Trading and Market Design – Intraday Trader

Abstract:
This report presents the theory and results of my trades as an intraday trader in the US stock market. I applied a long-only strategy utilising technical analysis to evaluate the effectiveness of my pre-data analysis, backtesting and forward testing techniques. This enabled me to identify potential trading opportunities and determine the most appropriate technical indicators such as the Exponential Moving Average (EMA), Simple Moving Average (SMA) and Relative Strength Index (RSI). Initially, I considered investing in AAPL, AMZN and TSLA but after a comprehensive review, I determined that investing in shares of TSLA offered the best option in terms of achieving a balance of high risk-adjusted returns and trade frequency, which was my primary objective for this experiment. I will discuss approximately 26 orders varying in size, market and frequency that I submitted in TWS. I will further evaluate the performance of these trades and the strategies that were implemented, whilst highlighting any insightful findings regarding the outcomes of the trades. Although I experienced overall profits, there was a significant inconsistency between backtests and forward tests. After a thorough analysis of my performance, I now understand why this situation may have arisen and how to rectify it in future trades.

Introduction:
In this report I will present an analysis of my orders as an intraday trader – a trader investing in financial instruments within the same trading day. I opted to pursue a long-only trading strategy and applied technical analysis, which entailed utilising historical market data in order to make informed decisions on trade executions. Prior to placing my orders, however, I conducted a pre-analysis to collect data on the securities of interest. This helped me determine the most appropriate trading strategy and understand the overall market sentiment. Following this, I performed backtests on the data collected to examine technical indicators and determine the potential profitability and risk profile of the investment. For this experiment, I chose to code the EMA which calculates the average price of a stock over a given period of time whilst placing a greater weighting on recent price data, thus making it more responsive to changes in price trends than other indicators, such as SMA. Additionally, I conducted forward tests, a strategy that uses past data to simulate real market conditions, enabling me to identify potential issues with my current trading strategy. This step is crucial as historical market data alone cannot always accurately predict current market conditions due to constant fluctuations. Subsequently, I will analyse my trading performance, evaluating the overall success by assessing the same variables used in the backtests such as PnL and Sharpe Ratio. This will assist me in determining whether my trading strategy was optimal, and in doing so, I can scrutinise whether unsuccessful trades were a result of misfortune or incompetence by computing T-tests and exploring any interesting findings uncovered during the experiment.

Main Body:

1. Theory – Exponential Moving Average
The technical indicator applied in this experiment was the EMA. EMA is calculated recursively using the formula; $EMA_t = \alpha * (p_t - EMA_{t-1}) + EMA_{t-1}$, where $\alpha = \frac{2}{n+1}$ (the smoothing factor) and *n* is the look-back period, p_t is the closing price for current period , and EMA_{t-1} is the EMA value for the previous time period. The look-back period determines the weight given to the most recent price compared to the previous period's EMA, with smaller values for *n* correlating to a more responsive but volatile EMA and vice versa. Also note that the first value of EMA_{t-1} is calculated using the SMA (= $\sum_{i=1}^{N} \frac{p_i}{N}$ where p_i is closing price at time period *i* and *N* is the total number of periods) as there is no previous EMA value to use (Chen, 2023).

2. Pre-analysis
To effectively conduct intraday trading, it is crucial to have a well-defined and succinct pre-analysis of the stocks that you intend to trade. Having collected and organized historical data on TSLA, AAPL, and AMZN, I was able to generate the following curves (see Figures 1 & 2).

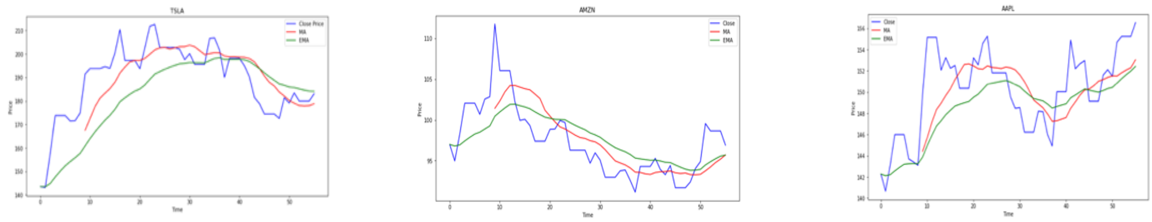

Figure 1 – Price TSLA, AMZN and AAPL respectively.

