The Comparative Analysis of the Trading Performance of an Adapted Opening Range Breakout (AORB) Strategy across Selected Financial Assets

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ABSTRACT

Financial markets differ in liquidity, volatility, and structure, yet little is known about whether one rule-based intraday strategy performs alike across them. This study compares a single standardized Adapted Opening Range Breakout (AORB) strategy on EURUSD, Bitcoin (BTCUSD), gold (XAUUSD), and crude oil (XTIUSD) to establish whether performance is uniform or depends on the asset traded. The study follows a positivist, deductive, quantitative design based on experimental simulation. An identical Expert Advisor was backtested in MetaTrader 5 on one-minute data from January 2017 to July 2026 with initial capital of USD 10,000, giving 115 monthly observations per asset. One-way analysis of variance (ANOVA), Tukey's honestly significant difference (HSD) tests, and Kruskal–Wallis tests were used to compare four performance measures, while the Sharpe ratio and profit factor were reported descriptively. Monthly net profit ($F = 31.57$, $p < 0.001$), win rate ($F = 176.93$, $p < 0.001$), and recovery factor ($F = 13.41$, $p < 0.001$) differed significantly across assets in ANOVA. Kruskal–Wallis tests confirmed these differences and also detected one in maximum drawdown ($\chi^2 = 163.04$, $p < 0.001$) that ANOVA missed ($F = 1.38$, $p = 0.248$). XAUUSD earned the highest mean monthly net profit (USD 156.10) and an annualized Sharpe ratio of 2.31, second to BTCUSD (3.71). BTCUSD had the highest win rate (94.43%), and XTIUSD was unprofitable (USD −8.47). The findings come from historical simulation with one parameter set, ideal execution, and four instruments, so generalization requires caution. Practitioners should test asset suitability before using a common breakout rule.

Keywords: *Algorithmic Trading, Cross-Asset Comparison, Expert Advisor, Opening Range Breakout, Trading Performance*

JEL Classification: G11, G14, G15, G17

1. INTRODUCTION

Algorithmic trading executes predefined rules without discretionary intervention, and the evidence on rule-based technical trading is mixed, with profitability that is often sensitive to the market, the sample period, and transaction costs (Menkhoff & Taylor, 2007; Park & Irwin, 2007). The Opening Range Breakout (ORB) approach captures the price range formed in an initial period and trades when price breaks out of it. Prior ORB research has mostly examined exchange-traded markets such as crude oil futures, index futures, and exchange-traded funds (Holmberg et al., 2013; Tsai et al., 2019; Zarattini et al., 2024). Market microstructure theory explains how liquidity and order flow shape short-term prices (Hasbrouck, 2007; Kyle, 1985; O'Hara, 1995), and activity concentrates when major financial centers trade together (Andersen & Bollerslev, 1998; Eross et al., 2019). Because foreign exchange, cryptocurrency, and metal markets lack a common daily opening, this study adapts the ORB by using a fixed pre-session range as the reference for breakout signals.

Existing work usually studies one market and tunes parameters to it, so differences between instruments cannot be separated from differences in strategy design. Gold (XAUUSD) is a useful additional case: a precious metal with hedging and safe-haven roles in portfolios (Baur & McDermott, 2010; Erb & Harvey, 2013), yet its behavior under intraday breakout rules is seldom compared with other asset classes under identical settings.

The issue is also relevant in Sri Lanka, where the Central Bank of Sri Lanka has warned the public about unauthorized online foreign exchange platforms (Central Bank of Sri Lanka, 2019) and about the risks of cryptocurrency trading (Central Bank of Sri Lanka, 2023). Retail foreign exchange traders elsewhere have been found to lose money (Hayley & Marsh, 2016), and many rely on pre-programmed Expert Advisors (EAs) in MetaTrader 5 (MT5).

