Rosillo, R.; Giner, J. & De la Fuente, D. (2014): "The effectiveness of the combined use of VIX and Support Vector Machines on the prediction of S&P 500", ***Neural Computing & Applications,*** vol. 25, nº 2, (321-332).

The influence of VIX in the S&P 500 index using Support Vector Machines

May 2013

Abstract

The aim of this research is to analyse the influence of the Chicago Board Options Exchange Market Volatility Index (VIX) using Support Vector Machines (SVMs) in order to forecast the weekly change in the S&P 500 index. The data covers the period between 03/01/2000 and 30/12/2011. A trading simulation is implemented so that statistical efficiency is complemented by measures of economic performance. The inputs retained are traditional technical trading rules commonly used in the analysis of equity markets such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), VIX and the daily return of the S&P 500.

The SVM determines the best situations to buy or sell the market. The two outputs of the SVM are the movement of the market and the degree of set membership.

The influence of VIX in the trading system that it has been developed is really significant when bearish periods appear. VIX allows the reduction of the Maximum DrawDown (MDD) and to increase the profit as it can be seen in the results of the research.

Keywords

Support Vector Machines, Quantitative Trading Strategies, VIX, RSI, MACD, Machine Learning.

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1. INTRODUCTION

Quantitative decision making in financial markets is a topic of constant innovation. Artificial Intelligence is helping investors in this decision making. In order to manage the money, trading systems are using Neural Networks (NN), Genetic Algorithm (GA), Fuzzy Logic and more recently Support Vector Machines (SVMs). In this article, a trading system based on Support Vector Machines is developed.

The goal of this study is to understand the influence of Volatility Index (VIX) in the decision making strategy over the S&P 500. A trading system for the prediction of the directional weekly movement of S&P 500 index has been developed in order to achieve the aim of the paper.

The methodology designed for predicting the directional movement of the S&P 500 index and the influence of the VIX is SVMs. SVMs are a supervised learning technique used for data analysis and pattern recognition mainly in classification problems with an increasing number of real-world applications including finance. The parameters of the SVM such as kernel and C parameter are changed in order to achieve better results.

Technical analysis is widely used by investors (Taylor and Allen, 1992) to make decisions. Due to this importance, two of the main indicators of this analysis have been considered like inputs of this SVM, such as, Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD).

In this paper, we propose an intelligent stock trading system based on Support Vector Machines using Technical Analysis and VIX. The results demonstrate that this algorithm obtains better profits than buy and hold strategy in bear markets.

The rest of the paper is structured as follows. In Section 2, the literature review relevant to the SVM, VIX and Technical Analysis is presented. Section 3 explains the trading algorithm created. Section 4 shows the empirical results of the trading system. Finally, Section 5 provides some concluding remarks.

2. BACKGROUND

In this section, the literature review relevant to the SVM, VIX and Technical Analysis is presented.

2.1 Support Vector Machines

A basic theory of the Support Vector Machine Classifier model is presented. SVMs are specific learning algorithms characterised by the capacity control of the decision function and the use of kernel functions (Vapnik, 1999; Cristianini and Taylor, 2000). The correct selection of the kernel function is very important.

SVMs were originally developed by Vapnik (1998). For a detailed introduction to the subject, Burges (1998) and Evgeniou et al. (2000) are recommended.

The methods based on kernel functions suggest that instead of attaching to each element an algebraic correspondence of the input domain represented by

$$\Phi : X \rightarrow F \qquad [1]$$

a kernel function

$$K : X \times X \rightarrow R \qquad [2]$$

is used to calculate the similarity of each pair of objects in the input set, an example is illustrated in Figure 1 (Huang and Sun, 2001).

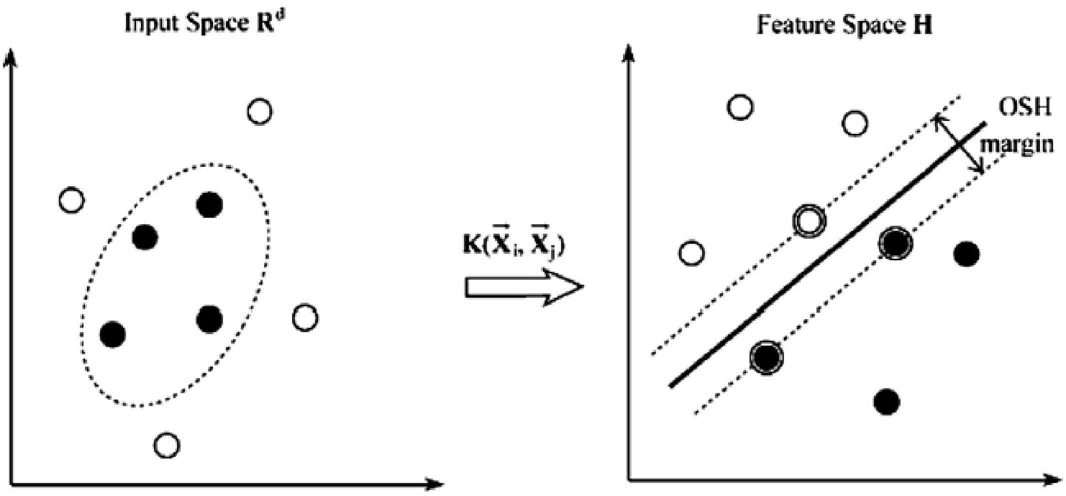

Fig. 1: An example of how a kernel function works

The biggest difference between SVMs and other traditional methods of learning is that SVMs do not focus on an optimisation protocol that makes few errors like other techniques. Traditionally, most learning algorithms have focused on minimising errors generated by the model. They are based on what is called the principle of Empirical Risk Minimization (ERM). The focus of SVM is different. It does not seek to reduce the empirical risk of making just a few mistakes, but pretends to build reliable models. This principle is called Structural Risk Minimization. The SVM searches a structural model that has little risk of making mistakes with future data.

