis of news feeds set the backdrop for computer automated trading which is enhanced by news (see e.g. [14], and [13]). News sentiment is regarded to be unique to each individual and encompasses lots of emotions occurring during brief moments. For the financial domain, it is commonly known that investors in the bull market are positive and optimistic, while in the bear markets they seem relatively pessimistic and fear of loss. In other words, good sentiments are usually based on the rise in stock prices and can further stimulate a continued rise i.e. builds momentum. Therefore, relevant transaction data can be used to build sentiment indicators as one of the forecasting technologies of the future trend of stock price fluctuations (see, e.g. [19]). As pointed out in [?], sentiment analysis usually refers to the methods that judge the content of positive or negative through the relative details of text or other forms.

1.4 Micro Blog Data for Trading and Fund Management

Micro blogs in general and Tweets in particular, stand apart as a platform for disseminating news. Because these are not subject to thorough editorial scrutiny and control they are far less reliable as a source of fact or evidence. On the other hand, these have the advantage of speed, that is, low latency of dissemination to a relatively larger readership. In this respect Twitter Data is ideal for enhancing Trading and Fund Management strategies. OptiRisk analytic team has been active in this domain and we have reported a number of studies. In 2015, for instance, Hochreiter [8], published a paper discussing automated trading strategy using genetic algorithms and Micro Blog sentiment data. Ms Shi an OptiRisk intern jointly with our analysts reported her findings of applying momentum strategy enhanced by StockTwits sentiment data in [28]. In the recently concluded study by [3], good results have been reported in volatility prediction, which can be used for volatility trading and Variance swaps.

1.5 Guided Tour

This report is structured as follows: In Section 2 we introduce the historical closing prices of the historical market data and the micro-blog meta data supplied by StockTwits. Section 3 sets out the asset allocation strategy used by OptiRisk; the details of the relevant SSD models are also included. In section 4 we present a novel method of restricting the asset universe of choice using our proprietary method of constructing filters. In Section 5 we describe our investigations and the findings of our investigation. A discussion of our work and the conclusions are presented in Section 6. Finally, in the Appendix an expanded version of our back-testing results are presented.

2 Market Data and Micro-blog Data

The investigation reported in this chapter uses four-and-half years of historical data of the S&P 500 index. The data spans the period starting from 1 January 2014 to 1 July 2019. The daily closing prices of the market data and the micro-blog sentiment data supplied by Stocktwits, for each of the S&P 500 assets are included in this study.

2.1 Market Data

The time series data used in this study is the stock market daily closing price of the S&P 500 companies. We first filter the whole market database to contain only the daily prices of the assets from S&P 500 index covering from 1 January 2014 to 1 July 2019. This will produce the following 8 columns: *Date*, *Index*, *RIC*[5], *Open*, *High*, *Low*, and *Close* prices in USD, and *Volume*. Table 1 shows a sample of the market data.

The data was collected from Thomson Reuters Data Stream platform and adjusted to account for changes in index composition. This means that our models use no more data than was available at the time, removing susceptibility to the influence of survivor bias. For each asset we compute the corresponding daily rates of return.

2.2 Micro-blog Data (StockTwits data)

Sentiment data is obtained from StockTwits which is a financial social media platform. The discussions in this platform are restricted to the domain of finance which

[5]The Reuters instrument code (RIC) is a code assigned by Thomson Reuters to label each asset

Date	Index	RIC	Open	High	Low	Close	Volume
20140102	S&P500	AMZN.O	398.8	399.36	394.02	397.97	2140246
20140103	S&P500	AMZN.O	398.29	402.71	396.22	396.44	2213512
20140106	S&P500	AMZN.O	395.85	397	388.42	393.63	3172207
20140107	S&P500	AMZN.O	395.04	398.47	394.29	398.03	1916684
20140108	S&P500	AMZN.O	398.47	403	396.04	401.92	2316903
20140109	S&P500	AMZN.O	403.71	406.89	398.44	401.01	2103793
20140110	S&P500	AMZN.O	402.53	403.764	393.8	397.66	2681701

Table 1: Market Data Sample

makes it a rich and focused data source for financial models. This platform is different from textual news. These are individual views and opinions of investors and domain experts. Also, unlike news-wire, StockTwits gets tweets posted 24 hours a day, 7 days of the week. The data for this research is fetched from StockTwits Firestream API. The API allows licensed users with access to live and historical data on messages, activity and sentiment scores. The historical data dates back to the year 2010. The data is streamed in JSON format. Table 2 shows the various attributes of a sample sentiment stream. Table 3 describes each of these attributes.

