University of Cape Town

STA5071Z

Simulation

Agent-Based Modeling: Simulating Dynamics in the Crypto Market

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May 2, 2024

Project Repository

Access the source code and project files for this report on GitHub:
https://github.com/LKHJAR001/STA5071Z-Final.git

Contents

1 Introduction

We aim to evaluate the dynamics of the cryptocurrency market by simulating trading within two cryptocurrency exchanges, and arbitrage between them, using an agent-based model. The study is divided into an examination of the arbitrage mechanics in the market and the trading strategies that can be employed to generate profits - including two commonly utilized momentum-based indicators employed by traders involving moving-averages. Additionally, we propose that this study serves as an introductory guide for individuals interested in analyzing their own specific trading strategies using the provided NetLogo program.

Figure 1 details the ABM algorithm for the trading mechanics on an individual exchange (the same algorithm to be used for both exchanges), and Figure 2 illustrates the algorithm for the entire conceptual model where the arbitrage step is shown (where trading on both exchanges is included). The ABM algorithm for one of the momentum-based strategies can be found Appendix A.4.

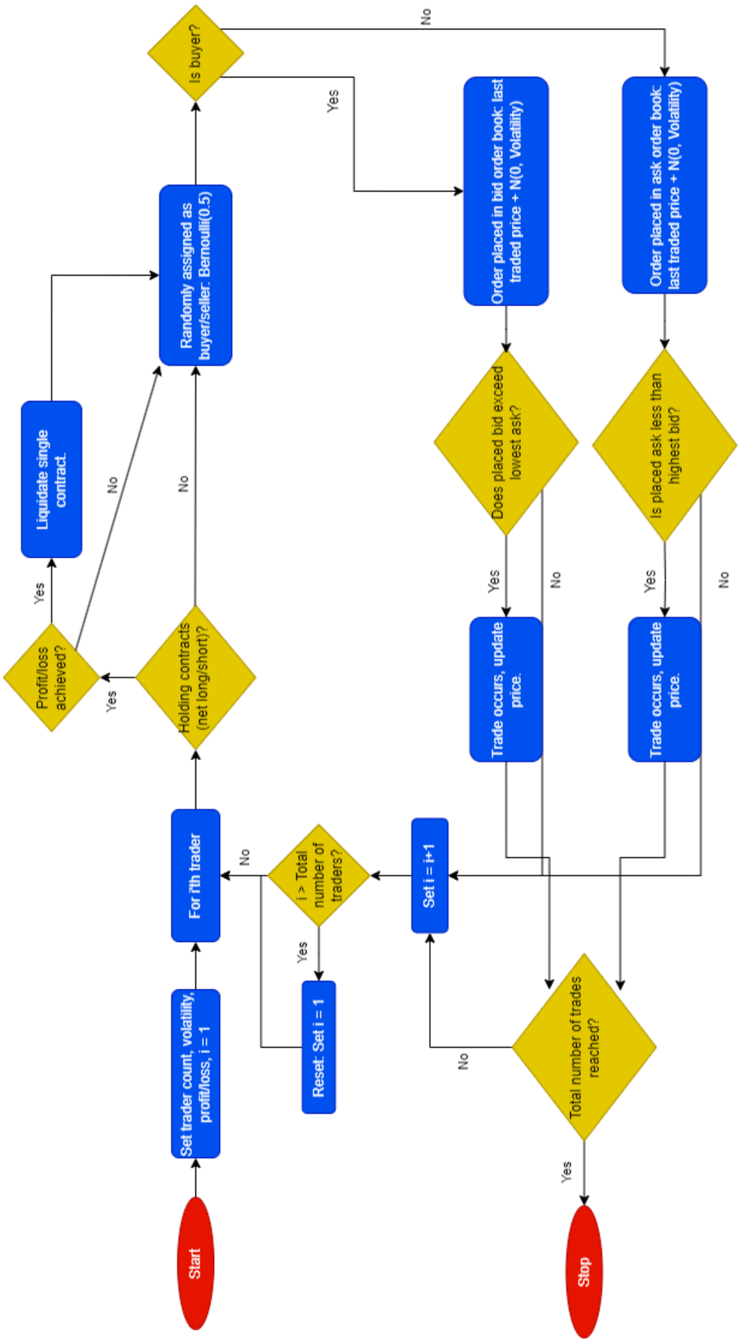


Figure 1: ABM Algorithm for a Single Exchange

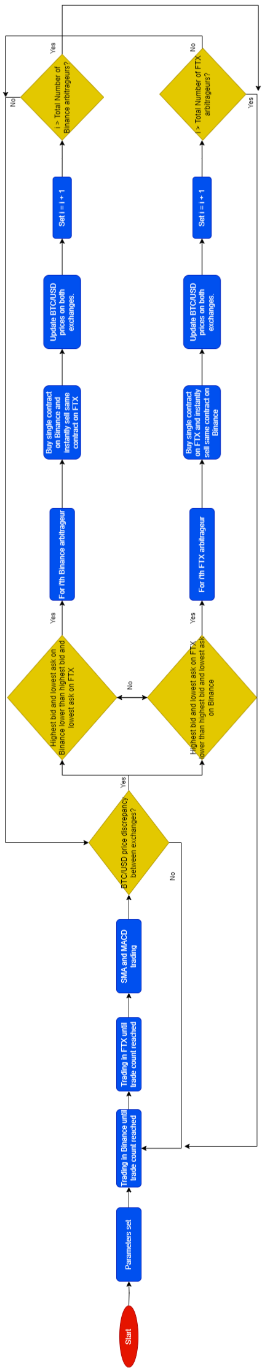


Figure 2: ABM Algorithm for the Overall Conceptual Model

2 Arbitrage

Our objective is to determine the distribution of the Arbitrage Spread for varying volatility, where we define random variable X as the difference between BTC/USD on the two exchanges. We ensure all arbitrage opportunities in the market are undertaken, by setting the number of arbitrageurs on both exchanges to be high relative to the total number of traders on the exchanges (so as to mimic reality). From Figure 4, we see that an increased volatility results in a larger spread of the distribution - indicating a greater opportunity for an arbitrageur to turn a profit. Symmetry about the mean of \$0 can also be seen. Additionally, we notice concave tails on said distributions - indicative of X: Arbitrage Spread being Laplace distributed (expounded upon in Appendix B.1). Being such, we fit Laplace distributions to each set through maximum likelihood maximization, where from Figure 3, we find that approximating the scale/diversity parameter $\hat{b} = 0.02 \times Volatility$ to be appropriate ($\hat{\mu} \approx 0$ regardless of volatility as anticipated).

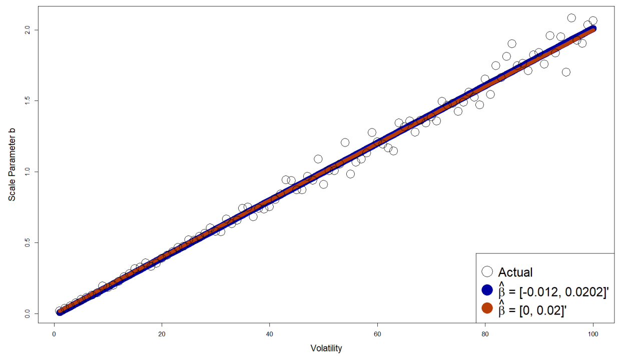
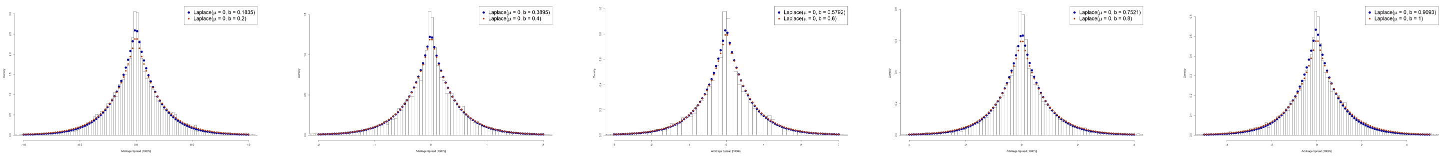


