

Modeling Cost-of-Carry Dynamics for Statistical Arbitrage on the Thailand Futures Exchange

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Abstract

This study evaluates the pricing efficiency of the cost-of-carry model within the Thailand Futures Exchange (TFEX) and investigates whether short-term pricing deviations can be systematically exploited. Employing the Engle-Granger two-step cointegration method, the Error Correction Model (ECM), and joint hypothesis testing, the study analyzes the dynamic relationship between index futures, single-stock futures, and their respective underlying assets using 15-minute and 1-hour timeframes. The empirical findings reveal that although a long-term cointegrating relationship exists, the relationship is not characterized by one-to-one equilibrium. Instead, most of the estimated slope is slightly below one, so the gap between the actual and theoretical price moves in the negative direction as the price level rises. By first identifying this specific relationship, the study then utilizes it as the baseline to design a systematic pair trading framework. Consequently, the short-term deviations used as trading signals are extracted from the residuals of this estimated linear relationship, rather than direct deviations between actual and theoretical prices. The model generates robust positive net returns across all tested assets and remains profitable even after fully accounting for transaction, borrowing, and bid-ask costs.

Keywords: Cost-of-Carry, Pair Trading, Cointegration, Error Correction Model

JEL Classification: G11, G13, G17

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การสร้างแบบจำลองพลวัตของต้นทุนการถือครองสำหรับกลยุทธ์อาร์บิทราจเชิงสถิติ ในตลาดสัญญาซื้อขายล่วงหน้าแห่งประเทศไทย

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บทคัดย่อ

งานวิจัยนี้ประเมินประสิทธิภาพการกำหนดราคาของแบบจำลองต้นทุนการถือครอง (Cost-of-carry model) ในตลาดสัญญาซื้อขายล่วงหน้าแห่งประเทศไทย (TFEX) และตรวจสอบว่าความคลาดเคลื่อนของการกำหนดราคาในระยะสั้นสามารถนำมาใช้แสวงหากำไรอย่างเป็นระบบได้หรือไม่ โดยใช้วิธีทดสอบความสัมพันธ์เชิงดุลยภาพระยะยาวแบบสองขั้นตอนของเอ็งเกล-แกรนเจอร์ แบบจำลองกลไกการปรับตัวเข้าสู่ดุลยภาพ และการทดสอบสมมติฐานร่วม งานวิจัยนี้ได้วิเคราะห์ความสัมพันธ์เชิงพลวัตระหว่างสัญญาซื้อขายล่วงหน้าอิงดัชนี สัญญาซื้อขายล่วงหน้าอิงหุ้นรายตัว และสินทรัพย์อ้างอิงที่เกี่ยวข้อง ในระดับกรอบเวลา 15 นาที และ 1 ชั่วโมง ผลการศึกษาเชิงประจักษ์พบว่า แม้จะมีความสัมพันธ์เชิงดุลยภาพระยะยาวเกิดขึ้น แต่ความสัมพันธ์ดังกล่าวไม่ได้เป็นแบบหนึ่งต่อหนึ่งอย่างสมบูรณ์ ในทางกลับกัน ความชันที่ประเมินไว้ส่วนใหญ่มีค่าน้อยกว่าหนึ่งเล็กน้อย ดังนั้นส่วนต่างระหว่างราคาจริงและราคาตามทฤษฎีจึงเคลื่อนไปในทิศทางลบเมื่อระดับราคาปรับตัวสูงขึ้น จากการระบุความสัมพันธ์ในเบื้องต้น การศึกษานี้จึงนำมาใช้เป็นเกณฑ์มาตรฐานในการออกแบบกรอบระบบการซื้อขายแบบจับคู่ ด้วยเหตุนี้ ความคลาดเคลื่อนระยะสั้นที่ใช้เป็นสัญญาณซื้อขาย จึงถูกสกัดมาจากส่วนตกค้างของความสัมพันธ์เชิงเส้นที่ประมาณการขึ้นมานี้ แทนที่จะใช้ความคลาดเคลื่อนโดยตรงระหว่างราคาจริงกับราคาทางทฤษฎี แบบจำลองดังกล่าวสามารถสร้างผลตอบแทนสุทธิที่เป็นบวกได้อย่างแข็งแกร่งในทุกสินทรัพย์ที่ทำการทดสอบ แม้จะหักต้นทุนการทำธุรกรรม ต้นทุนการกู้ยืม และต้นทุนส่วนต่างราคาเสนอซื้อเสนอขายออกทั้งหมดแล้ว

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1. Introduction

The cost-of-carry model is the theoretical basis for futures pricing, setting a no-arbitrage price. The model assumes that the futures price is equal to the spot price of the underlying asset, plus the net costs and benefits of holding the underlying asset until maturity of the contract. A large difference between the traded futures price and this theoretical value presents an arbitrage opportunity. If the futures are overpriced, traders can buy the underlying asset and sell the futures contract called cash-and-carry arbitrage. Alternatively, reverse cash-and-carry arbitrage can be performed by selling the asset short and buying the futures contract if the futures are underpriced. In both cases, the futures and spot prices converge and arbitrageurs can make a risk-free profit by holding both positions until contract maturity. In an efficient market such opportunities would not exist, because arbitrageurs would quickly correct any mispricing.

In reality, markets are not always perfectly efficient. Market frictions like transaction costs and liquidity question the assumption of costless arbitrage. These costs can allow the actual futures price to drift away from its theoretical value without the emergence of corrective arbitrage trades. Prices may move around the equilibrium price with divergence and convergence happening repeatedly. The main question of this study is whether these deviations are random noise or they are reflecting a stable, long-run equilibrium relationship. Understanding the nature of these deviations is important in order to evaluate the efficiency of the cost-of-carry model and the possibility of systematic trading opportunities from repeated short-term mispricing.

This study investigates these dynamics in the context of the Thailand Futures Exchange (TFEX) by testing whether the cost-of-carry model can adequately explain the actual futures prices. The results are directly used to develop a cointegration-based trading strategy after establishing the exact mathematical relationship between actual and theoretical prices and confirming the mean reverting property of the relationship. This strategy systematically exploits short-term deviations from this established relationship after accounting for transaction costs to ensure practical realism. This study's analysis is confined to the Thai financial market, focusing on SET50 index futures and the top 10 most actively traded single-stock futures based on trading volume and value during the observation period. Historical data from January 2023 to December 2025 are utilized and partitioned into an in-sample period (2023–2024) for analysis and model estimation, and an out-of-sample period (2025) for strategy validation. To assess the robustness of the results, the analysis employs intraday data at both 15-minute and 1-hour intervals, enabling a detailed examination of short-term price dynamics and market efficiency.