The main idea of SVMs is to construct a hyperplane as the decision surface so that the margin of separation between positive and negative examples is maximised (Xu et al., 2009); it is called the Optimum Separation Hyperplane (OSH), as shown in Figure 1.

Given a training set of instance-label pairs (x_i, y_i), i=1, ..., m where $x_i \in R^n$ and $y \in \{1, -1\}^l$, the SVMs require the solution of the following problem:

$$\min_{\mathbf{w},\xi,b} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \right\} \qquad [3]$$

subject to:

$$y_i(w * x_i - b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

where ξ_i are the slack variables introduced by the method which measure the degree of misclassification of the data X_i ;W is the normal vector to the hyperplane; b is the offset of the hyperplane from the origin along the normal vector w; and C>0 is the penalty parameter of the error term. Different values of parameter C are tested in order to achieve the best results to forecast the movement.

SVMs can be used in two different ways: classification or regression. Some applications of SVMs to financial forecasting problems have been reported recently. Two applications on SVM financial time series forecasting were developed in 2003: in Cao and Tay (2003), SVM are applied to the problem of forecasting several futures contracts from the Chicago Mercantile Market showing the superiority of SVMs over back-propagation and regularised Radial Basis Function Neural Networks; in Kim (2003), SVMs are used to predict the direction of change in the daily Korean composite stock index and they are benchmarked against back-propagation neural networks and Case Base Reasoning. The experimental results show that SVMs outperform the other methods and that they should be considered as a promising methodology for financial time-series forecasting. In Huang et al. (2005), a Support Vector Machines Classifier is used to predict the directional movement of the Nikkei225 index with extremely promising results. Also Ince and Trafalis (2006) try to solve portfolio problems optimisation using SVM.

Lastly, Lee (2009) explains a prediction model based on SVM with a hybrid feature selection to predict the trend of stock markets. It is shown that SVM outperforms Back Propagation Neural Network to the problem of stock trend prediction. Dunis et al. (2012) show that it is possible to forecast some periods of IBEX-35 index under some chosen risk-aversion parameters using SVM Classifier. In Dunis et al. (2013), a genetic algorithm was used to optimize the inputs selection procedure and the parameters of a SVM model. This methodology was applied to the one day ahead forecasting and trading problem using the FTSE100 and ASE20 indexes. A new financial oriented fitness function plus confirmation filters and leveraging techniques were applied to improve the performance of the overall methodology. Experimental results indicated that this method outperformed more classical techniques such as MACD, ARMA models, Bayesian predictors and Higher Order Neural Networks.

2.2 VIX

As a measure of future expected volatility, VIX has been considered by researchers as the world's first barometer of sentiments of the investors and market volatility (Whaley, 2000). CBOE Volatility Index (VIX) is a key measure of market expectations of near-term volatility based in the informational content of the SP&500 index option prices.

Forecasting volatility is an essential step in financial decision making. There are several techniques which can help to forecast volatility such us GARCH models (Bollerslev, 1986), implied volatility models (Blair et al, 2001), or simple standard deviations models (Andersen and Bollerslev, 1998). In Perez-Cruz et al. (2003) use a support vector machine in order to estimate the parameters of a GARCH model for predicting the conditional volatility of stock market returns. Other researchers try to solve this problem using neural network models Hajizadeh et al. (2012) introduce a hybrid modelling approach for forecasting the volatility of S&P 500 index return.

The VIX calculation method has changed since its introduction in 1993. The original VIX was constructed using the implied volatilities of eight different S&P 100 index options, using the Black Scholes option pricing model, trying to represent the implied volatility of a hypothetical at-the-money option with exactly 30 days until expiration. In September 2003, CBOE changed the VIX calculation method as an average of weighted prices of out-the-money puts and calls options on the S&P 500 index. The new VIX retains the name VIX, while the original index that uses S&P 100 Index options is now referred to as the VXO.

Volatility index has several characteristics that make it interesting to use in order to forecast stock markets. It grows when uncertainty and risks increase. During falling markets, the VIX rises, reflecting increasing market fear. Volatility index reverts to the mean after high volatility situations and after low volatility situations such us interest rates. Rising markets usually the VIX goes down, reflecting a reduction of fear. So VIX is negatively correlated with stock or index level, and usually stays high after large downward —moves in the market.

These tendencies can be seen in Figure 2.

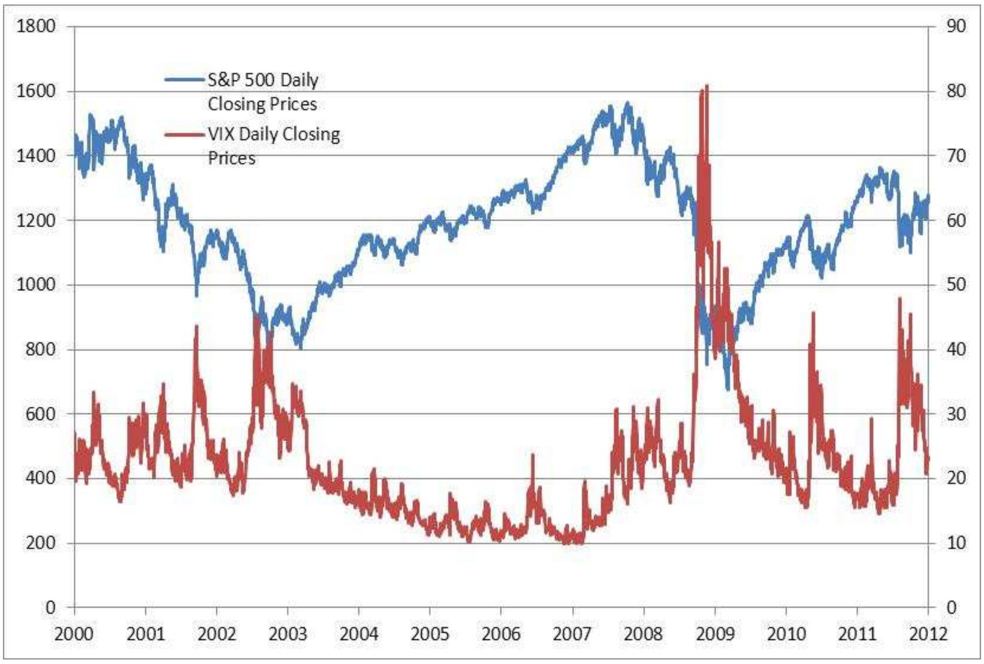

Fig.2 VIX and S&P Daily Closing Prices

In Figure 2, three different periods can be highlighted:

