Optimising Moving Average Percentage Bands and Parameters for Algorithmic Intraday Trading on the EUR/USD Forex Pair.

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Abstract

This study analyses the feasible range of the moving average (MA) percentage band rule (PBR) on intraday time frames (TFs) with dual exponential moving average (DEMA) combinations, for the EUR/USD forex market (FX). The objective is to find optimal model parameters and test if the PBR has a significant positive effect. Further analysis is conducted into the effects of exchange fees and the 'stop loss break-even rule' (SLBE) introduced in this paper. Large data sets are back-tested with a fixed quantitative algorithmic trading model, changing parameters with each iteration to identify parameter combinations that maximise model profitability. The results are particularly relevant to quantitative traders and financial institutions.

The research includes 304 iterations for comparison, covering 3 DEMA combinations (5/12, 9/12 & 12/21) and three intraday TFs (5-minute, 15-minute, and hourly).

Empirical results indicate the 5/12 DEMA combination yields the greatest returns in all cases, with the 9/21 also proving effective, particularly on the 5-minute TF. The hourly has the highest return per data set, but the 5-minute estimates has the highest return over time. Exchange fees have a significant negative impact on the smaller TFs, and the SLBE rule significantly improves all results. Analysis reveals a narrower range in the PBR for further study as well as interesting TF-related patterns.

This study builds on the work of Brock (1992) and Tom (2011) and contributes to the field of trading by presenting a PBR model for intraday TFs in the FX, as well as a new DEMA algorithmic trading strategy, exchange fee analysis, and SLBE rule. It's contribution to financial economics is explored through market efficiency, economic and firm stability and the use of econometric and statistical techniques.

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Glossary of Terms

- Candles – Blocks of summarised data set to a specified time frame. They contain date & time, opening, closing, low and high of price.
- Death Cross - Short EMA crosses the long EMA negatively. Signals a trend change to the downside.
- DJIA - Dow Jones Industrial Average stock indices.
- Downtrend – Price is depreciating over time.
- False signal – A failed change trend signal.
- Golden Cross – Shorter EMA crosses the longer EMA positively. Signals are a trend to change to the upside.
- High-Frequency Trading – Fast algorithmic trading at low time frames. i.e. 1min.
- Intraday – Trading time frames that you would open and close within the same day.
- Limit order – Placing an order at a specific value that you wait to be filled. Can be cheaper than market order.
- Local price data – Information located in a small area
- Long – Opening a position expected to appreciate.
- Market order – Opening a position at any current price.
- Noise - Price is trading in a tight price range with no clear trend, crisscrossing frequently between short and long signals. Creates redundant information.

- Ranging – Price is not trending in any direction and is tightly bound between 2 points.
- Retest – In technical analysis, a retest is when the price breaks through a significant level of interest such as the exponential moving average line, and then comes back to the same level of interest before continuing the new trend.
- Rejected – Price fails a retest.
- Risk reward ratios – The value of expected profit vs loss.
- Short – Opening a position expected to depreciate.
- Slippage – Price is not filled at the desired value but fills orders nearby. Can be costly in low liquidity assets.
- Spread – Distance between EMAs.
- Stop loss – An order set to close the open trade, set a specific price, that invalidates your analysis and prevents further downside loss.
- Time Frame – Consolidated data of all trades for a period. Each period produces a bar containing price information such as bid, ask, high, low, open, and close.
- Uptrend – Price is appreciating over time.

1. Introduction

Throughout this paper, the terms "price" and “value” refers to the exchange rate of the EUR/USD and will be used interchangeably to maintain consistency with the varying contexts in which these terms are applied in the analysis.

1.1 Background

In financial markets, “fundamental analysis focuses on the intrinsic value of financial instruments by considering the economic and financial factors that affect price. Technical analysis (TA) is an approach using historical price data”, pattern repetition and risk management, to design a profitable trading strategy with an estimated probability of success (Kalirungkut, 2020, p.52). “Not only do trading systems require that prices are predictable but also that the predictable component is financially exploitable.” (Toms, 2011, p.1). As systems are probability-based, all produce **false signals**, so traders need to find a balance between win rate and **risk-reward ratios** (RRR). TA exploits market inefficiencies, contradicting the efficient market hypotheses, though this comes with a degree of risk. (Toms, p.9). TA is primarily performed graphically, using mark-up software, as it’s easier to identify price patterns and behaviour visually than with large data sets. Analysts identify recurring patterns they believe will be profitable, back-test the strategy on historical data sets and, if successful, begin trading live. Due to the probabilistic nature of TA, results only pay off once the same setup is traded consistently over time; it is not a one-shot game, so many samples are needed.

Quantitative Traders automate these systems through programming, known as algorithmic trading (algo), which identifies and executes trades on exchanges. Algos are particularly useful for **high-frequency trading**, as they can process large amounts of data and execute numerous trades every second, drastically improving efficiency compared to the physical trader. This allows a broad range of new strategies, 24-hour trading in FX markets, and is more efficient than human traders, thereby improving overall market efficiency (Frino et al., 2016). This field has been rapidly growing, Groette (2024) estimates algos make up 80% of FX orders, up from 25% in 2006! This raises the question: At what point do human traders become obsolete? And what implications does this have?

1.2 Exponential Moving Averages (EMA)

EMAs are calculated over a specified number of historical prices, giving more weight to recent data. Combined with the current price, EMAs help identify ongoing and changing market trends. As Tom’s (2011) states, “MA trading refers to the practice of systematically buying and selling whenever the price crosses its average.” This means, if price is above its EMA, it is in an uptrend, if below, a downtrend. EMAs are known to lag which reduces their effectiveness as stand-alone trading signals. This is partially addressed by using a second, faster EMA in conjunction with a slower one, a strategy known as double exponential moving average (DEMA) (Folger, 2022). The terms ‘short/long EMA’ and ‘slow/fast EMA’ will be used interchangeably in this paper.

"In its simplest form, DEMA is expressed as buying when the short-period MA rises above the long period and vice versa… The idea being to smooth out a volatile series." (Brock et al, 1992) as shown in figure 1. These are two popular trading signals, known as the 'golden cross' and the 'death cross' and indicate a trend change. Traders typically go **long** after a golden cross and **short** after a death cross. This technique underpins the model presented in this paper. According to resources like Chart School, Investopedia, and FX Open, it is the most common DEMA strategy and, therefore the most useful for quantifying the percentage band rule (PBR).

Figure 1 *Visual examples of EMA Crossover rule, 28.07.24*

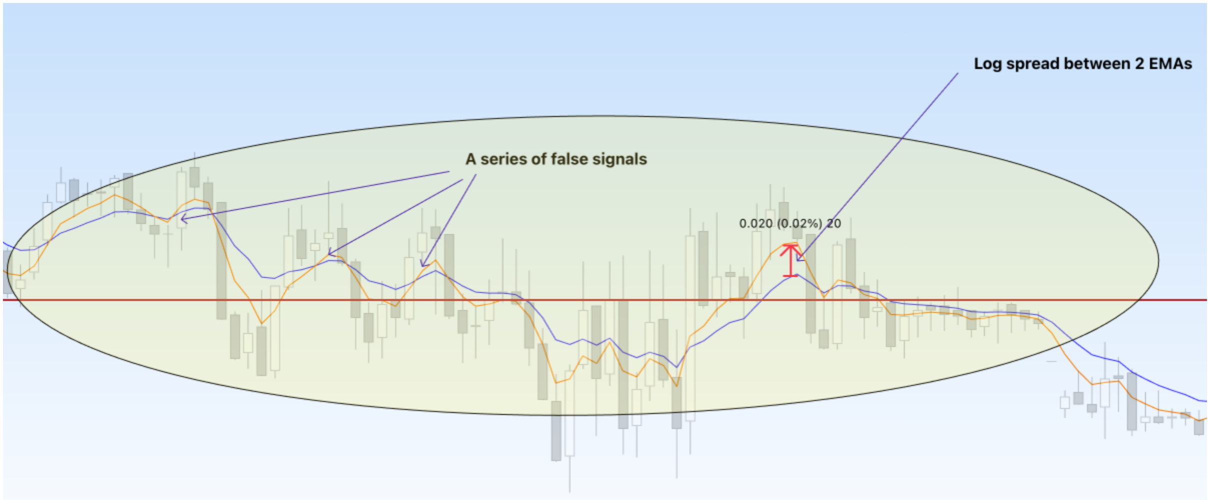

Figure 2 *Visual examples of false signals and EMA spread, 28.07.24*

As seen in Figure 2, when the DEMA strategy has **ranging** price behaviour it generates false signals, often in a row, resulting in financial loss by over-trading. The PBR aims to reduce these signals by waiting for a specified spread between the 2 EMAs, before activating a signal.

1.3 Forex

The foreign exchange market (FX) is where traders exchange currency pairs. The EUR/USD pair began trading in 1999 and is now the "most liquid currency pair in the world because it is heavily traded." (Chen, 2024). Therefore, it is the optimal pair for this research, as trade orders are highly likely to be filled at the asking price, with minimal exchange fees and slippage when compared to other assets.

1.4 Time Frames

Time frames (TF) are intervals of data grouped into uniform blocks, known as **candles**. Each candle summarises all transactions within a specified period incuding the open, close, high, and low of prices. For example, each black and white candle in Figure 1 represents this data summary and print a new candle every 5 minutes. EMAs are then calculated using this information to create a smoothed line. Lower TFs produce more data points, and this study investigates whether they provide more opportunities to profit or results in more false signals due to excess volatility.

1.5 Research

The main hypothesis of this study is to determine whether using the PBR improves results, and, if there exists a quantifiable optimal spread. This study changes the minimum PBR spread requirement to activate a trading signal, while holding other parameters constant, and analyses results against the benchmark of no PBR. The hypothesis is that the PBR improves profitability on intraday time frames and has an optimal value.

The PBR used in this paper is the logarithmic distance between the DEMA. This research expands on Brock's (1992) work which successfully uses a 1% PBR to avoid false signals in trading stock market indices. This study works on the hypothesises that 1% PBR will not hold in intraday TFs. A frequency density plot for each TF is produced showing the feasibility range for optimisation and the PBR adjusted accordingly for testing.

The second objective is to test a selection of commonly used DEMA combinations and TFs to identify the most effective ones, a long-debated conversation in the trading world.

The third objective is to demonstrate the impact of exchange fees on a trading model, backing up Tom's (2011) critique of Brock's (1992) model being unprofitable once these fees are introduced.

The final objective is to introduce and test the effectiveness of the stop-loss break-even rule (SLBE). S**top loss** will be moved to break even at a specified value to protect from downside risk. Like the empirical work done on trailing stop losses by Snorrason et al. (2009, p.36), this shows how managing downside risk improves profitability.

1.6 Economic Significance

This dissertation explores a trading model based on moving averages that is adaptable for all economic conditions and can be applied to all assets with minor adjustments. This adaptability allows for a constant income stream regardless of the economic environment. By maintaining such an income, entities enhance their stability, providing a buffer against economic downturns. During economic uncertainty, trading teams play a crucial role in mitigating the impact of adverse market conditions on their firms. The contribution of a EUR/USD algorithm is not merely a tool for generating profits, it also supports broader economic stability by providing liquidity and improving market efficiency.

Furthermore, this research utilises econometric and statistical techniques in its analysis and design, distinguishing it from bias directional strategies. The use of samples, moving averages and probability analysis allows for a more rigorous evaluation of the strategies' performance allowing for a degree of optimisation. This study not only contributes to the literature on trading strategies but also offers insights into how they can be aligned with broader economic goals. The application of traditional econometric techniques underscores the interdisciplinary nature of this work and its relevance to both financial markets and economic theory.

2. Literature Review

2.1 Efficient Market Hypothesis (EMH) & Benchmarks

This EMH hypothesis states, that because markets are efficient, asset prices reflect all available information, implying it is impossible to make returns above the market return without adding risk since prices should only react to new information. Downey (2024) writes, "While academics point to a large body of evidence in support of EMH, an equal amount of dissension also exists. For example, investors such as Warren Buffett have consistently beaten the market over long periods, which, is impossible according to the EMH." Some believe this is just luck while others argue if it was truly impossible, then technical analysis and forex trading would be redundant, yet there are industries built upon them. The Active vs Passive report 2023 shows only "24% of active managers outperformed their passive peers."

Most empirical work on the EMH is done on the higher TFs. K Meng's (2021) paper, 'The Adaptive Market Hypothesis and High-Frequency Trading' produced empirical work on the relationship between 1-minute TF and the EMH. Meng finds the measure of efficiency varies dynamically; it is not fully efficient. Through the data extracted from rapid algo communications with exchanges, he reveals a dichotomy between periods of high and low market efficiency. Algos produce less active trading and more passive trading during times of high efficiency and vice versa. Meng concludes, as the price adjusts to new information is a dynamic process, there exists a higher degree of inefficiency at the lower TFs one can take profitable advantage of. This is in line with the adaptive market hypothesis, a counterargument to the EMH studied by behavioural economists, which suggests markets are irrational and inefficient. As this paper uses intraday TFs for its study, it is relevant to show that one can 'beat the market' by adding a degree of risk.

Fama, (1970), distinguishes three forms of financial market efficiency through its informational content: Weak form, contains only historical price data, semi-strong form includes all public information and strong form contains all possible information. The strategy for this project relies on the weak form, as do many algos, however, other algos often respond instantly to new information such as interest rate changes and economic developments. As stated earlier, 80% of the Forex market is estimated to be algos. With this information, we reveal who is on the other side of trades and insight into their strategies, improving forecasting and strategy development.

