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The impact of volatility on the implementation of the relative strength index: evidence from the Shanghai stock exchange

Abstract

This paper examines the impact of volatility (measured as an exponentially-weighted moving average) on the implementation of a trading rule, based on the relative strength index (RSI) in the Chinese stock markets. In particular, using tick-by-tick data from the Shanghai stock exchange, the aouthors investigate how sensitive is the choice of RSI boundaries to different volatility regimes. The study reports empirical evidence that the return and the risk of our portfolios, in regimes of high and low volatility, are not significantly affected by the boundaries imposed to this technical indicator. However, we show that within each volatility regime some techniques provide a more desirable return-risk package than others.

Keywords: technical analysis, relative strength index, volatility regime, Shanghai stock exchange.

Introduction

Not only technical analysis is one of the most commonly used techniques in trading rooms around the world (Harris, 2003; Schwager, 1994), but it also represents typical traders' behavior[1]. It is, therefore, of interest to examine how technical trading rules can be implemented across different market designs and under different market conditions. Trading decisions, triggered by pattern screening techniques, are often significantly affected by the subjectivity of the investor, altering the quality of empirical examinations of their performance. In spite of the simplicity and relative objectivity[2] of the widespread RSI, its implementation, however, remains affected by the volatility of the market. This paper, accordingly, investigates the impact of volatility on the performance and on the intensity of the trading signals triggered by this technical indicator in the Chinese stock markets.

The motivation for investigating technical analysis in the Chinese stock markets is essentially fourfold. First, although being an emerging market, this market has grown increasingly important among the world stock markets. According to the world federation of echanges (WFE) (2009), the capitalization of the Chinese stock market accounts for 5.34% of the world total in 2008, a nearly threefold increase since 2002 (2.02%)[3]. Second, the Chinese stock markets are famous of being volatile. In this respect, the annual volatility of the Shanghai composite index was 0.102 in 2007, while the volatility of the FTSE100 and of the Dow Jones industrial average were 0.026 and 0.030, respectively. This provides an ideal ground for examining the impact of different volatility regimes on technical analysis models. Third, with the trading volume dominated by individual investors rather than institutional investors, these markets have a distinct investor base compared to stock markets from more developed economies. For example, between 2002 and 2004, the trading volume of individual accounts was 5.76 times bigger that of institutional accounts (Lee, Li and Wang, 2010). Due to different investment perspectives, levels of access to information and financial literacy, the efficiency of a market with a majority of individual investors is particularly of interest to investigate. Finally, the Chinese markets, i.e., the Shanghai and Shenzen stock exchanges, are marked by distinctive regulatory features. For example, shares may be suspended from trading around the time when a major news release is scheduled, such as a merger and acquisition deal. Companies will be labeled "ST (special treatment)" if their net profits are negative for two consecutive accounting years, in which case a 5% daily volatility and a more frequent auditing on the company's financial reporting will apply[4].

This paper contributes to the existing literature in the following manner. This is the first empirical study on technical analysis in the Chinese stock markets, relying on the information conveyed by high-frequency data[5]. The reported evidence sheds new light on the impact of different volatility regimes on the performance of technical analysis. Finally, the results provide further insight into the efficiency of the Chinese stock markets.

The remaining of this paper is organised as follow. Section 1 reviews relevant literature on technical analysis. Section 2 specifies the data and the methodology used in this study. Section 3 presents and interprets the results. The last Section concludes.

[1] The typical decision-making process is described as strong and repeated belief, justification of the belief by a favourable evidence, confirmation bias, and finally self-deception. See also Tversky and Kahneman (1974) or Sewell (2008).

[2] See Tripathi (2008).

[3] The Chinese stock market here refers to Shanghai and Shenzhen stock exchanges.

[4] See, www.sse.con.cn and www.szse.cn for more details.

[5] Li and Chen (2003) studied the predictability of a moving average model on Chinese stocks with daily prices.

1. Literature review

Technical analysis is generally compared to fundamental analysis, which is based on the intrinsic value of securities (see, Damodaran, 2002 or Kirkpatrick and Dahlquist, 2007). Fundamental analysis assumes that the price of a security reflects its true value, taking into consideration all the characteristics of the macroeconomic and microeconomic environment, a detailed analysis of the industry framework and an analysis of the security itself (Hooke, 1998). By contrast, the information set used in technical analysis, is limited to past prices and volumes.

