

# The Performance Analysis of Chart Patterns: Monte Carlo Simulation and Evidence from the Euro/Dollar Foreign Exchange Market

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## Abstract

We investigate the existence of chart patterns in the Euro/Dollar intra-daily foreign exchange market. We use two identification methods of the different chart patterns: one built on five-minute close prices only, and one based on both five-minute low and high prices. We look for twelve types of chart patterns and we study the detected patterns through two criteria : predictability and profitability. We run a Monte Carlo simulation to compute the statistical significance of the obtained results. We find an apparent existence of some chart patterns in the currency market. More than one half of detected charts present a significant predictability. Nevertheless, only two chart patterns imply a significant profitability which is however too small to cover the transaction costs. The second extrema detection method provides higher but riskier profits than the first one.

*Key words:* foreign exchange market, chart patterns, high frequency data, technical analysis.

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## 1 Introduction

Technical analysis is the oldest method for analyzing market behavior. It is defined by Murphy (1999) as the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends. The term ‘market action’ includes three main sources of information available to the technician: price, volume and open interest. Béchu and Bertrand (1999) distinguish three categories of technical analysis. Traditional analysis is entirely based on the study of charts and the location of technical patterns like the Head and Shoulders pattern. Modern analysis is composed of more quantitative methods like moving averages, oscillators, etc. The third category, qualified as philosophical, has the ambition to explain more than the overall market behavior. One of the most famous examples is the Elliot wave theory (for more details see Prost and Prechter, 1985) which assumes that every price movement can be decomposed into eight phases or waves: five impulse waves and three corrective ones.

In this paper, we focus on the traditional approach of technical analysis and particularly on chart patterns. These patterns have been studied, among others, by Levy (1971), Osler (1998), Dempster and Jones (1998a), Chang and Osler (1999), and Lo, Mamaysky, and Wang (2000) who have mainly focused on the profitability of trading rules related to chart patterns and also on the informational content that could generate such patterns. All these investigations conclude to the lack of profitability of technical patterns. However, Lo, Mamaysky, and Wang (2000) find that these patterns present an informational

content that affect stock returns.

We investigate twelve chart patterns in the Euro/Dollar foreign exchange market. Currency markets seem especially appropriate for testing technical signals because of their very high liquidity, low bid-ask spread, and round-the-clock decentralized trading (Chang and Osler, 1999). As our empirical evidence is built upon high frequency data, we rather focus on the speed of convergence to market efficiency than on the hypothesis of market efficiency per se. As argued by Chordia, Roll, and Subrahmanyam (2002), information takes a minimum of time to be incorporated into prices so that markets may be at the same time inefficient over a short-time (e.g. 5-minute) interval and efficient over a longer (e.g. daily) interval.

To test the existence of twelve chart patterns in the Euro/Dollar foreign exchange market, we use two identification methods (M1, M2) for detecting local extrema. The first method (M1), also used in the literature, considers only prices at the end of each time interval (they are called close prices). The second method (M2), which is new compared to those used in the literature, takes into account both the highest and the lowest price in each interval of time corresponding to a detected pattern.

The detected extrema are analyzed through twelve recognition pattern algorithms, each of them corresponding to a defined chart pattern. Our purpose is to analyze the predictability and profitability of each type of chart pattern. In addition, we intend to test the usefulness of our contribution regarding

the extrema detection method M2. Although Osler (1998) and Chang and Osler (1999) briefly mention these prices, most of the previous studies focused on chart patterns do not give much interest to high and low prices. This is in sharp contrast to the majority of practitioners (in particular dealers and traders) who use high and low prices in their technical strategies through bar charts and candlesticks. In addition, Fiess and MacDonald (2002) show that high, low and close prices carry useful information for forecasting the volatility as well as the level of future exchange rates. Consequently, in our framework, we investigate also the sensitivity of the chart patterns to the extrema detection methods M1 and M2. To evaluate the statistical significance of our results, we run a Monte Carlo simulation. We simulate a geometric Brownian motion to construct artificial series. Each of them has the same length, mean, variance and starting value as the original observations.

Our results show the apparent existence of some chart patterns in the Euro/Dollar intra-daily foreign exchange rate. More than one half of the detected patterns, according to M1 and M2, seem to have a significant predictive success. Nevertheless, only two patterns from our sample of twelve present a significant profitability which is however too small to cover the transaction costs. We show, moreover, that the extrema detection method M2 provides higher but riskier profits than those provided by M1. These findings are in accordance with those found by Levy (1971), Osler (1998), Dempster and Jones (1998a), Chang and Osler (1999).

The paper is organized as follows. In Section 2, we summarize the most re-

cent empirical studies which have focused on technical analysis, particularly on chart patterns. Section 3 is dedicated to the methodology adopted for both the extrema detection methods M1 and M2, and to the pattern recognition algorithms. The section also includes details about the two criteria used for the analysis of the observed technical patterns: predictability and profitability. In Section 4, we analyze and describe the data. Empirical results are exposed in Section 5. We conclude in Section 6.

## **2 Technical Analysis**

Technical analysis is widely used in practice by several dealers, also called technical analysts or chartists. According to Cheung and Wong (1999), 25 to 30 percent of the foreign exchange dealers base most of their trade on technical trading signals. More broadly, Allen and Taylor (1992) show, through questionnaire evidence, that technical analysis is used either as the primary or the secondary information source by more than 90% of the foreign exchange dealers trading in London. Furthermore, 60% judge charts to be at least as important as fundamentals. Most of them consider also chartism and fundamental analysis to be largely complementary. Menkhoff (1998) shows in addition that more than half of foreign exchange market participants in Germany give more importance to the information coming from non-fundamental analysis, i.e. technical analysis and order flows. Moreover, Lui and Mole (1998) show that technical analysis is the most used method for short term horizon on the foreign exchange market in Hong Kong.

Despite its broad use by practitioners, academics have historically neglected technical analysis, mainly because it contrasts with the most fundamental hypothesis in finance, namely market efficiency. Indeed, the weak form of the market efficiency hypothesis implies that all information available in past prices must be reflected in the current price. Then, according to this hypothesis, technical analysis, which is entirely based on past prices (Murphy, 1999), cannot predict future price behavior.

Recently, several studies have focused on technical analysis. Brock, Lakonishok, and LeBaron (1992) support the use of two of the simplest and most popular trading rules: moving average and trading range break (support and resistance levels). They show that these trading rules help to predict return variations in the Dow Jones index. These simple trading rules were studied, amongst others, by Dooley and Shafer (1984), Sweeney (1986), Levich and Thomas (1993), Neely (1997) and LeBaron (1999) in the context of the foreign exchange rate dynamics. Moreover, Andrada-Felix, Fernandez-Rodriguez, and Sosvilla-Rivero (1995), Ready (1997) and Detry (2001) investigate the use of these rules in stock markets. Still with the moving average trading rules, Gençay and Stengos (1997), Gençay (1998) and Gençay (1999) examine the predictability of stock market and foreign exchange market returns by using past buy and sell signals, and they find an evidence of nonlinear predictability of such returns.

In addition to these simple trading rules, technical analysis abounds of methods in order to predict future price trends. These methods have also been considered in empirical research. Jensen (1970) tests empirically the 'relative

strength' trading rule.<sup>1</sup> The estimated profit provided by this trading rule is not significantly bigger than the one obtained by the 'Buy and Hold' strategy.<sup>2</sup> Osler (2000) finds that the support and resistance technique provides a predictive success. Other studies make use of genetic programs to develop trading rules likely to realize significant profits (e.g., Neely, Weller, and Dittmar, 1997, Dempster and Jones, 1998a and Neely and Weller, 1999). Furthermore, Blume, Easley, and O'Hara (1994) demonstrate that sequences of volume can be informative. This would explain the widespread use by practitioners of technical analysis based upon volumes.

The different studies mentioned above have mainly focused on linear price relations. However, other researchers have oriented their investigations to non-linear price relations. Technical patterns, also called chart patterns, are considered as non-linear patterns. Both Murphy (1999) and Béchu and Bertrand (1999), argue that these kinds of patterns present a predictive success which allows traders to acquire profit by developing specific trading rules. In most studies, technical patterns are analyzed through their profitability. Levy (1971) focuses on the predictive property of the patterns based on a sequence of five price extrema and conclude, after taking into account the transaction costs, to the unprofitability of such configurations. Osler (1998) analyzes the most famous chart pattern, the head and shoulders pattern.<sup>3</sup> She underlines that

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<sup>1</sup> Once computing the ratio  $P_t/\bar{P}_t$  where  $\bar{P}_t$  corresponds to the mean of prices preceding the moment  $t$ , the relative strength trading rule consists in buying the asset if the ratio is bigger than a particular value and selling it when the ratio reaches a specific threshold.

<sup>2</sup> This strategy consists in buying the asset at the beginning of a certain period and keeping it until the end.