2. AIMS/OBJECTIVES

The aim is to establish whether a standardized AORB strategy produces significantly different trading performance across EURUSD, BTCUSD, XAUUSD, and XTIUSD when applied under identical conditions. Three hypotheses are tested. H1: profitability, measured by net profit and profit factor (PF), differs across the four assets. H2: risk and risk-adjusted performance, measured by maximum drawdown and the Sharpe ratio, differ across the assets. H3: consistency and recovery, measured by win rate and recovery factor, differ across the assets. PF and the Sharpe ratio are reported descriptively.

3. THEORY

The weak form of the Efficient Market Hypothesis implies that past prices contain no exploitable information (Fama, 1970). Yet simple trading-range break rules have

produced returns that are hard to reconcile with that view (Brock et al., 1992), and later reviews caution about data snooping and transaction costs (Park & Irwin, 2007). The Adaptive Markets Hypothesis reconciles these findings by proposing that efficiency varies across markets and over time (Lo, 2004), so a rule's profitability should depend on the market in which it is applied. Microstructure theory adds that participation and order flow affect short-horizon prices (Evans & Lyons, 2002), and a consolidation range followed by a surge in participation is the mechanism that breakout rules aim to exploit. Tsai et al. (2019) found that the best range definition differs across markets, implying that one specification may not suit every asset. These theories frame the interpretation; liquidity and order flow were not measured.

4. METHODS

The study is positivist, deductive, and quantitative, with experimental simulation as its strategy. an automated rule is applied to historical prices under identical conditions (Saunders et al., 2019). Four instruments were chosen purposively: EURUSD (currency), BTCUSD (cryptocurrency), XAUUSD (precious metal), and XTIUSD (energy). One-minute data were obtained through MT5 from an IC Markets server for 1 January 2017 to 31 July 2026. The unit of analysis is the asset-month, giving 115 observations per asset and 460 in total.

The EA records the high and low between 03:00 and 15:00 server time (GMT+2, or GMT+3 in daylight-saving periods), so the range closes as the London–New York overlap begins. Pending orders are placed at the range boundaries with a 20-point buffer, so a break above the high opens a long position and a break below the low opens a short position. Orders are deleted at 22:00 and open positions are closed at 22:30. One long and one short trade are allowed per day. The stop-loss equals the range width, no profit target is used, and a trailing stop starts after 100 points of profit, trails at a distance of 50 points, and moves in steps of 20 points. All parameters were identical across assets and were not optimized. Each month was tested separately from an initial deposit of USD 10,000, using every-tick modeling on real ticks, zero latency, and ideal execution; commission, swap, and slippage were not modeled..

Net profit is gross profit minus gross loss in USD, win rate is the share of profitable trades, and maximum drawdown is the largest peak-to-trough fall in account balance, reported as a decimal fraction. The recovery factor (RF) and PF are defined in Equations 1 and 2. The annualized Sharpe ratio (SR) was computed for each asset from monthly returns (monthly net profit divided by initial capital) with a zero risk-free rate (Equation 3), following Sharpe (1966). The √12 scaling assumes serially uncorrelated monthly returns (Lo, 2002).

$$RF = \frac{Net\ Profit}{Maximum\ Drawdown} \quad \text{..... (1)}$$

$$PF = \frac{Total\ Gross\ Profit}{Total\ Gross\ Loss} \quad \text{.....(2)}$$

$$SR = \frac{E[R_m]-R_f}{\sigma} \times \sqrt{12} \quad \text{..... .....(3)}$$

In Equation 3, E[Rm] is the mean monthly return, Rf is the risk-free rate, and σ is the standard deviation of monthly returns.

Differences in means were tested with one-way ANOVA, followed by Tukey's HSD test at the 5% significance level (Tukey, 1949). Because the measures are strongly skewed and Bartlett's test rejected equal variances for all four ($p < 0.001$), the rank-based Kruskal–Wallis test was also applied (Kruskal & Wallis, 1952). ANOVA tolerates moderate non-normality when group sizes are equal (Field, 2018). Data were processed in Microsoft Excel and analyzed in Stata.