Figure 3: Fitted Linear Model with $R^2 = 0.9902$ (blue) and Approximated Linear Model $R^2 = 0.9900$ (red) to the Scale/Diversity Maximum Likelihood Estimates (m.l.e's).

From inspecting Figure 4, we conclude X: Arbitrage Spread $\sim Laplace(\mu = 0, b = 0.02 \times Volatility)$ to be a satisfactory approximation.



(a) Distribution of X, Volatility = \$10 (b) Distribution of X, Volatility = \$20 (c) Distribution of X, Volatility = \$30 (d) Distribution of X, Volatility = \$40 (e) Distribution of X, Volatility = \$50

Figure 4: Distributions of X: Arbitrage Spread with Fitted Laplace Distributions with Estimated Scale Parameter from Fitted Linear Model (in Blue) and from Approximated Linear Model (in Red)

For real-world application, the notion of being able to determine the volatility of traders' bids and asks (the range of prices relative to the last traded price, which they believe the asset should be priced at) solely from knowing the parameters of the distribution of the arbitrage spread, is quite profound. It is well known that real-world order books do not represent the true intentions of traders (largely due to spoofing), hence ascertaining this true spread at which traders are willing to buy/sell at, proves difficult. We posit that determining this true spread by evaluating the arbitrage opportunities in the market, is a superior method.

We also note that the volatilities were the same across both exchanges. It it were such that the volatilities were different, the arbitrage spread would be asymmetric Laplace distributed. Additionally, the study neglects fees/commission that arbitrageurs would be subject to in the real-world market - potentially causing some arbitrageurs to forego arbitrage opportunities.

3 Trading Dynamics

In our study, we identify four distinct types of traders (with different strategies) for evaluation. The study endeavors to showcase how one can analyze a specific strategy's Profit and Loss (PnL) distribution to improve profitability (no strategy will guarantee a profit). The first type is the random-entry trader, who randomly places bids or asks in the order book for a single contract after every tick, regardless of market conditions. A variant of this trader is the risk-managed trader, who sets specific profit-taking and stop-loss levels for all trades taken. We find that there is essentially no difference in the PnL distributions between these two types of traders, as explored in Appendices A.1 and A.2.

Additionally, we examine two traders who base their trades on popular momentum-based strategies commonly used in the market: the smooth-moving-average (SMA) trader and the moving-average convergence-divergence (MACD) trader. More information about these indicators can be found in [1] and [2]. We detail the study's specific strategy and associated mechanics in Appendix A.4.