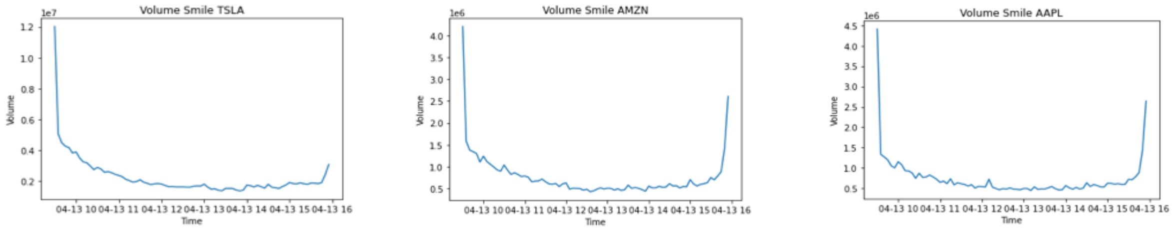

Figure 2 – Volume Smile TSLA, AMZN and AAPL respectively.

Upon evaluating the volume smile (geographical pattern of implied volume) of TSLA (as shown in Figure 2), it was observed that the curve is skewed to the left. This indicates that there is a higher trading activity at market open compared to market close. This coincides with theoretical expectations as markets tend to be more active during the market opening due to overnight news or other factors affecting the stock price. When observing AAPL and AMZN (refer to Figure 2), they also exhibit a left-skewed curve, but with increased trading frequency at market close. To gain proficiency in using technical indicators in my trading activities, I assessed the price trend of each stock (refer to Figure 1) by implementing an EMA curve alongside them.

3. Backtests

Backtesting to evaluate the effectiveness of a trading strategy is a fundamental step in the process of selecting the optimal approach to improve performance. There are different measures that can be used to evaluate the performance of a trading strategy. These include total return and PnL (Profit and Loss) which indicate the overall profitability of the strategy, while the win ratio is a measure of the probability of successful trades. The standard deviation (std) of returns helps to determine the level of risk associated with the strategy and the Sharpe Ratio is a useful measure to assess risk-adjusted returns. To simplify the interpretation of results, I opted to condense the numerous performance metrics by taking their averages. This method facilitated a streamlined analysis of the data and allowed for the identification of the most promising trading strategies. It is essential however to acknowledge that the use of averages may have limitations and potential biases i.e., may be heavily influenced by outliers. Additionally, when backtesting, one should consider the look-back period, which is the number of periods of historical data used for observation and calculation. Therefore, I frequently adjusted the period of each stock to assess its impact on the corresponding variables mentioned above.

After conducting comprehensive tests, the results were recorded (see Figure 3). From there, I was able to ascertain that a long position on TSLA would be advantageous due to its high win ratio (approximately 41%), average Sharpe Ratio (approximately 0.03), and high trade frequency (approximately 15). These findings suggest a higher likelihood of achieving profitable trades with effective risk management. Additionally, the comparatively low average standard deviation (approximately 0.005) indicates lower risk. Although the total PnL may not be the highest, the combination of these factors demonstrates a profitable strategy with high accuracy and consistency. The choice of a look-back window of 2 underpins these positive results by ensuring a greater number of trade signals. However, selecting a smaller window can increase the strategy's susceptibility to market noise and lag.

	A	B	C	D	E	F
1		**Avg.Tot.PnL**	**Avg.Std.Ret**	**Avg.Win.Ratio**	**Avg.Sharpe.Ratio**	**Avg.Num.Trade**
2						
3	**TSLA**	0.85242299	0.00466241	0.41264733	0.03173295	14.9285714
4						
5	**AMZN**	0.1330877	0.00339501	0.390474258	0.005322627	9.196428571
6						
7	**AAPL**	0.10092354	0.00240842	0.35317443	-0.0546184	11.4642857

Figure 3 – Results from backtest of TSLA, AMZN & AAPL

Upon further examination, it became clear that AAPL presented the weakest results. One of the most significant issues was that the average Sharpe Ratio was negative (roughly -0.05), indicating that its rate of return was low compared to its volatility. The average total PnL, win ratio, and number of trades were also inferior to TSLA shares (see Figure 3), making it pointless to consider further. Similarly, AMZN yielded lacklustre results comparatively (see Figure 3). It is however essential to note that AAPL and AMZN produced optimal results with a higher look-back period (4 and 6, respectively). A wider look-back implies that "more noise can be filtered from the financial data and better smoothness can be achieved" (Raudys and Pabarškaitė, 2018). This is because a wider window includes a more extensive range of historical data, enabling it to capture a broader range of market conditions and reduce the impact of short-term fluctuations.

