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Improved Martingale Betting System for Intraday Trading in Index Futures—Evidence of TAIEX Futures

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Abstract: In this paper we have proposed an innovative intraday trading policy which originated from the standard Martingale gambling system with a stop policy. Therefore we call the new trading method as the Improved Martingale Betting System (IMBS). The traditional martingale betting system was investigated in the case of Casino Roulette gambling. In this paper we have modified the method by adding a stop policy and applied the new method to intraday trading. We have investigated the efficacy of our modified IMBS in actual empirical tests. The results show that in the context of TAIEX futures (TX) trading with three different strategies, our IMBS has quite good performance and can be applied to TX intraday trading and other related markets.

Keywords: Martingale betting system, TAIEX futures, Intraday trading, Improved martingale betting system

1. INTRODUCTION

In probability theory and applied stochastic processes literature, almost all researchers have proved that in a fair random environment any naive betting strategy cannot gain positive profits. The standard martingale betting method probably leads to bankruptcy with a limited amount of initial capital. However, there are different views on whether stock price movement is a pure random walk as often being modeled as a geometric Brownian motion, while there are

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some traders who have achieved good performance in reality. A trading strategy in general can be divided into two parts: an entry and exit decision and a fund management policy. In order to test the profitability, Chen and Liao (2022) focused on the role of fund management policy and proposed a new betting strategy, the so called Improved Martingale Betting System (IMBS), in which the stop loss magnitude was set and the unlimited number of double bettings of the traditional Martingale Betting System (MBS) was modified, and the improvement was significant. On this basis, in this paper we have applied the IMBS to three intraday trading strategies of TAIEX futures (TX) contracts to verify IMBS. In order to avoid the optimisation of strategies and parameters for TX historical data, this research has conducted millions of Monte Carlo Simulations. The results show that the proposed IMBS has a significant improvement in mean return rate as compared to the Equal Weight Betting System (EWBS), and the standard MBS eventually leads to bankruptcy. After that, we selected some settings of IMBS and applied them to TX historical data, the results showed that IMBS has better performance than any other betting system. The rest of the paper has been arranged as follows: Section 2 is the literature review, subsection 2.1 discusses some previous researches concerning trading policy, emphasising the empirical investigation of actual application of investment rules. In 2.2 we present some popular betting systems including standard Martingale Betting System and Equal Weight Betting System. In subsection 2.3 we have introduced our new method, the Improved Martingale Betting System. Section 3 is discusses the research methods and Section 4 is about the empirical results. Finally Section 5 is the conclusion of the paper.

2. PREVIOUS RESEARCHES

2.1. Literature Review and Betting systems

In this sub-section we have first defined the terminology regarding betting systems and gambling policy and then presented the empirical study of the most popular application of gambling systems applied to the actual investment practice.

A gambling system is a sequence of an independent and identical binary random variables with probability p and q (= 1-p), the gambler bets at unit stake and he gains one dollar if one particular outcome appears (using coin tossing as an example, if the head (H) appears) and he loses one dollar if the tail (T) appears, this game goes on indefinitely. If the player follows some rules for betting head or tail then we call the system a selection system. Two commonly seen systems are momentum strategy and contraction strategy. For example, a momentum strategy is as follows : if the sequence of outcomes are HHH (TTT) , then one bets H (T) for the next game, on the other hand, the contraction strategy is: if HHH (TTT) appear, one bets T (H) for the next game (for detail exposition, see Billingsley (1986), Feller (1971)). If the player bets different amounts depending on some previous information, then we have a betting system. Furthermore, if the player has some target amount of wealth starting from an amount of initial capital then we call the system as a gambling policy (for example, the bold play or timid play). If the system has some form of stopping rule, we call the system an improved betting system as we will explain below.

In the following subsection we have focussed on the discussion on betting systems including martingale betting system and Kelly formula applied to intraday trading in various financial markets and in the next subsection we have proposed the Improved Martingale Betting system.

Suppose that a betting game has a winning probability p, a loss probability q (= 1-p), the winning payoff is w, the loss is l, and the random variable X_k defined as the outcome of the k^{th} bet, a winning bet is recorded as $X_k = 1$, and a losing bet is recorded as $X_k = -1$, i.e., X_k is the k^{th} game profit per unit stake, R_k is the profit of betting B_k, and CR_k is the cumulative profit up to k^{th} game. Then the expected profit of the k^{th} bet $E[X_k]$ will be:

$$E[X_k] = (p * w - q * l) = l[(w/l + 1)p - 1]. \qquad (1)$$

Assuming that the input amount of the k^th^ bet is $B_k (k = 1,2, ..., m)$, the profit or loss of k^{th} bet will be: $R_k = X_k B_k$. After m rounds of consecutive betting, the sum of profit and loss R_k will be: $CR_m = \Sigma_{k=1}^{m} X_k B_k$ and the expected value of CR_m will be:

$$E[CR_m] = \Sigma_{k=1}^{m} E[X_k B_k] = \Sigma_{k=1}^{m} E[X_k] E[B_k] = \Sigma_{k=1}^{m} l[\left(\frac{w}{l} + 1\right)p - 1] E[B_k].$$

In a fair random game, it is usually $w = l$ and $p = 0.5$, and the expected cumulative return is zero, but in the actual market trading, *w, l and p* are usually not these values. The expected value of CR_m shows that if $\left(\frac{w}{l} + 1\right)p - 1 > 0$,, then the expected value of the total profit and loss of trading would be positive. The values of *w, l and p* are determined by the given game; what we can do is to consider fund management policy, therefore we consider some of the well-known methods of betting capital B_k for each bet and assume that the initial capital is V_0.

(A) Martingale Betting System

The MBS method means that if one round of gambling is lost, the bet of next round will be doubled, and if a losing streak is repeated until a winning appears, then the bet starts anew of 1 dollar. The betting amount can be expressed as:

$$B_k = \begin{cases} 2 * B_{k-1}, & if \;\; X_{k-1} = -1, \\ 1, & if \;\; X_{k-1} = +1. \end{cases}$$

Therefore, the change of the bet amount B_k can be expressed as:

$$\begin{cases} B_k > B_{k-1}, & if \; R_{k-1} < R_{k-2}, \\ B_k < B_{k-1}, & if \; R_{k-1} > R_{k-2}. \end{cases}$$

Under the assumptions of $w = 1$, $l = 1$, this method can earn infinite amount of money, because one can bet until winning and start anew:

$$CR_{m+1} = -1 - 2^1 - 2^2 - \ldots - 2^{m-1} + 2^m = -(1 + 2^1 + 2^2 + \ldots + 2^{m-1}) + 2^m = 1 = CR_{m+1}$$

To actually implement this strategy it requires that the player have infinite amount of capital and time, but this is impossible in practice.

