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Impact of Range Bar and Ergodic Process on Early Price Trend Detection Using Evidence From USD/CNY Currency

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ABSTRACT

In this paper, range bars and the ergodic theory are combined to investigate early price movements for the USD/CNY currency pair in China from 2015 till 2019. The main findings suggested that early price trend detection may be accomplished within two standard deviations of the mean. During the duration of trading that was restricted to a narrow range, the sample revealed that at least 68 percent of the frequency mean result indicated that range bars solved price trend creation. This paper is subjected to additional analysis in order to acquire a correlation coefficient sample of at least 0.8. This sample revealed that ergodic theory prevented overpriced hedge trends. The goal of this paper is to improve the detection of price trends at an earlier stage than the methodology of trend tracking. Because of this, the authorities need to seriously consider putting early price trend detection models into place in order to boost the liquidity of the local currency.

Keywords: China, Currency, Ergodic Process, Range Bar

1. INTRODUCTION

Price trend performance in trading foreign exchange is an important issue that has received much attention in practical brokerage trading activities. In the past, attention has been giving to improving prior literature' gaps in stock market analyses. However, there is little research regards with the trend-following technical analyses focus on USD/CNY pair currency. Hence, this paper intends to introduce range bar and ergodic process variables to detect early price trends within two standard deviations away from average prices to predict the performance result of trading in USD/CNY pair currency. Both range bar as a mediator and ergodic process as a moderator would motivate the proposed research to solve the research gaps. They have not been proving in creating a new model to detect early trends within two standard deviations from average prices for USD/CNY pair currency. The range bar as a mediator would replace 60 minutes of time interval to create a new sample of a non-periodic bar to prevent failure price trend formation during the range-bound trading period within two standard deviations away from average prices.

This solution could solve challenges currently experienced by prior researchers to collect successful price trend formation samples to justify hedge position, (Han et al., 2016; Fong et al., 2012; Fong et al., 2011; Szakmary et al., 2010). This paper is further enhanced to include an ergodic process as a moderator to analyse a new sample of a non-periodic bar within two standard deviations away from average prices to prevent lagging higher prices during trend-following period. This additional solution could solve challenges currently experienced by prior researchers to collect undervalued price samples to justify hedge position (Liu & Zhang, 2008; Han et al., 2016); (Zhang et al., 2019).

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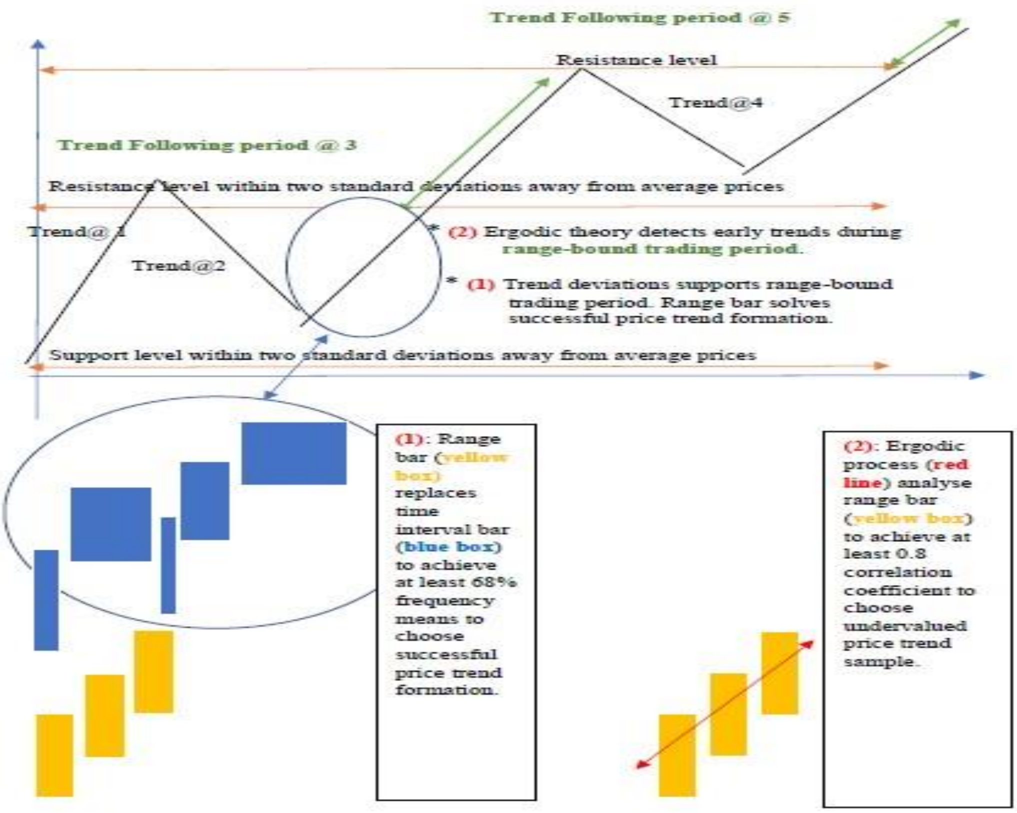