<sup>3</sup> This chart pattern is defined in Section 3.2.

agents who adopt this kind of technical pattern in their strategy must be qualified as noise traders because they generate important order flow and their trading is unprofitable. Dempster and Jones (1998a) and Chang and Osler (1999) obtain the same conclusion regarding the non profitability of the trading rules related to chart patterns. In contrast, Lo, Mamaysky, and Wang (2000) show that the informational content of chart patterns affects significantly future stock returns.

Some studies go beyond the scope of testing the performance of trading models. For example, Gençay, Ballocci, Dacorogna, Olsen, and Pictet (2002) and Gençay, Dacorogna, Olsen, and Pictet (2003) employ a widely used commercial real-time trading model as a diagnostic tool to evaluate the statistical properties of foreign exchange rates. They consider that the trading model on real data outperforms some sophisticated statistical models implying that these latter are not relevant for capturing the data generating process. They add that in financial markets, the data generating process is a complex network of layers where each layer corresponds to a particular frequency.

In our paper we choose to deal with high frequency data, believing that all our results are sensitive to the time scale. The results carried out from one hour or thirty minutes time scale are certainly different from those triggered by five minutes frequency. However, the goal of our study is to analyze the performance of some chart pattern at a specific time scale without generalizing our results to other frequencies. Our choice of high frequency data, as emphasized by Gençay, Dacorogna, Olsen, and Pictet (2003), is motivated by two main reasons. First, any position recommended by our strategy (defined below in



subsection 3.3.2) have to be closed quickly within a short period following the chart completion. The stop-loss objectives need to be satisfied and the high frequency data provides an appropriate platform for this requirement. Second, the trading positions and strategies, can only be replicated with a high statistical degree of accuracy by using high frequency data in a real time trading model.

However in practice, technical analysts often combine high and low time scales in order to monitor their positions in the short (five-minutes to one hour) and long run (one day to one month).

### **3 Methodology**

The methodology adopted in this paper consists in identifying regularities in the time series of currency prices by extracting nonlinear patterns from noisy data. We take into consideration significant price movements which contribute to the formation of a specific chart pattern and we ignore random fluctuations considered as noise. We do this by adopting a smoothing technique in order to average out the noise. The smoothing technique allows to identify significant price movements which are only characterized by sequences of extrema.

In the first subsection we present two methods used to identify local extrema. Then, we explain the pattern recognition algorithm which is based on the quantitative definition of chart patterns. In the third subsection, we present the two criteria chosen for the analysis of the detected charts: predictability and profitability. The last subsection is dedicated to the way we compute the

statistical significance of our results. It is achieved by running a Monte Carlo simulation.

### *3.1 Identification of Local Extrema*

Each chart pattern can be characterized by a sequence of local extrema, that is by a sequence of alternate maxima and minima. Two methods are used to detect local extrema. The first method, largely used in the literature, is based on close prices, i.e. prices which take place at the end of each time interval. The second method, which is one of the contribution of this paper to the literature, is built on the highest and the lowest prices in the same time intervals. We examine the usefulness of using high and low prices in the identification process of chart patterns. Taking these prices into account is more in line with practice as dealers use bars or candlestick charts to build their technical trading rules.<sup>4</sup> Moreover, Fiess and MacDonald (2002) show that high and low prices carry useful information about the level of future exchange rates.

The extrema detection method based on closed prices (M1) works as follows. The first step consists in smoothing the price curve to eliminate the noise in prices and locate the different extrema on the smoothed curve. To smooth the estimated curve we use the Nadaraya-Watson kernel estimator.<sup>5</sup>

We then determine different extrema by finding the moments at which the

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<sup>4</sup> Béchu and Bertrand (1999) stipulate that line charts are imprecise because they do not display all the information available as they are only based upon close prices of each time interval. In contrast, bar charts and candlesticks involve the high, low, open and close prices of each time interval.

<sup>5</sup> Details about this estimation are given in Appendix A.

kernel first derivative changes its sign. We therefore guarantee the alternation between maxima and minima. This smoothing technique has been also used by Lo, Mamaysky, and Wang (2000). Other methods to detect extrema have been adopted by Levy (1971), Osler (1998), Dempster and Jones (1998a) and Chang and Osler (1999). The second step involves orthogonal projections of the smoothed extrema on the original price curve. In other words, we deduce corresponding extrema on the original curve through orthogonal projection.

The second method (M2) is based on high and low prices. Local maxima must be determined on the high price curve and local minima on the low one. We smooth both curves and we select the corresponding extrema when there is a change of the sign for the kernel first derivative function. In such a case, alternation between extrema is not automatically obtained. Thus, we start by projecting the first extremum on the corresponding original price curve. If this extremum is a maximum (minimum), we project it into the high price curve (low price curve) and then we alternate between a projection of a minimum (maximum) on the low price curve (high price curve) and a projection of a maximum (minimum) on the high price curve (low price curve).

To detect local extrema we use a rolling window which goes through all the time periods with an increment of a single time interval. For each window, we apply both extrema detection methods and the pattern recognition algorithms in order to test if the detected sequence of extrema corresponds to one of our twelve chart pattern definitions (see the following section). The advantage of a rolling window is to concentrate on patterns that sequentially develop in the

same window and therefore to cancel the risk of look-ahead bias. This implies that the future evolution of the price curve is not yet known at the time of detection of technical patterns. A technical pattern is thus recorded only if all extrema have been detected in windows of identical time duration. Furthermore, we add a filter rule to keep only one record of each detected chart pattern. We present in Appendix B a detailed description of the two extrema detection methods.

### *3.2 Chart Patterns Quantitative Definitions*

By looking at specialized books on technical analysis like Murphy (1999) and Béchu and Bertrand (1999), which provide graphical descriptions of technical patterns, we build twelve quantitative definitions corresponding to the most famous chart patterns. Only the Head and Shoulders definition is presented in this Section. This pattern (HS) is defined from a particular sequence of extrema detected by the method presented in Appendix B. The other pattern definitions are presented in Appendix C. The eleven remaining chart patterns are the following: Inverse Head and Shoulders (IHS), Double Top (DT), Double Bottom (DB), Triple Top (TT), Triple Bottom (TB), Rectangle Top (RT), Rectangle Bottom (RB), Broadening Top (BT), Broadening Bottom (BB), Triangle Top (TRIT) and Triangle Bottom (TRIB).

From a series of price  $P_t$ , we denote by  $E_i$  ( $i = 1, \dots, I$ ) the local extremum  $i$  from a sequence composed of  $I$  extrema and  $t_{E_i}$  the moment when it occurs. The slope,  $p(E_i, E_j)$ , of the line passing through  $E_i$  and  $E_j$  and the

y-coordinate at  $t_k$  of a point of this line,  $V_{t_k}(E_i, E_j)$ , are defined as follows:

$$p(E_i, E_j) = \frac{E_j - E_i}{t_{E_j} - t_{E_i}} \quad (1)$$

$$V_{t_k}(E_i, E_j) = E_i + (t_k - t_{E_i}) \times p(E_i, E_j). \quad (2)$$

Figure 1 presents the theoretical Head and Shoulders chart pattern while Figure 2 illustrates the observed pattern after implementing both extrema detection methods. The theoretical figure serves mainly to help in the comprehension of the following definition:

The *HS* chart pattern is characterized by a sequence of five extrema  $E_i$  ( $i = 1, \dots, 5$ ) such that:

$$hs \equiv \left\{ \begin{array}{ll} E_1 > E_2 & \text{(a)} \\ E_3 > E_1, E_3 > E_5 & \text{(b)} \\ |p(E_1, E_5)| \leq tg(10) & \text{(c)} \\ |p(E_2, E_4)| \leq tg(10) & \text{(d)} \\ 0.9 \leq \frac{E_1 - V_{t_{E_1}}(E_2, E_4)}{E_5 - V_{t_{E_5}}(E_2, E_4)} \leq 1.1 & \text{(e)} \\ 1.1 \leq \frac{h}{s} \leq 2.5 & \text{(f)} \\ \frac{1}{2} \leq \frac{t_{E_2} - t_d}{t_f - t_{E_4}} \leq 2 & \text{(g)} \\ \frac{1}{2} \leq \frac{t_{E_4} - t_{E_2}}{m} \leq 2 & \text{(h)} \\ (P_{t_d} - P_{t_{min}}) \geq \frac{2}{3} \times h & \text{(i)} \end{array} \right.$$

where

- $h$  is the height of the head:  $h = E_3 - V_{t_{E_3}}(E_2, E_4)$
- $s$  is the average height of the two shoulders:  $s = \frac{(E_1 - V_{t_{E_1}}(E_2, E_4)) + (E_5 - V_{t_{E_5}}(E_2, E_4))}{2}$
- $t_d$  is the starting time for the pattern:  $t_d = \max_t (P_t \leq V_t(E_2, E_4), t < t_{E_1})$