The core analytical framework combines the cost-of-carry model with the Engle-Granger two-step method for cointegration testing between theoretical and actual futures prices. The analysis is supplemented by an Error Correction Model (ECM) to evaluate the speed of adjustment and a joint hypothesis test to identify any systematic pricing bias. By establishing this econometric framework first, the resulting linear relationship serves as the foundation for the trade design. The short-term deviations used as trading signals are extracted directly from the residuals of this relationship. The trading strategy derived from this analysis involves trading a spread, where each trade consists of one futures contract paired with an opposing position in the underlying stock. The hedge ratio is determined according to the contract size of each futures contract to ensure proper exposure alignment. This fixed position-sizing approach accounts for the relatively low liquidity of the Thai futures market, ensuring that the strategy remains both practical and implementable under real-world trading conditions.

2. Literature review

2.1 Cost of carry and futures mispricing

According to Hull (2018), futures pricing is explained by the cost-of-carry model. The cost-of-carry model describes the relationship between the futures price and the price of its underlying asset in order to determine the arbitrage-free price of a futures contract. The author defines the theoretical futures price as the spot price plus the cost of holding the asset until maturity minus any benefits of holding the asset until maturity. The general formula in case of known income is:

$$F_0 = (S_0 - I) \times e^{rT} \quad (1)$$

where F_0 is the futures price at time 0, S_0 is the spot price, r is the risk-free interest rate, T is the time to maturity in yearly units, and I represent the present value of all dividend payments during the life of the futures contract. The cost-of-carry model is based on the principle of arbitrage-free pricing. Any difference between the actual futures price and the price from the formula would create an arbitrage opportunity. If the futures price is higher than the theoretical value, an arbitrageur could sell the futures contract, while at the same time buying the asset, capturing the difference in price as the contract approaches maturity. On the other hand, if the futures price is below the theoretical value, the trader could buy the futures and sell the underlying asset and profit as the prices converge at maturity.

The cost of carry model remains the standard pricing model for futures but some studies have examined its efficiency across markets and found significant deviations from the theoretical value. The behavior of DAX index futures was studied by Bühler and Kempf (1994). They find the futures contracts to be significantly undervalued and the cost-of-carry model cannot explain the relationship between spot and futures prices. Further, even when transaction costs, brokerage fees, settlement fees, stock lending fees, bid-ask spread and market impact costs are taken into account, there are still many arbitrage opportunities. Fassas (2011) highlights the significant difference between theoretical and actual futures prices examined from the pricing of FTSE/ATHEX-20 index futures. The author concludes that the Greek benchmark index futures offer many arbitrage opportunities, which reflect the illiquidity in the Athens Exchange.

On the contrary, some studies claim that mispricings are not large enough to be exploited through arbitrage. The study results of Butterworth and Holmes (2000) showed that the FTSE 100 and FTSE Mid 250 index futures are priced efficiently with only minor deviations from the fair value. They also find that mispricing is larger for contracts with higher transaction costs and less liquidity. Likewise, Nemcova (2017) examines pricing of DAX index futures and observes significant deviations from the fair value. However, once transaction costs are considered, these deviations do not permit arbitrage, suggesting that DAX index futures are fairly priced.

Besides the international evidence, Techarongrojwong (2008) compares the pricing efficiency of the cost-of-carry model and the imperfect market model for the SET50 index futures and finds that the traditional cost of carry approach does not fully capture the dynamics of futures prices. In another study, Tharavanij (2017) studies the efficiency and unbiasedness of SET50 futures traded on the Thailand Futures Exchange. The author points out that in the long run, futures and their underlying prices are cointegrated and the null hypothesis of unbiasedness cannot be rejected. The results indicate that there is no systematic bias in the SET50 index futures. Futures are not always above or under the underlying prices.

2.2 Cointegration, pair trading, and application to futures mispricing

The concept of cointegration has been introduced by Engle and Granger (1987) and it is a framework for the analysis of the long-run relationship between non-stationary time series. A standard approach is the Engle–Granger two-step method. First a linear regression is estimated on the two series and then stationarity of the residuals is tested. If the residuals are stationary, the two series are said to be cointegrated. This means that they have a stable long-term relationship. Then we would expect short-term deviations from equilibrium to be corrected. The error term is mean-reverting, and tends to revert back to equilibrium over time.

Cointegration is the foundation of pair trading strategies. Vidyamurthy (2004) describes cointegration as the existence of a stable long-run relationship in the prices of two assets. This feature allows traders to establish a spread between the two assets that oscillates around an average value. Traders can enter into offsetting positions, long on the cheap and short on the expensive, expecting the prices to converge back to the equilibrium when the spread deviates significantly from its historical average.

Empirical studies have provided evidence for the effectiveness of pair trading strategies in the context of futures and their underlying spot price. Puspaningrum, Lin, and Gulati (2014) find that their proposed strategy for S&P 500 futures and the corresponding spot index performs very well, generating high returns for the selected pairs, with an average return per trade exceeding 10% for all periods. Similarly, Songyoo (2012) uses a pair trading strategy to trade futures and their underlying assets in the Thai market. The study finds that although there are arbitrage opportunities in the SET50 index futures, the strategy underperforms in the single stock futures because of liquidity constraints and short selling restrictions. Choedpasuporn (2015) proposes a variation of statistical arbitrage via a pair trading strategy with threshold parameters from Threshold Vector Error Correction Model. The approach is applied to SET50 index futures with different maturities and to single-stock futures and their underlying stocks. The results show that there are arbitrage opportunities. Thamphongsri (2018) further supports the profitability of pair trading between futures and spot price by applying the strategy to the high-frequency data of gold spot and futures. The results show that even after transaction costs, arbitrage profits still exist.

However, some studies point out the limitations of pair trading strategies between the futures and the underlying assets. Figuerola-Ferretti and Gonzalo (2010) examine the relationship between the S&P 500 index and its futures contract. Their empirical results show that the deviations in prices are generally too small to overcome trading costs. Similarly, Kim, Choi, and Kim (2016) report that pair trading within the same category often leads to poor performance, while trading across different categories is profitable. This is in contrast with the traditional idea of pair trading, especially for futures and their underlying spot prices which are usually highly correlated.

