A Professional Journal Published by the International Federation of Technical Analysts

IFTA Journal 23

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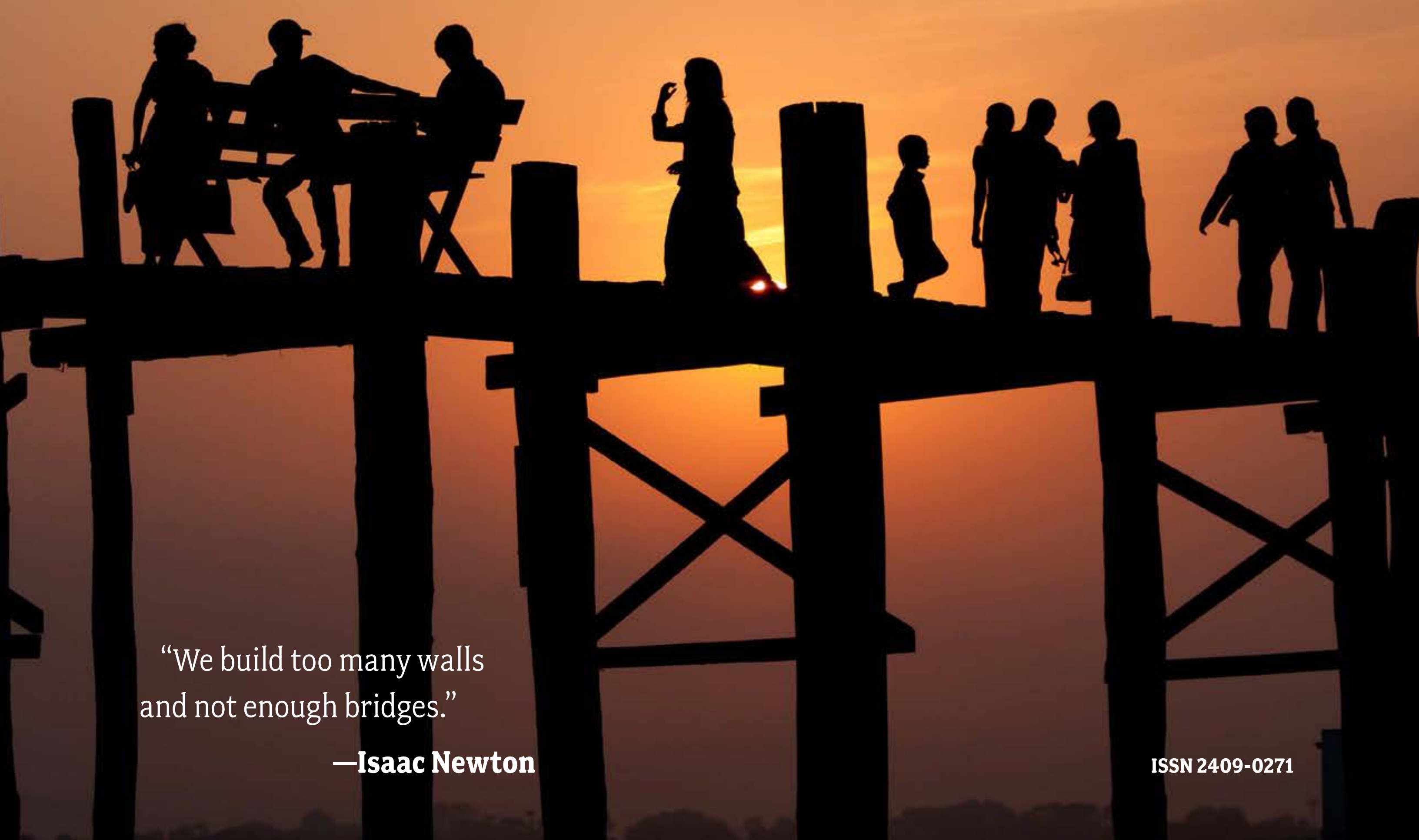

"We build too many walls and not enough bridges."

—Isaac Newton

ISSN 2409-0271

Letter From the Editor

By Dr. Rolf Wetzer, CFTe, MFTA

Dear IFTA Colleagues and Friends:

Another very eventful year has passed since the last *IFTA Journal.* It was a year in which a great deal of negative news and crises have dominated our daily lives. We are still living in the midst of a pandemic. In Europe, Russia is waging a brutal war against Ukraine. And around the world, we are experiencing the consequences of climate change more and more clearly. Therefore, it is more imperative than ever that we all reach out to each other again to bridge our problems and find good solutions for a peaceful future for all of us.

For us IFTA colleagues too, the last two years have been marked by the consequences of lockdowns and COVID restrictions. Many events could only take place virtually. I am therefore very pleased that we will be able to meet again this year for a joint conference. The Australian society, ATAA, invites us all to Melbourne for three days in October. It is a tradition that the *IFTA Journal* is published in time for the conference.

The Journal is a new challenge every year. It is produced by only a few people and lives on the fact that enough colleagues write interesting articles for it. It has been even more of a challenge over the last two years, as the activities in the national associations have shrunk somewhat due to COVID.

I am all the more pleased that we were able to find a collection of exciting and high-quality contributions this year. Therefore, we would like to thank all the colleagues who sacrificed their valuable time to write articles for the *IFTA Journal.* We would like to extend our special thanks again this year to the National Association of Active Investment Managers (NAAIM) for allowing us to publish entries from their annual award.

For myself, it is the 15th edition in which I am involved, so I know from experience that the biggest thanks must go to the production team consisting of Linda Bernetich, Lynne Agoston, and Tiffany Ward. Without their commitment, this *Journal* would not exist.

… it is more imperative than ever that we all reach out to each other again to bridge our problems and find good solutions for a peaceful future for all of us.

Best regards,
Dr. Rolf Wetzer, CFTe, MFTA

IFTA Journal

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Cover Photograph from iStock images

The IFTA Journal is published annually by the International Federation of Technical Analysts, 1300 Piccard Dr., Suite LL 14 Rockville, MD 20850 USA.

Are the Streets Still Smart? Evaluating Swing Trading Strategies in Modern Markets

By Davide Pandini, Ph.D., CFTe, MFTA, CMT

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Abstract

In 1995, Larry Connors and Linda Bradford Raschke published a book titled *Street Smarts: High Probability Short Term Trading Strategies* that soon became a reference milestone for many generations of traders. The book presented multiple strategies inherently discretionary and mostly focused on equities and futures. The strategies were based on three simple swing trading concepts: retracements, pattern breakouts, and climax reversals, which are among the fundamental pillars of technical analysis, and by which support and resistance levels are formed. Although several traders have used these strategies for many years, following some structural changes in the markets and an increasing adoption of mechanical trading systems, the strategies of *Street Smarts* lately ended up on a sidetrack and were no longer considered as mainstream by an increasing number of technical analysts and systematic traders.

In this work, some of the most popular strategies described in *Street Smarts* are reviewed. Moreover, an exhaustive backtesting on historical data across a significant time period, from 2005 to September 2021, is presented. This time period includes the most important events in the markets, from the global financial crisis (2007–2008) to the more recent COVID-19 sell-off. The backtesting covered the principal stock indexes, the S&P 500 sectors, real estate, bonds, commodities, and also the most important Forex currency pairs, which were not considered in the original book. Furthermore, a rigorous statistical hypothesis testing was performed on the *Street Smarts* strategies by means of inferential statistics multiple hypothesis testing and time series bootstrap. Such a comprehensive analysis of the *Street Smarts* strategies allows us to assess their effectiveness on different asset classes and markets. Moreover, this thorough study also provides a deeper insight on swing trading techniques in changing market scenarios and proposes to adopt statistical hypothesis testing as a best practice to evaluate a trading strategy.

Introduction

Published in 1995 by Larry Connors (LC) and Linda Bradford Raschke (LBR) (Connors, 1995), *Street Smarts* is considered by many to be one of the best books on trading equities, commodities, and futures. The backbone of this book's success is swing trading and the techniques which apply these methodologies. Moreover, strategies based on pattern recognition and volatility explosion are also presented, along with the use of popular technical indicators such as the ADX (Wilder, 1978) and the stochastic oscillator (Lane, 1984). Although most of the strategies described by LC and LBR were initially aimed at short-term swing trading, they can also be used by longer-term swing traders who could hold a position for days, weeks, and sometimes even months.

In this work, we will review the most popular strategies presented in *Street Smarts* by performing a thorough backtesting over several asset classes and across an exhaustive time window, covering more than 16 years of historical data. The purpose of this comprehensive study is to assess the validity and robustness of these strategies after more than 25 years since they were first published. Since then, most of the equities, commodities, futures, and Forex markets have changed their structural behavior and, unfortunately, most methods do not always work in all market conditions and market conditions never persist forever. Therefore, we believe that this work will provide a new and more in-depth insight on the effectiveness of the *Street Smarts* techniques. Moreover, a rigorous statistical hypothesis testing was performed on the *Street Smarts* strategies by means of inferential statistics multiple hypothesis testing and time series bootstrap. Even the most powerful strategies, or technical analysis rules, may deliver a highly variable performance depending on the time series of tested historical data. Statistical analysis is the only scientific approach to distinguish strategies that have a predictive power from those that do not have an intrinsic merit.

The paper is organized as follows: "Backtesting: Historical Period and Asset Classes" illustrates the historical period for backtesting the *Street Smarts* strategies and the asset classes considered for this analysis, while "Performance Metrics" describes the performance metrics used to assess the strategies. The *Street Smarts* strategies considered in this work, and the backtesting results are presented in "Street Smarts Strategies". The statistical hypothesis testing procedures are discussed in "Statistical Hypothesis Testing" and "The Bootstrap", while "Conclusion" summarizes our conclusive remarks.

Backtesting: Historical Period and Asset Classes

Look-Back Period

The choice of the time window for backtesting has always been of interest and concern to technical analysts to assess the robustness and performance of a strategy, since different periods and sizes of the window can lead to different experimental results and conclusions. The work presented in Inoue, 2012, assessed the robustness of the strategy's performance given the window size of the backtesting period. This study shows the impact that the chosen window can have on the results and, as such, the authors argue that the window should not be arbitrarily selected. In Zakamulin, 2014, it was demonstrated that an active market timing strategy outperforms the passive buy-and-hold strategy during bear markets and vice versa during bull markets. To account for these results, this study concluded that the look-back period should include bear and bull markets to analyze both these market conditions.

Therefore, the strategies of *Street Smarts* were tested across an historical data length covering the past 16 years (from September 2005 to September 2021) because it includes multiple bull and bear markets, some of which were quite significant, like the global financial crisis (2007–2008), the recent COVID-19 sell-off (March 2020), and the last bull market lasting over a decade.

Asset Classes

Usually, technical analysis strategies are not equally distributed and tested across all asset classes. It is frequent practice to find strategies that have been assessed only on some specific assets, like the major stock market indexes, commodities, bonds, or currency pairs. It is well-known that the performance of a given strategy can vary significantly depending on the tested asset class and market. Therefore, for a thorough and comprehensive analysis, the *Street Smarts* strategies were evaluated on all the above-mentioned asset classes. The following ETFs were considered (Figure 1): the most important U.S. stock market indexes (SPY, QQQ, DIA), the S&P 500 sectors (XLP, XLY, XLE, XLV, XLF, XLI, XLK, XLB, XLU, IYZ), real estate (IYR), gold (GLD), 7–10-year Treasury bonds (IEF), and 20+ year Treasury bonds (TLT). Furthermore, to complete the assessment of the *Street Smarts* strategies, the major Forex currency crosses were evaluated, as well. All the ETFs historical time series were downloaded from (Yahoo! Finance, 2022) and the Forex crosses from the site (Investing.com, 2022). The strategies analyzed in this work were implemented and tested with MS Excel and all the historical data used were on a daily timeframe.

Figure 1. Asset classes and Forex currency pairs

	Asset Class	ETF Ticker		FOREX Cross
Indexes	SP& 500	SPY		EURUSD
	DJIA	DIA		GBPUSD
	NASDAQ 100	QQQ		EURGBP
S&P 500 Sectors	Consumer Staples	XLP		USDCHF
	Consumer Discretionary	XLY		USDJPY
	Energy	XLE		USDCAD
	Healthcare	XLV		USDNZD
	Financials	XLF		AUDUSD
	Industrials	XLI		AUDNZD
	Technology	XLK		EURCAD
	Materials	XLB		EURNZD
	Utilities	XLU		NZDUSD
	Telecommunications	IYZ		EURAUD
	Real Estate	IYR		USDTRY
	Gold	GLD		
U.S. Treasury Bonds	7-10 years Treasury Bonds	IEF		
	20+ years Treasury Bonds	TLT		

Performance Metrics

There are various ways to measure a portfolio performance (Cogneau, 2009). The simplest and most common is the excess return. It measures the total return less the risk-free rate of return. However, it is not the best performance metric because it does not consider risk. A risk-adjusted metric is more appropriate because investors and traders require compensation for risk. Among the popular methods that are commonly utilized and include the risk factor, there is the Sharpe Ratio (Sharpe, 1994), which is the ratio of return, adjusted for the risk-free return of T-bills, to the annualized standard deviation of returns, which is considered as a proxy for risk:

$$Sharpe\ ratio = \frac{Annualized\ returns - Risk\ free\ returns}{Annualized\ risk}$$

Although the limitations of the Sharpe ratio are known and have been discussed in the literature (Kirkpatrick III, 2016), in this study we used it because of its overwhelming popularity. Additionally, practitioners commonly use the drawdown to assess the riskiness of any given strategy. The most common performance measure after the Sharpe ratio is the maximum drawdown, which in this work is measured as a percentage from a highest net asset value (NAV) to the subsequent lowest NAV. One metric that accounts for the maximum drawdown is the Calmar ratio (Young, 1991):

$$Calmar\ ratio = \frac{Annualized\ returns}{Maximum\ drawdown}$$

Therefore, both the Sharpe and Calmar ratios are used in this study, along with other popular metrics, such as the total returns, the annualized volatility, and the compound annual growth rate (CAGR).

Street Smarts Strategies

The strategies of *Street Smarts* were originally developed and evaluated mostly on U.S. equities and futures, and they were used for many years in those markets. However, a comprehensive and thorough backtesting also encompassing the Forex market and across a statistically significant look-back period has never been published. Hence, given the structural differences between the Forex and the equities markets, in this work a detailed analysis of some of the most popular *Street Smarts* strategies applied to equities, commodities, bonds, and the most important currency pairs listed in Figure 1 is presented.

All the *Street Smarts* strategies discussed in this paper were implemented considering both long and short trades, reversing the trade direction after closing the open trade when an opposite entry signal was triggered, and rolling over an open position when a new signal in the same direction of the current trade was generated. For the sake of conciseness, the *Street Smarts* strategies are not reviewed in this work and the interested reader may find their description and set-up in (Connors, 1995), while the principles of swing trading are outlined in the seminal book by Perry Kaufman (Kaufman, 2013).

Turtle

Before looking into the Turtle Soup strategy presented in (Connors, 1995), we first review its background. The Turtle Soup sets its roots into the famous strategy called Turtle (The Original Turtle Trading Rules, 2022), which was introduced by Richard Dennis (Schwager, 2006) and William Eckhardt (Schwager, 2008) in the 1980s to a group of novice traders called the Turtles. The Turtle is a trend-following strategy based on a 20-day breakout of prices, earlier introduced by Richard Donchian (Donchian, 1974). Like other trend-following techniques, even the Turtle strategy suffers from false breakouts. Instead of sustaining strong directional moves in the direction of the breakout, prices can trace back within the Donchian channel, originating whipsaws that result in losing trades. The backtesting of this strategy has demonstrated that to make it profitable, it is mandatory to implement a careful management of the stop-loss. Various stop-loss approaches were tested, and the best performances were obtained with a trailing stop-loss tracking the opposite limit of the Donchian channel with respect to the breakout.

Different take-profit targets were evaluated with respect to the maximum allowed loss. Furthermore, also assessed was the typical approach of trend-following strategies to let the profits run and use the trailing stop-loss as a dynamic take-profit level (i.e., to exit the trade when the trailing stop-loss is hit). The trailing-stop loss allowed to secure most of the gained profits, and for this trend-following strategy the backtesting evinced to be the best exit approach.

The monthly NAV for the indexes, equities, commodities, real estate, and bonds over the backtesting time window is reported in Figure 2, while Figure 3 shows the monthly drawdown. The best performances were achieved on QQQ (Nasdaq 100) and XLK (technology). It is worth noting that XLK and QQQ are highly correlated with a correlation coefficient of 0.9598 and consistently showed the best performances over the look-back period. The performances of the Turtle strategy are reported in Table 1.

The Turtle turned out to be less performing in the Forex market and the NAV results shown in Figure 4 did not reach the same values reported for the equity indexes and sectors in Figure 2. However, the drawdowns on the Forex shown in Figure 5 were smaller than the drawdowns of the other asset classes. The currency pair where the Turtle strategy's overall performance was better than the other currency crosses was USDTRY, which should be considered more as an outlier since the behavior of this currency pair over the backtesting period is significantly different from the typical behavior of the other currency pairs, as illustrated in Figure 6.