- $t_f$  is the ending time for the pattern:  $t_f = \min_t (P_t \leq V_t(E_2, E_4), t > t_{E_5})$
- $t_{d-(f-d)} = t_d - (t_f - t_d)$
- $t_{f+(f-d)} = t_f + (t_f - t_d)$
- $m$  is the average time that the shoulders take for their total completion:  

$$m = \frac{(t_{E_2} - t_d) + (t_f - t_{E_4})}{2}$$
- $P_{t_{min}}$  is the smallest price observed in the time interval  $[t_{d-(f-d)}, t_d]$ :  

$$P_{t_{min}} = \min(P_t) | t_{d-(f-d)} \leq t \leq t_d$$

If a sequence of five extrema satisfies the above conditions, they build up a Head and Shoulders chart pattern. Theoretically, at the completion of this chart pattern, the price must go down for at least the height of the head,  $h$ . Furthermore, the objective price detected by the chart pattern has to be reached within the time interval  $[t_f, t_{f+(f-d)}]$ . In other words, the price has to reach at least  $P(obj)$  such that:

$$P(obj) = P_{t_f} - h . \quad (3)$$

### 3.3 The Performance Measures

Detected chart patterns are analyzed in terms of predictability and profitability. In other words, we study the capability of each chart pattern to predict the future price trend just after the chart completion and the profit that a dealer could realize when he applies a trading rule.

#### 3.3.1 Predictability

Following its completion, the chart pattern can be used to forecast the future price trend. More precisely, it predicts the price objective which has to be

reached. We denote by  $h$  the predicted price variation, and by  $t_f$  and  $t_d$  respectively, the time at the end and at the beginning of the chart pattern. If the pattern predicts a downward trend, the price objective is given by equation (3). This price objective has to be reached within the time interval  $[t_f, t_{f+(f-d)}]$ . In such cases, we can measure the actual price reached in this time interval by computing  $P_a$  such that:

$$P_a = \min\{P_t | t_f \leq t \leq t_{f+(f-d)}\}. \quad (4)$$

The value of the observed trend is then:

$$trend = P_{t_f} - P_a. \quad (5)$$

The predictability criterion is defined as follows:

$$pred = \frac{trend}{h}. \quad (6)$$

We distinguish three possible cases:

- $0 \leq pred < 1$  : the price does not reach its predicted objective. It goes in the predicted direction but only for  $pred$  of the forecasted objective.
- $pred = 1$  : the price reaches exactly its objective.
- $pred > 1$  : the price exceeds its objective by  $(pred - 1)$ .

Consequently if  $pred \geq 1$ , the chart pattern can be said to predict successfully the future price trend.

### 3.3.2 Profitability

If a chart pattern presents a predictive success, is it sufficient to get a profit? To answer this question, we investigate the profitability that technical patterns could imply. When the price evolves in the direction predicted by the chart pattern, a trader who takes a position at a precise time could realize a profit. Nevertheless, if the price evolves in the opposite direction, the position taken at the same time would involve a loss. A profit or a loss is the result of the implementation of a trading rule chosen by a chartist trader at a given time according to the completion of the chart pattern.

We propose the following strategy: the trader opens a position at the end of the pattern (at the moment of its completion) and closes it according to the future price direction. We distinguish two cases for the future trend:

- If the price evolves in the predicted direction, the trader closes his position when the price reaches 50% of the predicted price variation,  $h$ .
- If the price evolves in the opposite direction, the trader closes his position after a loss corresponding in absolute value to 20% of the forecasted price variation.

However, if at the end of the interval  $[t_f, t_{f+(f-d)}]$ , the trader position is not yet closed, this latter is automatically closed at  $t_{f+(f-d)}$ . In both cases, the trader can be considered as risk averse. Indeed, he limits his eventual profit and accept only small losses.



Once the predictability and the profitability criteria of each pattern are computed, we compare the results for the two extrema detection methods M1 and M2. We adopt a test of difference of means in order to infer the statistical significance of such comparisons. It consists in computing the statistic,  $t$ , as follows:

$$t = \frac{m_{M1} - m_{M2}}{\sqrt{\left(\frac{s_{M1}^2}{n_{M1}} + \frac{s_{M2}^2}{n_{M2}}\right)}}, \quad (7)$$

where  $m_{M_i}$  and  $s_{M_i}^2$  are respectively the estimated mean and variance of the outputs (i.e. the number of detected charts, the predictability or the profitability criteria) obtained when method  $M_i$  ( $i=1,2$ ) is adopted. The t-statistic follows a Student distribution with  $n_{M1} + n_{M2} - 1$  degrees of freedom, where  $n_{M1}$  and  $n_{M2}$  are respectively the number of observations resulting from the methods M1 and M2.

The last step for the profitability analysis consists in taking into consideration the risk incurred by the strategy. This latter is measured by the variability of the achieved profits. We compute three measures in order to gauge our strategy performance. We start by computing the ratio of mean profit to its standard deviation. However, according to Dacorogna, Gençay, Müller, and Pictet (2001) and Dacorogna, Gençay, Müller, Olsen, and Pictet (2001), this kind of Sharpe ratio is numerically unstable, exhibits a lot of deficiencies, and does not take into consideration dealers risk-aversion. For a robust performance evaluation we adopt two other performance measures, proposed by these authors, which are directly related to the utility of a strategy to a risk-averse dealer. Both of them are based on the maximization of the expected utility

of a dealer. The first measure, called  $X_{eff}$ , considers a constant risk aversion, while the second one, named  $R_{eff}$ , supposes an asymmetric risk aversion (a higher risk-aversion when there is a loss). These performance measures adjust the mean profit from a kind of risk premium.<sup>6</sup> We have adapted these two performance measures to our context: for instance, we have computed  $X_{eff}$  and  $R_{eff}$  using the profit levels instead of returns realized after the completion of the chart pattern.

### 3.4 Monte Carlo Simulation

In order to assess the statistical significance of the obtained results, we run a Monte Carlo simulation. We create 200 artificial exchange rate series<sup>7</sup> and we implement both extrema detection methods and the pattern recognition algorithms. These series follow a geometric Brownian motion process and are characterized by the same length, mean, variance and starting value as the original observations.<sup>8</sup>

Nevertheless, there is an important difference between the artificial series and the original one: the simulated series are built in such a way that any detected pattern is meaningless, whereas in the original exchange rate series, this may or may not be true. The existence of technical patterns in the original series

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<sup>6</sup> The details about the computation of  $X_{eff}$  and  $R_{eff}$  are given in Dacorogna, Gençay, Müller, and Pictet (2001) and Dacorogna, Gençay, Müller, Olsen, and Pictet (2001).

<sup>7</sup> We limit our simulation to 200 series because the recognition pattern algorithm needs a lot of computer time.

<sup>8</sup> The same methodology was adopted by Chang and Osler (1999), Osler (1998), Gençay (1998), Gençay, Ballocci, Dacorogna, Olsen, and Pictet (2002), and Gençay, Dacorogna, Olsen, and Pictet (2003).

could be generated by trader behaviors which induce a particular pattern in the prices. We test the null hypothesis of the absence of chart patterns in the observed series. This hypothesis involves also the absence of both predictability and profitability. On the other hand, if a chart pattern really exists in the observed series, then the number of chart detections has to be significantly larger than those obtained when we deal with artificial observations. Consequently, the probability of accepting the null hypothesis is computed by the percentage of simulated series for which the results obtained on the simulated series are greater than those obtained on the observed one.

#### **4 Data Description**

The Euro/Dollar FOREX market is a market maker based trading system, where three types of market participants interact around the clock (i.e. in successive time zones): dealers, brokers and customers from which the primary order flow originates. The most active trading centers are New York, London, Frankfurt, Sydney, Tokyo and Hong Kong. A complete description of the FOREX market is given by Lyons (2001).

To compute the mid prices used for the estimation of the models reported in Appendix A, we bought from Olsen and Associates a database made up of ‘tick-by-tick’ Euro/Dollar quotes for the period ranging from May 15 to November 14, 2001 (i.e. 26 weeks and three days). This database includes 3,420,315 observations. As in most empirical studies on FOREX data, these Euro/Dollar quotes are market makers’ quotes and not transaction quotes

(which are not widely available).<sup>9</sup> More specifically, the database contains the date, the time-of-day time stamped to the second in Greenwich mean time (GMT), the dealer bid and ask quotes, the identification codes for the country, city and market maker bank, and a return code indicating the filter status. According to Dacorogna, Müller, Nagler, Olsen, and Pictet (1993), when trading activity is intense, some quotes are not entered into the electronic system. If traders are too busy or the system is running at full capacity, quotations displayed in the electronic system may lag prices by a few seconds to one or more minutes. We retained only the quotes that have a filter code value greater than 0.85.<sup>10</sup>

From the tick data, we computed mid quote prices, where the mid quote is the average of the bid and ask prices. As we use five-minute time intervals, we have a daily grid of 288 points. Because of scarce trading activity during the week-end, we exclude all mid prices computed between Friday 21h05 and Sunday 24h. The mean of the mid-quotes is equal to 0.8853, the minimum and maximum are 0.8349 and 0.9329.