Previous studies have examined the mispricing of futures compared to their theoretical cost of carry values, and other studies have examined pair trading strategies between the futures and the underlying stocks. However, no research has directly used the mispricing between futures and their theoretical values as the basis for a pair trading strategy. This study fills this gap by investigating the pricing efficiency of the cost-of-carry model in the TFEX market and the effectiveness of trading strategies based directly on futures mispricing relative to the theoretical values.

3. Methodology

3.1 Data collection

Historical market data of futures and underlying assets were collected from TQ Professional for the period from January 2023 to December 2025. The tradable proxy for the spot leg of the SET50 index was TDEX (ThaiDEX SET50 Exchange Traded Fund). The data set was split into an in-sample and out-of-sample period for the years 2023-2024. The out-of-sample period was reserved for testing in 2025. Futures contracts were rolled over from the expiring quarterly series to the next-nearest to expiry series to create a continuous time series. Sufficient liquidity was ensured by selecting the SET50 index futures and the 10 most active futures contracts during the in-sample period, with respect to both volume and traded value, for analysis. The chosen contracts are provided in Appendix A.

The analysis was carried out on intraday data on two time intervals: 15-minute and 1-hour to study the robustness of the results at different temporal resolutions. The risk-free rate time series was approximated by the 1-year Thai Bond Yield, which is the same benchmark that TFEX uses to calculate theoretical futures prices under the cost-of-carry model. The rate was obtained from the Thai Bond Market Association (ThaiBMA); stock dividend payments and SET50 index dividend yields are from SET SMART and TQ Professional, respectively.

3.2 Analysis of cost-of-carry pricing efficiency

To examine the pricing efficiency of the cost-of-carry model and its ability to explain futures prices, the following framework was adopted. First, the theoretical futures price for each underlying stock price was computed using the cost-of-carry formula:

$$F_{\text{Theoretical}} = (S_0 - \text{PV}(D)) \times e^{rT} \quad (2)$$

where S_0 is the spot price, r is the risk-free rate, T is the time to maturity, and $\text{PV}(D)$ represents the present value of dividends.

For the SET50 Index, where dividends are represented by a continuous dividend yield q , the theoretical price was given by:

$$F_{\text{Theoretical}} = S_0 \times e^{(r-q)T} \quad (3)$$

Engle-Granger cointegration test

As a preliminary step, both the F_{Actual} and the $F_{\text{Theoretical}}$ time series were formally tested for their order of integration using the Augmented Dickey-Fuller (ADF) test:

$$\Delta F(t) = \rho F(t-1) + \sum_{i=1}^k \gamma(i) \Delta F(t-i) + u(t) \quad (4)$$

where ρ is the coefficient on the lagged residual, $\gamma(i)$ are the coefficients of the lagged differences, and $u(t)$ is a white-noise error term. The null hypothesis $H(0): \rho = 0$ implies that

the series contains a unit root and is non-stationary, whereas the alternative hypothesis $H(1)$: $\rho < 0$ indicates that the series is stationary.

The ADF test was sequentially applied to the level, first-differenced, and, if necessary, second-differenced series to determine the integration order of each series. Although cointegration is traditionally applied to explain the relationship between non-stationary variables, this study retained stationary pairs as long as they were integrated of the same order. Because the basis strategy involves closing trades when the price corrects to its theoretical value, the only strict requirement is a mean-reverting spread. Thus, if both F_{Actual} and $F_{Theoretical}$ series were integrated of the same order, the 2-step Engle–Granger cointegration test was conducted to examine the long-run relationship. Futures and spot series with different orders of integration were excluded from further testing since they violate the assumptions required for Engle–Granger cointegration analysis.

In the first step, the actual futures were regressed on the theoretical futures to estimate the long-run relationship. The relationship was specified as:

$$F_{Actual} = \alpha + \beta(F_{Theoretical}) + \varepsilon \quad (5)$$

where the actual futures price of each contract is denoted as F_{Actual} , α and β are the intercept and coefficient, respectively, and ε is the error term capturing deviations of the observed futures price from its theoretical value.

In the second step, the residuals ε were tested for stationarity using the ADF test:

$$\Delta\varepsilon(t) = \rho\varepsilon(t-1) + \sum_{i=1}^k \gamma(i)\Delta\varepsilon(t-i) + u(t) \quad (6)$$

Stationary residuals indicate that F_{Actual} and $F_{Theoretical}$ are cointegrated, confirming the presence of a long-run equilibrium relationship rather than a spurious regression. If the residuals are non-stationary, no cointegration exists.

Error Correction Model (ECM)

Following the confirmation of cointegration, the Granger Representation Theorem provides the theoretical foundation for modeling the relationship as an Error Correction Model (ECM). The ECM was employed to assess the speed and significance of correction following short-term deviations. The model was specified as follows:

$$\Delta F_{Actual}(t) = c + \lambda\varepsilon(t-1) + \Phi\Delta F_{Theoretical}(t) + v(t) \quad (7)$$

where c is the intercept term, capturing drift not explained by variables in the model. λ is the error correction coefficient, measuring the speed of adjustment. $v(t)$ is the white-noise error term. Φ captures the short-run impact of a change in $F_{Theoretical}$.

The coefficient λ was evaluated to confirm that short-term deviations were corrected with statistical significance. A negative and significant λ suggests that the futures price has a tendency to revert towards its long-run equilibrium; deviations between actual and theoretical futures are corrected over time. The magnitude of λ quantifies the speed of this correction, with a larger absolute value implying a faster reversion to equilibrium.

Joint hypothesis test (FM-OLS)

While cointegration confirms that the long-run relationship is not spurious, it is necessary to determine if this equilibrium conforms to the strict one-to-one relationship proposed by the model's theory. A perfectly specified model would exhibit an intercept of zero and a slope of one.