1) The bubble .com since 2000 to the beginning of 2003 year. As it can be seen, while the S&P 500 goes down from 1400 to 800 points, the VIX prices grow from 20 to 45 in August 2002.
2) In the period between 2003 and 2007, the S&P 500 index slowly recovers the level of 1500 points. In this stage which the S&P 500 grows, the VIX goes down to the level of 10%, it is very close to its historical minimum (9.31% on December 22, 1993).
3) The period between 2008 and 2010 is shown in the chart. While the S&P 500 goes down, the VIX reaches its historical maximum (80.86% on November 20, 2008).

The Volatility index will be included in the trading strategy because this index contains relevant information and it can be taken advantage of by the SVM.

2.3 Technical Analysis

The main literature review on technical analysis is Menkhoff and Taylor (2007). Four arguments are analysed: technical analysis may exploit the influence of central bank interventions, the foreign exchange markets may be characterised by not-fully-rational behaviour, technical analysis may be an efficient form of information processing and it may provide information on non-fundamental influences on foreign exchange movements. This study will be focused on the last two arguments.

Almost all foreign exchange professional traders use technical analysis as a tool in decision making at least to some degree and the relative weight given to technical analysis as opposed to fundamental analysis rises as the trading or forecast horizon declines, as shown by Menkhoff and Taylor (2007). Technical analysis is used more than fundamental analysis; according to Taylor and Allen (1992), 90% of polled investors use it. Allen and Taylor (1990) and Taylor and Allen (1992) document systematically for the first time that technical analysis is, indeed, an important tool in decision making in the foreign exchange market.

There are many more recent studies which recommend the use of technical analysis for trading rules. Brock et al. (1992) prove that the use of moving averages and the use of supports and resistances as trading tools for the technical analysis of companies of the Dow Jones index from 1897 to 1986 generates better profitability than the buy and hold strategy for the same Index. Mills (1997) shows a similar result to the one considered in the previous article, but for the Financial Times Institute of Actuaries 30 (FT30 Index).

Kwon and Kish (2002) document that technical trading rules achieve better profitability than the buy and hold strategy in the NYSE while Chong and Ng (2008) recommend the use of technical trading rules using the RSI and MACD indicators for the FT30 index and they show that the use of both oscillators generates a greater profitability than the buy and hold strategy. Rosillo et al. (2013) recommend the use of technical trading rules using the RSI indicator for blue chips and Momentum indicator for small caps and they show that the use of both oscillators generates a greater profitability.

Finally, Rodriguez-Gonzalez et al. (2011) develop systems trading with Neural Networks based on RSI financial indicator.

As it has been described, there are studies that support the validity of Technical Analysis and stochastic indicators in order to forecast stock markets, and this is the main motivation which RSI and MACD have been used like inputs of the SVM.

3. TRADING RULE DESIGN

In this section, the trading rule design is explained. The algorithm has been developed in Matlab[1]. An outline of the design of the trading rule is shown in Figure 3.

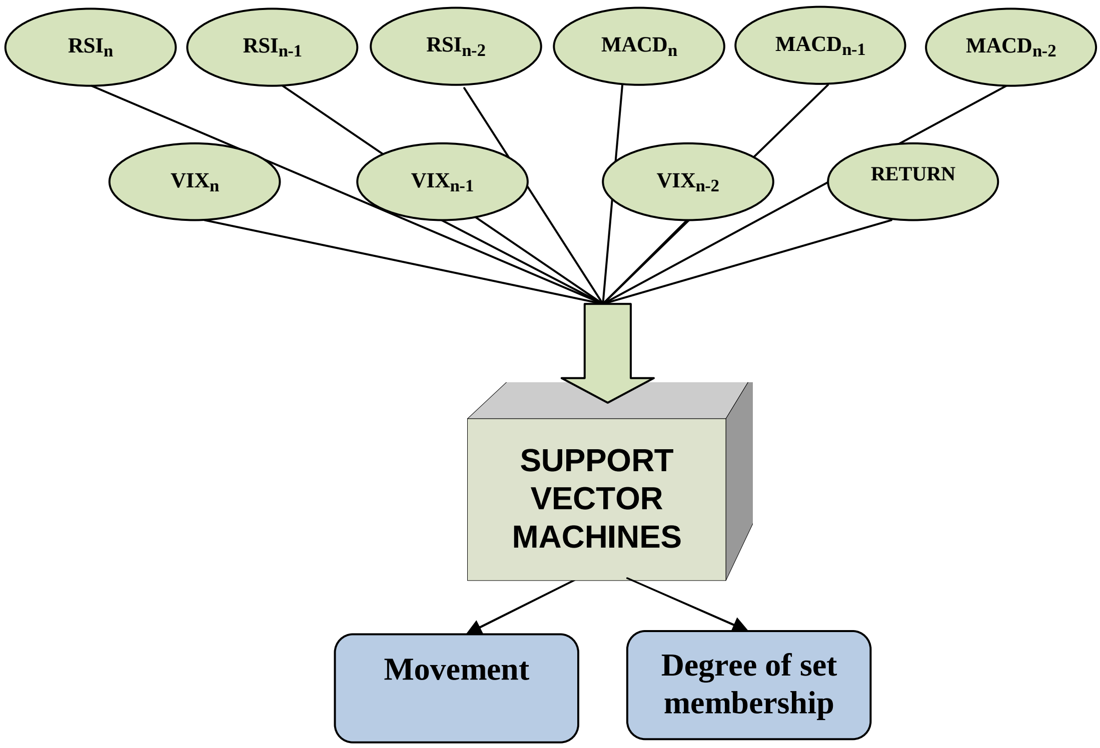

Figure 3. Design of the trading rule

3.1 The data

The dataset used in this study has been obtained from Datastream. The daily data covers the period between January 3th, 2000 and December 30th, 2011.

