The Technical Signal Based Trading Effects on Volatility: Evidence From the Euro/Dollar Currency Market

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Abstract

This paper examines the technical signal based trading impact on volatility. We show that technical chart patterns, occurring within the euro/dollar currency market, attract the attention of two categories of technical traders. Technical chart patterns provide signals that could increase both volatility and market activity. The technical signals take place at the end of the chart completion, creating heterogeneity within the market participants.

Key words: technical signal based trading, volatility, information, currency market.

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1 Introduction

There is a clear consensus that speculative activity triggered by technical traders and built on technical analysis, is used mainly as a guide to short term exchange rate behavior (Black, 1986, Allen and Taylor, 1990, Allen and Taylor, 1992, Osler, 2003, and Shiller, 2003). Technical traders generally employ a wide variety of technical trading tools, involving visually identifying recurring patterns, trend identification formulas, trend reversal signals, and genetic algorithms. They use extrapolation to predict the future behavior of prices, since they have only the time series in their information set, and they consider that prices embody all aspects of the market, balancing all the forces of supply and demand. In efficient markets, economists consider the chartists as noise traders since they base their trades on noise considered by chartists as "technical information".

On the other hand, and contrary to Friedman (1953)'s argument, Black (1986) and Frankel and Froot (1990) show that trading based on technical signals leads to excessive volatility. Carlson and Osler (2000) however, find that speculators' impact on exchange rate volatility varies according to the type of shocks hitting the market. Some shocks, such as changes in liquidity demand, do not increase volatility. Other shocks, such as changes of interest rates or risk, induce a rise on volatility.

This paper examines the effects of technical signal based trading (TSBT) on foreign exchange (FX) rate volatility. We use the basic technical signals, essentially the chart patterns trading signals and we implement the same methodology as Lo, Mamaysky, and Wang (2000) and Ben Omrane and Van Oppens (2006) to recognize chart patterns. Moreover, we check for the impact of four scheduled news announcements since they present a positive pre-announcement effect highlighted by Degennaro and Shrieves (1997) and recently by Bauwens, Ben Omrane, and Giot (2005).

Based on the euro/dollar time series, news announcements database, and chart pattern signals, we study the volatility dynamics around TSBT. We find that (1) volatility drops during the completion of technical chart patterns, before the occurrence of the chart signal, where the exchange rate moves within a resistance and support levels;[1] (2) when the technical signal oc-

[1] Pring (1985) defines the support level as a zone representing a concentration of demand, and the resistance area as a zone corresponding to a concentration of supply. Murphy (1986) defines the support level, otherwise, as the area on the chart under the market where buying interest is sufficiently strong to overcome selling pressure.

curs, it generates volatility increases. A breakout takes place once the exchange rate crosses the support or the resistance level just after the chart completion, attracting the attention of technical traders and creating heterogeneity within the market participants.

The remainder of the paper contains four sections and a conclusion. Section 2 provides a review of the principal theoretical and empirical studies which have examined the interaction between information and technical trading forces in the foreign exchange market. In Section 3 we explain our methodology to study the volatility dynamics around TSBT. Section 4 describes the data and gives some details about the chart patterns recognition algorithms. Section 5 presents the model and provides a discussion about the estimation results. We conclude in Section 6.

2 Technical Signal Based Trading

TSBT is considered by economists as noise trading, and is generated by the technical traders. They have been widely discussed since the eighties by several studies which examine the ability of such technical signals in predicting future price trends. Black (1986), Frankel and Froot (1990), and recently Shiller (2003) focus on financial markets anomalies that might be triggered by noise trading. Carlson and Osler (2000) examine the speculators' effect on exchange rate volatility with respect to the types of shocks hitting the market. Lo, Mamaysky, and Wang (2000) study the effect of chart patterns on the stock return distribution. Based on order clustering patterns in executed orders, Osler (2003) proposes an explanation for the price behavior through support and resistance levels. Regarding the studies which have focused on both fundamental information and TSBT, Frankel and Froot (1986) and Allen and Taylor (1990) present a comparison between fundamental and technical analysis. Allen and Taylor (1989,1992) and Lui and Mole (1998) report the results of questionnaire surveys on the influence of chartism and the use by foreign exchange dealers, respectively in London and Hong Kong, of fundamental and technical analysis to form their forecasts.

As a result, a decline is halted and prices turn back again. Resistance level is the opposite of support.

2.1 Noise Trading and Volatility

Black (1986) considers technical traders as noise traders and defines noise trading as the trading on noise as if it were information. He notes that prices embody information that both information and noise traders trade on. Thus, it is difficult for both kinds of traders to know if they are trading on information or noise. He adds that the short term volatility of price will increase since there is noise trading. Frankel and Froot (1990) confirm Black (1986)'s arguments and show that trading volume is influenced by the importance of heterogenous expectations and might be triggered by trading based on noise rather than news, leading in turn to excessive volatility. Shiller (2003) explains the notion of excess volatility through the feedback theory. This theory is built on the mimicking behavior of different market participants. When prices go up, creating success for some traders, this may attract other market participants attention and heighten expectations for further price increases. This process in turn enhances the demand and thus generates another round of price increases. If the feedback is not interrupted, it may produce after many rounds a speculative "bubble", in which high expectations for further price increases support very high current prices. The high prices are ultimately not sustainable, since they are high only because of the expectation of further price increases. Then, the bubble bursts and the prices start falling down. The same feedback may also produce a negative bubble, downward price movements propelling further downward price drops, until the price reaches an unsustainable low level.