Although the ordinary least squares estimate of α and β obtained in the Engle–Granger first stage is consistent, they cannot be used for hypothesis testing due to invalid inference on the cointegrating vector (α, β) . To obtain valid inference, the cointegrating vector is re-estimated using Fully-Modified OLS (FM-OLS) following Phillips and Hansen (1990). FM-OLS applies a semiparametric correction using long-run covariances estimated with a Bartlett kernel to eliminate endogeneity and adjust for serial correlation. The unrestricted model is the cointegrating regression of Eq. (5), re-estimated by FM-OLS. The restricted model assumes the theoretical ideal values:

$$F_{\text{Actual}} = F_{\text{Theoretical}} + \varepsilon \quad (8)$$

The joint null hypothesis $H_0: \alpha = 0 \text{ and } \beta = 1$ is evaluated with a Wald test constructed from the FM-OLS estimates and their covariance matrix:

$$W = (R\hat{\theta} - r)'[R\hat{V}R']^{-1}(R\hat{\theta} - r) \sim \chi^2(2) \quad (9)$$

where $\theta = (\alpha, \beta)'$ is the FM-OLS estimate of the cointegrating vector, $\hat{V}$ is its estimated covariance matrix, $R = I_2$ is the restriction matrix, $r = (0, 1)'$ collects the hypothesized values, and the number of restrictions is two. Under the null the statistic is distributed as χ^2 with two degrees of freedom. Rejecting the null indicates that the estimated long-run relationship departs from the strict one-to-one cost-of-carry benchmark; failing to reject implies that it is statistically indistinguishable from $F_{\text{Actual}} = F_{\text{Theoretical}} + \varepsilon$.

Evaluation

To evaluate the pricing efficiency of the cost-of-carry model, results from the cointegration, ECM, and joint hypothesis tests are combined. Based on this evidence, each contract's pricing relationship is classified into one of three categories:

Category 1: The cost-of-carry model explains futures prices accurately, and futures tend to correct to equilibrium. This conclusion is supported if:

1. The Engle-Granger test finds that cointegration exists between F_{Actual} and $F_{\text{Theoretical}}$.
2. The ECM yields a statistically significant and negative error correction coefficient (λ).
3. The Wald test fails to reject the joint null hypothesis that $\alpha = 0$ and $\beta = 1$.

Category 2: The cost-of-carry model has a stable but biased relationship. This conclusion is supported if:

1. The Engle-Granger test finds that cointegration exists between F_{Actual} and $F_{\text{Theoretical}}$.
2. The ECM yields a statistically significant and negative error correction coefficient (λ).
3. The Wald test rejects the joint null hypothesis that $\alpha = 0$ and $\beta = 1$.

Category 3: The cost-of-carry model is not a reliable framework for explaining futures prices. This conclusion is supported if:

1. The preliminary ADF tests show that F_{Actual} and $F_{Theoretical}$ have different order of integration, invalidating a key assumption for cointegration.
2. Alternatively, the Engle-Granger test fails to find cointegration between F_{Actual} and $F_{Theoretical}$.
3. Alternatively, cointegration exists, but the ECM yields an error correction coefficient (λ) that is not statistically significant or is positive, indicating the absence of a reliable correction mechanism.

Futures classified into Category 1 or Category 2 are selected for backtesting as they exhibit both a stable long-run relationship and a statistically significant tendency to correct deviations.

3.3 Trade design

Spread definition

Let the mispricing spread be as:

$$\text{spread}(t) = \varepsilon(t) = F_{Actual} - (\alpha + \beta(F_{Theoretical})) \quad (10)$$

where α and β are the estimated adjustment parameters from the cost-of-carry relationship. Trade positions are determined from the spread using the z-score:

$$z(t) = \frac{\text{spread}(t) - \mu_{\text{spread}}}{\sigma_{\text{spread}}} \quad (11)$$

where μ_{spread} represents the mean of the spread and σ_{spread} is the standard deviation of the spread. Both the cointegration parameters (α , β) and the spread's mean and standard deviation are re-estimated dynamically using a rolling window of 3 months to align with the quarterly futures expiration cycle and capture current market volatility.

Trading rules

Entry and exit signals are determined by two main parameters: an entry threshold (E), measured in units of standard deviation, and a time multiplier (χ), which dictates the maximum holding period based on the spread's half-life. These parameters evaluate the size and direction of the z-score—which measures how far the current spread deviates from its historical mean—along with the holding period, which limits how long a position is held. Specifically:

Entry:

1. A **short-spread position** is initiated when $z(t) > E$, indicating that the futures contract is overpriced relative to its adjusted theoretical value. To execute this trade, the strategy sells (shorts) the futures contract and buys (longs) the underlying stock.
2. A **long-spread position** is initiated when $z(t) < -E$, indicating that the futures contract is underpriced relative to its adjusted theoretical value. To execute this trade, the strategy buys (longs) the futures contract and sells (shorts) the underlying stock.

Exit:

1. An open position is exited for **profit-taking** when $z(t) * z(t - 1) \leq 0$. This condition signifies that the z-score has crossed zero, meaning the futures price has successfully reverted to its adjusted theoretical value.
2. A **time-based exit** is triggered when the holding period exceeds a multiple of the half-life (xH), acting as a stop-loss mechanism against non-reverting trades. The half-life (H) represents the expected time required for the spread to revert halfway back to its historical average and is computed from the error correction coefficient (λ) of the rolling window ECM using the formula:

$$H = \frac{\ln(0.5)}{\ln(1 + \lambda)} \quad (12)$$

3. Additionally, because futures contracts have a finite lifespan, any remaining open positions are forcibly closed (offset) at the end of the contract's final settlement day. This ensures the strategy avoids the expiration process and cash settlement complications.

The threshold E and the time multiplier x are jointly optimized to identify the combination that maximizes profit during the in-sample period. To find the optimal parameters, the study employs a two-dimensional grid search, which is an optimization algorithm that systematically tests every possible combination of parameters within a defined grid to find the best-performing pair.

In this grid search, E , measured in standard deviations, is evaluated across the range [1.0, 3.0] with increments of 0.1, and x , measured in number of half-lives, is evaluated across the range [1.0, 6.5] with increments of 0.5.

The time multiplier is deliberately capped at a maximum of 6.5 half-lives to enforce a mathematical stop based on the model's exponential decay function. Over a duration of 6.64 half-lives, a mean-reverting process mathematically reaches a 99% expected reversion ($0.5^{6.64} \approx 0.01$). Therefore, holding a position beyond 6.5 half-lives offers negligible mathematical expectation of further reversion.

The futures contract serves as the main position, while the underlying stock acts as the hedge leg with a fixed hedge ratio of 100%. Each trade is executed with one contract on the futures leg to account for the relatively low trading volume in single stock futures.

