Technical Analysis with a Long Term Perspective: Trading Strategies and Market Timing Ability♣

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Abstract
This article extends the literature on the profitability of technical analysis in three directions. First, we investigate the performance of complex trading rules based on moving averages over longer horizons than those usually considered. The different trading rules are simulated on daily prices of the S&P 500 index over the period 1990 to 2008 and we find that trading rules are more profitable when signals are generated over longer horizons. Second, we analyse if financial leverage can improve the profitability of the different strategies. It appears to be the case when leverage is achieved with debt. Third, we propose a new test of market timing that assesses whether a trading strategy is able to generate signals corresponding to longer market phases. According to this test, the signals generated by the complex rules investigated in this article coincide strongly with bull and bear markets.

Keywords: Technical trading, Moving average rules, Options, Forecasting, Leverage, Market timing

JEL Classification: C63, G11, G13, G17

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1. Introduction

The term technical analysis comprises a wide range of methods aimed at forecasting future price movements of stocks, currencies or commodities, based on their past prices and volumes. These methods might be classified into two broad categories, charting and technical trading systems. The first group consists in analysing price patterns with charts which are supposed to repeat themselves. The second group includes a variety of quantitative rules aimed at detecting trends and generating trading signals objectively. Among them, the moving average (MA thereafter) and the filter trading rule are the most popular[1].

Several surveys conducted with professional investment mangers show that the vast majority of them use some kind of technical analysis. Allen and Taylor (1990) in the London foreign exchange market, Lui and Mole (1998) in Hong Kong and Oberlechner (2001) in various European markets show that technical trading is broadly used in order to forecast short term trends. Nevertheless, its importance diminishes as the forecasting horizon gets longer. Furthermore, these techniques are not regarded as being in contradiction with fundamental analysis but are used in a complementary approach. Finally, Gehrig and Menkhoff (2006) find that the use of technical analysis increases during the nineties by comparing surveys conducted in 1992 and again in 2001 among German and Austrian foreign exchanger dealers and funds managers.

On the other hand, academics have been skeptical about the utility of these forecasting methods. Among the various conceivable reasons, we might cite their lack of theoretical basis and the process of parameters selection, which is usually not disclosed or justified. In addition, empirical evidences of profitability of technical trading are mixed and are strongly dependent on the choice of the time interval, the set of methods considered or the underlying asset. Another concern about technical analysis arises as reported evidences of profitability

[1] In this paper, the trading rule relates to the method according to which trading signals are generated. The trading system consists in using more than one indicator to produce these signals. Strategies reflect the effective positions taken in the market by either combining long and short position or using financial leverage.

might be biased by data snooping issues. Indeed, using repeatedly the same data and trading rules might very well results in finding a few profitable rules by luck.

The objective of this paper is to test some new MA strategies based on the out of sample approach of Sullivan, Timmermann and White (1999), Skouras (2001) or Fong and Yong (2005). Instead of choosing arbitrarily the parameters, we utilize various recursive algorithms which generate trading signals according to simple MA rules past performance. Furthermore, we consider a much wider range of parameters for both the short and the long moving averages. Indeed, the vast majority of studies related to MA trading rules concentrate on relatively short trends in the market as they usually use only a long moving average up to 200 days. As longer trends might be more easily identified and might be less noisy, our new trading rules might have more forecasting power. We find supportive evidences that our trading systems provide much higher returns than usual MA rules. Furthermore, these results are especially strong over the more recent period, whereas the majority of studies found that technical analysis performance decreases over time. A formal market timing test based on a block bootstrap methodology is also proposed in order to determine whether our strategies rely on longer trends related to the business cycle.

As technical trading is widely used by hedge funds or by commodity trading advisor (CTA) funds, leveraged strategies are also investigated. For this purpose, we consider debt leverage and exchange traded options. A second reason for using financial leverage is the fact than even strategies with good forecasting power will not be able to produce a significant abnormal return if the market is characterized by a strong upward trend. We find that the superior performance might not be attributed the leverage itself. Finally, we provide some insights about the trading strategies performance in a higher moments framework. We show that our strategies are interesting as they might hedge skewness risk without scarifying returns.

The structure of this paper is the following: Section 2 presents a literature review of related studies. We describe the data in section 3. Section 4 details the methodology in relation with our trading systems, the new market timing test and finally, how financial leverage is introduced in the investment strategy. The different results of the simulations are provided in section 5, while section 6 concludes.

2. Literature review

Even if the results of early studies do not speak in favour of technical analysis, Brock, Lakonishok and LeBaron (1992) find that simple trading rules produce significant excess returns over a long time period on the DJIA. Furthermore, they use a bootstrap technique and show that trading rules can not reproduce these profits on simulated price series based on various returns generating models, such as the random walk or GARCH models. Afterwards, other papers confirm these results, for instance, Fong and Ho (2001) find that basic MA rules are profitable when they are tested on US internet stocks, even after considering transaction costs and a time varying risk premium. Wong, Manzur and Chew (2003) utilize various specifications of MA rules and a counter trend indicator on the main Singaporean index between 1974 and 1994. The rules produce, on average, statistically significant returns with confidence levels ranging from 1% to 10%. Furthermore, even strategies which are not profitable show some level of predictability, as buy returns are higher than those following sell signals. Moreover, Levich and Thomas (1993) or Neely (2002) find similar results on the foreign exchange market.

However, more recent papers which report results in favour of technical trading employ complex trading system in order to incorporate more information. For instance, Skouras (2001) points out the sensitivity of MA rules performance to the choice of parameters. Indeed, he compares the profitability of every single MA rule with a one day short window and a long window ranging from two to 200 days and shows that the best performing rule yields a return 1270 higher than the worst performing specification. Therefore, he proposes a recursive method aiming to determine objectively the length of the long moving average. His "artificial technical analyst" produces excess returns more than three times higher, on average, than the specifications used by Brock, Lakonishok and LeBaron (1992). Hsu and Kuan (2005) construct complex trading rules with trading signals obtained by a wide selection of simple rules, including mathematic rules and graphic rules[2]. They perform tests, which include the impact of data-snooping, proposed by Sullivan, Timmermann and White (1999) and Hansen (2005). They find evidences in favour of using more information as there are much more profitable complex rules than simple rules across their universe of 39'832 rules. Allen and Karjalainen (1999) or Neely, Weller and Dittmar (1997) develop methods inspired by biology

[2] They consider various methods to combine simple rules and as this paper use a somewhat similar procedure, more details are given in section 4.

and natural evolution to combine simple technical trading indicators in an optimal way (i.e. based on a fitness criterion), namely genetic programming. As this method is entirely out-of-sample, it has the advantage of reducing the data snooping issue, however, they might have a obscure structure and are therefore rather difficult to interpret. Fang and Xu (2003) combine MA trading rules signals with forecasts generated by different time series models, such as the auto regressive or GARCH models. They show that both methods capture different aspects of price predictability and are hence complementary. Indeed, MA signals tend to produce better forecasts for upward trends, whereas time series forecasts are more precise for detecting downward trends. Their new trading rule proposes to take a long (short) position whether both indicators produce a buy (sell) signal. They show that break even costs are significantly higher when this trading rule is used in comparison with the two simple rules taken separately.

Following the same principle of aggregating more information, various complex trading systems are proposed. Pruitt and White (1988) investigate the profitability of their CRISMA trading system, standing for "Cumulative volume, Relative strength, Moving Average", combining three simple technical indicators. The system emits a buy signal when the three indicators produce simultaneously a buy signal. They find that the profitability is robust to transaction costs and risk bearing. Gençay, Dacorogna, Olsen and Pictet (2003) consider the performance of a commercial real-time trading model (RTT model) developed by Olsen & Associates. This model utilizes a trend following technique based on an equally weighted iterative moving average of 20 days, but considers also the size of the signal to determine the percentage of wealth to be invested. In addition, it contains as well a contrarian indicator to diminish the position exposure to extreme movements. The authors argue that this model might shed light on the usefulness of technical analysis, as its performance might proxy very well that of an investor (or a currency dealer) in a real trading setting. Indeed, they use intraday data, transaction costs are taken into account via the bid-ask spread, real trading hours are respected and the model trading frequency is realistic for a real trader. The RTT model performance is compared with a simple exponential moving average and they find that the RTT is superior with respect to all aspects considered. Finally, Dueker and Neely (2007) propose a trading strategy based on the estimation of a Markov switching model and they find that it produces better results than traditional MA rules. Nevertheless, they show that an equally weighted portfolio of these two rules provides the highest risk adjusted return, as they exploit different trends. These studies suggest that the refusal of technical analysis as a useful forecasting tool, especially over the most recent period, might have been premature.

While the majority of studies related to technical analysis focus on its empirical profitability, others are concerned with the fundamental reasons according to which technical analysis might have forecasting value. Neftci (1991) argues that technical trading rules might be useful for prediction if and only if prices follow a nonlinear process. If, on the contrary, the price process is linear then, according to the Wiener-Kolmogorov prediction theory, vector autoregressions (VAR) should provide the best prediction with regard to the mean square error criterion. By regressing prices on their lags and on signals generated by a trading rule, he finds significant evidences in favour of nonlinearities. These results are corroborate by Kwan, Lam, So and Yu (2000) who examine the trend model of Taylor (1980). In this framework, the optimal forecasting rule generates a buy signal whether the current log price is higher than a weighted average of past log prices. This rule is similar to the standard MA with a weighted average instead of a simple one. Furthermore, Dewachter (2001) argues that a Markov switching model, non linear by construction, is able to explain a higher proportion of profits arising from MA rules than its linear counterpart, an ARMA (1,1). In addition, he shows that these profits might also be replicated when the trading rule is applied, not on the original price series, but on simulations issued from the Markov model. In a similar framework, Reitz (2006) suggest that MA rules might help identifying changes in hidden fundamental price process and concludes that MA rules are a “cheap proxy of Bayesian learning”. Finally, another issue which might speak in favour of technical trading is its simple structure, as no parameter has to be estimated. This might be rather counterintuitive as the subjectivity in the choice of parameters is usually regarded as a drawback of technical analysis. Blanchet-Scalliet, Diop, Gibson, Talay and Tanré (2007) illustrate this point by comparing, in an investor utility framework, MA rules and mathematical model based trading strategies. They show that MA rules might outperform mathematic forecasts under uncertainty (i.e. as in reality). This uncertainty affects the estimation of parameters but as well the price generating model itself. These results, based on numerical simulation, are confirmed by Zhu and Zhou (2009). Both of these studies also point out a drawback of the standard strategy which invests (or short) in the market the entire available capital. On the contrary, the authors argue that the invested proportion should depend on the investor risk aversion but as well on the confidence given in the trading signal.

3. Data

3.1. Equity prices and returns

The different simulations in this article are performed on the Standard & Poors 500 index (S&P 500). The series considered is this study are daily closing prices of the S&P 500 ranging from January 1990 to December 2008. We use either index levels to compute moving averages or simple daily returns to assess the profitability of these trading rules. The first four years of data are kept as the initial estimation period and consequently, trading strategies are evaluated over the 1994-2008 interval which contains 3761 daily observations. We choose this relatively short interval as earlier periods have been widely examined and the recent literature suggests that technical trading profits are much more difficult to find recently than in the past. The index closing prices are obtained from *Thomson Financial Datastream*

3.2. Interest rates

Two interest rates are considered in this study. A lending rate is used to represent the return of the investment strategy when the signals generated by trading strategy are neutral. A borrowing rate is needed to represent the cost of the strategy using debt leverage. We use the one month Euro dollar deposit rate as the lending rate and the US Bank prime loan rate as the borrowing rate. The borrowing interest rate yields on average 2.3% p.a. more than the lending rate. The two two interest rates are also extracted from *Thomson Financial Datastream*.