Osler (2003) gives more details about the unsustainable levels in the exchange rate market. She shows that downtrends and up-trends tend to reverse their course respectively at support and resistance levels, which can be identified ex-ante and which are often round numbers. She finds also that trends tend to be unusually rapid after rates cross support and resistance levels. Based on price contingent orders data-set, she offers a prima facie evidence that order clusters just before round numbers are dominated by take profit orders. Thus, price trends might reverse course when they hit take profit dominated orders. However, order clusters beyond round numbers are dominated by stop-loss orders. She shows, furthermore, that the large stop-loss buy (sell) orders cluster just above (below) round numbers, thus could explain why prices tend to move rapidly once crossing round numbers. Osler (2002) provides evidence that the rapid trends after round numbers, are derived from stop-loss order clusters, and not from central bank intervention or any other possible source suggested in the literature.

Carlson and Osler (2000) show that the TSBT effect on exchange rate volatility varies according to the type of shocks hitting the market. Some shocks, such as changes in liquidity demand, have no direct impact on speculator's preferred portfolio position. Other shocks, such as changes of interest rates or risk, do directly change speculators' preferred portfolio positions. Then, increasing speculators' activity induces a raise in volatility.

Still on the TSBT literature, Lo, Mamaysky, and Wang (2000) propose a systematic approach to recognize technical patterns using a nonparametric kernel regression. They show that some technical chart patterns do provide incremental information which affects the conditional distribution of returns, especially for the Nasdaq stocks.

2.2 TSBT and News

Regarding the effect on prices of both fundamental information and TSBT, a number of studies compare the performance of each of these sources in terms of forecasting. Other studies investigate the influence and the use of each of them by foreign exchange traders. Allen and Taylor (1990) compare the accuracy of chartist predictions with various economic and statistical approaches, using the root mean square error (RMSE) of the forecasts of each as a performance measure. They find that chartist views generate a lower RMSE than the one carried out by ARIMA, vector auto-regressions (VAR),[2] and the random walk. Frankel and Froot (1986) propose a model involving three categories of actors: fundamentalists, chartists and portfolio managers. The latter form their expectations as a weighted average of the predictions of both former actors. They show that both fundamental and technical analysis represent competitive forces within the mind of a single representative agent. However, this finding is in contrast with those ofAllen and Taylor (1989,1992) and Lui and Mole (1998). These researchers have conducted questionnaire surveys in order to study the use of both fundamental and technical analysis by foreign exchange traders. They found that more than 85% of the respondents use both fundamental and technical signals to form their expectations. At short horizons, intra-day

[2] They estimate two types of fourth-order VAR; 1) an "economic" VAR based upon the exchange rate, the interest rate differential and relative stock market performance; 2) a VAR involving only three currencies quoted against US-Dollar.

to one week, there exists a skew towards technical analysis, with 60% judging charts to be at least as important as fundamentals. At longer forecast horizons, from one to three months or six months to one year, there is a more pronounced skew towards fundamentals, with nearly 30% of respondents relying on pure fundamentals and 85% judging fundamentals to be more important than charts. Allen and Taylor (1989) point out also that less than 8% of respondents consider the two approaches to be competing to the point of being mutually exclusive while the rest think the approaches are complementary to some degree. They find moreover, that only 2% are pure chartists, and never use fundamentals at any horizon.

3 Methodology and Hypotheses

With respect to the previous literature on FX volatility, the aim of this paper is twofold. Firstly, we check for the existence of technical traders within the FX market. Secondly, we study the volatility dynamics around TSBT. Using eight categories of chart patterns we investigate volatility dynamics during and after the chart completion.

We start by identifying regularities in the time series of the exchange rate by extracting nonlinear patterns from our raw data. A smoothing method is used for this task in order to extract nonlinear relations by purging out noise data. Then, we implement the pattern recognition algorithm used by Lo, Mamaysky, and Wang (2000) and recently by Ben Omrane and Van Oppens (2006), which can provide a reasonable approximation to some of the cognitive abilities of a human analyst. It consists in identifying some specific sequences of local extrema which define chart patterns. The procedure contains three steps; 1-define each chart pattern in terms of its geometric properties, e.g., local extrema; 2-smooth the exchange rate time series through the kernel estimator so that its extrema can be identified numerically; 3-determine the extrema on the original time series and analyze the sequences of local extrema for each chart pattern (see Lo, Mamaysky, and Wang, 2000, for more details).

It is worth pointing out that the above procedure is applied within a rolling window involving "y" fixed number of observations. We narrow our focus to charts that are achieved within the span of the window in order to avoid the emerging of many patterns corresponding to various durations, and escape going beyond the day trading hours. In order to ascertain the non-duplication of detected charts which have the whole or a part of the same extrema, we add in the procedure a check-test which keeps only charts corresponding to independent local extrema.