Czech et al (2012), consider the difficulty of testing the efficiency of the Forex market (FX) showing "most of the research concerning the efficiency of FX is based on the simple assumption of zero expected profit." He considers the uncovered interest rate parity (UIP) as the benchmark for testing efficiency and tests the EUR/USD pair. The UIP hypothesis states that participants in FX are risk-neutral with rational expectations and that the exchange between currencies offsets any profits through the interest rate differential. In summary, he concludes that the EUR/USD is not efficient as participants have irrational expectations and are not risk-neutral. Algo behaviour can be observed and new algos are designed specifically to beat them, thus strategies must be forever evolving. This information further backs up our benchmark of 0 expected profit, without increasing risk, and shows how inefficiencies can be exploited.

2.2 Technical Analysis of Moving Averages Bands

Brock’s et al (1992) paper ‘Simple Technical Trading Rules and the Stochastic Properties of Stock Returns’ produces empirical work on the DEMA crossover and percentage band rule (PBR), laying the groundwork for this paper. Brock begins by debunking the EMH using previous empirical works and provides proof that positive returns can be made through technical analysis, that cannot be explained by market correlation, using random walk, AR(1), and 2 Garch regression models.

He tests 2 strategies on **DJIA** data sets from 1897-1986: a traditional breakout method and DEMA crossover method, both utilised on the 1-day and 10-day TFs. The DEMA strategy uses a range of very short EMAs 1/2/5 against much longer ones 50/100/150/200, then compares the same method but with a 1% PBR. Brock appears to select the 1% value arbitrarily, without providing explanation. Significantly positive results are returned when the PBR rule is introduced, in all cases. 8-30% of false signals were removed with the PBR, significantly on the 1-50 MAs, the 2 lowest values. The mean profit away from the benchmark models increased in all cases from 2%-15%. This paper draws from this model to analyse the use of the PBR on intraday TFs and define its range to give empirical intuition to the 1% value Brock has chosen, as this is limited. In summary, Brock reveals that technical analysis does have an edge over the market return due to market inefficiency, the DEMA strategy is an effective method, and, when combined with the PBR rule, improves performance by reducing false signals.

Tom's (2011) thesis, ‘The Technical Analysis Method of Moving Average Trading: Rules That Reduce the Number of Losing Trades’ introduces a different MA band, while backing up the legitimacy of technical analysis and the power of the predictability of moving average strategies with empirical research. Tom describes the “whipsawing phenomenon”, referred to in this paper as a false signal, as the “absence of a trend” where the “shorter MA wanders around repeatedly crisscrossing the longer MA” producing signals “insufficient for trading to be profitable.”

Tom criticises Brock's model, suggesting it would not be profitable if exchange fees were accounted for. Adding a fee structure is vital to back-testing, which is subject to many biases already, as it can eliminate profitability as this study later shows. While Brock still demonstrates significant results, Tom points out the poor trading rules used in those methods and provides ideas for improvement, as does the model presented in this paper. Tom accounts for exchange fees in his analysis. He notes a property of trend-following strategies that we return to later: they “produce a small number of large winning trades and a large number of small losing trades.” Which the results of this paper support. He also uses high TFs and stock market indices which are characteristically different from FX markets.

Tom introduces the ‘bounded moving average trade reduction rule’ (BMA), a quantifiable derivative of Brock’s PBR. The BMA maps a minima and maxima band around 1 MA, normalised to a range from 1 to -1. The calculations are based on **local** historical price ranges and the MA. The BMA successfully improves the results of the crossover rule, giving a higher mean return. He hypothesises that the rule would reduce the number of losing trades and increase the number of winning trades. He weakly rejects the null. He notices the potential for survivorship bias and the existence of adverse selection in stocks, two problems the FX market does not need to be concerned with.

Tom's strategy activates buys and sells between the BMA boundaries at value 1 / -1, while consistently updating the BMA as new information is acquired, allowing "trades to run". This study takes a different approach to reducing losses by introducing the stop-loss break even (SLBE) rule which allows for trades to run against expected future EMA drawdown. Additionally, there was no information on his position sizing technique, something considered imperative to a strategy.

Unlike Brock's DEMA percentage spread, Tom's strategy only uses one MA with a price band. The paper did not analyse variation within the band so there is potential for further optimisation. The band also derived its value from previous price data while Brocks uses the characteristics of the DEMA themselves which seems more effective if used correctly.

Tom acknowledges the potential for a significant loss in his exit strategy when the price moves quickly. The model in this paper fixes this with the SLBE rule. The indexes tested in both papers are not as relevant in intraday TFs or subject to single asset volatility. All back-testing is subject to survivorship, look-ahead, and implementation bias.

Both papers read as written by analysts and not live traders, therefore, this research takes a different approach to strategy modelling, focusing on risk management, as well as quantifying the band rule differently and treating results as samples with potential outcomes.

2.3 Moving Average Convergence Divergence Indicator (MACD)

The MACD is another approach used by traders. The tool calculates a new MA that is the difference between the faster and slower EMAs. A new EMA called the signal line is then created from this. Both lines are plotted into a histogram which traders then use with the crossover rule. The calculations for the MACD are like the band modelled in this paper except not logarithmic.

In Cardo J's, (2019) paper: 'Technical Analysis on Foreign Exchange Markets: MACD and RSI', the MACD crossover is back-tested against a buy and hold (B&H) strategy in the FX with no significant results. Testing was again done on the daily TF, which the EMH shows to be weaker for profitable inefficiencies than lower TFs. All currency pairs over the sample period returned negative results as did B&H, the EUR/USD was the best performer against B&H by 6% and fees were not accounted for, which would eliminate the markup. The strategy, test criteria, and trading model are weak. No stop loss is used making drawdown possibilities large when the price moves quickly. As part of their risk management strategy, "The investor cannot start a new long or short position unless the previous position is closed (no fragmentation of investment)", a rule used in this paper's model. The buy & hold benchmark is unnecessary as the UIP suggests that it would always be 0 anyway. A percentage band rule applied to the MACD would make an interesting study.

The stop-loss break-even rule introduced in this research works on the theory, that, if the price is coming back toward the entry position after moving in the desired direction, the trade should be closed at break even. This is due to EMA at T+1 having a high probability of changing trends.

3. Theoretical Framework

So far PBR empirical work has been done on higher TFs, with a variety of trading models, with stop loss, exchange fee, and risk management restrictions. There is no optimisation to quantify bands or comparisons of DEMA or TF combinations. Past works have quantified results in different ways; win rate / profit vs loss or regressions against benchmarks. There are many combinations possible, and this paper attempts to reveal some of the stronger ones, using model parameters that improve aspects of previous works.

3.1 Asset Pair

The EUR/USD is selected as it is the most liquid tradable asset pair therefore has the lowest fees and the maximum likelihood that trades are executed with minimal slippage. (Hockicko M, 2014). Momtchil T. Pojarliev (2005), observed that 60% of the total FX turnover was done in three currency pairs; USD/EUR, USD/JPY, and USD/GBP, and the share of trading in local currencies in emerging markets was only 5%. EUR/USD is expected to provide the most accurate estimates.

3.2 DEMA

There is an abundance of utilised DEMA combinations each with bias and myopic arguments to support them.

This paper selects the most frequently used DEMA. One can easily drown in the abundance of literature and suggestions. There are 3 types of MAs: EMAs, Simple MAs, and Weighted MAs. The EMA is commonly used in financial markets.

For intraday trading, suggestions ranged between 5-35 periods, with some traders using higher numbers. Another popular, yet, superstitious choice for traders is the Fibonacci sequence, a pattern of numbers that reoccur in the formation of nature and galaxies: 0, 1, 1, 2, 3, 5, 8, 13, 21, etc. (Kolkova, A. 2017)

The 5 and 21 EMAs reoccurred in a lot of literature and articles and while 8 and 13 were another option in the Fibonacci sequence, frequency of discussion tended towards 9 and 12. For this model, the observational difference using the 9 and 12 instead of 8 and 13 doesn't make a difference to the outcomes. (Hockicko, 2014; Lien, 2024; Medium, 2023; Spyder Academy; Kolkova, 2017)

3 DEMA pairs were selected. 5/12, 9/12 and 12/21. Each pair is expected to behave differently:

- 5/12 is expected to be highly sensitive to recent price changes, providing early signals with more frequency but more false signals.

- 12/21 is expected to produce signals less frequently, filtering out more false signals and reducing the number of trades.
- 9/12 is expected to be in-between the 5/12 and 12/21.

3.3 Time Frames

Abdalla K (2012) studies EUR/USD on 5m TF for algo trading using MAs. They fail to produce positive results showing buy and hold to be better. Lein K's (2024) study suggests the 5m is very profitable. R Krishnan et al (2009) studied FX market results over various strategies and TFs ranging from 5m up to the daily. The MACD strategy has the 2nd best performance out of 11 tested. The study showed all TFs were profitable but there was no significant difference in their returns over 3 months. The hourly had the best performance. The conflicting results of different studies demonstrate the importance of the model itself. A study on the predictability of the 15m for EUR/USD (Argotty-Erazo et al. 2017) shows significant results on their algo trading model.

This paper tests 3 TFs: 5-minute (5m), 15-minute (15m), and 1-hour (1h) due to their popularity amongst traders and results from previous empirical work.

3.4 Benchmark

The benchmarks used for analysis in research papers varies. This paper's hypothesis is not to beat any benchmark, but to test the percentage band rule (PBR) at various spreads and see if it will improve on the already proven profitable strategy, the DEMA crossover. Therefore, the benchmark will be the results of no PBR (set at 0.1% as the value must still > absolute 0).

3.5 Percentage Band Testing

Thus far there has been no empirical work done on optimising the band spread and little work done using the band for intraday trading. This paper first analyses each model iteration PBR feasibility range by producing a frequency density chart discussed later.

4. Data and Methodology

4.1 Data

The maximum amount of data available, roughly 10,000 data points each, was extracted from the Forex.com exchange via TradingView, for 5m, 15m & 1h. Data includes:

- Candlestick price data: high, low, open, close, date/time.
- Exponential Moving Averages for 5, 9, 12, and 21 periods.
- Swing high/low indicator values.

The first 35 and final data points were removed due to missing/incomplete values and to allow the necessary iterations for EMA calculations to be relevant. The data is held constant throughout.

4.2 Data Constraints

Data available at the time of extraction only went back as follows:

- 5m: 10th March 2024
- 15m: 30th November 2023
- 1h: 3rd January 2022

As the data available is not for the same period, for consistency, results are compared by the number of data points (10,000 each) and the samples they produce. Estimates will be derived from these results so TFs can be compared across time. Note this model is designed for all market conditions.

4.3 Percentage Band Feasibility Range

Notation:

- $\mathbf{Y_S}$ = Short EMA.
- $\mathbf{Y_L}$= Long EMA.

Percentage band spread (**PBS**) is calculated for each data point shown in Equation 1.

$$\boldsymbol{PBS = (\frac{Y_S - Y_L}{Y_L})\ x\ 100}$$

Equation 1 *Percentage Band Spread*

A frequency distribution plot is produced from these results, giving the PBR feasibility range for each time frame and DEMA combination. The bottom and top 2.5% were removed from testing as they would not produce enough samples.

Figure 3 shows the feasibility range to be tested for the 5m, 5/12 DEMA. The rest are summarised below in notation form for ease of referencing in this paper and any future work. Corresponding plots can be found in Appendix A.

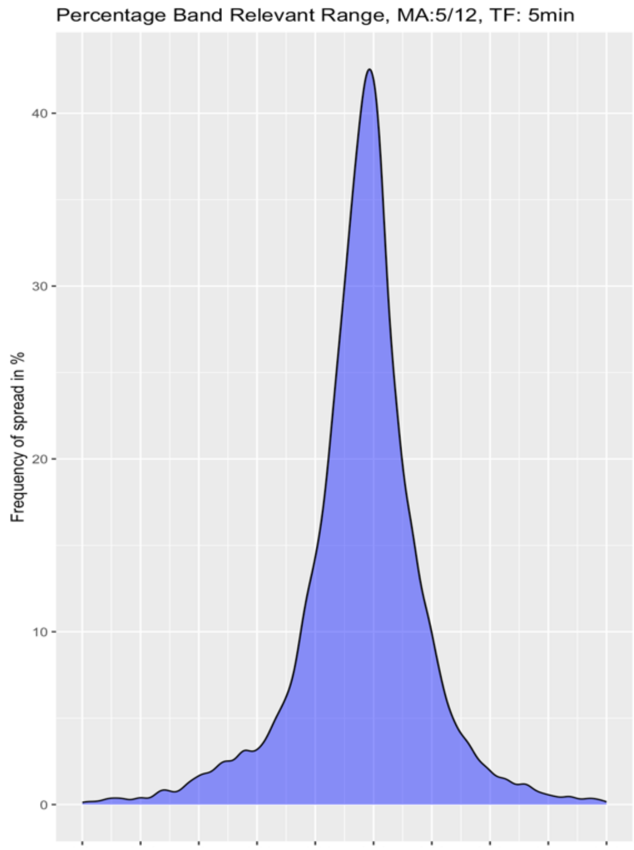

Figure 3 *Frequency Density Plot, relevant range, 5/12, 5-minute*

Notation:

- X_{TF}^{SET} | X = DEMA, SET = MA set, TF = time frame ∈ {Range low, range high}

Testing ranges of the PBR are as follows:

$X_{5m}^{5/12}$ **∈ {-0.07, 0.06}** $X_{5m}^{9/21}$ **∈ {-0.07, 0.06}** $X_{5m}^{12/21}$ **∈ {-0.05, 0.06}**

$X_{15m}^{5/12}$ **∈ {-0.07, 0.1}** $X_{15m}^{9/21}$ **∈ {-0.15, 0.15}** $X_{15m}^{12/21}$ **∈ {-0.1, 0.11}**

$X_{1h}^{5/12}$ **∈ {-0.31, 0.31}** $X_{1h}^{9/21}$ **∈ {-0.4, 0.4}** $X_{1h}^{12/21}$ **∈ {-0.27, 0.3}**

4.4 Swing High / Low Indicator

The swing high/low indicator (SHL), shown in Figure 4, is a shortcut tool that identifies the highest and lowest price points within a specified number of data points back and prints a new value each time new data penetrates specific values.