Given the typical mean-reverting structure of the Forex, the best approach to protect the gained profits was to close the trade after three trading days if the profit target had not been reached within this time window.

The overall performances and the trade statistics in the Forex market are reported in Table 2.

In summary, the Turtle strategy can deliver good performances on some S&P 500 sectors and equity indexes with a particular focus on the technology stocks if used with a trailing stop-loss set on the Donchian channel. In contrast, its performance was less effective in the Forex market. This outcome is consistent with the strategy's trend-following behavior and the structure of the Forex, which essentially is mean reverting. A lower performance of a trend-following strategy in a typical mean-reverting market should be expected.

Figure 2. Turtle strategy asset class monthly NAV

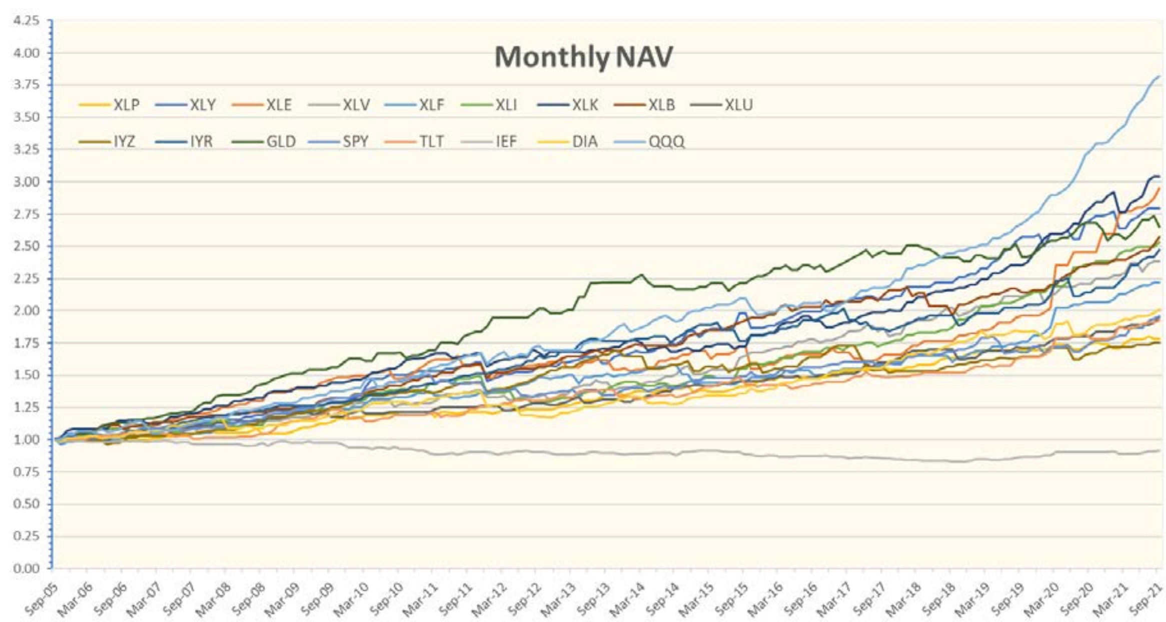

Figure 3. Turtle strategy asset class monthly drawdown

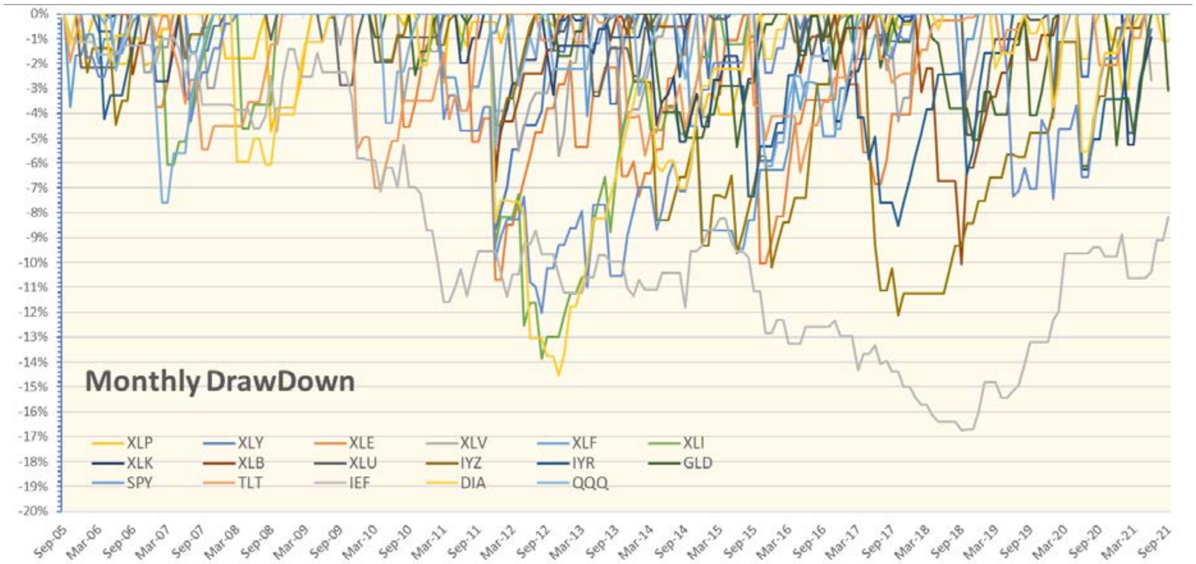

Table 1. Turtle strategy asset classes trade results

PERFORMANCE	XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU	IYZ	IYR	SPY	DIA	IEF	TLT	GLD	QQQ
Total Returns	78.1%	179.4%	195.0%	138.5%	122.0%	153.4%	204.1%	157.5%	94.8%	75.3%	146.9%	95.5%	101.1%	-8.2%	92.9%	165.1%	281.8%
CAGR	3.7%	6.6%	7.0%	5.6%	5.1%	6.0%	7.2%	6.1%	4.2%	3.6%	5.8%	4.3%	4.4%	-0.5%	4.2%	6.2%	8.7%
Volatility	3.3%	5.3%	7.0%	4.9%	4.5%	5.2%	4.8%	4.1%	3.5%	5.0%	4.5%	4.8%	5.0%	2.7%	4.4%	4.6%	5.0%
Maximum DrawDown	-4.7%	-8.7%	-10.7%	-5.7%	-9.4%	-13.9%	-6.2%	-10.1%	-4.9%	-12.1%	-8.5%	-12.0%	-14.6%	-16.7%	-7.0%	-5.4%	-7.6%
Sharpe Ratio	1.09	1.24	0.99	1.13	1.14	1.14	1.50	1.46	1.20	0.71	1.28	0.88	0.89	-0.20	0.95	1.35	1.75
Calmar Ratio	0.77	0.76	0.65	0.97	0.54	0.43	1.15	0.60	0.87	0.29	0.68	0.35	0.31	-0.03	0.60	1.16	1.14
Max Monthly Return	2.99%	5.69%	16.22%	6.00%	8.11%	5.12%	5.23%	4.32%	3.09%	4.23%	4.93%	3.73%	5.61%	2.66%	5.77%	5.18%	4.36%
Min Monthly Return	-4.74%	-8.72%	-10.05%	-4.22%	-4.52%	-9.30%	-6.21%	-6.75%	-4.87%	-5.71%	-6.27%	-6.34%	-8.40%	-2.51%	-5.48%	-4.09%	-5.37%
% Positive Months	38.3%	48.7%	46.1%	48.2%	39.4%	46.1%	49.7%	46.6%	35.8%	43.0%	49.2%	48.7%	48.2%	25.4%	45.1%	45.1%	62.2%

Figure 4. Turtle strategy Forex monthly NAV

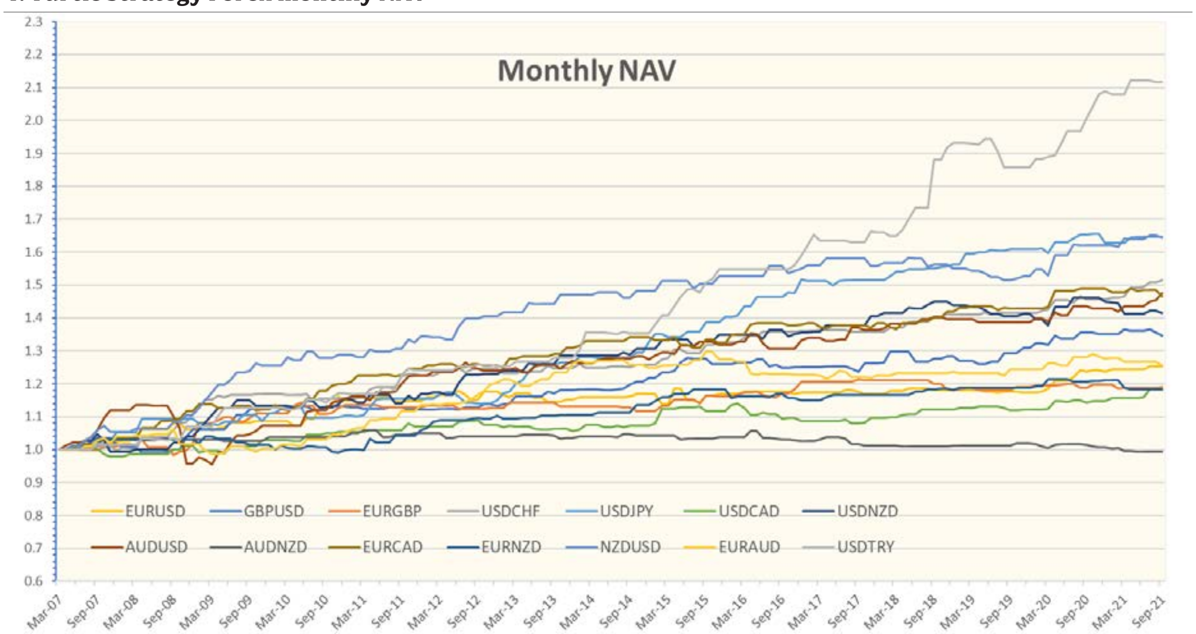

Figure 5. Turtle strategy Forex monthly drawdown

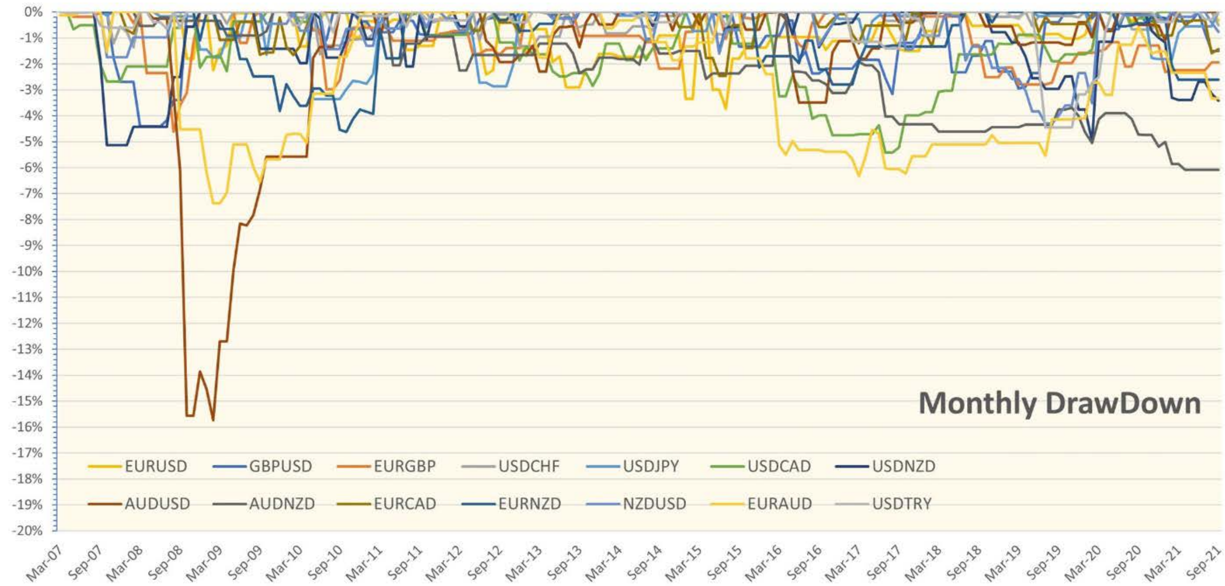

Figure 6. AUDUSD and USDNZD vs. USDTRY

Table 2. Turtle strategy Forex trade results

PERFORMANCE	EURUSD	GBPUSD	EURGBP	USDCHF	USDJPY	USDCAD	USDNZD	AUDUSD	AUDNZD	EURCAD	EURNZD	NZDUSD	EURAUD	USDTRY
Total Returns	24.9%	34.5%	19.0%	50.7%	66.4%	18.3%	41.1%	47.6%	-0.6%	46.9%	18.1%	63.9%	25.4%	112.9%
CAGR	1.5%	2.1%	1.2%	2.9%	3.6%	1.2%	2.4%	2.7%	0.0%	2.7%	1.1%	3.4%	1.6%	5.3%
Volatility	2.8%	2.6%	2.7%	2.4%	2.9%	2.4%	3.3%	4.3%	1.6%	2.6%	2.2%	3.0%	2.9%	3.9%
Maximum DrawDown	-3.7%	-4.4%	-4.6%	-1.6%	-3.4%	-5.4%	-5.1%	-15.7%	-6.1%	-2.5%	-4.6%	-4.3%	-7.4%	-4.5%
Sharpe Ratio	0.56	0.79	0.44	1.18	1.21	0.48	0.73	0.63	-0.03	1.01	0.53	1.13	0.55	1.35
Calmar Ratio	0.41	0.47	0.26	1.75	1.06	0.21	0.47	0.17	-0.01	1.09	0.25	0.80	0.21	1.19
Max Monthly Return	4.11%	4.04%	6.12%	4.04%	4.04%	4.04%	4.04%	4.04%	2.00%	3.62%	3.41%	4.04%	2.12%	8.48%
Min Monthly Return	-2.99%	-2.32%	-2.35%	-1.63%	-3.36%	-2.14%	-3.33%	-10.04%	-2.18%	-1.78%	-2.14%	-1.75%	-4.52%	-2.41%
% Positive Months	31.4%	30.9%	26.3%	37.1%	36.6%	29.7%	26.9%	35.4%	17.1%	32.6%	22.9%	29.1%	31.4%	29.7%

Turtle Soup

The Turtle Soup strategy attempts to identify a false breakout and to enter the trade trying to capture its reversal, since quite often when the market is in a strong trend, false breakouts may have a short duration and the breaks, instead of producing a strong movement, sometimes generate rapid and sudden reversals. To take advantage of these changes of direction, LC and LBR proposed the Turtle Soup. The Turtle Soup was backtested on the same assets and Forex crosses as the Turtle strategy. A trailing stop-loss on the Donchian channel limit where the false breakout occurred was set as soon as the position became profitable. Figure 7 and Figure 8 show the monthly NAV and the monthly drawdown of the Turtle Soup. The performance metrics results are summarized in Table 3.

Similarly to the Turtle, even the Turtle Soup generated worse results on the Forex, as illustrated in Figure 9, but with significantly less drawdowns, not exceeding 3%, as reported in Figure 10. It is worth remarking that in the Forex market the overall performance of the Turtle Soup was comparable with the Turtle's performance (except for USDTRY). Since the Turtle Soup attempts to capture a reversal after a false breakout, this outcome confirms that a trend-following strategy like the Turtle does not outperform a reversal strategy such as the Turtle Soup in a mean-reverting market like the Forex.

The performance metrics for the Turtle Soup backtested on the currency crosses are reported in Table 4. Even the Turtle Soup is more effective in the Forex market when the trades are closed after three days if the profit target has not been reached.

The Turtle and Turtle Soup are two strategies having a different behavior, and this is confirmed by the correlation analyses on all the asset classes and currency pairs, which are summarized in Table 5. Each table entry represents the correlation between the daily returns generated by the Turtle and Turtle Soup on a given asset. The correlation values are close to zero, which means that the two strategies are basically uncorrelated.