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<sup>9</sup> Danielsson and Payne (2002) show that the statistical properties of 5-minute Dollar/DM quotes are similar to those of transaction quotes.

<sup>10</sup> Olsen and Associates recently changed the structure of their HF database. While they provided a 0/1 filter indicator some time ago (for example in the 1993 database), they now provide a continuous indicator that lies between 0 (worst quote quality) and 1 (best quote quality). While a value larger than 0.5 is already deemed acceptable by Olsen and Associates, we choose a 0.85 threshold to have high quality data. We remove however almost no data records (Olsen and Associates already supplied us with data which features a filter value larger than 0.5), as most filter values are very close to 1.

## 5 Empirical Results

Table 1 presents the number of detected chart patterns for the extrema identification methods (M1 and M2). The results show the apparent existence of some chart patterns in the Euro/Dollar foreign exchange series. Using the first detection method (M1), we have more detected charts in the original price series than in the simulated one for six chart patterns (out of twelve), at the 5% significance level. When we implement the M2 method, we detect significantly only four chart patterns, which are also significantly detected by the method M1: DT, DB, RT and RB. By looking at the last column which represents the total number of detections, we can see that we have more detected chart patterns when only close prices are used (M1). These results confirm the idea that the presence of such chart patterns does not occur by chance, at least for some chart patterns, but it is due, amongst others, to a determined behavior of the chartist dealers.

The percentage of successful chart patterns (i.e. charts for which the price objective has been met) is given by the rows in bold in Table 1. For example, 40% of Head and Shoulders (HS) detected by M1 succeed to meet their objective, but this result is not significant since for 92% of the simulated series we obtain more successful HS. For M1, only two charts, DT and DB present a significant successful percentage.<sup>11</sup> For M2, in addition to DT and DB, the chart pattern BT presents a significant percentage of success.

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<sup>11</sup> Both chart patterns DT and DB have not been detected in any artificial series, whatever the extrema detection method implemented.

Nevertheless, this measure of predictive power, i.e. the percentage of charts that succeed to meet their price objective, is too drastic. It does not allow to capture to what extent the price objective is not met or to what extent the price objective is outclassed. That is why we quantified the predictability through the ratio *pred*.

Table 2 presents the average predictability *pred* for all detected chart patterns which succeed or fail to meet their objectives. For example, in the case of M1, HS has an average predictive power of 1,12. This average ratio is not significant at 5% since for 79% of the artificial series, we obtain a higher average ratio. However, the table shows that whatever the extrema detection methods implemented, more than one half of the whole chart patterns sample presents a predictability success statistically significant. At the 5% significance level, predictability varies from 0.86 to 9.45. The triangle chart patterns (TRIT and TRIB) offer the best predictability.

These results are consistent with those obtained in Table 1 in which M1 exhibits more predictability. This observation is even more striking in Table 2. The last column shows that M1 provide on average, a predicted value more than twice larger than M2. This is confirmed by positive significant signs for the difference of means test presented in the last line of the Table 2. Comparatively, Table 1 shows a percentage of 63% of successful chart patterns using M1 against 42% provided by M2.

Table 3 gives the maximum profitability that can be achieved by the use of

chart patterns. It is computed in basis points (i.e.: 1/10,000) and provided for each of the twelve chart patterns. It corresponds to the implementation of the trading rule related to each chart pattern whatever its success level. The maximum profit is equal to the difference, in absolute value, between the price at the end of the chart and the minimum/maximum<sup>12</sup> of the prices occurring after the chart pattern ( $|P_{t_f} - P_a|$ ). To compute these profits, we suppose that dealers are able to buy or to sell the currency at the mid price. The computed profits vary between 3 and 52 basis points, but are significant for only three chart patterns: DT, DB and BT.

However, this profit can not be realized surely by the chartists because they can not precisely guess if the price is at the end of its right trend or not. That is why they adopt a strategy for their intervention according to their risk aversion. Table 4 presents the results for the strategy described in Section 3.3.2. Profits are computed through the average of the whole detected chart patterns which succeed or fail to meet their objectives. This profit is statistically significant for only two charts, DT and DB whatever the detection method implemented. However, this profit more or less equal to one basis point for three cases out of four, seems too small to cover the transaction costs. Indeed, the transaction costs are often estimated as the observed bid-ask spread which varies on average, in the Euro/Dollar currency market, between 3 to 5 basis points (Chang and Osler,1999). Consequently, even by choosing a particular risk averse trading rule, strategies using chart patterns seem unprofitable.

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<sup>12</sup>We adopt the minimum if the price evolves, after the completion of the chart, into downward trend and we adopt the maximum when there is an upward trend.

Furthermore, the difference of means test shows that M2 is more profitable than M1. For the majority of charts, profitability computed by adopting M2 is significantly larger than the one provided by M1. We observe in Table 4 five significant negative signs versus two positive. This observation is confirmed by the significant negative sign for the weighted average profitability for all chart sample, presented in the last column.

This finding is quite important since at the light of the predictability results, we might conclude that only close prices matter. However, when the profitability is taken into consideration, the use of high and low prices seems to have an importance which is more in accordance with what is observed in practice (dealers use Bar charts and only profit matters).

Nevertheless, if we consider the profit adjusted for the inherent risk, the same two mean profits of one basis point obtained for DT have different risk levels. Taking into account the risk level by computing the three different performance measures; Sharpe ratio,  $X_{eff}$ , and  $R_{eff}$ , we obtain a smaller value for M2. This means that the second method M2 generates riskier profits than M1. Moreover,  $X_{eff}$  and  $R_{eff}$  performance measures carry out the same outputs as the Sharpe risk-adjusted profits which implies the robustness of our results in terms of performance evaluation.



## 6 Conclusion

Using five-minutes Euro/Dollar mid-quotes for the May 15 through November 14, 2001 time period, we shed light on the predictability and profitability of some chart patterns. We compare results according to two extrema detection methods. The first method (M1), traditionally used in the literature, considers only prices which occur at the end of each time interval (they are called close prices). The second method (M2) takes into account both the highest and the lowest price of each interval of time. To evaluate the statistical significance of the results, we run a Monte Carlo simulation.

We conclude on the apparent existence of some technical patterns in the Euro/Dollar intra-daily foreign exchange rate. More than one half of the detected patterns, according to M1 and M2, seem to have some significant predictive success. Nevertheless, only two out of twelve patterns present significant profitability, which is however too small to cover the transaction costs. We also show that the extrema detection method using high and low prices provides higher but riskier profits than those provided by the M1 method.

To summarize, chart patterns seems to really exist in the Euro/Dollar foreign exchange market at the five minute level. They also show some power to predict future price trends. However, trading rules based upon them seem unprofitable.

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## Appendices

### *A. Price Curve Estimation*

Before adopting the Nadaraya-Watson kernel estimator, we tested the cubic splines and polynomial approximations but we conclude empirically that the appropriate smoothing method is the kernel. Because the two first methods carry out too smoothed results and they are not flexible as the kernel method.

From the complete series of the price,  $P_t$  ( $t = 1, \dots, T$ ), we take a window  $k$  of  $l$  regularly spaced time intervals,<sup>13</sup> such that:

$$P_{j,k} \subset \{P_t \mid k \leq t \leq k + l - 1\}, \quad (8)$$

$j = 1, \dots, l$  and  $k = 1, \dots, T - l + 1$ . For each window  $k$ , we consider the following relation:

$$P_{j,k} = m(X_{P_{j,k}}) + \epsilon_{P_{j,k}}, \quad (9)$$

where  $\epsilon_{P_{j,k}}$  is a white noise and  $m(X_{P_{j,k}})$  is an arbitrarily fixed but unknown non linear function of a state variable  $X_{P_{j,k}}$ . Like Lo, Mamaysky, and Wang (2000) to construct a smooth function in order to approximate the time series of prices  $P_{j,k}$ , we set the state variable equal to time,  $X_{P_{j,k}} = t$ . For any arbitrary  $x$ , a smoothing estimator of  $m(x)$  may be expressed as:

$$\hat{m}(x) = \frac{1}{l} \sum_{j=1}^l \omega_j(x) P_{j,k}, \quad (10)$$

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<sup>13</sup> We fix  $l$  at 36 observations.

