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Theoretical Properties of Technical Range and Its Applications

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Abstract

As a technical indicator, technical range is widely used by chartists to read the minds of the markets. Theoretical properties and applications of this technical indicator would be of great interest to both academics and chartists. The main findings of this paper are: (1) technical range is a unit root process; (2) technical range is co-integrated with closing prices; (3) technical ranges are co-integrated if the corresponding closing prices are co-integrated. These findings are of great significance as it indicates that it is possible to scrutinize the predictive power of technical indicators by co-integration analysis. An empirical study performed on the US Apple Inc. stock prices demonstrates that trading strategy based on these findings could beat the simple buy-and-hold even after the trading costs have been removed.

Keywords: Parkinson range; Technical analysis; Technical range; Range decomposition; Co-integration MR (2000) subject classification

Introduction

For a long time in history, most of the research interests were devoted to investigating the behavior of the closing prices, totally ignoring the other available information such as the highest, the lowest, and the opening prices. Recently, more attention has been given to the extreme values in the stock prices for a fixed time interval partly due to the contribution of Parkinson [1], who, by employing the extreme value theory and some well-known propertied of range, forcefully argues and demonstrates the superiority of using range as a volatility estimator compared with the standard methods. Since then, great progress has been made in investigating the range estimator. Beckers [2], among others, further extends the range estimator by incorporating information about the opening and closing prices and other treatment of a time-varying drift, as well as other considerations. Other references concerning range estimator include Garman and Klass [3], Wiggins [4], Rogers and Satchell [5], Kunitomo [6], and more recently Yang and Zhang [7]. Alizadeh, et al. [8] prove theoretically and empirically that the log range is approximately normal. For more results on range volatility, we propose to refer [9].

Despite so much interest in the range estimator, no academic literature is so far available to explore the theoretical properties of technical range which is part of the Japanese candle stick. Candle stick charts are said to have been developed in the 18th century by a legendary Japanese rice trader Homma Munehisa. The charts give one an overview of opening, high, low, and closing market prices over a certain period. This style of charting is very popular due to the level of ease in reading and understanding the graphs, and believed to be a reliable tool to predict future. Some nice introduction books to the candle stick are Candlestick Charting Explained by Morris [10] and Japanese candlestick charting techniques by Nison [11].

This paper makes the first attempt to investigate the theoretical properties of technical range with range decomposition technique. The structures of this paper are as follows: Section 4 presents range decomposition technique. Section 5 presents the theoretical properties of the technical range. Section 6 performs an empirical study on Apple Inc. stock to argue that trading strategy based on these properties can beat the market. We conclude in Section 7.

Range Decomposition Technique

Before presenting the range decomposition technique, some preliminary knowledge on ranges are needed

Ranges: Parkinson range and technical range

The Parkinson range is obtained by taking log difference between the high and the low stock prices for a given time interval (t-1,t):

$$PR_t = \ln(H_t) - \ln(L_t) \tag{1}$$

where PRt is the Parkinson range, Ht the high price, and Lt the low price for the given time interval. Specifically $\underset{s\in(t-1,t]}{Max}\{P_s\}, L_t = \underset{s\in(t-1,t]}{Min}\{P_s\}, P_s$ is the security price. Based on the assumption of Brownian motion without drift, Parkinson [1] suggests the following volatility estimator:

$$\hat{\sigma}_t^2 = (\ln(Ht) - \ln(Lt))2/4\ln 2 = (PRt)2/4\ln 2 \tag{2}$$

Furthermore, Alizadeh, et al. [8] show both theoretically and empirically that the log Parkinson range is approximately normally distributed.

Different from the definition of Parkinson range, the technical range is obtained directly by taking difference between the high and the low prices:

$$TRt = Ht - Lt \tag{3}$$

where TR_t is the technical range. Technical range is part of the Japanese candle stick, which is widely employed by chartists for trading.

Both ranges can be used as volatility estimators, larger ranges mean more turbulent trading periods.