3.3. Exchange traded options

The alternative to implement trading strategies with financial leverage is to use options. In this article we use daily observations of exchange traded S&P 500 options obtained from the *Market Data Express service* of the *Chicago Board of Option Exchange*. Non continuous options and those with prices which violate significantly the arbitrage conditions are removed from the sample. The sample contains 11’464 different call and 11’377 put options corresponding to a total of 1’828’800 daily observations. The details on the choice of relevant options, their returns and descriptive statistics are provided in Appendix A.

4. Methodology

4.1. Trading rules

Each trading system in this study relies on simple MA rules. The purpose of using moving averages is to smooth price series and to detect underlying trends in its evolution. An upward (downward) trend occurs when the short moving average arises above (slide below) the long moving average. A band might also be added to avoid non informative or mixed signals when the difference between the two MA is small. Hence, the rules are defined only by three parameters which have to be chosen; the length of the short and the long moving average, respectively *S* and *L*, and the bandwidth, *B*. The two moving averages are computed as

$$M_{t,S} = \frac{1}{S}\sum_{j=1}^{S} p_{t-S+j} \quad \text{and} \quad M_{t,L} = \frac{1}{L}\sum_{j=1}^{L} p_{t-L+j} \tag{1}$$

where *p* is the asset price and their relative difference is

$$R_t = \frac{M_{t,S} - M_{t,L}}{M_{t,L}} \tag{2}$$

In practical implementation, the bandwidth *B* is usually set to 1% and hence, a buy signal is generated whether $Rt > B$ and a sell signal if $R_t < -B$. The investment strategy consists in taking a long (short) position in the market after a buy (sell) signal[3]. For rules with a band, no signal is emitted when the two MA are close from each others and thus, the strategy invests in the risk free rate. Positions are kept as long as no other signal is generated

A contribution of this paper to the technical analysis literature is the range of parameters we consider. Instead of limiting the length of the long moving average to 200 days, we use several lengths up to four years. Indeed, longer trends might be in line with the business cycle and might also produce a more stable strategy and thereby keep trading costs low. Our universe of simple MA rules comprises 1886 combinations of parameters: 23 different lengths for the short moving averages with values ranging from one day to 100 days. For the long moving average, we have 48 lengths between five and 1000 days. Finally, all rules obtained with these parameters are evaluated with and without a band of 1%. However, instead of examining the profitability of technical analysis according to these simple MA rules, we focus on complex trading rules as in Hsu and Kuan (2005). Beside of using more information by

[3] When empirical results are presented, this strategy is also named the global strategy. Indeed, we describe as well the results of the two components, the long and the short one.

combining signals from simple rules, they have another advantage. Indeed, they are designed to remove the subjectivity in the choice of parameters and should be less affected by data mining issues. The four complex rules are defined below:

OPT_ALL. The first rule (named Opt_all) is a continuous recursive process. Each day, cumulative return of the 1886 simple rules is computed over the entire history and the best performing rule is selected to generate the actual trading signal. The first trading signal is used to determine the position of the strategy in the first trading day in 1994. The procedure is then repeated every day by adding a day to the estimation period. For the last trading day, the estimation period to determine the best performing rule covers the period from 1990 to 2008.

The three other complex rules are based on a selection sample and a test sample. The length of each of these samples is set to four years in order to match the maximal length of the long moving average. The first four years of data, from January 1990 to December 1993, constitute the first selection sample. Each complex rule uses the information in a different manner, as explained below, and then the strategy consists in investing over the next four years (i.e. the test sample). Then, this four years sample, from January 1994 to December 1997, is used as the new selection sample and strategies take positions over the next four years. This process is repeated until the end of the year 2008 and thus, we have four test periods lasting four years each.

OPT_4. The second rule (Opt_4) is somewhat similar to the first one. They are learning processes, in the sense that they compare past individual MA rules performance to choose a specific set of parameters. However, instead of computing cumulated returns over the entire history, this rule records simple MA rule returns only over the selection period. Moreover, parameters are not revised every day but the selected rule is evaluated over the entire test sample. In summary, the best performing rule is identified during the selection sample and it is run to produce the effective trading signals over the test sample. The first rule (Opt_all) takes into account more information and is very flexible, however, it might suffer from over specification. Indeed, changes in parameters should arise from modifications in trends which are not likely to happen very often.

The last two complex rules are different. Indeed, they do not use past rules performance in order to select a single simple rule to generate trading signals. They attempt to combine signals from several simple MA rules. The first step consists in identifying rules which have a higher cumulated return than the market over the selection sample. Then, these rules are used over the next test sample to generate the effective trading signals. These two rules differ in the way of gathering information.

VOTE. The third rule (named Voting) counts, each trading day, the number of buy and sell signals suggested by the selected rules. The trading signal corresponds to the position which has received the highest number of “votes”.

PARTIAL. The last strategy (Partial) averages the suggested signals (-1 for sell, 0 for a neutral and 1 for a buy) and hence, produces a fraction. For example, there are 825 strategies with a higher cumulated return than the market over the first selection period. Then, during each day of the next test sample, each of these 825 rules produces a trading signal according to its parameters, for instance 500 buys and 325 sells for the first trading day. Consequently, the Voting rule returns a buy signal as there are more buys than sells and the Partial rule generates a fraction, 0.21. That means only 21% of the capital is invested over the next day, whereas the Voting strategy invests 100% of the available capital. The process is repeated every day over the test sample. This rule makes the amount to invest vary according to the confidence in the forecast. Indeed, if there are only a few more rules which produce a buy signal and the others indicate to short the market, only a small amount is invested. This is consistent with the finding of Blanchet-Scalliet, Diop, Gibson, Talay and Tanré (2007) and Zhu and Zhou (2009). The main difference with the complex strategies of Hsu and Kuan (2005) is that we consider only simple trading rules which outperform the market over a selection interval. Indeed, the Voting and Partial rules depend, obviously, on the initial choice of parameters. The initial selection of rules might help to mitigate the subjectivity in the universe of simple rules. It is important to note that each of these four complex trading rules follows an entirely out-of-sample process and they are not subject to any look ahead bias.

Beside the buy-and-hold strategy, we also compare the profitability of complex rules with two other benchmarks. The first is the random walk strategy which takes a long position at t_{+1} when the index return is positive at t and a short position otherwise. Finally, we also report results for the best performing rule (named Best) over the entire sample form 1994 to 2008. This rule cannot be used to find out whether technical trading has forecasting power as its performance is in-sample and raises data-mining issues. Before turning to the use of leverage in technical trading strategies, a market timing test is proposed in order to determine whether complex strategies follow more closely long term trends in the market.

4.2 A market timing test related to bull and bear markets

The first part of this test methodology is to define whether the market is in a bull or bear phase. Visual inspection could be utilized, nonetheless, this approach would be rather subjective. Instead, we consider a variation of the algorithm proposed by Pagan and Sossounov (2003) designed to identify turning points inside various cycles. A cycle is defined as two subsequent phases, a bull market following a bear market or the opposite. A central issue is to separate local peaks or troughs from turning points in the cycle. Indeed, a short decrease (increase) in prices during a bull (bear) market shouldn't indicate a change in the primary trend. This should be considered as a correction (rally) in a bull (bear) market. The algorithm is the following: Firstly, the highest and lowest points are identified over a 30 months window. The next step is to ensure that each market phase persists for at least nine months or if it is not the case, its absolute return difference between the highest and lowest price should be larger than 25%. The last stage of the algorithm warrants that a market cycle lasts for two years at least.

[Insert Figure 1: Bull and Bear markets]

Once the bull and bear phases are identified, the trading signals of the complex and the simple MA rules are analysed in this framework. Four different statistics describing whether long (short) positions coincide with bull (bear) markets are computed. For each series, we compute the following statistics: the percentage of days during which strategies have long (short) positions during bull (bear) market and the total percentage of right or wrong[4] signals. They are computed as:

$$\text{\% buy-Bull} = \frac{\sum_{t=1}^{N}\left(S_{rule,t} = 1 \middle| S_{BH,t} = 1\right)}{\sum_{t=1}^{N}(S_{BH,t} = 1)} \quad (3)$$

[4] Here, right (wrong) signals are defined as long (short) position during a bull (bear) market, whatever the market return.

$$\% \text{ sell-Bear} = \frac{\sum_{t=1}^{N} \left(S_{rule,t} = -1 \middle| S_{BH,t} = -1 \right)}{\sum_{t=1}^{N} (S_{BH,t} = -1)} \tag{4}$$

$$\% \text{ right} = \frac{\sum_{t=1}^{N} \left(S_{rule,t} = S_{BH,t} \right)}{N} \tag{5}$$

$$\% \text{ wrong} = \frac{\sum_{t=1}^{N} \left(S_{rule,t} \neq S_{BH,t} \right)}{N} \tag{6}$$

where $S_{rule,t}$ is the trading rule signal at time t, $S_{BH,t}$ takes the value of 1 or -1 whether the market is in a bull or bear phase and N is the total number of trading days. Let us denotes one of these statistics as V. In order to determine the significance of these statistics, we use a bootstrap methodology. For each strategy, N random trading signals series are created by using a block bootstrap[5] in order to keep, to some extent, the same structure as the original series. Then, the same statistic is computed for each of this N artificial series, V^*, and they are ranked such as $V^*_1 < V^*_2 < \ldots < V^*_N$. We calculate the empirical p-value, P, as:

$$V^*_m \leq V < V^*_{(m+1)} \tag{7}$$

$$P = 1 - M / N \tag{8}$$

Intuitively, this p-value corresponds to the percentage of simulated series which have a higher value than the original statistic. This test differs to standard market timing test (as for instance Henriksson and Merton (1981)) by using market phases instead of market returns as turning points. Therefore, the methodology we propose should not be used to detect short term market timing (over a few trading days).

4.3 Financial leverage

Firstly, we evaluate the complex trading rules in the traditional framework i.e., the whole capital is invested after a buy signal, a sell signal implies to short the market and a neutral

[5] Various lengths of blocks ranging from 10 to 188 days are used.

signal results in investing the capital in the risk free asset[6]. However, as pointed out, among others, by Fung and Hsieh (1999) some hedge funds and the majority of managed future funds (also called Commodity Trading advisor or CTA) use a trend following strategy. As these funds are likely to use financial leverage, it makes sense to consider the trading rules performance with leverage as well. This approach is also relevant as even a trading rule with superior predictive power might not be able to produce abnormal returns in an upward trending market. To our knowledge, the only studies which consider technical trading with options are Pruitt and White (1989) and Goodacre, Bosher and Dove (1999). We consider two methods to obtain financial leverage,: with exchange traded options and with debt.

4.3.1. Leverage with exchange traded options.

Options provide the possibility to take positions with leverage since the premium of the option represent only a fraction of the underlying's price. However it is rather unlikely that an investor would invest her entire capital in traded options because of the possibility of experiencing a return of -100% and therefore losing the total value of her investment. For this reason strategies with options are also evaluated with three different proportions of options included, namely 5%, 10% and 15%. For instance, a buy (sell) signal involves taking a long (short) position in the market equal to 95%, 90% or 85% of the available capital and buying call (put) options for the remaining amount.