Figure 1. Trend Following

Price trending occurs when the current price is exceeded two standard deviations from the average prices, as indicated in Figure 1 of trend following graphical chart and supported by (Covel, 2009). Chen (2021) mentioned the price consolidation phase, a resistance level is found at the upper level to resist price going upward, and hence the price will bounce downward at resistance level upon contact and vice versa. This research intends to introduce a range bar as a mediator with the expectation of choosing successful price trend-formation during the range-bound trading period. Sliwiak et al. (2020)investigated the Ergodic Theory that proposes time mean of their input properties is equal to the mean over the entire time sequence space for specific operating systems. For input properties, we can use Ergodic Theory to detect early price trends as a preventive lagging higher prices during the trend-following period within two standard deviations.

Current methodology, namely trend following, detect price trend after two standard deviations from the average prices, has caused two problems faced by prior researchers. During range-bound trading period, this research suggested that at least 68% of frequency sample selected indicated range bar solved price trend formation This paper is further analysed to obtained at least a 0.8 correlation coefficient sample suggested that Ergodic Theory prevented overpriced hedge trends. This paper intends to improve price trend detection earlier than trend following methodology. Given such gaps, this research solved price trend detection within two standard deviations as compared to trend-following strategy. The range bar as a mediator to replace the minutes of a time interval. It creates a new sample of the non-periodic bar within two standard deviations away from average prices to prevent failure price trend formation during the range-bound trading period.

The first research objective is supported by trend deviations whereby the range bar is expecting to choose successful price trend formation within two standard deviations away from average prices after creating a new sample of the non-periodic bar. This research is further enhanced to include Ergodic Theory to support ergodic process as moderator to analyse a new sample of the non-periodic bar to prevent lagging higher price after two standard deviations from the average prices during trend following period.

The influence of the Ergodic Theory for the second research objective is expecting to choose an undervalued price sample on early price trend detection. They noted that the early price trend detection period occurs after creating a new sample of a non-periodic bar during a range-bound trading period within two standard deviations away from average prices.

Recently with the absence of this research proposal, from May 2015 to December 2019 (barchart.com/forex), USD/CNY pair currency suffered a loss of negative -12.25%. The loss indicates a severe need with an expectation to investigate range bar and ergodic process because both newly introduced variables have yet tested in early price trend detection. It aims to construct a significant relationship with the expectation to prevent failure price trend formation within two standard deviations away from average prices during the range-bound trading period and lagging higher price prevention after two standard deviations from the average prices during the trend following period.

2. LITERATURE REVIEW

As of to date, Ergodic Theory has yet to be used to detect early trends for any financial derivatives. This paper is using Ergodic Theory because it primarily investigation is that the time average of each price is equal to the average over the entire space for a specific time interval period. The advantage of using Ergodic Theory as compares to other weighted moving averages is because the behaviour of a dynamical system when it could evolve for an extended period of duration and elapsed its initial started point of the stage. As such, Ergodic Theory analyses a better accuracy with correlation coefficient to reveal trends during uncertain volatility conditions of the prices as compares to other weighted moving averages.