message_id	user_id	sentiment_score	symbol_id	created_at	exchange	industry	sector	symbol	title
149482996	1695974	-0.1605	1	2019-01-02T 16:44:58.000Z	NASDAQ	Conglomerates	Conglomerates	ACC	AAC Holdings

Table 2: Sentiment Stream Attributes

Attribute	Description
message_id	Unique message ID
user_id	Unique user ID
sentiment_score	The sentiment score for this message. Range from -1 to 1 -1 implies very bearish +1 implies very bullish 0 implies neutral
symbol_id	Unique stock ID
created_at	Message timestamp
exchange	Exchange this stock is found at
industry	Stock's industry
sector	Stock's sector
symbol	Stock's symbol
title	Stock's title

Table 3: Description of each Attribute

Generating Micro-blog Impact Scores

In this study, we use the idea that was first proposed by [32] and used by [25], [26] to construct micro-blog impact scores. These micro-blog impact scores can be used as proxies of firm-specific news impact in the new model. To calculate the micro-blog impact scores, the following steps have to be done:

1. The Timestamp for each micro-blog message has to be converted from UTC to EST time, which is the timing convention of the S&P 500 constituents from the New York Stock Exchange (NYSX).

2. Separating the positive and negative sentiment scores so that two different time series can be obtained.

3. After separating the scores, in a similar fashion to [25], the positive and negative micro-blog impact scores for each sentiment score is calculated.

4. Finally, two daily time series are generated that represent the daily positive and negative micro-blog impact scores.

3 Asset Allocation Strategy

3.1 Portfolio Construction Models

The challenging problem of "active" portfolio selection is how to construct a portfolio such that its return at the end of the investment period is maximised. Since portfolio returns are random variables, models that specify a preference relation among random returns are required. A portfolio is then chosen, such that its return is non-dominated with respect to the preference relation that is under consideration; computationally, this is achieved using an optimisation model.

For portfolio selection, mean-risk models have been by far the most popular. They describe and compare random variables representing portfolio returns by using two statistics: the expected value (mean), where high values are desired and a risk value, where low values are desired. The first risk measure for portfolio selection was variance, proposed by Markowitz [12], who also introduced the concept of efficient portfolio: a portfolio whose return has the lowest risk for a given mean value. A portfolio chosen for implementation should be efficient and is found via optimisation, where typically risk is minimised with a constraint on mean. Various risk measures, quantifying different "undesirable" aspects of return distributions, have been proposed in the literature, see for example [7], [15], [16],[20] and [21].

Mean-risk models are convenient from a computational point of view and have an intuitive appeal. However, they summarise a distribution with only two statistics; hence, a lot of information is overlooked and the resulting return distribution might still have undesirable properties.

Another paradigm in portfolio construction is Expected Utility Theory [30]; here, random returns are compared by comparing their expected utilities (larger values are preferred). However, the expected utility values depend on the chosen utility function, which is a subjective choice. There are progressively stronger conditions on utility functions in order to correctly represent preference on wealth. The non-arguable requirement is that utility functions should be non-decreasing: higher wealth is preferred to lower wealth. Thus, non-decreasing utility functions represent rational behaviour. Furthermore, financial decision makers have been observed to be risk averse: the same increase in wealth is valued more at low wealth levels.

3.2 The Second Order Stochastic Dominance

Stochastic dominance provides a framework for comparing and ordering random variables (e.g. representing portfolio returns) that is closely connected to the expected utility theory, but it eliminates the need to explicitly specify a utility function (see, e.g. [31] for a detailed description of stochastic dominance relations, [10] for a review).

Progressively stronger assumptions about the form of utility functions used in investment lead to first, second and higher orders of SD. For example, first order stochastic dominance (FSD) is connected to "non-satiation" behaviour. A random return is preferred to another with respect to FSD if its expected utility is higher, for any non decreasing utility function. This is a strong condition and thus many random returns cannot be ordered with respect to FSD.