4.3.2. Leverage with debt

When investment strategies use debt, a buy signal results in borrowing 100% of the capital and thus, in investing 200% of the capital. After a sell signal, the strategy consists in shorting 200% of the capital. We assume that the capital is enough to cover shorting requirements as collateral and therefore, no other cost is taken into account. The returns, after transaction costs, are computed as

[6] The Partial rule doesn't invest, or short, the entire capital but consider a fraction of it according to the trading signal.

$$r_{t+1} = \begin{cases} S_t \cdot 2 \cdot \left[\left(\frac{P_{t+1} - P_t}{P_t} \right) - R_{B,t+1} - \left| S_{t+1} - S_t \right| \cdot TC \right] & \text{if } 0 < S_t \leq 1 \\ S_t \cdot 2 \cdot \left[\left(\frac{P_{t+1} - P_t}{P_t} \right) - \left| S_{t+1} - S_t \right| \cdot TC \right] & \text{if } -1 \leq S_t < 0 \\ R_{L,t+1} & \text{if } S_t = 0 \end{cases} \qquad (9)$$

where P_t the index price at time t, $R_{B,t}$ is the borrowing rate and $R_{L,t}$ the lending rate. S_t represents the trading signal and it takes 1 (-1) for a buy (sell) trading signal , or the fractional trading signal for the Partial strategy, and zero for a neutral signal. *TC* corresponds to transaction costs and they are set at 0.02%. As different investors have different borrowing costs, we compute results with three different levels: a higher borrowing rate for retail investors, the lending rate which might be realistic for high net wealth investors and zero borrowing cost which might proxy the profitability of investing with futures but as well for banks or hedge funds.

5. Empirical results

5.1. Preliminary results

Before turning to complex trading rules, Figure 2 presents the annualized mean simple returns of all MA rules considered in this study. These figures show that MA rules usually used in academic studies, which rely on short term trends, perform poorly. Indeed, their returns are at best equal to the buy-and-hold and even often negative. On the other hand, rules with longer length of the long moving average generate average returns up to more than two times the benchmark return. This might indicates that these trading rules are able to detect and exploit longer trends. Furthermore, these results do not take transaction costs into account, which overstate the performance of rules based on short term trends as they change trading positions more often. It’s also worth noting that trading rules performances are rather insensitive to small variations in parameters. Even if no test can be made, this might indicate that these results are probably not strongly affected to data snooping issues.

[Insert Figure 2: Simple MA rules returns]

[Insert Figure 3: Simple MA rules returns: subsamples]

Figure 3 presents a sub samples analysis. Firstly, the rules performance is consistent in all sub samples in the sense that traditionally used specifications generate a very poor performance. Second, these results are in contradiction with a large number of recent studies dedicated to technical trading. Indeed, the performance of a larger set of rules does not diminish over time. On the contrary, rules evaluated over the two last sub sample provide, generally, a much higher return than the buy-and-hold. Nevertheless, this figure shows that rules returns relative to the buy-and-hold depend strongly on the latter. During periods when the benchmark performs very well, it's practically impossible to generate abnormal returns without some financial leverage. On the other hand, during bear markets, lots of trading rules generates economically significant abnormal returns. This is clearly illustrated over the last sub sample, which includes the Lehman Brothers bankruptcy related financial crisis. Whereas the buy-and-hold return is negative, most rules, except those based on very short moving averages, generate higher returns.

We show that all complex rules also rely on large values for long moving averages lengths. Indeed, 99% of these lengths for the Opt_all rule take only three values over the entire sample: 615, 665 and 940 days[7]. Furthermore, its smallest length is 340 days. Table provides some insights about the performance of the optimization process used by the Optim_4 strategy. Although the out-of-sample performance of the selected rule is the not the best among all specifications, only a small fraction of rules is able to generate higher returns, while the vast majority of rules have lower returns.

[Insert Table I: Out of sample performance of the Optim_4 strategy]

Finally, it is worth noting the rule with the highest in-sample return (i.e. the Best rule) has a long moving average length of 465 days. All these results suggest that MA rules are successful when parameters are not subjectively constraint to capture short term trends in the price evolution. As some of these results are subject to data-snooping issues, the next section focuses on complex trading system. Indeed, these rules follow an entirely out-of-sample parameters selection process and therefore, they should at least limit this issue.

[7] The steadiness in the parameter is also explained by the optimization process. Indeed, if more than one rule produce the highest cumulated return over more than two periods, the optimization process will keep the same parameter.

5.2 Strategies without leverage

5.2.1 Performance

Table II presents the results of the simulations for complex strategies and the returns obtained for the different strategies.

[Insert Table II: Complex rules returns]

We first observe that each strategy has a higher performance than the market, ranging from an annual mean return of 9.2% to 13.6%, whereas the buy-and-hold yields 6.1%. Conclusions from testing whether these returns are statistically significant are mixed. First of all, the Tstat do not allow to reject the null hypothesis of equal means between strategies returns and the buy-and-hold. The results are similar whether the whole strategy is tested or only the long or short components. It is important to realize that standard student tests are not powerful in the sense that a high abnormal return is required to reject the null hypothesis. Indeed, by inverting the student test:

$$\frac{r_{ex}}{\sqrt{2 \cdot \frac{Var}{N}}} = \frac{r_{ex}}{\sqrt{2 \cdot \frac{0.0001461}{3761}}} = 1.96 \ \rightarrow \ r_{ex} = 0.0005463 \qquad (10)$$

where r_{ex} is the required mean excess return, *Var* is the series variance and *N* the number of observations. By replacing these two variables with our series statistics (an annual volatility of 19% and 15 years of data), the excess return required to reject the null hypothesis is 13.77% p.a. It means that all tests based on strategies with an annual average return lower than 20% would fail. The test power would be even lower with shorter intervals. Nevertheless, alphas, corresponding to the abnormal return in the CAPM framework, are all positive. Furthermore, one strategy has a significant alpha at the 5% level, two others at the 7% level and the last one at the 11% level. These abnormal returns might not be attributed to risk, at least when volatilities or betas are taken as a proxy. Indeed, three strategies have volatility equal to the market and the fourth one has even a lower one. This is reflected in the Sharpe ratio as well, as strategies have higher values. Transaction costs are not taken into account directly in these results. Nevertheless, as the various strategies change positions only between seven and 39 times over the whole 15 years of the test sample, the inclusion of realistic transaction costs would only diminish the overall performance marginally. This is shown in the very high break even transaction costs level. Figure 4 presents the compounded returns of the various strategies over the entire sample. Although excess returns are not statistically significant according to standard student tests, they are economically significant. Indeed, complex strategies yield a compounded return ranging from 274% to 572% over the evaluation sample, whereas the market returns only 90%. A visual inspection of this figure reveals that excess returns arise from long term trends as strategies performances differ positively during bear markets.

[Insert Figure 4: Complex rules compounded returns]

5.2.2 Market timing test results

In order to confirm the above results, we conduct the formal tests explained in section 4.2. We also provide these statistics for standard simple MA rules widely used in the literature. Panel A of the Table III documents the bootstrap process.

[Insert Table III: Rules positions during Bull and Bear markets]

It displays the median, minimum and maximum value of the four statistics for 500 artificial series. The length of the block is set to 40 days and thus, 94 blocks are available for the bootstrap. First, there is a clear relationship between the parameters length used in the MA rules and the percentage of right signal. The longer (shorter) the length of the MA window is, the higher (lower) the percentage of long position in bull markets is. Nevertheless, the opposite is true for the percentage of short positions during bear markets. This panel supports also the bootstrap methodology (i.e. performing simulations based on each original signals series) used for the test, as the simulated statistics distribution varies widely according to the original structure of trading signal. Indeed, comparing a strategy which is approximately in and out of the market 50% of the time with simulated series being in the market much longer would clearly biased the results[8]. Results in Panel B provide strong evidences that our complex rules exploit long term trends in the market cycle to provide their excess returns. Each complex rule is long during more than 90% of bull markets days. The results are

[8] Indeed, comparing the (2,10) strategies with simulations based on the Opt_4 strategy would be problematic. As simulations have more long positions than the (2,10) strategy (2871 days for the former and only 2329 for the latter), it would be almost impossible for the (2,10) strategy to have an higher percentage of long positions during bull markets, even if it has good timing abilities.

somewhat weaker for bear market, but percentages (between 61% and 74%) are much higher than what it could be achieved by luck, as proved by *p*-values of 0. Furthermore, the total percentage of trading signals corresponding to the various market phases ranges between 83% and 88%. This is higher than the 75% achieved by the buy-and-hold. These results support the timing abilities of complex rules with respect to long term market trends. The results for simple MA rules are also significant, however, percentages levels indicate that complex strategies follow more closely and accurately long term markets trends. In addition, rules based on very short trends have lower percentages than the buy-and-hold.

A critique could arise about the aforementioned results in the sense that the length of block used in the bootstrap process doesn't correspond to the trends, as complex rules keep their trading positions for much longer than our 40 days blocks. To mitigate this issue, Table IV presents similar tests with a block length of 470 days.

[Insert Table IV: Rules positions during Bull and Bear markets]

The main difference in simulated statistics distributions is range of values. Indeed, minimum (maximum) are systematically lower (higher), however, medians are only marginally influenced by the change of the block length. As the new simulated series correspond more closely to the originals, *p*-values associated with the first statistic rise[9]. Nonetheless, evidences in favour of market timing abilities are not reconsidered as *p*-values of the last two statistics, which describe the whole strategy (both long and short positions), remain very low. The findings that complex rules have forecasting power provide justifications regarding financial leverage. Otherwise, it might only bias standard measure of performance.

5.3 Strategies with debt leverage

Table V shows results for the three levels of borrowing costs. We also display the buy-and-hold performance obtained with leverage as well. For the three level of borrowing costs, we obtain an average yearly compounded return of 0%, 1.97% and 5.01%. In contrast, our

[9] As the block bootstrap is performed with replacement, a few of the simulated trading signal series consist only in long positions. However, for these series, the overall performance is not positively biased as they have no short position in bear markets. By investigating every simulated statistics, we find a negative correlation coefficient between the first 2 statistics. Reading *p*-value for the whole strategy (the last two) provide a wider picture and thus mitigate this issue. For very long length of the block (such as the 470 days), a permutation method (i.e. without replacement) might be more appropriate. However, we doubt that such a method would have strong impacts on our results

strategies produce average yearly compounded returns ranging from 9.2% to 19.1% with the first borrowing rate. When the risk free rate is used as borrowing costs, they generate a return ranging from 5.5 times to 10.6 times the leverage buy-and-hold. These ratios are lower when no borrowing costs are considered but remain large (between 2.7 times and 4.7 times). This difference arises from how borrowing costs are taken into account. Indeed, the buy-and-hold is always long and thus has to pay the borrowing costs every day. On the other hand, trading strategies have a significant amount of short positions during which no interest is due. Figure 5 presents the compounded returns over the entire sample for the Optim_4 strategy as well as for various specifications of the buy-and-hold. These results indicate that the higher performance of leveraged strategies is not due to the sole fact of using leverage but genuinely to the forecasting power of these trading systems.

[Insert Table V: Complex rules returns: debt leverage]

[Insert Figure 5: Optim_4 strategy compound returns with debt leverage]

This is confirmed by analysing alphas. Indeed, using leverage without forecasting power would only increase the beta, and thus the normal return for bearing more market risk, but not the alpha. However, we might observe that the alpha of the leverage buy-and-hold without borrowing cost is positive and strongly significant. The average annualized alpha for the four complex strategies without leverage is 9.4%, whereas it is between 1.83 times and 2.2 times higher for the leverage strategies. They are all higher than the 2% p.a. obtained by the leverage buy-and-hold without borrowing costs. On the other hand, annual Sharpe ratios are not significantly higher for leverage strategies. Nevertheless, they consider the standard deviation as a risk measure and therefore require a normal distribution. This is not the case when leverage is used[10]. In a subsequent section, other risk measures taking into account non normal returns are discussed.