Figure 7. Turtle Soup strategy asset classes monthly NAV

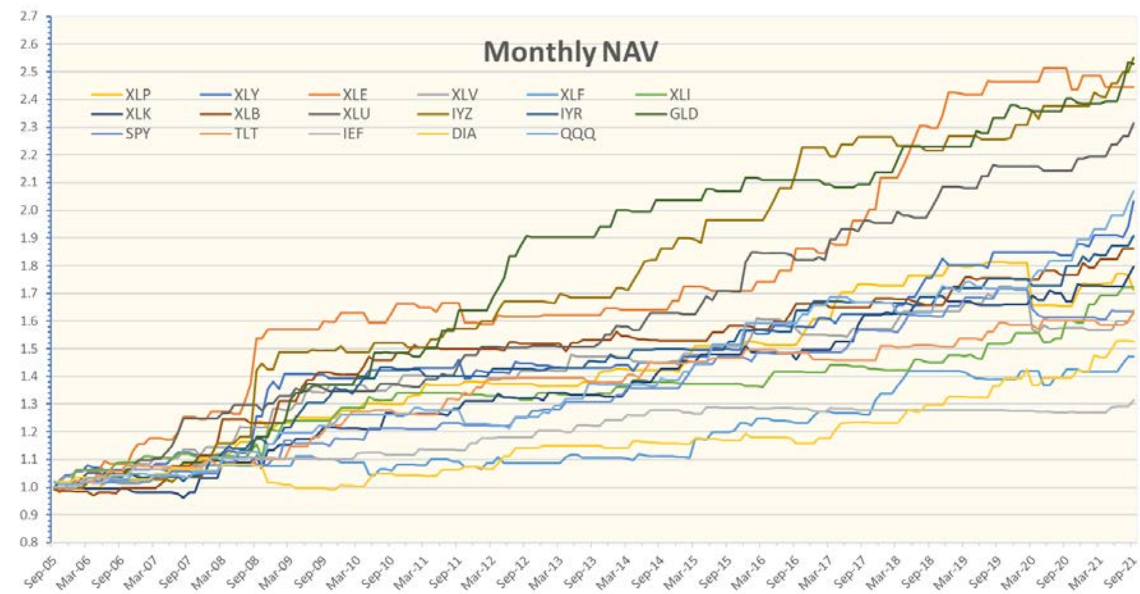

Figure 8. Turtle Soup strategy asset classes monthly drawdown

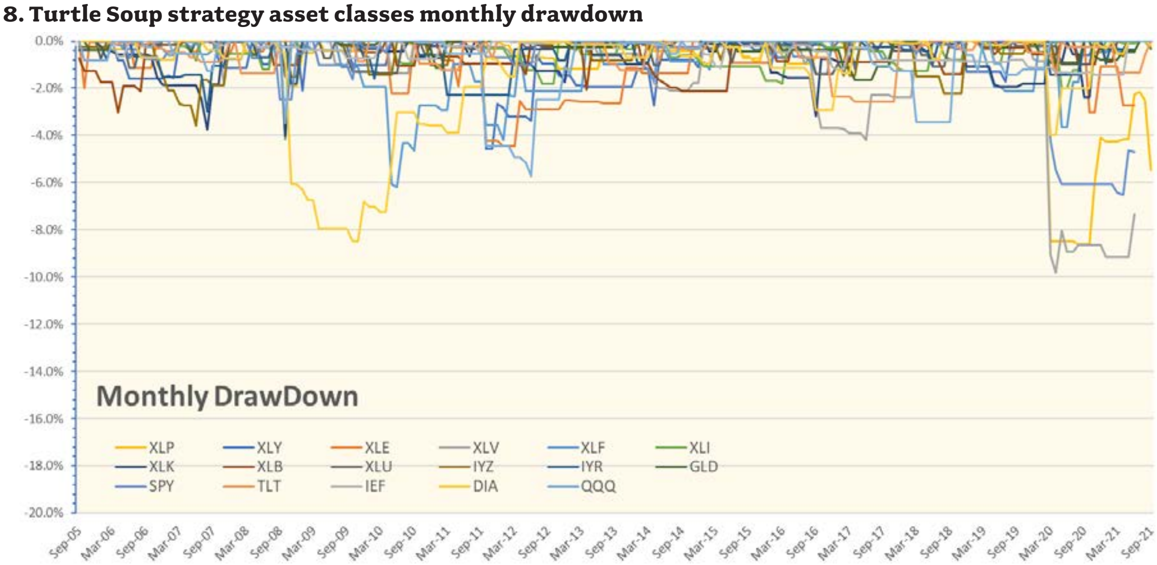

Table 3. Turtle Soup strategy asset classes trade results

PERFORMANCE	XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU	IYZ	IYR	SPY	DIA	IEF	TLT	GLD	QQQ
Total Returns	71.2%	103.4%	144.4%	63.0%	47.2%	72.3%	79.6%	86.2%	131.4%	155.0%	90.9%	63.6%	52.5%	31.3%	63.8%	152.8%	106.9%
CAGR	3.4%	4.5%	5.7%	3.1%	2.4%	3.4%	3.7%	3.9%	5.4%	6.0%	4.1%	3.1%	2.7%	1.7%	3.1%	5.9%	4.6%
Volatility	4.0%	4.7%	5.4%	4.2%	3.6%	4.1%	4.1%	3.9%	3.7%	6.3%	3.5%	3.5%	3.5%	2.0%	3.0%	4.3%	4.3%
Maximum DrawDown	-8.6%	-4.6%	-4.5%	-9.8%	-6.2%	-4.2%	-4.0%	-3.0%	-1.5%	-3.6%	-3.0%	-6.5%	-8.5%	-1.4%	-2.6%	-1.6%	-5.7%
Sharpe Ratio	0.85	0.96	1.06	0.73	0.68	0.84	0.91	1.01	1.44	0.96	1.17	0.89	0.76	0.86	1.03	1.38	1.07
Calmar Ratio	0.40	0.99	1.28	0.31	0.39	0.83	0.92	1.30	3.60	1.67	1.37	0.48	0.31	1.19	1.21	3.62	0.81
Max Monthly Return	6.41%	9.74%	12.32%	5.61%	6.12%	9.13%	6.15%	7.31%	6.12%	20.44%	4.94%	6.01%	4.04%	2.10%	4.04%	6.79%	6.01%
Min Monthly Return	-8.37%	-4.57%	-4.23%	-8.29%	-4.19%	-4.16%	-4.02%	-1.82%	-1.49%	-1.52%	-1.80%	-4.23%	-5.61%	-0.67%	-1.67%	-0.83%	-3.92%
% Positive Months	21.8%	20.2%	20.7%	19.2%	18.7%	17.1%	18.1%	18.1%	25.9%	24.4%	20.2%	17.1%	18.1%	14.0%	18.1%	20.7%	19.7%

Figure 9. Turtle Soup strategy Forex monthly NAV

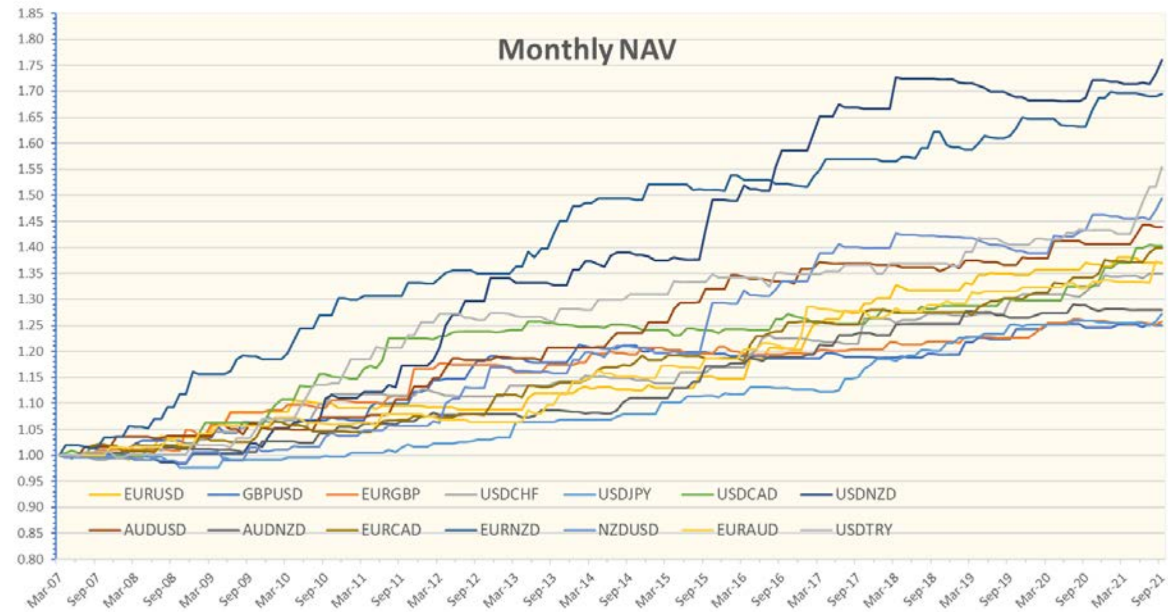

Figure 10. Turtle Soup strategy Forex monthly drawdown

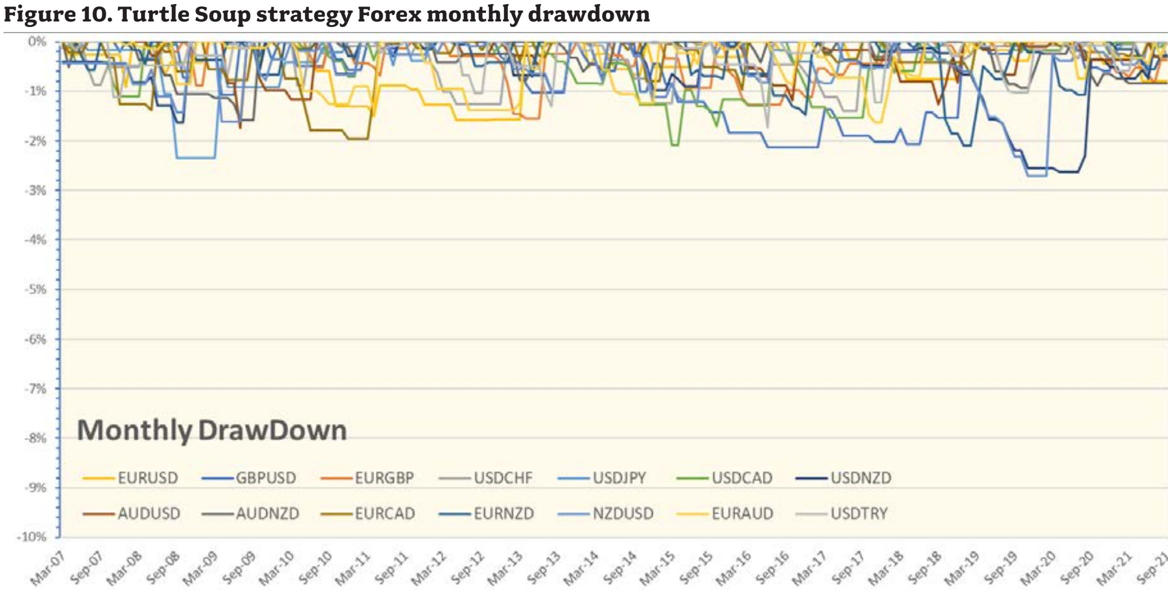

Table 4. Turtle Soup strategy Forex trade results

PERFORMANCE	EURUSD	GBPUSD	EURGBP	USDCHF	USDJPY	USDCAD	USDNZD	AUDUSD	AUDNZD	EURCAD	EURNZD	NZDUSD	EURAUD	USDTRY
Total Returns	37.0%	26.3%	25.7%	34.6%	27.2%	43.2%	76.1%	43.9%	27.9%	42.2%	69.5%	49.4%	38.1%	55.4%
CAGR	2.2%	1.6%	1.6%	2.1%	1.7%	2.5%	4.0%	2.5%	1.7%	2.4%	3.7%	2.8%	2.2%	3.1%
Volatility	2.1%	1.9%	2.1%	2.2%	1.6%	2.2%	3.3%	2.3%	1.7%	2.0%	2.7%	2.9%	2.4%	2.5%
Maximum DrawDown	-1.6%	-2.1%	-1.6%	-1.4%	-2.3%	-2.1%	-2.6%	-1.7%	-1.6%	-2.0%	-2.1%	-2.7%	-1.6%	-1.7%
Sharpe Ratio	1.02	0.87	0.74	0.95	1.03	1.11	1.19	1.11	1.00	1.20	1.37	0.96	0.92	1.21
Calmar Ratio	1.37	0.76	1.02	1.47	0.71	1.19	1.50	1.46	1.08	1.25	1.75	1.03	1.36	1.78
Max Monthly Return	3.20%	2.33%	4.84%	4.04%	2.77%	3.47%	4.11%	2.70%	2.63%	2.62%	3.81%	4.04%	4.62%	2.53%
Min Monthly Return	-0.73%	-1.07%	-0.77%	-0.89%	-1.31%	-0.82%	-0.68%	-0.91%	-0.53%	-0.94%	-1.57%	-1.62%	-0.85%	-1.23%
% Positive Months	20.0%	19.4%	17.7%	20.6%	22.9%	22.9%	21.7%	19.4%	20.0%	28.6%	27.4%	20.0%	19.4%	21.7%

Table 5. Turtle vs. Turtle Soup correlations

XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU
-0.1216	-0.0052	-0.0046	-0.0036	-0.0021	-0.0003	-0.0057	0.0007	-0.0064
IYZ	**IYR**	**SPY**	**DIA**	**IEF**	**TLT**	**GLD**	**QQQ**	
-0.0027	-0.0070	-0.0031	-0.0030	0.0156	-0.0040	-0.0072	-0.0073	

EURUSD	GBPUSD	EURGBP	USDCHF	USDJPY	USDCAD	USDNZD
-0.0021	-0.0025	-0.0018	-0.0041	-0.0044	-0.0019	-0.0037
AUDUSD	**AUDNZD**	**EURCAD**	**EURNZD**	**NZDUSD**	**EURAUD**	**USDTRY**
-0.0027	0.0007	-0.0043	-0.0026	-0.0043	-0.0019	-0.0055

Anti

The Anti strategy is an example of retracement pattern. It enters in the direction of the long-term trend after a retracement (either a throwback or pullback, depending on whether the long-term trend is bullish or bearish) of the short-term trend towards the long-term trend. The basic principle of this strategy is that often a short-term trend tends to resolve in the direction of the long-term trend. Anti worked better on the sectors XLF, XLE, XLB, and XLY, which outperformed the technology stocks (QQQ and XLK) and the other assets, as shown in Figure 11. The drawdowns were less than 7% across the look-back period, as represented in Figure 12. The numerical results for the Anti are reported in Table 6.

The same Anti setup was used for the Forex market. The monthly NAV and drawdown are illustrated in Figure 13 and Figure 14. The numerical results are summarized in Table 7, with the worst drawdowns around 4%.

Even the overall performance of the Anti was better on the stock indexes and S&P 500 sectors than on the Forex crosses, thus showing a consistent behavior with the other *Street Smarts* strategies.