Range decomposition

The idea of range decomposition is straight forward and is presented as follows:

$$\begin{aligned}(H_t - L_t)/C_t &= (H_t - C_t)/C_t + (C_t - L_t)/C_t \\ &= \ln(H_t/C_t) + \ln(C_t/L_t) \\ &= \ln(H_t/L_t),\end{aligned}$$

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where C_t is the closing price. Taking logarithmic transformation on both sides and rearranging yields

$$\ln(C_t) = \ln(H_t - L_t) - \ln(\ln(H_t / L_t)). \quad (4)$$

Substituting TR_t and PR_t for $H_t - L_t$ and $\ln(H_t) - \ln(L_t)$ respectively, we get

$$\ln(C_t) = \ln(TR_t) - \ln(PR_t). \quad (5)$$

(5) is called the range decomposition technique as it indicates that price can be approximated by two ranges.

Properties of Technical Range

We first present the main properties of technical range and then list the proofs for each property in detail. The main properties of technical range are as follows:

Proposition1. Technical range is a unit root process.

Proposition2. Closing price and technical range are co-integrated of order (1,1).

Proposition3. Technical ranges are co-integrated if their corresponding prices are co-integrated

Before giving the proofs for each proposition, it is necessary to clarify the definition of co-integration. The use of the notation of co-integration as a long-run equilibrium relationship between time series was suggested by Engle and Granger [12]. A series is said to be integrated of order d, denoted as I(d), if it has a stationary, invertible autoregressive moving average (ARMA) representation after applying the differentiating operator $(1 - L)^d$. Consider in general a pair of series, x_{1t} and x_{2t}, which are I(d). Let $X_t = (x_{1t}, x_{2t})'$. The linear combination

$$\theta_t = \alpha X_t \quad (6)$$

Will generally also be I(d). If a vector α exists such that θ_t is I(d-b) with b>0, however, x_{1t} and x_{2t} are said to be co-integrated of order (d,b), and $\alpha X_t=0$ represents an equilibrium constraint operating on the long-run components of X_t.

Proof for Propositions 1-2: Given the facts that closing price is a unit root process and that Parkinson range, as a volatility estimator, is a stationary process, it is self-evident that technical range is a unit root process. Since $\ln(C_t) - \ln(TR_t) = \ln(PR_t)$ and $\ln(PR_t)$ is a stationary process, it is obvious by the definition of co-integration that closing price and technical range are co-integrated of order (1, 1).

Proof for Proposition 3: Suppose two price series C_{1t} and C_{2t} are co-integrated of order (d, b) with a co-integration vector of (α_1, α_2). By the definition of co-integration, there exists a linear combination

$$\omega_t = \alpha_1 C_{1t} + \alpha_2 C_{2t} \quad (7)$$

such that ω_t is I(d-b) with b>0. Substitute Eq. (5) for $C_{i,t}$ in Eq. (7), one obtains

$$\omega_t = \alpha_1 \ln(C_{1t}) + \alpha_2 \ln(C_{2t}) \quad (8)$$

$$= \alpha_1[\ln(TR_{1t}) - \ln(PR_{1t})] + \alpha_{1t}[\ln(TR_{2t}) - \ln(PR_{2t})] \quad (9)$$

$$= [\alpha_1 \ln(TR_{1t}) + \alpha_2 \ln(TR_{2t})] - [\alpha_1 \ln(PR_{1t}) + \alpha_2 \ln(PR_{2t})] \quad (10)$$

By rearranging, we get

$$\omega_t + [\alpha_1 \ln(PR_{1t}) + \alpha_2 \ln(PR_{2t})] = \alpha_1 \ln(TR_{1t}) + \alpha_2 \ln(TR_{2t}) \quad (11)$$

Equ.(11), by definition, indicates co-integration between $\ln(TR_{1t})$ and $\ln(TR_{2t})$ of order (d, b) with a co-integration vector of (α_1, α_2).