We focus on four pairs of chart patterns. They only involve configurations where the exchange rate clusters within two borders corresponding to support and resistance levels. We consider two categories of technical traders. The first one believes that the price reverses its course at support and resistance levels. These levels correspond respectively to a concentration of supply and demand. The second one involves the chartists who believe on the chart predictive success and profitability. Technical chart patterns selected to deal with are: Broadening Bottom (BB), Broadening Top (BT), Double Bottom (DB), Double Top (DT), Rectangle Bottom (RB), Rectangle Top (RT), Triple Bottom (TB), and Triple Top (TT). Figure 1 shows the configurations corresponding to each chart pattern. Just after the completion of the chart, the exchange rate can evolve within two directions. It may cross the support or the resistance level. It could also reverse its course and pursue its trend within the charts' borders. In this case the chart fails to meet its predictive goal. We point out that we consider only technical charts of which the exchange rate crosses the borders.

Nevertheless, the objective of our study is not to check for the predictive success of different charts. We want to examine the volatility dynamics during and after the completion of the chart, despite its success or failure to fulfill its prediction. According to Osler (2002, 2003), stop-loss orders placed just after support and resistance levels trigger a rapid downtrend (uptrend) in exchange rate. This means that volatility could increase once the exchange rate crosses these levels. Black (1986) and Frankel and Froot (1986) attribute the swings in volatility to the heterogeneous expectations among traders, whereas Admati and Pfleiderer (1988), Degennaro and Shrieves (1997), Andersen and Bollerslev (1998), Evans and Lyons (1999), Melvin and Yin (2000), and Bauwens, Ben Omrane, and Giot (2005) argue about the positive effect of public and private information.

On the other hand, Shiller (2003) explains how market participants rely on mimicking behavior to trade. In such a case, they create homogeneous behavior which could lead to a drop on volatility. Black (1986) notices that market participants have to go along the herd, otherwise they lose money. Moreover, Friedman (1953) claims that rational speculation reduces volatility, since irrational speculators regularly lose money and they will be driven out of the market by rational speculators with more successful strategies. In turn, volatility drops, since that rational speculation can't be destabilizing.

Based on the above literature, our hypotheses regarding volatility dynamics before and after the TSBT can be stated as follows:

H1: *In the FX market technical chart patterns could exist.*
Statistical tests should highlight a difference between simulated and original series. The simulated series are built in such a way that any detected patterns are meaningless, whereas in the original exchange rate series, this may or may not be true. The existence of technical patterns in the original series could be generated by traders behaviors which could induce a particular pattern in the prices.

H2: *If technical chart pattern signals attract the attention of technical traders then the market activity should rise when the chart signal occurs.*
When technical traders focus their attention on the technical chart signal, they take positions according to the signal. Thus, they increase their order flow and amplify the activity within the market.

H3: *During the chart completion, before the occurrence of the technical chart signal, the market is dominated by fundamental information trading, featuring homogeneous behavior that could trigger a volatility drop.*
There is no excess volatility before the chart signal. Because the market participants feature a homogeneous behavior. The market is dominated by fundamental dealers and could involve a minority of technical dealers. However, the latter category of dealers have to go along the herd, otherwise they lose money. Moreover, they they behave homogeneously since there is no signal that could trigger divergent objectives.

H4: *At the chart completion, the technical signal occurs, it could attract the attention of technical traders. TSBT takes place once the exchange rate crosses the support or the resistance level triggering an increase in volatility.*
When the signal occurs, the market becomes dominated by the two categories of technical traders

who don't share the same objectives. The first category, who believes on the price reverse course at the support and resistance levels, place stop-loss orders beyond these levels and generate an acceleration of the exchange rate trend (Osler, 2003). The second category, the chartists, who believe on the basic chart patterns predictive success, place take-profit orders instead of stop-loss ones (Murphy, 1999, Béchu and Bertrand, 1999, Lo, Mamaysky, and Wang, 2000, and Ben Omrane and Van Oppens, 2006). Clearly both categories of technical traders have divergent objectives and create heterogeneity within the market. Moreover, there is obviously a third category involving mainly fundamental traders who trade only on fundamental information. The meeting of three divergent behaviors heightens the degree of heterogeneity and feeds a boost in volatility.

4 Data Description

4.1 The euro/dollar Exchange Rate and News Announcements Data

The exchange rate data are tick-by-tick observations on the euro/dollar quotes, bought from Olsen and Associates database, for the period ranging from May 15 through November 14, 2001. News announcements database includes the news headlines that were released on the Reuters news-alert screens over the same period.

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 returns, we have a daily grid of 288 points. At the end of each interval, we used the closest previous and next mid-quotes to compute the relevant price by interpolation. The mid-quotes are weighted by their inverse relative time distance to the interval endpoint. Next, the return at time t is computed as the difference between the logarithms of the interpolated prices at times $t-1$ and t, multiplied by 10,000 to avoid small values. Because of scarce trading activity during the week-end, we excluded all returns computed between Friday 22h05 and Sunday 24h. We control, also, for the day light-saving-time (the time change between the winter and the summer). In addition, we excluded the first return of each Monday to avoid possible biases due to the lack of activity during the week-end. The total number of returns is 37,653.