(B) Kelly Formula

Regarding the coin tossing game, Kelly (1956) proposed Kelly Criterion to define the limit of capital growth rate G of the gambler's mth game as:

$$G = \lim_{m \to \infty} \frac{1}{m} \log_2 \left(\frac{V_m}{V_o} \right). \tag{2}$$

Here V_0 is the gambler's initial capital and V_m is the total capital after n bets. Since Kelly Criterion assumes the winning rate $p > 1/2$, the gambler only considers the betting ratio f^*. After n bets, the total capital can be expressed as:

$$V_m = (1 + f^*) w \, (1 - f^*)^l V_0,$$

where w is the number of games won by the bet, L is the number of games lost by the bet, and $w + l = m$. To maximise the value of G, he showed that the gambler will get the largest V_m via betting at a ratio of $f^* = 2p - 1$. Later, Thorp (1967) introduced the concept of odds b, the ratio of the amount to win divided by the amount to lose, that is $b = w/l$ in equation (1) and proposed a revised Kelly Formula to be used in the stock market:

$$f^* = p - q/b = (p(b + 1) - 1)/\, b \tag{3}$$

Following Kelly's Formula, the k^{th} bet amount B_k can be expressed as $B_k = f^* * V_{k-1}$, and the capital after the kth bet is the sum of previous capital and the gain from k^{th} bet is $V_k = V_{k-1} + R_k$. Therefore, the change of the bet amount B_k can be expressed as:

$$\begin{cases} B_k > B_{k-1}, & if \;\; R_{k-1} > 0, \\ B_k < B_{k-1}, & if \;\; R_{k-1} < 0. \end{cases}$$

There are some previous researches applying Kelly's formula in a generalised framework, e.g., Byrnes and Barnett (2018). For the empirical test of the formula, Hu (2019) applied the formula to the investment in Taiwan stock market under the framework of LSTM (Long Short-Term Memory). He found that the Kelly's formula cannot effectively increase the return of the portfolio, but rather it can help reduce the risk level of the portfolio. Ohlsson and Markusson (2017) applied the formula to test its effect in Swedish stock market and found similar results. Wu and Chung (2018) applied the formula to construct option portfolio and obtained a satisfactory result.

(C) Equal Weight Betting System, EWBS

In this system, $B_k = a * V_0$, $0 < a < 1$, where a is the betting ratio. In each bet a is a fixed value that does not change with k, which is also the most commonly used fund management policy for actual trading strategy. We have also applied this betting system in our empirical test and compared it with other methods.

2.2. IMBS — Improved Martingale Betting System

This approach was proposed by Chen and Liao (2022), and they named it as the Improved Martingale Betting System (IMBS). We can see that in the original MBS, the gambler would encounter excessive increase in betting amount and the consequent sharp increase in risk or it needed an unlimited amount of capital, which is unpractical in the real world. Thus, they designed a new betting mechanism. The IMBS means that if one round of gambling is lost, the betting of next round will be a times the amount of this round. If one loses consecutively, it will be multiplied until winning the game. Same as Kelly's Formula, the capital after the k^{th} bet is the capital of the $(k-1)^{th}$ plus the gain of the k^{th} bet, however, the number of multiples is limited to n folds and the betting amount can be expressed as:

$$B_k = \begin{cases} \min\left(a * B_{k-1}, a^n * B_1\right) & if \;\; X_{k-1} = -1 \\ 1, & if \;\; X_{k-1} = +1. \end{cases} \tag{4}$$

The change of the betting amount B_k is the same as in MBS and can be expressed as:

$$\begin{cases} B_k > B_{k-1}, \ if \ R_{k-1} < R_{k-2}, \\ B_k < B_{k-1}, \ if \ R_{k-1} > R_{k-2}. \end{cases}$$

As shown in the B_k expression, when the B_k exceeds the upper bound $a_n * B_1$ the trade stops and starts anew. It can be seen from the above expressions that MBS, IMBS and Kelly's Formula, all want to increase the total profit by increasing or decreasing the bet, but the mechanism of MBS, IMBS vs. Kelly Formula are in opposite directions; for the first two approaches the bet will decrease to the initial level until winning the game, but for the third method (Kelly's formula) the bet will increase because relative risk is smaller, therefore it is more like momentum strategy.

3. RESEARCH METHOD

3.1. Research Data

In this research we had taken TAIEX futures: Taiwan Stock Exchange Capitalisation Weighted Stock Index futures (TX) as our sample and collected the historical intraday data on the near month contracts from 2005 to 2019.

3.2. Strategies

There were three kinds of entry-exit strategies to examine our system using 5-minutes intraday data with opening, closing, lowest and highest prices. Strategies would start from 8:45 to 13:45 every trading day.

3.2.1. Channel Breakout Strategy (CBS)

The concept of CBS strategy is to calculate today's market strength and weakness range based on yesterday's prices, and when the current price breaks through the upper edge of the range, it is assumed that it will continue to rise and long the position, and when the price falls below the lower edge of the range, it is assumed that it will continue to fall and short the position. In addition, the stop loss mechanism is added.

The definition of channel refers to the CDP (Counter Daily Potential) indicator proposed by Wilder (1978). To build the channel, first we calculate the reference price of the day (CDP_{D_t}) by finding average of yesterday's highest price ($H_{D_{t-1}}$) plus yesterday's lowest price ($L_{D_{t-1}}$) and twice yesterday's closing price ($C_{D_{t-1}}$). Then we calculate the highest price channel of the day (AH_{D_t})

which is equal to CDP_{D_t} plus $H_{D_{t-1}}$ and minus $L_{D_{t-1}}$. Secondly, we calculate the next highest price channel of the day (NH_{D_t}) which is equal to twice CDP_{D_t} minus twice $L_{D_{t-1}}$. Then we calculate the lowest price channel of the day AL_{D_t}) which is equal to CDP_{D_t} minus $H_{D_{t-1}}$ and plus $L_{D_{t-1}}$. Lastly we calculate the next lowest price channel of the day NL_{D_t} which is equal to twice CDP_{D_t} minus twice $H_{D_{t-1}}$. We can express the above terms as follows:

$$CDP_{D_t} = \frac{H_{D_{t-1}} + L_{D_{t-1}} + (C_{D_{t-1}} * 2)}{4}$$
$$AH_{D_t} = CDP_{D_t} + (H_{D_{t-1}} + L_{D_{t-1}})$$
$$NH_{D_t} = CDP_{D_t} * 2 - L_{D_{t-1}} * 2$$
$$AL_{D_t} = CDP_{D_t} - (H_{D_{t-1}} - L_{D_{t-1}})$$
$$NL_{D_t} = H_{D_{t-1}} * 2 - CDP_{D_t} * 2$$

The CBS will open long position once 5-minute closing price (C_{K_t}) is greater than or equal to AH_{D_t}, and will sell out long position to stop loss when current price (P_t) is less than or equal to the maximum value of entry price (EP) minus EP times stop loss rate (SL) and AL_{D_t}. The CBS will open short position once C_{K_t} is less than or equal to AL_{D_t}, and will buy back short position to stop loss when P_t is greater than or equal to the minimum value of EP plus EP times SL and NL_{D_t}. Table 1 shows four signals' condition of Channel Breakout strategy and Figure 1 shows an example of opening long position and holding it until the market closes.

Table 1: Signal and Condition of Channel Breakout Strategy

Signal	*Condition*
Long Entry	$C_{K_t} \geq AH_{D_t}$
Long Stop Loss	$P_t \leq \max[EP * (1 - SL), NH_{D_t}]$
Short Entry	$C_{K_t} \leq AL_{D_t}$
Short Stop Loss	$P_t \geq \min[EP * (1 + SL), NL_{D_t}]$

Figure 1 shows a long position entering example. We can see that once if the highest price crosses over the AH channel on a particular day, the CBS will execute the long position entering order and hold it until the current price going down to touch the NH channel or less than the entry price minus stop loss value. In this case, the price keeps going up so the CBS keeps holding the

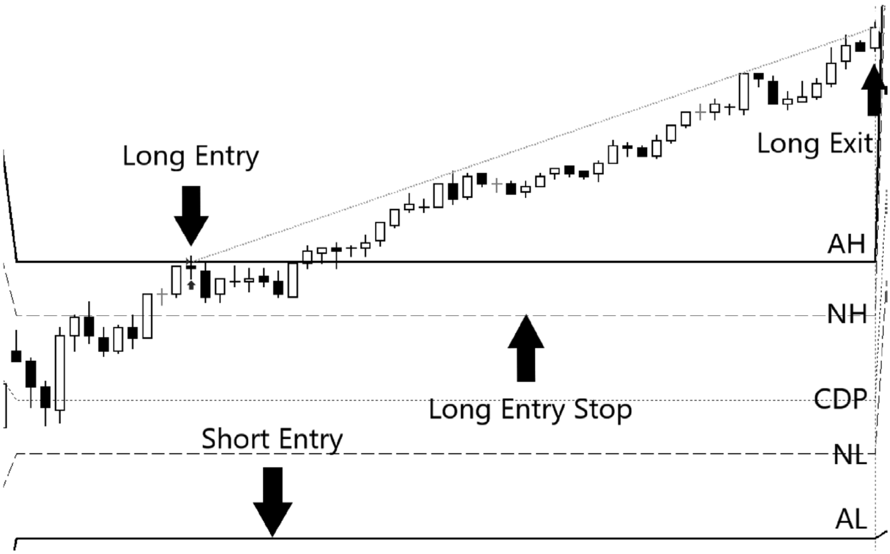


Figure 1: Example of Long Entry signal by Channel Breakout Strategy

position till the market closing time.