Co-integration Trading Strategy

It has been well recognized that financial markets are rather efficient, thus it is of great difficulty to predict the market using history price information. In this section, we are going to answer whether or not trading strategy based on the technical range can beat the simple buy-and-hold.

Data preparation

As technical indicators are widely used to analyze individual stock, we collect the monthly index data of the Apple Inc. for the sample period from September, 1984 to April, 2012 with 332 observations. We collect the Apple Inc. stock price for the following reasons: first it is now the most charming stock and attracts the global attention; second, it now has the largest capital value; finally, the stocks of Apple Inc are of high liquidity. These features make the Apple Inc. stock price more efficient in reflecting information, which makes it a nice stock for verifying the efficiency of technical analysis. For each month, four pieces of information, opening, closing, high, low are reported. The data sets are downloaded from the finance subdirectory of the website "Yahoo.com". Figure 1 presents the high (H_t), low (L_t) and closing (C_t) price plots of Apple Inc. on the left panel. The plot of technical range is presented on the right panel in figure 1.

Table 1 presents the summary statistics for returns, closing price and technical range. Consistent with the well known facts, stock returns shows left skewness and high kurtosis and deviates from the normal distribution with great significance. Augmented Dickey-Fuller (AD-F) statistics cannot reject the hypothesis of unit root for both technical range and closing price, which is consistent with Proposition 1. Numbers in () are *p*-values. Table 2 reports the Johansen co-integration test for technical range and closing price. The results

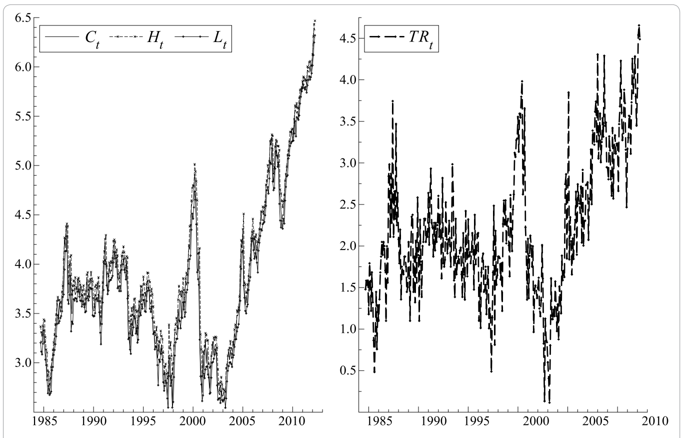

Figure 1: High, Low, Closing and Technical Range: Apple Inc.

	Returns	Closing Price	Technical Range
Mean	0.00951	3.890	2.203
Median	0.0241	3.714	2.048
Max	0.374	6.396	4.656
Min	-0.861	2.575	0.113
Std. Dev	0.150	0.851	0.859
Skewness	-1.263	0.918	0.476
Kurtosis	7.647	3.284	2.880
ADF	−16.394	−0.364	−1.659
	(0.000)	(0.912)	(0.451)

Table 1: Summary statistics for returns, closing price and technical range of Apple Inc.

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Trace Test without Trend Assumption				
No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	P-*value*
None	0.0871	31.277	20.262	0.0010
At most 1	0.00451	1.479	9.165	0.877

Table 2: Johansen co-integration test for technical range and closing price: Apple Inc.

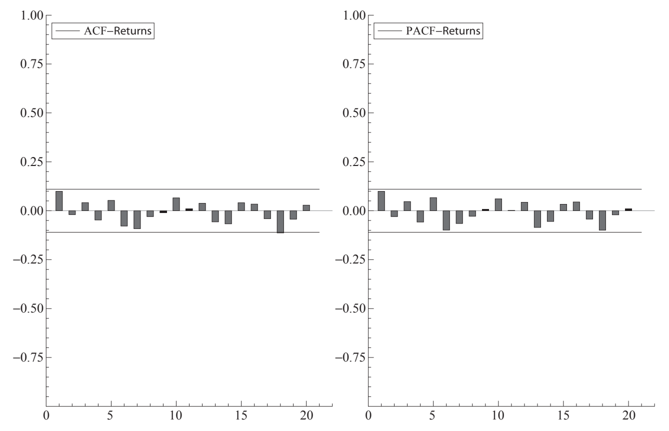

Figure 2: ACF and PACF of Stock Returns: Apple Inc.

indicate co-integration between technical range and closing price at a significance level of 1%, which is consistent with Proposition 2. Figure 2 presents the auto regression functions (ACF) on the left panel and partial auto regression functions (PACF) on the right panel. Consistent with the arguments of efficient market hypothesis, figure 2 indicates no linear dependence between stock returns.