Figure 11. Anti strategy asset classes monthly NAV

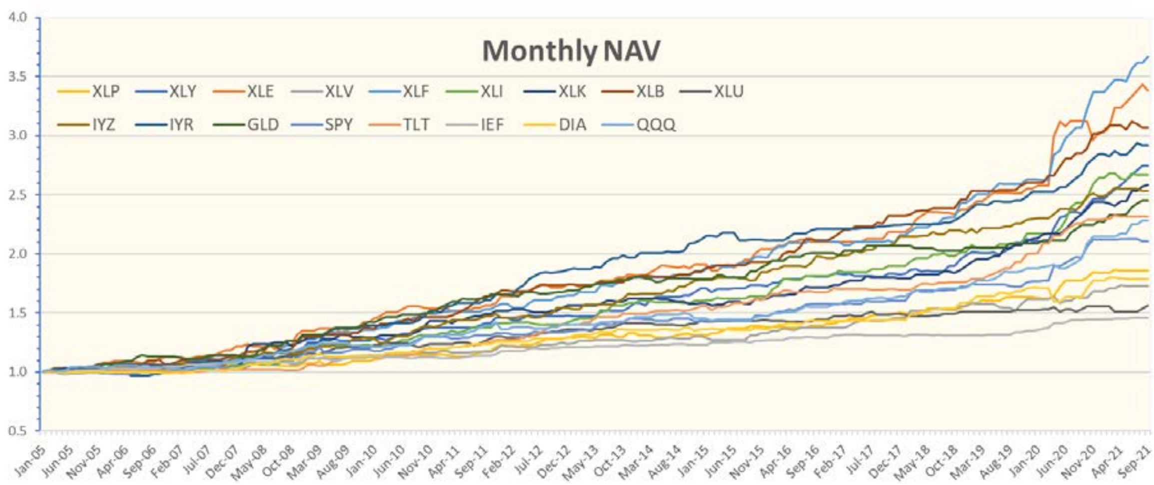

Figure 12. Anti strategy asset classes monthly drawdown

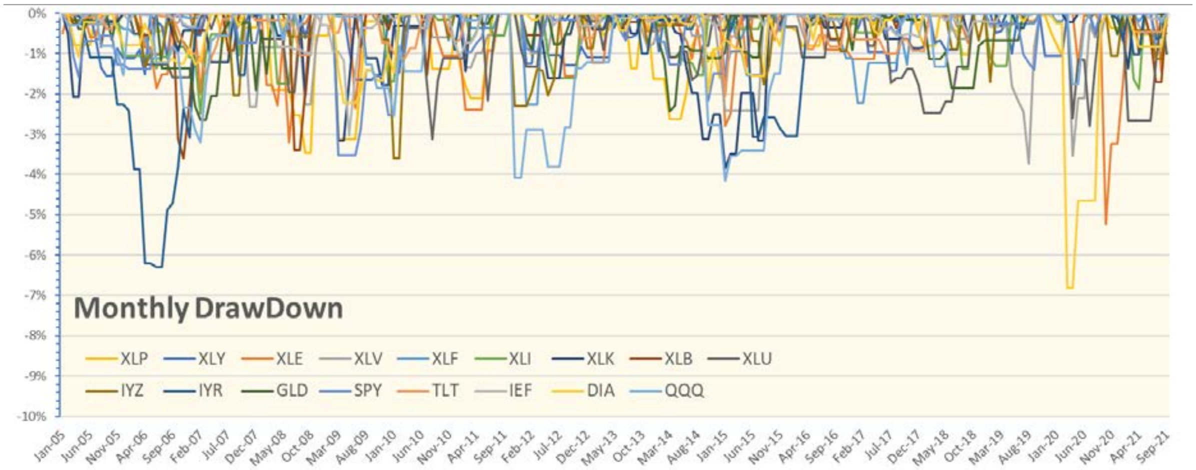

Table 6. Anti strategy asset classes trade results

PERFORMANCE	XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU	IYZ	IYR	SPY	DIA	IEF	TLT	GLD	QQQ
Total Returns	88.6%	174.7%	247.3%	72.6%	282.4%	171.1%	162.5%	214.2%	55.0%	156.8%	200.4%	113.3%	81.2%	46.0%	132.2%	144.8%	135.0%
CAGR	3.8%	6.2%	7.7%	3.3%	8.3%	6.1%	5.9%	7.0%	2.6%	5.8%	6.8%	4.6%	3.6%	2.3%	5.1%	5.5%	5.2%
Volatility	3.1%	3.9%	6.0%	3.2%	4.4%	4.1%	4.6%	3.9%	2.8%	3.7%	3.7%	3.6%	3.3%	2.0%	3.0%	3.4%	3.6%
Maximum DrawDown	-3.5%	-1.7%	-5.2%	-3.7%	-2.3%	-2.5%	-3.8%	-3.6%	-3.1%	-3.6%	-6.3%	-3.5%	-6.8%	-3.0%	-2.1%	-2.6%	-4.2%
Sharpe Ratio	1.22	1.59	1.29	1.04	1.89	1.50	1.29	1.82	0.94	1.57	1.81	1.27	1.09	1.16	1.73	1.60	1.45
Calmar Ratio	1.11	3.69	1.47	0.88	3.66	2.45	1.54	1.96	0.84	1.60	1.07	1.30	0.53	0.75	2.50	2.07	1.25
Max Monthly Return	4.67%	5.43%	16.22%	3.78%	8.11%	6.11%	12.92%	4.52%	2.07%	4.57%	5.37%	6.72%	4.57%	3.55%	4.03%	4.26%	6.27%
Min Monthly Return	-3.12%	-1.55%	-5.03%	-3.55%	-2.27%	-1.74%	-3.15%	-3.38%	-2.67%	-2.97%	-3.06%	-3.53%	-6.58%	-1.88%	-2.06%	-1.68%	-4.07%
% Positive Months	35.8%	38.8%	40.8%	30.3%	38.8%	35.8%	36.8%	40.3%	30.8%	41.8%	44.8%	34.8%	33.8%	37.8%	42.3%	36.8%	41.8%

Figure 13. Anti strategy Forex monthly NAV

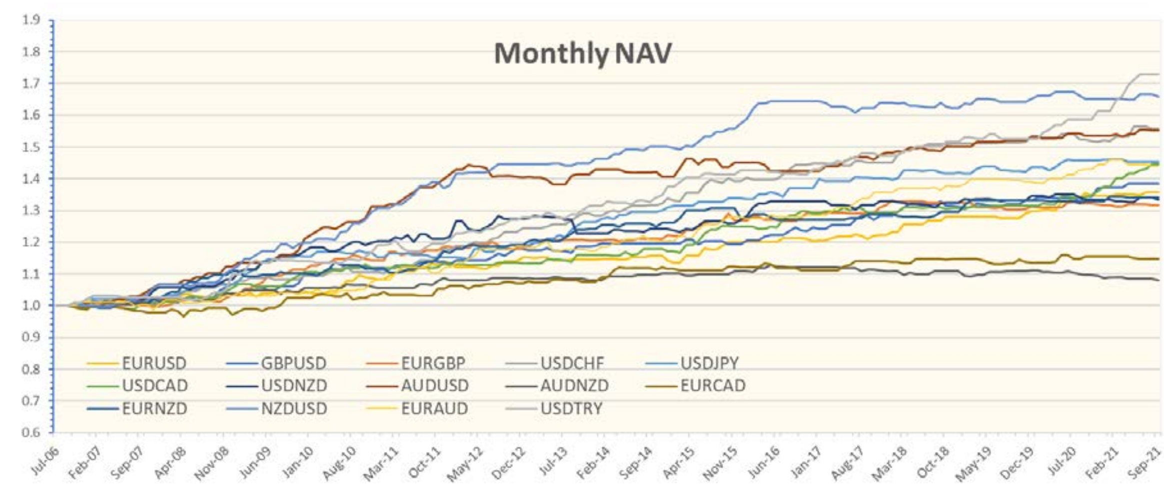

Figure 14. Anti strategy Forex monthly drawdown

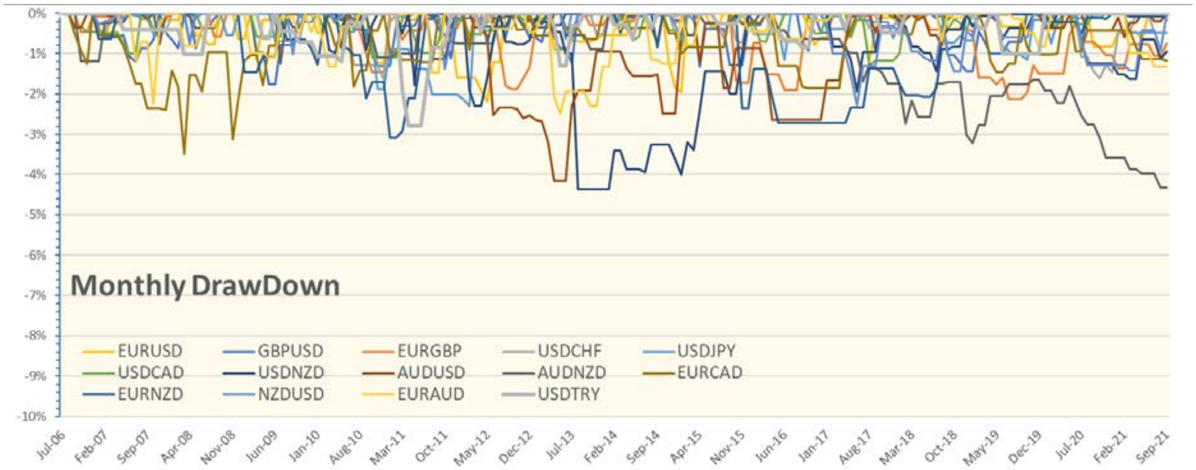

Table 7. Anti strategy Forex trade results

PERFORMANCE	EURUSD	GBPUSD	EURGBP	USDCHF	USDJPY	USDCAD	USDNZD	AUDUSD	AUDNZD	EURCAD	EURNZD	NZDUSD	EURAUD	USDTRY
Total Returns	34.8%	39.7%	31.9%	57.2%	45.4%	45.6%	35.1%	55.8%	8.0%	15.7%	33.7%	70.4%	44.0%	76.4%
CAGR	2.0%	2.2%	1.8%	3.0%	2.5%	2.5%	2.0%	2.9%	0.5%	0.9%	1.9%	3.5%	2.4%	3.8%
Volatility	2.0%	2.0%	1.9%	2.0%	2.0%	2.0%	2.5%	2.3%	1.4%	2.1%	2.0%	2.3%	2.2%	2.4%
Maximum DrawDown	-2.2%	-1.8%	-2.1%	-1.6%	-2.3%	-1.3%	-4.4%	-4.2%	-4.3%	-3.5%	-3.1%	-2.3%	-2.5%	-2.8%
Sharpe Ratio	0.99	1.08	0.96	1.50	1.20	1.24	0.78	1.28	0.35	0.45	0.93	1.55	1.06	1.55
Calmar Ratio	0.89	1.24	0.85	1.81	1.06	1.92	0.45	0.70	0.12	0.27	0.62	1.54	0.96	1.34
Max Monthly Return	2.21%	2.60%	2.30%	2.38%	2.75%	2.01%	4.06%	3.03%	1.21%	2.01%	2.01%	2.59%	2.01%	4.56%
Min Monthly Return	-1.21%	-1.33%	-1.67%	-1.28%	-1.23%	-1.12%	-3.39%	-1.98%	-1.31%	-2.18%	-2.36%	-1.37%	-2.07%	-1.90%
% Positive Months	29.3%	32.1%	30.4%	39.1%	31.0%	33.2%	28.8%	34.2%	21.7%	23.9%	25.5%	35.9%	31.0%	34.2%

ID-NR4

Swing trading can be profitable when there are price oscillations and a good amount of volatility (Kaufman, 2013). The internal-day narrow-range 4 (ID-NR4) strategy attempts to identify a pattern where a period of volatility expansion usually follows a period of volatility contraction. When the volatility is cyclical, then the market can experience sequences of range contractions followed by range expansions, and usually after the market has been inactive (or in a period of range contraction), a trend period often follows (Crabel 1990). The ID-NR4 strategy was backtested closing an open position after three days, since volatility explosions are not often followed by trend movements. The experimental results are shown in Figure 15 and Figure 16. GLD delivered the best performance along the backtesting period. The numerical results are summarized in Table 8.

It is quite important to assess the effectiveness of stopping and reversing in a whipsaw (or trading range). This means that if the trade is a loser, not only it will be stopped out with a small loss, but it will reverse direction. The Stop & Reverse technique was part of the ID-NR4 set-up and it was backtested with the strategy. The overall performance, with respect to the implementation without Stop & Reverse, has only slightly improved, as shown in Figure 17 and Figure 18. After a Stop & Reverse pattern, it is more likely to enter a trading range than a true trend reversal. The numerical results summarizing the performance of the Stop & Reverse technique are shown in Table 9.

The ID-NR4 strategy was also tested on the Forex currency pairs. The monthly NAV and drawdown are reported in Figure 19 and Figure 20. In the Forex market, large volatility movements after a period of volatility compression are not likely to happen very often. Therefore, a better performance was obtained locking in the accrued profits by closing the positions after three days, instead of relying on a trailing stop-loss to exit the trade. The numerical results are outlined in Table 10 and they confirm that ID-NR4 is not suited for the Forex.

Figure 15. IN-NR4 strategy asset classes monthly NAV

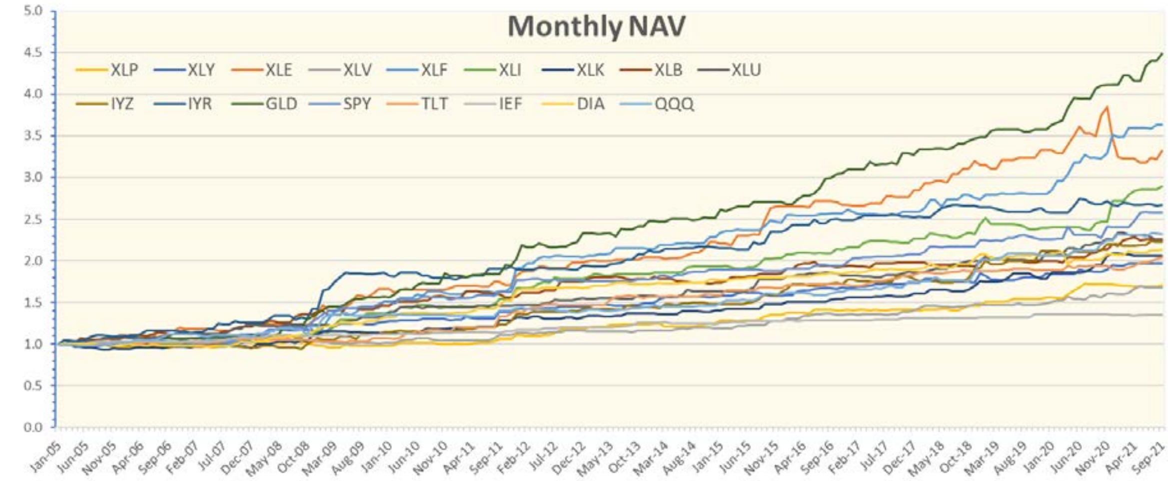

Figure 16. IN-NR4 strategy asset classes monthly drawdown

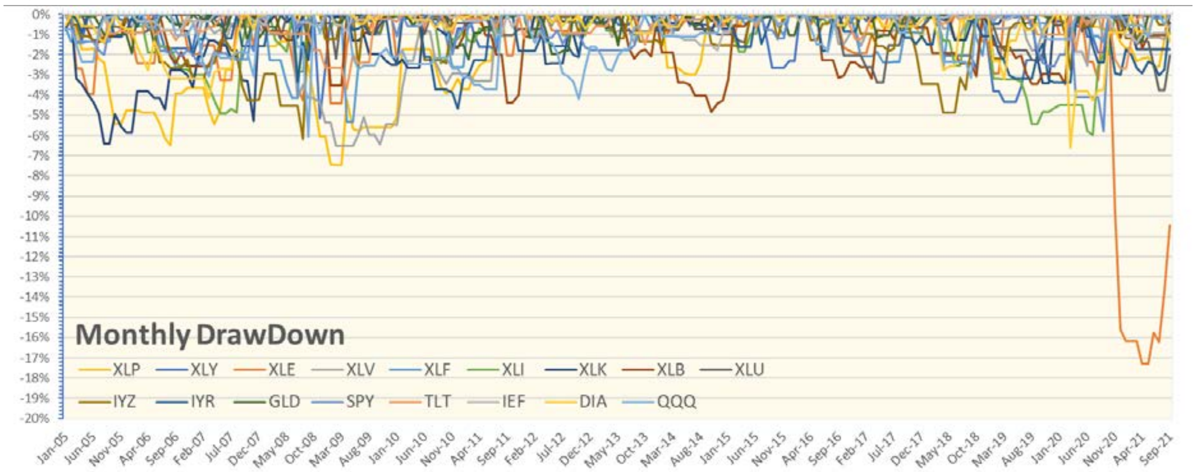

Table 8. ID-NR4 strategy asset classes trade results

PERFORMANCE	XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU	IYZ	IYR	SPY	DIA	IEF	TLT	GLD	QQQ
Total Returns	71.6%	97.0%	244.3%	71.3%	259.0%	209.6%	105.6%	136.8%	129.1%	129.6%	173.6%	181.3%	110.7%	35.2%	104.4%	348.2%	134.8%
CAGR	3.3%	4.1%	7.6%	3.3%	7.9%	6.9%	4.4%	5.3%	5.0%	5.1%	6.2%	6.3%	4.5%	1.8%	4.3%	9.3%	5.2%
Volatility	3.7%	4.3%	7.4%	3.4%	6.6%	6.0%	4.6%	5.1%	4.0%	5.3%	6.4%	5.4%	4.2%	1.8%	4.3%	5.6%	5.5%
Maximum DrawDown	-7.5%	-5.1%	-17.3%	-6.5%	-5.3%	-6.0%	-6.4%	-4.8%	-3.8%	-6.2%	-4.7%	-5.8%	-6.6%	-1.8%	-3.7%	-2.2%	-6.1%
Sharpe Ratio	0.88	0.95	1.04	0.95	1.19	1.16	0.96	1.04	1.25	0.96	0.96	1.17	1.07	1.03	1.02	1.67	0.94
Calmar Ratio	0.44	0.80	0.44	0.50	1.48	1.16	0.68	1.09	1.34	0.82	1.32	1.10	0.69	1.02	1.17	4.20	0.86
Max Monthly Return	3.89%	6.41%	9.27%	3.64%	13.74%	10.24%	6.09%	6.09%	5.18%	6.50%	15.19%	8.95%	7.40%	2.63%	10.73%	8.39%	9.27%
Min Monthly Return	-2.65%	-5.08%	-9.79%	-3.02%	-5.33%	-3.17%	-3.16%	-3.41%	-1.77%	-2.60%	-3.35%	-4.11%	-6.58%	-1.10%	-2.09%	-1.61%	-4.52%
% Positive Months	36.3%	30.8%	31.8%	34.8%	34.3%	36.3%	33.8%	33.3%	35.8%	32.3%	34.8%	37.8%	42.8%	35.3%	35.3%	48.3%	33.3%