where the weight  $\omega_j(x)$  is large for the prices  $P_{j,k}$  with  $X_{P_{j,k}}$  near  $x$  and small for those with  $X_{P_{j,k}}$  far from  $x$ . For the kernel regression estimator, the weight function  $\omega_j(x)$  is built from a probability density function  $K(x)$ , also called a kernel:

$$K(x) \geq 0 \quad , \quad \int_{-\infty}^{+\infty} K(u)du = 1 . \quad (11)$$

By rescaling the kernel with respect to a parameter  $h > 0$ , we can change its spread:

$$K_h(u) \equiv \frac{1}{h} K(u/h) \quad , \quad \int_{-\infty}^{+\infty} K_h(u)du = 1 \quad (12)$$

and define the weight function to be used in the weighted average (10) as:

$$\omega_{j,h} \equiv K_h(x - X_{P_{j,k}}) / g_h(x) \quad (13)$$

$$g_h(x) \equiv \frac{1}{l} \sum_{j=1}^l K_h(x - X_{P_{j,k}}) . \quad (14)$$

Substituting (14) into (10) yields the *Nadaraya-Watson* kernel estimator  $\hat{m}_h(x)$  of  $m(x)$ :

$$\hat{m}_h(x) = \frac{1}{l} \sum_{j=1}^l \omega_{j,h}(x) P_{j,k} = \frac{\sum_{j=1}^l K_h(x - X_{P_{j,k}}) P_{j,k}}{\sum_{j=1}^l K_h(x - X_{P_{j,k}})} . \quad (15)$$

If  $h$  is very small, the averaging will be done with respect to a rather small neighborhood around each of the  $X_{P_{j,k}}$ 's. If  $h$  is very large, the averaging will be over larger neighborhoods of the  $X_{P_{j,k}}$ 's. Therefore, controlling the degree of averaging amounts to adjusting the smoothing parameter  $h$ , also known as the bandwidth. Choosing the appropriate bandwidth is an important aspect of any local-averaging technique. In our case we select a Gaussian kernel with

a bandwidth,  $h_{opt,j}$ , computed by Silverman (1986):

$$K_h(x) = \frac{1}{h\sqrt{2\pi}} e^{-\frac{x^2}{2h^2}} \quad (16)$$

$$h_{opt,k} = \left(\frac{4}{3}\right)^{1/5} \sigma_k l^{-1/5}, \quad (17)$$

where  $\sigma_k$  is the standard deviations for the observations that occur within the window  $k$ . However, the optimal bandwidth for Silverman (1986) involves a fitted function which is too smooth. In other words this optimal bandwidth places too much weight on prices far away from any given time  $t$ , inducing too much averaging and discarding valuable information in local price movements. Like Lo, Mamaysky, and Wang (2000), through trial and error, we found that an acceptable solution to this problem is to use a bandwidth equal to 20% of  $h_{opt,k}$ :

$$h^* = 0.2 \times h_{opt,k}. \quad (18)$$

### *B. Extrema Detection Methods*

Technical details for both extrema detection methods and projection procedure are presented below:

#### *B.1 M1*

M1 is the extrema detection method using the close prices. After smoothing the data by estimating the Nadaraya-Watson kernel function,  $\hat{m}_h(X_{P_{j,k}})$ , we compute maxima and minima respectively noted by  $max_{\hat{m}_h(X_{P_{j,k}})}$  and  $min_{\hat{m}_h(X_{P_{j,k}})}$ :

$$\begin{aligned} \max_{\hat{m}_h(X_{P_{j,k}})} &= \{\hat{m}_h(X_{P_{j,k}}) \mid S(\hat{m}'_h(X_{P_{j,k}})) = +1, S(\hat{m}'_h(X_{P_{j+1,k}})) = -1\} \\ \min_{\hat{m}_h(X_{P_{j,k}})} &= \{\hat{m}_h(X_{P_{j,k}}) \mid S(\hat{m}'_h(X_{P_{j,k}})) = -1, S(\hat{m}'_h(X_{P_{j+1,k}})) = +1\}, \end{aligned}$$

where  $S(X)$  is the sign function, equal to +1 (-1) when the sign of  $X$  is positive (negative), and  $\hat{m}'_h(X_{P_{j,k}})$  is the first derivative of the kernel function  $\hat{m}_h(X_{P_{j,k}})$ . By construction we obtain alternate extrema. We denote respectively by  $t_M(\hat{m}_h(X_{P_{j,k}}))$  and  $t_m(\hat{m}_h(X_{P_{j,k}}))$  the moments correspondent to detected extrema such that:

$$t_M(\hat{m}_h(X_{P_{j,k}})) = \{j \mid j \in \max_{\hat{m}_h(X_{P_{j,k}})}\} \quad (19)$$

$$t_m(\hat{m}_h(X_{P_{j,k}})) = \{j \mid j \in \min_{\hat{m}_h(X_{P_{j,k}})}\}. \quad (20)$$

After recording the moments of the detected extrema we realize an orthogonal projection of selected extrema, from the smoothing curve, to the original one. We deduce the corresponding extrema to construct the series involving both maxima,  $\max_{P_{j,k}}$  and minima,  $\min_{P_{j,k}}$  such that:

$$\begin{aligned} \max_{P_{j,k}} &= \max\left(P_{t_M(\hat{m}_h(X_{P_{j,k}}))-1,k}, P_{t_M(\hat{m}_h(X_{P_{j,k}})),k}, P_{t_M(\hat{m}_h(X_{P_{j,k}}))+1,k}\right) \\ \min_{P_{j,k}} &= \min\left(P_{t_m(\hat{m}_h(X_{P_{j,k}}))-1,k}, P_{t_m(\hat{m}_h(X_{P_{j,k}})),k}, P_{t_m(\hat{m}_h(X_{P_{j,k}}))+1,k}\right). \end{aligned}$$

For each window  $k$  we get alternate maxima and minima. This is assured by the bandwidth  $h$  which provide at least two time intervals between two consecutive extrema. The final step consists to scan the extrema sequence to identify an eventual chart pattern. If the same sequence of extremum was observed in more than one window, only the first sequence is retained for the recognition study to avoid the duplication of results.



## B.2 M2

M2 is the extrema detection method built on high and low prices. According to this method, maxima and minima have to be detected onto separate curves. Maxima on high prices curve and minima on the low one.

Let  $H_t$  and  $L_t$  ( $t = 1, \dots, T$ ), be respectively the series for the high and the low prices, and  $k$  a window containing  $l$  regularly spaced time intervals such that:

$$H_{j,k} \subset \{H_t \mid k \leq t \leq k + l - 1\} \quad (21)$$

$$L_{j,k} \subset \{L_t \mid k \leq t \leq k + l - 1\}, \quad (22)$$

$j = 1, \dots, l$  and  $k = 1, \dots, T - l + 1$ . We smooth these series through the kernel estimator detailed in Appendix A to obtain  $\hat{m}_h(X_{H_{j,k}})$  and  $\hat{m}_h(X_{L_{j,k}})$ . We detect maxima on the former series and minima on the latter one in order to construct two separate extrema series  $max_{\hat{m}_h(X_{H_{j,k}})}$  and  $min_{\hat{m}_h(X_{L_{j,k}})}$  such that:

$$\begin{aligned} max_{\hat{m}_h(X_{H_{j,k}})} &= \{\hat{m}_h(X_{H_{j,k}}) \mid S(\hat{m}'_h(X_{H_{j,k}})) = +1, S(\hat{m}'_h(X_{H_{j+1,k}})) = -1\} \\ min_{\hat{m}_h(X_{L_{j,k}})} &= \{\hat{m}_h(X_{L_{j,k}}) \mid S(\hat{m}'_h(X_{L_{j,k}})) = -1, S(\hat{m}'_h(X_{L_{j+1,k}})) = +1\}, \end{aligned}$$

where  $S(x)$  is the sign function defined in the previous Section.