3.2.2. Price Breakout Strategy (PBS)

The design principle of PBS is based on pure price breakthrough. When the current price is greater than the closing price yesterday plus a breakthrough value, we assume that it will continue to rise today and will long the position; and when the current price is lower than the closing price yesterday by a certain amount, we assume that it will continue to fall today and short the position. The stop loss mechanism is also added.

The PBS is based on the immediate price rise or fall beyond a certain range of $C_{D_{t-1}}$ as the basis for trading. First, we set a breakthrough rate, BPr= (0.5%, 0.75%, 1.0%, 1.25%, 1.5%) as a parameter with reference to the historical daily fluctuation range of TX. Then we calculate a breakthrough point (BP) by BPr times $C_{D_{t-1}}$, and take real-time price change of the day as today's breakthrough value (DP). In other words, DP is the difference between current candle bar's closing price and closing price of yesterday, and BP is a given value calculated according to the ratio BPr.

The PBS will open long position when both, DP is larger than BP and C_{K_t} is higher than the highest closing price in the past thirty minutes $(H_{K_{(t-6\sim t-1)}})$ are met and will sell out long position to stop loss when P_t is lower than or equal to EP minus EP times SL. The PBS will open short position when both, DP is less than BP and C_{K_t} is lower than the lowest closing price in the past thirty minutes $(L_{K(t-6\sim t-1)})$ are met and will buy back short position to stop loss when P_t is higher than or equal to EP plus EP times SL. Table 2 shows four signals' condition of PBS and Figure 2 shows an example of opening long position and holding it until the market closes.

Table 2: Signal and Condition of Price Breakout Strategy

Signal	*Condition*
Long Entry	$[(DP > BP)\ and\ (C_{K_t} \geq H_{K(t-6\sim t-1)})]$
Long Stop Loss	$P_t \leq [EP * (1 - SL)]$
Short Entry	$[(DP < BP)\ and\ (C_{K_t} \leq L_{K(t-6\sim t-1)})]$
Short Stop Loss	$P_t \geq [EP * (1 + SL)]$

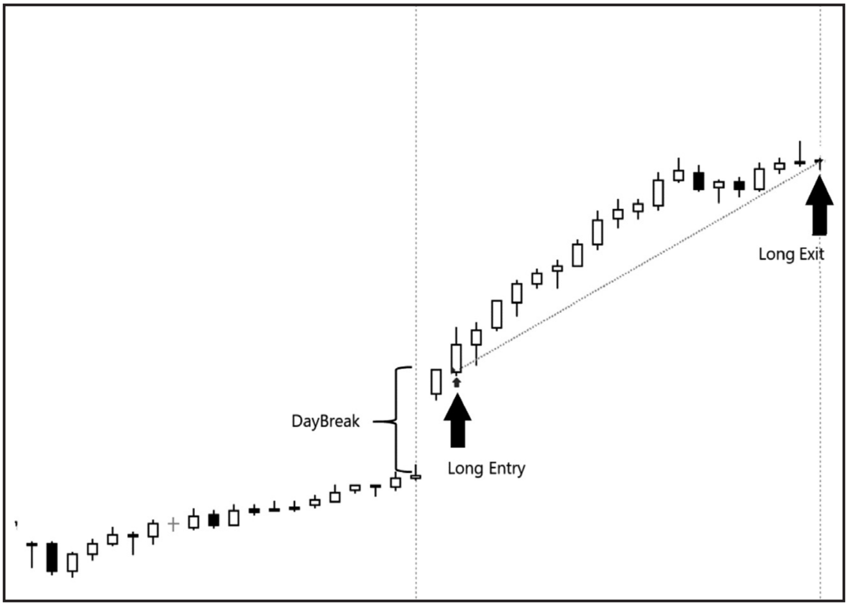


Figure 2: Example of Long Entry signal by Price Breakout strategy

From Figure 2 we can see that the first candle bar's closing price is larger than the BP, so the PBS will execute the long entering order. If the price does not touch the stop loss setting after entry, the strategy will hold it till market closing time.

3.2.3. Volatility Breakout Strategy (VBS)

The design idea of the VBS is to compare the magnitude of volatility. If today's volatility is greater than the largest volatility of the past two days, we assume today's volatility will be amplified. After today's volatility breakout, if the price also hits a new high today, a long order will be executed, and if the price hits a new low today, a short order will be executed. Also there is a stop loss mechanism after position entering.

The price volatility of the day (V_{D_t}) means that today's highest price minus today's lowest price divided by yesterday's closing price. The VBS is to take the maximum value of the last two days' price volatility as the benchmark, and enter the market when V_{D_t} exceeds a certain ratio of the benchmark. We set this ratio as a parameter BVr= (0.25, 0.5, 0.75, 1.0, 1.25, 1.5).

The VBS will open long position once both, P_t is the highest price of the day and V_{D_t} is larger than the maximum value of the last two days' price volatility times BVr and will sell out long position to stop loss if P_t is less than or equal to the EP minus EP times SL. The VBS will open short position once both, P_t is the lowest price of the day and V_{D_t} is greater than the maximum value of the last two days' price volatility times BVr and will buy back short position to stop loss if P_t is greater than or equal to the EP plus EP times SL. Table 3 shows four signals' condition of VBS and Figure 3 shows an example of opening long position and holding it until the market closes.

Table 3: Signal and Condition of Volatility Breakout Strategy

Signal	*Condition*
Long Entry	$V_{D_t} > [\max(V_{D_{t-1}}, V_{D_{t-2}}) * BVr \ and \ (C_{K_t} \geq H_{D_t})]$
Long Stop Loss	$P_t \leq [EP * (1 - SL)]$
Short Entry	$V_{D_t} > [\max(V_{D_{t-1}}, V_{D_{t-2}}) * BVr \ and \ (C_{K_t} \leq L_{D_t})]$
Short Stop Loss	$P_t \geq [EP * (1 + SL)]$

In the lower part of Figure 3, there is a dashed line representing the maximum volatility over the past two days and the dotted line representing the volatility of the day. We can see that once the volatility of the day exceeds the past two days's maximum volatility and the closing price is the highest price of the day, the VBS will execute long entering order, and it will hold the position till the market closing time unless it triggers the stop loss mechanism.