Sliwiak et al. (2020) investigated the space-split sensitivity or S3 algorithm using an ergodic averaging method to distinguish statistics in ergodic, chaotic systems, hyperbolic dynamical systems. Hence, this paper has similarity objective of using Ergodic Theory to detect early trends within two standard deviations given the long-time average space is either averaging of the time-series or ensemble averaging.

Fernández et al. (2021) investigated in an open Hamiltonian system, revealed that any energy that escapes from a certain bounded region is referred to as chaotic scattering. The meaning of bounded region as according to the open Hamiltonian system as per (Fernández et al., 2021) studies, it is a similar situation whereby two standard deviations of trading any financial instrument is referring to bounded region. As compared to the current method of detecting price directional using trend following, it would be trending in a bias directional after two standard deviations. Hence, bias trending directional after two standard deviations has similarity to chaotic scattering.

(Dennunzio et al., 2020) proved that the significant properties describing complicated behaviour as ergodicity, chaos, topological transitivity, and topological mixing are decidable for one-dimensional linear cellular automata. The results have similarity to this research because Ergodic Theory is introduced to enhance the detection of an early trend within two standard deviations. The trend is categorised when prices are moving in a bias directional as comparable to one-dimensional linear automata studies by him.

Such advantage of using an Ergodic Theory reveals an important discovery when it is examining with a correlation coefficient, the parameter reaches its significant level of 0.8 indexes would detect an early trend of prices before two standard deviations from the average prices. As compared to trend following, the trend could be detected after two standard deviations from average prices.

Trend deviations was analysed by Roudjane et al. (2021), who investigated the trend from event logs database. They contributed a result showed at different distance of deviations would detect trend in real time from thousands of events per second. Farrugia and Micallef (2006) developed an algorithm to predict wind directional on trend deviations instead of required large data storage on wind data. This improvement contributed on algorithm predictive model of using trend deviations. Such a trend deviation is supporting this paper for the range-bound trading period is within two standard deviations before a bias directional of prices trending after two standard deviations, namely trend following. This research would detect an early trend within range-bound trading period as compares to prior research namely trend following who could only predict trend after two standard deviations.

3. METHODS

3.1 Range Bar

First research objective: To identify the impact of range bar to choose successful price trend formation within two standard deviations away from average prices.

Mediator of range bar is supported by trend deviations, based on prior literatures (Roudjane et al., 2021); (Farrugia & Micallef, 2006). Such trend deviation is supporting this research for the successful price trend formation during range-bound trading period within two standard deviations. This research made an improvement over prior trend following methods that the latter could predict a bias directional of prices trending after two standard deviations. (Chen, 2021) mentioned range-bound trading period, that price tends to consolidate after experiencing trending either upward or downward directional. The logical trend deviations literature is supporting a successful price trend formation could occurs during range-bound trading period within two standard deviations.

First, a time interval set at minutes periodic throughout data collection from 2015 to 2019. Let 't' be the time interval, and 'i' denotes the periodic interval. Let 'OHLC' denotes completion of price bar movement that moves within the interval period of 'i' from Opening price, then moves to either High price for accelerating uptrend or Low price for decelerating downtrend and Close price of the end of the price movement. Let t{OHLC(i)} denotes the movement of a price bar given 'i' minutes of time interval period. Let t{OHLC(i)(sequence1)}, t{OHLC(i)(sequence2)}, t{OHLC(i)(sequence3)}, sequences to be printed for each time interval bar, whereby 'ni' denotes sequence of time interval of price bar.

Hence, t{OHLC(i)(ni)}…[1]

Second, set the input of the range bar at an incremental of ticks. Let 'r' denotes the range bar and 'n' denote incremental ticks. Each price movement's 'OHLC' is defined by 'n' incremental ticks bar movement to replace with 'i' of time interval period. Hence, r{OHLC(n)(sequence1)}, r{OHLC(n)(sequence2)}, r{OHLC(n)(sequence3)} are to be printed, whereby 'nt' denotes sequence of each bar incremental ticks, hence represented each range bar.

Hence, r{OHLC(n)(nt)}…[2]

These r{OHLC(n)(nt)} will replace all t{OHLC(i)(ni)} of time interval bar thereafter. Subsequently, each price bar is to be printed at r{OHLC(n)(nt)} of each range bar interval period.