Transaction costs

The design of the strategy explicitly takes into account the real costs that define the no-arbitrage band. The ongoing costs include a 5.3% per annum rate to finance the futures leg, consistent with the effective interest rate observed in the block trade transactions. Short-spread positions are financed at the normal margin loan rate of 5.15% p.a. This is the rate charged to fund the purchase of the underlying stock in the hedge leg. On the other hand, long-spread positions are charged a Security Borrowing and Lending (SBL) cost of 5.5% per annum to reflect the cost of borrowing and shorting the underlying stock on the hedge leg. This SBL cost is consistent with the typical SBL rates provided by major securities brokerages in Thailand during the study period.

In addition, the model incorporates futures trading and clearing fees. For example, the trading fee and clearing fee for single stock futures with a price of less than 100 baht will be 0.5 baht

per contract, while those with a price of more than 100 baht will be 3.65 baht. The trading and clearing fee together for SET50 index futures is 6 baht per contract, which is the same as the TFEX exchange fee. The total of such trading, clearing and regulatory fees for the underlying stock is 0.007% of the transaction value. Further, the bid-ask spread is added as well. The cost is estimated at half of one tick for the stock leg, the size of which depends on the stock's price tier as defined by the Stock Exchange of Thailand (SET). For the futures leg, a slippage penalty of one tick (0.01 for single stock futures, 0.1 for index futures) is added to the execution price to account for the price improvement needed to move ahead of the historical order queue and guarantee a fill. Finally, one can also hold a short stock position over the ex-dividend (XD) date, but the dividend amount must be paid back to the lender of the borrowed shares.

3.4 Evaluation metrics

To assess the performance of mispricing spread strategies and determine whether arbitrage opportunities can be exploited, the following evaluation metrics are employed:

Cumulative Return (P&L): The total profit or loss generated by the strategy over the testing period.

Average Return per Trade: The total profit or loss from all trades divided by the number of trades executed.

Average Holding Period: The average duration for which trades are held open, from entry to exit.

Win Rate: The percentage of trades that are profitable out of the total number of trades executed.

The S50 Futures and the average values of each evaluation metric across all single stock futures within each timeframe are analyzed to assess the overall effectiveness of the spread mispricing strategy. In addition, the performance of individual pairs is examined to evaluate futures-specific results. A deeper analysis is conducted on trades from selected futures, including the best-performing pair for each data frequency, to gain further insights.

4. Evaluation and results

4.1 In-sample analysis and futures selection

Following the calculation of theoretical futures prices, the in-sample analysis and futures selection procedures were conducted.

Cointegration results

Initial analysis confirmed that the futures series and theoretical futures prices for all selected assets were integrated of the same order as shown in Table 1. Subsequently, the two-step Engle-Granger cointegration method was applied to all in-sample data at both 15-minute and hourly frequencies.

Table 1: Order of Integration Results on the 15-Minute Frequency

Underlying	F actual			F theoretical		
	ADF p-value (Level)	ADF p-value (1st Diff)	Result	ADF p-value (Level)	ADF p-value (1st Diff)	Result
TDEX	0.2493	<0.001	I(1)	0.2156	<0.001	I(1)
ADVANC	0.9528	<0.001	I(1)	0.9552	<0.001	I(1)
BANPU	0.0081	-	I(0)	0.0100	-	I(0)
DELTA	0.8898	<0.001	I(1)	0.8784	<0.001	I(1)
EA	0.3554	<0.001	I(1)	0.3334	<0.001	I(1)
KBANK	0.6415	<0.001	I(1)	0.6454	<0.001	I(1)
KTB	0.7093	<0.001	I(1)	0.7036	<0.001	I(1)
PTTEP	0.5659	<0.001	I(1)	0.5831	<0.001	I(1)
SIRI	0.0179	-	I(0)	0.0176	-	I(0)
TTB	0.4392	<0.001	I(1)	0.3593	<0.001	I(1)
TRUE	0.9269	<0.001	I(1)	0.9229	<0.001	I(1)

Pairs of futures and their theoretical values that passed the ADF test on regression residuals at the 0.05 significance level were considered cointegrated and retained for further analysis. The test identified 10 out of 11 pairs across both frequency datasets, with EA being the only futures-stock pair that failed the cointegration test. This deviation likely occurred because EA experienced a severe corporate governance and liquidity crisis during the in-sample period: in July 2024, the Securities and Exchange Commission (SEC) of Thailand filed a criminal complaint against EA's founder and two other executives over alleged fraudulent procurement transactions dating to 2013–2015 and referred the case to the Department of Special Investigation (SEC, 2024), and shortly afterward, TRIS Rating cut EA's company and senior unsecured debt ratings from 'BBB+' to 'BB+', citing heightened liquidity and refinancing risk (TRIS Rating, 2024). This extreme distress broke the cost-of-carry arbitrage channel, as dividend uncertainty and short-selling constraints prevented the futures market from tracking theoretical prices. Table 2 presents the complete list of futures and their corresponding test statistics for the 15-minute frequency data.

Table 2: Cointegration Test Results on the 15-Minute Frequency

Underlying	Residual ADF p-value	Conclusion
TDEX	0.0003	Cointegrated
ADVANC	<0.001	Cointegrated
BANPU	<0.001	Cointegrated
DELTA	0.0436	Cointegrated
EA	0.0818	Not Cointegrated
KBANK	<0.001	Cointegrated
KTB	<0.001	Cointegrated
PTTEP	<0.001	Cointegrated
SIRI	0.0018	Cointegrated
TTB	<0.001	Cointegrated
TRUE	<0.001	Cointegrated

Error Correction Model (ECM) dynamics

The error correction model was applied to the cointegrated pairs to examine how futures prices adjust toward the long-run equilibrium following deviations from it. For both the 15-minute and 1-hour frequencies, the cointegrated pairs exhibit a negative and statistically significant error correction coefficient at the 0.05 level, indicating that whenever the error between the actual and theoretical futures prices widens, the futures price corrects the disequilibrium in the subsequent period. Notably, KBANK, TRUE, and KTB exhibit the most negative coefficients, indicating a rapid speed of correction. Conversely, TDEX, DELTA, and SIRI display coefficients closer to zero. This slower pace of mean reversion suggests that mispricings persist longer, which potentially lowers the profitability of arbitrage strategies due to higher holding periods. The error correction coefficients and their p -values for the 15-minute sampling frequency are reported in Table 3.