Second Order Stochastic Dominance (SSD) has been widely recognised as the soundest framework for financial decision making, since it includes the preference of rational and risk averse investors, which is the observed attitude. A random return is preferred to another with respect to SSD if its expected utility is higher, for any non-decreasing and concave utility function. There are equivalent definitions for SSD preference, underlying the close connection with tail risk measures such as Conditional Value-at-Risk (CVaR), proposed by [20]. For $\alpha \in (0, 1)$, the α-tail of a return distribution is approximately defined as the average or expected value of the worst $A\%$ of its outcomes, where $\alpha = A\%$ (e.g. $\alpha = 0.05$ corresponds to 5% tail.) SSD involves comparison of increasingly higher portions of left tails: a random return is preferred to another with respect to SSD if its α-tail is higher, for all $\alpha \in (0, 1)$.. Equivalently, a random return is preferred to another with respect to SSD if its expected shortfall with respected to any target is lower. For rigorous definitions and treatment of SSD, please see, for example [22] and [23].

SSD has always been regarded as a sound choice framework, as it does not lose information on the distributions involved. To obtain a portfolio whose return distribution is non-dominated with respect to SSD (thus attractive to all risk averse decision makers) has always been considered as highly desirable. Until recently, however, this was thought to be computationally intractable. Since the 2000s, there has been considerable research on computationally tractable optimisation models employing the SSD criterion. OptiRisk and its research team have been a leader in the field, producing several seminal papers and employing SSD commercially as its asset allocation engine. Two leading contributions are listed here: [5] and [6].

4 Construction of Filters

We explain the rationale of why we need to use Filters and the advantage of using Filters. We then expand this section to describe the different type of filters which we have used. Our approach to incorporating filters for the choice of assets for inclusion in our portfolios has the aim of achieving only Micro-blog based choice or Market Price based choice of asset allocation. In this approach we are able to choose (i) no influence of Micro-blog or (ii) Partial influence of Micro-blog or (iii) even the extreme of Only Influenced by Micro-blog and no Price Data influence.

4.1 Why Use Filters

The asset allocation strategy used by OptiRisk system uses the SSD model. The scenarios are the historical return data which captures accurately correlation structure of the constituent assets. As a consequence, the asset allocation is fairly robust in the long run and also achieves control of tail risk. The asset allocation is a static one period model; so it suffers from the draw back that the near term asset price movements are not taken into consideration. We have therefore introduced a method of restricting the asset universe for the choice of long assets and short assets which are to be held in the portfolio using a technique which we call asset filter. In the construction of the filter we take into account the near term behaviour of each of the assets in the asset universe. The near term behaviour is captured by the use of a well known technical indicator, namely, the relative strength index (RSI). We have extended this concept of applying the filter by taking into account the micro-blog sentiment and the impact of the micro-blog sentiment in respect of each asset. In rest of this Section 4 we describe the method by which we combine these two approaches.

4.2 Relative Strength Index

The Technical Indicator, Relative Strength Index (RSI) is an established momentum oscillator. The RSI compares the magnitude of a stock s recent gains to the magnitude of its recent losses and turns that information into a number that ranges from 0 to 100. The RSI indicator uses the daily closing prices over a given period is computed for each constituent asset of the market index under consideration. It is driven by the measure of the momentum of each asset. The RSI measure is expressed as:

$$RSI(t) = 100 - \frac{100}{1 + RS(t)}; \tag{1}$$

The RSI and RS are re-expressed for the time bucket (t) as $RSI(t)$.

Computation of RSI

Formally, Relative Strength uses Exponential Moving Average (EMA); thus $RS(t)$ the relative strength is computed as the ratio of average gains and losses.

$$RS(t) = \frac{EMA(Gain_t)}{EMA(Loss_t)} \ldots \text{calculated using market data of stock prices} \tag{2}$$

$$RSI(t) = 100 - \frac{100}{1 + RS(t)}; \tag{3}$$

$$EMA(X_t) = \sum_{tn=1}^{N} e^{(-\lambda tn)} X_{tn} \tag{4}$$

Where $Xt = Gain_t$ or $Loss_t$, λ = decay factor and N=RSI period.

The typical $RSI(t)$ value is calculated with average gains and losses over a period of N = 14 days (lookback period). The number of days N is a parameter in the RSI function and can be chosen in accordance with the characteristics of the data set. Secondly, the number of offset days can be varied. Gains and losses can therefore be daily gains and losses (days=1) or gains and losses over larger time intervals.

The $RSI(t)$ is considered to highlight overbought or oversold assets; when the $RSI(t)$ is above the thresholds of 70 and oversold when it is below the threshold of 30.

4.3 Micro-blog Relative Strength Index

We have introduced the concept of Micro-blog Relative Strength Index ($MRSI$). In this we extend the concept of RSI which is computed using Market Data by replacing it with the Impact of the streaming micro-blog sentiment Data.