5.4 Strategies with traded options

Even if it’s rather unlikely that a fund manager invests his entire capital in traded options, Table describes characteristics of the pure options component of the complex strategies. That

[10] The mean skewness of strategies with debt and options is respectively -0-21 and 2.99, whereas the average kurtosis is 13.40 and 33.85.

corresponds in investing the entire capital in options. Another issue is that returns of -100% are likely and thus, would eliminate the entire wealth. Table VI presents the results of complex strategies investing the totality of the capital in options.

[Insert Table VI: Options returns]

In this table, the buy-and-hold strategy in Panel A (B) consists in having a continuous position in call (put) options. For complex trading strategies, Panel A (B) displays various statistics describing the returns of call (put) options taken after a buy (sell) signal. Panel C provides the same statistics for the global strategies (i.e. call options during long positions and put options during short positions). Firstly, the buy-and-hold call option series over the entire sample provide some insight into the potential and drawbacks of using options. Indeed, both the mean and the median simple returns are negative, whereas the mean underlying return is positive. This is due to options theta, the loss of value due to the passage of time[11]. Another issue arising from options is the systematic difference between mean and median returns. Indeed, the mean is predominantly positive for each strategy and for both the call and put components, whereas the median is systematically negative (or equal to zero for the call options of the Opt_4 strategy). The positive asymmetry is clearly due to the options payoff, as the maximum daily call return is 600% and they range between 183% and 517% for puts. Nevertheless, negative medians indicate that most of returns are negative, even tough trading rules possess market timing abilities. This is reflected in the percentage of days having a negative return, whereas the trading signal was right. They are named as *% neg ret after correct* in the table and they are computed, respectively for calls and puts, as

$$\frac{\sum_{t=1}^{N} 1\left\{ R_{C,t+1} < 0 \middle| R_{BH,t+1} > 0 \text{ \& } S_t = 1 \right\}}{\sum_{t=1}^{N} 1\left\{ R_{BH,t+1} > 0 \text{ \& } S_t = 1 \right\}} \tag{11}$$

$$\frac{\sum_{t=1}^{N} 1\left\{ R_{P,t+1} < 0 \middle| R_{BH,t+1} < 0 \text{ \& } S_t = -1 \right\}}{\sum_{t=1}^{N} 1\left\{ R_{BH,t+1} < 0 \text{ \& } S_t = -1 \right\}} \tag{12}$$

[11] This effect might be magnified in our study as we use options with a relative short time to maturity in order to limit options mispricing.

where N is the number of trading signals, $R_{C,t}$, $R_{P,t}$ and $R_{BH,t}$ stand for the call, put and index return at time t, and S_t the rule trading signal at time t. The operator $1\{A=B\}$ returns one if the condition is true and zero otherwise. This level is situated around 15% for call options and slightly above for puts. Mispricing and decreases in volatility might also be an explanation, however the opposite statistic (i.e. the percentage of positive returns after a erroneous signal) is much lower. These results suggest that options should be used only when the trading strategies possess very strong market timing abilities but they might be counterproductive otherwise.

These findings are naturally reflected in Table VII, which describes the profitability of options in trading strategies, but only as a part of the invested capital as explained in section 4.3.1.

[Insert Table VII: Complex rules with options]

The difference between means of simple and compounded returns is especially noteworthy. Nevertheless, only compounded returns reflect the effective performance obtained by an investor who follows these strategies. Options affect the strategies performance very differently. Indeed, the mean compounded return of the Opt_4 strategy increases from 13.5% annually to 19.2% when 15% of the capital is invested in options. On the other hand, performance of the Opt_all strategy becomes negative. Furthermore, another element in favour of using debt leverage instead is the very large increase in volatility arising from using options. For the Opt_4 strategy, the mean compounded return of 19.2% is associated with an annual volatility of 89%, whereas strategies with debt generate a mean return ranging from 19% to 24% with volatilities lower than 40%. Sharpe ratios are not computed as this measure is not suited for non normal distributions. The next section proposes some risk measures related to higher moments for every strategy examined so far.

5.5 Higher moments and asymmetric risk measures

The abovementioned risk measures rely on the returns normality (the Sharpe ratio) and on the CAPM framework (alphas). Thus, they are not suitable for our leverage strategies. We propose to examine other measures linked to the downside risk and the coskewness. Risk averse investors require a premium for holding assets which either vary more strongly with the market when the latter declines or when an asset decreases the portfolio skewness. This implies that assets with high downside betas and/or low coskewness should have a higher expected return. Ang, Chen and Xing (2006) find that these two risks are priced independently in the cross-sections of stocks returns and they both bear a statistically and economically significant risk premium. We examine, for each strategy, the downside and upside betas (β^- and β^+), the Sortino ratio, the unconditional coskewness (*cos*) and the downside coskewness (cos^-):

$$\beta^- = \frac{\operatorname{cov}\left(R, R_{BH} \,\middle|\, R_{BH} < 0)\right)}{\operatorname{var}\left(R_{BH} \,\middle|\, R_{BH} < 0\right)} \tag{13}$$

$$\beta^+ = \frac{\operatorname{cov}\left(R, R_{BH} \,\middle|\, R_{BH} > 0)\right)}{\operatorname{var}\left(R_{BH} \,\middle|\, R_{BH} > 0\right)} \tag{14}$$

$$Sortino = \frac{\bar{R}}{\sqrt{\sum_{t=1}^{N}\left(R_t \,\middle|\, R_{BH,t} < 0\right) \Big/ \sum_{t=1}^{N} 1\left\{R_{BH,t} < 0\right\}}} \tag{15}$$

$$\cos = \sum_{t=1}^{N}\left(R_t - \bar{R}\right)\left(R_{BH,t} - \bar{R}_{BH}\right)^2 \Big/ N \tag{16}$$

$$\cos^- = \sum_{t=1}^{N}\left[\left(R_t - \bar{R}\right)\left(R_{BH,t} - \bar{R}_{BH}\right)^2 \,\middle|\, R_{BH,t} < 0\right] \Big/ \sum_{t=1}^{N} 1\left\{R_{BH,t} < 0\right\} \tag{17}$$

where R and R_{BH} are the strategy and buy-and-hold returns. Table VIII shows that conclusions obtained with either the Sharpe or the Sortino ratios are similar. However, leverage strategies have positive lower co skewness and in addition, their value is higher than those of standard strategies. In this framework, leverage (especially with debt) increases returns and reduce, at the same time, the risk associated with skewness. In short, combining our strategies with the buy-and-hold would generate a portfolio with a higher skewness when returns are negative. The downside market skewness is -3.1. Our strategies are especially interesting for investors as this “skewness insurance” does not imply lower returns, as it is even the opposite.

[Insert Table VIII: Alternative risk measures]

6. Conclusions and perspectives

No conclusive agreement has been reached in the financial literature about the usefulness of technical analysis as an efficient predictive tool. However, it is obvious that these methods are widely used in practice. This paper adds new insights about the ongoing debate by examining three related issues. First, we examine trading systems based on moving average rules which are not restricted to forecast short term trends, as it is usually done. Indeed, we consider a much wider range of parameters which might also exploit long term trends. Based on recent papers, we use various kinds of complex trading strategies with the aim of using more information and to mitigate the data snooping issue. Then, we propose a new market timing test based on simulations in order to determine whether the new trading strategies tend to follow long term trends in the market. Finally, we also examine the use of financial leverage in the trading strategies, as out performing a market which follows a strong upward trend would require a very high level of predictability. To that purpose, we evaluate the performance of standard strategies combined with debt leverage and with exchange traded options.

We find that combining complex trading strategies with a wider range of parameters generate profitable strategies, especially over the last four years sub sample ending in December 2008. Over our entire test sample, from 1994 to 2008, they produce a compounded return ranging from 274% to 572% whereas the market yields only 90%. These trading systems rely on rules with a length of the long moving average clearly higher than the 200 days used in other studies. The formal tests show that long and short positions coincide strongly with bull and bear market phases, to an extend that might not be reached by luck. The use of debt leverage increases substantially strategies returns. Furthermore, when the buy-and-hold is considered with the same leverage, its return does not increase. That indicates the trading strategies performance is due to their forecasting abilities. However, the investor borrowing rate influences clearly the potential of using debt. On the other hand, exchange traded options are subject to the loss of value as the time pass and thus, provide mixed evidences. Moreover, the investment of a limited part of the available capital in options generates highly volatile series. Finally, we show that our strategies are especially worthwhile in a context which considers the skewness risk.

The above results leave some interesting issues to explore. First of all, considering exchange traded options more in line with the nature of these strategies might produce different conclusions. Indeed, it would make sense to use long term options which have a lower theta. A limit of our results is related to statistical tests. Even if the abnormal returns are economically significant, they are not statistically significant. Indeed, regular student tests require returns which are at least three times higher than the buy-and-hold in order to reject the null hypothesis of equal means. This is clearly difficult to achieve and a solution could be to design new tests based on Markov chains simulations which should be more powerful and flexible. The development of these alternative tests is left for future research.

Appendix A: Description of exchange traded options and their returns

A1. Choice and returns of exchange traded options

Some preliminary work has to be done on the exchange traded option database since it does not include returns. We must use simple returns since a log-transformation would give a minus infinity return for options which expire worthless. First of all, we compute closing prices with the last bid or last ask prices and with the last sale prices according to the methodology given by the *CBOE*[12]. The bid-ask spread is also included in options returns in order to have a realistic proxy. Consequently, the option return differs from days to days whether a new position is initiated or not. It is given by

$$r_{opt,t+1} = \begin{cases} \dfrac{O_{C,t+1} - O_{C,t}}{O_{C,t}} & \text{if } S_{t-1} = S_t = S_{t+1} \\ \dfrac{O_{C,t+1} - O_{B,t}}{O_{B,t}} & \text{if } S_{t-1} \neq S_t = S_{t+1} \\ \dfrac{O_{A,t+1} - O_{C,t}}{O_{C,t}} & \text{if } S_{t-1} = S_t \neq S_{t+1} \\ \dfrac{O_{A,t+1} - O_{B,t}}{O_{B,t}} & \text{if } S_{t-1} \neq S_t \neq S_{t+1} \end{cases} \tag{18}$$

where $O_{C,t}$, $O_{B,t}$, $O_{A,t}$ are respectively the closing, bid and ask option price at time *t* and S_t is the trading signal. The first equation is used when there is no change in the trading position, hence closing prices are used. The second one corresponds to the initiation of a new position which lasts at least two days. The option is bought at the bid price at time *t* and the closing price is used at time *t+1* as there is no trade. The next equation enables to compute returns for the last day of a position, the ask price is used as the option is sold. The return of a position which is kept only one day is calculated with the last equation. Naturally, we apply the same method when the trading signal does not change but the selected option does change.