We denote our random variable X as PnL at a given point in time, measured in thousands of dollars ($1000). Our stop criterion is set at 10,000 ticks, indicating that the outcomes of these trading strategies depend on the duration for which they are employed, and is investigated further in Appendix A.3. Moreover, the study utilized PnL data from 200 repetitions in NetLogo simulations, to replicate the various trading strategies adopted at different 'times' in the market.

3.1 Volatility Influence

We investigate how the volatility of the market affects profit distributions of the trading strategies. In our study however, volatility is an agent attribute, rather than the standard deviation of returns of the asset (as is typically calculated). That is, given that a trader (buyer or seller) places a bid/ask on the order book with price = last traded price + $N(0, Volatility)$, indicates that volatility is rather the spread of prices buyers/sellers believe the asset should be priced at relative to the last traded price (where said prices are normally distributed).

3.1.1 Random-Trader

We determine the influence of volatility on the PnL distribution of a random trader: from Figure 6 we posit that Laplace distributions fit adequately to the PnL distributions for each volatility set. We determine a linear relationship between the volatility and the scale parameter maximum likelihood estimates (m.l.e's), where we approximate $\hat{b} = 0.47 \times Volatility$ in Figure 5. Furthermore, we conclude X: PnL of random trader $\sim Laplace(\mu = 0, b = 0.47 \times Volatility)$ to be an adequate approximation.

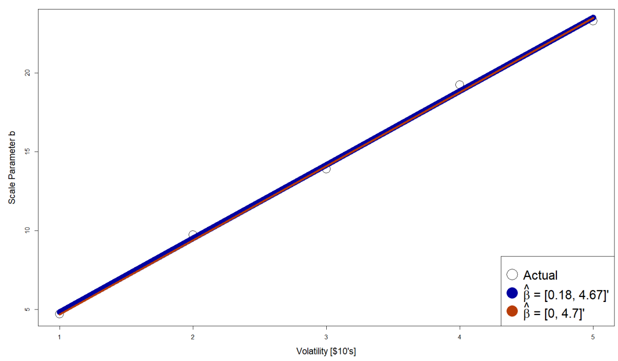
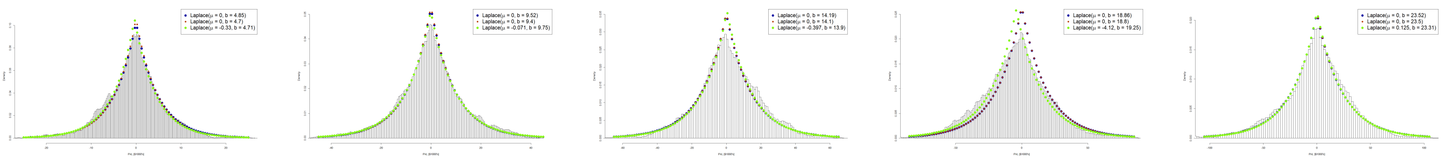


Figure 5: Fitted Linear Model with $R^2 = 0.9984$ (blue) and Approximated Linear Model $R^2 = 0.9982$ (red) to the Scale/Diversity Maximum Likelihood Estimates (m.l.e's).



(a) Distribution of X, Volatility = \$10 (b) Distribution of X, Volatility = \$20 (c) Distribution of X, Volatility = \$30 (d) Distribution of X, Volatility = \$40 (e) Distribution of X, Volatility = \$50

Figure 6: Distributions of X: PnL of Random Trader with Fitted Laplace Distributions with Scale Parameters from Fitted Linear Model (in Blue), from Approximated Linear Model (in Red) and from Actual Estimated m.l.e's (in Yellow).

3.1.2 Smooth-Moving-Average (SMA) Trader

Similarly, we investigate the effect of volatility on the PnL distribution of an SMA trader. From Figure 8, we posit that asymmetric Laplace distributions (ALD) fit satisfactorily (ALD theory expounded on in Appendix B.2) where we fit an exponential model to the scale parameter m.l.e's ($\hat{\lambda}$'s) in Figure 7. Hence we approximate X : PnL of SMA trader $\sim Laplace(m = 0, \lambda = 0.276e^{-0.038Volatility}, \kappa = 1.8)$.

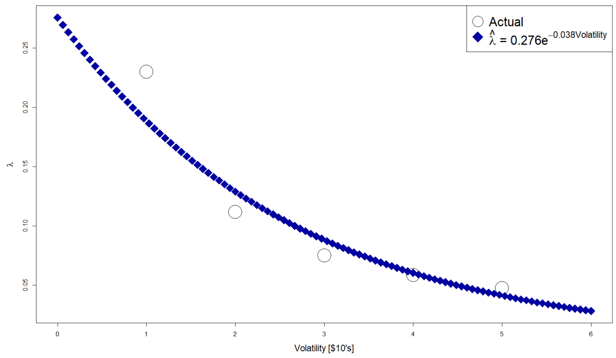
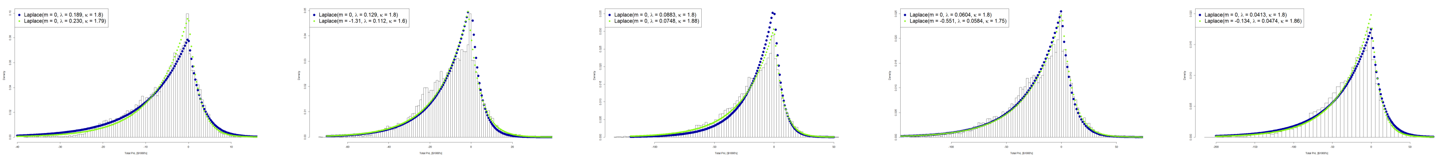


Figure 7: Fitted Exponential Model with $R^2 = 0.8988$ (blue) to the Scale/Diversity m.l.e's ($\hat{\lambda}$).