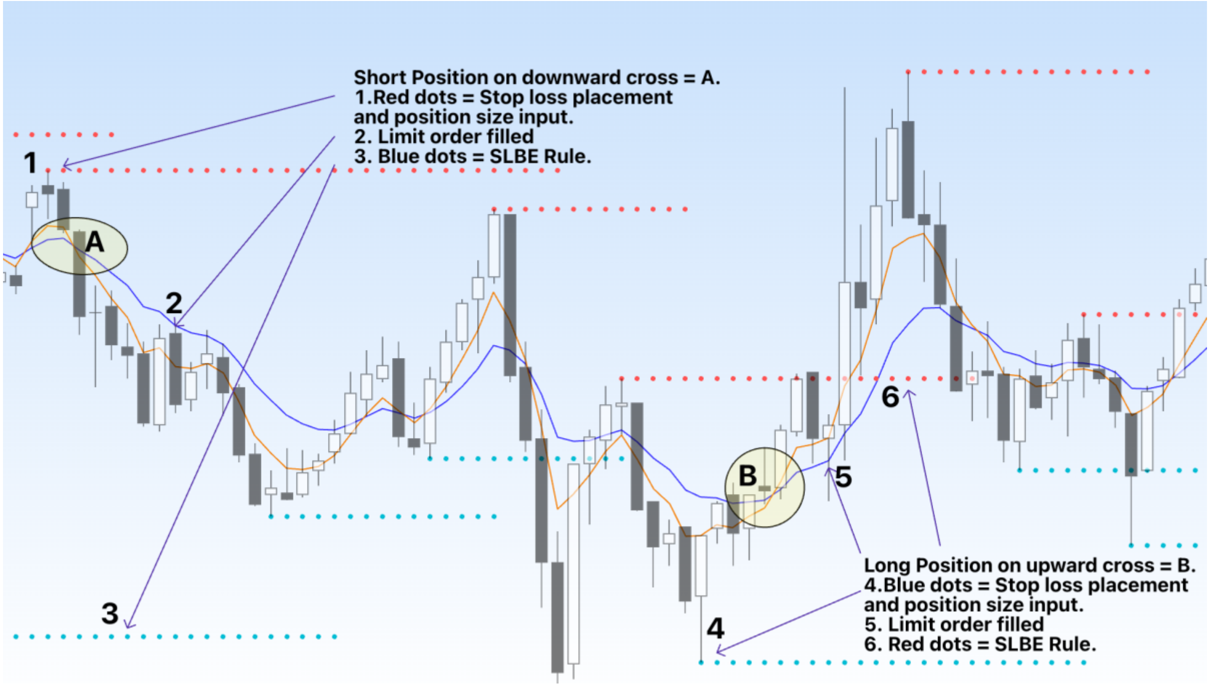

Figure 4 *Visual guide of the constant model rules, produced for purpose 29.07.24*

The algo ensures the SHL values are a minimum distance from the buy price and adjusts if not. This provides robustness to the samples created, by avoiding stop losses and SLBE values with a close proximity to the open price. Otherwise, it would cause negative values, large position sizes, and high probability stop loss hits. It also removes outliers from the results, as 1 to 2 samples per period were returning 30-80x. The algo would have made these trades, however, data is normalised to 5x returns (an average return of a successful trade), removing the outliers to get more accurate estimates. Less than 1% of samples opened trades with the stop loss reversed, an issue that would not occur live, as the order would be rejected, these samples were normalised to the correct stop loss value of -1%.

Algos were rigorously tested by observation for robustness until they performed exactly as required.

4.5 EMA Formulae

Notation:

- Y_t = Current EMA
- P_t = Price (Current exchange rate of EUR/USD).
- N = Number of data points to look back

Equation 2 shows the formulae for the EMAs where 5 is a smoothing line. The smoothing line reduces data noise by applying more weight to recent values.

$$\boldsymbol{Y_t = P_t\left(\frac{5}{(1+N)}\right) + Y_{t+1}\left[1-\left(\frac{5}{(1+N)}\right)\right]}$$

Equation 2 *EMA formulae with smoothing line*

4.6 Limit Order

So far none of the empirical work used **limit orders**. Limit orders can significantly improve position size via entry price. This paper uses the 'retest model'. When analysing patterns observationally it can be seen, with a high probability, that price revisits the long EMA as a **retest** before continuing its new trend, often allowing for a better entry price than **market orders**. This can be seen in figure 4 at points 2 and 5. Placing limit orders enables the use of the stop-loss break-even rule. A study into the profitability of limit vs market orders would be interesting for future work.

4.7 Trade Management

The model in this paper utilises a stop loss above/below the EMAs, at the **swing high** (SH) or **swing low** (SL) values. This allows for position size calculations and an early close if the EMAs cross back again. Maximum loss is set at 1%. Position size is calculated per equation 3.

$$\textit{Position size} = \frac{\textbf{Portfolio Value x 0.01}}{\textbf{Open price} - \textbf{stop loss price}}$$

Equation 3 *Position size formulae*

Technical Analysts educator, Inks, C (TWC, 2024), stresses the importance of trade management if one is to be a successful trader. Going live with a model reveals back-testing's many flaws that previous empirical works do not discuss. Those models are likely to fail live. Managing trades can have significant impact on profits by protecting positions along the way including cutting losses early. This model introduces a stop-loss break-even rule as discussed earlier.

4.8 Exchange Fee Structure

Oanda is one of the most popular exchanges in the UK for trading forex. It is the staple fee calculator for QuantConnect back-testing and has an absolute spread averaging 0.6, which will be used to calculate fees for this model. This paper analyses the amount of p&l taken by exchange fees at each iteration, giving a more accurate representation of live trading results. Exchange fees are calculated per equation 4.

$$\textit{Exchange fee} = [\textit{Position size x 0.00006}]$$

Equation 4 *Exchange fee estimate formulae*

Equation 5 shows the formulae to calculate the cost of exchange fees relative to the p&l and is in percent to keep a consistent measure across all models.

$$\textbf{Fee cost as}\ \%\ \textbf{of p\&l} = \left(\frac{\textbf{Exchange fee}}{\textbf{p\&l before fees}}\right) \textbf{x100}$$

Equation 5 *Cost of fees in percentage of p&l*

4.9 Model Assumptions

- Only 1 position will be open at a time in the direction of the trend. A trend change signal closes the open position and creates a new limit order.
- Trading is done 24/7, 5 days a week, excluding bank holidays.
- Maximum loss per trade is always 1% of the portfolio minus exchange fees.
- The model compounds p&l by adding it to the portfolio total as each sample is complete.
- All data and parameters are held constant per test, except for the desired parameter changes being tested.
- t cannot be observed until t_{+1}.

4.10 Analysis Method

The algorithm performs as if it were a live trader and produces samples. It follows through the data sets chronologically until specific conditions occur. When a signal is triggered, it becomes a sample. The sample reveals 1 of 3 exit conditions and is then complete, and results are produced. The algorithm continues onto the data point after the exit condition and repeats the steps above.

Hundreds of samples are gathered from each set and assessed. The results reveal the probability of the 3 outcomes, an estimate of profits over 10,000 data points, an analysis of longs vs shorts, and quantifies the effect of the SLBE rule amongst other statistical analysis possibilities.

Results are expressed in percentage terms and a starting portfolio of $10,000 is used on each iteration. Return is calculated as a risk-reward ratio (equation 6), which shows how much your portfolio has changed per trade.

Risk = Open price – stop loss price

Reward = Close price - open price

Risk reward ratio = Reward / Risk

Equation 6 *Risk reward ratio formulae*

Win rate and SLBE success rate are calculated per equations 7 and 8.

$$\text{Win rate} = \left(\frac{\textbf{Number of samples}}{\textbf{Number of Sample with } p\&l > 0}\right) x\ 100$$

Equation 7 *Win rate formulae*

$$SLBE\ succcess\ rate = \left(\frac{\textbf{Number of samples}}{\textbf{Number of samples with } p\&l = 0}\right) x100$$

Equation 8 *Stop loss break even rule success rate formulae*

4.11 The Model

The model is kept constant across all TFs, DEMA combinations, and PBR changes.

Notation:

- $\boldsymbol{Y_S^t}$ = Short EMA, current period.
- $\boldsymbol{Y_L^t}$ = Long EMA, current period.
- $\boldsymbol{C^{t-1}}$ = Closing price at the previous data point.
- $\boldsymbol{PBS^{t-1}}$ = Percentage band spread at the previous data point

4.11.1 Opening and Closing Trades

When a data point completes with no open position:

- **Long condition:** If, $\{\boldsymbol{C^{t-1} > Y_S^{t-1} > Y_L^{t-1}}\}$, set limit order equal to Y_L^{t-1} with a position size equal to 1% of portfolio value against the previous SL. Close open short position. As each data point completes, dynamically move the limit order toY_L^{t-1} until an order is filled.

- **Short condition:** If, $\{\boldsymbol{C^{t-1} < Y_S^{t-1} < Y_L^{t-1}}\}$, set limit order equal to Y_L^{t-1} with a position size equal to 1% of portfolio value against the previous SH. Close open long position. As each data point completes, dynamically move the limit order to Y_L^{t-1} until an order is filled.

A position can close under 2 other conditions:

- **Price = Initial stop loss value –** If the signal is false, the price will equal the stop loss value before a closing condition above, and the trade is exited at a loss of 1%.

- **Stop loss break-even rule –** The signal is initially good and the price moves in the desired direction taking the EMA line with it. Price reaches the values of SL/SH and the stop loss is moved to the entry value. Price action can often reverse quickly when reaching these values pushing it below the newly formed EMA line. Before the lagged exit signal occurs, the trade is closed at entry value, sparing a loss.

1.11.2 Percentage Band Rule

Ceteris paribus, the PBR is introduced, and the price must be strictly higher/lower than its value before activating a trading signal in attempt to reduce the number of false signals.

Notation:

- M = Selected percentage band spread threshold.
- **Long condition:** If $\{C^{t-1} > Y_S^{t-1} > Y_L^{t-1}\}$ **and** $\{C^{t-1} > PBS^{t-1} > M\}$
- **Short condition:** If $\{C^{t-1} < Y_S^{t-1} < Y_L^{t-1}\}$ **and** $\{C^{t-1} < PBS^{t-1} < M\}$

The effect of the change in M is the main analysis of this paper. The crossover rule requires the shorter EMA to be positive or negative so M cannot equal 0 and has been set to a minimal value of 0.1% for no PBR.

5. Empirical Analysis and Discussion

5.1 Introduction

This section analyses and discusses the empirical data collected during the research process. The analysis and discussion are presented together to provide a cohesive understanding and interpretation of the various discussion points. The EMA crossover rule requires

5.2 Feasibility Range Outcome

The feasibility range had no significant variance between the DEMA on the 5m, shown in section 4.3. The 15m and 1h had a notably wider range on the 9/21 DEMA, which is to be expected, as the distance between those EMAs is larger. There is no information revealed from the feasibility range analysis other than the range itself.

As expected, the larger the M, the fewer samples were produced. The win rate has no significant change as M increases and remains in a 21-37% range, averaging 29%. Range extremities produce outliers, however, there are not enough samples to validate the outcome. This supports Tom's (2011) findings for trend-based strategies. Table 1 demonstrates this with the $X_{1h}^{5/12}$, with no PBR (M = 0.1%) samples total 1082 and gradually decline towards the range tails, M = 20%, where there are only 65 samples. For the full summary of all iterations, see the Appendix B.

Parameters	Direction	Samples	Win Rate
M = 0.1% 5 & 12	Long Short	540 542	27% 28%
M = 0.5% 5 & 12	Long Short	491 495	28% 30%
M = 1% 5 & 12	Long Short	431 437	29% 30%
M = 2% 5 & 12	Long Short	348 351	30% 31%
M = 5% 5 & 12	Long Short	219 221	30% 28%
M = 7.5% 5 & 12	Long Short	161 158	27% 26%
M = 10% 5 & 12	Long Short	116 115	28% 27%
M = 15% 5 & 12	Long Short	59 61	25% 30%
M = 20% 5 & 12	Long Short	35 30	29% 37%

Table 1 *Samples and win rate of the 1h 5/12 DEMA at M values*

5.3 Summary Model Iterations

The study tested 304 iterations of the default model, changing combinations and rules each iteration. The percentage of profitable iterations shown by the blue line in figure 5, are: 5m - 74.47%, 15m - 85.71%, and 1h - 94.34%. The higher the TF, the more profitable the model is per data set. Further studies on other TFs could provide more insight and optimal TFs for the DEMA crossover strategy.

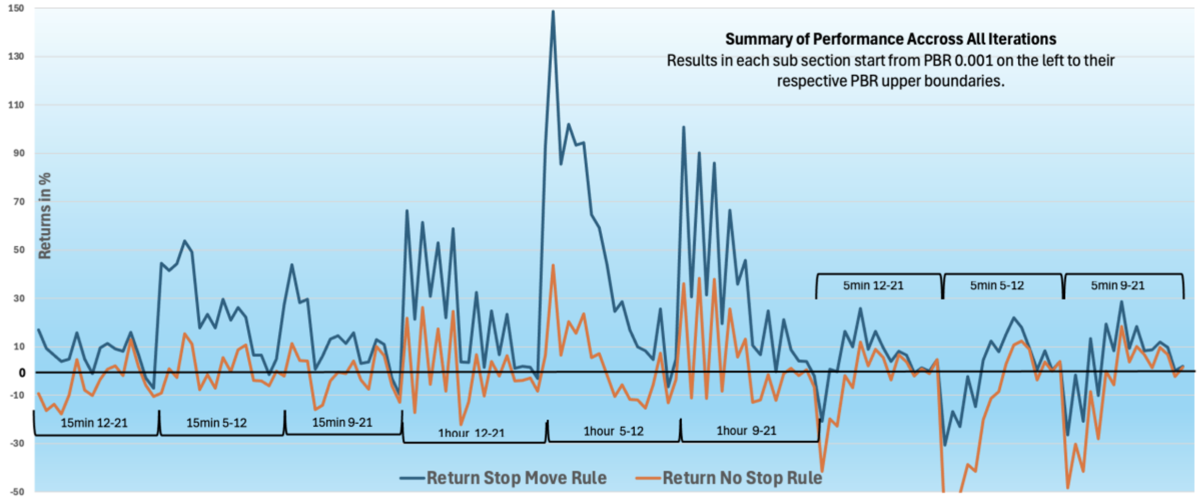

Figure 5 *Summary of returns per DEMA & TF combination across the feasibility range*

5.4 Stop Loss Break Even Rule (SLBE)

99% of iterations with the SLBE rule improved performance. The orange line in Figure 5 show performance without the SLBE. The rule protected 30% of trades from losses on average and made significant improvements to all results, backing up the importance of managing a trade. The hypothesis that the SLBE rule improves results is not rejected.