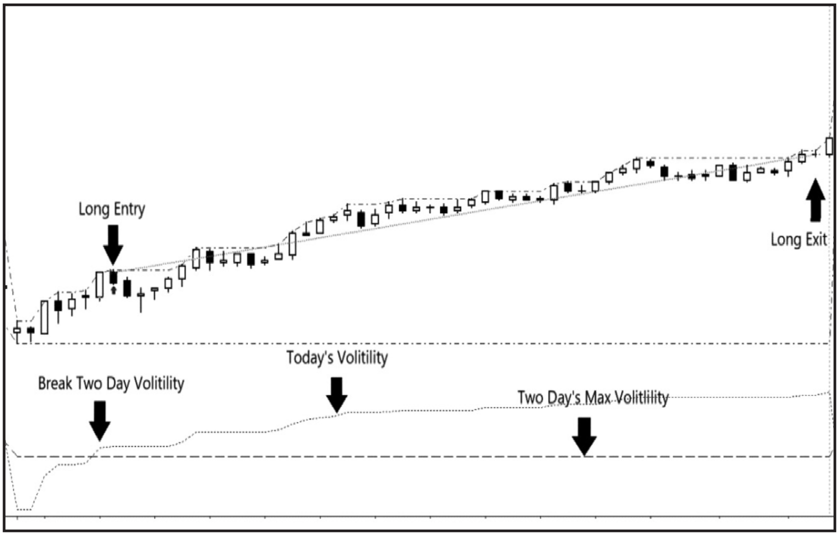


Figure 3: Example of Long Entry signal by Volatility Breakout strategy

3.3. Betting Methods

Regardless of the performance of the strategies, the improvement of the overall return by the betting method and fund management was the core of this research. We tested all strategies with the following betting methods.

3.3.1. EWBS

EWBS means each bet amount is equal. In this research we set it to be the initial capital. Considering that futures are traded on margin, the bet amount should be the contract market value rather than the margin amount, therefore we assumed that the capital is V, the trading entry price is S, point value of the contract is PV, and the number of order volume CN will be: $CN_k = V_k/(S_k * PV)$ Profits or losses will be accumulated into the capital, which becomes the basis for calculating the capital of the next bet: $V_k = V_{k-1} + R_{k-1}$.

3.3.2. Stop Loss

As mentioned above, the effectiveness of fund management is based on the basis that the price process is not a super-martingale or a sub-martingale, therefore, IMBS will have stop loss mechanism. We calculated the historical average range θ for the difference between the daily opening price and closing price of TX contracts , and took 0.25 times, 0.5 times, 0.75 times, and 1 time as the daily stop loss rate: SL = θ * (0.25, 0.5, 0.75,1)

The average difference between daily opening price and closing price of TX, θ, was 0.76%. The trading entry conditions and mechanisms of EWBS with SL are like EWBS without SL, and the exit condition is to hold until the close of the market unless it hits the stop loss price.

3.3.3 IMBS and MBS

We set the IMBS parameters $\boldsymbol{a}$ = (1,1.25,1.5,1.75,2), $\boldsymbol{n}$ = (1,2,5,8), SL = (0.25θ,0.5θ,0.75θ,1θ,0), here 0 means no stop loss mechanism, EWBS equals to IMBS (a=1, n=1), and MBS is as IMBS (a=2, n=1,2,5,8). Furthermore we limited the maximum number of multiples $a^n \leq 20$. The reason for limiting $a^n \leq 20$ is that the margin required for equity index futures trading is normally 5% of the contract market value, which is a leverage level of 20 times , hence even if MBS doubles the bet at 2^n, it is impossible to trade more than 20 times of the market value of the contract V. From this setup, we can see that the popular trading strategy EWBS and the standard gaming method MBS are all special cases of our innovative scheme IMBS.

3.4. Monte Carol Simulation

The entry mechanism of the three strategies mentioned above is not random; therefore, we conducted Monte Carol simulation of TX's price to eliminate strategies' optimisation and ad hoc character. The simulated price process is:

$$S_t = S_{t-dt} e^{\left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma\sqrt{dt} * Z_t} \qquad (5)$$

μ = expected return per unit time, σ = volatility of the asset per unit time, and $Z_t \sim N(0,1)$.

Based on TX's historical data from 2005 to 2019, the initial price (S_0) was 6189. To simulate 1-minute opening, highest, lowest, closing data, we divided the daily return of TX into 1800 intervals of instantaneous time (*dt*) which is equal to 10 seconds, because there are 5 trading hours in TX daily market. Under this time frame the expected return μ of TX will be 1.6779e-7, the volatility σ of TX will be 5.2249e-4. One round of the test simulates 252 trading days, and we simulated 100,000 rounds for each parameter's combination. Table 4 shows total number of simulations for various parameter combinations of each strategy.

Table 4: Combinations and Total Simulations of each strategy

	CBS	*PBS*	*VBS*
SL	(0,0.25,0.5,0.75,1) θ	(0,0.25,0.5,0.75,1) θ	(0,0.25,0.5,0.75,1) θ
a	1,1.25,1.5,1.75,2,2.5	1,1.25,1.5,1.75,2,2.5	1,1.25,1.5,1.75,2,2.5
n	1,2,5,8	1,2,5,8	1,2,5,8
PBr	***	(0.5,0.75,1,1.25,1.5)%	***
VBr	***	***	0.25,0.5,0.75,1,1.25
Combinations	120	600	600
Total Simulations	12 millions	60 millions	60 millions

3.5. IMBS settings for TX historical data

According to Monte Carlo simulation results, we chose parameters from better performance clusters for TX historical data testing, to see if IMBS was really better than EWBS and MBS in TX. In these tests, we deducted 2 ticks' value for each contract in every trading as the fee cost.

4. EMPIRICAL RESULTS

4.1. Monte Carlo Simulation

As the settings of bet amount and leverage are different, it was not meaningful to simply compare the total profit between EWBS and IMBS, so we used the Calmar ratio, Sharpe ratio, and Average Win Value/Average Loss value ratio (Avg.W/Avg.L) for the performance comparison, especially the Calmar ratio.

If it is only based on the final result, whether or not the stop loss mechanism is added, Calmar ratio is positively correlated with ***a*** and ***n***, which also verifies that if the capital and betting limits are not considered, MBS can definitely get a profitable result. Figures 4 to 6 show the results of Monte Carlo Simulation by each strategy, each one point represents the mean Calmar ratio of 100,000 simulations.

By the Channel Breakout Strategy (CBS), we can see that ones with the higher mean Calmar Ratio values are mostly in the upper right, especially a=2.5, n=8. The CBS seems to be more sensitive to the setting of parameters.