As several authors show, technical analysis is linked to market efficiency. Malkiel (2003) argues that in the case of an efficient market, in the sense of strong-form efficiency (Fama, 1970), neither technical analysis nor fundamental analysis can generate excess returns compared to a randomly selected portfolio. Even in weak-form efficient market, in which current prices fully reflect the information conveyed by historical prices and volumes, technical analysis is not expected to add value (Bessembinder and Chan, 1998).

Against this background, several empirical studies assess the ability of investors of achieving positive returns with portfolio decisions triggered by technical rules. Neftci (1991) checks the predictive power of technical analysis. In the case of Gaussian time series, generated predictions seemed to be useless, and in the case of a non-linear process, technical analysis might capture some information. Brock, Lakonishok and Lebaron (1992) test moving average models and trading range breaks on the Dow Jones industrial average index. Their results show that the signals generated by the technical models provide higher than expected returns. Similar findings are reported in Mills (1997), who conducted an empirical study of the FTSE 30 Index. The evidence presented in Lucke (2003) nevertheless fails to support the profitability of the popular head-and-shoulders rule in the foreign exchange market. Park and Irwin (2007) survey the empirical evidence on the profitability of technical analysis. Among 95 studies, 56 report positive results regarding technical trading strategies, 20 studies lead to negative results, while 19 studies indicate mixed results.

The relative strength index (RSI), introduced in Welles Wilder (1978), is a momentum oscillator capturing the speed of price adjustments (momentum). Its oscillating property makes it move between 0 and 100, which simplifies its interpretation and allows its users to determine when a security should be bought or sold. According to the author, by relying on average values, the RSI has the additional advantage of further eliminating erroneous erratic market movements. Regarding the implementation of the RSI, Welles Wilder (1978) recommends the use of a 14-day period of calculation. In a subsequent work, Achelis (2001) however argues that the period of calculation depends on the predominant cycle of the security and that longer periods of calculation lead to less volatile values of the indicator. Petitjean (2004) further argues that the optimal period has to fit with the trading style of the investor. The author identifies four trading style classes, each with a specific time period for the calculation of the RSI. For day trading, he recommends periods of 5 to 15 minutes. For short-run trading, periods are chosen between 60 minutes and one day. A medium-term trader would use weekly periods. Finally, for long-run trading, the author recommends monthly periods of calculation.

In Wong, Manzur and Chew (2003), the RSI triggers a buy or sell signal in one of the following manner. The touch method generates a sell signal when the RSI touches the upper bound, typically set at 70 for a 14-day RSI, and generates a buy signal when the RSI touches the lower bound, typically 30 for a 14-day RSI. The peak method sells the security when the RSI crosses the higher bound and then turns back. By contrast, when the RSI crosses the lower bound and turns back, it is considered a sell signal. The retracement method leads to a buy signal when the RSI crosses the lower bound and goes back to the same lower bound or goes higher. Similarly, it generates a sell signal when the RSI crosses the higher bound and goes back to this one or a lower level. Finally, the 50-crossover method triggers a buy signal when the oscillator rises above 50 and generates a sell signal when it drops under 50. These authors show that the RSI can be used to achieve positive returns over the period from January 1974 to December 1994 by trading the Singapore straits times index (STI). In the same vein, Schulmeister (2009) tests 2,580 models in the S&P 500 spot and futures markets between 1960 and 2000. The reported evidence similarly points to the superior performance of the models based on the RSI relative to moving average trading rules.

2. Data and methodology

2.1. Data. The dataset contains tick-by-tick records of the transactions executed on the Shanghai stock exchange from October 2007 to March 2008. Our sample includes the thirty largest companies by market capitalization from the constituents of the SSE 50 index, which tracks the dynamics of the largest and most liquid stocks on the Shanghai stock exchange[1]. The tick data is aggregated at the 5-minute frequency. A trading day is deleted if the stock starts trading after 10:30 or is suspended from trading for more than 50 minutes on that day.

[1] The Shanghai stock exchange is larger than the Shenzhen stock exchange in terms of the number of listed companies, number of listed shares, total market value, tradable market value, securities turnover in value, and stock turnover in value around the world. Source: http://www.stockmarket.com.au/world-stock-markets/shanghai-stock-market.