The final data transformation consists in adjusting the returns for the intra-daily component of volatility. Ben Omrane and de Bodt (2005) show that when seasonality involves only a deterministic component (and not a stochastic one), the intra-daily average observations method (IAOM) succeeds in estimating periodicity almost perfectly. This method consists in dividing the returns by their cross-sectional intra-daily average volatility, producing the seasonality adjustment (SA) returns. Because our sample does not involve any holiday which might trigger stochastic cycles, we use IAOM to adjust for seasonality. An average value of volatility is computed and attributed to the endpoint of every 5 minute interval. The time series of these values constitutes an intra-daily 'seasonal index' of volatility. This can be done by considering all days of the week as similar (an overall index), or by computing a specific index for each day of the week. In our work we consider the latter index (see Ben Omrane and de Bodt, 2005, for more details). In order to remove the seasonal factor from the market activity, we introduce the flexible Fourier form (FFF in what follows), i.e. a sum of sinusoids, to detect intra-day cycles.

Bauwens, Ben Omrane, and Giot (2005) show that volatility increases in the pre-announcement periods, particulary before scheduled events. In order to control for this effect and avoid the omitted variable bias, we introduce news announcement variables in our study. News variables involve only scheduled events (i.e. news for which the day and the time of announcement are displayed in advance on Reuters economic agenda). We consider four categories of news displayed in Table 1. They are represented by US macroeconomic figures (e.g. employment reports, producer and consumer price indices, gross domestic product and other important figures), European macroeconomic figures, scheduled speeches of senior officials of the government and of public agencies, such as the Chairman of the Federal Reserve, the Chairman of the European Central Bank, and economy and finance ministers. We also consider the US and European interest rate reports.

4.2 The Chart Pattern Data

The identification of technical chart patterns is done through the period ranging from May 15 to November 14, 2001. The goal is to recognize some exchange rate movements which contribute to the formation of specific chart patterns. As we explained in Section 3, the recognition procedure is adopted within a rolling window involving 36 time intervals of five minutes. We choose such a window length of three trading hours to focus on chart patterns that may be relevant for FX chartists.

To each time interval, corresponds a mid-quote, computed by the average of the bid and ask prices that occur just before the end of the time interval. The recognition process starts by identifying the sequences of local extrema, and ends by doing the correspondence between the different sequences and the quantitative specification of the four pairs of chart patterns.[3] Once the chart pattern is detected, we identify its starting time, its completion time, and we compute its duration. Then, we use this information to create the dummy variables corresponding to the pre- and post- completion periods relative to the chart pattern.

In order to evaluate the statistical significance of identified charts, we use a Monte Carlo simulation. We test the null hypothesis (*H0*) according to which the number of charts detected within the simulated series is larger than the number identified in the original observed data series. The alternative hypothesis *H1* means that the identification process is not relevant, i.e. there are no chart patterns in the observed data series.

Table 2 reports the number of detected chart patterns as well as their durations. The BB chart pattern presents the maximum number of detection. However, the recognition process identifies only one TT and one TB chart pattern. Regarding the p-values, there is overwhelming significance for DB, DT, RB and RT chart patterns, with p-values that are very close to zero. This result leads to accept *H1.* In contrast, the TB and TT chart patterns carry out no statistical significance (at 5% significance level). The duration of different charts (i.e. the time taken by the chart from its beginning to its completion) ranges from 16 to 35 time intervals (of five minutes).

5 Models and Empirical results

5.1 Models

We start by studying the sensitivity of the quoting activity, taken as a proxy for market activity, to the chart signals. Our goal is to check if the chart signals attract indeed the attention of chartists. In such a case, chartists could initiate TSBT and generate more activity within the

[3]The quantitative specifications of the four pairs of chart patterns are presented in detail in Ben Omrane and Van Oppens (2006).

market. The post-completion period corresponding to the technical chart pattern j is represented through the dummy variable $Chart^{post}_{j,t}$ taking the value 1 five-minute after the signal and 0 otherwise. The model to be estimated is

$$q_t = c_0 + \sum_{j=1}^{8} \rho_j \, Chart^{post}_{j,t} + \sum_{i=0}^{2} \lambda_i \, \varepsilon_{t-i} + \sum_{p=1}^{P} (\delta_{c,p} \cos y_{t,p} + \delta_{s,p} \sin y_{t,p}), \tag{1}$$

where $\lambda_0 = 1$ and ε_t is the error term. We use the quoting activity q_t as a proxy for the market activity. To control for seasonality we introduce the flexible Fourier form. The variable $y_{t,p}$ is equal to $2\pi p \, n_k/N_k$ and N_k indicates the number of hours per day: $N_k = 288$, for all open days of the week except for Fridays ($N_5 = 264$), and n_k takes the values $1, 2, \ldots, N_k$. The FFF order is limited at $P = 4$.