Econometric methodology

Following the conventional framework for analyzing stock price predictability, the following predictive regression model is used:

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_t + 1\,, \quad (12)$$

Where r_{t+1} is the return on stock price from period t to t + 1, x_t is a predictor, and ε_{t+1} is a zero-mean disturbance term. In this paper, x_t is the residual produced by the following regression:

$$\ln(C_t) = c + \gamma\ln(TR_t) + \mu_t, \quad (13)$$

Where μ_t is a mean-zero disturbance term also known as error correction term, which will be used as the predictor:

$$r_{t+1} = \alpha + \beta\mu_t + \varepsilon_{t+1}. \quad (14)$$

Notice that μ_t can be thought of as an equilibrium error (or disequilibrium term) occurred in the previous period. If it is non-zero, r_{t+1} will be corrected to restore equilibrium. As it is possible that the way how r_{t+1} will be corrected depends on the conditions of μt taking positive values or negative values. Taking this into consideration, we adopt the following regression framework:

$$r_{t+1} = \alpha + \beta_1\mu_t^- + \beta_2\mu_t^+ + \varepsilon_{t+1}, \quad (15)$$

where $\mu_t^- = -|\mu_t| + \mu_t$ and $\mu_t + = |\mu_t| + \mu_t$.

To mimic the actual technical forecasting, we employ rolling window technique to produce out-of-sample forecasts. Suppose there are T observations, the rolling window out-of-sample forecasting procedures are presented as follows:

First, $\{\hat{\mu}t\}_{t=i}^{L+i-1}$ are generated from the following regression:

$$\hat{\mu}t = \ln(C_t) - \hat{c} - \hat{\gamma}\ln(TR_t), \quad (16)$$

Where $\hat{c}$, $\hat{\gamma}$ are the least ordinary squares (OLS) estimates of c and γ, respectively, in (13) computed by regressing $\{\ln(C_t)\}_{t=i}^{L+i-1}$ on a constant c and $\{\ln(TR_t)\}_{t=i}^{L+i-1}$. L is the window length, and i=1,2,...,T−L+1 is the starting point in the window.

Second, we regress $\{r_t\}_{t=i}^{L+i-1}$ on a constant c, $\{\hat{\mu}_t^-\}_{t=i}^{L+i-1}$ and $\{\hat{\mu}_t^+\}_{t=i}^{L+i-1}$

$$r_t = \alpha + \beta_1\hat{\mu}_{t-1}^- + \beta_2\hat{\mu}_{t-1}^+ + \varepsilon_t \quad (17)$$

If F-statistics in (17) are statistically significant at a level of 5%, the out-of-sample forecast r^i+L+1 is produced as follows:

$$\hat{r}_{i+L+1} = \hat{\alpha} + \hat{\beta}_1\hat{\mu}_{i+L}^- + \hat{\beta}_2\hat{\mu}_{i+L}^+ \quad (18)$$

Where â, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the OLS estimates of α, β_1 and β_2, respectively, in (17). $\hat{\mu}_{i+L}$ Produced from the following regression:

$$\hat{\mu}_t = \ln(C_t) - \hat{c} - \hat{\gamma}\ln(TR_t) \quad (19)$$

Where $\hat{c}$, $\hat{\gamma}$ are the OLS estimates of c and γ, respectively, computed by regressing $\{\ln(C_t)\}_{t=i+1}^{L+i}$ on a constant c and $\{\ln(TR_t)\}_{t=i+1}^{L+i}$.