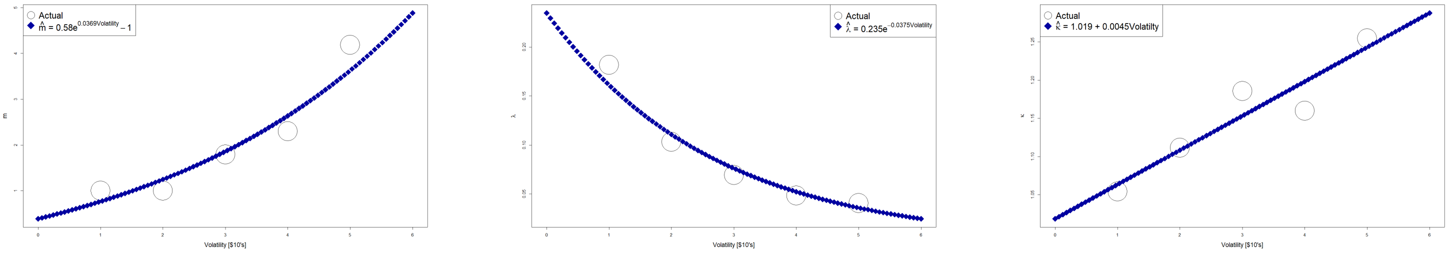


(a) Distribution of X, Volatility = \$10 (b) Distribution of X, Volatility = \$20 (c) Distribution of X, Volatility = \$30 (d) Distribution of X, Volatility = \$40 (e) Distribution of X, Volatility = \$50

Figure 8: Distributions of X: PnL of SMA Trader with Fitted Asymmetric Laplace Distributions with Scale Parameters from Fitted Exponential Model (in Blue), and from Actual Estimated m.l.e's (in Yellow), with Scale Parameter $m = 0$ and Asymmetry Parameter $\kappa = 1.8$

3.1.3 Moving-Average-Convergence-Divergence (MACD) Trader

Finally, we explore volatility's influence on the PnL distribution of a MACD trader. From Figure 10, we propose that asymmetric Laplace distributions (ALD) are a satisfactory fit, where we fit an exponential model to the location parameter m.l.e's ($\hat{m}$'s) and scale parameter m.l.e's ($\hat{\lambda}$'s), and a linear model to the asymmetry parameter m.l.e's ($\hat{\kappa}$'s) in Figure 9. Hence we approximate X : PnL of MACD trader $\sim Laplace(m = 0.58e^{0.0369Volatility} - 1, \lambda = 0.235e^{-0.0375Volatility}, \kappa = 1.02 + 0.0045Volatility)$.

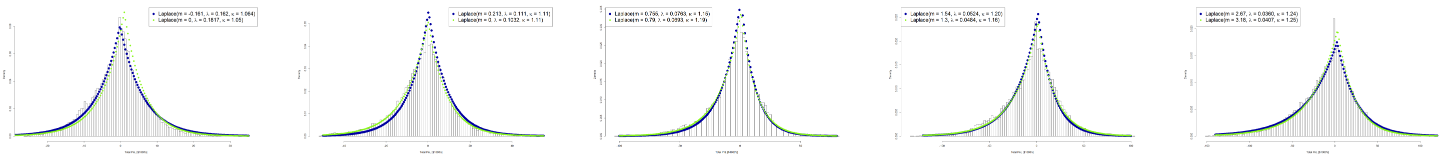


(a) Fitted Exponential Model with $R^2 = 0.9458$ (blue) to the Location m.l.e's ($\hat{m}$).

(b) Fitted Exponential Model with $R^2 = 0.9575$ (blue) to the Scale/Diversity m.l.e's ($\hat{\lambda}$).

(c) Fitted Linear Model with $R^2 = 0.8804$ (blue) to the Asymmetry m.l.e's ($\hat{\kappa}$).

Figure 9: Fitted Regressions to M.L.E's of Location, Scale and Asymmetry Parameters



(a) Distribution of X, Volatility = \$10

(b) Distribution of X, Volatility = \$20

(c) Distribution of X, Volatility = \$30

(d) Distribution of X, Volatility = \$40

(e) Distribution of X, Volatility = \$50

Figure 10: Distributions of X: PnL of MACD Trader with Fitted Asymmetric Laplace Distributions with Approximated Parameters (in Blue), and from Actual Estimated m.l.e's (in Yellow).

The findings from the study clearly indicate that one can indeed generate a profit using all the mentioned strategies as X : PnL can take on positive values (shown in all PnL distributions). With insights gained from the PnL distributions, traders could potentially enhance their profitability by gaining understanding of their potential profits or losses under specific market conditions. For instance, traders could determine when to cease using a particular strategy if they are significantly profitable, or conversely, when to persist with the strategy despite losses.