Micro-blog RSI (MRSI) Computation

It is computed in a way comparable to that of ***RSI(t)*** whereby the up and down price movements are replaced by positive and negative micro-blog impact scores, respectively. Thus

$$MRS(t) = \frac{EMA(Positive\ Impact\ Scores)}{EMA(Negative\ Impact\ Scores))} \ldots \text{is computed for each stock} \quad (5)$$

Hence,

$$MRSI(t) = 100 - \frac{100}{1 + MRS(t)}; \quad (6)$$

Thus, the $MRSI(t)$ values range between $0 - 100$.

The Micro-blog (sentiment) impact scores are computed in the same way as News (sentiment) impact score in $NRSI(t)$. For an explanation of the computational model for $NRSI(t)$ and of News Impact scores the readers are referred to [27], [32], [33] and [25, 26]], respectively.

4.4 Derived RSI (DRSI) Computation

We define the measure ***Derived RSI*** computation by taking a linear combination of $RSI(t)$ and $MRSI(t)$. So for the time bucket t, the measure Derived RSI ($DRSI(t)$) is defined as

$$DRSI(t) = \theta * RSI(t) + (1 - \theta) * MRSI(t), \quad (7)$$

where $0 \leq \theta \leq 1$. The micro-blog impact scores are used to compute the $MRSI$. They reflect the same modelling paradigm of computing RSI. Thus, for the time bucket t we compute $RSI(t)$ and $MRSI(t)$ to calculate $DRSI(t)$:

$$DRSI(t) = \begin{cases} RSI(t) & \text{if } \theta = 1 \\ MRSI(t) & \text{if } \theta = 0 \\ DRSI(t) & \text{otherwise, that is, } 0 < \theta < 1 \end{cases} \quad (8)$$

4.5 Applying the Filters: RSI (t), MRSI (t), DRSI (t)

As explained earlier the purpose of these filters are to restrict the choice of long and short positions of assets as they appear in the asset universe of the available assets. The choice is restricted in the following way: We apply a threshold of 70 to define the long and short bins; Long Bin is filled with the assets whose $RSI(t)$, or $MRSI(t)$, or $DRSI(t)$ values are below 70, and the Short Bin is filled with the assets whose $RSI(t)$, or $MRSI(t)$, or $DRSI(t)$ values are above 70. Finally the SSD method of asset allocation is applied to this restricted asset universe.

5 Empirical Investigation

5.1 The Framework

Our empirical investigation uses two time series datasets, namely, Market Data supplied by Thomson Reuters (Refinitiv) and Micro-blog Sentiment data supplied by StockTwits. We will use the following time-series in our experiments:

- 5 years of historical daily adjusted closing prices of the S&P 500 assets that covering the time period from 2014-2019.
- 5 years of daily Micro-blog impact scores (positive and negative) are then derived from for each asset in the S&P 500 index. We set the looking back period of considering previous Micro-blog items to 4320 minutes (3 days), and consider that the sentiment value decays to half of its initial value in 240 minutes.

5.2 Experimental Setup

Back-Testing study was carried out using the Framework described in Section 5.1 and the experimental setup is best explained by describing the Parameter Settings which are set out in Table 4. These Parameter Settings are used to control the trading that is done at each trading day of the Back-Testing period.

Parameter	**Value**	**Parameter**	**Value**
Index	SP500	Risk free rate	2.0% a year
Cash lend rate	2.0% a year	Cash borrow rate	2.0% a year
Proportion in long/short	100/0	Proportion in SSD cash	Up to 50%
Gearing	Not applied	Money mgmt. (prop. in cash)	No
Use lot sizing	Yes	Transaction costs	5 basis points
In-sample	500 days	SSD rebalancing frequency	3 days
UCITS compliant	No	Slippage	25 basis point
Cardinality constraints	Not enforced	Extra assets	Futures and VIX
Asset universe	Full OR Reduced	Stop Loss	Not enforced

Table 4: Parameter settings of the trading strategy

The following parameters set out in Table 4 were used in the investigation.

1. **Index:** S&P 500. <This model is generic apply to other indices: Hang Seng, Topix >
2. **Risk free rate:** 2% <Risk free rate is set by default for the Market/Index geography>.