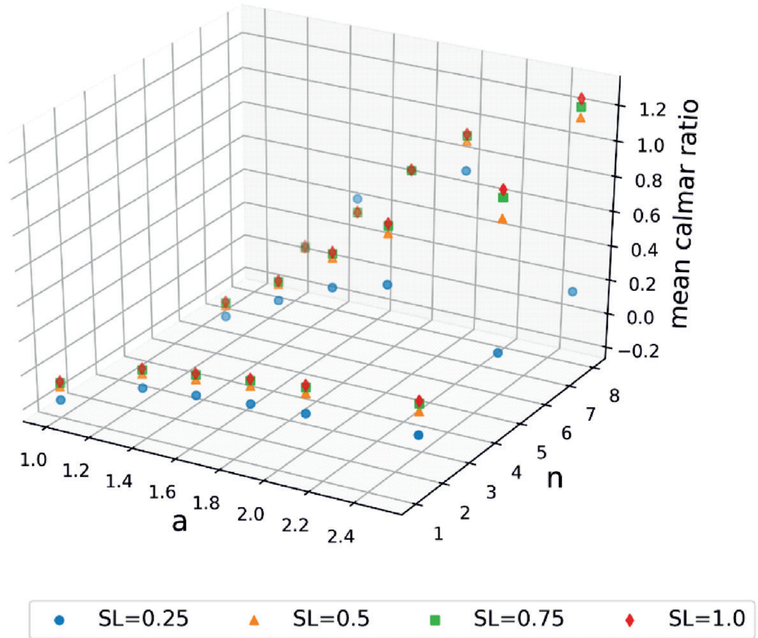


Figure 4: Mean Calmar Ratio Drop Map of Monte Carlo Simulation by CBS

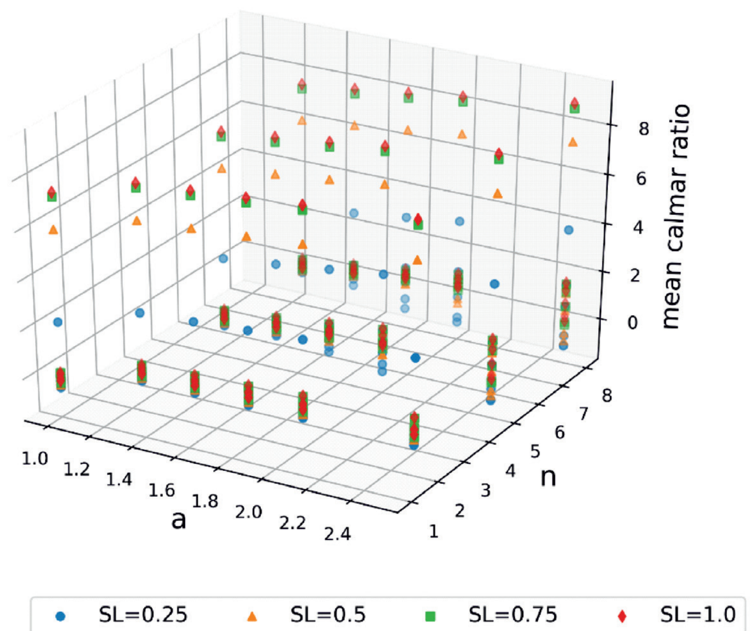


Figure 5: Mean Calmar Ratio Drop Map of Monte Carlo Simulation by PBS

By the Price Breakout Strategy (PBS), we can see that the drop points are more scattered than CBS, and most of them are above 0. Overall PBS has the highest results of Calmar Ratio value.

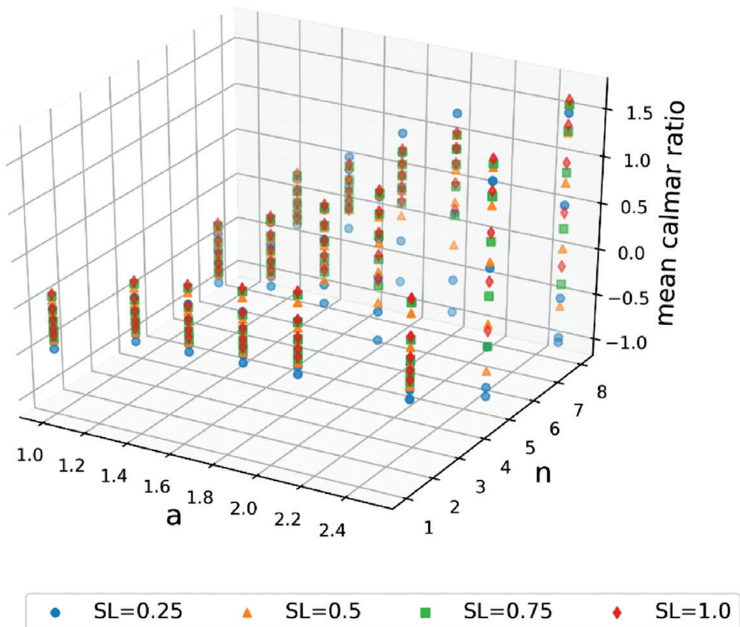


Figure 6: Mean Calmar Ratio Drop Map of Monte Carlo Simulation by VBS

For Volatility Breakout Strategy (VBS), the drops are roughly between CBS and PBS, and the higher Calmar Ratio Values are on the upper right, but there are more combinations to achieve such results than CBS.

However, if we consider the amount of initial capital, the results will be much different. During the round of tests, once the amount of loss is greater than the capital, the round will be terminated and consequently the total profit is recorded as the negative value of initial capital. If the results for a set of parameters are significantly (>95%) negative value of initial capital, we record the mean value as "Broken". This can reflect the real risk of taking leverage.

After considering the real situation, MBS eventually incurs bankruptcy in all parameter combinations of the three strategies as shown in Table 5, and the T-TEST results of the unbroken IMBS parameter combinations show that they are significantly better than EWBS especially in PBS as shown in Table 6.

Table 5: Strategies with different betting methods

		CBS	*PBS*	*VBS*
Mean Calmar Ratio	EWBS	(0.0647)	(0.0659)	(0.0621)
	MBS	Broken	Broken	Broken
	IMBS average	(0.0615)	(0.0589)	(0.0620)
Mean Sharpe Ratio	EWBS	(0.0578)	(0.0771)	(0.1580)
	MBS	Broken	Broken	Broken
	IMBS average	0.0208	1.6392	(0.0041)
Mean Avg.W/ Avg.L Ratio	EWBS	0.9071	0.9020	0.8906
	MBS	Broken	Broken	Broken
	IMBS average	0.9209	2.5049	0.9363

Table 6: Strategies with different betting methods compared to EWBS

		CBS	*PBS*	*VBS*
Mean Calmar Ratio	EWBS	1	1	1
	MBS	Broken	Broken	Broken
	IMBS average	1.0786	2.7163	1.1539
Mean Sharpe Ratio	EWBS	1	1	1
	MBS	Broken	Broken	Broken
	IMBS average	1.0032	1.0070	1.0001
Mean Avg.W/ Avg.L Ratio	EWBS	1	1	1
	MBS	Broken	Broken	Broken
	IMBS average	1.0138	2.6029	1.0457

From Table 6, we can see that no matter which strategy or performance measure is used, the mean value of MBS in millions of Monte Carlo simulations will lead to bankruptcy. Compared with EWBS, IMBS has greatly improved the results, especially with the Price Breakout Strategy (PBS).

Figure 7 to 9 show the results of unbroken Monte Carlo Simulation by each strategy, each one point represents the mean Calmar ratio of 100,000 simulations. We can see that after shaving off "Broken" conditions, the points on the figure are obviously reduced than in Figures 4 to 6. And it shows that we can get better Calmar ratio by setting $a \leq 1.5$, $n \leq 5$ and $SLr \geq 0.75\ \theta$.