Notably, the MACD trading strategy emerges as the most lucrative option (or rather, grants a higher chance of being profitable). The location parameter exhibits an exponential relationship with volatility, as depicted in Figure 9, suggesting the potential for greater profitability during periods of higher market volatility (the PnL distribution will start to shift greatly towards the profitable side). We also notice the PnL distributions of the SMA trader to be highly negatively skewed - suggesting that merely trading randomly (the Random Trader strategy) offers a higher likelihood of profitability.

4 Conclusion: Limitations and Recommendations

Given that these strategies rely on market volatility, which is defined in the study as the true spread at which traders are willing to buy or sell, we recommend examining the distribution of the arbitrage spread to gauge this volatility, as previously mentioned. Additionally, an overarching assumption made in the study was that this volatility remained constant throughout the duration for which the strategy was employed - this assumption may pose challenges for said strategies being employed in real-world market scenarios.

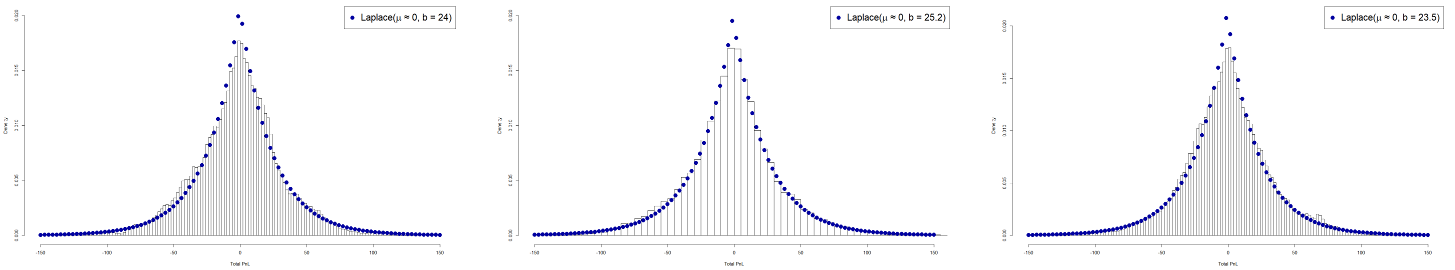
Future studies may benefit from exploring variations of the aforementioned momentum-based strategies. This could involve examining the impact of different profit-taking and stop-loss levels on PnL, assessing how the number of contracts liquidated at each profit-taking point affects PnL, or modifying the moving averages used and observing their influence on PnL. All these parameters can be adjusted within the provided NetLogo program. Additionally, an assumption made in the study was that the prices at which buyers or sellers on the exchanges place their orders, followed a normal distribution. It may be worthwhile to change this assumption to a different distribution and assess the effects on the arbitrage spread or PnL distributions.

Appendices

A Trading Dynamics

A.1 Risk-Reward Ratio

With regard to the risk managed/disciplined trader, we find it worthwhile to investigate whether greater profit margins may be obtained by varying the risk-reward ratios (ratio of profit takes to stop losses e.g. a profit take of \$30 and a stop-loss of \$10 would result in a risk-reward ratio of 3). Additionally, the ratio of profit-takes to volatility was also varied: initially, by setting the profit-takes to be within the volatility range (profit takes at $\$10, \$20$ & $\$30$ with stop-loss set at \$10 and volatility set at \$50) in Figure 11, and then by setting the profit-takes to be greater than or equal to the set volatility (profit takes at $\$50, \$100$ & $\$150$ with stop-loss set at \$50 and volatility set at \$50) in Figure 12. We note that fitted Laplace distributions seem to be appropriate with satisfactory fit from inspection.

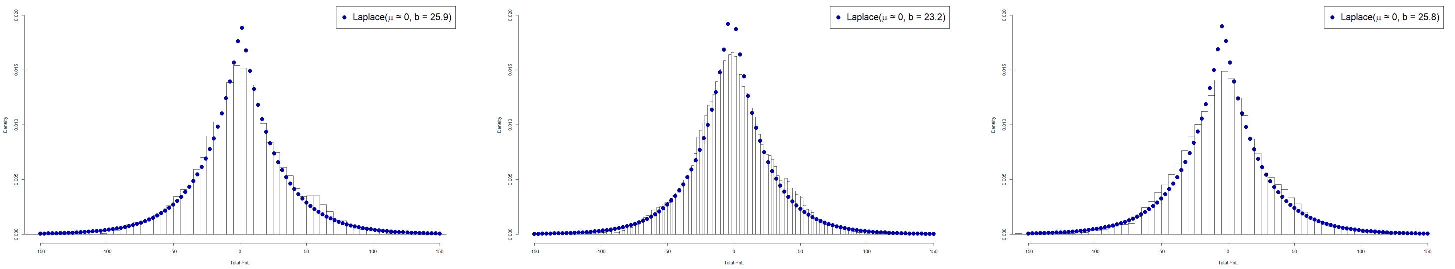


(a) Distribution of X with Risk-Reward of 1

(b) Distribution of X with Risk-Reward of 2

(c) Distribution of X with Risk-Reward of 3

Figure 11: Distributions of X: PnL with Profit-Takes set at $\$10, \$20$ & $\$30$ and Stop-Loss set at \$10, Volatility at \$50 (Fitted Laplace Distributions included).