The SVM is trained on different periods of time with this database in order to achieve different results for comparison. Although our database uses data from a

[1] The software used is MATLAB 7.8.0 (R2009a).

daily basis, the trading strategy relies on a weekly prediction of the S&P 500 price move. A weekly forecast was selected as the expected price move, up or down, over a week is more significant.

As it can be seen in Figure 4, a non-separable case is considered, it is not possible to separate buying and selling recommendations without errors. The x, y and z axes are normalised from -1 to +1.

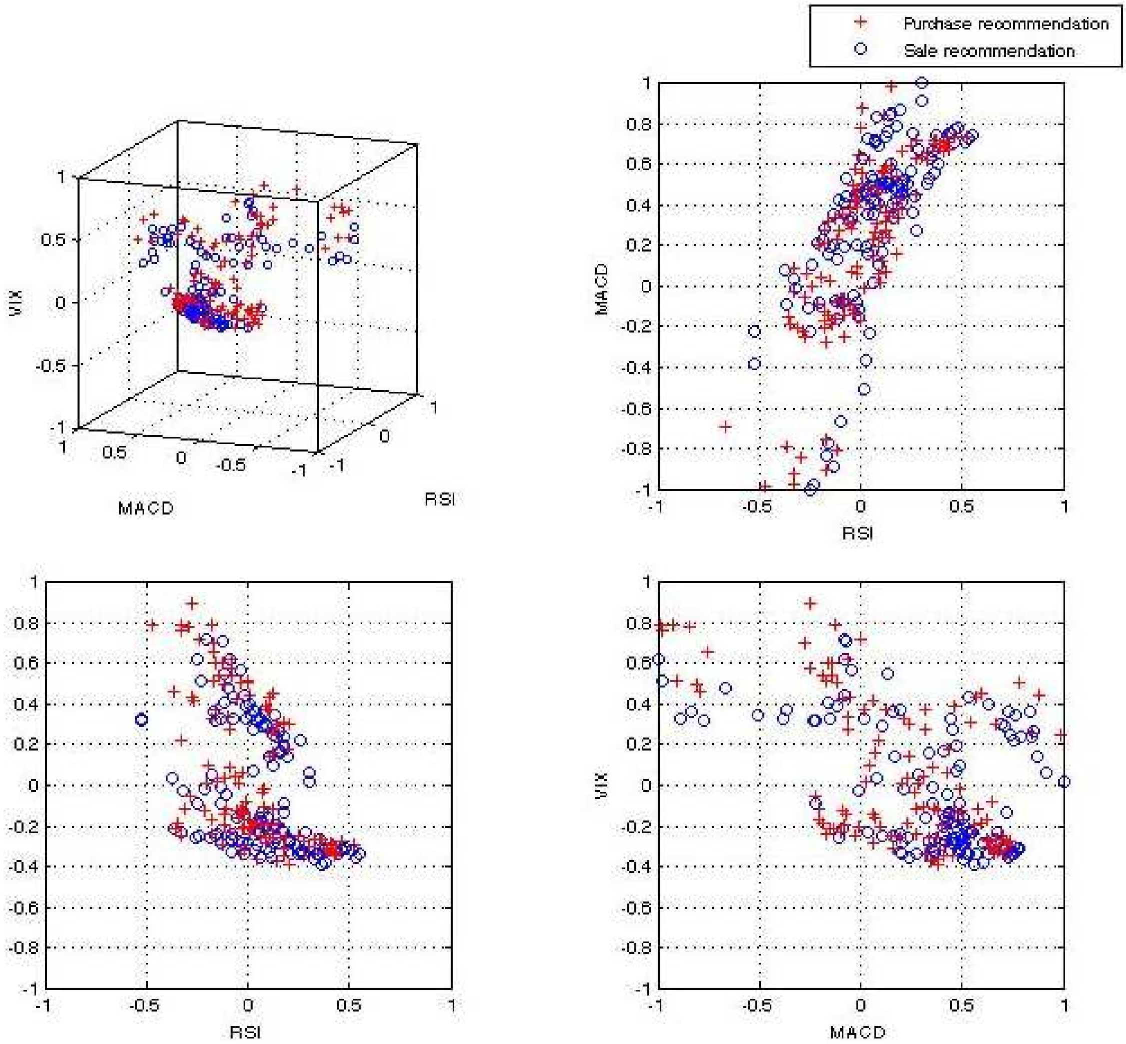

Fig. 4: Inputs of the Support Vector Machine from January 5th, 2011 to December 29th, 2011.

The application of an SVM is necessary in order to classify the training data correctly, because this is one of the non-separable cases.

3.2 The inputs

The inputs of the SVM are the VIX, the RSI and the MACD indicators. RSI and MACD indicators have been chosen because they are the most frequently used in quantitative technical analysis. VIX has been chosen in order to determine the profits that can be achieved with it or without it.

The daily return has also been included in the inputs, because in this research we are trying to forecast the future of the S&P 500 and this variable improves the final results. It is better to use returns in the inputs instead of daily prices because daily prices can cause errors in the SVM with the scale problems.

3.2.1 MACD

The MACD is designed mainly to identify trend changes. It is constructed based on moving averages and is calculated by subtracting a longer exponential moving average (EMA) from a shorter EMA. The MACD is shown in equation 4:

$$MACD\,(n) = \sum_{i=1}^{n} EMA_k(i) - \sum_{i=1}^{n} EMA_d(i)$$

Where k=12 and d=26 [4]

$$EMA_n(i) = \alpha * p(i) + (1-\alpha) * EMA_n(i-1)$$

$$\alpha = \frac{2}{1+n}$$

Where n is number of days and p(i) is asset price on i^{th} day.