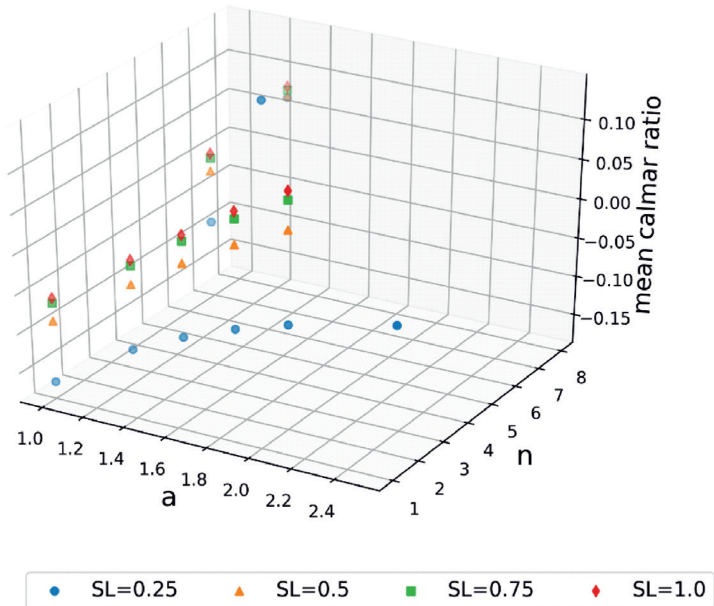


Figure 7: Unbroken Mean Calmar Ratio Drop Map of Monte Carlo Simulation by CBS

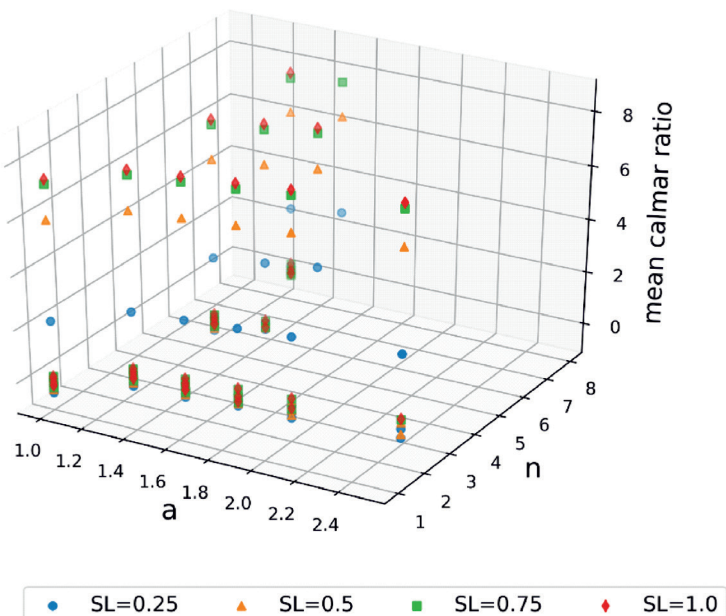


Figure 8: Unbroken Mean Calmar Ratio Drop Map of Monte Carlo Simulation by PBS

After excluding the results of bankruptcy, we can see that the drop points of CBS are greatly reduced, and there are only a few combinations with Calmar Ratio value above 0, such as (*a*=1, *n*=8, *SL*=0.25) and (*a*=1.25 , *n*=8, and several *SL* settings).

In PBS, the number of drop points after bankruptcy are also greatly reduced, but the Calmar Ratio value is generally greater than 0, and many parameter combinations have good results. It can also be seen from Figure 8 that PBS is a better strategy for TX in nature.

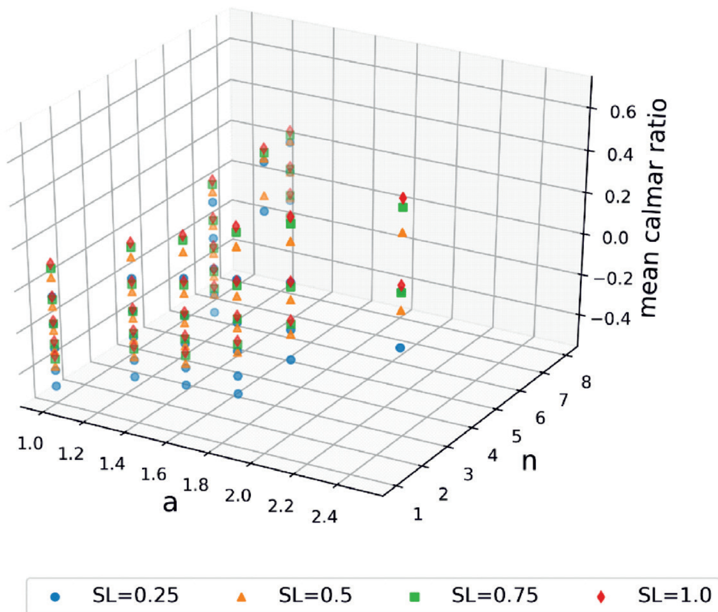


Figure 9: Unbroken Mean Calmar Ratio Drop Map of Monte Carlo Simulation by VBS

The volatility breakout strategy (VBS) presents another interesting phenomenon, the parameter combinations that are not bankrupt are concentrated in eight combinations, and there are only a few results with Calmar Ratio values greater than 0.

4.2. IMBS settings for TX historical data

According to the results of Monte Carlo simulation, MBS settings (***a***=2) lead to bankruptcy in all the three strategies and we conducted tests for each strategy with TX historical data by setting ***a*** = (1,1.25,1.5), ***n*** = (1,2,3,4,5), SL

= (0,0.75 θ, 1θ) for CBS, and ***a*** = (1,1.25,1.5), ***n*** = (1,2,3,4,5), SL = (0,0.75 θ,1θ), BPr=1% for PBS, and ***a*** = (1,1.25,1.5), ***n*** = (1,2,3,4,5), SL = (0,0.75 θ,1θ), VPr = 1 for VBS. Table 7 shows the IMBS setting of each strategy.

Table 7: IMBS setting of each strategy

	CBS	*PBS*	*VBS*
a	1,1.25,1.5	1,1.25,1.5	1,1.25,1.5
n	1,2,3,4,5	1,2,3,4,5	1,2,3,4,5
SL	(0,0.75,1) θ	(0,0.75,1) θ	(0,0.75,1) θ
PBr	***	1%	***
VBr	***	***	1
Combinations	45	45	45
Total tests	45	45	45

The results of all strategies and IMBS settings relative to EWBS's setting (***a*** = 1, ***n*** = 1) can be found in Appendix 1. We deducted fee cost for each transaction by 2 ticks' value for every contract to make the result as close to reality as possible. Figures 10 to 12 show the three-dimensional distribution of net profit and profit factor. Here net profit (NP) means the summation of total gross profit and total gross loss, and profit factor (PF) means total gross profit divided by total gross loss. The vertical axis represents NP and PF, and the x-axis and y-axis represent *a* and *n*, the gray horizontal plane represents the break-even value in each setting.

Net Profit = Total Gross Profit - Total Gross Loss
Profit Factor = Total Gross Profit/ Total Gross Loss

Net profit (NP) is a simple and objective measurement of performance, and if net profit is less than 0, there is usually no value to apply such a strategy or settings of parameter. Profit factor (PF) means how much return will the strategy get when it suffers a loss of one unit. The biggest problem with leveraged trading is that risks taken are disproportionate to rewards, and the results of PF help us to notice this.

In Figure 10, we can see that EWBS (***a*** = 1, ***n*** = 1) is worse than other IMBS's settings both in NP and PF. Overall, NP and PF will have better result as ***a*** gets closer to 1.5 and ***n*** gets closer to 5.