5.5 Exchange Fee Impact

The impact of fees varies across TFs. Without fees the 5m results skew heavily to the positive side. When fees are included, they take 89% of the profits on average. The smaller the M, the larger percent of profits were taken by fees, sometimes being above 100% of profits. The $\boldsymbol{X_{5m}^{9/21}}$ *and* $\boldsymbol{X_{5m}^{12/21}}$ become profitable as M exceeds 0.5% while $\boldsymbol{X_{5m}^{5/12}}$ requires M to be at least 1%, however, as illustrated in Figure 6, fees continue to significantly reduce profits.

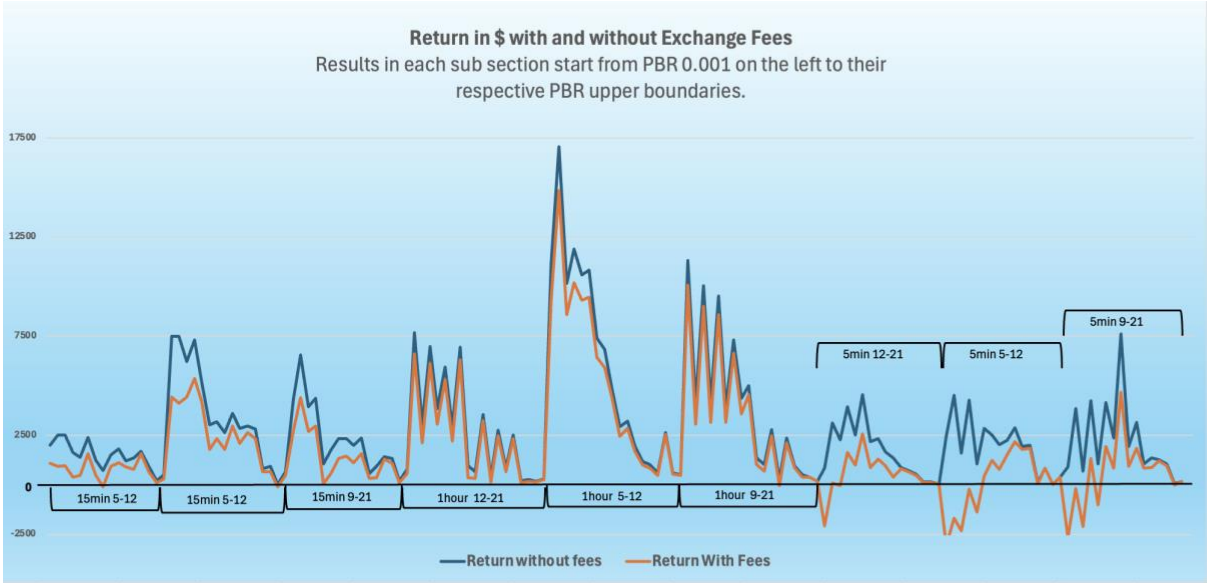

Figure 6 *Impact of fees on returns*

The 15m TF fees cost 49% of profits on average, but the final p&l remained mostly positive. The fee percentage decreased as M increased on the $\boldsymbol{X_{15m}^{5/12}}$, but no distinctive pattern emerged on the other DEMA combinations.

The 1h TF was minimally impacted by fees averaging 19% of profits, with most results skewed towards the 10-15% range.

This backs up Tom's (2011) critique of Brock's (1992) model who states the model would not have been profitable if he had accounted for exchange fees. This demonstrates not only the importance of including fees in any financial analysis but also the low fee structure of the EUR/USD compared to stock indices, which saw a significant impact to profits on the daily TF. Back-testing without fees should not be used as a metric for real returns.

5.6 DEMA Combinations and Time Frames

Table 2 shows that with no PBR, $\boldsymbol{X^{5/12}}$ performed the best on the 1h and 15m TFs followed closely by $\boldsymbol{X^{9/21}}$**.** Both have significantly better performance than $\boldsymbol{X^{12/21}}$**.** These results are reversed for the 5m which were all negative. This suggests the $\boldsymbol{X^{5/12}}$ increases the results of a strategy, IE if the strategy is profitable, it will improve returns over the other DEMA, if it is not profitable it will increase losses. DEMA combinations behaved as expected with 5/12 producing the most samples and 12/21 producing the least.

Parameters	Direction	Return
15m M=0.1%	Long	17.06%
12 & 21	Short	9.37%
15m M=0.1%	Long	44.43%
5 & 12	Short	41.42%
15m M=0.1%	Long	27.42%
9 & 21	Short	43.99%
1h M=0.1%	Long	66.27%
12 & 21	Short	21.3%
1h M=0.1%	Long	92.93%
5 & 12	Short	148.57%
1h M=0.1%	Long	100.77%
9 & 21	Short	30.59%
5m M=0.1%	Long	-20.74%
12 & 21	Short	0.76%
5m M=0.1%	Long	-30.56%
5 & 12	Short	-16.84%
5m M=0.1%	Long	-26.45%
9 & 21	Short	-1.79%

Table 3 *No PBR DEMA crossover performance*

Parameters	Direction	Return
15m M=0.1%	Long	68.24%
12 & 21	Short	37.48%
15m M=0.1%	Long	177.72%
5 & 12	Short	165.68%
15m M=0.1%	Long	109.68%
9 & 21	Short	175.96%

Table 2 *Estimates of the 15-minute returns normalised*

In all cases, the 1h and 15m TFs have positive p&ls but the 1h combinations outperform all 15m iterations. As this is a comparison across data sets, multiplying the 15m performance by 4 normalised the returns for time and results are shown in Table 2. The EUR/USD intraday study by R Krishnan et al (2009) showed no significant difference between the 5m, 15m, and 1h when compared over time, however, the strategy studied in this paper reveals the 15m to be superior. The estimations are weak and should be taken as such. If more data was available further studies could account for real estimates across time.

5.7 Percentage Band Rule

In line with Tom (2011), the PBR has ambiguous results, varying greatly across combinations, showing significant improvement, deterioration or insignificant differences. The 5m was not profitable until a few iterations of the PBR, showing it had a significantly positive impact on performance supporting the hypothesis.

Brock's (1992) 1% PBR on the daily TF reduced trading signals by 8-30% many of which were false signals. The 5m TF showed significantly positive results after reducing samples by 47-80%, the 15m TF is ambiguous, varying greatly at different values. The 1h showed no significant results after reducing signals. This papers research indicates that eliminating false signals may not be the cause of improved results, an investigation for further empirical work.

The results were using the PBR makes no significant difference to not using it, is beneficial to traders. Traders should use the PBR, reducing workload for similar results. This adds a utility to the PBR that is not just based on profit. Research into other utilities gained from trading would make for an interesting study.

Each model either identifies a narrower optimised PBR range for use / further study or provides no positive results. Shorts and longs have different outcomes, no specific optimised points can be identified. The values identified in the results are approximations, with the actual values likely falling somewhere around the reported figures.

5.7.1 5min Time Frame

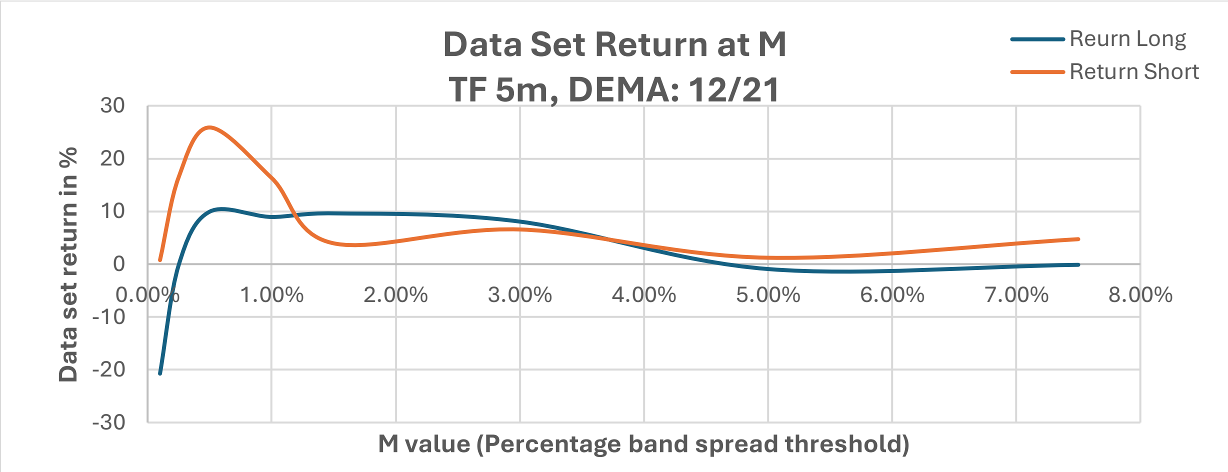

Figure 7 *Return in % at M conditional value of the 5-minute time frame, 12/21 DEMA.*

$X_{5m}^{12/21}$: Long become profitable at M=0.25%, with an optimal range of M=0.5% - 3% returning 10%. Shorts have an optimal range between M=0.25% - 0.75% returning 20-25%. The optimal point suggested when combined would be M=0.5%.

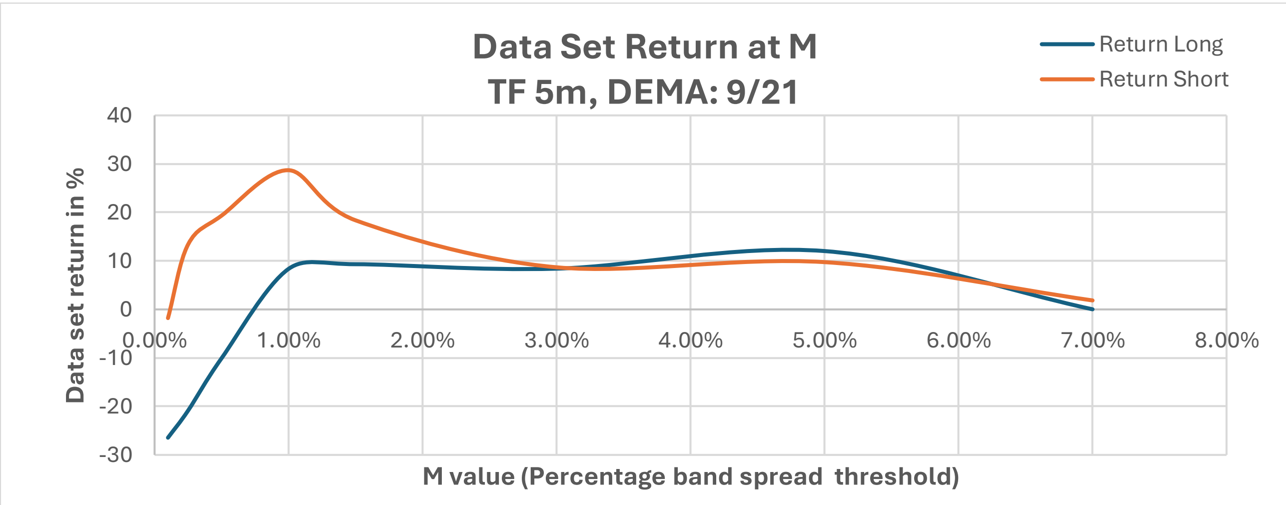

Figure 8 *Return in % at M conditional value of the 5-minute time frame, 9/21 DEMA.*

$X_{5m}^{9/21}$: Longs become profitable at M=0.75%, with an optimal range of M=1% - 6% returning 10%. Shorts have an optimal range between M=0.5% - 1.25% returning 20%-30%. The optimal point suggested when combined would be M=1%.

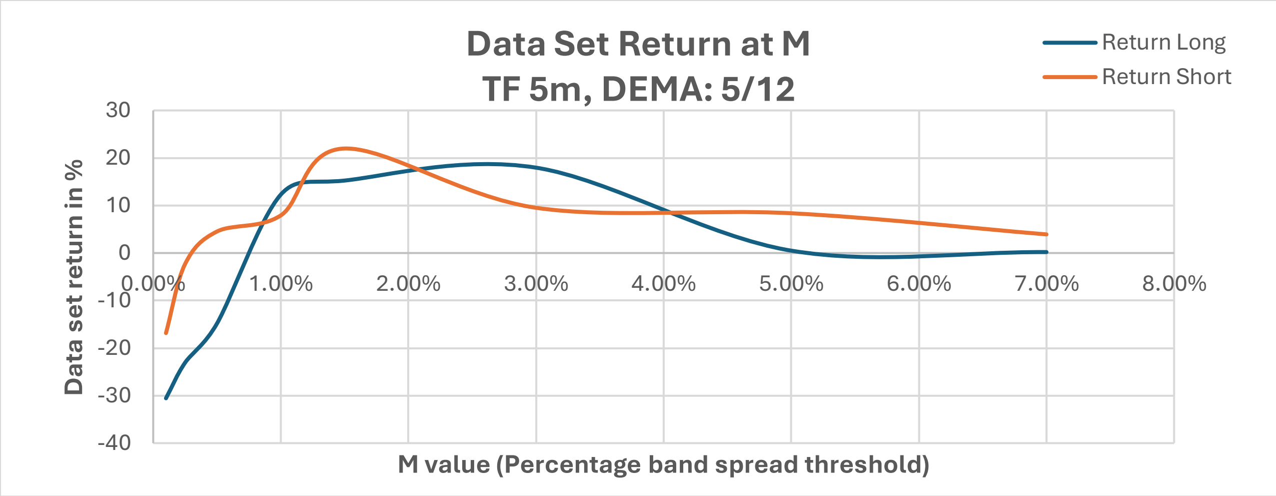

Figure 9 *Return in % at M conditional value of the 5-minute time frame, 5/12 DEMA.*

$\boldsymbol{X_{5m}^{5/12}}$: Longs become profitable at M=0.75%, with an optimal range of M=1% - 4% returning 15-20%. Shorts become profitable at M=0.5% with an optimal range between M=1.25% - 2.25% returning 20%. The optimal range suggested when combined would be M=1.5-2.5%.