The second step of our approach consists in studying the volatility dynamics around TSBT. We use the EGARCH model of Nelson (1990) to model the SA returns (denoted r_t) and their conditional variance, denoted h_t (to measure volatility).[4] The level of returns is modeled by a moving average process of order two to account for the detected autocorrelation, such that:

$$r_t = \theta_0 + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2}, \tag{2}$$

and the error term u_t by an EGARCH(2,2) process:[5]

$$u_t = \sqrt{h_t} \, \epsilon_t, \tag{3}$$

$$\begin{aligned} \ln h_t \;\; = \;\; & \omega + \sum_{i=1}^{2} \left(\beta_i \ln h_{t-i} + \alpha_i \left[\mid \epsilon_{t-i} \mid - \sqrt{2/\pi} \right] + \gamma_i \epsilon_{t-i} \right) \\ & + \sum_{j=1}^{8} \sum_{\tau=1}^{2} \eta_{j,\tau} Chart_{j,\tau,t} + \sum_{n=1}^{4} \varphi_n d_{n,t}. \end{aligned} \tag{4}$$

The innovations ϵ_t are assumed identically and independently distributed. We estimate the model by the quasi maximum likelihood (QML) method, we proceed as if their distribution was normal. The variable denoted $Chart_{j,\tau,t}$ is a dummy variable corresponding to the chart pattern of category j identified during the period τ, relative to the five-minute return time

[4] Since we model SA returns, h_t is the deseasonalized conditional variance.

[5] An EGARCH(1,1) structure was not sufficient to clean the autocorrelation of the squared standardized residuals.

t. The index τ indicates an observation window: a period corresponding to the chart pattern completion ($\tau = 1$), and a period just after the completion ($\tau = 2$). The first observation window corresponds to the time period in which the chart pattern evolves from its beginning until its completion, and the second to the five minutes occurring just after the completion. The variable denoted $d_{n,t}$ is also a dummy variable corresponding to the pre-announcement scheduled news of category n.

The coefficients of Equation (1) allow to test our second hypothesis (*H2*). The coefficients of Equation (4) allow to test the hypotheses *H3* and *H4*.

5.2 Robustness Test

In order to test the robustness of our results, we generate four dummies that take the value of one when a random "event" occurs and zero otherwise. This random event does not convey any information and is not related to any fundamental or technical information. There are 13 random events per dummy of which the duration lies in between 24 and 35 time intervals.[6] We estimate Equations (1) and (4) with the dummy variables corresponding to the chart patterns replaced by those for the random events. We test that the latter dummies have no impact on market activity or volatility, since they do not convey any information.

5.3 Empirical Results

To evaluate *H2*, we test the hypothesis that ρ_j is equal to zero against positive ρ_j (since we guess a positive impact). Rejecting the null hypothesis means that the chart signal attract the attention of chartists who could generate TSBT and consequently increase market activity. To test *H3*, the null hypothesis is that $\eta_{j,1} = 0$ for all j, and the alternative is that $\eta_{j,1} < 0$ (since we guess a negative impact). Rejecting the null implies that volatility drops, before TSBT, during the chart pattern completion. Finally, to test *H4*, the null hypothesis is $\eta_{j,2} = 0$ for all j, and the alternative is $\eta_{j,2} > 0$ (since we guess a positive impact). Rejecting the null implies that the post-completion period for the technical chart feeds TSBT that generates an increase on volatility.

[6]The number of the random events is equal to the mean number of the detected charts.

Tables 3 and 4 report the estimation results of the TSBT effects respectively on quoting activity and volatility. Table 3 shows positive estimated coefficients for six dummies (out of eight) of which three are statistically significant (two at 1% and one at 5%).[7] TSBT occurring just after the completion of BB, RB and TT chart patterns triggers an increase on quoting activity. This result means that some technical signals attract the attention of technical traders that trigger an increase on market activity. Clearly, we accept *H2*, since the joint hypothesis of nullity of the 8 ρ_j coefficients is rejected at the 1% level.

Table 4 displays the estimation results for Equations (2)-(4). The standardized residuals and squared residuals are not autocorrelated (according to Q-statistics). The EGARCH coefficients are significant (except for the asymmetry effects) and compatible with a stationary process. The table shows, moreover, negative significant estimated coefficients for dummies corresponding to the chart completion period, and positive significant coefficients for the post-completion period. Clearly, both *H3* and *H4* are accepted. Volatility decreases by 25 percent, during the completion of DB chart pattern. It drops by 20 percent for DT, 17 percent for RT, and 48 percent during the completion of TB. In turn, during the chart pattern completion, there are no technical signals, deals could be dominated by fundamental traders who build their trade on fundamental information and feature homogeneous behavior. They share the same expectations that weigh on the exchange rate movement. Such behavior dampens the price changes and triggers a drop on volatility, since the important order flows are generated by fundamental information trades.

However, just after the completion of the technical chart patterns, once the exchange rate crosses the support or the resistance level, technical traders are attracted to initiate trades triggering an increase in volatility: DB (25 percent), DT (18 percent), RT (16 percent) and TB (48 percent). In such a period, there are two categories of dealers: fundamental and technical traders. These two kinds of dealers are indeed different. However, heterogeneity is also created by the divergent objectives of the two main categories of technical traders. One category, believing only in the price reverse course at support and resistance levels, has already placed stop loss (take profit) orders after (before) the chart completion. However, the second category which involves the chartists, trust on the basic chart patterns, and has already placed their take profit orders after the chart completion. The difference of objectives characterizing both categories of

[7]The estimation is done by quasi maximum likelihood with Newey-West (HAC) standard errors.

technical traders heightens the price cluster and generates a boost in volatility.