3. **Cash lend rate:** 2% <above comments apply>.
4. **Cash borrow rate:** 2% <above comments apply>.
5. **Proportion in long/short:** Long only 100/0 <specifies limits of long and short positions>.
6. **Proportion in SSD cash:** 0.5 [= 50%] <In the portfolio the Long position in cash is 0.5 or less of the Portfolio mark-to-market value>.
7. **Gearing:** <In some exchanges, namely, NIFTY or KOSPI traders instead of trading in underlying stock exploit gearing by using the futures contract>.
8. **Money management:** not applied here.
9. **Lot size:** traded only in available lot sizes.
10. **Transaction costs:** transaction costs is 5 basis point, that is, 0.0005.
11. **In-sample:** 500 <in sample trading days of historical data roughly two years worth of data>.
12. **SSD rebalancing frequency:** performs a rebalancing every 1, 2, ... days.
13. **UCITS complaint:** not applied here .
14. **Cardinality:** exact number of assets to be chosen in the portfolio.
15. **Extra assets:** Yes <whether to include index futures or/and VIX as an asset>.
16. **Asset universe:** whether or not a filter is applied.
17. **Stop Loss:** stop loss rule to be applied for individual assets.

The investigation is carried out using the concept of 'rolling window'; in this case the window has a span of 500 trading days. The period investigated spans 5 years and 4 months (January 2014 to June 2019).

5.3 Back-testing Results

Back-testing was done using the experimental set Up described in Section 5.2. In these tests three different strategies were applied and their outcomes examined and compared. The three strategies are:

1. Full Asset Universe: This strategy takes into consideration the whole available assets from the S&P 500 index. It is included as a second benchmark, such that we are able to measure the improvements made by using different filters.
2. RSI: This is a momentum based strategy, which uses the RSI filter to restrict the choice of the long bins and the short bins of the asset universe.
3. DRSI: This is a derived strategy that combines RSI and MRSI which are defined in Section 4. In the results reported in this section we have set the following value:
$$DRSI = \theta * RSI + (1 - \theta) * MRSI, \tag{9}$$
where θ is set to $\theta = 0.4$.

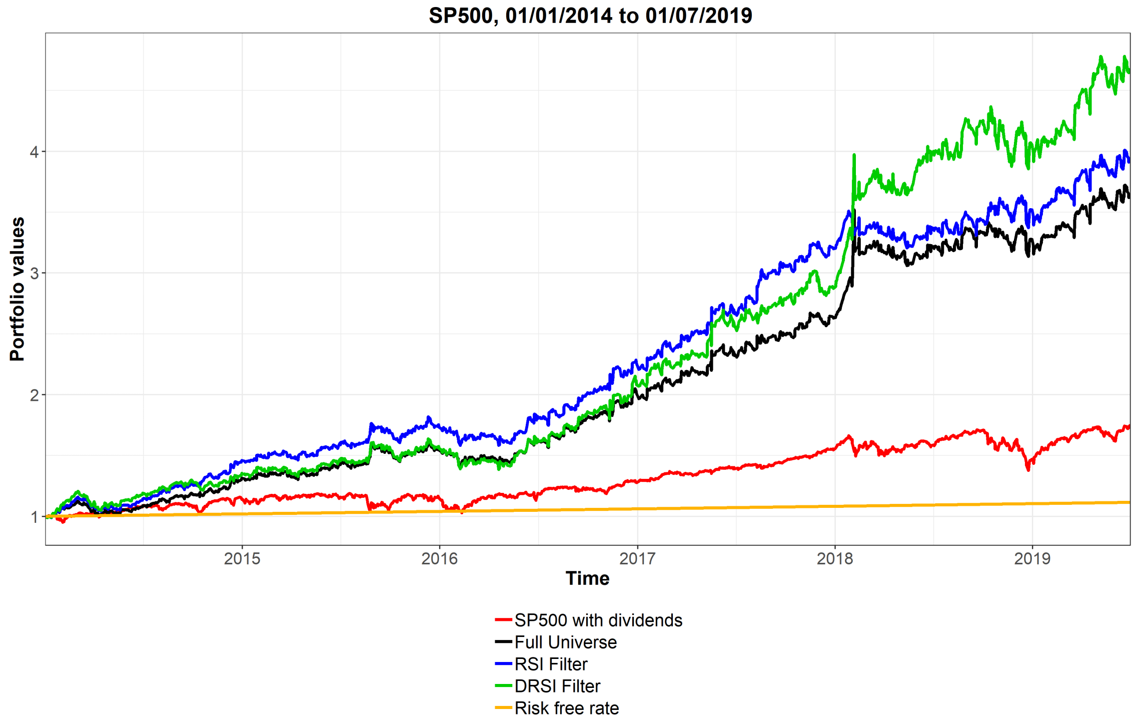

Figure 1: Comparison of the portfolio performance of two investment strategies

In Figure 1 the charts of the [– SP500 Index], [– Full Universe], [– RSI Filter],[– DRSI Filter] and [– Risk free rate] are presented. A complete set of charts which provide further detailed information about the portfolio composition such as SSD Cash, Cardinality and VIX position are supplied in the *Appendix*.