The 5m TF is not profitable without the PBR, results show significant improvement when applied across all DEMA combinations, and a profitable range can be defined with results declining after. Expected returns from the optimal ranges are 30-40%. No DEMA combination can be identified as significantly better than any other, but the 5/12 performed the best.

5.7.2 15min Time Frame

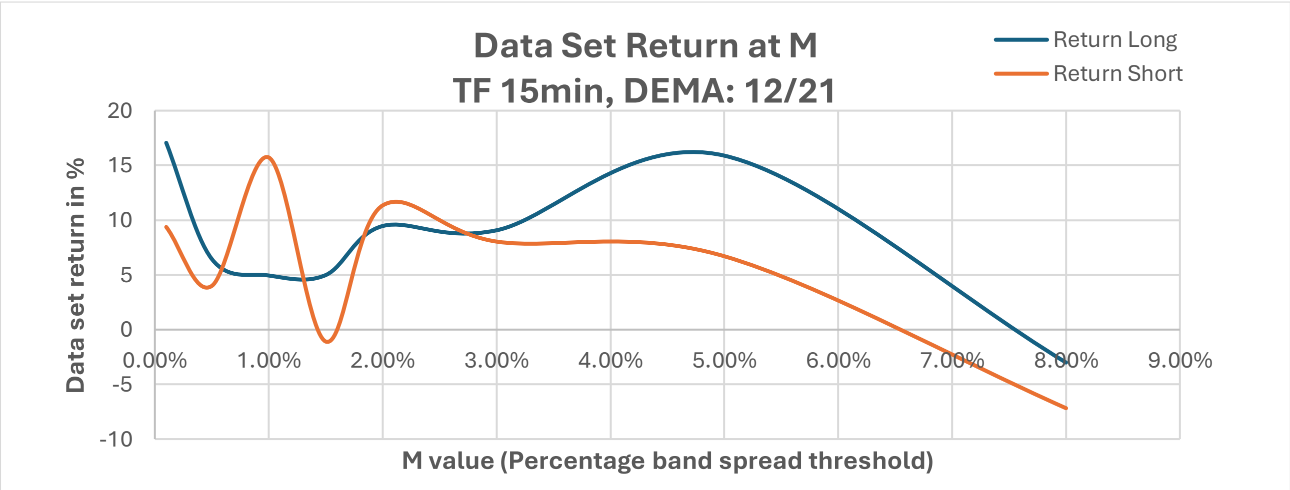

Figure 10 *Return in % at M conditional value of the 15-minute time frame, 12/21 DEMA.*

$\boldsymbol{X_{15m}^{12/21}}$: Longs are profitable without the PBR and equally profitable at M=4-5.5%, returning 15%. Shorts have an optimal range between M=0.75% - 1.25% returning 15%. When combined, results are ambiguous and have no significant optimal point. No PBR, M=2%, and M=4-5.5% both have slightly optimal returns of 25%.

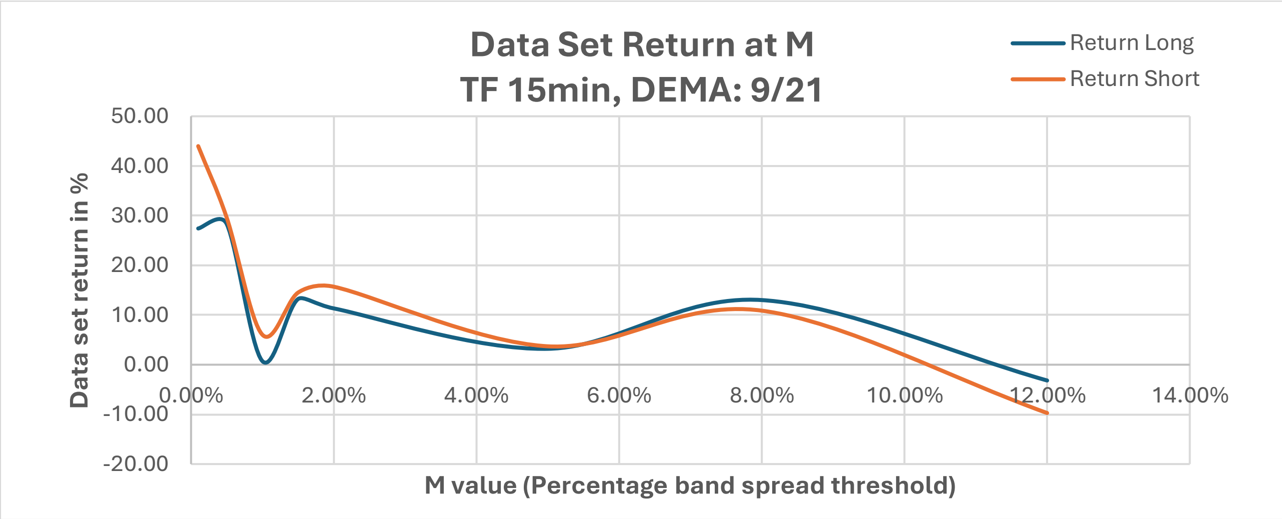

Figure 11 *Return in % at M conditional value of the 15-minute time frame, 9/21 DEMA.*

$\boldsymbol{X_{15m}^{9/21}}$**:** All trades are maximised without the PBR rule returning 30% and 45% respectively. All points significantly reduce the profitability of the model with a slight uptick around M=1.75% and 8%.

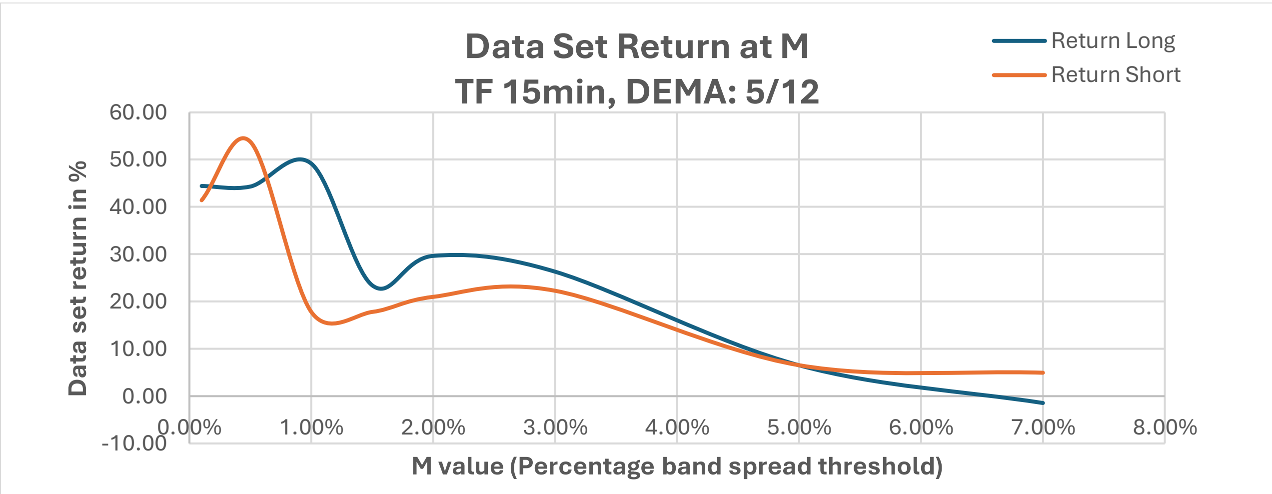

Figure 12 *Return in % at M conditional value of the 15-minute time frame, 5/12 DEMA.*

$\boldsymbol{X_{15m}^{5/12}}$**:** All trades are significantly profitable with no PBR. Short performance is maximised at M=0.5%, returning 55%, and longs at M=1%, returning 50%, after which they rapidly decline. The combined optimal range is M=0.5-1.25% with a return of 90%.

The PBR on the 15m improves the 5/12 DEMA but worsens the others. The prevailing DEMA is 5/12 with expected returns from the optimal range being 90%.

5.7.3 1 Hour Time Frame

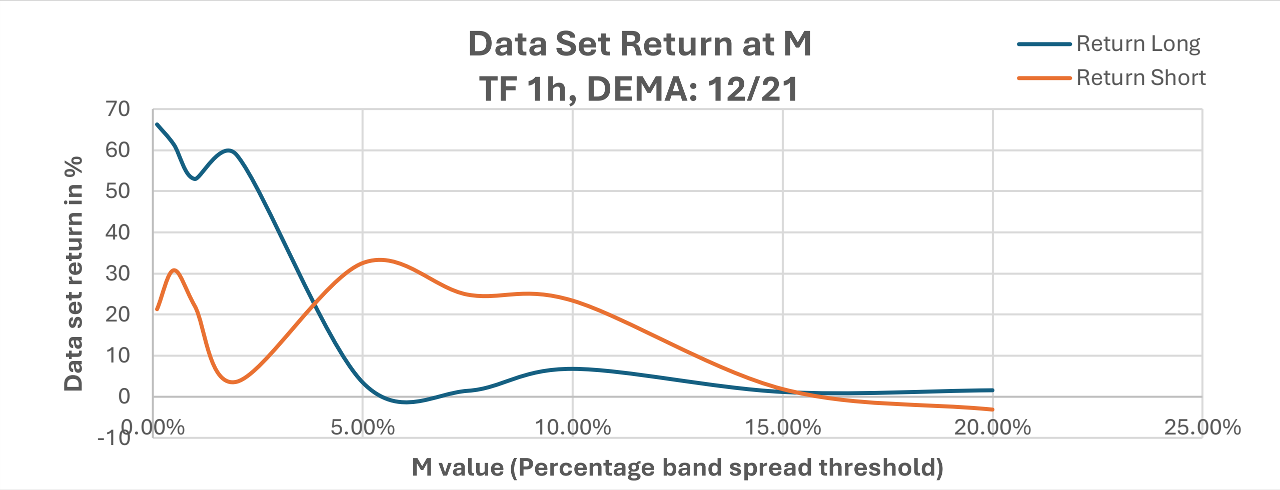

***Figure 13** Return in % at M conditional value of the 1-hour time frame, 12/21 DEMA.*

$\boldsymbol{X_{1h}^{12/21}}$**:** Longs are profitable without the PBR returning 65%. Shorts have an optimal point at M=5%, returning 30% but this is not much of an improvement from no PBR. When combined, the optimal point is M=0.05% returning 90%.

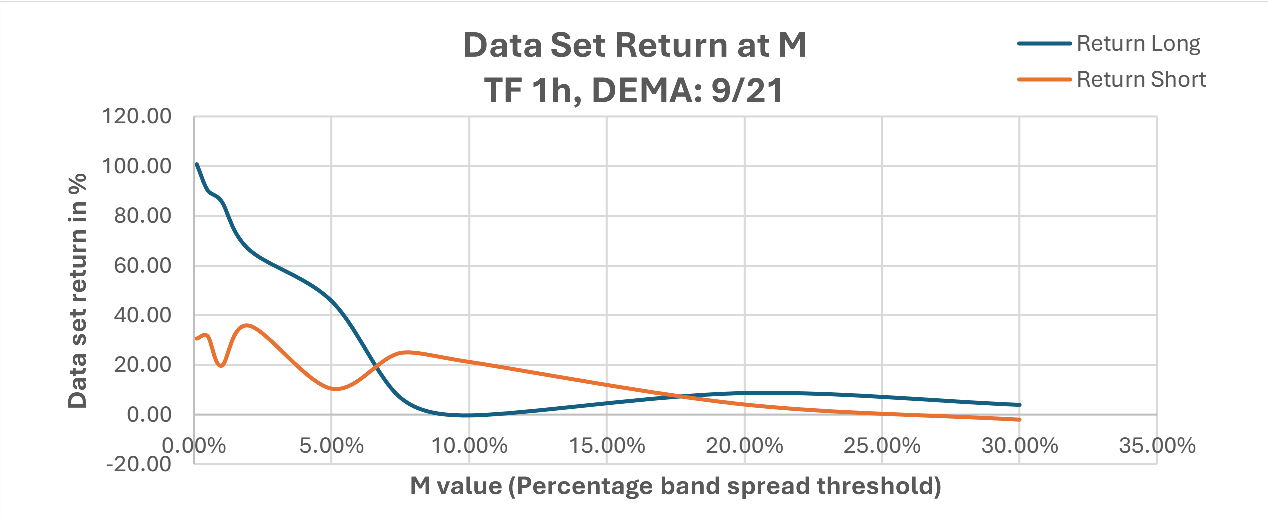

***Figure 14** Return in % at M conditional value of the 1-hour time frame, 9/21 DEMA.*

$\boldsymbol{X_{1h}^{9/21}}$**:** Longs are profitable without the PBR, returning 100%, before declining rapidly after introduction. Shorts have an optimal point at M=2% returning 30%, but this is not much of an improvement from no PBR. When combined, the optimal point is no PBR returning 130%.