Third, identify price trend to be incurred before trend following period and noted that trend following is known as the current method of detecting lagged overpriced to choose expensive price hedge position. An exponential moving average can measure price trend movement. Let 'EMA' denotes exponential moving average within selected r{OHLC(n)(nt)} interval bar. The calculation of EMA can explain below.

a) Calculate the simple moving average as denotes as 'SMA.'

The calculation of 'SMA' is similar to the mean for a given duration interval. The 'SMA' given number of range bar intervals is simply the sum of the closing price bars for that range bar interval. Let 'N' denotes the number of each range bar r{OHLC(n)(nt)}. During these formations of price trend movement, sum all range bar from the beginning of price trend until the end of the formation but before trend following.

Hence, SMA = (N – sum r{OHLC(n)(nt)})/ N…[3]
whereby period sum = sum r{OHLC(n)(nt)}.

b) Calculate the multiplier for weighting the EMA.
Let 'k' denotes as weighted multiplier = 2/ (SMA +1) %...[4]
whereby SMA denotes the number of range bars selected to compute EMA.

c) Calculate the current EMA.
EMA = Range price bar(c) x k + EMA(d) x (1-k)…[5]
whereby c = current range price bar; d = prior range price bar.

An improved Triple Exponential Moving Average (TEMA) is added to smooth the price trend movement measurement. It designed to identify price trends without the lag relating to conventional moving averages. Alevizakos et al. (2020) proposed the triple exponential moving average (TEMA) of the control chart model to improve the precedent of the exponential weighted moving average. The control chart method was applied in most industrial processes to improve the time-based event of the quality characteristic. TEMA operates with multiple EMA of the initial EMA and subtracting other of the lag measurement. The benefits of TEMA can be elaborated to indicate a short-term price direction, remove lag trend identification, confirm an earlier price uptrend if the range bar is moving above TEMA and vice versa, it measures a pulling back or reversing if the range bar is crossing TEMA.
TEMA = {3 x EMA(1)} – {3 x EMA(2)} + EMA(3)…[6]
whereby EMA(1) is current period, EMA(2) is prior EMA(1), EMA(3) is prior EMA(2). The price trend movement can be concluded with hypotheses as below scenarios.

Hypothesis one (a): OHLC > TEMA denotes a closing price headed to up-trend directional by lag prevention measured by equation 6, or
Hypothesis one (b): OHLC < TEMA denotes a closing price headed to a downtrend directional by lag prevention measured by equation 6.

Fourth, trend strength can analyse with the average directional index (ADX). Bruni (2017) mentioned that ADX does not reveal directional price trends but measures trend strength. The computation is relying upon the positive directional indicator (+DI), the negative directional indicator (-DI), and the true average range (ATR). The definition of such upward movement as up(nt) = max(nt) – max(n-t) and the downward movement as dw(nt) = min(nt-1) – min(nt),

If up(nt) > dw(nt) and up(nt) > 0 then + DM(nt) = up(nt), otherwise +DM(nt) = 0; If dw(nt) > up(nt) and dw(nt) > 0 then -DM(nt) = dw(nt), otherwise -DM(nt) = 0.

Let exponential moving average that EMA(nt) denotes the period over the last nt, then we compute;

$$+DI(nt) = [100 * EMA(nt)(nt+DM)/ ATR(nt)] - DI(nt) = [100*EMA(nt)(nt-DM)]/ ATR(nt) \ldots[7]$$

ADX can be computed as below given abs(.) denotes the absolute value,

$$ADX(nt) = 100 * EMA(nt)(abs(+DI-(-DI)))/ +DI+(-DI) \ldots[8]$$

(Bruni, 2017) concluded that ADX parameter index that above 20 is considered a strong trend.

Hypothesis two: The effectiveness of price trend movement can measure by the strength of the ADX above 20.

Fifth, average the price trend formation attributed from the range bar. Let ‘a’ denotes successful price trend formation percentage. Let ‘N’ denotes the number of each range bar r{OHLC(n)(nt)}.

$$\text{Hence, } a = \{\text{sum } r\{OHLC(n)(nt)\} / N\} \% \ldots[9]$$

Therefore, ‘a’ > 1 standard deviation of 68% hypothesised the successful price trend formation within two standard deviations.