Figure 17. ID-NR4 strategy asset classes NAV with Stop & Reverse

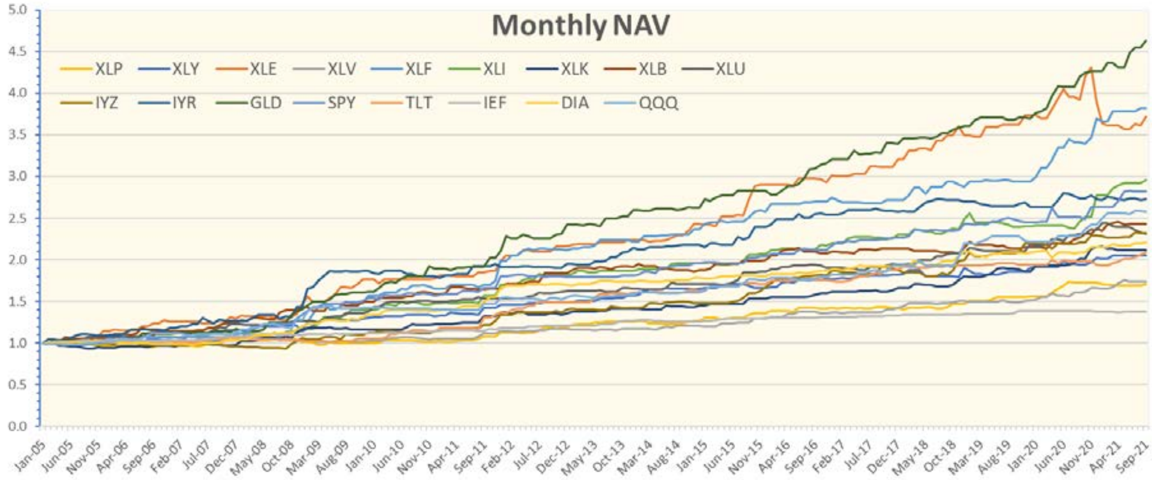

Figure 18. ID-NR4 strategy asset classes monthly drawdown with Stop & Reverse

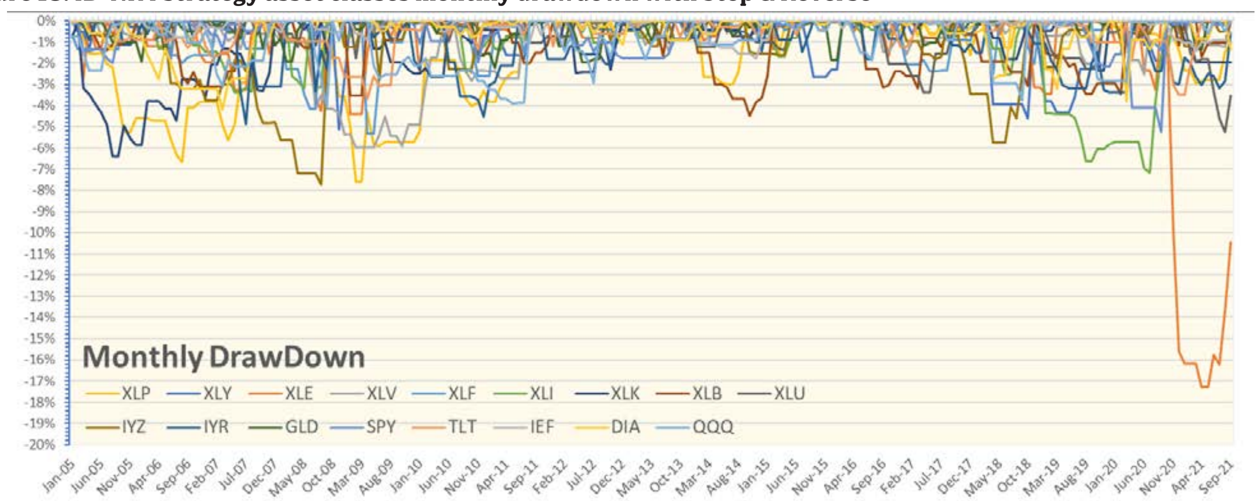

Table 9. ID-NR4 strategy asset classes trade results with Stop & Reverse

PERFORMANCE	XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU	IYZ	IYR	SPY	DIA	IEF	TLT	GLD	QQQ
Total Returns	71.9%	104.9%	286.1%	77.3%	277.8%	216.0%	111.7%	155.4%	135.5%	138.9%	178.9%	207.4%	118.3%	38.1%	108.6%	363.5%	160.6%
CAGR	3.3%	4.4%	8.4%	3.5%	8.2%	7.1%	4.6%	5.7%	5.2%	5.3%	6.3%	6.9%	4.7%	1.9%	4.5%	9.5%	5.9%
Volatility	3.8%	4.5%	7.4%	3.4%	6.7%	6.1%	4.5%	5.2%	4.0%	5.3%	6.5%	5.5%	4.0%	1.8%	4.3%	5.9%	5.6%
Maximum DrawDown	-7.6%	-5.1%	-17.3%	-6.0%	-5.3%	-7.2%	-6.4%	-4.5%	-5.3%	-7.7%	-4.9%	-5.3%	-4.2%	-1.8%	-3.7%	-2.2%	-4.1%
Sharpe Ratio	0.86	0.98	1.13	1.02	1.23	1.16	1.01	1.11	1.29	1.01	0.97	1.25	1.18	1.09	1.04	1.63	1.05
Calmar Ratio	0.43	0.85	0.48	0.58	1.54	0.99	0.71	1.28	0.99	0.69	1.29	1.31	1.13	1.09	1.21	4.29	1.44
Max Monthly Return	3.89%	6.41%	9.27%	3.64%	13.74%	10.24%	6.09%	6.09%	5.18%	6.50%	15.19%	8.95%	7.40%	2.63%	10.73%	8.39%	9.27%
Min Monthly Return	-2.73%	-5.08%	-9.79%	-3.02%	-5.33%	-4.39%	-3.16%	-3.41%	-1.77%	-2.82%	-3.35%	-4.11%	-3.78%	-1.10%	-2.09%	-1.72%	-2.94%
% Positive Months	37.3%	32.3%	33.8%	35.8%	35.3%	36.8%	34.8%	34.3%	37.3%	33.8%	36.3%	38.3%	42.8%	36.8%	35.8%	47.8%	34.8%

Figure 19. ID-NR4 strategy Forex monthly NAV

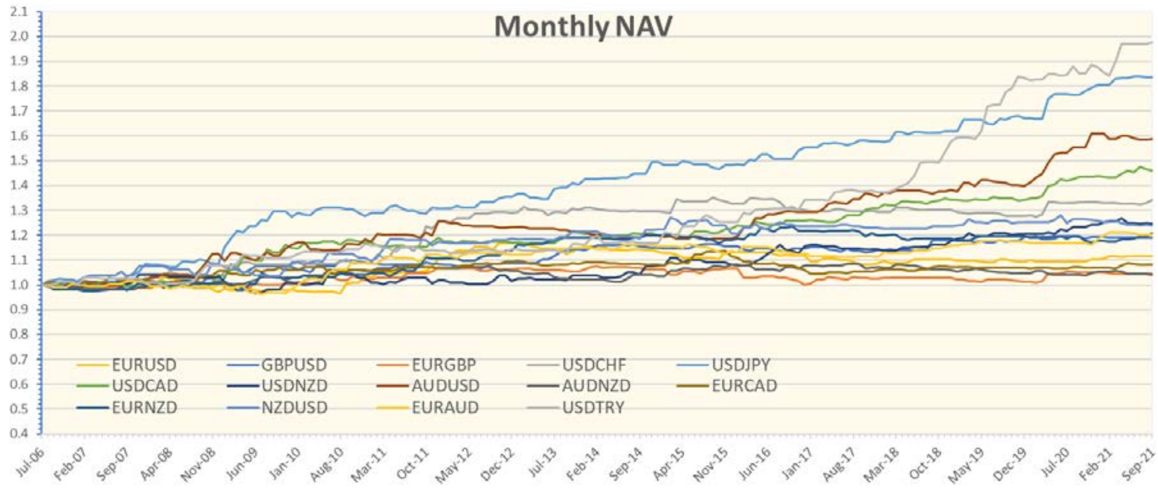

Figure 20. IN-NR4 strategy Forex monthly drawdown

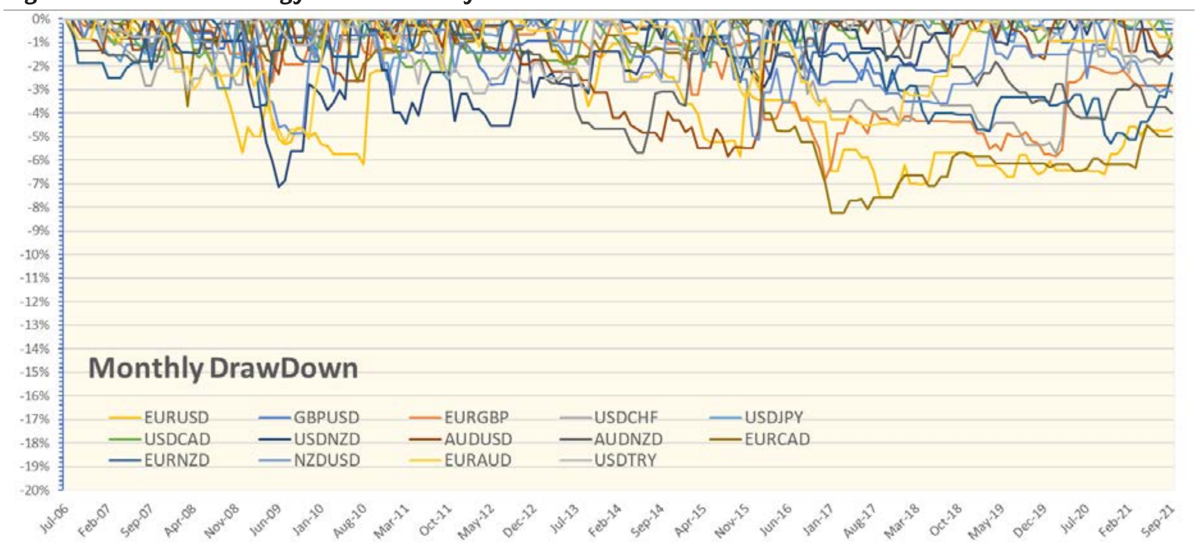

Table 10. IN-NR4 strategy Forex trade results

PERFORMANCE	EURUSD	GBPUSD	EURGBP	USDCHF	USDJPY	USDCAD	USDNZD	AUDUSD	AUDNZD	EURCAD	EURNZD	NZDUSD	EURAUD	USDTRY
Total Returns	11.5%	19.1%	4.3%	33.9%	83.5%	45.2%	26.3%	56.8%	4.1%	8.4%	21.5%	25.6%	19.5%	106.8%
CAGR	0.7%	1.1%	0.3%	1.9%	4.0%	2.4%	1.5%	3.0%	0.3%	0.5%	1.3%	1.5%	1.2%	4.8%
Volatility	2.6%	2.6%	2.2%	3.5%	3.6%	3.0%	3.2%	3.6%	2.0%	2.2%	2.9%	3.5%	2.5%	4.2%
Maximum DrawDown	-7.6%	-3.2%	-6.8%	-5.7%	-2.6%	-3.0%	-7.1%	-5.9%	-5.7%	-8.3%	-5.3%	-5.1%	-5.3%	-3.1%
Sharpe Ratio	0.27	0.43	0.12	0.55	1.12	0.82	0.47	0.82	0.13	0.23	0.44	0.43	0.46	1.14
Calmar Ratio	0.09	0.35	0.04	0.33	1.54	0.82	0.21	0.51	0.05	0.06	0.24	0.29	0.22	1.53
Max Monthly Return	4.10%	5.26%	3.00%	6.42%	6.09%	4.47%	4.74%	4.72%	2.27%	3.00%	4.42%	4.42%	3.01%	6.09%
Min Monthly Return	-2.17%	-2.06%	-3.39%	-2.01%	-1.50%	-1.46%	-2.13%	-2.53%	-1.79%	-2.26%	-2.55%	-2.49%	-2.52%	-2.66%
% Positive Months	26.6%	26.6%	21.7%	23.4%	37.0%	34.8%	30.4%	31.5%	23.9%	29.3%	28.8%	26.6%	25.5%	38.0%

Holy Grail

This pattern is based on Welles Wilder's Average Directional Index (ADX) (Wilder, 1978) and is supposed to work in any market and in any timeframe. The Holy Grail is a strategy that enters a position after a retracement. Once we are in the trade, we look for a continuation of the previous trend. In the Holy Grail, when prices retrace after a strong move, a 20-period exponential moving average acts as support/resistance for these retracements. The monthly NAV and drawdown are reported in Figure 21 and Figure 22. The numerical results of the Holy Grail for the equity indexes and sectors are summarized in Table 11. A trailing stop-loss with a fixed amplitude of 1% was used and positions were closed after three days if the profit target had not been reached.

Even on the Forex crosses, the performance of the Holy Grail was worse than on the other asset classes, as confirmed by the results shown in Figure 23, Figure 24, and Table 12, respectively.