Regarding the robustness test, it is clearly shown in Table 5 that the random event dummies have no significant impact on either market activity or volatility. All the p-values are much larger than 10%. Since the random event does not convey any fundamental or technical information, it does not attract the dealers' attention that could impact market activity and volatility. As a consequence, the results found in Tables 3 and 4 are not random. They are indeed the results of the significant effect of the TSBT. On the other hand, there are some chart patterns, for instance BB, BT, RB and TT that have no direct significant impact on volatility. They have, elsewhere, an indirect impact through the market activity, since this latter variable has a positive impact on volatility (highlighted by Degennaro and Shrieves, 1997 and Bauwens, Ben Omrane, and Giot, 2005). Nevertheless, BT chart patterns have no significant impact on either volatility or market activity. This means that this kind of chart patterns does not attract the attention of technical traders and does not trigger TSBT.

Table 6 displays the results corresponding to the total impact (before and after the completion) of the chart pattern on volatility. Volatility decreases before the completion of the chart since there is no TSBT. After the chart completion, and once the exchange rate crosses the support or the resistance level, TSBT occurs and volatility increases to revert slowly to its initial level. The total impact of TSBT is null except for BT and DT which present respectively small positive and negative (of the order of 1.1 and 1.7 percent) effects on volatility. Reversion to the initial level is implied by stationarity of the EGARCH model: the persistence is carried out through the sum of the coefficients β_1 and β_2 estimated at 0.97.

Regarding the news announcements impact on volatility, the estimation results displayed in Table 4 are consistent with those found by Bauwens, Ben Omrane, and Giot (2005). Volatility increases by 15 percent prior to the release of US figures. It rises by 3 percent prior to European figures, by 6 percent prior to official speeches and 17 percent prior to the release of US and European interest rate reports. A possible explanation of such volatility increases is that they are caused by anticipatory trades, i.e. by traders who open positions hoping that their anticipations will coincide with the contents of the news. However, another category of traders may also take part in the trading. These traders, who are characterized by a high level of risk aversion, prefer to execute their clients' orders right before the news release to avoid possible reversals of trends in the currency rate (Lyons, 1991, Bauwens, Ben Omrane, and Giot, 2005).

6 Conclusion

This paper focuses on technical signal based trading effect on exchange rate volatility. Using five-minute euro/dollar returns, news announcements, and technical chart patterns trading signals, we shed light on volatility dynamics around TSBT.

The paper results show that volatility decreases during the technical chart pattern completion, when the exchange rate moves within the support and resistance levels, corresponding respectively to a concentration of demand and supply. A possible explanation for such a volatility drop, is that the foreign exchange market is dominated by fundamental traders, sharing the same expectations and featuring a homogeneous behavior. The second result consists of volatility increase just after the chart completion, when the exchange rate crosses the support or resistance level. In such an area, the attention of technical traders is attracted and TSBT occurs creating heterogeneity within the market participants and triggering a rise in volatility.

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Figure 1: The Geometric Configuration for the technical charts

The four pairs of technical chart patterns: Broadening Bottom (BB), Broadening Top (BT), Double Top (DT), Double Bottom (DB), Rectangle Bottom (RB), Rectangle Top (RT), Triple Top (TT) and Triple Bottom (TB).