Table 3: ECM Results on the 15-Minute Frequency

Underlying	Error Correction Term $\varepsilon(t-1)$	
	Coefficient	p-value
TDEX	-0.0181	<0.001
ADVANC	-0.2102	<0.001
BANPU	-0.2062	<0.001
DELTA	-0.0526	<0.001
KBANK	-0.2770	<0.001
KTB	-0.2438	<0.001
PTTEP	-0.1642	<0.001
SIRI	-0.0578	<0.001
TTB	-0.0885	<0.001
TRUE	-0.2744	<0.001

Joint hypothesis test (FM-OLS) results

The joint hypothesis test reported in Table 4 shows that all cointegrated pairs reject the null hypothesis across both data frequencies. This finding suggests that the observed futures prices deviate from their theoretical values with statistical significance. While the slope coefficients (β) across all pairs are close to 1.0, indicating that futures contracts move in close alignment with their theoretical values, the slopes for most pairs lie slightly below one, which means the gap between the actual and theoretical prices moves downward as the price level rises. The only pairs where the gap moves upward as the price level increases are TDEX and SIRI.

Table 4: Wald Test Results on the 15-Minute Frequency

Underlying	Estimated Coefficients		Joint Test ($H_0: \alpha = 0, \beta = 1$)	
	Intercept (α)	Slope (β)	p-value	Conclusion
TDEX	12.2265	1.0071	<0.001	Reject H_0
ADVANC	1.8311	0.9916	<0.001	Reject H_0
BANPU	0.0312	0.9972	<0.001	Reject H_0
DELTA	1.0702	0.9875	<0.001	Reject H_0
KBANK	1.4064	0.9904	<0.001	Reject H_0
KTB	0.2299	0.9869	<0.001	Reject H_0
PTTEP	2.7615	0.9815	<0.001	Reject H_0
SIRI	-0.0145	1.0119	<0.001	Reject H_0
TTB	0.0158	0.9850	<0.001	Reject H_0
TRUE	0.0178	0.9951	<0.001	Reject H_0

Evaluation summary

Based on the evaluation criteria established from the Engle-Granger cointegration tests, the Error Correction Model (ECM), and the joint hypothesis tests, the results were consolidated to classify the pricing efficiency of each futures contract. Table 5 presents a summary of these classifications at both 15-minute and 1-hour frequencies.

Table 5: Evaluation Results on the 15-Minute and 1-Hour Frequency

Category	Description	Underlying
1	The futures price strictly adheres to the theoretical cost-of-carry model.	-
2	The futures price maintains a cointegrated relationship with the theoretical model but exhibits a persistent structural bias.	TDEX, ADVANC, BANPU, DELTA, KBANK, KTB, PTTEP, SIRI, TTB, TRUE
3	The futures price does not maintain a stable relationship with the theoretical cost-of-carry model.	EA

Notably, no futures contracts met the criteria for Category 1. While most pairs demonstrated a strong tendency to revert to equilibrium, their rejection of the joint null hypothesis confirms that the cost-of-carry model does not hold perfectly in reality.

4.2 Backtesting performance results*Parameter Optimization*

Across both the 15-minute and 1-hour sampling frequencies, the optimal entry threshold (E) for each pair typically converged at approximately one standard deviation. This threshold captured spreads large enough to cover the transaction cost and the bid-ask spread while maintaining a sufficient trading frequency to maximize profitability. Conversely, the optimal time-stop multiplier (x) consistently trended toward the upper boundary of the grid search. This tendency suggests that profitability increases with longer or unbounded holding periods; however, capping the multiplier aligns with the mathematical limit of expected correction outlined in the

methodology. Table 6 shows the optimal entry thresholds and time multipliers for each pair at the 15-minute frequency.

Table 6: Optimal Parameters on the 15-Minute Frequency

Underlying	Entry Threshold (E)	Time Multiplier (x)
TDEX	1.0	6.0
ADVANC	1.1	5.5
BANPU	1.1	6.5
DELTA	1.1	6.5
KBANK	1.3	6.0
KTB	1.3	6.5
PTTEP	1.1	6.5
SIRI	1.1	4.0
TTB	1.2	5.5
TRUE	1.3	6.5

Strategy performance

As shown in Table 7, at the 15-minute sampling interval, the strategy successfully capitalized on a high volume of intraday pricing inefficiencies. Highly liquid pairs generated the most significant cumulative returns for example, DELTA and ADVANC yielded 76,807.31 and 68,781.51, respectively, driven by robust trade counts of 288 and 291 over the out-of-sample period. The price of the underlying assets also influenced the cumulative returns. Because the backtesting framework assumed a standardized position size of exactly one contract per trade, a methodological choice designed to reflect realistic execution scalability, assets with higher absolute share prices naturally produced larger spreads when crossing the entry threshold. Consequently, higher-priced assets captured a larger absolute profit per transaction compared to lower-priced assets.

Table 7: Out-of-Sample Performance Metrics on the 15-Minute Frequency

Underlying	Cumulative Return (P&L)	Total Trades	Average Return per Trade	Average Holding Period (Days)	Win Rate
TDEX	40805.36	194	210.34	1.05	77.84%
ADVANC	68781.51	291	236.36	0.52	60.14%
BANPU	4752.80	254	18.71	0.53	75.98%
DELTA	76807.31	288	266.69	0.68	71.53%
KBANK	38149.10	117	326.06	1.09	72.65%
KTB	10132.58	194	52.23	0.59	73.71%
PTTEP	56990.93	240	237.46	0.56	67.92%
SIRI	1076.46	70	15.38	1.27	78.57%
TTB	650.35	184	3.53	0.70	58.70%
TRUE	9682.09	262	36.95	0.56	75.95%

Holding periods ranged from 0.5 to 1.3 days for all pairs at the 15-minute frequency. This fast turnover directly validated the strategy's key exit mechanic. The model aggressively executes the exits rather than hold the position to maturity, thus limiting the long term recurring costs of financing the trade as the spread mean reverts.

Overall, the model was found to be statistically very reliable, with consistently high win rates across the portfolio. Pairs with lower aggregate P&L also had similar win rates, suggesting that

while the absolute profit magnitudes differ due to asset price levels and number of trades, the probability of spread reversion is very consistent.