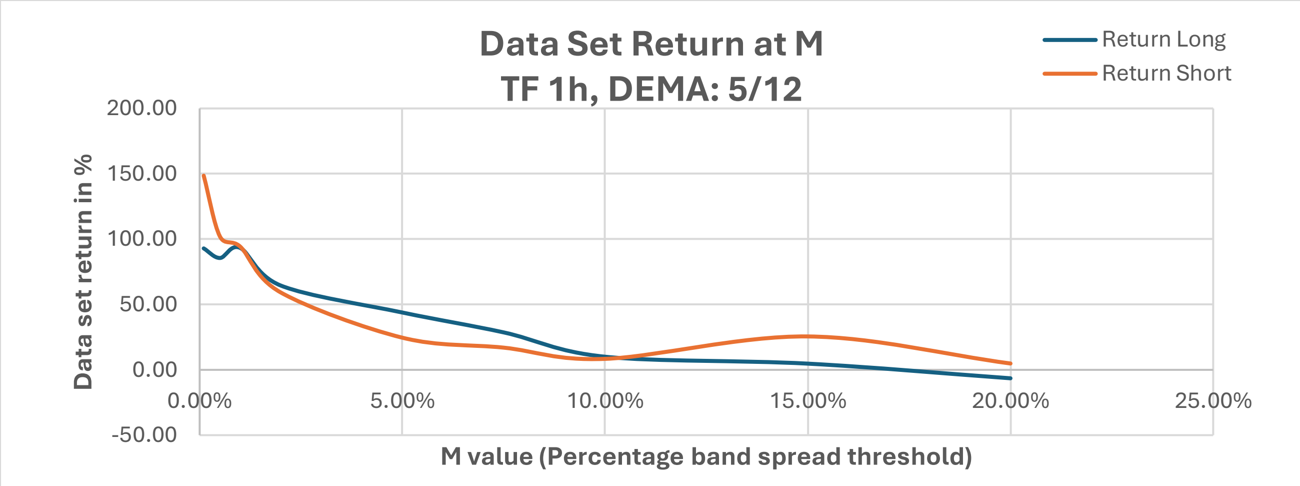

Figure 15 *Return in % at M conditional value of the 1-hour time frame, 5/12 DEMA.*

$\boldsymbol{X_{1h}^{5/12}}$**:** Longs are profitable without the PBR up to M=1%, returning 90%, before declining rapidly. Shorts are profitable without the PBR, returning 150%, then decline rapidly when introduced. When combined, the optimal point is no PBR returning 240%.

The PBR has no positive effect on $\boldsymbol{X_{1h}^{5/12}}$ and $\boldsymbol{X_{1h}^{9/21}}$with only a slight uptick on $\boldsymbol{X_{1h}^{12/21}}$. The 5/12 DEMA has significantly better results due to the performance of shorts.

5.8 Time Frame Results Comparison

The 5/12 is the best-performing DEMA in all cases. Using the optimal estimates, the 5m and 15m are normalised to match the trading period of the 1h to compare results across time. The 15m results are multiplied by 4 and the 5m by 12. Estimates are as follows:

Parameters	Direction	Return
5m M=1.5% 5 & 12	Long Short	183% 263.88%
15m M=0.5% 5 & 12	Long Short	177.28% 215.04%
1h M=0.1% 5 & 12	Long Short	92.93% 148.57%

Table 4 *Estimates, normalised for time periods, of the best performing combinations for each time frame*

Contrary to R Krishnan et al (2009) who identified no optimal TF, the estimates suggest the algo running the 5m TF would have the highest returns over the same period, followed by 15m and 1h. Despite the high fee structure and lower performance per data set, there is increased opportunity given by faster trading.

The data suggests the higher the TF, the better the model, however, more empirical work should be done on other TFs to verify this. Further work may reveal an optimal TF lower than 5m but the assumption that there exists a breaking point, where, due to the impact of fees and position size, the model would no longer hold.

As the PBR was necessary to make the 5m TF profitable, and the 5m estimates are the highest, the PBR has a significant impact overall on this trading strategy, supporting the hypothesis of improving profitability and finding an optimal value. However, the impact on individual models is ambiguous so the hypothesis should be weakly rejected.

6. Conclusion

6.1 Hypothesis Revisited & Future Studies

The hypothesis that PBR improves profitability on intraday TFs and has an optimal value, is weakly rejected. Significant positive results are found on the 5m, however the 15m was ambiguous and the 1h had significantly negative results. Quant Traders can use these findings as a base for future algos. This study is limited to 3 TFs and research on more TFs < 5m and > 1h should be done.

The best DEMA combination is the 5/12, the fastest-reacting pair. It produces more samples and allows for quicker exits and larger position sizes. The best TF performance was the 1h by data set analysed but estimates reveal it is worth using the 5m to maximise profit. Quant Traders can use this research when making decisions on intraday parameters and this research can be used as a base for analysis of more DEMA as this study is limited to 3 of each.

Exchange fees on EUR/USD are low but take a huge portion of profits as the TFs get smaller. Only with the introduction of the PBR at 0.5%+ does the 5m become profitable. Future research must be done with fees as without them results are not reliable. The fee analysis provides analysts with an insight into what can be expected in the FX market.

The SLBE hypothesis was not rejected and produced significant results improving 99% of iterations. It stresses the importance of trade management in algos which empirical research does not implement. Future empirical research could help demonstrate the need for more trade management strategies in algorithmic trading.

6.2 Limitations

Results will likely vary widely when initiated in live trading. Although the maximum data points were used, selection bias exists. Time period estimates are not an accurate representation of real results. As the macro environment changes price behaviour changes drastically, and what worked in one period may not work in the next. This is referred to as overfitting bias. Slippage is not accounted for but should be minimal with the liquidity of the EUR/USD pair. The the algo has imperfections with position sizing and swing high / swing low calculations, though these are below 1% of the samples.

The model sets limit orders $\boldsymbol{Y_L^t}$ however, in real time this would not be observable. Setting them just below $\boldsymbol{Y_S^{t-1}}$ would be optimal with minimal impact on results.

The model is straightforward, choosing only a few popular combinations and one risk management strategy out of many available options.

6.3 Other Future Work

A study into utilities besides profit gained from different trading strategies could yield interesting results. With the growing number of algos vs physical traders at what point do human traders become obsolete? And what implications does this have?

Analysis suggests improving performance is not correlated with removing false signals, an investigation for further empirical work.

A study into the correlation between probability and profitability of buying a retest with limit orders vs market orders would be interesting.

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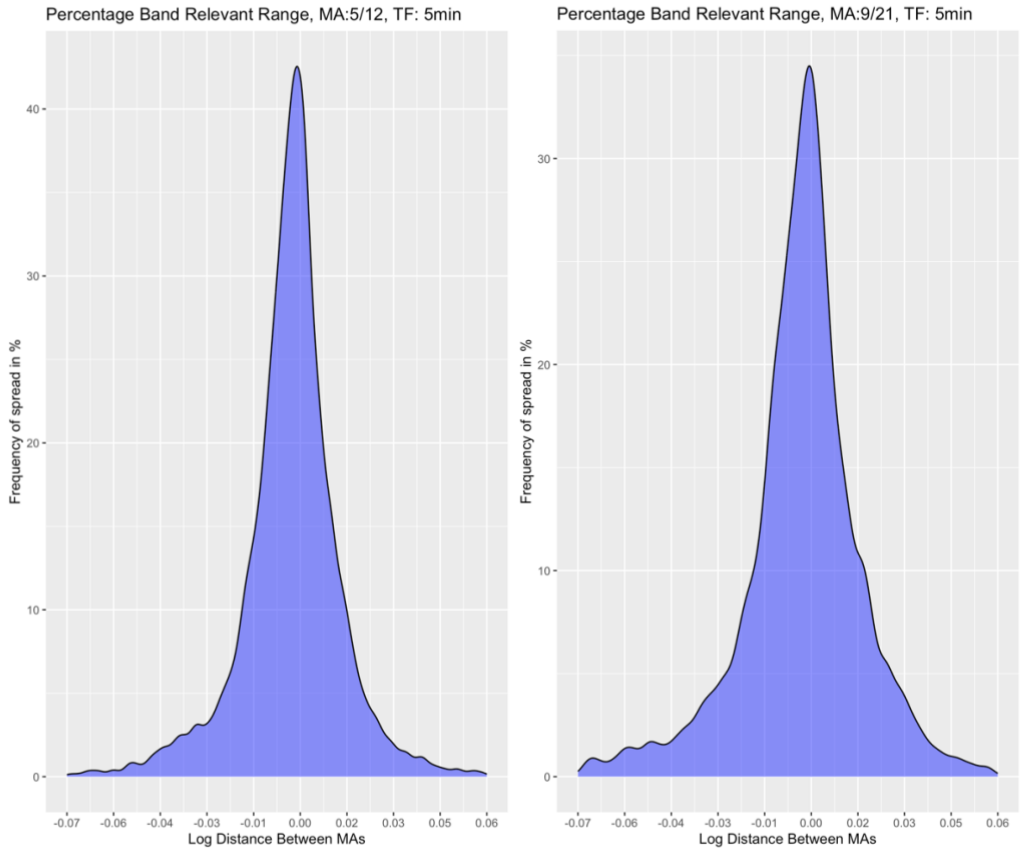
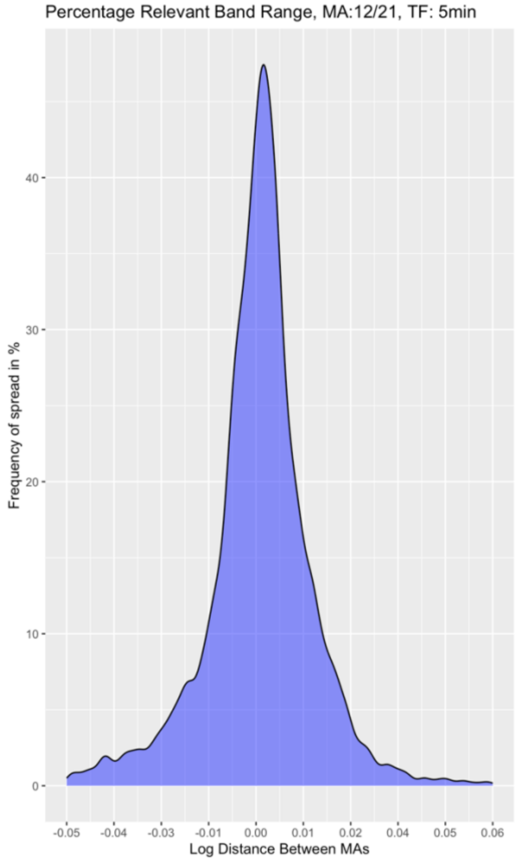
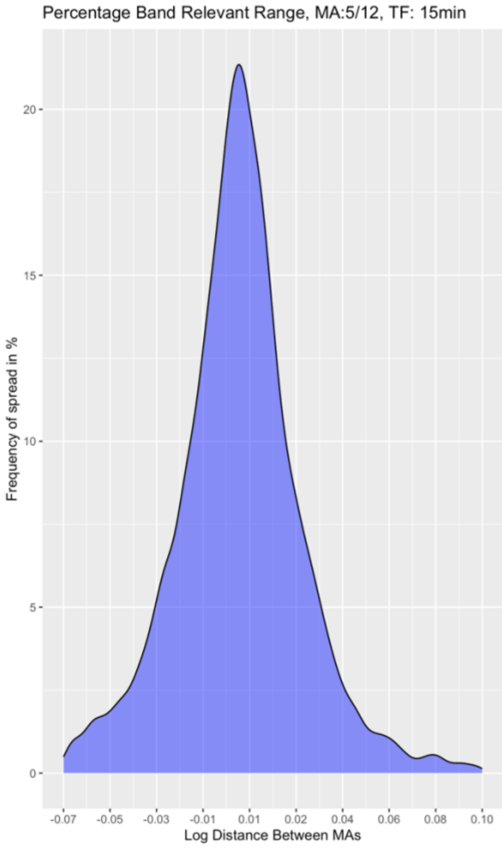
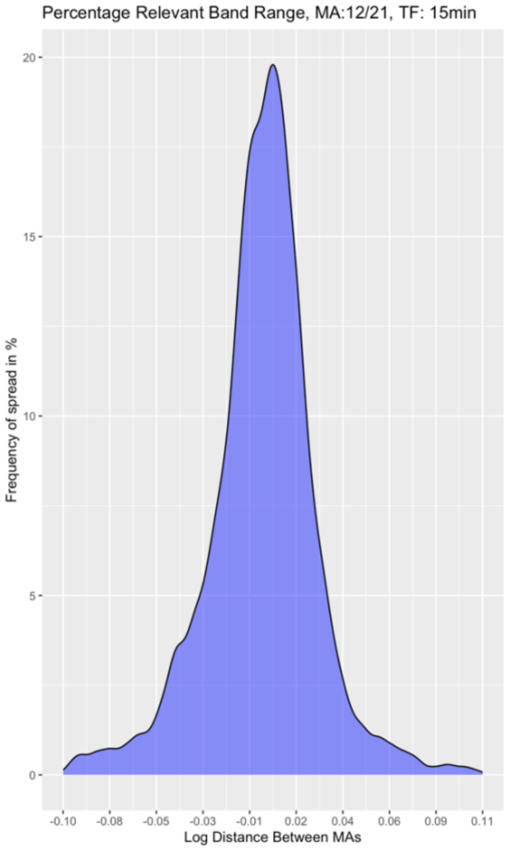
Appendices