Indeed, a continuous options time series has to be extract from the whole options database. In line with studies dedicated to the analysis of options returns, we propose the following method: For every trading day, a single put and call option is selected according to the following criterions: Firstly, we identify options with a maturity between 25 and 90 days and a moneyness level between -5% and +5%. This level is computed for call and put options as

[12] If the last sale is between the last bid and last ask the close is on the last sale. If the last sale is less than or equal to the last bid the option series is closed on the last bid and similarly if the last sale is greater than or equal to the last ask, the close is on the last ask. In the case where there is no last sale for an option series the previous day's close is looked at as if it were the last sale and the same rules are applied.

$$
\begin{aligned}
Money_{call,t} &= \frac{P_{C,t} - X}{X} \\
Money_{put,t} &= \frac{X - P_{P,t}}{P_{P,t}}
\end{aligned}
\tag{19}
$$

where $P_{C,t}$ and X are respectively the option closing price at time t and its strike. This calculation ensures that in (out of) the money options have a positive (negative) moneyness level. Then, the option with the highest daily open interest is chosen. The use of a liquidity measure in the selection process should limit mispricing which is more likely to happen when there is no trade in a while. Finally, this option is kept until its time to maturity reaches 10 days.

A2. Descriptive statistics of options returns

Table IX presents option returns descriptive statistics for various groups of options formed according to their maturity and moneyness. Daily returns are calculated with closing prices. The last line of each panel contains the mean option beta obtained under the Black and Scholes assumptions:

$$
\beta_C = \frac{S}{C}\Phi\left[\frac{\ln\left(S/X\right) + \left(r + \sigma^2/2\right)t}{\sigma\sqrt{t}}\right]\beta_s \tag{20}
$$

where S is the underlying current price, C is the call option price (according to the Black and Scholes formula), X is the strike, r is the risk free rate, t is the time to maturity as a fraction of a year, β_S is the underlying beta and σ^2 the volatility estimated by the implied volatility index (VIX).

[Insert Table IX: Statistics of options returns divided according to their maturity and moneyness]

Call option returns share similarities with results in Wilkens (2007) who investigates option returns on the German DAX index according to the CAPM framework. First of all, returns increase from deep-in-the-money call options to at-the-money call options due to a higher leverage however, returns of out-of-the-money options are usually negative and particularly as the maturity decreases. This is in contradiction with the hypothesis of positive expected call option returns and it is probably due to a big loss in temporal value which is not compensated by an increase in intrinsic value, even if the underlying has an upward trend. Obviously, this is more important for option with short time to maturity. It's worth noting that each group, including the put options, has a positive skewness which is consistent with the option asymmetric payoff. The 2% mean daily return for at-the-money call options with a medium maturity represents a massive 500% annualized return which is much higher than its risk measured by its beta. Nevertheless, the not less massive variance and skewness and a mean return equal to zero indicate that this mean return depends strongly on a few positive extreme observations. Indeed, the maximum daily return reaches 473%. Constantinides, Jackwerth and Perrakis (2009) show that similar options are overpriced relative to their theoretical bounds during the 1997-2006 sample. Furthermore, as this is particularly pronounced for out-of-the-money call options, their results confirm our finding that return of out-of-the-money options are systematically lower than their at or in-the money counterparts. This is not compatible with the CAPM framework nonetheless, this might be in line with the economic theory. For instance, out-of-the-money put options are widely used as insurance against a decrease in the index price. These options have consequently a positive coskewness with the market and they should have, according to the Kraus and Litzenberger (1976) framework, an higher price and therefore a lower return. Indeed, investors prefer to hold a portfolio with positive skewness and agree to sacrifice some returns in order acquire an asset which increases their portfolio skewness. This hypothesis requires that such put options are non redundant securities. These various issues might have a negative influence on the performance of trading strategies with traded options. Hence, the option selection method tries to lessen them by choosing at-the-money options.

[Insert Table X Statistics of selected call and put options]

Table X presents statistics of options which are effectively used in our strategies. On average, the relative bid-ask spread is between 6% and 7%[13]. As changing options every day would result in very high trading costs, we keep the same options as long as no other signal is emitted and its maturity is higher than two weeks. Nevertheless, it is important to include this bid-ask spread in order to obtain realistic results, as using closing prices would overestimate the profitability.

[13] The reported spread might be overstated as it is calculated with last bid and last price and does not correspond to an effective trade.

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Table I: Out of sample performance of the Optim_4 strategy

	01.1994-12.1997	01.1998-12.2001	01.2002-12.2004	01.2005-12.2008
Long MA	665	515	415	240
Short MA	65	35	25	50
Selected rule	0.1871	0.1294	0.1035	0.1202
Mean	0.1564	0.0680	0.0513	0.0737
% high	0.00	0.09	0.03	0.03
% low	0.56	0.91	0.97	0.97

Note: Long and Short MA are respectively the length of the long and short MA of the rule selected by the optimization process used by the Optim_4 strategy. Selected rule is the out-of-sample mean yearly return of this strategy. Mean is the mean yearly return on average across the whole set of trading rules considered. % high is the percentage of rules with a higher return than the selected rule and % low is the percentage of rule with a lower return.

Table II: Complex rules returns

	BH	RW	Best	Opt_all	Voting	Opt_4	Partial
Nb buy	3761	1999	2893	2907	2924	2872	2924
% right buy	53.1%	51.3%	54.6%	54.2%	54.4%	54.7%	54.4%
Nb sell		1758	868	853	837	889	837
% right sell		44.6%	51.8%	50.5%	51.1%	51.7%	51.1%
% right strategy	53.1%	48.2%	54.0%	53.4%	53.7%	54.0%	53.7%
Mean buy		-0.0001	0.0005	0.0004	0.0005	0.0005	0.0005
Annual Mean buy		-0.0223	0.1332	0.1098	0.1167	0.1360	0.1157
Tstat		*-1.03*	*1.05*	*0.70*	*0.80*	*1.09*	*0.80*
Mean sell		-0.0006	0.0007	0.0004	0.0005	0.0007	0.0004
Annual Mean sell		-0.1577	0.1771	0.0975	0.1312	0.1789	0.1132
Tstat		*-2.41*	*0.90*	*0.28*	*0.54*	*0.92*	*0.40*
Mean strategy	0.0002	-0.0003	0.0006	0.0004	0.0005	0.0006	0.0005
Annual Mean	0.0616	-0.0855	0.1433	0.1070	0.1200	0.1461	0.1151
Tstat		*-2.10*	*1.16*	*0.65*	*0.83*	*1.20*	*0.78*
Mean an comp	0.0441	-0.0988	0.1330	0.0925	0.1068	0.1362	0.1032
Vol buy	0.138	0.172	0.149	0.151	0.151	0.148	0.145
Vol sell	0.146	0.212	0.293	0.291	0.293	0.292	0.279
Vol strategy	0.192	0.192	0.192	0.192	0.192	0.192	0.183
Nb trade	1	3895	7	39	7	11	11.54
Break even TC		-0.06%	17.43%	1.74%	12.45%	11.48%	6.93%
Beta	1	-0.15	-0.08	-0.04	-0.03	-0.09	-0.03
Tstat		*-9.07*	*-4.68*	*-2.75*	*-2.12*	*-5.74*	*-1.92*
Alpha		-0.0004	0.0005	0.0003	0.0004	0.0005	0.0003
Annual alpha		-0.1102	0.1164	0.0790	0.0917	0.1198	0.0867
Tstat		*-2.25*	*2.35*	*1.59*	*1.85*	*2.42*	*1.83*
SR	0.011	-0.038	0.037	0.025	0.030	0.038	0.029
Annual SR	0.168	-0.599	0.594	0.404	0.472	0.609	0.467

Note: This table reports results of complex strategies over the entire evaluation period, from 01.1994 to 12.2008. Nb buy and Nb sell are the number of long and short positions, % right correspond to the percentage of returns higher than zero. This statistic is proposed for the buy, sell and strategy signals. Mean buy (sell) is the mean return of long (short) positions with their associated Tstat. These tests aim at determining whether the mean of the specific series is higher than the mean return of the buy-and-hold. Mean an comp is the mean annual compounded return. Vol buy, sell and strategy are respectively the annual volatility of the long, short and overall positions. Break even TC is the level of transaction cost that makes the excess return equal to zero. Beta and Alpha are estimated in the static CAPM framework and SR is the Sharpe Ratio.

Table III: Rules positions during Bull and Bear markets

Panel A: Block Bootstrap estimation (block length of 40 days)

	Best	Opt_all	Voting	Opt_4	Partial	(2,10)	(10,50)	(5,100)	(50,200)
% buy-Bull									
median	77.4	77.6	78.0	76.5	77.8	57.2	62.2	64.6	69.4
min	58.4	62.9	61.4	61.9	62.9	51.6	44.1	52.5	52.5
max	91.8	91.8	90.0	89.4	92.1	62.3	72.5	77.1	83.7
% sell-Bear									
median	23.1	22.4	21.5	23.3	22.2	42.6	37.9	34.9	29.0
min	2.3	1.6	3.2	0.0	0.0	31.7	20.8	9.9	7.5
max	52.0	52.8	48.0	51.5	49.9	51.9	62.0	56.7	52.1
% right									
median	63.8	63.8	64.0	63.4	64.0	53.6	56.4	57.4	59.6
min	47.4	50.3	48.9	50.4	49.1	48.0	39.2	44.8	46.4
max	77.9	80.7	75.1	74.1	75.9	58.2	65.8	67.4	73.4
% wrong									
median	36.2	36.2	36.0	36.6	36.0	46.4	43.6	42.6	40.4
min	22.1	19.3	24.9	25.9	24.1	41.8	34.2	32.6	26.6
max	52.6	49.7	51.1	49.6	50.9	52.0	60.8	55.2	53.6

Panel B: Statistics of strategies

	Best	Opt_all	Voting	Opt_4	Partial	(2,10)	(10,50)	(5,100)	(50,200)
Nb buy	2892	2906	2923	2871	2923	2329	2323	2426	2632
Nb sell	868	853	837	889	837	1431	1437	1334	1128
% buy-Bull	92.4	90.2	91.8	93.0	91.8	62.2	71.0	76.7	85.9
p value	*0*	*0*	*0*	*0*	*0*	*0.01*	*0.01*	*0.002*	*0*
% sell-Bear	70.2	61.9	65.0	74.0	65.0	57.9	66.1	72.4	78.1
p value	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
% right	86.9	83.2	85.2	88.3	85.2	61.1	69.8	75.6	83.9
p value	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
% wrong	13.1	16.8	14.8	11.7	14.8	38.9	30.2	24.4	16.1
p value	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*

Note: The first five columns refers to the complex trading rules considered in this study whereas the last four correspond to standard simple MA rules. For instance, the first of these simple rules has a length of the short MA of 2 days for a long MA of 10 days. No bandwidth are used. The statistics in panel A describe the distribution of the 500 simulated series created independently with the original trading signal series. The *p*-values in panel B correspond to the percentage of simulated series which have a statistic higher than the original.