5.3.1 Analysis of Results

The performance of these three strategies are compared using the Industry Standard performance measures. These measures are tabulated and displayed in Table 5.

Portfolio	Final value	Excess RFR (%)	Sharpe ratio	Sortino ratio	Max draw- down (%)	Max. rec. days	Beta	Av. turnover	Wins	Losses
SP500 with dividends	1.75	8.76	0.62	0.86	19.49	218				
Full Universe	3.62	24.46	1.23	2.19	13.04	288	-0.05	6.84	662	720
RSI Filter	3.92	26.30	1.50	2.58	12.98	179	0.13	15.75	724	658
DRSI Filter	4.68	30.50	1.37	2.34	15.47	133	0.26	13.31	740	642

Table 5: Performance measurements for three portfolios

- Final value: Normalised final value of the portfolio at the end of the Back-testing period.
- Excess over RFR (%): Annualised excess return over the risk free rate. For S&P500 we used a yearly risk free rate of 2%.
- Sharpe ratio: Sharpe ratio computed using annualised returns.
- Sortino ratio: Sortino ratio computed using annualised returns.
- Max drawdown (%): Maximum peak-to-trough decline (as percentage of the peak value) during the entire Back-testing period.

- Max recovery days: Maximum number of days for the portfolio to recover to the value of a former peak.

- Beta: Portfolio beta when compared to the S&P500 index.

- Av. turnover: Av. turnover per day as a percentage of portfolio mark-to-market.

- Wins: Number of days that the portfolio makes profits throughout the Back-testing period.

- Losses: Number of days that the portfolio makes losses throughout the Back-testing period.

The relative performances can be compared and summarised under each headings of the Table 5.

Final value: The values as displayed in the Table show a steady improvement from the Index (1.75), ... until DRSI (4.68).
Excess RFR (%): As above and quite naturally, the values as displayed in the Table show a steady improvement from the Index (8.76), ... until DRSI (30.50).
Sharpe and Sortino ratios: We find these have improved: **Sharpe** Index (0.62), ... until DRSI (1.37) and **Sortino** Index (0.68), ... until DRSI (2.34). We observe the increase for Sharpe is not monotone which not surprising as the SSD asset allocation strategy minimises 'Tail Risk'.
Max draw- down (%) and Max. rec. days which are 'Dynamic Risk' measures do not show consistent improvement. Our perspective on this is that on a long Back-Testing study spanning over multiple years **Max draw- down** (%) and **Max. rec. days** are less meaningful than if they are computed on a quarterly basis.
Beta and Av. Turnover are reasonable whereas **Wins** and **Losses** of DRSI is clearly best.

6 Discussions and Conclusion

In an associated report by [3], we have presented a descriptive analysis of Stocktwits sentiment data. In this study we have (i) processed the the StockTwits sentiment data and computed the impact on the returns for individual stocks in the S&P500 index. We have then (ii) created an asset filter $MRSI$ and then a derived filter $DRSI$. This filter is then applied to restrict the asset universe of choice. These filter restrictions which are based on tweets by Market participants prove to be beneficial and are seen to enhance our daily trading strategy. The back-testing results that we have presented vindicate our assertions.

We plan further work to explore how news sentiment time series data can be fused with Microblog time series data. Since the information contents of these two sources are fairly different. Given the positive results that we have found in using this data we wish to find other data sources from which we can obtain financial market tweets for other geographical trading venues and Indices such as TOPIX, Hang Seng, NIFTY and Euro STOXX.