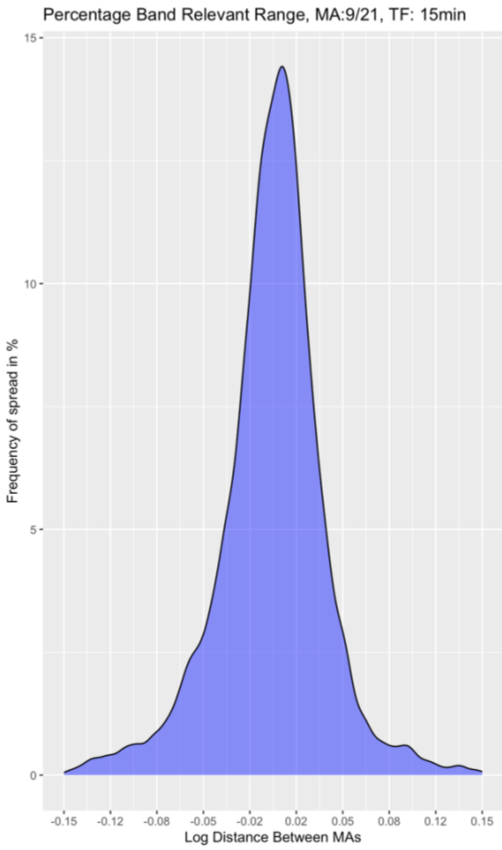
Appendix A: Frequency Density Plots for the PBR Spread Feasibility Range

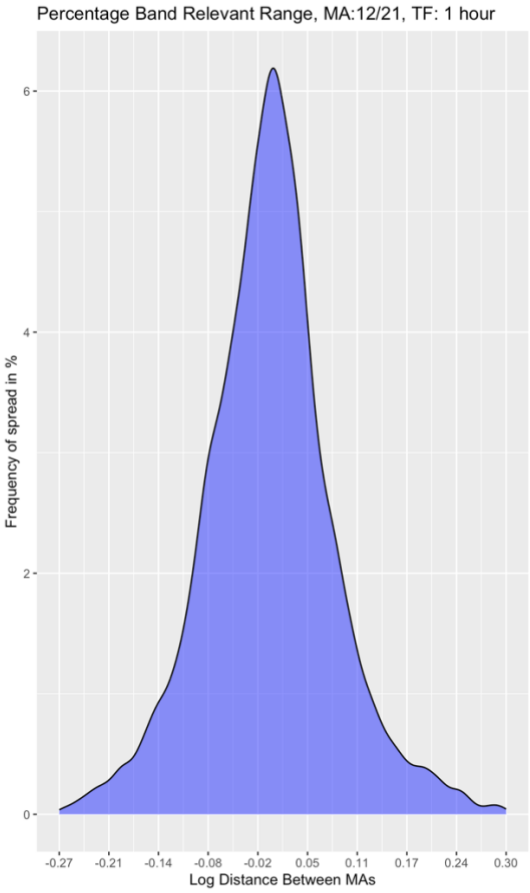


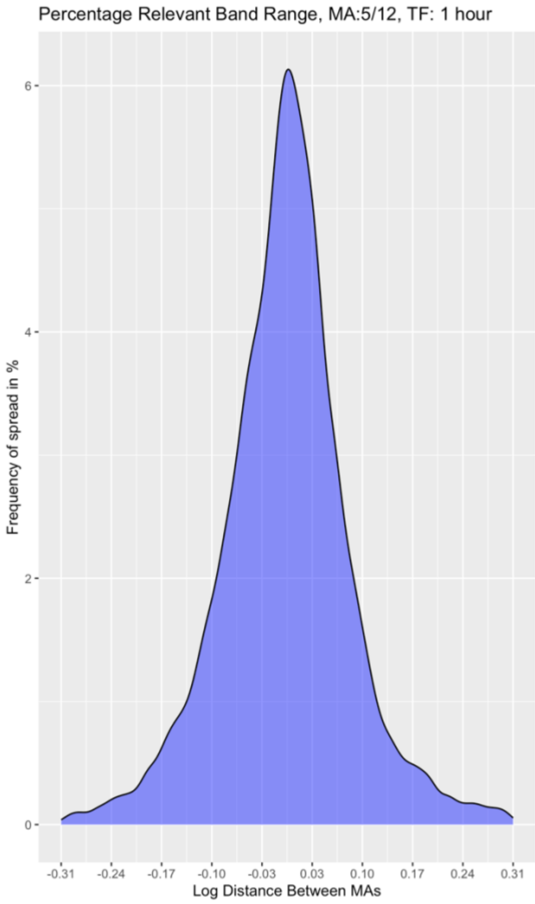

Percentage Relevant Band Range, MA:12/21, TF: 5min
Frequency of spread in %
0
10
20
30
40
-0.05
-0.04
-0.03
-0.01
0.00
0.01
0.02
0.04
0.05
0.06
Log Distance Between MAs

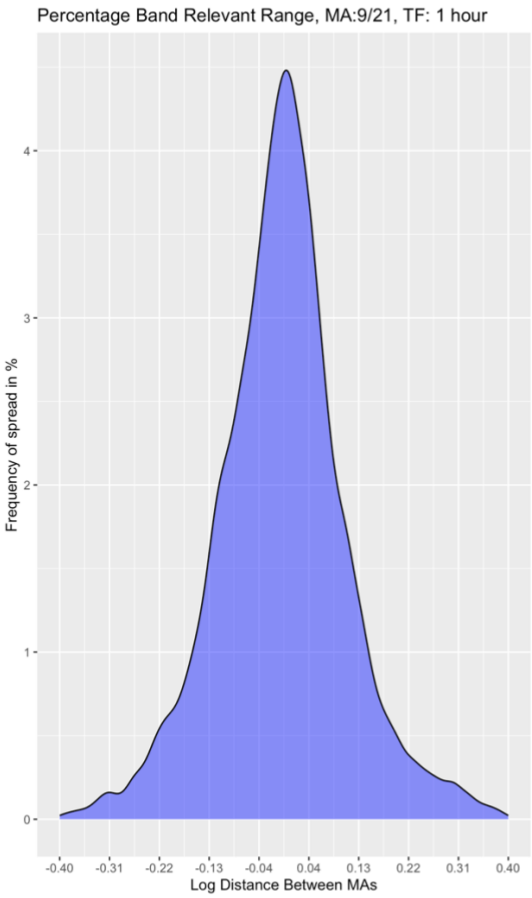

Percentage Band Relevant Range, MA:5/12, TF: 15min
Frequency of spread in %
0
5
10
15
20
-0.07
-0.05
-0.03
-0.01
0.01
0.02
0.04
0.06
0.08
0.10
Log Distance Between MAs


Percentage Relevant Band Range, MA:12/21, TF: 15min
Frequency of spread in %
0
5
10
15
20
-0.10
-0.08
-0.05
-0.03
-0.01
0.02
0.04
0.06
0.09
0.11
Log Distance Between MAs


Percentage Band Relevant Range, MA:9/21, TF: 15min
Frequency of spread in %
0
5
10
15
-0.15
-0.12
-0.08
-0.05
-0.02
0.02
0.05
0.08
0.12
0.15
Log Distance Between MAs


Percentage Band Relevant Range, MA:12/21, TF: 1 hour
Frequency of spread in %
0
2
4
6
-0.27
-0.21
-0.14
-0.08
-0.02
0.05
0.11
0.17
0.24
0.30
Log Distance Between MAs


Percentage Relevant Band Range, MA:5/12, TF: 1 hour
Frequency of spread in %
0
2
4
6
-0.31
-0.24
-0.17
-0.10
-0.03
0.03
0.10
0.17
0.24
0.31
Log Distance Between MAs


Percentage Band Relevant Range, MA:9/21, TF: 1 hour
Frequency of spread in %
0
1
2
3
4
-0.40
-0.31
-0.22
-0.13
-0.04
0.04
0.13
0.22
0.31
0.40
Log Distance Between MAs

Appendix B: Full Summary of Results

Summary of Data Set results from Combination							No SBLE		FEEs			
Parameters	Direction	Return	Samples	Win Rate	Protects	Loss	Return	Variance	Fees	% of P&L	S. Red	M
15m 0.001	Long	17.06	184.00	23%	29%	48%	-9.43	-26.49	918.52	46%	0.00	0.001
12 & 21	Short	9.37	180.00	21%	33%	46%	-16.39	-25.76	1571.86	63%	0.00	0.001
15m 0.005	Long	6.45	135.00	24%	29%	47%	-13.80	-20.25	1547.23	61%	26.63	0.005
12 & 21	Short	3.99	135.00	20%	34%	46%	-17.74	-21.73	1236.15	76%	25.00	0.005
15m 0.01	Long	4.94	97.00	30%	26%	44%	-10.04	-14.98	906.34	65%	47.28	0.010
12 & 21	Short	15.72	95.00	32%	21%	47%	4.67	-11.05	816.18	34%	47.22	0.010
15m 0.015	Long	4.98	80.00	26%	28%	46%	-7.99	-12.97	757.86	60%	56.52	0.015
12 & 21	Short	-1.09	83.00	28%	23%	49%	-10.13	-9.04	840.23	115%	53.89	0.015
15m 0.02	Long	9.46	63.00	30%	29%	41%	-3.44	-12.90	562.23	37%	65.76	0.020
12 & 21	Short	11.34	66.00	27%	24%	48%	0.72	-10.62	700.24	38%	63.33	0.020
15m 0.03	Long	9.07	41.00	29%	22%	49%	2.15	-6.92	305.63	25%	77.72	0.030
12 & 21	Short	8.04	43.00	21%	30%	49%	-1.91	-9.95	582.09	42%	76.11	0.030
15m 0.05	Long	15.89	16.00	31%	25%	44%	12.88	-3.01	117.59	7%	91.30	0.050
12 & 21	Short	6.70	23.00	22%	22%	57%	1.65	-5.05	260.94	28%	87.22	0.050
15m 0.08	Long	-3.01	6.00	17%	50%	33%	-5.92	-2.91	95.85	47%	96.74	0.080
12 & 21	Short	-7.18	12.00	8%	33%	58%	-10.55	-3.37	207.63	41%	93.33	0.080
15m 0.001	Long	44.43	374.00	26%	35%	39%	-9.08	-53.51	3056.90	41%	0.00	0.001
5 & 12	Short	41.42	372.00	25%	28%	46%	0.87	-40.55	3348.14	45%	0.00	0.001
15m 0.005	Long	44.32	271.00	29%	34%	38%	-2.82	-47.14	1800.75	29%	27.54	0.005
5 & 12	Short	53.76	268.00	31%	29%	39%	15.46	-38.30	1929.19	26%	27.96	0.005
15m 0.01	Long	49.15	196.00	32%	30%	38%	11.24	-37.91	986.92	19%	47.59	0.010
5 & 12	Short	17.78	195.00	34%	30%	36%	-7.65	-25.43	1263.94	42%	47.58	0.010
15m 0.015	Long	23.41	160.00	32%	29%	39%	-1.59	-25.00	858.55	27%	57.22	0.015
5 & 12	Short	17.81	159.00	31%	30%	39%	-7.23	-25.04	871.45	33%	57.26	0.015
15m 0.02	Long	29.66	131.00	32%	33%	35%	5.55	-24.11	642.85	18%	64.97	0.020
Summary of Data Set results from Combination							No SBLE		FEEs			
Parameters	Direction	Return	Samples	Win Rate	Protects	Loss	Return	Variance	Fees	% of P&L	S. Red	M
5 & 12	Short	21.00	130.00	29%	33%	38%	-0.28	-21.28	741.56	26%	65.05	0.020
15m 0.03	Long	26.31	79.00	37%	38%	25%	8.74	-17.57	329.03	11%	78.88	0.030
5 & 12	Short	22.28	78.00	35%	31%	35%	10.69	-11.59	498.32	18%	79.03	0.030
15m 0.05	Long	6.53	40.00	28%	40%	33%	-3.90	-10.43	150.07	19%	89.30	0.050
5 & 12	Short	6.54	41.00	20%	41%	39%	-4.08	-10.62	288.89	31%	88.98	0.050
15m 0.07	Long	-1.45	20.00	30%	35%	35%	-6.19	-4.74	120.17	488%	94.65	0.070
5 & 12	Short	4.95	21.00	29%	33%	38%	-0.17	-5.12	184.36	27%	94.35	0.070
15m 0.001	Long	27.42	204.00	24%	30%	46%	-2.10	-29.52	1575.36	36%	0.00	0.001
9 & 21	Short	43.99	203.00	25%	30%	46%	11.41	-32.58	2165.90	33%	0.00	0.001
15m 0.005	Long	28.32	163.00	25%	29%	46%	4.26	-24.06	1255.14	32%	20.10	0.005
9 & 21	Short	29.59	163.00	25%	29%	46%	4.03	-25.56	1403.35	32%	19.70	0.005
15m 0.01	Long	0.72	136.00	24%	27%	49%	-15.97	-16.69	989.26	93%	33.33	0.010
9 & 21	Short	6.03	136.00	21%	33%	46%	-14.24	-20.27	1200.42	67%	33.00	0.010
15m 0.015	Long	13.22	105.00	29%	27%	45%	-4.05	-17.27	1000.50	43%	48.53	0.015
9 & 21	Short	14.51	107.00	27%	26%	47%	-0.48	-14.99	879.03	38%	47.29	0.015
15m 0.02	Long	11.33	88.00	31%	24%	45%	-1.09	-12.42	871.61	43%	56.86	0.020
9 & 21	Short	15.70	89.00	31%	21%	47%	4.02	-11.68	800.27	34%	56.16	0.020
15m 0.05	Long	3.20	40.00	23%	20%	58%	-3.70	-6.90	264.47	45%	80.39	0.050
9 & 21	Short	3.70	42.00	14%	38%	48%	-7.45	-11.15	558.58	60%	79.31	0.050
15m 0.08	Long	13.01	16.00	31%	25%	44%	10.08	-2.93	113.22	8%	92.16	0.080
9 & 21	Short	10.88	18.00	28%	28%	44%	6.37	-4.51	245.06	18%	91.13	0.058
15m 0.12	Long	-3.18	7.00	14%	43%	43%	-6.08	-2.90	95.70	43%	96.57	0.120
9 & 21	Short	-9.72	12.00	0%	33%	67%	-12.99	-3.27	198.95	26%	94.09	0.120
1h 0.001	Long	66.27	274.00	28%	25%	47%	21.84	-44.43	1047.11	14%	0.00	0.001
12 & 21	Short	21.30	281.00	24%	32%	43%	-17.13	-38.43	910.82	30%	0.00	0.001