Parameters estimates

To be robust, different windows are used. To be specific, we choose

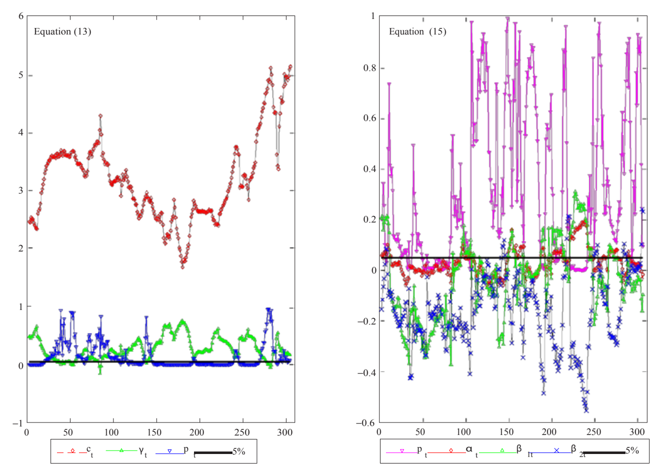

Figure 3: Parameters Estimates for L=24: Apple Inc.

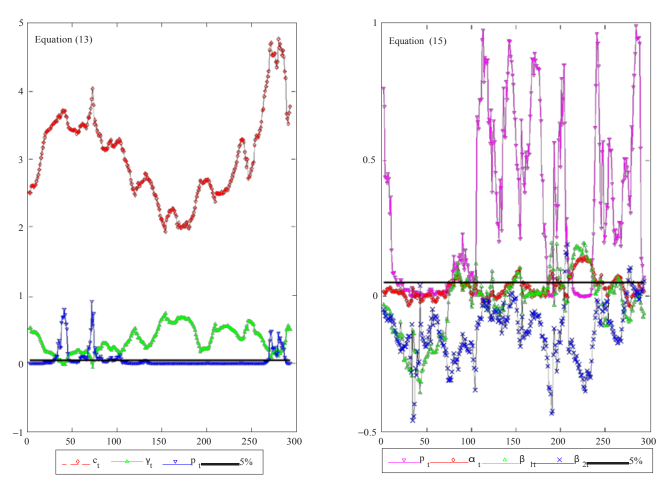

Figure 4: Parameters Estimates for L=36: Apple Inc.

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L=24, 36, 60, which corresponds to two, three and five years, respectively. Figures 3-5 present the plots of parameters estimates of c_t, γ_t, α_t, β_{1t} and β_{2t} evolving with the rolling window. p_t is p value corresponding to the F statistics. We use subscript t to highlight that these parameters are vary with the window rolling. Plots in the left panel of each figure present c_t and γ_t, and plots in the right panel of each figure presents α_t, β_{1t} and β_{2t}. Figures 3-5 demonstrate something of great interest:

first, the co-integration relationship between closing price and technical range becomes stronger as window length (L) extends since more p values (p_t) falls below 5%.

Second, the co-integration vector is time varying given the evidence that c_t and γ_t change with the window rolling.

Third, c_t and γ_t are negatively correlated. It can be observed from figures 3-5 that ct and γ_t are negatively correlated, when c_t goes up, γ_t tends to go down.

Fourth, returns are corrected in an asymmetric way. Returns are corrected more when μt taking positive values, since β_{2t} are almost unanimously larger than β_{1t} in terms of absolute value, which is more obvious by observing the plots in the right panel in figures 3-5.

Finally, the stock prices of Apple Inc. are in-sample predictable for some time. It can be observed from the right panel in figures 3-5 that there are some periods when pt values are persistently below 5%.