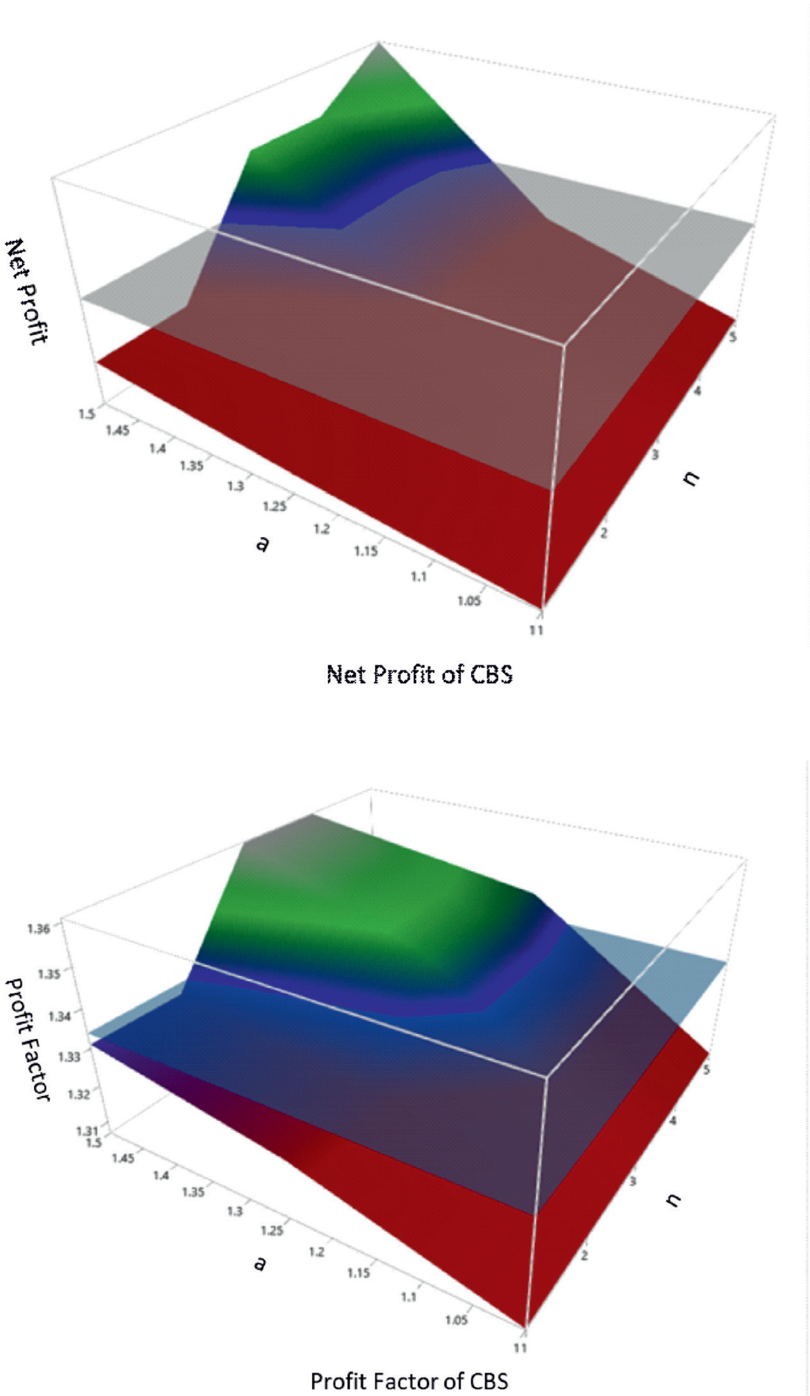
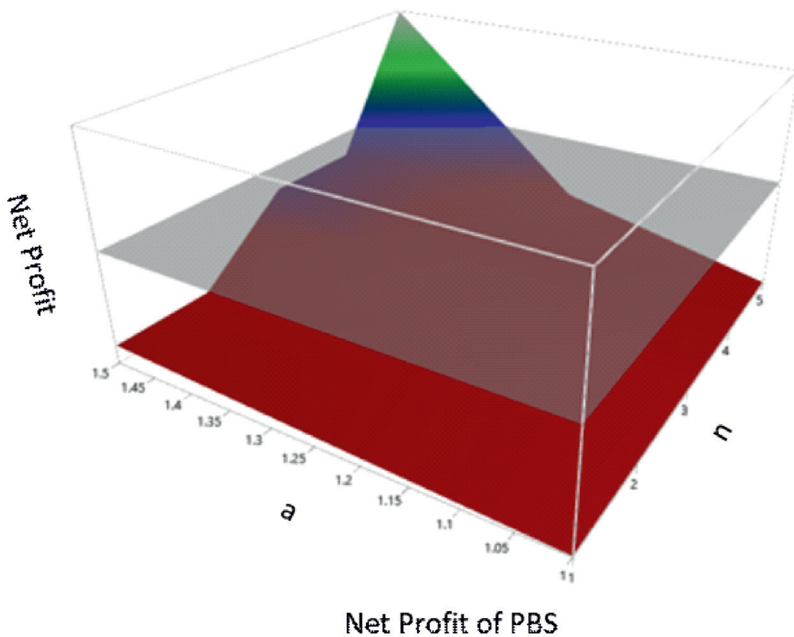


Figure 10: NP and PF of Channel Breakout Strategy (CBS)



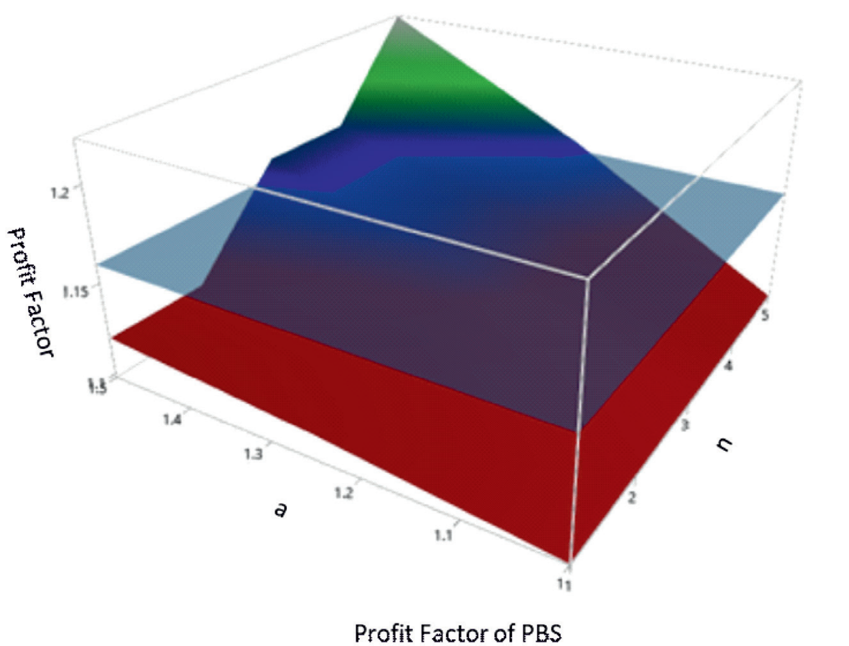


Figure 11: NP and PF of Price Breakout Strategy (PBS)

In Figure 11 we can see that EWBS is worse than other IMBS's settings both in NP and PF and will also have better result as ***a*** gets closer to 1.5 and ***n*** gets closer to 5. From Figure 10 and Figure 11, it seems that we will have better results when the leverage increases as long as total leverage setting (a^n) does not exceed a certain threshold.

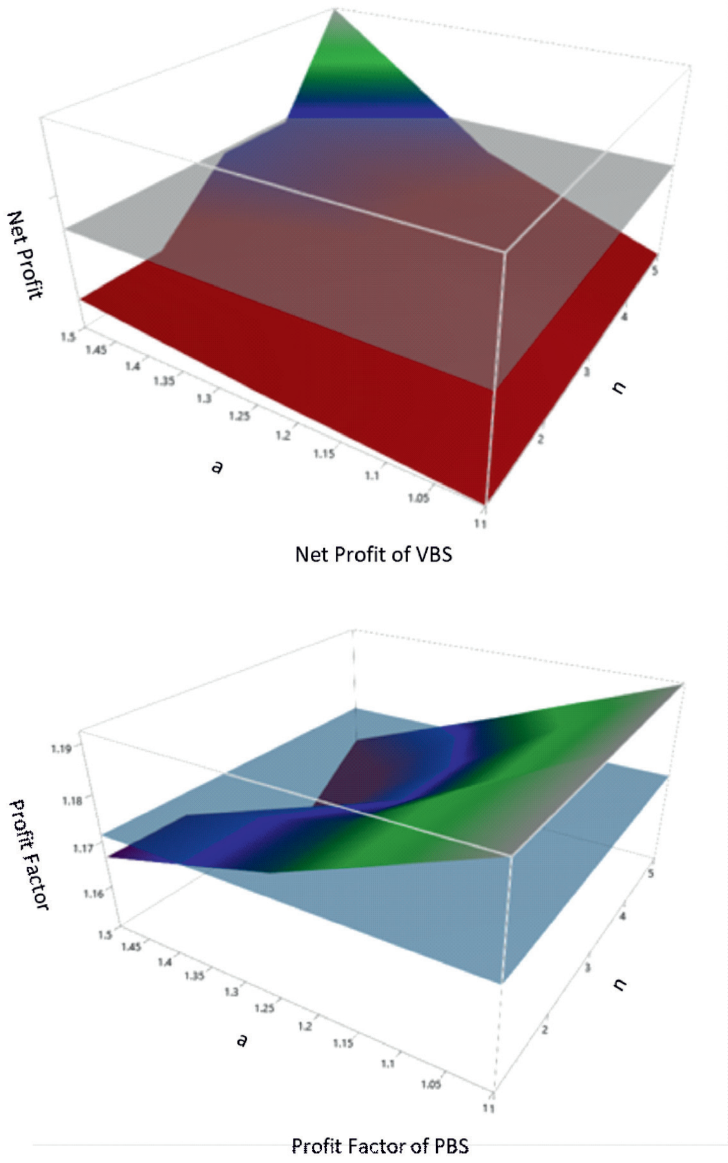


Figure 12: NP and PF of Volatility Breakout Strategy (VBS)