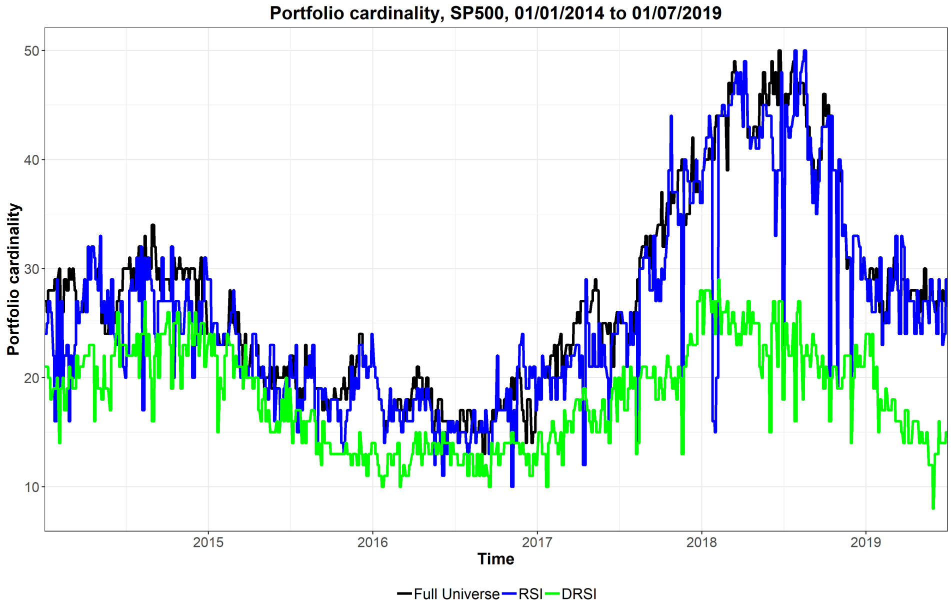

Figure 2: Portfolio Cardinality

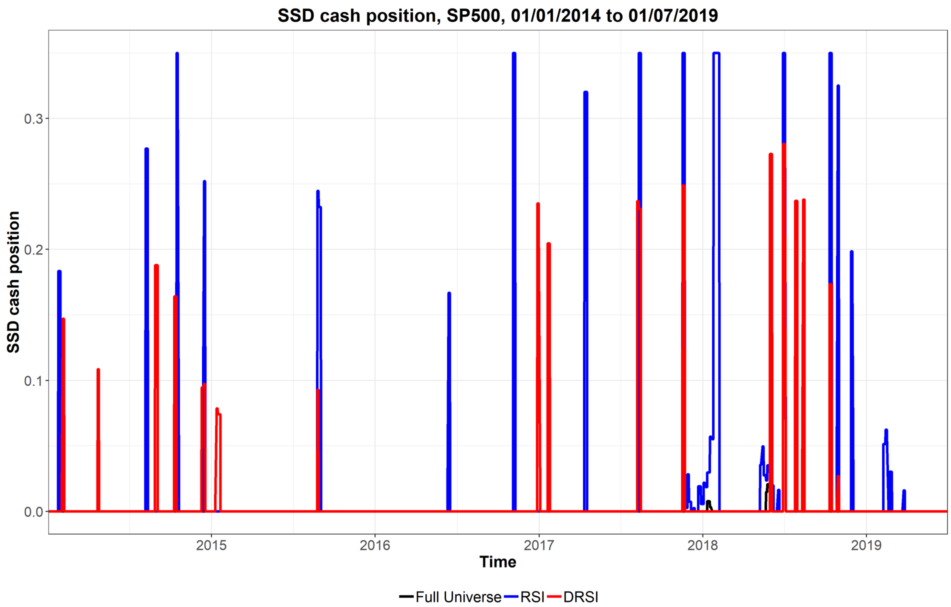

Figure 3: SSD Cash Position

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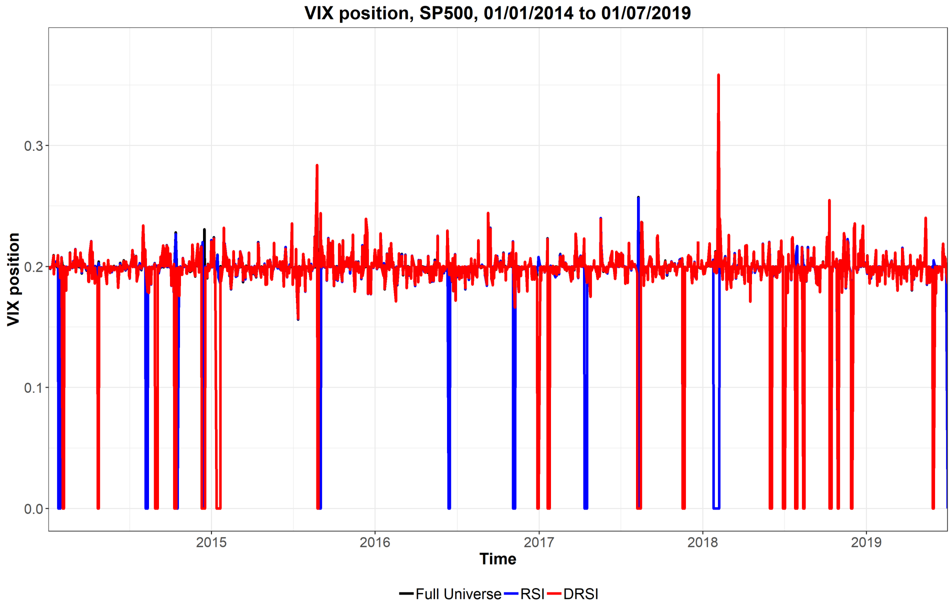