4. Forward Tests

Forward testing involves implementing the optimal strategy concluded by the backtests, to validate its effectiveness in the real-time market. Figure 4 clearly illustrates how I applied this to my trading style.

Figure 4 – Price of TSLA (21/04/23)

To provide context, green candlesticks represent a bullish price movement, in which the close price is higher than the open price. Whereas a red candlestick signifies a bearish price movement, where the close price is lower than the open price, and the EMA is displayed by the blue line. The indication to enter or hold a long position is determined by price closing above the EMA curve. Similarly, one must exit a position if price closes below the EMA curve. However, when attempting to submit trades there were instances when it was challenging to determine the appropriate course of action, such as whether to enter, exit or hold the current position. This was due to the EMA curve closely aligning with or slightly deviating from the close price (indicated by the white arrow in Figure 4), which inherently increases the risk of making the wrong trading decision, potentially causing more losses and opportunity costs (cost incurred from missing an opportunity). To mitigate this risk, utilising other trading indicators, such as Moving Average Convergence Divergence (MACD) or RSI in conjunction with the EMA may be employed to confirm or invalidate the signals – "multiple indicators offer 20%

enhancement in decision making" (Nugroho et al., 2014). Furthermore, to increase the frequency of trading opportunities, a 5-minute time frame was chosen. The effectiveness of this approach was demonstrated by the ability to execute up to 8 trades on some days, aligning with the backtest results. However, it is worth noting that on occasion I missed the signal to submit a trade which resulted in missed opportunities and potential profits, with a less favourable entry/exit price.

5. Trading Performance & Interesting Findings

Following the submission of my trades I was able to download and conduct further analysis on my performance. In doing so I conducted a Student's T-Test (see Figure 5) to determine whether my performance can be attributed to luck or skill. During this analysis, $\bar{r} \leq 0$ was the Null Hypothesis (average return less than or equal to zero). At the 95% confidence level, the critical value was 1.71 and the T ratio was -0.66, leading me to accept the null hypothesis, which implies that I was unlucky. However, it is important to acknowledge that the accuracy of this test is inhibited by the small number of orders that were executed. To improve its validity more orders need to be filled (50+). Additionally, the T-Test assumes that all trades follow the same distribution, this is unrealistic as market conditions constantly fluctuate and different trades may have different characteristics, such as size, time, etc.

	A	B	C	D	E	F	G	H	I	J	K
1	Avg.Tot.PnL	Avg.Std.Ret	Avg.Win.Ratio	Avg.Sharpe.Ratio	Avg Comm/Fee Buy		Avg Comm/Fee Sell		T Ratio	Confidence Level 95%	
2	-0.1123604	0.00451052	0.26923077	-0.1299176	-8.37		-10.82817		-0.6624522	1.706	

Figure 5 - Significant results from trades

After examining my results, I was able to replicate all the variables analysed in the backtests. Generally, there was a clear mismatch between the prior tests and the trade implementation, in which the forward tests performed considerably worse (see Figure 5). The average PnL was lower than the backtest and it was negative, which strongly suggests that the strategy implemented did not perform as expected. This is reinforced by the negative Sharpe Ratio, which indicates returns achieved were not proportionate to the level of risk taken. Furthermore, the win ratio was 15% lower which implies that the strategy produced fewer winning trades than expected. These combined results indicate that the strategy underperformed in actual market conditions. Nonetheless, it is worth noting that backtests rely on past data and are therefore subject to biases and limitations. To rectify this issue, it may be beneficial to incorporate more sophisticated risk-adjusted return models such as the Treynor measure, Jensen's Alpha or M^2. Such models provide a more nuanced evaluation of the trading strategy's performance and could enhance the prospect of profits in live market conditions. Also, executing more orders would be required to fully test the effectiveness of the approach.