2.2. Methodology. To assess the performance of the RSI, we compute RSI scores for each stock over every 5-minute intraday interval. The score, computed at time t, relies on a rolling window of 14 past observations[1] and is measured as:

$$RSI_t = \frac{\frac{1}{14}\sum_{n=1}^{14}\max(r_{t-n},0)}{\frac{1}{14}\sum_{n=1}^{14}\max(r_{t-n},0) - \frac{1}{14}\sum_{n=1}^{14}\min(r_{t-n},0)}, \quad (1)$$

where r_t is the 5-minute return measured over intraday interval t.

Trading signals are triggered by a touch method (see Section 1 for more details). In this paper, we compare two sets of threshold values for the RSI to trigger a buy or a sell signal: 70/30 (hereafter, loose boundaries, consistent with the original boundaries used in Welles Wilder, 1978) and 60/40 (hereafter, tight boundaries, which increases the sensitivity of the RSI to market moves). By construction and depending on the bound values, signals are only generated for some intraday intervals, since the RSI scores do not always touch or cross the boundaries. The first trade of a day takes place at the time the first buy signal is triggered. The order is placed so that all the available funds are invested at this time. Hence, available funds become equal to zero and the next trade must accordingly be a sell. So long as the program does not identify a sell signal, the position in the stock remains unchanged even though its marked-to-market value is allowed to change over time. When a sell signal is reached, the whole position is liquidated at the prevailing market value. The money generated by the trade is then considered available to open a new position once a new buy signal is triggered. To reinforce the robustness of our findings, each trade is adjusted for the transaction costs prevailing in the market by incorporating the half of the bid/ask spread supported by impatient traders. Buy orders are accordingly executed at the best ask, prevailing in the market at the time of the trade. By contrast, a sell signal triggers a trade at the best bid quote. At the end of each day, each position is marked to the market. The performance of the technique is then measured by the return of the portfolio over the day by computing the equally-weighted average of the returns of each stock included in our sample at the close of the market.

To assess the influence of market volatility on the performance of the technique, we further separate high-volatility days from low-volatility days. The MSCI China index is used to calculate volatility in the form of an exponentially-weighted moving average. We set the persistence parameter equal to 0.94 in line with the value reported in Riskmetrics (1996). The data is extracted from Thomson Reuters Datastream. The classification follows the smoothed regime probabilities computed by the following Markov switching model:

$$h_t = \mu_s + \varepsilon_t, \quad \varepsilon_t \sim iid\left(0, \sigma_s^2\right), \quad (2)$$

where h_t is the volatility proxy; μ_s is a regime-dependent constant capturing the mean level of volatility in each regime; ε_t is the error term; and σ_s^2 is the regime-dependent variance of this error term. Based on the above regime decomposition, we compute the average return of each technique in tranquil and volatile markets.

Appendix B reports the results from the estimation of model (2). The results from the Markov switching model indicate that during the whole sample period there are two volatility regimes, i.e., one with relatively low volatility and one with relatively high volatility. The null hypothesis of a single regime of volatility is strongly rejected by a likelihood ratio test of linearity. The low volatility regime has 64.5 days, while the high volatility regime has 66.5 days. As the transition probabilities determined endogenously by the model suggest, the regime of high volatility (regime 2) is slightly more persistent than the low volatility state: the probability that volatility remains high on two consecutive days is 98.43%.

4. Results and interpretation

Table 1 (see Appendix A) reports descriptive statistics of the returns generated by a trading rule based on the RSI indicators in the two volatility regimes. The mean daily returns range from 0.011% to -0.085% depending on the volatility regime and on the choice of RSI boundaries. Overall, the RSI with loose boundaries (70/30) is more profitable over the entire period (0.08%). For both sets of boundaries (70/30 and 60/40), market volatility alters the size of the returns generated by a trading rule following the RSI. The standard deviation indicates that loose 70/30 boundaries (0.280) are less risky than tight 60/40 values (0.786). In addition, for a given set of boundaries, the variability of returns is larger in the regime of high volatility than in low volatility periods. The skewness, computed on low-volatility days, is negative, which points to a left-skewed distribution for the returns on such days. During periods of high volatility, the returns are less skewed to the left and are right-skewed with loose boundaries. Kurtosis is always larger than three regardless of the volatility periods, meaning that the empirical distribution always has a higher peak and heavier tails than a normal distribution. Kurtosis is however systematically larger in periods of low volatility than in periods of high volatility.

[1] The number of periods used in the estimation of RSI scores follows Welles Wilder (1978), where the author relies on a rolling window of the past 14 days.