In this article, 12 and 26-day EMAs are selected, which are commonly used time spans in order to calculate MACD (Murphy, 1999).

The range of MACD has been normalised between -1 and +1 in order to use it in the SVM.

3.2.2 RSI

It was designed by J. Welles Wilder Jr. (1978). A brief explanation of this indicator is shown below in equations 5 and 6. If more details are needed it can be seen in J. Welles Wilder Jr. (1978).

The RSI is an oscillator that shows the strength or speed of the asset price by means of the comparison of the individual upward or downward movements of the consecutive closing prices.

For each day, an upward change (U) or downward change (D) is calculated. “Down days” are characterised by the daily close being lower than the close of the previous day.

U = $close_t$ - $close_{t-1}$

D = 0

“Up days” are characterised by the daily close being higher than the close of previous day.

U = 0

D = $close_t$ - $close_{t-1}$

$$RS = \frac{EMA[N]\_of\_U}{EMA[N]\_of\_D} \quad [5]$$

$$RSI = 100 - 100\frac{1}{1+RS} \quad [6]$$

where RSI_t is the Relative Strength Index at time t.

The 14-day RSI, a popular length of time utilised by traders, is also applied in this study. The RSI ranges from 0 to 100 however the range has been normalised between -1 and +1 in order to place it in the SVM.

3.2.3 VIX

The VIX index is really relevant for investors because it shows a strong negative correlation with S&P 500.

In Figure 5, 3019 daily data of S&P 500 and VIX between the years 2000 and 2011 are analysed. The correlation between the log returns of the S&P 500 and the log returns of the VIX is -0.7623, a result that is worth highlighting because of the strong negative value. Although there is only instantaneous correlation and there are no remarkable lead-lag effects. This evidence merely documents correlation and is not intended to express causality.

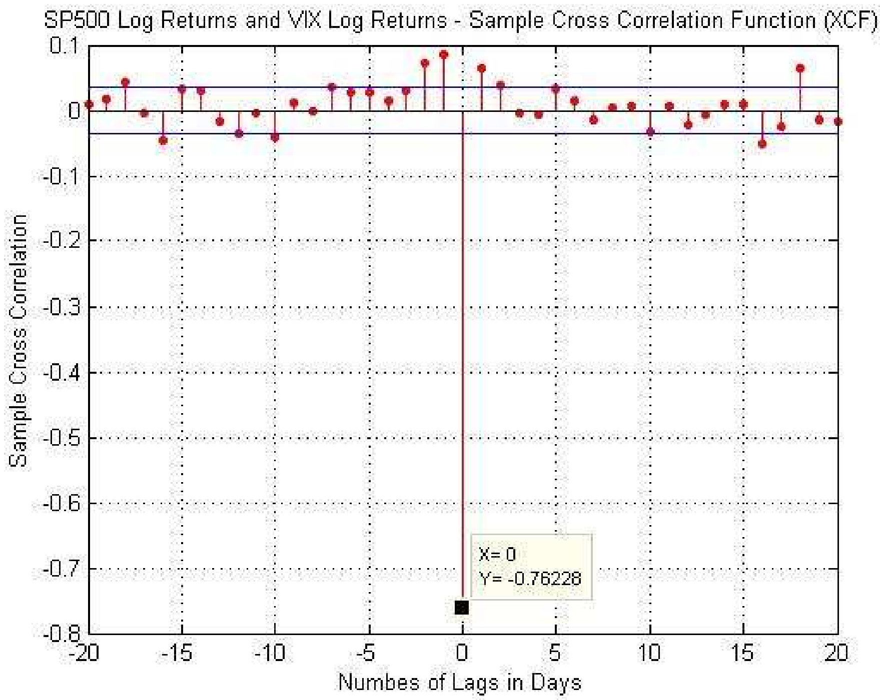

Figure 5. Cross correlation between log returns VIX and log returns S&P 500.

This special feature can also be translated in terms of beta, it would be very useful if the VIX could be bought or sold directly. Instead of this, VIX can be negotiated using future contracts listed in CBOE.

The beta for the whole period studied is -3.46, an excellent value that can be used in order to manage portfolios, as is suggested in Szado (2009).

There is a converse relationship between VIX changes and S&P 500 changes. The VIX realises panic situations better than bull movements, so the relation between VIX changes and S&P 500 changes is asymmetric. VIX is more a barometer of investors' fear of the downside than it's a barometer of investors' excitement (or greed) in a market rally (Whalley, 2009).This sentence can be showed in the lineal regression analysis below:

$$RVIX_t = \beta_o + \beta_1 RSPX_t + \beta_2 RSPX_t^- + \varepsilon_t \qquad [7]$$

where RVIX is the log return of the VIX, RSPX the log returns of the S&P 500 index and RSPX- the log return of the S&P 500 portfolio conditional on the market going down and 0 otherwise.

The estimated relation in the period 2000-2011 is:

$$RVIX_t = -0.0048 - 2.95 RSPX_t - 0.99\, RSPX_t^- \qquad [8]$$

being Student's 't for the three calculated coefficients 4.8, 32 and 6.8. The regression coefficient R^2 is 0.587. The expression showed before explains correlation but a causality relation cannot be assumed.

The estimated β_o coefficient is -0.0048, a value very close to zero which means that if the S&P 500 does not change from the previous day, the variation of VIX is practically insignificant. The estimated β_1 y β_2 coefficients are both negative and significant, and clearly reflect not only the inverse relation between movements in VIX and movements in the S&P 500 but also the asymmetry of the movements. -

A way of interpret the coefficients is for example to considerer a S&P 500 increases by 100 points, so VIX decreases by:

$$RVIX_t = -2.95 \cdot (0.01) = -2.95\% \qquad [9]$$

If the S&P 500 index decreases by 100 points, the VIX increases by:

$$RVIX_t = -2.95 \cdot (-0.01) - 0.99\,(-0.01) = 3.93\% \qquad [10]$$

The strong asymmetry between VIX and S&P 500 changes is highlighted.