We record the moments for such maxima and minima, denoted respectively by  $t_M(\hat{m}_h(X_{H_{j,k}}))$  and  $t_m(\hat{m}_h(X_{L_{j,k}}))$  and we project them on the original high and low curves to deduce the original extrema series  $max_{H_{j,k}}$  and  $min_{L_{j,k}}$ , such that:

$$\begin{aligned} \max_{H_{j,k}} &= \max\left(H_{t_M(\hat{m}_h(X_{H_{j,k}})) - 1, k}, H_{t_M(\hat{m}_h(X_{H_{j,k}})), k}, H_{t_M(\hat{m}_h(X_{H_{j,k}})) + 1, k}\right) \\ \min_{L_{j,k}} &= \min\left(L_{t_m(\hat{m}_h(X_{L_{j,k}})) - 1, k}, L_{t_m(\hat{m}_h(X_{L_{j,k}})), k}, L_{t_m(\hat{m}_h(X_{L_{j,k}})) + 1, k}\right). \end{aligned}$$

However, this method does not guarantee alternate occurrences of maxima and minima. It is easy to observe, in the same window  $k$ , the occurrence of two consecutive minima on the low series before observing a maximum on high series. To resolve this problem we start by recording the moments for the selected maxima on high curve,  $t_M(H_{j,k})$ , and minima in low curve,  $t_m(L_{j,k})$ . Then we select, for window  $k$  the first extremum from these two series,  $E_{1,k}$ , and its relative moment,  $t_{E_{1,k}}$ , such that:

$$t_{E_{1,k}} = \min_t(t_M(H_{j,k}), t_m(L_{j,k})) \quad (23)$$

$$E_{1,k} = (\{\max_{H_{j,k}}\} \cup \{\min_{L_{j,k}}\} \mid j = t_{E_{1,k}}) . \quad (24)$$

If we meet a particular case such that a minimum and a maximum occur at the same first moment, then we retain arbitrarily the maximum. To build the alternate series, we have to know the type of the last extremum introduced into the series. If it is a maximum (minimum) then the next extremum has to be a minimum (maximum) selected from the low (high) series such that:

$$\begin{aligned} E_{j,k} \mid_{E_{(j-1),k} \in \{\max_{H_{j,k}}\}} &= \{\min_{L_{j,k}} \mid j = \min(t_m(L_{j,k})), t_m(L_{j,k}) > t_{E_{(j-1),k}}\} \\ E_{j,k} \mid_{E_{(j-1),k} \in \{\min_{L_{j,k}}\}} &= \{\max_{H_{j,k}} \mid j = \min(t_M(H_{j,k})), t_M(H_{j,k}) > t_{E_{(j-1),k}}\}, \end{aligned}$$

where  $E_{j,k}$  is the extremum detected on original series.

Finally, the obtained series is scanned by the recognition patterns algorithms to identify an eventual chart pattern.

## C. Definition of Chart Patterns

### C.1 Inverse Head and Shoulders (IHS):

IHS is characterized by a sequence of 5 extrema  $E_i$  ( $i = 1, \dots, 5$ ) such that:

$$IHS \equiv \left\{ \begin{array}{l} E_1 < E_2 \\ E_3 < E_1, E_3 < E_5 \\ |p(E_2, E_4)| \leq tg(10) \\ |p(E_1, E_5)| \leq tg(10) \\ 0.9 \leq \frac{V_{t_{E_1}}(E_2, E_4) - E_1}{V_{t_{E_5}}(E_2, E_4) - E_5} \leq 1.1 \\ 1.1 \leq \frac{h}{s} \leq 2.5 \\ \frac{1}{2} \leq \frac{t_{E_2} - t_d}{t_f - t_{E_4}} \leq 2 \\ \frac{1}{2} \leq \frac{t_{E_4} - t_{E_2}}{m} \leq 2 \\ (P_{t_{max}} - P_{t_d}) \geq \frac{2}{3} \times h \end{array} \right.$$

where

- $h$  is the height of the head :

$$h = V_{t_{E_3}}(E_2, E_4) - E_3$$

- $s$  is the height average of the two shoulders :  $s = \frac{(V_{t_{E_1}}(E_2, E_4) - E_1) + (V_{t_{E_5}}(E_2, E_4) - E_5)}{2}$

- $P_{t_{max}}$  is the highest price observed into the time interval  $[t_{d-(f-d)}, t_d]$  :

$$P_{t_{max}} = \max(P_t) \mid t_{d-(f-d)} \leq t \leq t_d$$

- $t_d$  is the starting time for the pattern

- $t_f$  is the ending time for the pattern

- $t_{d-(f-d)} = t_d - (t_f - t_d)$

- $t_{f+(f-d)} = t_f + (t_f - t_d)$

- $m$  is the average time which the shoulders take for their total completion

*C.2 Double Top (DT):*

*DT* is characterized by a sequence of 3 extrema  $E_i$  ( $i = 1, \dots, 3$ ), such that :

$$DT \equiv \left\{ \begin{array}{l} E_1 > E_2 \\ \frac{E_1 - E_2}{V_{t_{E_2}}(E_1, E_3) - E_2} = 1 \\ \frac{E_3 - E_2}{V_{t_{E_2}}(E_1, E_3) - E_2} = 1 \\ \frac{1}{2} \leq \frac{t_{E_2} - t_d}{(t_f - t_d)/2} \leq 2 \\ \frac{1}{2} \leq \frac{t_f - t_{E_2}}{(t_f - t_d)/2} \leq 2 \\ (P_{t_d} - P_{t_{min}}) \geq \frac{2}{3} \times (V_{t_{E_2}}(E_1, E_3) - E_2) \end{array} \right.$$

*C.3 Double Bottom (DB):*

*DB* is characterized by a sequence of 3 extrema  $E_i$  ( $i = 1, \dots, 3$ ), such that :

$$DB \equiv \left\{ \begin{array}{l} E_1 < E_2 \\ \frac{E_2 - E_1}{E_2 - V_{t_{E_2}}(E_1, E_3)} = 1 \\ \frac{E_2 - E_3}{E_2 - V_{t_{E_2}}(E_1, E_3)} = 1 \\ \frac{1}{2} \leq \frac{t_{E_2} - t_d}{(t_f - t_d)/2} \leq 2 \\ \frac{1}{2} \leq \frac{t_f - t_{E_2}}{(t_f - t_d)/2} \leq 2 \\ (P_{t_{max}} - P_{t_d}) \geq \frac{2}{3} \times (E_2 - V_{t_{E_2}}(E_1, E_3)) \end{array} \right.$$

*C.4 Triple Top (TT):*

*TT* is characterized by a sequence of 5 extrema  $E_i$  ( $i = 1, \dots, 5$ ) such that:

$$TT \equiv \left\{ \begin{array}{l} E_1 > E_2 \\ |p(E_1, E_5)| \leq tg(10) \\ |p(E_2, E_4)| \leq tg(10) \\ 0.9 \leq \frac{h}{E_1 - V_{t_{E_1}}(E_2, E_4)} \leq 1.1 \\ 0.9 \leq \frac{h}{E_5 - V_{t_{E_5}}(E_2, E_4)} \leq 1.1 \\ \frac{1}{2} \leq \frac{t_{E_2} - t_d}{(t_f - t_d)/3} \leq 2 \\ \frac{1}{2} \leq \frac{t_{E_4} - t_{E_2}}{(t_f - t_d)/3} \leq 2 \\ \frac{1}{2} \leq \frac{t_f - t_{E_4}}{(t_f - t_d)/3} \leq 2 \\ (P_{t_d} - P_{t_{min}}) \geq \frac{2}{3} \times h \end{array} \right.$$

*C.5 Triple Bottom (TB):*

*TB* is characterized by a sequence of 5 extrema  $E_i$  ( $i = 1, \dots, 5$ ) such that:

$$TB \equiv \left\{ \begin{array}{l} E_1 < E_2 \\ |p(E_2, E_4)| \leq tg(10) \\ |p(E_1, E_5)| \leq tg(10) \\ 0.9 \leq \frac{h}{V_{t_{E_1}}(E_2, E_4) - E_1} \leq 1.1 \\ 0.9 \leq \frac{h}{V_{t_{E_5}}(E_2, E_4) - E_5} \leq 1.1 \\ \frac{1}{2} \leq \frac{t_{E_2} - t_d}{(t_f - t_d)/3} \leq 2 \\ \frac{1}{2} \leq \frac{t_{E_4} - t_{E_2}}{(t_f - t_d)/3} \leq 2 \\ \frac{1}{2} \leq \frac{t_f - t_{E_4}}{(t_f - t_d)/3} \leq 2 \\ (P_{t_{max}} - P_{t_d}) \geq \frac{2}{3} \times h \end{array} \right.$$

*C.6 Rectangle Top (RT):*

*RT* is characterized by a sequence of 6 extrema  $E_i$  ( $i = 1, \dots, 6$ ) such that:

$$RT \equiv \left\{ \begin{array}{l} E_1 > E_2 \\ |p(E_1, E_5)| \leq 0.001 \\ |p(E_2, E_6)| \leq 0.001 \\ \frac{V_{t_{E_3}}(E_1, E_5)}{E_3} = 1 \\ \frac{E_4}{V_{t_{E_4}}(E_2, E_6)} = 1 \\ (P_{t_d} - P_{t_{min}}) \geq \frac{2}{3} \times h \end{array} \right.$$

*C.7 Rectangle Bottom (RB):*

*RB* is characterized by a sequence of 6 extrema  $E_i$  ( $i = 1, \dots, 6$ ) such that:

$$RB \equiv \left\{ \begin{array}{l} E_1 < E_2 \\ |p(E_2, E_6)| \leq 0.001 \\ |p(E_1, E_5)| \leq 0.001 \\ \frac{E_3}{V_{t_{E_3}}(E_1, E_5)} = 1 \\ \frac{V_{t_{E_4}}(E_2, E_6)}{E_4} = 1 \\ (P_{t_{max}} - P_{t_d}) \geq \frac{2}{3} \times h \end{array} \right.$$