Figure 12 shows the results of VBS. There are some differences between VBS and other two strategies that PF in VBS is not really positively correlated with the setting of (***a***, ***n***). It shows $a = 1$ will mostly have better results, in other words, it means that it is not appropriate to take leverage in VBS strategy, but IMBS still has better NP results in VBS.

5. CONCLUSIONS

This research shows that before a certain threshold is exceeded, as the leverage increases, the return will also increase, and the traditional MBS method of double betting after every loss will have high probability leading to bankruptcy.

The control of ***a, n*** and total leverage in IMBS has significant improvement over EWBS and MBS, whether there is a stop loss mechanism or not. Of course it would be better to set SL function. The test of TX historical data also shows that IMBS has a significant improvement compared to EWBS and MBS, especially in PBS. This implies that price breakout is the most profitable strategy in TX intraday trading.

This research shows that we may apply IMBS mechanism with appropriate settings on total leverage (a^n) to gain a better performance for intraday trading strategies in TX. Hence, we should put more attention on settings of a and n, since they have more impacts than other parameters.

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Appendix 1: Results of all strategies and IMBS settings

CBS (Channel Breakout Strategy)				
SL (θ)	***a***	***n***	**NP**	**PF**
0.75	1	1	1	1
0.75	1	2	1	1
0.75	1	3	1	1
0.75	1	4	1	1
0.75	1	5	1	1
0.75	1.25	1	1.3858	1.0063
0.75	1.25	2	1.3858	1.0063
0.75	1.25	3	2.0135	1.0177
0.75	1.25	4	2.0135	1.0177
0.75	1.25	5	2.2326	1.0157
0.75	1.5	1	1.8837	1.0097
0.75	1.5	2	1.8837	1.0097
0.75	1.5	3	4.3754	1.0204
0.75	1.5	4	4.3754	1.0204
0.75	1.5	5	6.0077	1.0059
1	1	1	1	1
1	1	2	1	1
1	1	3	1	1
1	1	4	1	1
1	1	5	1	1
1	1.25	1	1.4057	1.0115
1	1.25	2	1.4057	1.0115
1	1.25	3	2.0320	1.0279
1	1.25	4	2.0320	1.0279
1	1.25	5	2.1925	1.0256
1	1.5	1	1.9197	1.0184
1	1.5	2	1.9197	1.0184
1	1.5	3	4.4179	1.0412
1	1.5	4	4.4179	1.0412
1	1.5	5	5.5088	1.0243
0	1	1	1	1
0	1	2	1	1
0	1	3	1	1
0	1	4	1	1
0	1	5	1	1
0	1.25	1	1.3798	1.0105
0	1.25	2	1.3798	1.0105
0	1.25	3	2.0244	1.0308

0	1.25	4	2.0244	1.0308
0	1.25	5	2.2890	1.0339
0	1.5	1	1.8625	1.0175
0	1.5	2	1.8625	1.0175
0	1.5	3	4.4865	1.0491
0	1.5	4	4.4865	1.0491
0	1.5	5	6.5361	1.0439
PBS (Price Breakout Strategy)				
SL (θ)	*a*	*n*	*NP*	*PF*
0.75	1	1	1	1
0.75	1	2	1	1
0.75	1	3	1	1
0.75	1	4	1	1
0.75	1	5	1	1
0.75	1.25	5	2.6599	1.0506
0.75	1.25	3	2.0089	1.0279
0.75	1.25	4	2.0089	1.0279
0.75	1.25	1	1.3539	1.0103
0.75	1.25	2	1.3539	1.0103
0.75	1.5	5	9.4815	1.0924
0.75	1.5	3	4.2546	1.0432
0.75	1.5	4	4.2546	1.0432
0.75	1.5	1	1.7858	1.0175
0.75	1.5	2	1.7858	1.0175
1	1	1	1	1
1	1	2	1	1
1	1	3	1	1
1	1	4	1	1
1	1	5	1	1
1	1.25	5	2.4982	1.0482
1	1.25	3	1.9024	1.0281
1	1.25	4	1.9024	1.0281
1	1.25	1	1.3287	1.0102
1	1.25	2	1.3287	1.0102
1	1.5	5	8.1170	1.0889
1	1.5	3	3.8032	1.0483
1	1.5	4	3.8032	1.0483
1	1.5	1	1.7242	1.0190
1	1.5	2	1.7242	1.0190
0	1	1	1	1
0	1	2	1	1

0	1	3	1	1
0	1	4	1	1
0	1	5	1	1
0	1.25	5	2.4976	1.0529
0	1.25	3	1.9640	1.0344
0	1.25	4	1.9640	1.0344
0	1.25	1	1.3650	1.0145
0	1.25	2	1.3650	1.0145
0	1.5	5	7.4488	1.1018
0	1.5	3	3.8449	1.0605
0	1.5	4	3.8449	1.0605
0	1.5	1	1.7440	1.0233
0	1.5	2	1.7440	1.0233
VBS (Volatility Breakout Strategy)				
SL (θ)	*a*	*n*	*NP*	*PF*
0.75	1	1	1	1
0.75	1	2	1	1
0.75	1	3	1	1
0.75	1	4	1	1
0.75	1	5	1	1
0.75	1.25	1	1.1018	0.9922
0.75	1.25	2	1.1018	0.9922
0.75	1.25	3	1.2865	0.9904
0.75	1.25	4	1.2865	0.9904
0.75	1.25	5	1.5417	1.0040
0.75	1.5	1	1.1924	0.9847
0.75	1.5	2	1.1924	0.9847
0.75	1.5	3	1.6978	0.9810
0.75	1.5	4	1.6978	0.9810
0.75	1.5	5	2.7010	1.0072
1	1	1	1	1
1	1	2	1	1
1	1	3	1	1
1	1	4	1	1
1	1	5	1	1
1	1.25	1	1.0580	0.9867
1	1.25	2	1.0580	0.9867
1	1.25	3	1.2097	0.9831
1	1.25	4	1.2097	0.9831
1	1.25	5	1.3317	0.9871
1	1.5	1	1.1414	0.9785

1	1.5	2	1.1414	0.9785
1	1.5	3	1.4572	0.9651
1	1.5	4	1.4572	0.9651
1	1.5	5	1.9543	0.9749
0	1	1	1	1
0	1	2	1	1
0	1	3	1	1
0	1	4	1	1
0	1	5	1	1
0	1.25	1	1.1355	0.9973
0	1.25	2	1.1355	0.9973
0	1.25	3	1.2384	0.9880
0	1.25	4	1.2384	0.9880
0	1.25	5	1.3032	0.9864
0	1.5	1	1.2583	0.9931
0	1.5	2	1.2583	0.9931
0	1.5	3	1.4811	0.9704
0	1.5	4	1.4811	0.9704
0	1.5	5	1.6805	0.9639