5. RESULTS

Table 1 summarizes performance by asset.

Table 1. Descriptive Performance of the AORB Strategy by Asset (n = 115 Months per Asset)

Measure	BTCUSD	XAUUSD	EURUSD	XTIUSD
Net profit, mean (SD), USD	114.46 (106.75)	156.10 (233.63)	10.73 (72.53)	−8.47 (145.91)
Win rate, mean (SD)	0.9443 (0.1613)	0.8883 (0.0879)	0.7051 (0.1176)	0.4843 (0.2541)
Maximum drawdown, mean (SD)	0.0013 (0.0033)	0.0127 (0.0130)	0.0155 (0.0823)	0.0377 (0.2649)
Recovery factor, mean (SD)	58.65 (169.72)	1.56 (2.70)	0.36 (0.97)	0.15 (0.91)
Overall PF	10.05	1.98	1.08	0.60
Annualized SR	3.71	2.31	0.51	−0.20

Source: Author's analysis based on MT5 backtesting and Stata output, 2026

One-way ANOVA (Table 2) showed that mean net profit, win rate, and recovery factor differed significantly across the four assets, whereas maximum drawdown did not.

Table 2. One-Way ANOVA Results (df = 3, 456)

Measure	F	p	η^2	Significant
Net profit	31.57	< 0.001	0.172	Yes
Win rate	176.93	< 0.001	0.538	Yes
Maximum drawdown	1.38	0.248	0.009	No
Recovery factor	13.41	< 0.001	0.081	Yes

Source: Author's analysis based on MT5 backtesting and Stata output, 2026. η^2 = eta squared (effect size).

Table 3 reports the Tukey HSD comparisons. For net profit, XAUUSD and BTCUSD each exceeded EURUSD and XTIUSD but did not differ from each other (p = 0.162), and EURUSD and XTIUSD did not differ (p = 0.774). Win rate differed for every pair except XAUUSD–BTCUSD (p = 0.056). For recovery factor, only BTCUSD differed from the other three assets. No pairwise maximum drawdown difference was significant.

Table 3. Tukey HSD Mean Differences (Adjusted p-value)

Pair	Net profit	Win rate	Maximum drawdown	Recovery factor
EURUSD – BTCUSD	−103.73 (< 0.001)	−0.2392 (< 0.001)	0.0142 (0.867)	−58.29 (< 0.001)
XAUUSD – BTCUSD	41.64 (0.162)	−0.0560 (0.056)	0.0114 (0.925)	−57.08 (< 0.001)
XTIUSD – BTCUSD	−122.93 (< 0.001)	−0.4600 (< 0.001)	0.0364 (0.195)	−58.49 (< 0.001)
XAUUSD – EURUSD	145.37 (< 0.001)	0.1831 (< 0.001)	−0.0028 (0.999)	1.20 (1.000)
XTIUSD – EURUSD	−19.19 (0.774)	−0.2209 (< 0.001)	0.0222 (0.619)	−0.21 (1.000)
XTIUSD – XAUUSD	−164.57 (< 0.001)	−0.4040 (< 0.001)	0.0250 (0.522)	−1.41 (0.999)

Source: Author's Analysis Based on Mt5 Backtesting and Stata Output, 2026

Table 4 reports the Kruskal–Wallis equality-of-populations rank tests for the four measures.

Table 4. Kruskal–Wallis Equality-of-Populations Rank Test Results (df = 3)

Measure	χ^2 (unadjusted)	χ^2 (tie-adjusted)	p
Net profit	112.89	112.89	< 0.001
Win rate	303.14	304.81	< 0.001
Maximum drawdown	161.20	163.04	< 0.001
Recovery factor	205.41	205.42	< 0.001

Source: Author's analysis based on MT5 backtesting and Stata output, 2026

The Kruskal–Wallis tests rejected equality of distributions for all four measures ($p < 0.001$). Mean ranks were highest for XAUUSD in net profit (301.4) and for BTCUSD in win rate (369.1) and recovery factor (369.0), and lowest for XTIUSD on all three (156.5, 92.7, and 142.0). BTCUSD had the lowest maximum drawdown rank (95.4) and XAUUSD the highest (288.3).