Upon analysing my trades, I uncovered some noteworthy findings regarding market impact, which refers to the effect that trades can have on the price of a security. To evaluate the market impact, I analysed two trades executed in the AMEX market with an order size of 5200. The first trade was filled near the market open at 09:55, with prices ranging from 158.49 to 158.56 – a price difference of 0.07. Typically, at market open, there is a surge of trading activity (see Figure 1) and this contributes to the liquidity of the market (higher level). The order itself required a total of 41 trades to be filled completely. On the other hand, the second trade was placed at 2:30 PM and was executed uniformly at a price of 161.54 which suggests that the market impact was negligible. The order required 17 trades to be filled. A deeper order book was observed in this trade which indicates a higher level of liquidity (and therefore less market impact). This was further validated by the fact that it took 2 seconds to fill this order compared to 9 seconds for the order placed near market open. This finding contradicts the TSLA volume smile (Figure 1) and prevailing theory which suggests that during the middle of the trading day, activity and liquidity decrease, which can lead to a higher market impact i.e., higher price difference than at market open. There are potential reasons for this irregularity – either the order size was not large enough or another trader submitted an order of a similar size at the same time. Furthermore, it is worth noting that the fees associated with executing sell orders were typically higher than those of buy orders (see Figure 5). This can occur as a consequence of lower liquidity (market impact was higher for sell orders too), making it more challenging for brokers to find a suitable counterparty for executing sell orders, resulting in higher transaction costs. Finally, my best trade occurred within the first hour of the trading day at 9:55 (market open) where I made $14355.54. This is likely due to the increased volatility near market open, suggesting that the strategy performed better during periods of higher volume. However, more orders must be executed at this time to validate this.

6. Discussion

While certain trades yielded limited profits due to my lack of experience and unfavourable market conditions, my overall portfolio performance was successful and yielded a profit of $4,118.76. Moving forward it is vital to recognise and tackle the underlying factors that contributed to the challenges I encountered in these trades to enhance future performance. One example of a challenge faced was making fat finger errors, where I selected the incorrect order size to sell. This resulted in undue losses as it inhibited my ability to exit a position when the stock performance turned bearish. Through increased practice and attention to detail, I took measures to avoid repeating these mistakes, as evidenced by the improved profitability of my more recent trades. In addition, I realized that selecting a look-back window of 2 resulted in an EMA that was overly sensitive to price fluctuations, making me prone to entering false positions due to its failure to capture long-term trends accurately. To address this issue, choosing a wider look-back period would provide the perfect balance between trade frequency and a more accurate perception of market conditions. Additionally, on April 20th, 2023, I experienced significant losses as a result of Tesla's quarterly report which revealed negative returns. Technical analysis alone does not reflect fundamental price movements; hence, it is plausible to utilise both methods of analysis to gain a more comprehensive understanding of the market, enabling better informed trading decisions. Given the circumstances, it would have been prudent to suspend trading activities on that particular day as a risk mitigation measure. Additionally, if I had adopted both a long and short strategy, I may have been able to capitalise on bullish and bearish market conditions. Although investing solely in large-cap stocks such as TSLA can offer stability due to lower volatility, it may lead to limited profits due to slower price movements. The analysis of trading performance revealed that submitting larger orders were necessary to yield significant profits. To overcome this, investing in smaller firms may be advantageous to experience the size effect which suggests small-caps outperform larger firms and experience higher risk-adjusted returns. According to research, "Small-caps have grown by more than 250% – five times more than large caps" and "have outperformed large companies in 14 of the past 20 years" (Urbahn and Kraus, 2020). Finally, while market orders are easy to execute and require minimal input, implementing limit or stop orders could be considered to ensure that trades are executed at the desired price and to mitigate the risks of slippage, which can lead to unfavourable prices and increased losses.

Conclusion:

In conclusion, while my trading performance fell short of my desired profit expectations, the experience gained was invaluable. I effectively implemented all necessary steps in a rational manner to become a proficient intraday trader, including interpreting pre-analysis results from the volume smile and price trends, as well as selecting appropriate stocks for trading through backtesting. While the trading results demonstrated positive profitability, there was a notable discrepancy between the backtests and the forward tests, as illustrated in Figures 3 and 5. This could be attributed to limitations in the prior tests, such as the use of a narrow look-back period of 2. However, this is likely due to the idealised assumptions underlying backtesting, which may not accurately reflect real-world market conditions. To address these issues and improve my results I would adopt both a long and short strategy to capitalize on bullish and bearish market conditions. I would select a small-cap stock for trading, utilising fundamental analysis to identify stocks with robust financials and growth potential (thorough due diligence). Subsequently, I would employ technical analysis to critically analyse past data (of the stock) and determine entry and exit points, incorporating multiple indicators (i.e., MACD) alongside the EMA with a look-back period between 5-10, thereby fostering a more comprehensive and well-informed investment approach. In addition, I would execute significantly more trades (involving limit orders), over an extended timeframe to fully realise the strategy’s potential, whilst maintaining a vigilant and adaptable approach.

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