Figure 21. Holy Grail strategy asset classes monthly NAV

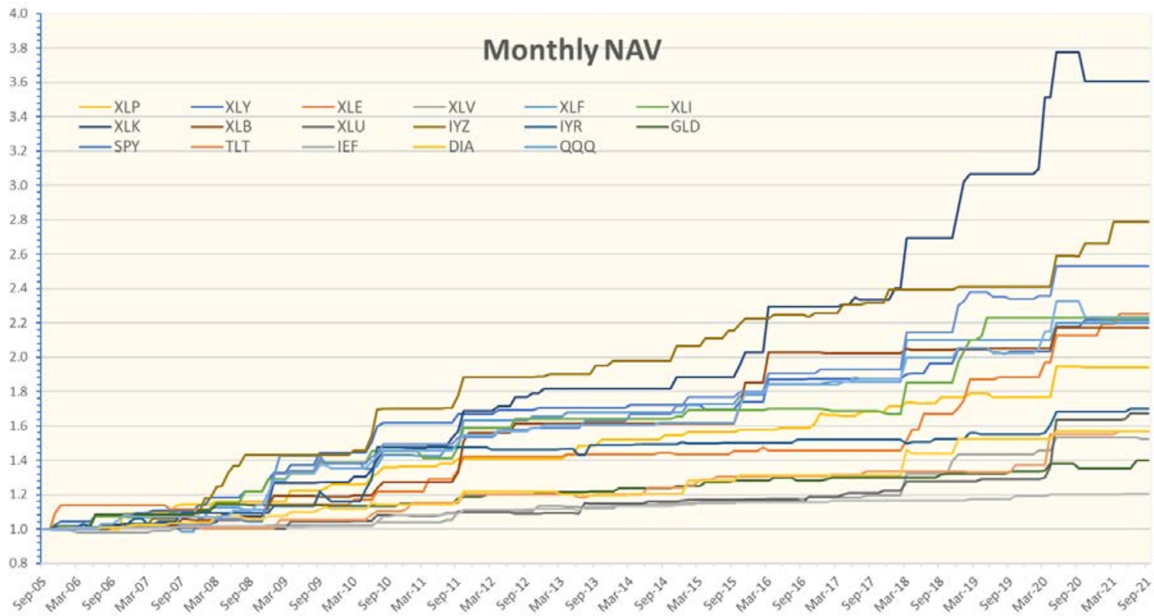

Figure 22. Holy Grail strategy asset classes monthly drawdown

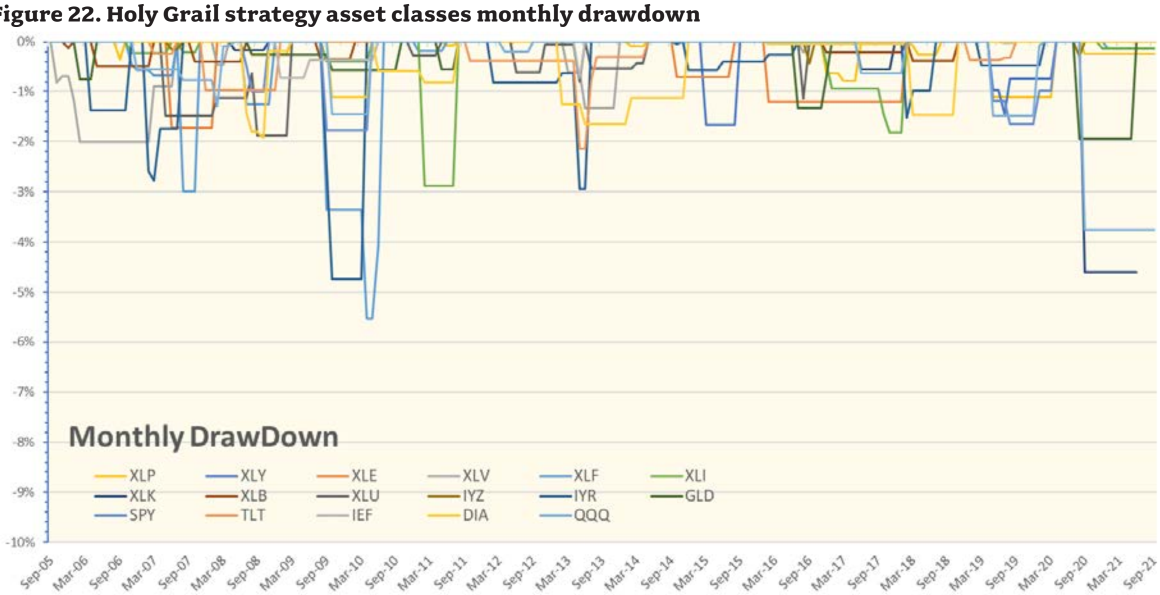

Table 11. Holy Grail strategy asset classes trade results

PERFORMANCE	XLP	XLY	XLE	XLV	XLF	XLI	XLK	XLB	XLU	IYZ	IYR	SPY	DIA	IEF	TLT	GLD	QQQ
Total Returns	94.4%	121.6%	125.3%	52.3%	119.8%	122.7%	260.5%	117.3%	70.4%	178.7%	69.8%	153.3%	57.0%	20.3%	56.9%	39.7%	123.6%
CAGR	4.2%	5.1%	5.2%	2.6%	5.0%	5.1%	8.3%	4.9%	3.4%	6.6%	3.3%	5.9%	2.8%	1.2%	2.8%	2.1%	5.1%
Volatility	4.3%	4.4%	5.1%	3.8%	7.2%	5.2%	7.6%	5.8%	5.7%	5.5%	5.3%	6.4%	4.1%	1.4%	4.1%	2.7%	4.8%
Maximum DrawDown	-1.1%	-1.7%	-1.7%	-2.0%	-5.5%	-2.9%	-4.6%	-0.5%	-1.9%	-0.4%	-4.7%	-1.8%	-1.9%	-0.7%	-2.1%	-1.9%	-3.8%
Sharpe Ratio	0.97	1.14	1.01	0.70	0.69	0.97	1.09	0.85	0.59	1.21	0.64	0.93	0.69	0.81	0.68	0.77	1.06
Calmar Ratio	3.80	3.05	3.01	1.33	0.91	1.77	1.80	10.21	1.79	15.07	0.71	3.36	1.48	1.60	1.33	1.08	1.37
Max Monthly Return	10.20%	7.41%	9.04%	10.72%	17.41%	10.86%	13.34%	13.67%	20.03%	9.93%	14.20%	12.94%	11.12%	2.79%	13.18%	7.50%	8.02%
Min Monthly Return	-1.11%	-1.66%	-1.72%	-0.86%	-3.36%	-2.88%	-4.60%	-0.48%	-1.48%	-0.44%	-2.59%	-1.77%	-1.47%	-0.72%	-1.77%	-1.95%	-3.75%
% Positive Months	16.6%	17.1%	12.4%	11.9%	12.4%	12.4%	17.6%	10.4%	15.5%	19.2%	13.5%	15.5%	9.8%	11.4%	10.9%	11.9%	15.0%

Figure 23. Holy Grail strategy Forex monthly NAV

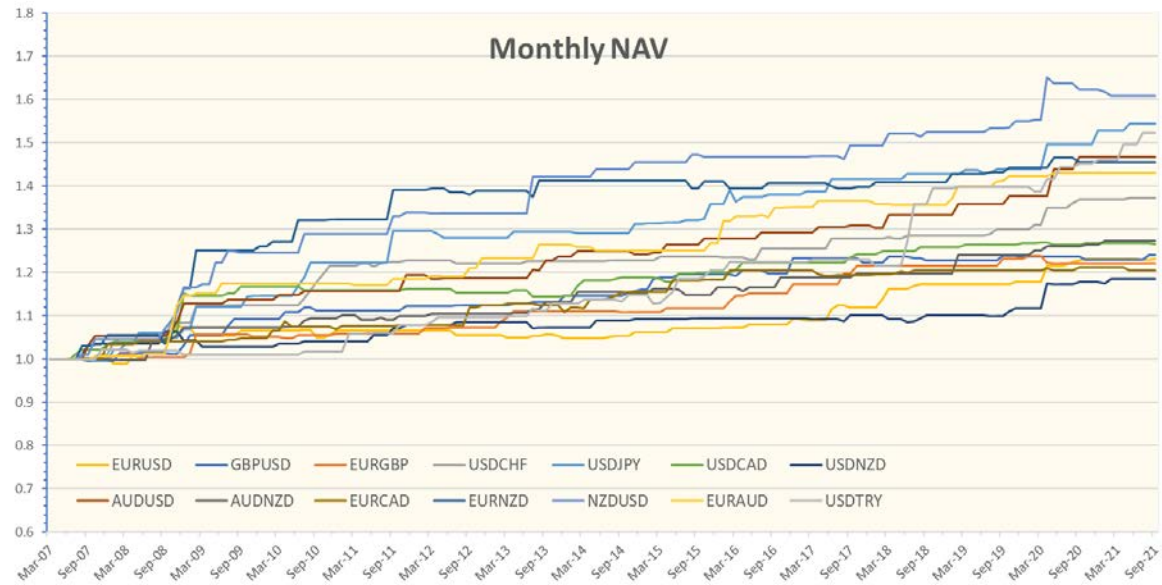

Figure 24. Holy Grail strategy Forex monthly drawdown

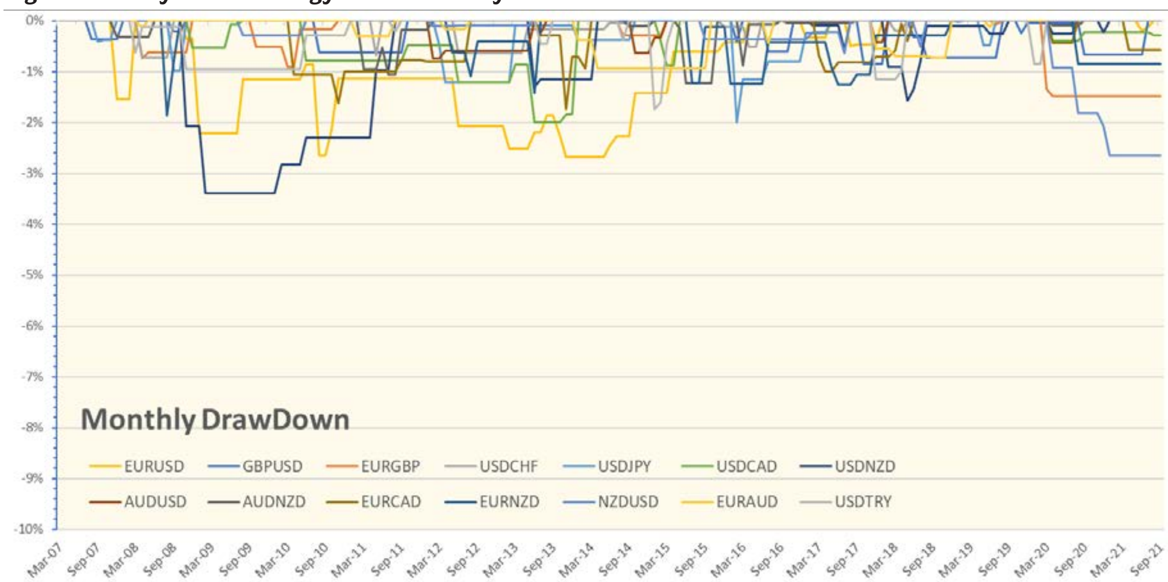

Table 12. Holy Grail strategy Forex trade results

PERFORMANCE	EURUSD	GBPUSD	EURGBP	USDCHF	USDJPY	USDCAD	USDNZD	AUDUSD	AUDNZD	EURCAD	EURNZD	NZDUSD	EURAUD	USDTRY
Total Returns	23.2%	24.1%	22.1%	37.3%	54.5%	26.6%	18.5%	46.8%	27.3%	20.5%	45.4%	60.8%	43.0%	52.2%
CAGR	1.4%	1.5%	1.4%	2.2%	3.0%	1.6%	1.2%	2.7%	1.7%	1.3%	2.6%	3.3%	2.5%	2.9%
Volatility	2.1%	1.7%	1.7%	2.2%	3.1%	2.6%	2.0%	2.5%	2.0%	1.9%	3.7%	3.5%	2.7%	3.1%
Maximum DrawDown	-2.7%	-0.8%	-1.5%	-0.7%	-2.0%	-2.0%	-3.4%	-0.7%	-1.2%	-1.7%	-1.9%	-2.6%	-0.9%	-1.7%
Sharpe Ratio	0.68	0.87	0.80	1.00	0.99	0.63	0.57	1.07	0.85	0.68	0.71	0.94	0.91	0.96
Calmar Ratio	0.54	1.77	0.93	3.07	1.52	0.82	0.34	3.58	1.36	0.74	1.40	1.25	2.68	1.69
Max Monthly Return	4.04%	3.02%	4.31%	4.36%	5.99%	8.64%	5.13%	4.53%	4.37%	3.89%	7.51%	6.34%	5.91%	6.83%
Min Monthly Return	-1.87%	-0.84%	-1.34%	-0.72%	-2.00%	-1.15%	-2.08%	-0.74%	-1.08%	-1.47%	-1.85%	-0.92%	-0.56%	-1.73%
% Positive Months	20.0%	13.7%	13.1%	17.1%	17.1%	17.1%	13.7%	14.3%	14.9%	16.0%	13.7%	14.9%	14.3%	18.3%

Statistical Hypothesis Testing

"There are three types of lies: lies, damn lies, and statistics…" —Benjamin Disraeli (1804–1881), Prime Minister of Great Britain (1874–1880)

The strategies of *Street Smarts* were backtested on several times series of historical data, and we used inferential statistics to have a better insight on whether they can generate excess returns different than and above zero. The hypothesis testing is a rigorous inference procedure to decide when a trading rule or a strategy has some intrinsic value (i.e., it can generate positive excessive returns and, therefore, it can help us to decide whether it can be used for trading in the future). In this work, we considered multiple hypothesis testing adjustments and time series bootstrap. All the results presented in Appendix A and Appendix B were obtained with the statistical software R (The R Project for Statistical Computing, 2022).

Multiple Hypothesis Testing

Multiple hypothesis testing consists of statistical inference by not rejecting or rejecting assumptions on an unknown population parameter, such as mean, standard deviation, skewness, or kurtosis, from its representative or random samples associated statistics[1] with a specific degree of statistical significance or confidence. The statistical inference parameter for hypothesis testing considered in this work is the mean return by means of probability value (i.e., p-value) assessment.

First, we calculate the multiple hypothesis testing p-values, and then we perform the corresponding adjustments. The p-value is the probability that the observed value of the test statistic could have occurred given that the hypothesis being tested (i.e., the null hypothesis) is true. The smaller the p-value, the greater is the justification to challenge the truth of the null hypothesis H_0 and reject it in favor of the alternative hypothesis H_1. When the p-value is less than a given threshold, then H_0 is rejected and H_1 is accepted. Therefore, a statistically significant result has a p-value low enough to justify the rejection of the null hypothesis H_0.

The p-value adjustments are done through the family-wise error rate or Bonferroni procedure (Bonferroni, 1936) and the false discovery rate or Benjamini-Hochberg procedure (Benjamini,1995), where these adjustments are compared with the corresponding original p-value calculations. The population mean p-value is evaluated through the following steps:

1. Define the unknown population mean null (H_0) and alternative (H_1) hypothesis, which must be mutually exclusive and exhaustive propositions. In the two-tail test hypothesis we define $H_0{:}\mu = \mu_0;\ H_1{:}\mu \neq \mu_0$. In the one-tail (i.e., right-tail) test hypothesis we define $H_0{:}\mu \leq \mu_0;\ H_1{:}\mu > \mu_0$. For both tests, the unknown population mean is assumed $\mu_0 = 0$;
2. Define the unknown population mean degree of statistical significance or confidence with the associated non-rejection (where the null hypothesis cannot be rejected) and rejection regions. For the two-tail test, the critical values for the rejection vs. non rejection region are: $\pm t^* = \pm cdf_t\,(1\text{-}\alpha/2)$, where α is the level of statistical significance and $\pm cdf_t$ is the cumulative distribution function of the t-student probability distribution. Therefore, for the two-tail test, the null hypothesis non-rejection region is $[-t^*, t^*]$. For the one-tail test, the critical value is given by $t^* = cdf_t\,(1\text{-}\alpha)$ and the null hypothesis non-rejection region is $[-\infty, t^*]$;
3. Calculate the standardized representative or random samples mean statistics and test whether their values are within the multiple hypothesis testing non-rejection or rejection regions.

The standardized representative of a random sample mean statistic is the t-statistic, which is equal to the corresponding random sample mean $\hat{\mu}$ minus the null hypothesis mean $\mu_0 = 0$ divided by the random sample standard error ($\hat{\sigma}$ is the random sample standard deviation, while $\hat{n}$ is the number of observations within the random sample):

$$t_{\hat{\mu}} = \frac{\hat{\mu} - \mu_0}{\hat{\sigma}/\sqrt{\hat{n}}}.$$

Therefore, the H_0 two-tail test non-rejection region is $-t^* < t_{\hat{\mu}} < t^*$, while the H_0 one-tail test non-rejection region is $t_{\hat{\mu}} < t^*$. The t-statistic p-value is tested as follows:

- If $p(t_{\hat{\mu}}) > \alpha$ then do not reject the null hypothesis H_0 with $(1\text{-}\alpha)$ of statistical confidence.
- If $p(t_{\hat{\mu}}) < \alpha$ then reject the null hypothesis H_0 with $(1\text{-}\alpha)$ of statistical confidence.

In the hypothesis testing, if α is the level of statistical significance, then $(1\text{-}\alpha)$ is the degree of statistical confidence. In this assessment, we use a level of statistical significance of 5%, which is translated into a 95% degree of statistical confidence. It is worth noting that when computing the cdf_t for a two-tail test, α is divided by two because we are considering both the lower and upper distribution tail.

Probability Value Adjustment

The population mean p-value adjustment consists of decreasing the expected rate of false positives when conducting multiple comparisons through the family-wise and the false discovery error rate filtering methods. The type I error (or false positive) consists of incorrectly rejecting an assumption on an unknown population mean parameter from its representative or random sample associated statistic. The statistical significance level α is the probability of making a type I error. A type II error (or false negative) consists of incorrectly not rejecting an assumption on an unknown population mean parameter from its representative or random sample associated statistic. Reducing the probability of making a type I error increases the probability of making a type II error and vice versa if the sample size remains constant.

The methods for multiple hypothesis testing adjust α, so that the probability of getting at least one significant result due to chance remains below a significance level α. Type I error leads to mistakenly rejecting the null hypothesis H_0, thus investing in a worthless strategy which exposes the capital to risk without the prospect of gain. The Bonferroni correction can be quite conservative, leading to a higher rate of false negatives (type II error). However, while the Bonferroni correction is considered too conservative in many fields, the higher bar to significance may be regarded as appropriate by many traders and investors for backtesting a trading strategy. Type II errors cause a potentially profitable strategy to be ignored, thus resulting in lost investing opportunities. From the investor or trader's perspective, a type I error is more serious because lost capital is considered worse than lost investment opportunities. The family-wise error rate, or Bonferroni procedure, adjusts the population mean p-values by decreasing the expected rate of false positives (type I errors). The false discovery rate, or Benjamini-Hochberg procedure, yields a more relaxed p-value adjustment than the Bonferroni procedure. With respect to the Bonferroni correction, there is a slight increase in type I error rate, but at the same time a significant reduction in type II error rate.

Strategy Evaluation

The techniques of multiple hypothesis testing and p-value adjustments were applied to the *Street Smarts* strategies on the daily returns of all the asset classes and Forex crosses for the length of the look-back period from September 2005 to September 2021. The purpose of this evaluation was to assess whether the mean returns of the strategies were statistically significant with respect to the null hypothesis and could consistently bring some excess returns with respect to the zero return of the null hypothesis. The results for each strategy are reported in Appendix A and the tables summarize the p-values and their adjusted values according to the Bonferroni and false discovery rate (i.e., fdr) procedures. All the p-values greater than 0.05 (the level of statistical significance considered for this assessment), where the null hypothesis cannot be rejected, are marked in light red. The p-values show that the null hypothesis for most of the asset classes and currency pairs can be rejected in favor of the alternative hypothesis.