Hypothesis three: The effectiveness of non-periodic range bar as a mediator to replace minutes of each bar time interval achieving at least 68% of one standard deviation for frequency mean sample. The range bar can enhance the accuracy of price trend formation during a range-bound trading period within two standard deviations.

This study uses parametric statistics with numerical data to conclude a significant relationship on the effectiveness that 68% of one standard deviation for frequency mean success rate for range bar to replace minutes of time interval to answer hypotheses. Noted that the ticks incremental of range bar that a 68% frequency success rate for range bar to replace minutes of time interval are subject to data snooping biases as suggested by Park & Irwin (2010).

3.2 Ergodic Process

Second research objective: To determine the ergodic process's impact on choosing undervalued price samples within two standard deviations from the average prices on lagging higher price prevention.

The equations from 1 to 8 and hypotheses one and two have remained the same as research objective one. The new equation 9 continues from the research objective two. The proposed research studies the calculation and displays Bill Blau's Ergodic indicator, the True Strength Index. This study calculates three lines, the Ergodic (True Strength Index), the Ergodic Signal Line (exponential moving average of the TSI), and the Ergodic Oscillator (Difference of Signal and TSI).

Let XX be a random variable denoting the Input Data, and let the Long Moving Average Length, Short Moving Average Length, Signal Line Moving Average Length, and Multiplier Inputs denotes as,

$$nLnL,\ nSnS,\ nSignSig, \text{ respectively} \ldots[9]$$

We denote the Ergodic, Ergodic Signal Line, and Ergodic Oscillator at index t for the given inputs as,

$$TSIt(X,nL,nS,v)TSIt(X,nL,nS,v),\ SIt(nL,nS,nSig,v)\overline{TSI}t(nL,nS,nSig,v) \ldots[10]$$

$$\text{and } TSIOsct(X,nL,nS,nSig,v)TSIOsct(X,nL,nS,nSig,v), \text{ respectively} \ldots[11]$$

and we calculate them in terms of Exponential Moving Averages as follows,

$$TSIt(X,nL,nS,v)=v\cdot EMAt(EMA(\Delta X,nL),nS)/ EMAt(EMA(|\Delta X|,nL),nS) \ldots[12]$$

In the above formula, $\Delta Xt=Xt-Xt-1$ is calculated for $t\geq1$, the first EMA is calculated for $t\geq nL-1$, and the second EMA is calculated for $t\geq nL+nS-2$.

$$TSIt(X,nL,nS,nSig,v)=EMAt(TSI(X,nL,nS,v),nSig) \ldots[13]$$

$$TSIOsct(X,nL,nS,nSig,v)=TSIt(X,nL,nS,v)-TSIt(X,nL,nS,nSig,v) > 0.8 \ldots[14]$$

therefore, Ergodic process oscillator with equation [14] concludes early price trend detection should correlation coefficient above 0.8 with significant parameter. Each of the above is calculated for $t \geq nL+nS+nSig-3$. The above calculation can be found from sierrachart.com.

Hypothesis four: The effectiveness of lagging higher price prevention achieving at least 0.8 correlation coefficient sample reveals the Ergodic Theory works well on price trend formation than the price trend following.

This study uses parametric statistics with numerical data to conclude that 0.8 correlation efficiently forms a significant relationship on an ergodic process's effectiveness to analyse a new sample of a non-periodic bar to answer research question two. The 0.8 correlation coefficient to derive early price trend detection is subject to data snooping biases, as suggested by (Park & Irwin, 2010).

4. RESULTS AND DISCUSSIONS

During four and half years from May 2015 to December 2019, USD/CNY pair currency suffered a loss of -12.25%. The raw data was collected based on a taped reading of the historical intraday trading sequence, the price data is select at an average of the best bid and best ask. These data analyses concluded two research objectives based on a proven four hypotheses altogether. Each research objectives one and two are based on ten secondary data samples collected based on an identifiable trend-following pattern of formation. As such, each sample would prove the four hypotheses to conclude successful price trend formation for research objective one and early price trend detection for research objective two and its impact of significant contribution.