(a) Distribution of X with Risk-Reward of 1

(b) Distribution of X with Risk-Reward of 2

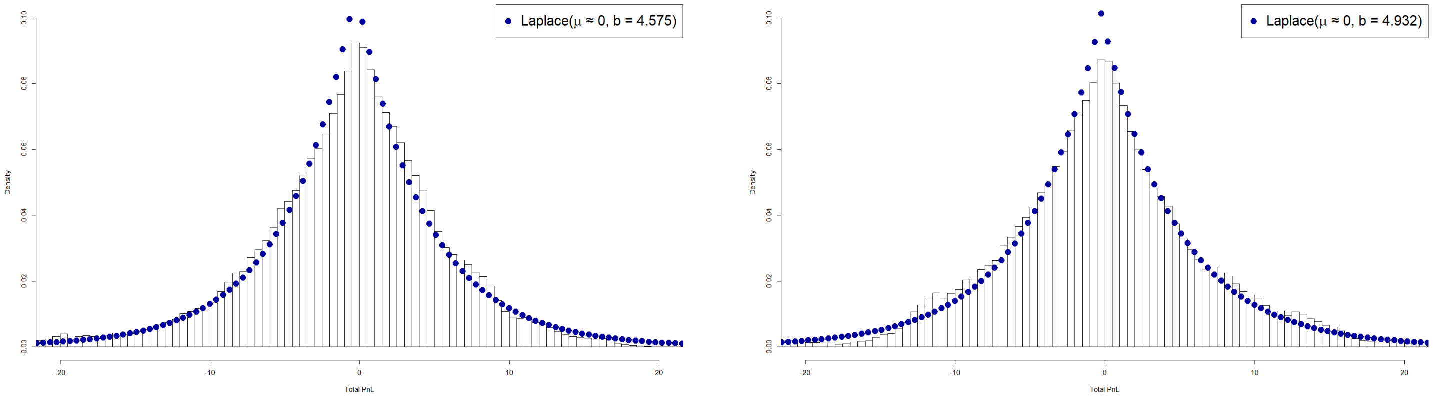
(c) Distribution of X with Risk-Reward of 3

Figure 12: Distributions of X: PnL with Profit-Takes set at $\$50, \$100$ & $\$150$ and Stop-Loss set at \$50, Volatility at \$50 (FiLted Laplace Distributions included).

Noting the scale/diversity parameters of the fitted Laplace distributions to be $b \approx 25$ for all sets, we conclude that altering the risk-reward ratio of one's trades do not bring about a change in PnL (regardless of their dollar values relative to the volatility).

A.2 Random-Entry Trader vs. Risk-Managed Trader

Following the conclusion of the previous section, we should now inquire whether there is indeed a difference in the PnL between a random-entry trader and a risk-managed trader. Furthermore, we conduct the investigation by setting the volatility at \$10, and compare the random-entry trader to a risk-managed trader with a risk-reward of 3 in Figure 13



(a) Distribution of X of Random-Entry Trader (b) Distribution of X of Risk-Managed Trader

Figure 13: Distributions of X of both a Random-Entry Trader and Risk-Managed Trader with Volatility at \$10 (Fitted Laplace Distributions included).

Noting the similarities in histograms and the scale/diversity parameter of the fitted Laplace distributions ($b \approx 5$), we conclude that there seems not to be a difference between a random-entry trader and a risk-managed trader (we infer this conclusion applies to all volatilities, contingent on the conclusions of the previous section).

A.3 Duration Influence

We investigate the influence of the duration (measured in ticks) for which the random-trading strategy was employed (for a Volatility of \$10) on PnL (similar studies may be done for the SMA and MACD traders' PnLs). From Figure 14, we find a cubic relationship between the scale parameter m.l.e's ($\hat{b}$) of the Laplace distribution, and duration. We approximate X : PnL of random trader at a \$10 volatility $\sim Laplace(m = 0, \lambda = 0.63 + 0.00084Duration - 0.0000069Duration^2 + 0.000000029Duration^3)$ seen in Figure 15.

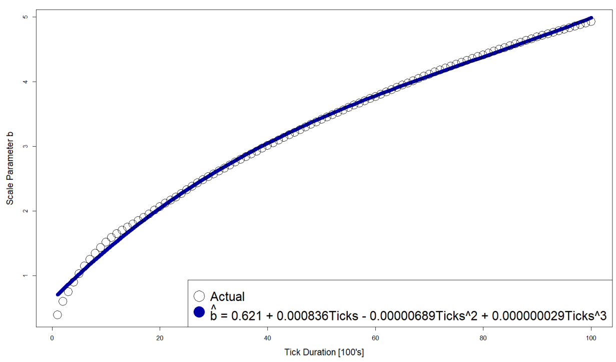
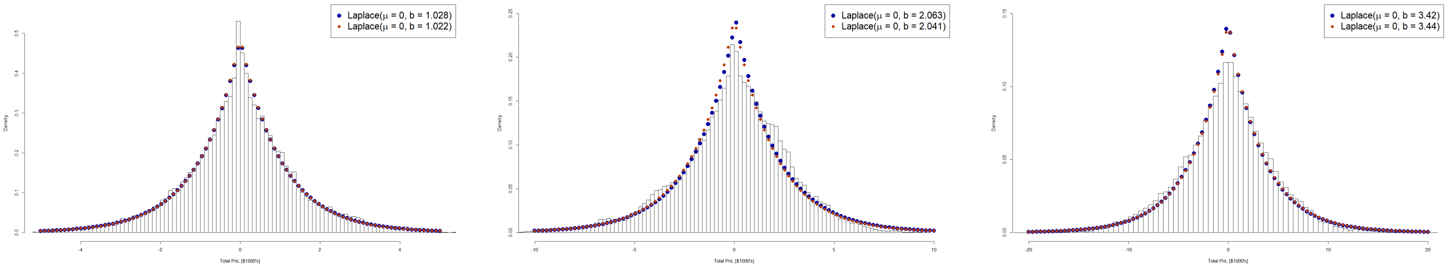