Table 2 (see Appendix A) displays descriptive statistics for the number of signals generated by the RSI. The average number of signals per day is significantly higher with tight boundaries: 12.745 signals per day with the 60/40 boundaries compared to 2.030 signals with loose boundaries (70/30). Interestingly, the number of signals decreases slightly during periods of high volatility, compared to periods of low volatility. Signals are less dispersed when the boundaries are loose: the standard deviation is 0.841 with the 70/30 thresholds and reaches 2 with the 60/40 values. Regardless of the choice of boundaries and the volatility regime, skewness is small and the distribution is well split into the tails. Skewness is slightly higher when volatility is high, pointing to a longer right tail. Kurtosis is close to 3, whatever the set of boundaries used or the regime of volatility.

Table 3 (see Appendix A) finally presents descriptive statistics of the number of trades generated by the technical indicators. As expected, the average number of trades is greater with tight boundaries (0.223 transactions per day with the 70/30 boundaries versus 1.109 trades with a 60/40 RSI). Tight boundaries similarly inflate the dispersion of the number of trades around their daily mean. Consistent with a slightly lower number of signals in high-volatility markets reported above, the number of trades is also slightly lower when market participants face more stress.

Table 4 (see Appendix A) provides additional insight into the sensitivity of the technique to the choice of boundaries, by checking the statistical significance of the above observations. Test statistics are provided to assess the equality of distribution parameters (mean and variance) for the returns, the number of signals and the number of trades, when different boundaries are applied to the RSI scores. Combined with the evidence from Table 1, it can be concluded that whereas the average return achieved with tight and loose boundaries is statistically similar, the dispersion of these returns around their mean is however larger with tight boundaries (60/40). This shows that relying on loose boundaries (70/30) decreases the risk of a trading rule based on RSI scores without however altering the performance of the technique. This remains true when low-volatility days are separated from high-volatility periods. Combined with the evidence from Tables 2 and 3, Table 4 further shows that the mean and the variance of the number of signals and the number of trades triggered by tight and loose boundaries are significantly different over the whole sample period but also in the high and low volatility regimes. On average, more signals and more trades are triggered when tight boundaries are applied. Such boundaries also increase the variability of signals and trades around their mean.

Finally, Table 5 (see Appendix A) assesses the role played by market volatility by checking the equality of the mean and of the variance of the returns across volatility regimes. As the reported evidence shows, there is no statistical difference between the returns in the high and low regimes of volatility. An increase in market volatility nevertheless leads to a larger dispersion of the returns generated by a trading rule based on RSI scores. As expected, technical trading is riskier in periods of high volatility than when the volatility of the market is low. By contrast, volatility regimes do not significantly influence the number of signals generated or the number of trades.

Conclusion

This study examines the impact of volatility on the implementation of a trading rule based on the RSI, one of the most popular technical analysis techniques, on the Shanghai stock exchange, the larger of the two Chinese stock markets. By estimating a Markov switching model, we have shown that the volatility of this market is not constant and switches between two regimes during the sample period considered in this study.

The preliminary analysis indicates that overall a RSI with loose boundaries (70/30) is more profitable (i.e., the return generated is higher) over the entire period used in this paper. For both sets of boundaries (70/30, 60/40) there is a difference in the mean daily returns during low and high volatility periods. Our test statistics however fail to confirm the statistical significance of this difference. An increase in market stress (captured by the volatility of this market) however leads to a larger variance of the returns. Technical trading is riskier in periods of high volatility than in quiet markets. A RSI with loose boundaries (70/30) is also significantly less risky than a RSI with tight boundaries (60/40), which indicates that relying on loose boundaries decreases the risk of a trading rule based on RSI scores without however significantly altering the performance of the technique. In addition, for a given set of boundaries, returns are more volatile in high volatility periods than in low volatility periods.

The number of signals per day is higher when the boundaries are tighter. Interestingly, there are fewer signals during periods of high volatility than during periods of low volatility. Regardless of the choice of boundaries and the volatility regime, skewness is small and the distribution is well split into the tails. As expected, the number of trades is statistically greater when the boundaries are tighter. This remains true in the low and in the high regimes of volatility.