6. DISCUSSION

H1 is supported by the ANOVA and Kruskal–Wallis results for net profit. XAUUSD earned the highest mean monthly profit (USD 156.10), although its profit was also the most variable (SD = USD 233.63) and did not differ significantly from that of BTCUSD. The PF ordering (10.05, 1.98, 1.08, and 0.60) points the same way, but PF was not tested statistically. Profitability that depends on the market agrees with the technical trading literature (Park & Irwin, 2007) and with the Adaptive Markets Hypothesis (Lo, 2004). The loss on crude oil contrasts with positive ORB returns reported for crude oil futures (Holmberg et al., 2013). That rule used exchange-traded futures with a defined opening, so the weak XTIUSD result may reflect rule–instrument fit rather than any inherent unsuitability of breakouts in energy markets.

A high win rate does not guarantee profit. XAUUSD averaged a monthly win rate of 88.83%, yet its average winning trade (USD 19.50) was about a quarter of its average losing trade (USD 76.31), which limits its PF to 1.98. The very high BTCUSD win rate likely reflects stop management: a trailing stop that starts after only 100 points of profit is a very small distance relative to the BTCUSD price, so most trades close with small gains. This raises the win rate and limits drawdowns regardless of the breakout's predictive power, so BTCUSD's apparent superiority is provisional until verified with realistic costs and slippage.

H2 is supported on a rank basis but not by the ANOVA. The annualized Sharpe ratio ordered the assets as BTCUSD (3.71), XAUUSD (2.31), EURUSD (0.51), and XTIUSD (−0.20), but it was not tested. Maximum drawdown did not differ in the ANOVA ($F = 1.38$, $p = 0.248$), yet the Kruskal–Wallis test detected a significant difference ($\chi^2(3) = 163.04$, $p < 0.001$), driven by the much lower drawdown ranks of BTCUSD (mean rank 95.4 against 259.6–288.3 for the other assets). Because the standard deviation of drawdown far exceeds its mean for EURUSD and XTIUSD, a few extreme months probably masked the difference in means, making the rank-based result more reliable.

H3 is supported. Win rate and recovery factor differed significantly across assets in both tests. The recovery factor result is driven by BTCUSD (mean 58.65 against 1.56 or less for the others), because its very small drawdowns shrink the denominator in Equation 1, and it should be read alongside the large standard deviation (169.72). Overall, the results are consistent with Tsai et al. (2019): settings that suit one market need not suit another, so a common AORB specification is not asset-neutral. Tukey's

test assumes equal variances, which Bartlett's test rejected, so the pairwise results should be read with caution (Field, 2018).

7. IMPLICATIONS AND LIMITATIONS

For theory, the asset-dependent results are consistent with the Adaptive Markets Hypothesis and with microstructure accounts of short-term prices, although neither was tested directly. For practice, retail traders who buy or use ready-made EAs, including those in Sri Lanka, should test a rule on each instrument before deploying it and should not treat a high win rate or PF as proof of profitability.

Several limitations apply. The results rely on historical backtesting with zero latency, ideal execution, and no commission, swap, or slippage, so they may not carry over to live trading. Each month was tested from a fresh deposit, so compounding and continuous account history are not reflected, and months without trades are recorded as zeros. BTCUSD trades at weekends while the other assets do not, and the point-based trailing-stop distances are not equivalent in relative terms across assets. The measures are skewed and heteroscedastic, and the Sharpe ratio and PF were computed once per asset without statistical testing. Only four instruments, one broker's data, and one parameter set were examined, and macroeconomic announcements and other market shocks were not modeled. Future research could add realistic costs and slippage, volatility-scaled stops, further assets and sessions, and walk-forward and live forward testing.

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