The 15-minute interval is the optimal mix of signal frequency and profitability, although the methodology was also applied to a 1-hour sampling frequency in order to observe structural differences in behavior. The longer interval smoothed intraday inefficiencies, which led naturally to fewer triggered trades. Higher holding periods lead to higher financing costs which result in lower aggregate P&L across the portfolio due to fewer execution opportunities. But the 1 hour result was still at similarly high win rates.

15-Minute frequency case study

As shown in Table 8, this case study isolates the first three trades triggered for the DELTA pair at the beginning of the out-of-sample period, using a 15-minute sampling frequency.

Table 8: Trade Log of Delta Pairs on the 15-Minute Frequency

Entry_Time	Exit_Time	Type	Entry_Z_Score	Days_Held	Exit_Reason	Gross_PnL	Total_Costs	Net_PnL
1/2/2025 10:00	1/2/2025 14:45	Long Spread	-1.517763	0.197917	Mean Reversion	1100	535.99	564.01
1/2/2025 15:30	1/2/2025 15:45	Long Spread	-1.154169	0.010417	Mean Reversion	940	527.40	412.60
1/2/2025 16:15	1/3/2025 15:30	Long Spread	-1.841956	0.96875	Time Stop	500	566.78	-66.78

The first trade was the strategy working under ideal circumstances. A divergence triggered a Long Spread entry at 10:00 AM. A few hours later the model successfully identified the mean-reversion. The position was closed intraday with a holding period of ~0.20 days and a net profit of 564.01 THB.

The second trade was entered same day at 15:30. The spread had a short term anomaly which got resolved in one 15 minute candle. The model did the entry and exit almost immediately. This momentary inefficiency has resulted in a net profit of 412.60 THB.

The third trade at 16:15 shows the impact of the carry costs. The model held the position overnight and eventually hit the Time Stop after 0.97 days. The trade generated a positive gross profit of 500.00 THB but the total costs were higher than the gross return, resulting in a net loss of -66.78 THB.

1-Hour frequency case study

This case study, detailed in Table 9, isolated the first three trades triggered for the PTTEP pair at the beginning of the out-of-sample period, using a 1-hour sampling frequency.

Equation 9

Table 9: Trade Log of PTTEP Pairs on the 1-Hour Frequency

Entry_Time	Exit_Time	Type	Entry_Z_Score	Days_Held	Exit_Reason	Gross_PnL	Total_Costs	Net_PnL
1/2/2025 10:00	1/3/2025 10:00	Short Spread	1.439722	1	Time Stop	-510	559.12	-1069.12
1/3/2025 11:00	1/6/2025 10:00	Short Spread	2.485544	2.958333	Mean Reversion	1440	629.01	810.99
1/6/2025 12:00	1/6/2025 15:00	Long Spread	-1.539352	0.125	Mean Reversion	1850	529.49	1320.51

The first trade was opened at market opening on January 2nd with a z-score of 1.44. However, the spread did not revert, and a day later the model triggered a Time Stop. The trade lost -510.00 THB. Transaction and Financing costs further reduced this by -559.12 THB, bringing the total net loss to -1,069.12 THB.

The second trade, entered into on January 3rd, serves as a reminder of the duration risk and carry costs involved in holding positions over the weekend. The model did catch a significant divergence (z-score 2.49) that eventually mean reverted, but the trade sat there for almost 3 days due to the weekend market gap. The trade was excellent in terms of gross PnL (1,440.00 THB), but the long holding period meant that total costs added up to 629.01 THB which took a big chunk out of the final net profit (810.99 THB).

The third trade was a very efficient execution. After a sharp divergence, a Long Spread was entered at 12:00 PM and mean reversion was achieved just three hours later. The model closed the position intraday at 0.13 days and earned a strong net profit 1,320.51 THB while reducing financing costs.

5. Conclusion and future work

This study analyzed the pricing efficiency of the cost-of-carry model by investigating the relationship between actual and theoretical futures prices. By employing cointegration tests, Error Correction Models (ECM) and Joint hypothesis test, this research investigated the extent to which market prices are consistent with theoretical values and examined the presence of possible statistical arbitrage. Specifically, the statistical arbitrage strategy employed a pair trading strategy to take advantage of these discrepancies. When a futures contract is overpriced compared to its theoretical price, the strategy takes a short position in the futures contract and a long position in the underlying stock. On the other hand, if the futures contract is underpriced, the strategy goes long on the futures contract and short on the underlying stock. These positions are then held until the spread reverts to its historical mean.

The results show that real and theoretical prices are cointegrated, indicating a long-run equilibrium relationship, with the exception of one asset that had a specific market event. Moreover, ECM corrects the discrepancies of prices in the long run. However, the Joint hypothesis test reject null of perfect pricing efficiency across all assets. This confirms that the strict theoretical assumptions of the cost-of-carry model do not hold perfectly in reality.

Moreover, the trading strategy produced positive net returns for all assets, demonstrating robustness even when fully accounting for transaction costs, borrowing costs, recurring fees and bid-ask spreads. Such persistent profitability is almost a demonstration that the mispricing of futures contracts with respect to their theoretical equilibrium can be exploited by using a pair trading approach.

5.1 Limitations of the study

The current study provides a strong theoretical background for finding mispricing. However, there are structural limitations in the current methodology that need to be acknowledged. The first limitation is the data quality for the hedging leg and the cost of the bid-ask spread. The backtest is based on Level 1 data which contains only the deal price but not the bid and ask quotes. Since it is impossible to know whether a historical trade was matched on the bid or the ask side, a fixed trading cost of half a tick per trade is utilized under the assumption that the probability of executions occurring on the bid and the offer is equal.

Second, the cost-of-carry model introduces a look-ahead bias with respect to dividends. For purposes of simplicity, this paper utilizes actual, announced dividend amounts in the calculation of theoretical future prices. But in a live trading environment, expected dividend payouts are not known until the official announcement date. By using actual data rather than forecasts, the model eliminates dividend forecast risk.

Finally, the pair selection is based on the long-run cointegration relationship of the whole in-sample period. This approach is static and therefore cannot easily adapt to changing market conditions. It may miss new trading opportunities or continue with trading relationships that have broken down.

5.2 Recommendations for further study

To address the unknown bid-ask price, future research should utilize Level 2 or Level 3 historical order book data. Access to complete bid and ask quotes would allow for exact transaction cost calculations based on true market liquidity. This approach would remove the reliance on a static, half-tick assumption, ensuring that the modeled cost of the bid-ask spread accurately reflects real-world market conditions.