For future research, the following aspects could be considered. First, our investigation of the profitability of the RSI technique is limited by the lack of a benchmark investment strategy. It would be of interest to test the profitability of the RSI relative to other investment strategies to shed more light on the efficiency of the Chinese stock markets. Second, as previously pointed out, the price impact of trades is not considered in this study. Liquidity-adjusted profits would provide more evidence on the usefulness of such technical trading rules. Finally, the constant use of 14 periods is rather subjective. Further tests should be run to determine the optimal periods that are adapted to the Chinese stock markets.

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Appendix A

Table 1. Returns (descriptive statistics)

	Returns – loose boundaries (70/30)			Returns – tight boundaries (60/40)		
	Whole	Low volatility	High volatility	Whole	Low volatility	High volatility
Mean	0.008	0.004	0.011	-0.052	-0.012	-0.085
Standard deviation	0.280	0.233	0.317	0.786	0.523	0.958
Skewness	-0.162	-0.955	0.099	-0.419	-1.497	-0.152
Kurtosis	4.519	5.459	3.827	5.748	5.865	4.457

Note: This Table reports descriptive statistics for the daily returns generated by the RSI with loose (70/30) and tight (60/40) boundaries for the whole sample and in the regimes of low and high volatility. The mean and standard deviation are in percent.

Table 2. Number of signals (descriptive statistics)

	Signals – loose boundaries (70/30)			Signals – tight boundaries (60/40)		
	Whole	Low volatility	High volatility	Whole	Low volatility	High volatility
Mean	2.030	2.139	1.937	12.745	12.920	12.595
Standard deviation	0.841	0.752	0.906	2.000	1.812	2.150
Skewness	0.585	0.401	0.779	0.321	0.277	0.404
Kurtosis	3.019	3.120	3.074	3.013	2.589	3.144

Note: This Table reports descriptive statistics for the daily number of signals triggered by the RSI with loose (70/30) and tight (60/40) boundaries for the whole sample and in regimes of low and high volatility.

Table 3. Number of trades (descriptive statistics)

	Trades– loose boundaries (70/30)			Trades– tight boundaries (60/40)		
	Whole	Low volatility	High volatility	Whole	Low volatility	High volatility
Mean	0.223	0.227	0.220	1.109	1.117	1.102
Standard deviation	0.206	0.206	0.212	1.121	1.134	1.118
Skewness	0.123	0.124	0.124	0.260	0.221	0.291
Kurtosis	0.494	0.612	0.397	-0.449	-0.007	-0.568

Note: This Table reports descriptive statistics for the daily number of trades generated by the RSI with loose (70/30) and tight (60/40) boundaries for the whole sample and in regimes of low and high volatility.

Table 4. Interboundary comparison

		Whole	Low volatility	High volatility
Returns	Mean	0.574	0.042	0.555
	Variance	30.869***	11.368***	21.562***
Signals	Mean	2756.146***	1570.172***	1272.327***
	Variance	49.741***	32.222***	21.985***
Trades	Mean	1071.284***	643.000***	475.241***
	Variance	37.675***	16.318***	22.020***

Note: This Table reports test statistics for the equality of the mean and the variance of daily returns (resp. number of signals or number of trades) when the boundaries imposed to the RSI change. The reported values correspond to the values of the ANOVA F-statistic (mean) and the Brown-Forsythe (variance) tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Intraboundary comparison

	Returns		Signals		Trades	
Boundaries	70/30	60/40	70/30	60/40	70/30	60/40
Mean	0.016	0.243	1.614	0.738	0.104	0.093
Variance	3.270*	7.749**	1.523	0.404	0.062	1.792

Note: This Table reports test statistics for the equality of the mean and the variance of daily returns (resp. number of signals or number of trades) across regimes of high and low volatility. The reported values correspond to the values of the ANOVA F-statistic (mean) and the Brown-Forsythe (variance) tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix B. Markov switching model

	Matrix of transition probabilities	
	Regime 1	Regime 2
Regime 1	0.9693	0.0307
Regime 2	0.0157	0.9843
	Regime properties	
	Observations	Duration
Regime 1	64.5	32.52
Regime 2	66.5	63.53
	Coefficients	
μ_1	0.0243***	
μ_2	0.0347***	
σ_1^2	0.0021	
σ_2^2	0.0054	
LR linearity test	151.0401***	

Note: This Table reports estimate of the Markov switching model used to separate high-volatility days from low-volatility days. Volatility is measured in the form of an exponentially-weighted moving average replicating the methodology presented in Riskmetrics (1996). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.