In order to be processed in the SVM, the range of VIX, typically in the range of a yearly standard deviation, has been normalised between -1 and +1. When a daily VIX data is not available, we have used the previous daily data available.

3.3 The SVM trading rule

The design of the trading rule is the hardest section. In order to achieve better results, some of the parameters of the SVM have been modified and will be explained below. Several experiments have been done and the most relevant are shown.

An SVM has been chosen in order to make the quantitative decision. As it was explained in section 2, Support Vector Machines are helping investors in the decision making and many experiments demonstrate that SVMs generate better results than other artificial intelligence techniques. An SVM Classifier has been used.

The training period has been designed with 249 days and the next day is tested by the SVM in order to know if the result is a good decision or not. Other periods such as 200 days, 300 days and 500 days have been tested as well but the best results are achieved with 250. So, the training period is 249 days and the testing period is 1 day. The total of data for each experiment is 250 days, very similar to one business year.

Although our dataset is daily, the trading strategy relies on a weekly prediction of the S&P 500 price move. A weekly forecast was selected as the expected price move, up or down, over a week is more significant.

The only problem that has been detected is the situation when the SVM is being trained and it does not exist data to compare in order to make the decision to buy or sell. This situation happens for the last 5 days of the training period. In this way, the study is more real. In order to fix this, four experiments have been done, such as, compare these 5 days with the last day known, delete these 5 days, compare these 5 days with a simple moving average of that 5 days and compare these 5 days with a weighted average of that 5 days. The best results achieved are shown in the results section.

The following example is presented in order to clarify the previous explanation:

Let us start with the following situation:

	Training									Testing
Day	241	242	243	244	245	246	247	248	249	250
Value	7	5	3	3	4	6	10	8	1	7
Decision	Sell	Buy	Buy	Sell	?	?	?	?	?	?

Table 1. Training data with unknown values.

Training data are from day 1 to day 249. In table 1, data from day 241 to 250 are shown. Sell/buy decision is done by comparing the current day value with the value of 5 days ahead. In the case of days 245 to 249, the 5 days ahead value is unknown. Thus, to have a value to compare with, a simple moving average with values of days 245 to 249 is done.

Table 2 would be as follows:

Simple Moving Average: 4 + 6 + 10 + 8 + 1 = 29 / 5 = 5.8

	Training									Testing
Day	241	242	243	244	245	246	247	248	249	250
Value	7	5	3	3	4	6	10	8	1	7
Decision	Sell	Buy	Buy	Sell	Buy	Sell	Sell	Sell	Buy	SVM decision

Table 2. Training data with known values.

In consequence, SVM would be trained using the table above. Day 250 decision would be taken by the SVM.

The SVM procedure can be described as follow.

First, the SVM analyses the inputs classified in buy situations or sell situations.

Second, the SVM tries to separate the different prices of the S&P 500 in two classes: buying and selling situation, with the inputs mentioned earlier.

Third, the SVM uses the kernel function Heavy Tailed Radial Basis Function (HTRBF, equation 11) in order to make the forecasting. HTRBF was developed by Chapelle et al. (1999) and is used by SVM-KM Matlab toolbox developed by Canu et al. (2005). The parameter C of the SVM is tested in several tests and its optimal value is 10.

$$e^{-\rho \sum_i |x_i^a - y_i^a|^b} \text{ with } a \leq 1 \text{ and } b \leq 2 \qquad [11]$$

Fourth, the hit ratio is calculated for the different testing periods.

Finally, given a value of the RSI, MACD and VIX, the SVM predicts the upward or downward movement for the following week and the intensity of that movement.

3.4 The outputs

The outputs of the SVM are the up or down movements, expected for the index the following week, and its degree of set membership.

In Figure 6, the separation hyperplane created by the SVM for the training period between January 5th, 2011 and December 30th, 2011 is shown in function of RSI, MACD and VIX.

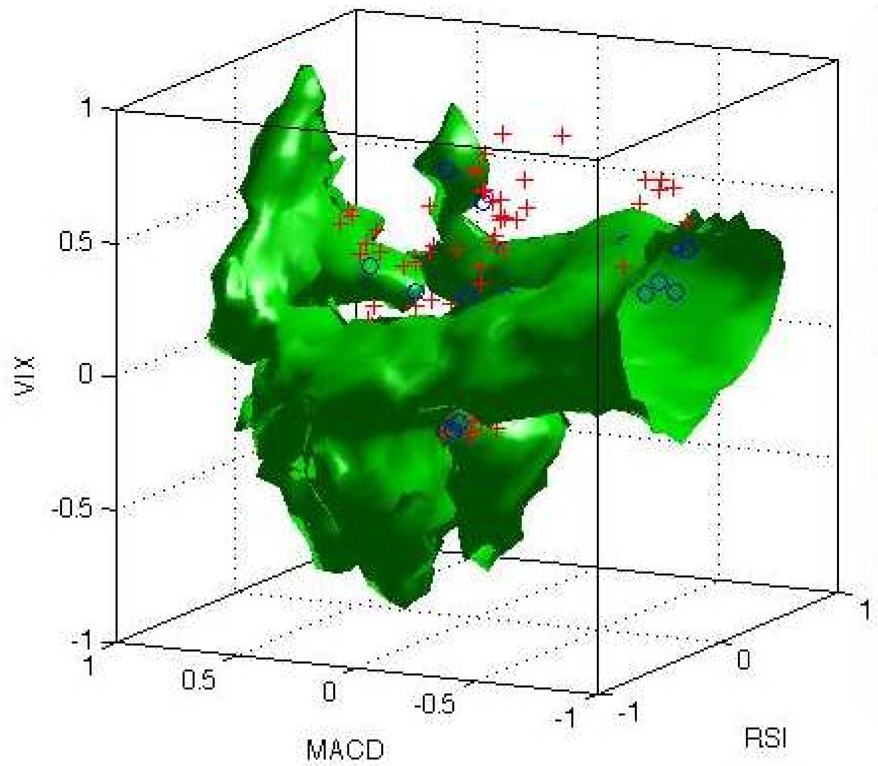

Figure 6. the separation hyperplane created by the SVM for the training period between January 5th, 2011 and December 30th, 2011.