Table IV: Rules positions during Bull and Bear markets

Panel A: Block Bootstrap estimation (block length of 470 days)

	Best	Opt_all	Voting	Opt_4	Partial	(2,10)	(10,50)	(5,100)	(50,200)
% buy-Bull									
median	78.4	78.7	78.3	77.6	78.1	57.8	62.5	65.3	71.0
min	22.8	21.1	31.4	28.5	22.8	46.4	40.7	39.0	23.8
max	100.0	100.0	100.0	99.3	100.0	65.6	78.9	86.1	95.2
% sell-Bear									
median	21.5	17.5	22.7	23.6	21.8	43.2	38.5	37.7	31.3
min	0.0	0.0	0.0	0.0	0.0	31.8	14.7	10.2	0.0
max	89.8	85.8	100.0	100.0	100.0	59.5	70.9	76.1	100.0
% right									
median	64.7	64.6	65.1	64.4	64.5	54.1	56.6	58.4	60.9
min	30.6	22.9	30.3	30.1	20.9	45.9	38.5	36.4	25.3
max	86.4	86.4	86.5	88.8	88.9	60.4	71.6	79.1	82.7
% wrong									
median	35.3	35.4	34.9	35.6	35.5	45.9	43.4	41.6	39.1
min	13.6	13.6	13.5	11.3	11.1	39.6	28.4	20.9	17.3
max	69.4	77.1	69.7	69.9	79.1	54.1	61.5	63.6	74.7

Panel B: Statistics of strategies

	Best	Opt_all	Voting	Opt_4	Partial	(2,10)	(10,50)	(5,100)	(50,200)
Nb buy	2892	2906	2923	2871	2923	2151	2323	2426	2632
Nb sell	868	853	837	889	837	1609	1437	1334	1128
% buy-Bull	92.4	90.2	91.8	93.0	91.8	62.2	71.0	76.7	85.9
p value	*0.111*	*0.145*	*0.123*	*0.091*	*0.137*	*0.055*	*0.095*	*0.062*	*0.066*
% sell-Bear	70.2	61.9	65.0	74.0	65.0	57.9	66.1	72.4	78.1
p value	*0.015*	*0.042*	*0.045*	*0.007*	*0.045*	*0.012*	*0.011*	*0.004*	*0.005*
% right	86.9	83.2	85.2	88.3	85.2	61.1	69.8	75.6	83.9
p value	*0*	*0.009*	*0.002*	*0.001*	*0.001*	*0*	*0.005*	*0.001*	*0*
% wrong	13.1	16.8	14.8	11.7	14.8	38.9	30.2	24.4	16.1
p value	*1*	*0.991*	*0.998*	*0.999*	*0.999*	*1*	*0.995*	*0.999*	*1*

Note: The length of the block is equal to 470 and the number of simulation is 1000.

Table V: Complex rules returns: debt leverage

Panel A: borrowing rate = US Bank prime loan

	BH	Best	Opt_all	Voting	Opt_4	Partial
Buy	0.073	0.213	0.166	0.18	0.219	0.18
Sell		0.354	0.195	0.262	0.358	0.226
Strategy	0.073	0.244	0.162	0.197	0.249	0.187
Tstat		*1.21*	*0.63*	*0.88*	*1.25*	*0.83*
Compound	0.000	0.185	0.092	0.13	0.191	0.127
Volatility	0.384	0.383	0.384	0.384	0.383	0.367
Beta	2.000	-0.152	-0.09	-0.069	-0.186	-0.06
Tstat	*22418*	*-4.68*	*-2.75*	*-2.12*	*-5.73*	*-1.92*
Alpha	-0.02	0.22	0.136	0.169	0.226	0.16
Tstat	*-74.63*	*2.22*	*1.37*	*1.71*	*2.28*	*1.68*
SR	0.11	0.56	0.346	0.436	0.573	0.43

Panel B: borrowing rate =risk free rate

	BH	Best	Opt_all	Voting	Opt_4	Partial
Buy	0.093	0.234	0.186	0.2	0.239	0.199
Sell		0.354	0.195	0.262	0.358	0.226
Strategy	0.093	0.26	0.178	0.212	0.264	0.202
Tstat		*1.18*	*0.6*	*0.85*	*1.22*	*0.79*
Compound	0.020	0.204	0.109	0.148	0.21	0.144
Volatility	0.384	0.383	0.384	0.384	0.383	0.367
Beta	2.000	-0.152	-0.09	-0.069	-0.186	-0.06
Tstat	*22727*	*-4.68*	*-2.75*	*-2.12*	*-5.73*	*-1.92*
Alpha	0.00	0.235	0.151	0.185	0.241	0.175
Tstat	*-1.00*	*2.37*	*1.52*	*1.87*	*2.44*	*1.84*
SR	0.17	0.6	0.387	0.477	0.613	0.471

Panel C: no borrowing cost

	BH	Best	Opt_all	Voting	Opt_4	Partial
Buy	0.123	0.266	0.22	0.233	0.272	0.231
Sell		0.354	0.195	0.262	0.358	0.226
Strategy	0.123	0.285	0.203	0.238	0.289	0.227
Tstat		*1.15*	*0.57*	*0.82*	*1.19*	*0.76*
Compound	0.050	0.235	0.138	0.178	0.24	0.173
Volatility	0.384	0.383	0.384	0.384	0.383	0.367
Beta	2.000	-0.152	-0.089	-0.069	-0.186	-0.06
Tstat	*18242*	*-4.67*	*-2.75*	*-2.11*	*-5.72*	*-1.92*
Alpha	0.03	0.26	0.177	0.211	0.266	0.2
Tstat	*87.17*	*2.63*	*1.78*	*2.12*	*2.69*	*2.1*
SR	0.24	0.666	0.454	0.544	0.678	0.539

Note: BH corresponds to the leverage buy-and-hold according to the respective borrowing costs. All these statistics are annualized, including the alpha. Buy, Sell and Strategy correspond respectively to the mean annual simple return of the long positions, sell positions and complete strategy. Compound is the mean annual compounded strategy return and Volatility the annual volatility. The Tstat results from a student test for equality in means between the specific statistics and the buy-and-hold return. Beta and alpha are obtained from an OLS regression with excess returns. SR is the Sharpe ratio.

Table VI: Options returns

Panel A: Long position - call options

	BH	Best	Opt_all	Voting	Opt_4	Partial
Nb obs	3761	2893	2907	2924	2872	2924
Mean return	-0.0042	0.0030	0.0018	0.0019	0.0045	0.0026
Annual mean	-1.0573	0.7608	0.4599	0.4851	1.1335	0.6521
Median return	-0.0079	-0.0017	-0.0027	-0.0027	0	-0.0022
Annual median	-2	-0.4297	-0.6792	-0.6758	0	-0.5557
Min return	-1	-1	-1	-1	-1	-1
Max return	6	6	6	6	6	5.9698
Skewness	4.50	4.86	5.20	5.16	4.87	5.15
Kurtosis	56.68	63.28	66.51	65.66	62.79	66.74
% neg ret after correct	0.152	0.152	0.152	0.153	0.151	0.153
% pos ret after wrong	0.047	0.047	0.047	0.047	0.048	0.047
Volatility	0.336	0.330	0.341	0.342	0.331	0.330

Panel B: Short position - put options

	BH	Best	Opt_all	Voting	Opt_4	Partial
Nb obs	3761	868	853	837	889	837
Mean return	-0.0166	0.0132	-0.0019	0.0066	0.0136	0.0058
Annual mean	-4.1843	3.3183	-0.4758	1.6533	3.4201	1.4715
Median return	-0.0538	-0.0355	-0.0429	-0.0400	-0.0357	-0.0267
Annual median	-13.55	-8.95	-10.80	-10.08	-9.00	-6.73
Min return	-1	-0.69	-0.69	-0.69	-0.69	-0.68
Max return	9.23	5.17	1.83	5.17	5.17	2.29
Skewness	7.15	5.00	1.10	5.21	5.06	1.92
Kurtosis	163.04	71.98	6.42	75.68	73.01	13.59
% neg ret after correct	0.177	0.162	0.174	0.173	0.154	0.173
% pos ret after wrong	0.033	0.005	0.005	0.005	0.005	0.005
Volatility	0.341	0.330	0.279	0.329	0.327	0.263

Panel C: Strategy - call and put options

	BH	Best	Opt_all	Voting	Opt_4	Partial
Nb obs		3761	3760	3761	3761	3761
Mean return		0.0054	0.0010	0.0030	0.0066	0.0033
Annual mean		1.3510	0.2476	0.7451	1.6740	0.8345
Median return		-0.0091	-0.0110	-0.0101	-0.0083	-0.0088
Annual median		-2.29	-2.77	-2.55	-2.08	-2.23
Min return		-1	-1	-1	-1	-1
Max return		6	6	6	6	5.97
Skewness		4.89	4.68	5.17	4.91	4.79
Kurtosis		65.27	60.90	67.69	65.10	62.79
Volatility		0.339	0.330	0.328	0.339	0.330

Note: This table presents various statistics of options returns obtained with the strategies trading signals. The series consist only in options. BH describes the buy-and-hold strategy with the selected options. *% neg ret after correct* is the percentage of negative option returns, whereas the trading signal was correct (for instance, a negative call options return whereas the underlying return was positive). *% pos ret after wrong* is the opposite. Volatility is the daily volatility of the options used in the trading strategies.

Table VII: Complex rules with options

Panel A: 5% of options

	BH	Best	Opt_all	Voting	Opt_4	Partial
Mean buy	0.0156	0.0009	0.0007	0.0008	0.0010	0.0008
Mean sell	-0.0171	0.0015	0.0005	0.0010	0.0015	0.0008
Mean strategy	0.0003	0.0010	0.0007	0.0008	0.0011	0.0008
Annual mean	0.0737	0.2575	0.1705	0.2068	0.2760	0.2032
Compound	0.0000	0.0007	0.0004	0.0005	0.0008	0.0005
Annual compound	-0.0070	0.1959	0.0964	0.1342	0.2182	0.1431
Vol buy	0.023	0.023	0.024	0.024	0.023	0.023
Vol sell	0.015	0.031	0.030	0.031	0.031	0.027
Vol strategy	0.026	0.025	0.025	0.026	0.025	0.024
Annual Vol strategy	0.408	0.402	0.402	0.409	0.402	0.378

Panel B: 10% of options

	BH	Best	Opt_all	Voting	Opt_4	Partial
Mean buy	0.0233	0.0013	0.0011	0.0011	0.0014	0.0011
Mean sell	-0.0257	0.0022	0.0005	0.0014	0.0023	0.0012
Mean strategy	0.0003	0.0015	0.0009	0.0012	0.0016	0.0012
Annual mean	0.0858	0.3718	0.2341	0.2936	0.4059	0.2912
Compound	-0.0005	0.0007	0.0002	0.0004	0.0008	0.0005
Annual compound	-0.1088	0.1944	0.0415	0.0969	0.2359	0.1286
Vol buy	0.040	0.039	0.040	0.040	0.039	0.038
Vol sell	0.023	0.046	0.042	0.046	0.046	0.038
Vol strategy	0.041	0.041	0.040	0.041	0.041	0.038
Annual Vol strategy	0.655	0.644	0.643	0.658	0.645	0.602

Panel C: 15% of options

	BH	Best	Opt_all	Voting	Opt_4	Partial
Mean buy	0.0310	0.0016	0.0014	0.0014	0.0018	0.0015
Mean sell	-0.0344	0.0030	0.0006	0.0019	0.0031	0.0016
Mean strategy	0.0004	0.0019	0.0012	0.0015	0.0021	0.0015
Annual mean	0.0980	0.4860	0.2977	0.3804	0.5357	0.3792
Compound	-0.0011	0.0005	-0.0002	0.0000	0.0007	0.0003
Annual compound	-0.2417	0.1343	-0.0593	0.0067	0.1922	0.0662
Vol buy	0.058	0.055	0.056	0.056	0.055	0.053
Vol sell	0.031	0.062	0.055	0.061	0.061	0.049
Vol strategy	0.057	0.056	0.056	0.058	0.056	0.052
Annual Vol strategy	0.909	0.893	0.890	0.914	0.893	0.832

Note: This table presents the performance of the trading strategies with traded options according to the three level of leverage. Mean buy, sell and strategy are respectively the simple mean of the long, short and global positions. Compound is the mean compound return of the strategies and Annual compound is it annualized value. Vol buy, sell and strategy are the volatilities of the two parts of the strategies and the entire one. Annual Vol strategy is the annual volatility of the global strategy.