4.1 Discussion for Objective One

The research objective is to introduce a mediator of range bar to replace 60 minutes of time interval to create a new sample of a non-periodic bar to prevent failure of price trend formation during a range-bound trading period with the expectation to choose a successful price trend formation. This research has set a triple exponential moving average either higher or lower than the current price closed 'OHLC' during the investigation to prove the first hypothesis. Secondly, this research has set the average directional movement 'ADX' to be greater than 20 index points to prove the second hypothesis. Thirdly, this research has set an average the 68% of one standard deviation for frequency mean to qualify to prove the third hypothesis. The mean indicates the average of time taken per bar from the duration set of trends following. The standard deviation shall reveal the character of sample selection for the higher the mean would influence a narrower deviation rate and vice versa. The limitation of discussion for objective one for all three hypotheses are subjective and bias judgemental since the price trend analysis is data snooping as per prior researchers' suggestion Park and Irwin (2010).

Table 1 Result of Objective One

No sample	Duration Begin	End	**H1** H1(a): OHLC>TEMA or H1(b): OHLC<TEMA	**H2** ADX>20	**H3** Frequency filter >1 hour	Mean hours	Standard deviation
1	13/3/2015 4:32	10/8/2015 20:47	OHLC>TEMA	33.616	71%	15:51:39	0.77
2	12/10/2015	13/11/2015	OHLC>TEMA	30.683	81%	6:47:17	0.45

	1:13	0:16					
3	13/01/2016 16:07	09/02/2016 21:47	OHLC<TEMA	**17.601**	69%	4:46:17	0.40
4	19/07/2016 16:01	11/10/2016 05:22	OHLC>TEMA	27:42	92%	11:01:06	0.56
5	05/01/2017 16:07	31/05/2017 1:32	OHLC<TEMA	27.162	68%	5:51:17	0.46
6	15/10/2017 16:06	25/12/2017 23:52	OHLC<TEMA	**17:836**	90%	7:24:37	0.48
7	07/02/2018 22:33	25/05/2018 6:57	OHLC>TEMA	20:457	77%	4:27:44	0.36
8	02/12/2018 19:35	09/01/2019 07:54	OHLC<TEMA	24.19	76%	4:44:19	0.40
9	21/02/2019 19:30	02/05/2019 10:04	OHLC>TEMA	**16.069**	90%	8:18:40	0.49
10	19/05/2019 16:01	01/08/2019 13:28	OHLC>TEMA	38:604	79%	7:17:53	0.49

All samples for hypothesis 1 are satisfied. Bullish trends were collected from sample 1,2,4,7,9,10. Bearish trends were collected from sample 3,5,6,8. Three samples from 3,6,9 failed to meet hypothesis 2. Seven samples from 1,2,4,5,7,8,10 satisfied hypothesis 2. Although sample 3,6,9 failed to meet hypothesis 2, they qualified to satisfy the hypothesis 3 respectively. All samples for hypothesis 3 are satisfied. Therefore, trend deviations revealed that all hypothesis 3 are satisfied to choose successful price trend formation during the range-bound trading period to meet objective one.

The implication of introducing the range bar is expected to choose successful price trend formation to qualify the third hypothesis. There are eight samples selected with a low standard deviation below 0.5, and the range of meantime interval is between 4:27:44 and 8:18:40. These samples proved that a lower mean time interval contributes to a narrower standard deviation rate. The highest mean time interval is sample no.1 at 15:51:39 causes a wider of 0.77 standard deviations. The two lowest frequencies mean of success replaced 60 minutes of time interval derived from sample no.5 at 68% and sample no.3 at 69%. The highest frequency means of success replacing 60 minutes of time interval are collected from sample no.4 at 92%, sample no.6 at 90%, and sample no.9 at 90%. The important of objective one has contributed to replace range bar to create a new sample of non-periodical bar. Hence, its new sample would solve price trend formation. It further analyses the ergodic process as moderator to influence to detect early price trend of USD/CNY pair currency.