Table 13 confirms that the Turtle does not generate statistically significant excess returns above zero on IEF and the null hypothesis (both for the two-tail and one-tail test) cannot be rejected. In the Forex market, in agreement with the results shown in Figure 4, the null hypothesis cannot be rejected for the currency cross AUDNZD. Furthermore, the Bonferroni adjustment (to reduce the type I errors) does not reject the one-tail test null hypothesis for EURUSD, EURGBP, USDCAD, AUDUSD, AUDNZD, EURNZD, and EURAUD. This result may seem quite conservative since these currency crosses have a positive CAGR from the backtesting. However, it is worth noting that the returns generated by these currency pairs are smaller than the other returns and more likely to incur in type I errors. It is the investor or trader's responsibility to decide whether this conservative filtering is consistent with her/his own risk profile. The Turtle Soup (Table 14) generated statistically significant excess returns on all asset classes after the fdr filtering procedure (the Bonferroni did not reject the null hypothesis only for the one-tail test of XLF).

Both the two-tail and one-tail test for the ID-NR4 (Table 15) showed a consistent statistical significance (confirmed by Bonferroni and fdr adjustments) on all the equity indexes and sectors, bonds, gold, and real estate. In contrast, the ID-NR4 results were less significant on the Forex crosses, where only USDJPY, USDCAD, AUDUSD, and USDTRY delivered statistically significant excess returns according also to the p-value adjustments of both the Bonferroni and fdr procedures. This statistical analysis confirms the backtesting results shown in Figure 19 and reported in Table 10, where these currency pairs have the higher CAGR values. In summary, the multiple hypothesis testing supported the conclusion that ID-NR4 delivered a robust performance on the stock indexes and sectors, but it is not particularly suited for the Forex market. The Holy Grail strategy generated statistically significant excess returns on all the asset classes and most of the currency pairs (Table 16) also based on the Bonferroni and fdr procedures. Even the Anti (Table 17) yielded statistically significant excess returns on all asset classes and most of the currency pairs, also confirmed by the Bonferroni and fdr adjustments. It is worth pointing out that the p-value adjustments obtained with the Bonferroni procedure are more conservative, thus reducing the probability of type I errors, but also the trading opportunities.

In general, the backtesting results presented in "Street Smart Strategies" were validated by the multiple hypothesis testing. The strategies generated excess returns on all the asset classes, except for ID-NR4, that on most of the Forex currency pairs did not deliver statistically significant excess returns with respect to the null hypothesis.

The Bootstrap

The bootstrap method derives a sampling distribution shape of the test statistic[2] (or sample statistic) by randomly resampling with replacement from an original sample of observations. The test statistic is a point estimate (in our case, the population mean) and is computed on each sample (i.e., time series historical data). Assuming that certain conditions are satisfied, the bootstrap technique converges to a correct sampling distribution as the sample size goes to infinity. In practice, this means that given a single sample of observations, bootstrapping can produce the sampling distribution needed to test the significance of a technical analysis rule, parameter, or strategy.

Resampling with replacement reuses the same data in the original sample (Efron, 1993). For stationary data, random resamples are used (Politis, 1994), while for non-stationary data, random fixed-block resamples or random distributed block resamples are used (Kuensch, 1989). In this work, the simulation of the population mean probability distribution is performed by means of random fixed-block resampling with replacement, with blocks of fixed length equal to 10, while the number of resamplings is equal to 1000. At the end of the procedure, we calculate the test statistic for the bootstrap, which is the arithmetic mean, where B is the number of bootstrap estimates and μ_i^* is the mean of each bootstrap resampling:

$$\mu \approx \hat{\mu} = \frac{1}{B}\sum_{i=1}^{B} \mu_i^*.$$

The bootstrap statistical inference parameter estimations are point estimates with their associated confidence intervals. Such interval estimate is a range of values within which the (unknown) population mean lies with a given level of probability (1–α).

Bootstrap Hypothesis Testing

The bootstrap statistical inference parameters hypothesis testing is given by the probability value estimations (MacKimmon, 2007) and by not rejecting or rejecting assumptions on an unknown population mean from its representative or random sample associated bootstrap test statistic, with a specific degree of statistical significance or confidence, similarly to what was described in "Statistical Hypothesis Testing".

Bootstrap Probability Value Adjustment

The bootstrap population mean p-value multiple test adjustment consists of decreasing the expected rate of false positives in the individual statistical significance test when conducting multiple comparisons through the family-wise error rate or the Sidak filtering method (Sidak, 1967). The Sidak procedure assumes that the trials are independent and the corresponding probability value adjustment is done for an individual time series bootstrap hypothesis testing. It is slightly less conservative than the Bonferroni procedure.

Bootstrap Strategy Evaluation

The bootstrap confidence intervals for the test statistic point estimates are reported in Appendix B for each *Street Smarts* strategy and for all the asset classes and currency pairs used for backtesting. The critical values marked in light yellow highlight when the confidence range (DiCiccio, 1996) includes the condition $\mu_0 = 0$, where the null hypothesis cannot be rejected. Moreover, the tables in Appendix B also show the mean values of the original time series and the mean values obtained from the bootstrap sampling distribution. The bootstrap mean values are in good agreement with the original sample means.

It is possible to observe that the statistical significance tests based on the two-tail test p-values obtained with the multiple hypothesis testing described in "Statistical Hypothesis Testing" and summarized in Appendix A are consistent with the p-values generated by the bootstrap procedure (two-tail test) reported in Appendix B. The results obtained with the Sidak procedure are aligned with the adjusted p-values generated by the Bonferroni procedure, since both methods are family-wise error rate procedures. The numerical results summarized in Appendix B confirm that Sidak is slightly less conservative than Bonferroni.

Conclusions

In this work, some of the most popular strategies published in the book *Street Smarts* (Connors, 1995) by LC and LBR more than 25 years ago were backtested across stock indexes, S&P 500 sectors, real estate, commodities, bonds, and all the major Forex currency pairs. The strategies of *Street Smarts* are inherently discretionary and were proposed for the stock and futures markets of a quarter of a century ago. Since then, most of the markets have changed their structure and behavior. Therefore, in this paper the addressed problem was to determine whether those strategies are still valid in the current markets and can be profitably traded. The robustness of the backtesting results presented in this work is supported by the completeness of the asset classes considered and by the length of the historical data look-back period.

The settings of the strategies were kept substantially aligned with the original settings proposed by the authors. Moreover, by testing the strategies on many different markets and for a very representative look-back period, we assume that the results presented in this paper are robust and not over-fitted. The backtests confirmed that the performance of the strategies can vary depending on the underlying assets and markets.

Another relevant contribution of this work has been a rigorous and comprehensive statistical assessment of the *Street Smarts* strategies. We believe that randomness can have a larger impact in the financial markets than in other sectors. Hence, a complete evaluation and a deeper insight on a trading strategy and on its intrinsic value can be achieved through hypothesis testing with the techniques of inferential statistics and bootstrap. The backtesting results and the statistical assessment presented in this work confirm that the *Street Smarts* strategies have delivered statistically significant results across the look-back period on most of the asset classes. Only ID-NR4 (a volatility explosion pattern) did not produce statistically significant excessive returns on most of the currency pairs given the typical mean-reverting structure of the Forex.

After more than 25 years since they were presented, the *Street Smarts* techniques can still deliver good performances on several asset classes and in a changing market scenario. Even if these strategies are inherently discretionary, the robustness of the statistical assessment performed in this work makes some of the strategies' underlying techniques, like swing trading, pattern breakouts, and retracements, still effective options to be implemented in automatic trading systems.

In conclusion, the *Street Smarts* strategies can still be of interest to many traders and investors, both from an educational and trading perspective. Reading *Street Smarts* is highly recommended to all traders. It probably remains one of the most valuable books on trading and every trader should be familiar with the techniques proposed by LC and LBR.

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Notes

[1] The term sample statistic refers to the parameter being used to test a hypothesis, like the average or mean return. The term sample statistic is interchangeable with the term test statistic.

[2] A test statistic is a statistic (i.e., a quantity derived from the sample) used in statistical hypothesis testing.

Acknowledgements

In memory of my beloved father Alberto, 09/15/1930–10/29/2021.

Appendix A: Multiple Hypothesis Testing

Table 13. Turtle strategy p-values

	Turtle (two-tail)			Turtle (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
XLP	6.000E-06	1.060E-04	1.000E-05	3.000E-06	5.300E-05	5.000E-06
XLY	0.000E+00	5.000E-06	1.000E-06	0.000E+00	3.000E-06	1.000E-06
XLE	7.600E-05	1.286E-03	1.070E-04	3.800E-05	6.430E-04	5.400E-05
XLV	3.000E-06	4.300E-05	6.000E-06	1.000E-06	2.200E-05	3.000E-06
XLF	6.000E-06	1.090E-04	1.000E-05	3.000E-06	5.500E-05	5.000E-06
XLI	4.000E-06	7.600E-05	8.000E-06	2.000E-06	3.800E-05	4.000E-06
XLK	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
XLB	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
XLU	3.000E-06	5.600E-05	7.000E-06	2.000E-06	2.800E-05	4.000E-06
IYZ	3.873E-03	6.584E-02	4.115E-03	1.936E-03	3.292E-02	2.057E-03
IYR	0.000E+00	7.000E-06	1.000E-06	0.000E+00	3.000E-06	1.000E-06
SPY	2.050E-04	3.481E-03	2.490E-04	1.020E-04	1.740E-03	1.240E-04
DIA	3.070E-04	5.217E-03	3.480E-04	1.530E-04	2.609E-03	1.740E-04
IEF	4.580E-01	1.000E+00	4.580E-01	7.710E-01	1.000E+00	7.710E-01
TLT	1.090E-04	1.851E-03	1.420E-04	5.400E-05	9.250E-04	7.100E-05
GLD	0.000E+00	2.000E-06	0.000E+00	0.000E+00	1.000E-06	0.000E+00
QQQ	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00

	Turtle FOREX (two-tail)			Turtle FOREX (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
EURUSD	2.903E-02	4.065E-01	4.517E-02	1.452E-02	2.032E-01	2.258E-02
GBPUSD	2.914E-03	4.080E-02	6.800E-03	1.457E-03	2.040E-02	3.400E-03
EURGBP	4.585E-02	6.418E-01	5.349E-02	2.292E-02	3.209E-01	2.674E-02
USDCHF	2.000E-05	2.770E-04	9.200E-05	1.000E-05	1.390E-04	4.600E-05
USDJPY	6.000E-06	8.400E-05	4.200E-05	3.000E-06	4.200E-05	2.100E-05
USDCAD	8.908E-02	1.000E+00	9.593E-02	4.454E-02	6.235E-01	4.797E-02
USDNZD	4.563E-03	6.388E-02	9.126E-03	2.281E-03	3.194E-02	4.563E-03
AUDUSD	1.319E-02	1.846E-01	2.308E-02	6.593E-03	9.230E-02	1.154E-02
AUDNZD	9.456E-01	1.000E+00	9.456E-01	5.272E-01	1.000E+00	5.272E-01
EURCAD	6.200E-05	8.650E-04	1.730E-04	3.100E-05	4.330E-04	8.700E-05
EURNZD	4.384E-02	6.138E-01	5.349E-02	2.192E-02	3.069E-01	2.674E-02
NZDUSD	4.800E-05	6.740E-04	1.690E-04	2.400E-05	3.370E-04	8.400E-05
EURAUD	3.915E-02	5.481E-01	5.349E-02	1.958E-02	2.741E-01	2.674E-02
USDTRY	1.000E-06	1.500E-05	1.500E-05	1.000E-06	8.000E-06	8.000E-06

Table 14. Turtle Soup strategy p-values

	Turtle Soup (two-tail)			Turtle Soup (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
XLP	6.420E-04	1.091E-02	8.480E-04	3.210E-04	5.453E-03	4.240E-04
XLY	4.400E-05	7.400E-04	9.200E-05	2.200E-05	3.700E-04	4.600E-05
XLE	3.000E-06	4.700E-05	1.200E-05	1.000E-06	2.400E-05	6.000E-06
XLV	1.851E-03	3.147E-02	2.098E-03	9.250E-04	1.573E-02	1.049E-03
XLF	1.476E-02	2.509E-01	1.476E-02	7.379E-03	1.254E-01	7.379E-03
XLI	5.540E-04	9.414E-03	8.480E-04	2.770E-04	4.707E-03	4.240E-04
XLK	1.850E-04	3.143E-03	3.140E-04	9.200E-05	1.571E-03	1.570E-04
XLB	2.400E-05	4.150E-04	6.900E-05	1.200E-05	2.080E-04	3.500E-05
XLU	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
IYZ	1.760E-04	2.990E-03	3.140E-04	8.800E-05	1.495E-03	1.570E-04
IYR	3.000E-06	5.000E-05	1.200E-05	1.000E-06	2.500E-05	6.000E-06
SPY	6.480E-04	1.102E-02	8.480E-04	3.240E-04	5.511E-03	4.240E-04
DIA	3.633E-03	6.176E-02	3.860E-03	1.817E-03	3.088E-02	1.930E-03
IEF	9.100E-04	1.547E-02	1.105E-03	4.550E-04	7.737E-03	5.530E-04
TLT	3.300E-05	5.690E-04	8.100E-05	1.700E-05	2.850E-04	4.100E-05
GLD	0.000E+00	1.000E-06	0.000E+00	0.000E+00	0.000E+00	0.000E+00
QQQ	1.000E-05	1.740E-04	3.500E-05	5.000E-06	8.700E-05	1.700E-05

	Turtle Soup FOREX (two-tail)			Turtle Soup FOREX (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
EURUSD	1.860E-04	2.609E-03	3.220E-04	9.300E-05	1.304E-03	1.610E-04
GBPUSD	1.424E-03	1.993E-02	1.424E-03	7.120E-04	9.965E-03	7.120E-04
EURGBP	8.150E-04	1.142E-02	8.780E-04	4.080E-04	5.707E-03	4.390E-04
USDCHF	2.300E-04	3.221E-03	3.220E-04	1.150E-04	1.610E-03	1.610E-04
USDJPY	2.240E-04	3.138E-03	3.220E-04	1.120E-04	1.569E-03	1.610E-04
USDCAD	1.700E-05	2.430E-04	6.100E-05	9.000E-06	1.220E-04	3.000E-05
USDNZD	1.000E-06	9.000E-06	8.000E-06	0.000E+00	5.000E-06	4.000E-06
AUDUSD	4.200E-05	5.930E-04	9.900E-05	2.100E-05	2.960E-04	4.900E-05
AUDNZD	3.040E-04	4.253E-03	3.870E-04	1.520E-04	2.127E-03	1.930E-04
EURCAD	3.900E-05	5.460E-04	9.900E-05	1.900E-05	2.730E-04	4.900E-05
EURNZD	1.000E-06	1.500E-05	8.000E-06	1.000E-06	8.000E-06	4.000E-06
NZDUSD	6.300E-05	8.870E-04	1.270E-04	3.200E-05	4.430E-04	6.300E-05
EURAUD	5.210E-04	7.300E-03	6.080E-04	2.610E-04	3.650E-03	3.040E-04
USDTRY	1.700E-05	2.380E-04	6.100E-05	9.000E-06	1.190E-04	3.000E-05

Table 15. ID-NR4 strategy p-values

	ID-NR4 (two-tail)			ID-NR4 (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
XLP	1.010E-03	1.717E-02	1.010E-03	5.050E-04	8.583E-03	5.050E-04
XLY	1.630E-04	2.779E-03	1.740E-04	8.200E-05	1.390E-03	8.700E-05
XLE	1.000E-06	1.500E-05	3.000E-06	0.000E+00	8.000E-06	2.000E-06
XLV	1.040E-04	1.761E-03	1.170E-04	5.200E-05	8.800E-04	5.900E-05
XLF	0.000E+00	5.000E-06	1.000E-06	0.000E+00	3.000E-06	1.000E-06
XLI	0.000E+00	2.000E-06	1.000E-06	0.000E+00	1.000E-06	0.000E+00
XLK	8.300E-05	1.409E-03	1.010E-04	4.100E-05	7.050E-04	5.000E-05
XLB	6.000E-06	9.600E-05	1.100E-05	3.000E-06	4.800E-05	5.000E-06
XLU	1.000E-06	2.300E-05	4.000E-06	1.000E-06	1.200E-05	2.000E-06
IYZ	9.000E-06	1.500E-04	1.500E-05	4.000E-06	7.500E-05	7.000E-06
IYR	2.100E-05	3.510E-04	2.700E-05	1.000E-05	1.760E-04	1.400E-05
SPY	0.000E+00	1.000E-06	0.000E+00	0.000E+00	0.000E+00	0.000E+00
DIA	6.000E-06	9.800E-05	1.100E-05	3.000E-06	4.900E-05	5.000E-06
IEF	1.300E-05	2.200E-04	1.800E-05	6.000E-06	1.100E-04	9.000E-06
TLT	3.000E-06	5.500E-05	8.000E-06	2.000E-06	2.700E-05	4.000E-06
GLD	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
QQQ	1.000E-05	1.630E-04	1.500E-05	5.000E-06	8.200E-05	7.000E-06