Figure 14: Fitted Cubic Model with $R^2 = 0.9978$ (blue) to the Scale/Diversity Maximum Likelihood Estimates (m.l.e's).



(a) Distribution of X at 500 Ticks (b) Distribution of X at 2000 Ticks (c) Distribution of X at 5000 Ticks

Figure 15: Distributions of X: PnL of Random Trader at Volatility \$10 for 500, 2000 and 5000 Ticks with Fitted Laplace Distributions with Scale Parameters from Fitted Cubic Model (in Red) and from Actual Estimated m.l.e's (in Blue)

A.4 Momentum-Based Strategy Specifications

We detail the specific trading strategy of the SMA and MACD trader used in the study. Specifics of the profit-takes and stop-loss can be altered in Netlogo, along with the amount of contracts liquidated at each profit take, including which moving-average periods to use. The ABM algorithm for SMA trading can be found in Figure 16.

For the SMA trader, a buy entry is triggered when the short-term moving average (set at 50 ticks) crosses above the long-term moving average (set at 200 ticks) - known as a 'golden cross'. A sell entry is triggered for the opposing cross of the moving averages - called a 'death cross'. For the MACD trader, a similar mechanic is used, yet involving a signal line (set at 900 ticks) and a MACD line (calculated as the difference between the 2600 tick and 1200 ticks exponential moving average). Additionally, we set the number of contracts to 5 (traders can only be long or short 5 contracts), with the 1^{st} profit-take at $2 \times Volatility/100$ liquidating 2 contracts, the 2^{nd} at $3 \times Volatility/100$ liquidating another 2 contracts, and the 3^{rd} at $5 \times Volatility/100$ liquidating the last contract. A stop-loss is set at $1.2 \times Volatility/100$, where the stop-loss is moved to the entry price if the 1^{st} profit-target is triggered (so to guarantee the trader at least breaks even for a winning trade). We ensure the the profit-takes and stop-losses are proportional to the set volatility.

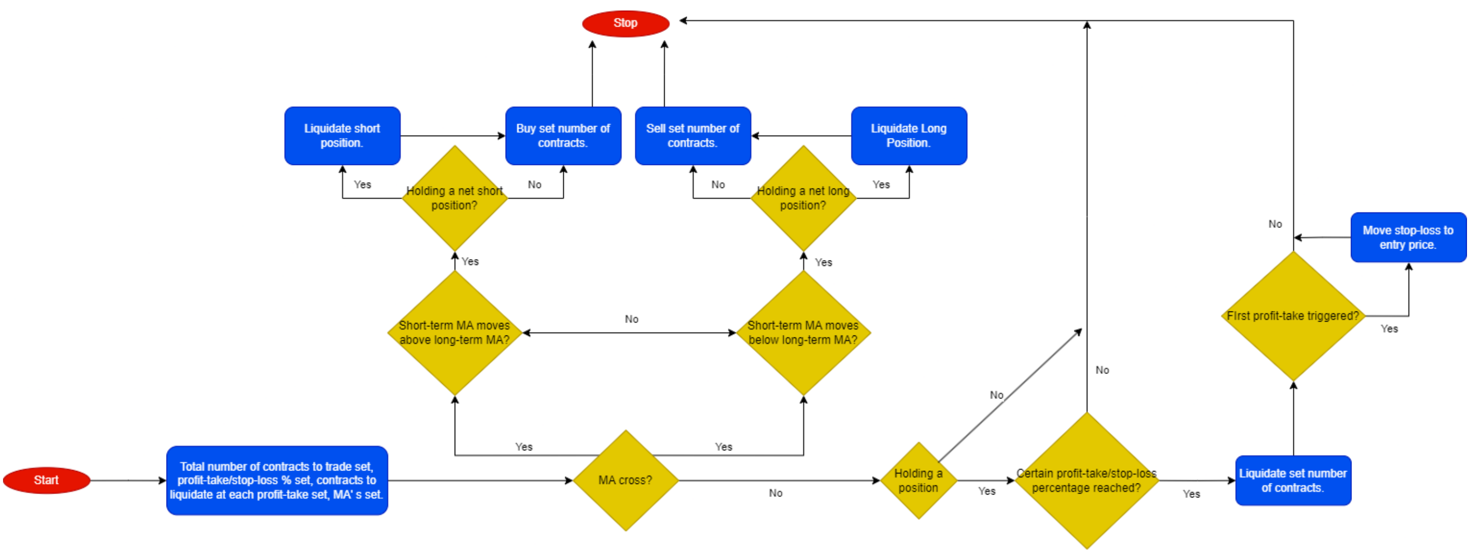


Figure 16: ABM Algorithm for SMA Trading

B Theory

B.1 Laplace Distribution

The Laplace distribution, also known as the double exponential distribution, is a probability distribution that is symmetric about its mean. The probability density function (PDF):

$$f(x|\mu, b) = \frac{1}{2b}e^{-\frac{|x-\mu|}{b}} \tag{1}$$

where μ is the location parameter, and $b > 0$ is the scale/diversity parameter which controls the spread.