Furthermore, to eliminate the look-ahead bias associated with the cost-of-carry model, subsequent iterations should incorporate a realistic, chronological dividend forecasting mechanism. In the real world, theoretical futures pricing must dynamically adapt to the corporate action timeline. Future research should rely on forecasted dividend values before the official corporate announcement. Specifically, it would be valuable to investigate the use of forecasting models such as an Autoregressive (AR(1)) model utilizing data from the previous dividend period to forecast these yields, alongside traditional consensus estimates. Once the dividend is officially announced, the model must transition to utilizing the exact announced value up until the ex-dividend (XD) date. Following the XD date, the expected dividend value must immediately drop to zero. Implementing this sequence ensures the model accurately reflects real-world dividend forecast risk.

The current method is successful at using a rolling window to execute trades, however, the initial cointegration testing should also be performed using a rolling look-back period across assets. This dynamic screening would allow the strategy to systematically remove pairs when their historical relationship breaks down and automatically identifies and adds newly cointegrated pairs to the trading universe.

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Appendix A

List of Selected Futures Contracts

A.1 Index Futures

1. S50

A.2 Single Stock Futures

- | | |
|-----------|----------|
| 1. DELTA | 2. TTB |
| 3. SIRI | 4. BANPU |
| 5. KBANK | 6. KTB |
| 7. PTTEP | 8. EA |
| 9. ADVANC | 10. TRUE |

Appendix B

Results on the 1-Hour Frequency

Table B.1: Order of Integration Results on the 1-Hour Frequency

Underlying	F_actual			F_theoretical		
	ADF p-value (Level)	ADF p-value (1st Diff)	Result	ADF p-value (Level)	ADF p-value (1st Diff)	Result
TDEX	0.2735	<0.001	I(1)	0.1986	<0.001	I(1)
ADVANC	0.9625	<0.001	I(1)	0.9601	<0.001	I(1)
BANPU	0.0089	-	I(0)	0.0105	-	I(0)
DELTA	0.9309	<0.001	I(1)	0.9225	<0.001	I(1)
EA	0.4009	<0.001	I(1)	0.3729	<0.001	I(1)
KBANK	0.6631	<0.001	I(1)	0.6431	<0.001	I(1)
KTB	0.7003	<0.001	I(1)	0.6837	<0.001	I(1)
PTTEP	0.5805	<0.001	I(1)	0.7856	<0.001	I(1)
SIRI	0.0154	-	I(0)	0.0143	-	I(0)
TTB	0.4332	<0.001	I(1)	0.3699	<0.001	I(1)
TRUE	0.9308	<0.001	I(1)	0.9316	<0.001	I(1)

Table B.2: Cointegration Test Results on the 1-Hour Frequency

Underlying	Residual ADF p-value	Conclusion
TDEX	0.0003	Cointegrated
ADVANC	<0.001	Cointegrated
BANPU	<0.001	Cointegrated
DELTA	0.0226	Cointegrated
EA	0.1496	Not Cointegrated
KBANK	<0.001	Cointegrated
KTB	<0.001	Cointegrated
PTTEP	0.0002	Cointegrated
SIRI	0.0090	Cointegrated
TTB	0.0008	Cointegrated
TRUE	<0.001	Cointegrated

Table B.3: ECM Results on the 1-Hour Frequency

Underlying	Error Correction Term $\varepsilon(t-1)$	
	Coefficient	p-value
TDEX	-0.0446	<0.001
ADVANC	-0.3698	<0.001
BANPU	-0.3556	<0.001
DELTA	-0.0674	<0.001
KBANK	-0.4801	<0.001
KTB	-0.4311	<0.001
PTTEP	-0.2703	<0.001
SIRI	-0.1239	<0.001
TTB	-0.1759	<0.001
TRUE	-0.5064	<0.001

Table B.4: Wald Test Results on the 1-Hour Frequency

Underlying	Estimated Coefficients		Joint Test ($H_0: \alpha = 0, \beta = 1$)	
	Intercept (α)	Slope (β)	p-value	Conclusion
TDEX	12.3668	1.0070	<0.001	Reject H_0
ADVANC	2.0257	0.9906	<0.001	Reject H_0
BANPU	0.0322	0.9972	<0.001	Reject H_0
DELTA	1.0825	0.9875	<0.001	Reject H_0
KBANK	1.3592	0.9908	<0.001	Reject H_0
KTB	0.2240	0.9873	<0.001	Reject H_0
PTTEP	2.6965	0.9820	<0.001	Reject H_0
SIRI	-0.0148	1.0123	<0.001	Reject H_0
TTB	0.0163	0.9847	<0.001	Reject H_0
TRUE	0.0109	0.9958	<0.001	Reject H_0

Table B.5: Optimal Parameters on the 1-Hour Frequency

Underlying	Entry Threshold (E)	Time Multiplier (x)	In-Sample Cumulative Return (P&L)	In-Sample Total Trades
TDEX	1.2	6.5	20262.85	117
ADVANC	1.0	6.0	110753.82	236
BANPU	1.3	6.0	4611.39	214
DELTA	0.9	6.0	45672.83	278
KBANK	1.1	6.5	58824.18	288
KTB	1.1	6.0	7496.19	275
PTTEP	1.0	6.5	65809.32	230
SIRI	1.6	6.5	1372.18	75
TTB	1.2	6.0	1216.39	164
TRUE	1.1	6.5	6917.69	246

Table B.6: Out-of-Sample Performance Metrics on the 1-Hour Frequency

Underlying	Cumulative Return (P&L)	Total Trades	Average Return per Trade	Average Holding Period (Days)	Win Rate
TDEX	8638.01	70	123.40	2.28	70.00%
ADVANC	46702.69	167	279.66	1.28	60.14%
BANPU	3117.91	117	26.65	0.93	84.62%
DELTA	20396.72	127	160.60	1.83	70.87%
KBANK	33525.67	96	349.23	1.60	72.92%
KTB	8721.42	172	50.71	0.76	73.26%
PTTEP	51959.55	161	322.73	1.03	74.53%
SIRI	626.14	25	25.05	2.20	88.00%
TTB	622.86	117	5.32	1.13	68.38%
TRUE	4055.53	172	23.58	0.98	72.67%