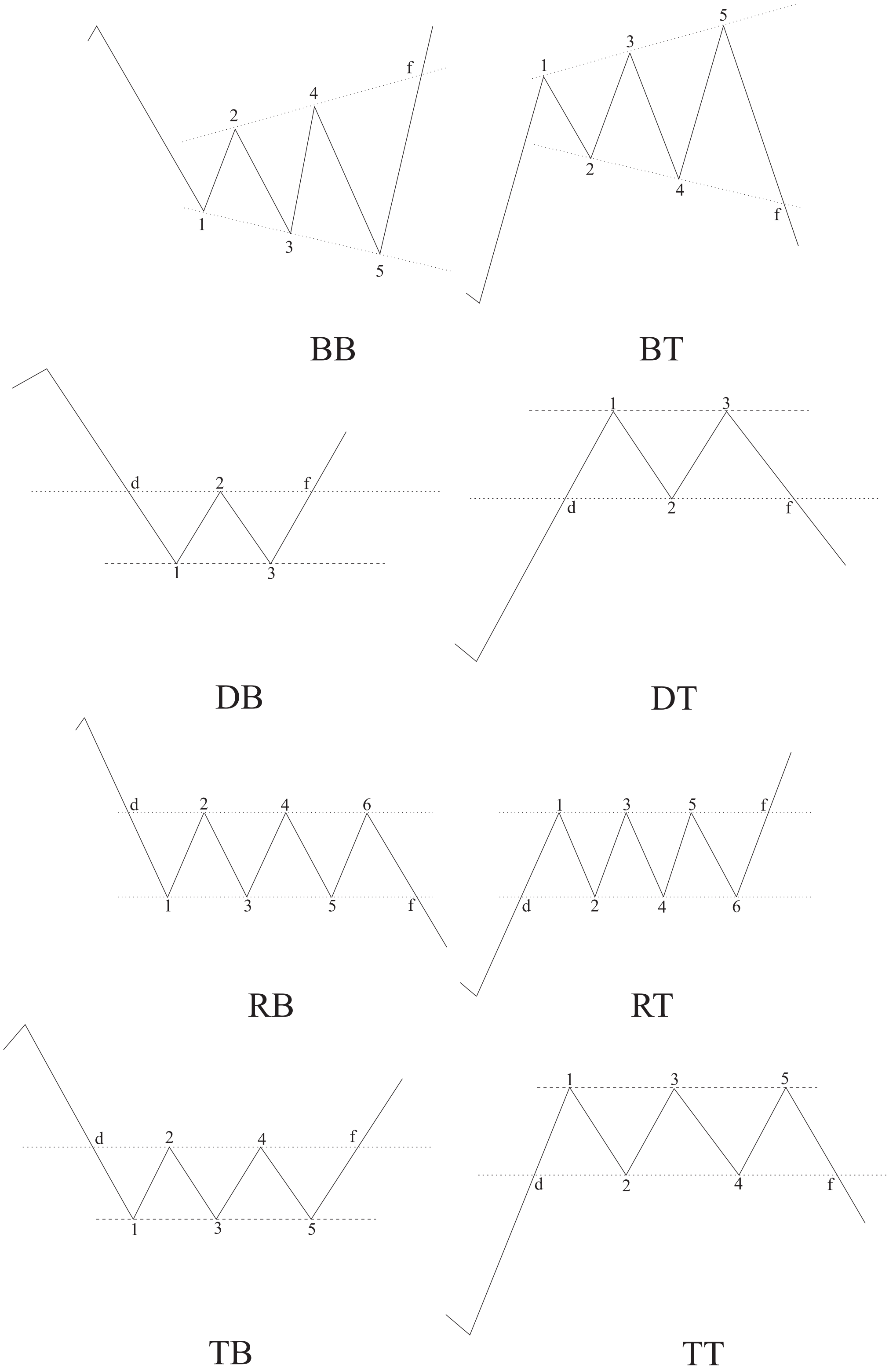

Table 1: **News categories**

Scheduled news announcements	regression coefficient
1-US macroeconomic figures	φ_1
Employment report	
ISM index(ex NAPM)	
Whole sales	
Gross domestic product (GDP)	
Producer price index (PPI)	
Retail sales	
Housing starts	
Consumer confidence index	
Consumer price index (CPI)	
Construction spending	
Car sales	
Business inventories	
Housing completions	
Import prices	
Current account deficit	
Non-farm productivity	
Personal income	
Real earnings	
House sales	
3-European macroeconomic figures	φ_2
4-Speeches of senior officials of the government and of public agencies	φ_3
5-US and European interest rate reports	φ_4

The events are the news headlines released on the Reuters money news-alerts.
The employment report includes the unemployment figures.
ISM is the abbreviation for the Institute of Supply Management, ex NAPM, National Association of Purchasing Management. It is a monthly composite index and gives the earliest indication of the health of the manufacturing sector.
The symbol φ_n is the coefficient of the dummy variable $d_{n,t}$ in the equations reported in Table 4.

Table 2: **Detected chart patterns**

	BB	BT	DB	DT	RB	RT	TB	TT
Detection	28	18^{*}	14^{**}	11^{**}	10^{**}	22^{**}	1	1
p-value	*9%*	*2.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*91%*	*96%*
Mean Duration	25	25	19	16	29	20	35	23

Entries are the number of detected chart patterns. The p-values, computed through a Monte-Carlo simulation represent the percentage of times the results on the simulated series are greater than the ones on the original price series. The last row presents the mean duration of each chart pattern. ** and * indicate respectively significance at 1% and 5%.

Table 3: **The TSBT effects on quoting activity**

$$q_t = c_0 + \sum_{j=1}^{8} \rho_j \, Chart_{j,\,t}^{post} + \sum_{i=0}^{2} \lambda_i \, \varepsilon_{t-i} + \sum_{p=1}^{4} (\delta_{c,p} \cos y_{t,p} + \delta_{s,p} \sin y_{t,p}) \quad (1)$$

Coefficient	Estimation	P-Value (%)	Coefficient	Estimation	P-Value (%)
c_0	0.904^{**}	0.0	ρ_3	0.058	40
λ_1	0.739^{**}	0.0	ρ_4	0.022	63
λ_2	0.444^{**}	0.0	ρ_5	0.171^{**}	0.3
ρ_1	0.079^{*}	2.4	ρ_6	-0.021	50
ρ_2	0.016	77	ρ_7	-0.023	48
			ρ_8	0.660^{**}	0.0
Obs.	37 650	R^2	83.18%	$W(\rho_j = 0)$	598.4^{**}

** and * indicate respectively significance at 1% and 5%.
Estimation by the quasi maximum likelihood method with the Newey-West HAC standard errors. To save space, coefficients for FFF are not shown. All the FFF coefficients are statistically significant at 1% level. $W(\rho_j = 0)$ is the Wald statistic for the hypothesis of nullity of the 8 coefficients ρ_j. $j = 1, 2, \ldots, 8$ corresponds respectively to the chart patterns BB, BT, DB, DT, RB, RT, TB, and TT..
q_t is the the percentage of the quoting activity. $Chart_{j,\,t}^{post}$ is a dummy variable corresponding to the post-completion period for the chart category j.