Table VIII: Alternative risk measures

		β^-	β^+	Sortino	Cos	Cos^-
Standard	BH	1.000	1.000	0.0195	-0.007	-0.250
	Opt_all	-0.053	-0.036	0.0342	-0.024	0.179
	Voting	-0.047	-0.022	0.0383	-0.026	0.176
	Opt_4	-0.124	-0.061	0.0469	-0.020	0.188
	Partial	-0.044	-0.015	0.0385	-0.023	0.177
Debt Borrowing cost	BH	2.004	1.996	0.0117	-0.013	-0.499
	Opt_all	-0.103	-0.075	0.0260	-0.048	0.359
	Voting	-0.091	-0.045	0.0315	-0.051	0.352
	Opt_4	-0.245	-0.123	0.0402	-0.040	0.378
	Partial	-0.086	-0.032	0.0315	-0.045	0.355
Debt RF	BH	2.000	2.000	0.0149	-0.014	-0.499
	Opt_all	-0.106	-0.072	0.0285	-0.048	0.359
	Voting	-0.094	-0.042	0.0340	-0.051	0.352
	Opt_4	-0.248	-0.120	0.0426	-0.040	0.377
	Partial	-0.088	-0.029	0.0340	-0.045	0.355
Debt no cost	BH	1.994	2.007	0.0195	-0.014	-0.499
	Opt_all	-0.110	-0.067	0.0325	-0.048	0.359
	Voting	-0.098	-0.037	0.0380	-0.052	0.352
	Opt_4	-0.252	-0.115	0.0465	-0.041	0.377
	Partial	-0.093	-0.024	0.0381	-0.046	0.355
Options 5%	BH	1.726	1.974	0.0131	0.052	-0.321
	Opt_all	0.044	0.373	0.0314	0.055	0.281
	Voting	0.034	0.401	0.0380	0.057	0.280
	Opt_4	-0.115	0.309	0.0516	0.057	0.304
	Partial	0.063	0.396	0.0400	0.051	0.277
Options 10%	BH	2.452	2.949	0.0102	0.111	-0.392
	Opt_all	0.142	0.781	0.0289	0.134	0.382
	Voting	0.115	0.824	0.0363	0.140	0.384
	Opt_4	-0.107	0.679	0.0511	0.135	0.419
	Partial	0.169	0.806	0.0387	0.125	0.376
Options 15%	BH	3.179	3.923	0.0087	0.169	-0.464
	Opt_all	0.239	1.189	0.0275	0.213	0.484
	Voting	0.196	1.246	0.0351	0.223	0.488
	Opt_4	-0.099	1.049	0.0505	0.212	0.534
	Partial	0.275	1.217	0.0378	0.199	0.476

Note: This table display statistics presented in section 0 for all complex strategies and the buy-and-hold. The five first line grouped under the Standard name correspond to strategies without financial leverage. The six subsequent groups refer to the debt leverage strategies according to the three level of borrowing costs and to the strategies with options. Values in the two last columns are multiplied by 10’000.

Table IX: Statistics of options returns divided according to their maturity and moneyness

Panel A: Call options

	Short maturity					Medium maturity					Long Maturity				
	Moneyness					Moneyness					Moneyness				
	DOM	OM	AM	IM	DIM	DOM	OM	AM	IM	DIM	DOM	OM	AM	IM	DIM
Nb option	1291	3083	5352	3688	2936	1272	3288	5505	3615	2841	860	1509	2116	1417	1169
Nb obs	17079	34822	71749	46301	48326	28465	55248	108380	64042	75692	57716	65754	86811	64729	108737
Mean	-0.020	-0.093	0.019	0.018	0.006	-0.011	-0.035	0.020	0.009	0.004	-0.010	-0.004	0.005	0.005	0.005
Median	0.000	0.000	-0.028	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Min	-1	-1	-1	-0.62	-0.39	-0.98	-0.90	-0.83	-0.46	-0.34	-0.98	-1.00	-0.64	-0.37	-0.79
Max	14.70	19.00	72.68	3.81	1.82	19.00	11.00	473.00	1.28	0.93	8.00	9.64	1.74	0.82	104.77
Var	0.267	0.268	0.912	0.018	0.004	0.212	0.123	2.279	0.008	0.003	0.061	0.026	0.009	0.003	0.167
Skewness	9.41	6.03	28.78	4.42	3.05	15.27	5.06	290.13	1.42	1.99	12.11	7.04	1.62	0.88	232.35
Kurtosis	168.05	123.06	1501.21	72.47	60.92	398.89	78.16	89480.54	13.73	28.39	279.52	255.72	19.15	11.30	55428.55
Beta	221.74	146.30	57.39	11.88	4.75	34.51	29.08	19.87	9.83	4.49	14.23	12.80	9.91	6.83	3.80

Panel B: Put options

	Short maturity					Medium maturity					Long Maturity				
	Moneyness					Moneyness					Moneyness				
	DOM	OM	AM	IM	DIM	DOM	OM	AM	IM	DIM	DOM	OM	AM	IM	DIM
Nb option	2528	3852	5312	2942	1403	2494	3743	5462	3227	1376	1053	1417	2047	1373	830
Nb obs	41448	51105	70719	31811	17857	67322	71400	107006	49920	29674	101269	72713	81903	52709	48093
Mean	-0.050	-0.107	-0.010	0.039	0.022	-0.019	-0.017	-0.001	0.021	0.021	-0.006	-0.006	0.000	0.006	0.009
Median	0.000	-0.111	-0.072	0.000	0.003	0.000	-0.031	-0.014	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Min	-1	-1	-1	-0.66	-0.43	-0.974	-0.84	-0.73	-0.51	-0.41	-0.9	-0.65	-0.52	-0.43	-0.36
Max	16.00	19.10	152.17	3.75	1.69	10.50	9.27	11.78	2.20	0.88	8.00	2.71	1.95	21.46	0.66
Var	0.159	0.376	1.181	0.041	0.013	0.097	0.093	0.046	0.019	0.009	0.025	0.014	0.011	0.016	0.004
Skewness	5.62	9.07	63.69	3.77	2.75	6.70	5.88	5.37	1.95	1.70	6.70	2.65	1.83	93.22	1.35
Kurtosis	133.40	181.70	6944.85	34.75	22.61	126.40	101.40	163.52	14.13	11.70	159.10	34.92	18.94	15455.42	11.35
Beta	-69.04	-136.23	-57.76	-11.76	-4.04	-58.96	-40.62	-20.58	-9.65	-3.82	-27.06	-16.22	-10.86	-6.77	-3.17

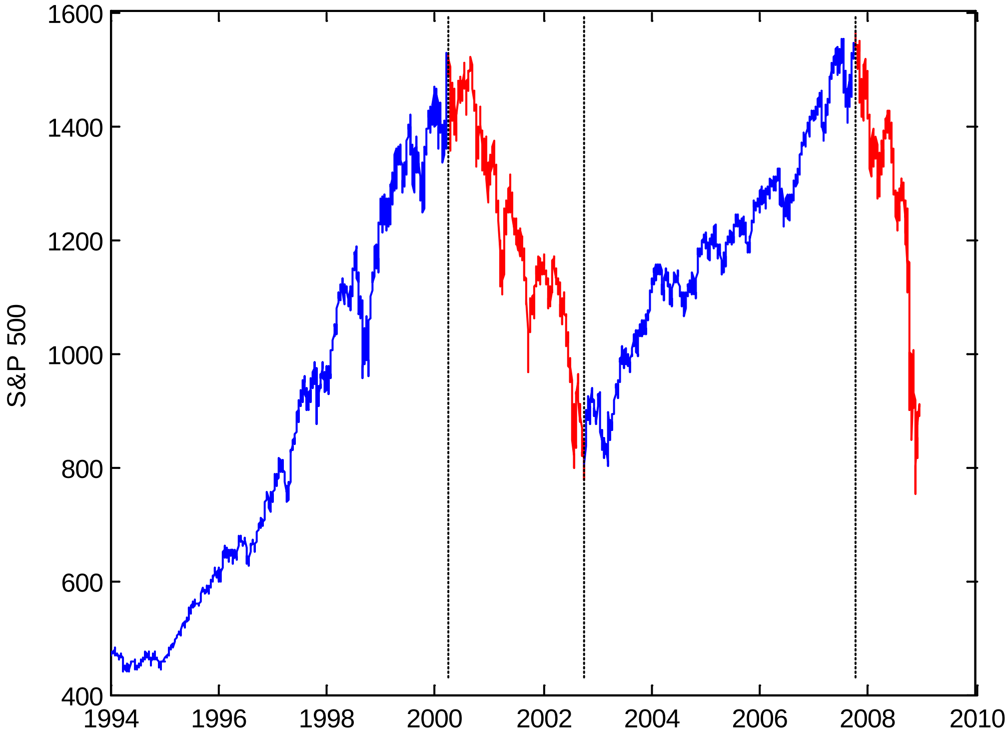
Note: These statistics relates to the entire option sample, from January 1990 to December 2008. Short (long) maturity contains option with less (more) than 30 (90) days to maturity. Medium maturity comprises options with a maturity between 30 and 90 days. DOM stands for deep-out-of-the money (moneyness < -0.15), OM for out-of-the-money (-0.15 ≤ moneyness < -0.05), AM for at-the-money (-0.05 ≤ moneyness < 0.05), IM for in-the-money (0.05 ≤ moneyness < 0.15) and DIM for deep-in-the-money (money >= 0.15). Returns are calculated with options closing prices and Beta is the average beta obtained under the Black and Scholes assumptions.

Table X: Statistics of selected call and put options

	Call	Put
mean return	0.0048	-0.0076
median return	-0.0069	-0.0292
Open interest	41915.7	45851.3
daily volume	2806.0	3660.1
relative BA spread	0.0685	0.0674
moneyness	-0.0048	-0.0164
maturity	51.1	51.1
BS beta	20.5	-24.2

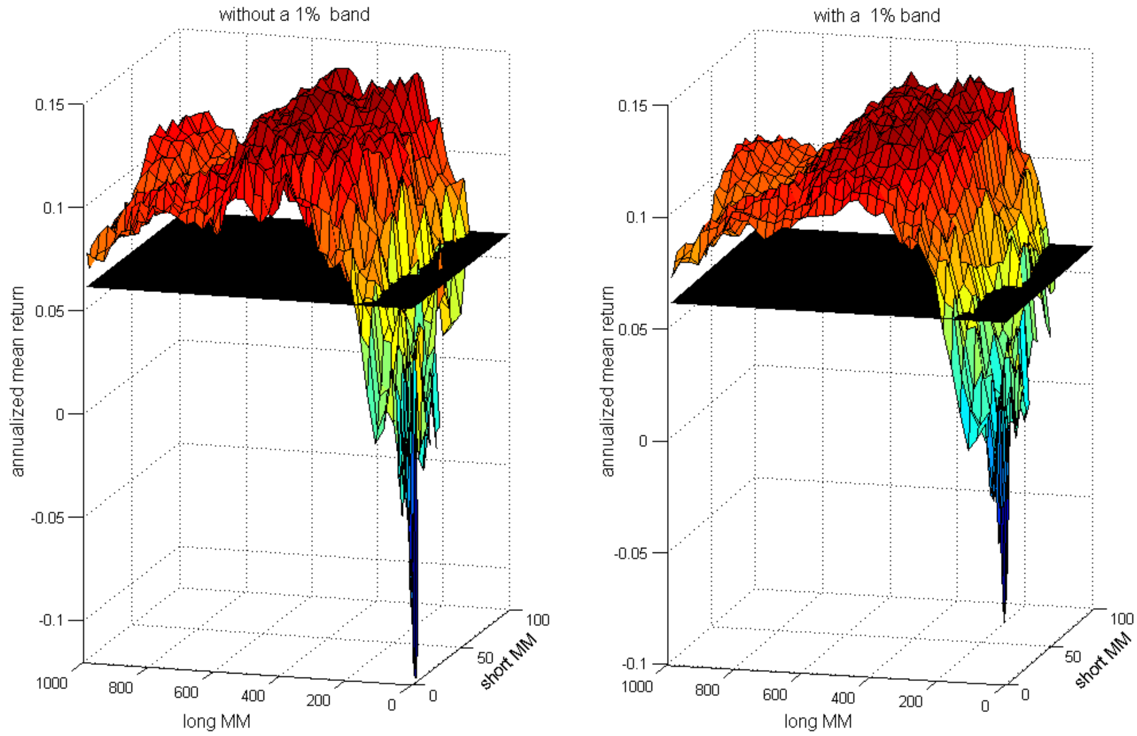
Note: Statistic calculated over the entire sample, from 1990 to 2008. Mean return is the simple daily or weekly mean return, daily volume is the number of contract traded during this day, relative BA spread is the relative bid-ask spreak and BS beta is the beta obtained under the Black and Scholes assumptions.