Sell zones (blue circles) appear inside the hyperplane and buy zones (red crosses) are outside the hyperplane.

4. RESULTS

The results of the different implemented tests are shown in table 3. This data separation has been considered in order to understand the results better, taking into account two big crises: bubble.com and Sub-prime mortgage. These crises are described below as it appears in Rosillo et al. (2013).

The Bubble.com crash occurred due to the burst of the speculative bubble growing between 1995 and 2000. During this time many technological companies were created, especially the internet companies that later failed. It began in March 2000 to the beginning of 2003.

The Crisis of the sub-prime mortgage: It began in January 2008, although the periods of greater and decrease have been:

(1) The Crash of the USA stock market in October 2008 – At the beginning of October 2008: The panic was due to the crisis of the sub-prime mortgages, the bad economic data and the problems of different financial entities in USA.

(2) World Financial Crisis began in September 2008 and is still in force: The mortgage crisis started in the USA and spread to the whole world, when it was

known that many financial entities and insurance companies were also implicated in Europe. The government quickly implemented elaborate rescue plans to guarantee the deposits of the savers in order to avoid the panic. A decrease in the kind of interest and massive injections of liquidity was coordinated in order to not worsen the crisis. Furthermore, the Greek situation has increased the World Financial Crisis and this situation can be spread to other European countries.

Three trading strategies are compared holding five contracts at the same time at most. They are explained below:

a) V (VIX-SVM strategy): All the inputs which appear in Figure 3 are used.

b) S (SVM strategy): All the inputs which appear in Figure 3 are used except VIX, VIX-1 and VIX-2.

c) BH (BUY AND HOLD) strategy: It is the Buy and Hold strategy holding five contracts all the time in order to follow the V and S trading strategies. It is used like a Benchmark.

The trading strategy method is the same for the three trading strategies: For each day, the S&P 500 index is bought or sold depending on the trading system recommendation. After 5 days, the reverse operation over the S&P 500 is applied in order to be out of the market. This sequence is repeated every day.

A little variation of Buy and Hold strategy is used like a Benchmark. It consists in purchasing the S&P 500 index daily and selling the S&P 500 index after 5 days. The profit or loss for n periods would be:

$$\sum_{i=6}^{n}\Delta_i = (S_n + S_{n-1} + S_{n-2} + S_{n-3} + S_{n-4}) - (S_5 + S_4 + S_3 + S_2 + S_1) \qquad [12]$$

where $\Delta_i = S_i - S_{i-5}$ is the profit or loss S&P 500 points daily.

Different ratios have been calculated in order to compare the three strategies: Annualised return, Standard deviation, Sharpe ratio, Maximum Drawdown. The formulas of these ratios appears on appendix.

In table 3, the yearly results of the three strategies with the different ratios appear. Furthermore, at the end of the table, three different period groups are shown.

	SP Points			R			σ			SR			MDD (Points)		
Year	**V**	**S**	**BH**	**V**	**S**	**BH**	**V**	**S**	**BH**	**V**	**S**	**BH**	**V**	**S**	**BH**
2000	1531	821	-707	0.194	0.109	-0.104	0.078	0.075	0.092	2.5	1.4	-1.1	465	1057	1129
2001	-362	-455	-844	-0.057	-0.072	-0.139	0.084	0.082	0.097	-0.7	-0.9	-1.4	988	829	1859
2002	1035	957	-1344	0.162	0.151	-0.260	0.075	0.076	0.107	2.2	2.0	-2.4	373	389	1853
2003	-392	392	1104	-0.089	0.081	0.214	0.068	0.067	0.068	-1.3	1.2	3.1	511	305	568
2004	-133	87	536	-0.024	0.015	0.091	0.046	0.047	0.046	-0.5	0.3	2.0	368	337	421
2005	-64	152	229	-0.011	0.025	0.037	0.039	0.039	0.042	-0.3	0.6	0.9	403	169	349
2006	239	76	811	0.037	0.012	0.119	0.039	0.040	0.040	0.9	0.3	3.0	281	350	412
2007	162	482	320	0.022	0.066	0.044	0.055	0.058	0.062	0.4	1.1	0.7	688	621	664
2008	2538	-102	-3013	0.302	-0.014	-0.544	0.076	0.105	0.148	3.9	-0.1	-3.7	284	933	3300
2009	-688	-1022	1218	-0.160	-0.249	0.233	0.115	0.117	0.110	-1.4	-2.1	2.1	1123	1487	1159
2010	-233	87	669	-0.042	0.015	0.110	0.076	0.078	0.076	-0.5	0.2	1.4	591	555	901
2011	941	-229	10	0.137	-0.036	0.002	0.081	0.091	0.095	1.7	-0.4	0.0	470	813	1139
00-05	1616	1955	-1026	0.034	0.040	-0.026	0.051	0.053	0.083	0.7	0.8	-0.3	1050	1188	3630
06-11	2959	-707	15	0.063	-0.019	0.000	0.059	0.080	0.094	1.1	-0.2	0.0	1520	1987	4345
00-11	4575	1247	-1011	0.041	0.013	-0.013	0.048	0.055	0.092	0.9	0.2	-0.1	1520	1987	4345

Table 3. Yearly results of the three strategies.

In the first column of table 3 the points that can be achieved with each strategy are shown, in the second column the annualised return, in the third column the Sharpe ratio and in the fourth column the maximum Drawdown are shown.

The highlighted numbers present the best result of each strategy for a determinate indicator.

As it can be seen in the table 3, the V strategy is better in years with a bearish trend than S strategy and Buy and Hold strategy. Furthermore, the volatility is lower in V strategy than the others.

The influence of VIX using SVM is really important because V strategy is the winner in bearish movements as it can be seen in 2000, 2001, 2002 and 2008. Also V strategy has the best Sharpe ratio in these years.

In the next charts two periods are shown: 2000-2005 and 2006-2011.