Figure 4: VIX Position

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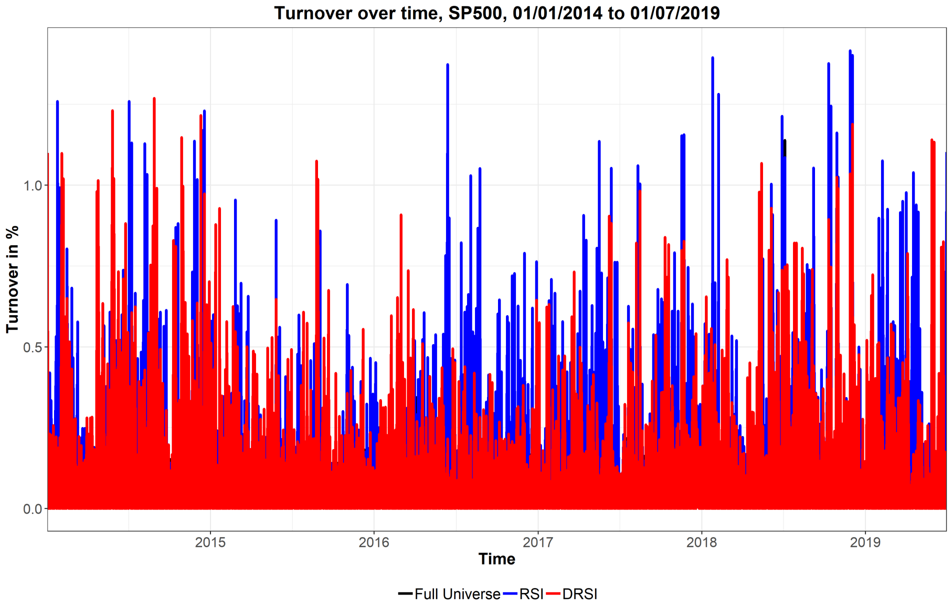

Figure 5: Turnover Over Time

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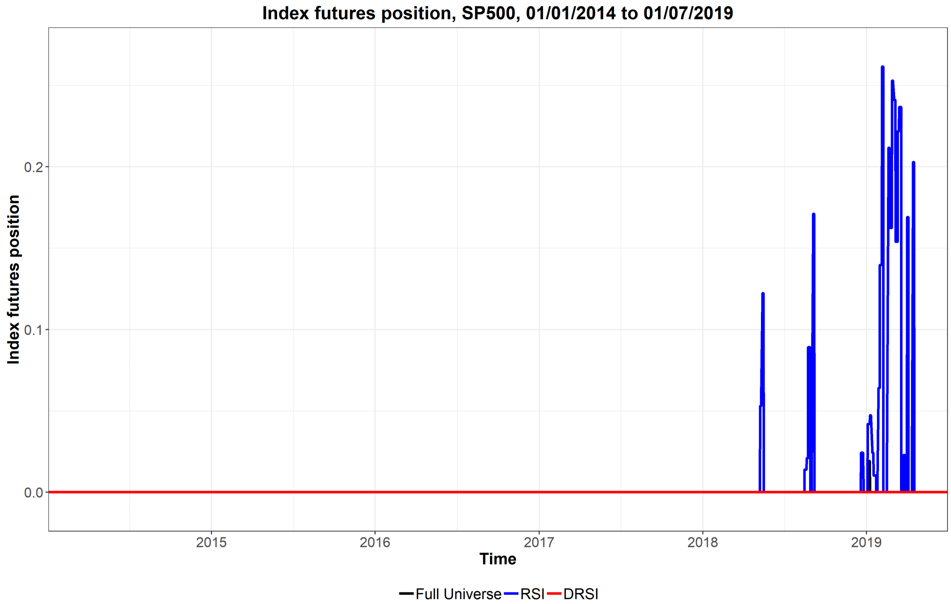

Figure 6: Index Futures Position

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