Table 4: **The TSBT Effect on Volatility**

$$r_t = \theta_0 + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} \tag{2}$$

$$u_t = \sqrt{h_t}\epsilon_t \tag{3}$$

$$\begin{aligned}\ln h_t = \omega + \textstyle\sum_{i=1}^{2} \left(\beta_i \ln h_{t-i} + \alpha_i \left[\mid \epsilon_{t-i} \mid - \sqrt{2/\pi}\right] + \gamma_i \epsilon_{t-i}\right) \\ + \textstyle\sum_{j=1}^{8} \sum_{\tau=1}^{2} \eta_{j,\tau} Chart_{j,\tau,t} + \sum_{n=1}^{4} \varphi_n d_{n,t}\end{aligned} \tag{4}$$

Coefficient	Estimation	P-Value (%)	Coefficient	Estimation	P-Value (%)
θ_0	0.003	44	θ_1	-0.134**	0.0
θ_2	-0.028**	0.0	ω	-0.067**	0.0
α_1	0.307**	0.0	$\eta_{8,1}$	-0.063	85
α_2	-0.229**	0.0	$\eta_{1,2}$	0.041	40
γ_1	-0.005	39	$\eta_{2,2}$	-0.066	22
γ_2	0.007	20	$\eta_{3,2}$	0.249**	0.0
β_1	1.292**	0.0	$\eta_{4,2}$	0.179	6.5
β_2	-0.321**	0.0	$\eta_{5,2}$	0.058	48
$\eta_{1,1}$	-0.039	42	$\eta_{6,2}$	0.164**	0.0
$\eta_{2,1}$	0.076	16	$\eta_{7,2}$	0.476**	0.2
$\eta_{3,1}$	-0.254**	0.0	$\eta_{8,2}$	0.072	83
$\eta_{4,1}$	-0.196*	4.9	φ_1	0.149**	0.0
$\eta_{5,1}$	-0.054	51	φ_2	0.032**	3.1
$\eta_{6,1}$	-0.166**	0.0	φ_3	0.056**	0.3
$\eta_{7,1}$	-0.482**	0.3	φ_4	0.170**	0.0
Obs.	37 650	$W(\eta_{j,1} = 0)$	5.177**	$W(\eta_{j,2} = 0)$	5.178**
j	1	2	12	24	
$Q(j)$	1.21	1.88	10.88	20.72	
$Q^2(j)$	3.21	4.94	10.98	30.13	

** and * indicate respectively significance at 1% and 5%. $W(\eta_{j,1} = 0)$ is the Wald statistic for the hypothesis of nullity of the 8 coefficients $\eta_{j,1}$ for all j, and $W(\eta_{j,2} = 0)$ is the same statistic corresponding to the 8 coefficients $\eta_{j,2}$. $Q(j)$ and $Q^2(j)$ are the Ljung-Box statistics of order j respectively for standardized residuals and for their square. Twelve lags correspond to 1 hour. Variables in Equations (2), (3), and (4): r_t is the SA return (multiplied by 10,000). $Chart_{j,\tau,t}$ is a dummy variable for the chart j corresponding respectively to the period of its completion ($\tau = 1$), and the period that occurs just after the completion ($\tau = 2$), relative to time t. $j = 1, 2, \ldots, 8$ corresponds respectively to the chart patterns BB, BT, DB, DT, RB, RT, TB, and TT. $d_{n,t}$ is a dummy variable corresponding to the category of news n. Estimation was done by the quasi maximum likelihood method.

Table 5: **Robustness Tests**

Random Event Dummies	*Effects on activity*	*Effects on volatility*
RE_1	89.30%	48.71%
RE_2	21.16%	85.80%
RE_3	94.63%	22.56%
RE_4	96.47%	35.40%

The first column gives the random event dummy variable category. The second column show the p-values of the estimated impact of the random event dummies on market activity. The last column displays the p-values of the estimated impact of the random event dummies on volatility.

Table 6: **The TSBT total impact on volatility**

Chart pattern category (j)	$\hat{\eta}_{j,1}$	$\sum_{\tau=1}^{2} \hat{\eta}_{j,\tau}$
1-Broadening Bottom (BB)	-0.039	0.002
2-Broadening Top (BT)	0.076	0.01**
3-Double Bottom (DB)	-0.254**	-0.005
4-Double Top (DT)	-0.196*	-0.017*
5-Rectangle Bottom (RB)	-0.054	0.004
6-Rectangle Top (RT)	-0.166**	-0.002
7-Triple Bottom (TB)	-0.482**	-0.006
8-Triple Top (TT)	-0.063	0.009

The second column gives the technical chart pre-completion impact and the last column the total impact. Estimates are taken in Table 4.

** and * indicate respectively significance at 1% and 5%, for one-tail tests.