4.2 Discussion for Objective Two

Research objective two is to introduce a moderator variable of an ergodic process to analyse a new sample of a non-periodic bar to prevent lagging higher prices during the following period with the expectation to choose an undervalued price sample to justify hedge position an early price trend formation. The ergodic process value is positive to reveal a bullish trend or negative to indicate a bearish trend. The higher the ergodic process value, the higher would be the early trend detection effects. The correlation coefficient is set at 0.8 to prove the fourth hypothesis that there is a relationship between ergodic process and range bar to detect an early price formation. The limitation of discussion for objective two for the inputs of 0.8 correlation coefficient to derive the price trend is subject to data snooping biases as suggested by prior researchers such as Park and Irwin (2010).

Table 2 Result of Objectives Two

No sample	Duration Begin	End	**H1** H1(a): OHLC> TEMA H1(b): OHLC< TEMA	**H2** ADX>20	**H4** Correlation Coefficient	Ergodic value	Early Price trend detection (Mean =1.3%)	Conclusion
1	13/3/2015 4:32	10/8/2015 20:47	OHLC> TEMA	33.616	0.95	0.21	3.1%	Bullish early up tend
2	12/10/2015 1:13	13/11/2015 0:16	OHLC> TEMA	30.683	0.90	0.13	0.8%	Bullish early up tend
3	13/01/2016 16:07	09/02/2016 21:47	OHLC< TEMA	**17.601**	0.92	-0.13	0.4%	Bearish early up tend
4	19/07/2016 16:01	11/10/2016 05:22	OHLC> TEMA	27.42	0.85	0.12	1.1%	Bullish early up tend
5	05/01/2017 16:07	31/05/2017 1:32	OHLC< TEMA	27.162	0.94	-0.23	0.6%	Bearish early up tend
6	15/10/2017 16:06	25/12/2017 23:52	OHLC< TEMA	**17.836**	0.91	-0.16	1.3%	Bearish early up tend
7	07/02/2018 22:33	25/05/2018 6:57	OHLC> TEMA	20.457	0.82	0.09	0.8%	Bullish early up tend
8	02/12/2018 19:35	09/01/2019 07:54	OHLC< TEMA	24.19	0.86	-0.15	1.3%	Bearish early up tend
9	21/02/2019 19:30	02/05/2019 10:04	OHLC> TEMA	**16.069**	0.84	0.07	1.1%	Bullish early up tend
10	19/05/2019 16:01	01/08/2019 13:28	OHLC> TEMA	38:604	0.96	0.21	2.6%	Bullish early up tend

All samples for hypothesis 1 are satisfied. Bullish trends were collected from sample 1,2,4,7,9,10. Bearish trends were collected from sample 3,5,6,8. Three samples from 3,6,9 failed to meet hypothesis 2. Seven samples from 1,2,4,5,7,8,10 satisfied hypothesis 2. Although sample 3,6,9 failed to meet hypothesis 2, they qualified to satisfy the hypothesis 4 respectively. All samples for hypothesis 4 are satisfied. Therefore, Ergodic Theory revealed that all hypotheses are satisfied to choose undervalued price sample during early price trend detection within two standard deviations to meet objective two.

The implication of introducing an ergodic process is expected to choose an undervalued price sample to qualify the fourth hypothesis. Six samples were selected with a positive value of an ergodic process to indicate a bullish trend direction. Four samples were selected with a negative value to indicate a bearish trend direction. The two highest ergodic values were selected from sample no.1 at 0.21 value with an impact of 3.1% early price trend detection and sample no.10 at 0.21 value with an impact of 2.1% early price trend detection. The important of objective two is to prevent over price hedge sample. It has contributed to solve early price trend detection by choosing an undervalued hedge sample. The success of analysing objective two results would contribute to a 1.3% average of an early price trend detection of USD/CNY pair currency.

5. CONCLUSION

The third hypothesis achieved research objective one: all the ten samples selected reported at least a 68% frequency success rate for a new sample of non-periodic range bar to replace the time interval bar of 1 hour. Such research objective one would eventually allow to proceed to perform testing to achieve research objective two.

The fourth hypothesis achieved research objective two, that all the ten samples selected reported at least 0.8 correlation coefficient between variables to range bar and ergodic process. The ergodic process indicated a positive value for a bullish trend and a negative value for a bearish trend.

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