In figure 7, the accumulative points for each strategy in the period from 2000 to 2005 are presented. Y-axe indicates the number of the points that the strategy has achieved. X-axe indicates the dates.

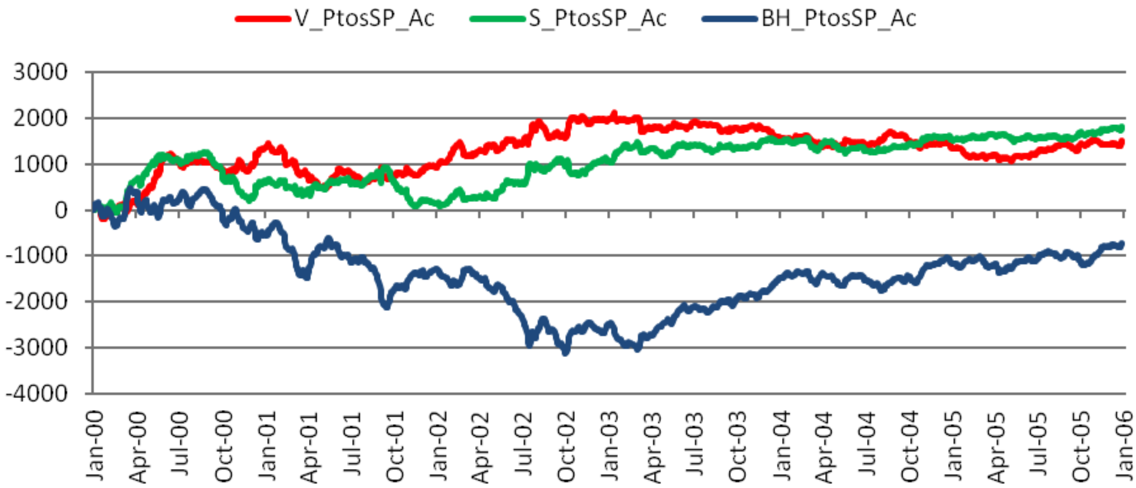

Figure 7. Accumulative S&P 500 points for each strategy from 2000 to 2006.

As it can be seen in figure 7, the Bubble.com crash had a negative influence in Buy and Hold strategy and S strategy. At the beginning of 2003, the best result was achieved by V strategy.

In figure 8, the Sub-prime mortgage crisis has to be highlighted (after January 2008). It is shown that V strategy achieves better results than others strategies. The influence of VIX is relevant in this crisis because V strategy is always having a positive result while S strategy and Buy and Hold strategy are having negative results.

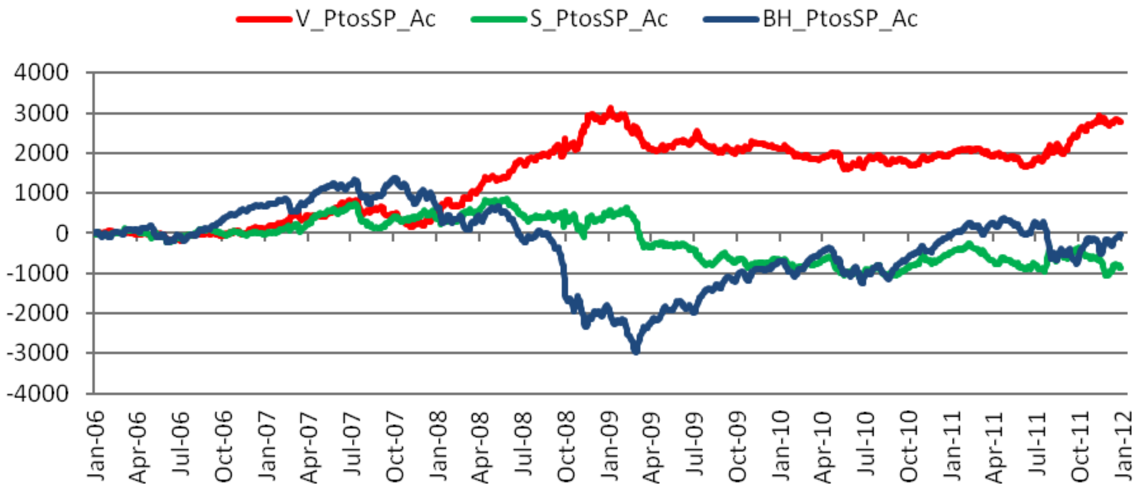

Figure 8. Accumulative points for each strategy from 2006 to 2012.

The difference between the three strategies is big. S strategy and Buy and Hold strategy are not able to achieve the same results as V strategy in bearish markets.

5. CONCLUSION

Overall, this study shows that SVMs with VIX produce better results when a bearish movement is produced. This may be caused by the influence of VIX in the bearish movement. It is usually that in a bearish movement, the volatility grows up more than a bullish movement, so VIX helps the SVM more in bearish situation than bullish situation.

SVMs manage to achieve good trading results. The SVM allows for a reduction in the Maximum Drawdown. It would be advisable to use a trend indicator in order to determine when a bearish movement will occur. Then, VIX-SVM strategy will help the investor to achieve a high profit.

The trading system that has been developed it will be useful when a bearish market starts.

Appendix

Annualised return:

$$R^A = 250 * \frac{1}{n}\sum_{i=1}^{n} r_i \qquad [13]$$

Standard deviation:

$$\sigma^A = \sqrt{250}\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2} \qquad [14]$$

Sharpe ratio:

$$SR = \frac{R^A}{\sigma^A}$$ [15]

Maximum Drawdown calculated in S&P 500 points:

$$MDD = \min_{t=1,\dots,n}\left(F_t - \max_{t=1,\dots,t}(F_t)\right)$$ [16]

where F_t is the accumulated fund with each different strategy.

ACKNOWLEDGMENT

Financial support given by the Government of the Principality of Asturias is gratefully acknowledged. The authors would like to thank the reviewers for their comments, which have greatly contributed to improving our paper. Any remaining shortcomings are, of course, our exclusive responsibility.

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