*C.8 Broadening Top (BT):*

*BT* is characterized by a sequence of 5 extrema  $E_i$  ( $i = 1, \dots, 5$ ) such that:

$$BT \equiv \left\{ \begin{array}{l} E_1 > E_2 \\ E_3 > E_1, E_4 < E_2, E_5 > E_3 \\ (P_{t_d} - P_{t_{min}}) \geq \frac{2}{3} \times h \end{array} \right.$$

*C.9 Broadening Bottom(BB):*

*BB* is characterized by a sequence of 5 extrema  $E_i$  ( $i = 1, \dots, 5$ ) such that:

$$BB \equiv \begin{cases} E_1 < E_2 \\ E_3 < E_1, E_4 > E_2, E_5 < E_3 \\ (P_{t_{max}} - P_{t_d}) \geq \frac{2}{3} \times h \end{cases}$$

*C.10 Triangle Top(TRIT):*

*TRIT* is characterized by a sequence of 4 extrema  $E_i$  ( $i = 1, \dots, 4$ ) such that:

$$TRIT \equiv \begin{cases} E_1 > E_2 \\ p(E_1, E_3) \leq tg(-30) \\ 0.9 \leq \frac{|p(E_1, E_3)|}{p(E_2, E_4)} \leq 1.1 \\ t_f \leq t_{E_1} + 0.75 \times (t_{int} - t_{E_1}) \\ (P_{t_{E_1}} - P_{t_{min}}) \geq \frac{2}{3} \times h \end{cases}$$

where  $t_{int}$  is the moment of support and

resistance lines interSection:

$$t_{int} = \min_t (V_t(E_1, E_3) \leq V_t(E_2, E_4), t > t_{E_4}).$$

*C.11 Triangle Bottom(TRIB):*

*TRIB* is characterized by a sequence of 4 extrema  $E_i$  ( $i = 1, \dots, 4$ ) such that:

$$TRIB \equiv \begin{cases} E_1 < E_2 \\ p(E_2, E_4) \leq tg(-30) \\ 0.9 \leq \frac{|p(E_2, E_4)|}{p(E_1, E_3)} \leq 1.1 \\ t_f \leq t_{E_1} + 0.75 \times (t_{int} - t_{E_1}) \\ (P_{t_{max}} - P_{t_{E_1}}) \geq \frac{2}{3} \times h \end{cases}$$

where  $t_{int}$  is the moment of support and resistance lines interSection:

$$t_{int} = \min_t (V_t(E_2, E_4) \leq V_t(E_1, E_3), t > t_{E_4}).$$



Table 1  
**Detected chart patterns**

Meth	HS	IHS	DT	DB	TT	TB	RT	RB	BT	BB	TRIT	TRIB	$\Sigma$
M1	78	4	7**	12**	5	12	107**	89**	57*	135	38	73*	617
	(0.42)	(0.86)	(0.00)	(0.00)	(0.96)	(0.91)	(0.00)	(0.00)	(0.02)	(0.09)	(0.18)	(0.02)	(0.12)
	40%	25%	57%**	33.**	60%	42%	58%	73%	72%	67%	76%	74%	63%
	(0.92)	(0.84)	(0.00)	(0.00)	(0.51)	(0.90)	(0.79)	(0.17)	(0.39)	(1.00)	(0.38)	(0.72)	(0.66)
M2	28	14	35**	44**	16	20	24**	33**	26	57	15	23	335
	(1.00)	(0.45)	(0.00)	(0.00)	(0.36)	(0.50)	(0.00)	(0.00)	(0.92)	(1.00)	(1.00)	(1.00)	(0.50)
	21%	21%	29%**	43.**	19%	35%	46%	45%	69%**	49%	53%	61%	42%
	(0.44)	(0.64)	(0.00)	(0.00)	(0.69)	(0.34)	(0.19)	(0.24)	(0.00)	(0.10)	(0.35)	(0.60)	(0.23)

Entries are the number of detected chart patterns and the percentage of chart patterns that reached their price objective, according to the extrema detection methods M1 and M2 (described in Appendix B). The p-values, computed through a Monte-Carlo simulation, and given in parenthesis represent the percentage of times the results on the simulated series are greater than the one of the original price series. The last column presents results for the whole sample, whatever is the chart pattern. \*\* and \* indicate respectively significance at 1% and 5%.

Table 2  
**Predictability of the chart patterns**

Meth	HS	IHS	DT	DB	TT	TB	RT	RB	BT	BB	TRIT	TRIB	$\mu$
M1	1.12	0.88	1.93**	0.86**	1.72	1.33	2.56	3.52**	4.38**	4.00	9.35*	9.45**	4.15
	(0.79)	(0.70)	(0.00)	(0.00)	(0.41)	(0.80)	(0.10)	(0.00)	(0.00)	(0.06)	(0.03)	(0.01)	(0.15)
M2	0.70	0.87	0.88**	1.19**	0.74	1.16	1.05	1.46*	2.52**	1.68**	2.58	3.42	1.50
	(0.14)	(0.14)	(0.00)	(0.00)	(0.42)	(0.08)	(0.17)	(0.02)	(0.00)	(0.00)	(0.43)	(0.31)	(0.10)
M1-M2	+**	+	+	-	+	+	+**	+**	+**	+**	+**	+**	+**

This table shows the predictability of different chart patterns according to the extrema detection methods M1 and M2 (described in Appendix B). The predictability criterion is detailed in Section 3.3.1. The last column shows the weighted average predictability for the whole sample of charts. The p-values, computed through a Monte-Carlo simulation, are given in parenthesis. The last line of the table reports the sign of the difference between both method's outputs and its statistical significance according to the difference of means test. \*\* and \* indicate respectively significance at 1% and 5%.

Table 3  
**MAXIMUM profitability of the chart patterns**

Meth	HS	IHS	DT	DB	TT	TB	RT	RB	BT	BB	TRIT	TRIB	$\mu$
M1	8	14	9**	3**	6	9	11	13	16	14	52	37	17
	(1.00)	(0.71)	(0.00)	(0.00)	(0.98)	(0.92)	(0.99)	(0.76)	(0.42)	(0.99)	(0.29)	(0.84)	(0.81)
M2	10	16	10**	12**	8	15	7	12	22*	16	28	51	16
	(0.99)	(0.51)	(0.00)	(0.00)	(0.90)	(0.49)	(0.98)	(0.84)	(0.02)	(0.72)	(0.89)	(0.64)	(0.53)

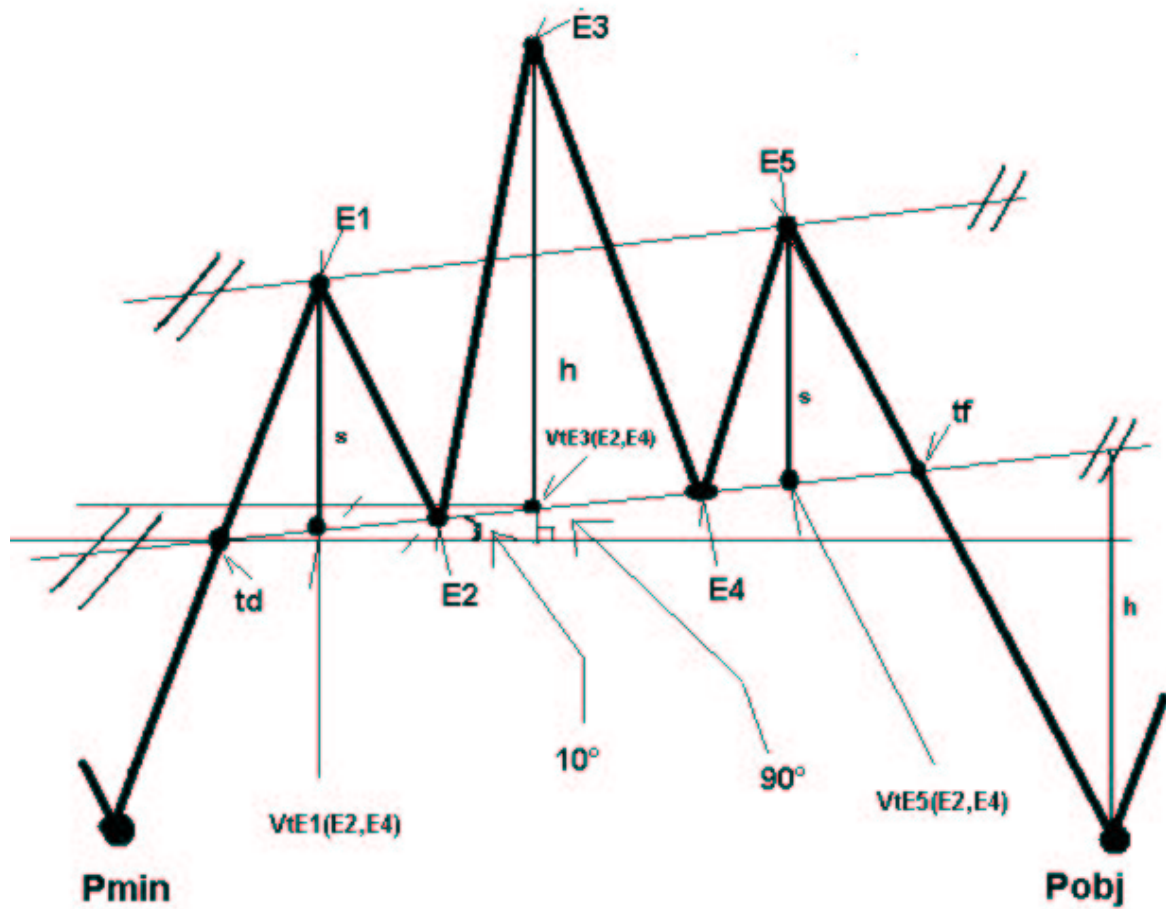
This table shows the maximum computed profit, according to the extrema detection methods M1 and M2 (described in Appendix B), expressed in basis points. The p-values, computed through a Monte-Carlo simulation, are given in parenthesis. The last column shows the weighted average maximum profitability for the whole charts. \*\* and \* indicate respectively significance at 1% and 5%.