B.2 Asymmetric Laplace Distribution

The asymmetric Laplace distribution, a generalization of the Laplace Distribution, has a probability density function (PDF):

$$f(x|m, \lambda, \kappa) = \frac{\lambda}{\kappa + 1/\kappa}e^{-(x-m)\lambda s\kappa^s} \tag{2}$$

where $s = sgn(x - m)$, m is the location parameter, $\lambda > 0$ is the scale/diversity and κ is the asymmetry parameter.

C Simulation Specifications in Netlogo

We state, within Netlogo's behaviour space environment, the values to report, stop criterion, and parameter sets.

C.1 Arbitrage

In Netlogo's behaviour space, report: Binance_BTC/USD - FTX_BTC/USD, with stop criterion: ticks = 10000 (results do not alter if stop criterion extended) and repetitions = 1. Here we set parameters 'Binance-Volatility' and 'FTX-Volatility' to 'vol', 'binance_profit' and 'FTX_profit' to 'profit_set', and 'binance_loss' and 'FTX_loss' to 'loss'.

Parameter	**Value**
nbinancians	1000
nbinance_arbitrageurs	100
nftxians	1000
nftx_arbitrageurs	100
vol	[1 1 100]
profit_set	30
loss	10

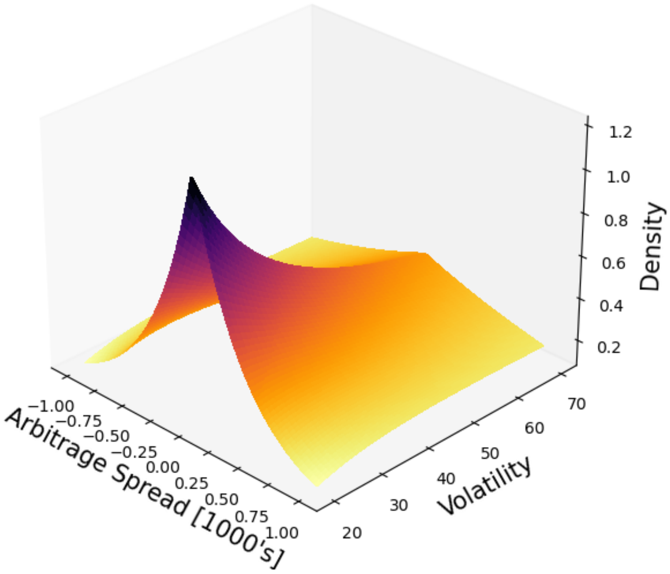


Figure 17: Density vs. Volatility and Arbitrage Spread [in \$1000′s] where $X \sim Laplace(\mu = 0, b = 0.02 \times Volatility)$

C.2 Risk-Reward Ratio

In Netlogo's behaviour space, report: [profit] of binancian 0, with stop criterion: ticks = 10000 and repetitions = 200. Tick charts were chosen as 133 due to its popularity amongst traders.

Parameter	Value
nbinancians	1000
nbinance_arbitrageurs	100
nftxians	1000
nftx_arbitrageurs	100
vol	10 / 50
profit_set	10 20 30 / 50 100 150
loss	10 / 50
binance_tick_count	133
FTX_tick_count	133

C.3 Random-Entry Trader vs. Risk-Managed Trader

In Netlogo's behaviour space, report: [profit] of binancian 0, with stop criterion: ticks = 10000 and repetitions = 200. A random-entry trader may be acquired by setting both profit_set and loss to 0.

Parameter	Value
nbinancians	1000
nbinance_arbitrageurs	100
nftxians	1000
nftx_arbitrageurs	100
vol	10
profit_set	0 / 30
loss	0 / 10
binance_tick_count	133
FTX_tick_count	133

C.4 Volatility Influence

In Netlogo's behaviour space, report: [profit] of binancian 0 (for random-trader PnL), last sma_totalprofit (for SMA trader PnL) and last macd_totalprofit (for MACD trader PnL) , with stop criterion: ticks = 10000 and repetitions = 200.

Parameter	**Value**
nbinancians	1000
nbinance_arbitrageurs	100
nftxians	1000
nftx_arbitrageurs	100
vol	[10 10 50]
profit_set	30
loss	10
binance_tick_count	133
FTX_tick_count	133

References

[1] Adam Hayes. Golden cross definition. `https://www.investopedia.com/terms/g/goldencross.asp`, 2023. Accessed: April 14, 2024.

[2] Boris Schlossberg. How to interpret macd divergence. `https://www.investopedia.com/articles/forex/05/macddiverge.asp`, 2024. Accessed: April 14, 2024.