Summary of Data Set results from Combination							No SBLE		FEEs			
Parameters	Direction	Return	Samples	Win Rate	Protects	Loss	Return	Variance	Fees	% of P&L	S. Red	M
1h 0.005	Long	61.37	238.00	30%	22%	48%	26.13	-35.24	829.96	12%	13.14	0.005
12 & 21	Short	30.78	243.00	26%	30%	43%	-5.55	-36.33	764.39	20%	13.52	0.005
1h 0.01	Long	52.99	205.00	31%	25%	44%	17.32	-35.67	638.79	11%	25.18	0.010
12 & 21	Short	22.05	213.00	26%	29%	45%	-8.35	-30.40	710.20	24%	24.20	0.010
1h 0.02	Long	58.79	173.00	31%	24%	45%	24.64	-34.15	640.00	9%	36.86	0.020
12 & 21	Short	3.66	183.00	25%	33%	42%	-22.31	-25.97	597.38	62%	34.88	0.020
1h 0.05	Long	3.46	107.00	31%	25%	44%	-12.75	-16.21	325.39	48%	60.95	0.050
12 & 21	Short	32.54	110.00	26%	35%	38%	6.74	-25.80	306.75	9%	60.85	0.050
1h 0.075	Long	1.45	79.00	37%	22%	42%	-10.28	-11.73	251.20	63%	71.17	0.075
12 & 21	Short	24.85	80.00	26%	34%	40%	3.94	-20.91	283.40	10%	71.53	0.075
1h 0.1	Long	6.79	53.00	34%	21%	45%	-2.09	-8.88	156.04	19%	80.66	0.100
12 & 21	Short	23.38	55.00	29%	36%	35%	6.32	-17.06	175.64	7%	80.43	0.100
1h 0.15	Long	1.17	25.00	36%	28%	36%	-4.07	-5.24	84.16	42%	90.88	0.150
12 & 21	Short	1.87	27.00	30%	22%	48%	-3.86	-5.73	74.33	28%	90.39	0.150
1h 0.2	Long	1.58	16.00	38%	31%	31%	-2.84	-4.42	27.29	15%	94.16	0.200
12 & 21	Short	-3.12	16.00	19%	38%	44%	-8.35	-5.23	23.21	8%	94.31	0.200
1h 0.001	Long	92.93	540.00	27%	30%	42%	6.55	-86.38	1840.62	17%	0.00	0.001
5 & 12	Short	148.57	542.00	28%	32%	41%	43.64	-104.93	2221.70	13%	0.00	0.001
1h 0.005	Long	85.59	491.00	28%	30%	42%	6.54	-79.05	1576.97	16%	9.07	0.005
5 & 12	Short	102.06	495.00	30%	29%	41%	20.39	-81.67	1692.80	14%	8.67	0.005
1h 0.01	Long	93.26	431.00	29%	30%	41%	15.55	-77.71	1280.19	12%	20.19	0.010
5 & 12	Short	94.28	437.00	30%	28%	42%	23.55	-70.73	1363.03	13%	19.37	0.010
1h 0.02	Long	64.51	348.00	30%	29%	41%	5.50	-59.01	957.98	13%	35.56	0.020
5 & 12	Short	59.20	351.00	31%	28%	40%	7.19	-52.01	900.42	13%	35.24	0.020
1h 0.05	Long	43.85	219.00	30%	32%	37%	-1.73	-45.58	471.74	10%	59.44	0.050

Summary of Data Set results from Combination							No SBLE		FEEs			
Parameters	Direction	Return	Samples	Win Rate	Protects	Loss	Return	Variance	Fees	% of P&L	S. Red	M
5 & 12	Short	24.58	221.00	28%	32%	40%	-10.59	-35.17	470.79	16%	59.23	0.050
1h 0.075	Long	28.64	161.00	27%	37%	37%	-5.68	-34.32	349.86	11%	70.19	0.075
5 & 12	Short	16.96	158.00	26%	38%	36%	-11.69	-28.65	285.10	14%	70.85	0.075
1h 0.1	Long	10.02	116.00	28%	34%	38%	-11.88	-21.90	192.69	16%	78.52	0.100
5 & 12	Short	8.39	115.00	27%	37%	36%	-15.41	-23.80	189.16	18%	78.78	0.100
1h 0.15	Long	4.73	59.00	25%	31%	44%	-5.68	-10.41	130.39	22%	89.07	0.150
5 & 12	Short	25.54	61.00	30%	39%	31%	7.38	-18.16	86.81	3%	88.75	0.150
1h 0.2	Long	-6.48	35.00	29%	29%	43%	-13.26	-6.78	53.77	9%	93.52	0.200
5 & 12	Short	4.83	30.00	37%	37%	27%	-3.61	-8.44	35.19	7%	94.46	0.200
1h 0.001	Long	100.77	313.00	27%	30%	42%	35.99	-64.78	1252.67	11%	0.00	0.001
9 & 21	Short	30.59	321.00	25%	30%	45%	-11.10	-41.69	1042.52	25%	0.00	0.001
1h 0.005	Long	90.20	282.00	29%	26%	44%	38.28	-51.92	1031.57	10%	9.90	0.005
9 & 21	Short	31.48	289.00	24%	33%	43%	-11.37	-42.85	1015.54	24%	9.97	0.005
1h 0.01	Long	85.85	255.00	30%	25%	45%	37.87	-47.98	956.37	10%	18.53	0.010
9 & 21	Short	19.68	261.00	25%	31%	44%	-8.27	-27.95	772.12	20%	18.69	0.010
1h 0.02	Long	66.41	209.00	30%	25%	44%	25.62	-40.79	668.79	9%	33.23	0.020
9 & 21	Short	35.79	213.00	28%	30%	42%	5.62	-30.17	778.51	18%	33.64	0.020
1h 0.05	Long	45.69	146.00	30%	29%	41%	13.25	-32.44	450.66	9%	53.35	0.050
9 & 21	Short	10.45	152.00	25%	32%	43%	-13.07	-23.52	320.99	24%	52.65	0.050
1h 0.075	Long	6.81	116.00	31%	28%	41%	-12.06	-18.87	356.97	34%	62.94	0.075
9 & 21	Short	24.79	119.00	25%	34%	41%	-1.48	-26.27	321.66	11%	62.93	0.075
1h 0.1	Long	-0.34	92.00	32%	23%	46%	-12.10	-11.76	305.48	112%	70.61	0.100
9 & 21	Short	21.19	92.00	26%	36%	38%	-1.06	-22.25	260.13	11%	71.34	0.100
1h 0.2	Long	8.65	32.00	34%	28%	38%	1.15	-7.50	104.49	11%	89.78	0.200
9 & 21	Short	4.06	32.00	31%	28%	41%	-1.89	-5.95	96.11	19%	90.03	0.200

Summary of Data Set results from Combination							No SBLE		FEEs			
Parameters	Direction	Return	Samples	Win Rate	Protects	Loss	Return	Variance	Fees	% of P&L	S. Red	M
9 & 21	Short	-2.05	15.00	20%	40%	40%	-6.72	-4.67	19.46	11%	95.33	0.300
5m 0.001	Long	-20.74	193.00	22%	28%	50%	-41.43	-20.69	2928.37	343%	0.00	0.001
12 & 21	Short	0.76	192.00	19%	30%	51%	-19.80	-19.80	3037.00	98%	0.00	0.001
5m 0.0025	Long	-0.22	145.00	25%	30%	45%	-22.79	-22.57	2298.00	101%	24.87	0.003
12 & 21	Short	16.43	143.00	24%	27%	50%	-1.84	-18.27	2304.00	58%	25.52	0.003
5m 0.005	Long	9.93	101.00	33%	32%	36%	-7.03	-16.96	1515.03	60%	47.67	0.005
12 & 21	Short	25.88	98.00	28%	22%	50%	12.02	-13.86	1962.95	43%	48.96	0.005
5m 0.01	Long	8.93	58.00	36%	22%	41%	2.11	-6.82	1298.60	59%	69.95	0.010
12 & 21	Short	16.31	58.00	29%	19%	52%	8.97	-7.34	1020.00	44%	69.79	0.010
5m 0.015	Long	9.62	39.00	36%	18%	46%	5.61	-4.01	701.00	42%	79.79	0.015
12 & 21	Short	3.94	41.00	24%	34%	41%	-3.66	-7.60	979.92	71%	78.65	0.015
5m 0.03	Long	8.06	11.00	45%	18%	36%	6.73	-1.33	81.55	9%	94.30	0.030
12 & 21	Short	6.57	14.00	57%	21%	21%	3.80	-2.77	82.36	11%	92.71	0.030
5m 0.05	Long	-0.93	4.00	25%	50%	25%	-2.15	-1.22	49.00	9%	97.93	0.050
12 & 21	Short	1.21	6.00	33%	17%	50%	0.92	-0.29	41.37	25%	96.88	0.050
5m 0.075	Long	-0.13	1.00	0%	100%	0%	-1.13	-1.00	13.33	9%	99.48	0.075
12 & 21	Short	4.73	1.00	100%	0%	0%	4.73	0.00	1.53	9%	99.48	0.075
5m 0.001	Long	-30.56	380.00	20%	32%	48%	-62.75	-32.19	5508.10	225%	0.00	0.001
5 & 12	Short	-16.84	379.00	18%	33%	48%	-53.67	-36.83	6191.88	137%	0.00	0.001
5m 0.0025	Long	-23.06	313.00	21%	30%	49%	-50.95	-27.89	3903.00	244%	17.63	0.003
5 & 12	Short	-2.30	312.00	20%	34%	46%	-38.69	-36.39	4515.12	105%	17.68	0.003
5m 0.005	Long	-14.82	229.00	24%	34%	42%	-41.41	-26.59	2420.12	231%	39.74	0.005
5 & 12	Short	4.53	230.00	23%	33%	45%	-20.14	-24.67	2399.84	84%	39.31	0.005
5m 0.01	Long	12.30	136.00	29%	39%	32%	-11.36	-23.66	1286.33	51%	64.21	0.010

Summary of Data Set results from Combination							No SBLE		FEEs			
Parameters	Direction	Return	Samples	Win Rate	Protects	Loss	Return	Variance	Fees	% of P&L	S. Red	M
5 & 12	Short	7.92	136.00	28%	32%	40%	-8.57	-16.49	1242.02	61%	64.12	0.010
5m 0.015	Long	15.25	79.00	33%	35%	32%	2.97	-12.28	728.80	32%	79.21	0.015
5 & 12	Short	21.99	82.00	28%	30%	41%	10.75	-11.24	670.32	23%	78.36	0.015
5m 0.03	Long	17.96	27.00	37%	33%	30%	12.31	-5.65	145.33	7%	92.89	0.030
5 & 12	Short	9.52	26.00	46%	31%	23%	8.87	-0.65	127.78	6%	93.14	0.030
5m 0.05	Long	0.50	11.00	18%	73%	9%	-3.81	-4.31	81.90	62%	97.11	0.050
5 & 12	Short	8.37	13.00	23%	46%	31%	3.74	-4.63	23.57	3%	96.57	0.050
5m 0.07	Long	0.20	2.00	50%	50%	0%	-0.13	-0.33	17.90	47%	99.47	0.070
5 & 12	Short	3.92	2.00	50%	0%	50%	3.92	0.00	2.58	1%	99.47	0.070
5m 0.001	Long	-26.45	228.00	21%	29%	50%	-48.39	-21.94	3555.79	390%	0.00	0.001
9 & 21	Short	-1.79	228.00	18%	34%	48%	-30.34	-28.55	4043.35	105%	0.00	0.001
5m 0.0025	Long	-20.87	190.00	21%	28%	51%	-41.44	-20.57	2772.27	404%	16.67	0.003
9 & 21	Short	13.38	189.00	20%	30%	51%	-8.55	-21.93	2912.98	69%	17.11	0.003
5m 0.005	Long	-10.07	143.00	24%	31%	45%	-28.08	-18.01	2057.65	196%	37.28	0.005
9 & 21	Short	19.34	140.00	26%	28%	46%	-0.11	-19.45	2220.04	53%	38.60	0.005
5m 0.01	Long	8.36	88.00	33%	32%	35%	-5.75	-14.11	1518.34	65%	61.40	0.010
9 & 21	Short	28.70	86.00	28%	20%	52%	18.42	-10.28	2943.72	39%	62.28	0.010
5m 0.015	Long	9.32	59.00	41%	20%	39%	3.61	-5.71	1015.34	52%	74.12	0.015
9 & 21	Short	18.37	59.00	32%	20%	47%	10.20	-8.17	1311.78	42%	74.12	0.015
5m 0.03	Long	8.40	27.00	37%	15%	48%	6.67	-1.73	232.22	22%	88.16	0.030
9 & 21	Short	8.68	28.00	32%	39%	29%	1.30	-7.38	510.10	37%	87.72	0.030
5m 0.05	Long	12.03	9.00	56%	22%	22%	9.78	-2.25	78.19	6%	96.05	0.050
9 & 21	Short	9.75	11.00	36%	27%	36%	6.64	-3.11	98.76	9%	95.18	0.050
5m 0.07	Long	0.02	5.00	20%	60%	20%	-2.31	-2.33	51.73	96%	97.81	0.070
9 & 21	Short	1.85	6.00	33%	17%	50%	1.55	-0.30	7.20	4%	97.37	0.070