Table 4  
**Profitability of the trading strategy**

Meth	HS	IHS	DT	DB	TT	TB	RT	RB	BT	BB	TRIT	TRIB	$\mu$
<i>Profit</i>													
M1	1.42 (1.00)	2.80 (0.70)	1.10** (0.00)	0.60** (0.00)	-0.13 (0.99)	1.54 (0.92)	1.10 (1.00)	1.52 (0.98)	1.25 (1.00)	1.39 (1.00)	2.77 (0.82)	2.13 (1.00)	1.50 (0.95)
M2	0.07 (0.99)	0.05 (0.94)	1.10** (0.00)	3.10** (0.00)	0.99 (0.85)	3.23 (0.63)	0.70 (0.95)	1.87 (0.84)	4.15 (0.27)	2.20 (0.99)	2.44 (0.96)	5.18 (0.85)	2.16 (0.64)
M1-M2	+*	+*	-	-**	-	-*	+	-	-**	-*	+	-**	-**
<i>Sharpe</i>													
M1	0.44 (0.99)	0.48 (0.65)	0.54** (0.00)	0.37** (0.00)	-0.05 (1.00)	0.50 (0.91)	0.61 (0.98)	0.98 (0.57)	0.78 (0.92)	0.79 (1.00)	0.74 (0.94)	0.76 (0.99)	0.71 (0.88)
M2	0.01 (1.00)	0.01 (0.95)	0.26** (0.00)	0.73** (0.00)	0.22 (0.78)	0.64 (0.33)	0.19 (0.91)	0.51 (0.57)	1.30** (0.01)	0.53 (0.92)	0.42 (0.89)	0.78 (0.83)	0.50 (0.55)
<i>X<sub>eff</sub></i>													
M1	0.92 (0.99)	1.56 (0.64)	0.89** (0.00)	0.48** (0.00)	-0.43 (0.99)	1.13 (0.91)	0.93 (0.99)	1.40 (0.96)	1.12 (1.00)	1.24 (1.00)	2.26 (0.84)	1.78 (0.99)	1.26 (0.95)
M2	-1.06 (0.94)	-1.93 (0.84)	0.29** (0.00)	2.20** (0.00)	0.13 (0.70)	2.01 (0.35)	0.10 (0.87)	1.22 (0.58)	3.64* (0.04)	1.37 (0.93)	0.88 (0.81)	3.19 (0.75)	1.18 (0.54)
<i>R<sub>eff</sub></i>													
M1	0.99 (1.00)	1.90 (0.46)	0.94** (0.00)	0.50** (0.00)	-0.65 (0.99)	1.23 (0.91)	0.96 (0.99)	1.45 (0.97)	1.16 (1.00)	1.29 (1.00)	2.44 (0.82)	1.89 (0.99)	1.31 (0.95)
M2	-1.32 (0.94)	-2.59 (0.81)	0.32** (0.00)	2.40** (0.00)	0.13 (0.55)	2.24 (0.29)	0.03 (0.80)	1.33 (0.54)	3.83 (0.06)	1.49 (0.95)	0.80 (0.80)	3.74 (0.59)	1.25 (0.51)

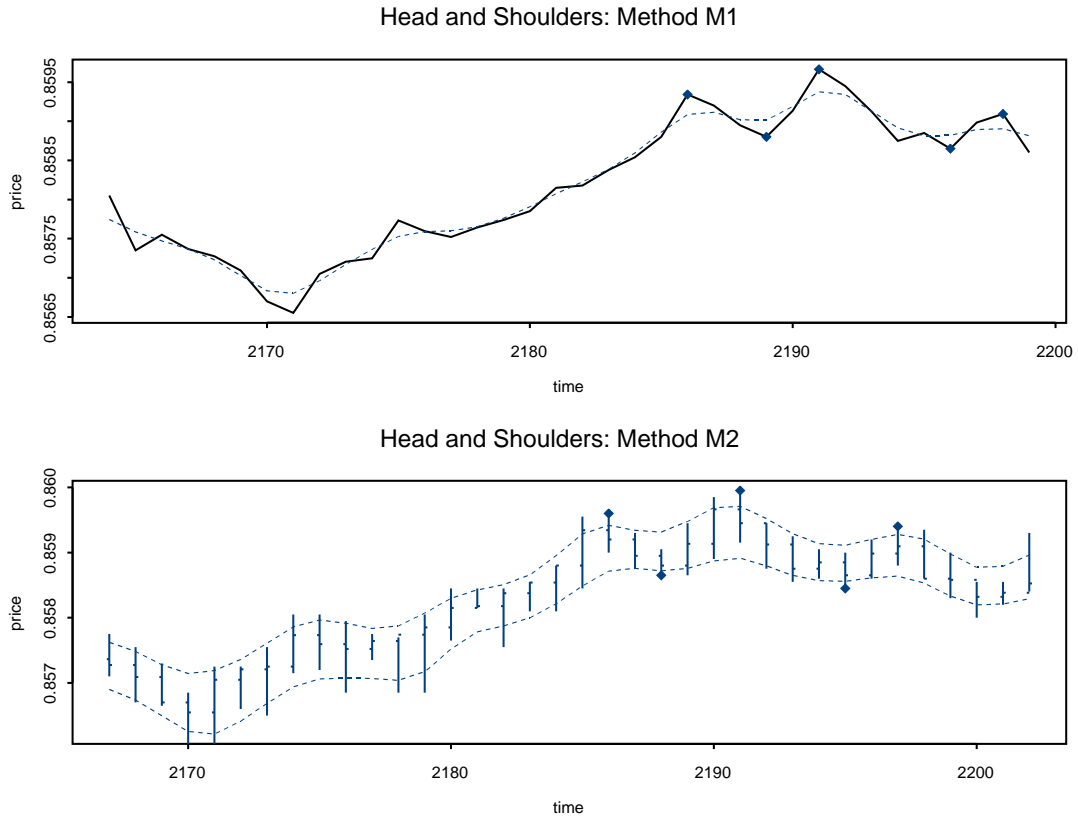
This table includes the average profits, expressed in basis points, realized after adopting the strategy detailed in Section 3.3.2, according to the extrema detection methods M1 and M2 (described in Appendix B). M1-M2 indicates the computed difference results between the two methods. It shows the sign of this difference and its statistical significance through the difference of means test. The Sharpe ratio measure the profit adjusted for risk. However,  $X_{eff}$  and  $R_{eff}$  are also a measure of profit adjusted for risk but they take into account respectively symmetric and asymmetric dealers risk aversion (more details for the computation of these two measures are provided in Dacorogna, Gençay, Müller, and Pictet (2001)). The p-values, computed through a Monte-Carlo simulation, are given in parenthesis. The last column shows the weighted average profitability for the whole charts. \*\* and \* indicate respectively significance at 1% and 5%.

Fig. 1. The Head and Shoulders: Theoretical chart pattern



The figure above presents the Head and Shoulders theoretical chart pattern (HS). The quantitative definition for such chart is presented in Section 3.2.

Fig. 2. The Head and Shoulders: Observed chart pattern



This figure shows an observation window in which the Head and Shoulders chart pattern is detected through both M1 and M2 methods (detailed in Appendix B). The dashed lines in both graphs illustrates the smoothed price curves and the solid line, for the first graph, presents the original price curve. The second graph shows the original price series through bar charts. Each of them involves the maximum, the minimum, the open and the close price for each five-minute time interval.