Figure 1: Bull and Bear markets



Note: This graphs present trends identified as bull markets in blue and bear markets in red.

Figure 2: Simple MA rules returns



Note: These figures report annual mean returns of all individual MM rules over the entire sample ranging from 1990 to 2008. The horizontal plane is the average buy-and-hold return over this period, i.e. 6.1%.

Figure 3: Simple MA rules returns: subsamples

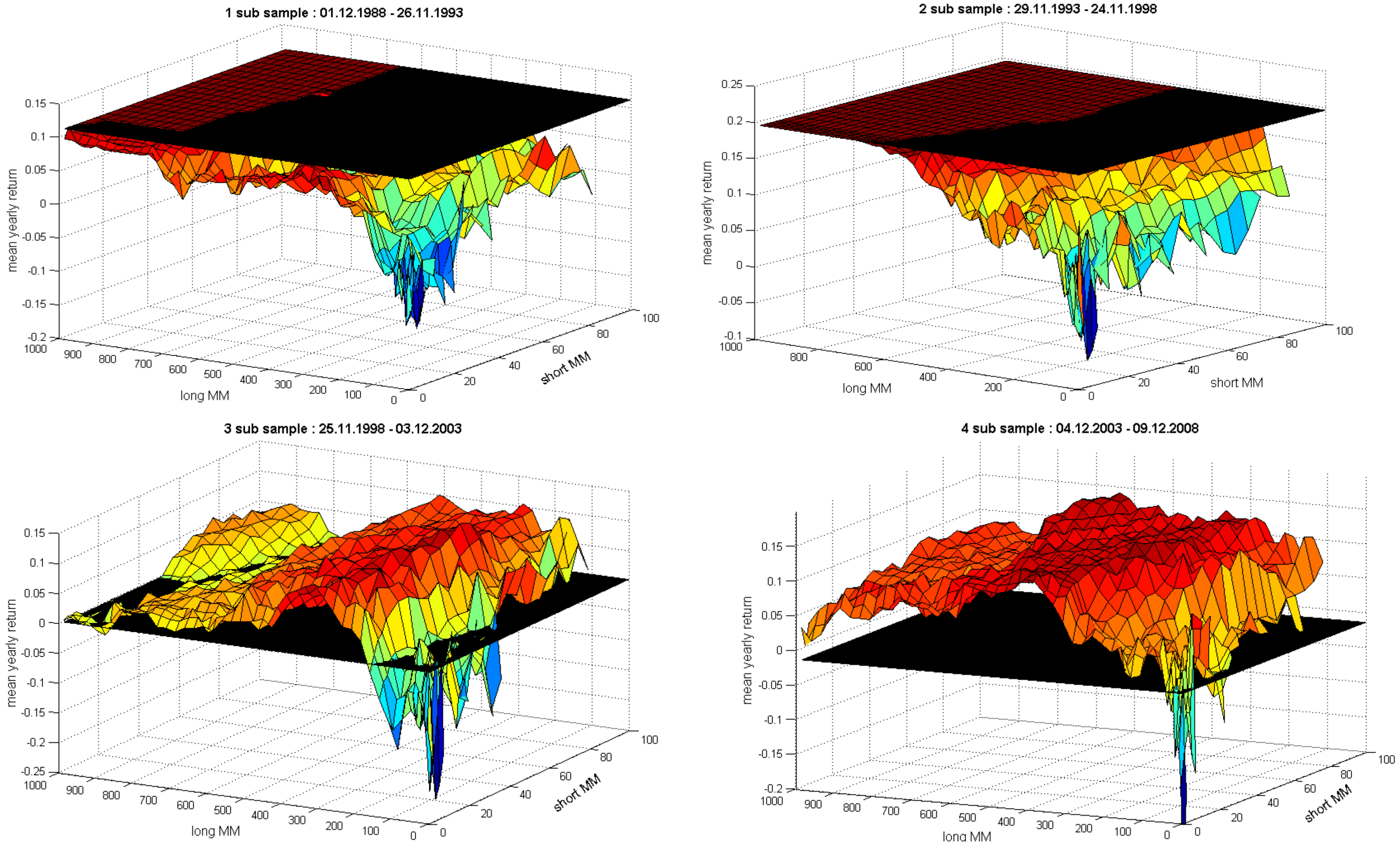
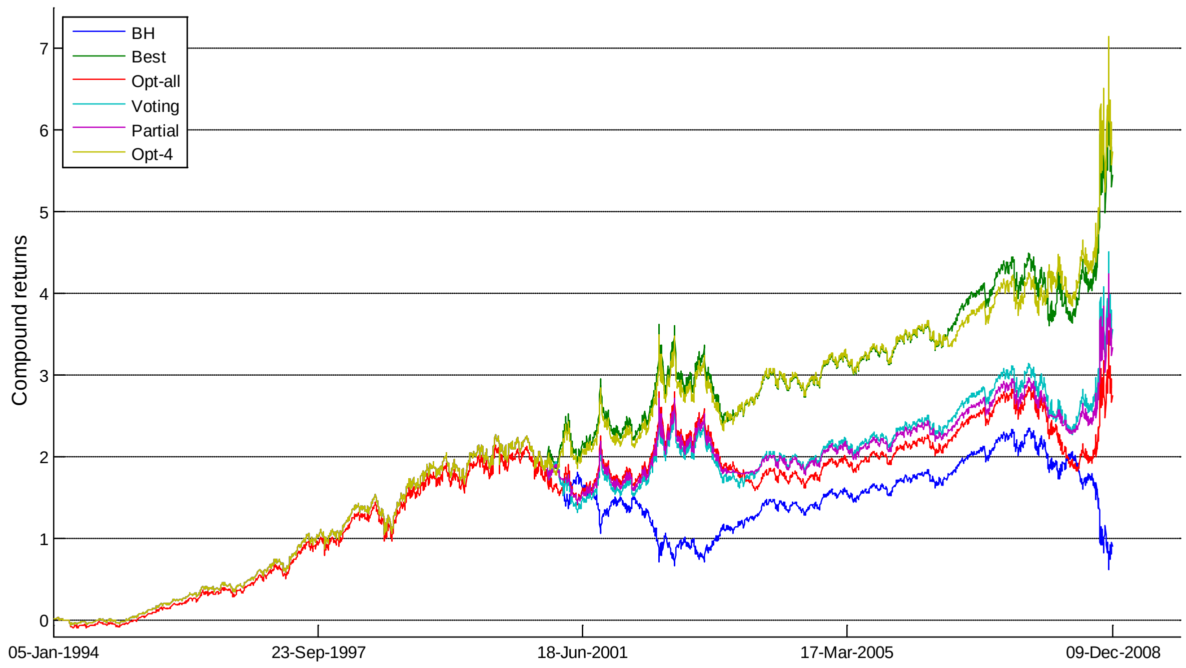
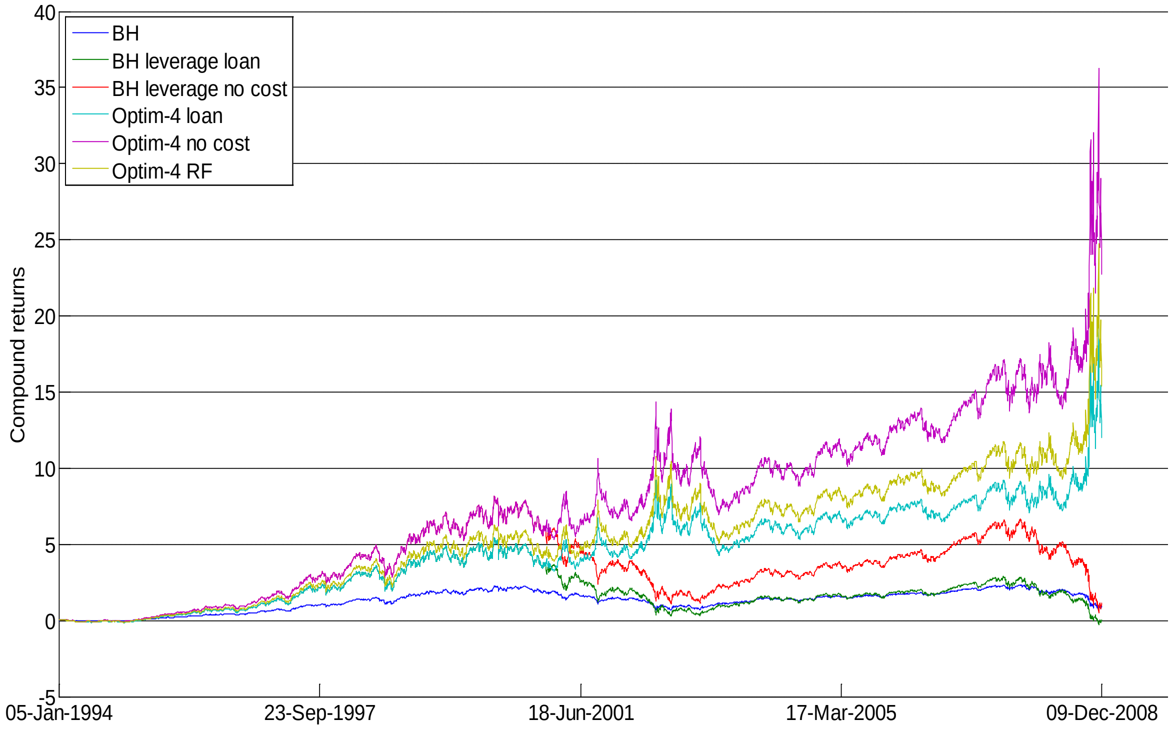


Figure 4: Complex rules compounded returns



Note: This figure presents the compounded return over the entire test period for two benchmark strategies, the buy-and-hold and the Best strategy and the four complex strategies.

Figure 5: Optim_4 strategy compound returns with debt leverage



Note: This figure presents the compound return over the entire test period. BH, BH leverage loan and BH leverage no cost correspond respectively to the buy-and-hold without leverage, the buy-and-hold return with leverage when the US bank loan rate is used as borrowing rate and the last one when no borrowing cost are considered. The three last series are those of the Optim_4 strategy with the three levels of borrowing costs taken into account.