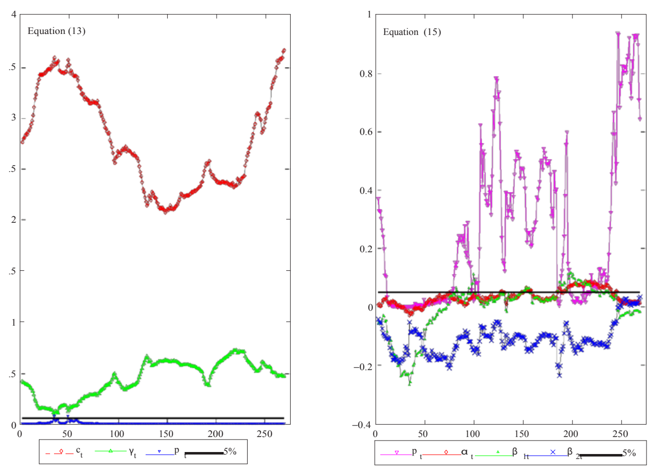

Figure 5: Parameters Estimates for L=60: Apple Inc.

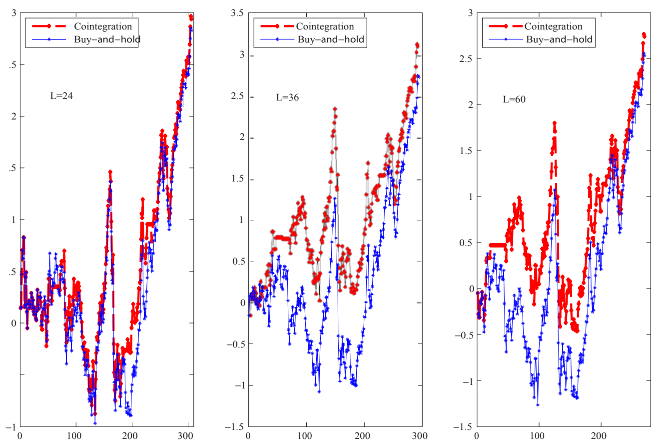

Figure 6: Trading Strategy: Cointegration vs Buy-and-hold.

Out-of-sample forecasts

The efficient market hypothesis (EMH) argues that financial markets are informationally efficient, thus it is impossible to beat the market by predicting using history information [13]. A natural conclusion from EMH is that we cannot beat the market by technical indicators.

In this subsection, we are going to investigate whether or not trading strategies based on the out-of-sample forecasts of (18) can beat the simple buy-and-hold. The trading strategy in the present paper is going as follows: if the forecasts are negative, we sell the Apple Inc. stock and hold cash, otherwise we hold the stock. Since the forecasts are produced using co-integrating relation between technical range and closing price, the trading is denoted as co-integration trading strategy.

Suppose our initial investment is one US dollar, Figure 6 presents how the accumulative returns evolve with the investment period. Plots from left to right in figure 6 present different accumulative returns when window length L taking different values. For L=24, the accumulative returns from co-integration strategy is about 293.856% which is 11.341% larger than buy-and-hold; for L=36, the accumulative returns from co-integration strategy is about 311.984% which is 40.401% larger than buy-and-hold; for L=60, the accumulative returns from co-integration strategy is about 273.937% which is 20.896% larger than buy-and-hold. Even after removing the trading costs, the co-integration trading strategy still outperforms the simple buy-and-hold. Suppose for each trading, the cost is 0.3%. If N tradings are made then the total trading costs are 0.3%*N. The trading costs for L=24 are 4.2% (N=14); trading costs for L=36 are 7.2% (N=24); trading costs for L=60 are 6% (N=20).

Conclusion

As part of the Japanese candlestick, technical range is widely employed by chartists to read the markets. This paper makes the first attempt to investigate the theoretical properties of this technical indicator. The main findings of the present paper are that: first, technical range is a unit root process; second, technical range and closing price are co-integrated; third, technical ranges are co-integrated if their corresponding closing prices are co-integrated. An empirical study performed on the Apple Inc. stock indicates that stock markets are not sometimes inefficient, thus trading strategy based on these properties are profitable. The findings in this paper are also suggestive, as they indicate that these properties can be used to design automatic trading strategies, which will be the future studies.

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