	ID-NR4 FOREX (two-tail)			ID-NR4 FOREX (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
EURUSD	2.578E-01	1.000E+00	3.281E-01	1.289E-01	1.000E+00	1.641E-01
GBPUSD	7.590E-02	1.000E+00	1.181E-01	3.795E-02	5.313E-01	5.904E-02
EURGBP	6.030E-01	1.000E+00	6.030E-01	3.015E-01	1.000E+00	3.015E-01
USDCHF	2.435E-02	3.408E-01	6.817E-02	1.217E-02	1.704E-01	3.409E-02
USDJPY	7.000E-06	9.200E-05	6.000E-05	3.000E-06	4.600E-05	3.000E-05
USDCAD	1.396E-03	1.954E-02	6.357E-03	6.980E-04	9.769E-03	3.178E-03
USDNZD	7.379E-02	1.000E+00	1.181E-01	3.689E-02	5.165E-01	5.904E-02
AUDUSD	1.816E-03	2.543E-02	6.357E-03	9.080E-04	1.271E-02	3.178E-03
AUDNZD	5.606E-01	1.000E+00	6.030E-01	2.803E-01	1.000E+00	3.015E-01
EURCAD	2.894E-01	1.000E+00	3.376E-01	1.447E-01	1.000E+00	1.688E-01
EURNZD	7.393E-02	1.000E+00	1.181E-01	3.696E-02	5.175E-01	5.904E-02
NZDUSD	9.372E-02	1.000E+00	1.312E-01	4.686E-02	6.561E-01	6.561E-02
EURAUD	6.592E-02	9.229E-01	1.181E-01	3.296E-02	4.614E-01	5.904E-02
USDTRY	9.000E-06	1.210E-04	6.000E-05	4.000E-06	6.000E-05	3.000E-05

Table 16. Holy Grail strategy p-values

	Holy Grail (two-tail)			Holy Grail (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
XLP	0.000E+00	3.000E-06	1.000E-06	0.000E+00	2.000E-06	0.000E+00
XLY	1.000E-06	2.100E-05	3.000E-06	1.000E-06	1.100E-05	2.000E-06
XLE	2.000E-06	3.200E-05	4.000E-06	1.000E-06	1.600E-05	2.000E-06
XLV	1.498E-03	2.547E-02	1.592E-03	7.490E-04	1.274E-02	7.960E-04
XLF	2.600E-04	4.419E-03	4.350E-04	1.300E-04	2.209E-03	2.170E-04
XLI	1.000E-06	1.000E-05	2.000E-06	0.000E+00	5.000E-06	1.000E-06
XLK	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
XLB	2.000E-06	3.800E-05	4.000E-06	1.000E-06	1.900E-05	2.000E-06
XLU	5.740E-04	9.758E-03	6.840E-04	2.870E-04	4.879E-03	3.420E-04
IYZ	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
IYR	3.520E-04	5.983E-03	4.980E-04	1.760E-04	2.991E-03	2.490E-04
SPY	0.000E+00	2.000E-06	1.000E-06	0.000E+00	1.000E-06	0.000E+00
DIA	6.030E-04	1.026E-02	6.840E-04	3.020E-04	5.129E-03	3.420E-04
IEF	3.810E-04	6.479E-03	4.980E-04	1.910E-04	3.240E-03	2.490E-04
TLT	2.810E-04	4.780E-03	4.350E-04	1.410E-04	2.390E-03	2.170E-04
GLD	3.920E-03	6.664E-02	3.920E-03	1.960E-03	3.332E-02	1.960E-03
QQQ	1.000E-06	1.400E-05	2.000E-06	0.000E+00	7.000E-06	1.000E-06

	Holy Grail FOREX (two-tail)			Holy Grail FOREX (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
EURUSD	6.244E-03	8.742E-02	6.724E-03	3.122E-03	4.371E-02	3.362E-03
GBPUSD	1.830E-04	2.556E-03	3.450E-04	9.100E-05	1.278E-03	1.730E-04
EURGBP	1.123E-03	1.572E-02	1.429E-03	5.610E-04	7.858E-03	7.140E-04
USDCHF	1.900E-05	2.620E-04	5.600E-05	9.000E-06	1.310E-04	2.800E-05
USDJPY	3.000E-06	3.800E-05	3.500E-05	1.000E-06	1.900E-05	1.800E-05
USDCAD	4.540E-04	6.349E-03	6.750E-04	2.270E-04	3.175E-03	3.370E-04
USDNZD	6.603E-02	9.244E-01	6.603E-02	3.302E-02	4.622E-01	3.302E-02
AUDUSD	1.600E-05	2.230E-04	5.600E-05	8.000E-06	1.110E-04	2.800E-05
AUDNZD	2.000E-05	2.800E-04	5.600E-05	1.000E-05	1.400E-04	2.800E-05
EURCAD	5.095E-03	7.133E-02	5.944E-03	2.548E-03	3.567E-02	2.972E-03
EURNZD	1.970E-04	2.764E-03	3.450E-04	9.900E-05	1.382E-03	1.730E-04
NZDUSD	5.000E-06	7.100E-05	3.500E-05	3.000E-06	3.500E-05	1.800E-05
EURAUD	1.800E-04	2.516E-03	3.450E-04	9.000E-05	1.258E-03	1.730E-04
USDTRY	4.820E-04	6.747E-03	6.750E-04	2.410E-04	3.374E-03	3.370E-04

Table 17. Anti strategy p-values

	Anti (two-tail)			Anti (one-tail)				Anti FOREX (two-tail)			Anti FOREX (one-tail)		
	two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr		two-tail test	bonferroni	fdr	one-tail test	bonferroni	fdr
XLP	1.000E-06	2.000E-05	1.000E-06	1.000E-06	1.000E-05	1.000E-06	EURUSD	8.300E-05	1.167E-03	1.170E-04	4.200E-05	5.840E-04	5.800E-05
XLY	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	GBPUSD	4.300E-05	5.980E-04	7.500E-05	2.100E-05	2.990E-04	3.700E-05
XLE	0.000E+00	5.000E-06	0.000E+00	0.000E+00	2.000E-06	0.000E+00	EURGBP	5.900E-05	8.210E-04	9.100E-05	2.900E-05	4.110E-04	4.600E-05
XLV	1.100E-05	1.810E-04	1.100E-05	5.000E-06	9.000E-05	6.000E-06	USDCHF	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
XLF	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	USDJPY	1.000E-06	1.700E-05	3.000E-06	1.000E-06	8.000E-06	1.000E-06
XLI	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	USDCAD	1.000E-06	1.700E-05	3.000E-06	1.000E-06	9.000E-06	1.000E-06
XLK	1.000E-06	1.300E-05	1.000E-06	0.000E+00	7.000E-06	1.000E-06	USDNZD	9.250E-04	1.296E-02	1.080E-03	4.630E-04	6.478E-03	5.400E-04
XLB	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	AUDUSD	1.000E-06	1.700E-05	3.000E-06	1.000E-06	9.000E-06	1.000E-06
XLU	2.540E-04	4.311E-03	2.540E-04	1.270E-04	2.155E-03	1.270E-04	AUDNZD	2.042E-01	1.000E+00	2.042E-01	1.021E-01	1.000E+00	1.021E-01
IYZ	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	EURCAD	6.167E-02	8.634E-01	6.641E-02	3.083E-02	4.317E-01	3.321E-02
IYR	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	EURNZD	3.370E-04	4.712E-03	4.280E-04	1.680E-04	2.356E-03	2.140E-04
SPY	0.000E+00	1.000E-06	0.000E+00	0.000E+00	0.000E+00	0.000E+00	NZDUSD	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
DIA	1.000E-05	1.620E-04	1.100E-05	5.000E-06	8.100E-05	5.000E-06	EURAUD	2.100E-05	2.950E-04	4.200E-05	1.100E-05	1.480E-04	2.100E-05
IEF	0.000E+00	3.000E-06	0.000E+00	0.000E+00	2.000E-06	0.000E+00	USDTRY	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
TLT	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00							
GLD	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00							
QQQ	0.000E+00	4.000E-06	0.000E+00	0.000E+00	2.000E-06	0.000E+00							

Appendix B: Bootstrap

Table 18. Turtle strategy bootstrap confidence intervals and p-values

	Turtle (two-tail bootstrap)							Turtle FOREX (two-tail bootstrap)					
	sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak		sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak
XLP	1.450E-04	1.454E-04	8.044E-05	2.087E-04	0.000E+00	0.000E+00	EURUSD	6.323E-05	6.387E-05	6.016E-06	1.182E-04	3.000E-02	3.472E-01
XLY	2.597E-04	2.616E-04	1.593E-04	3.655E-04	0.000E+00	0.000E+00	GBPUSD	7.832E-05	7.704E-05	2.878E-05	1.261E-04	2.000E-03	2.764E-02
XLE	2.777E-04	2.765E-04	1.369E-04	4.217E-04	0.000E+00	0.000E+00	EURGBP	4.674E-05	4.712E-05	9.063E-07	9.828E-05	4.400E-02	4.674E-01
XLV	2.196E-04	2.144E-04	1.190E-04	3.067E-04	0.000E+00	0.000E+00	USDCHF	1.091E-04	1.079E-04	6.010E-05	1.563E-04	0.000E+00	0.000E+00
XLF	2.015E-04	1.987E-04	1.065E-04	2.953E-04	0.000E+00	0.000E+00	USDJPY	1.357E-04	1.373E-04	8.164E-05	1.966E-04	0.000E+00	0.000E+00
XLI	2.356E-04	2.331E-04	1.187E-04	3.380E-04	0.000E+00	0.000E+00	USDCAD	4.548E-05	4.590E-05	-9.539E-06	1.004E-04	9.000E-02	7.330E-01
XLK	2.795E-04	2.776E-04	1.808E-04	3.640E-04	0.000E+00	0.000E+00	USDNZD	9.220E-05	9.487E-05	3.162E-05	1.590E-04	8.000E-03	1.064E-01
XLB	2.376E-04	2.385E-04	1.493E-04	3.221E-04	0.000E+00	0.000E+00	AUDUSD	1.060E-04	1.086E-04	1.955E-05	1.849E-04	2.000E-02	2.464E-01
XLU	1.677E-04	1.683E-04	9.373E-05	2.341E-04	0.000E+00	0.000E+00	AUDNZD	-1.104E-06	-1.652E-06	-3.451E-05	3.015E-05	9.420E-01	1.000E+00
IYZ	1.442E-04	1.457E-04	3.234E-05	2.457E-04	6.000E-03	9.725E-02	EURCAD	1.024E-04	1.017E-04	4.965E-05	1.555E-04	0.000E+00	0.000E+00
IYR	2.279E-04	2.269E-04	1.324E-04	3.125E-04	0.000E+00	0.000E+00	EURNZD	4.478E-05	4.522E-05	-1.354E-06	8.989E-05	5.600E-02	5.537E-01
SPY	1.703E-04	1.703E-04	8.156E-05	2.521E-04	0.000E+00	0.000E+00	NZDUSD	1.317E-04	1.331E-04	7.027E-05	2.044E-04	0.000E+00	0.000E+00
DIA	1.780E-04	1.781E-04	7.093E-05	2.720E-04	0.000E+00	0.000E+00	EURAUD	6.123E-05	6.096E-05	3.918E-07	1.193E-04	4.600E-02	4.828E-01
IEF	-1.974E-05	-1.846E-05	-7.013E-05	3.295E-05	4.860E-01	1.000E+00	USDTRY	2.020E-04	2.024E-04	1.247E-04	2.880E-04	0.000E+00	0.000E+00
TLT	1.664E-04	1.655E-04	8.099E-05	2.499E-04	0.000E+00	0.000E+00							
GLD	2.457E-04	2.450E-04	1.524E-04	3.371E-04	0.000E+00	0.000E+00							
QQQ	3.370E-04	3.379E-04	2.294E-04	4.287E-04	0.000E+00	0.000E+00							

Table 19. Turtle Soup strategy bootstrap confidence intervals and p-values

	Turtle Soup (two-tail bootstrap)							Turtle Soup FOREX (two-tail bootstrap)					
	sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak		sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak
XLP	1.364E-04	1.357E-04	4.683E-05	2.132E-04	2.000E-03	3.346E-02	EURUSD	8.377E-05	8.337E-05	4.196E-05	1.291E-04	0.000E+00	0.000E+00
XLY	1.796E-04	1.811E-04	9.528E-05	2.710E-04	0.000E+00	0.000E+00	GBPUSD	6.209E-05	6.180E-05	2.464E-05	1.028E-04	2.000E-03	2.764E-02
XLE	2.259E-04	2.233E-04	1.246E-04	3.239E-04	0.000E+00	0.000E+00	EURGBP	6.086E-05	6.173E-05	2.461E-05	1.032E-04	0.000E+00	0.000E+00
XLV	1.243E-04	1.245E-04	4.425E-05	1.995E-04	0.000E+00	0.000E+00	USDCHF	7.901E-05	8.140E-05	4.124E-05	1.274E-04	0.000E+00	0.000E+00
XLF	9.906E-05	9.875E-05	2.912E-05	1.704E-04	6.000E-03	9.725E-02	USDJPY	6.383E-05	6.447E-05	3.334E-05	9.826E-05	0.000E+00	0.000E+00
XLI	1.378E-04	1.394E-04	6.225E-05	2.239E-04	0.000E+00	0.000E+00	USDCAD	9.533E-05	9.657E-05	5.684E-05	1.463E-04	0.000E+00	0.000E+00
XLK	1.480E-04	1.482E-04	7.864E-05	2.345E-04	0.000E+00	0.000E+00	USDNZD	1.505E-04	1.491E-04	9.159E-05	2.125E-04	0.000E+00	0.000E+00
XLB	1.566E-04	1.578E-04	8.741E-05	2.370E-04	0.000E+00	0.000E+00	AUDUSD	9.919E-05	9.926E-05	5.270E-05	1.468E-04	0.000E+00	0.000E+00
XLU	2.106E-04	2.107E-04	1.354E-04	2.937E-04	0.000E+00	0.000E+00	AUDNZD	6.532E-05	6.500E-05	3.290E-05	1.011E-04	0.000E+00	0.000E+00
IYZ	2.393E-04	2.379E-04	1.309E-04	3.885E-04	0.000E+00	0.000E+00	EURCAD	9.360E-05	9.409E-05	5.073E-05	1.409E-04	0.000E+00	0.000E+00
IYR	1.625E-04	1.628E-04	9.734E-05	2.309E-04	0.000E+00	0.000E+00	EURNZD	1.403E-04	1.407E-04	9.066E-05	1.987E-04	0.000E+00	0.000E+00
SPY	1.245E-04	1.268E-04	5.684E-05	2.040E-04	0.000E+00	0.000E+00	NZDUSD	1.070E-04	1.060E-04	5.193E-05	1.618E-04	0.000E+00	0.000E+00
DIA	1.073E-04	1.074E-04	2.867E-05	1.789E-04	8.000E-03	1.276E-01	EURAUD	8.595E-05	8.565E-05	3.566E-05	1.458E-04	0.000E+00	0.000E+00
IEF	6.821E-05	6.865E-05	3.154E-05	1.130E-04	0.000E+00	0.000E+00	USDTRY	1.172E-04	1.164E-04	6.386E-05	1.709E-04	0.000E+00	0.000E+00
TLT	1.240E-04	1.241E-04	6.721E-05	1.862E-04	0.000E+00	0.000E+00							
GLD	2.332E-04	2.311E-04	1.525E-04	3.162E-04	0.000E+00	0.000E+00							
QQQ	1.835E-04	1.821E-04	1.038E-04	2.702E-04	0.000E+00	0.000E+00							

Table 20. ID-NR4 strategy bootstrap confidence intervals and p-values

	ID-NR4 (two-tail bootstrap)							ID-NR4 FOREX (two-tail bootstrap)					
	sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak		sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak
XLP	1.320E-04	1.333E-04	4.836E-05	2.136E-04	2.000E-03	3.346E-02	EURUSD	2.870E-05	2.785E-05	-2.092E-05	8.121E-05	2.980E-01	9.929E-01
XLY	1.748E-04	1.741E-04	9.282E-05	2.578E-04	0.000E+00	0.000E+00	GBPUSD	4.525E-05	4.493E-05	3.462E-07	9.926E-05	4.600E-02	4.828E-01
XLE	3.303E-04	3.288E-04	2.031E-04	4.662E-04	0.000E+00	0.000E+00	EURGBP	1.167E-05	1.080E-05	-3.436E-05	5.492E-05	6.080E-01	1.000E+00
XLV	1.386E-04	1.375E-04	7.185E-05	2.068E-04	0.000E+00	0.000E+00	USDCHF	7.557E-05	7.589E-05	1.173E-05	1.480E-04	1.800E-02	2.245E-01
XLF	3.240E-04	3.258E-04	2.040E-04	4.457E-04	0.000E+00	0.000E+00	USDJPY	1.550E-04	1.545E-04	8.713E-05	2.278E-04	0.000E+00	0.000E+00
XLI	2.789E-04	2.779E-04	1.876E-04	3.803E-04	0.000E+00	0.000E+00	USDCAD	9.550E-05	9.458E-05	3.544E-05	1.583E-04	0.000E+00	0.000E+00
XLK	1.826E-04	1.809E-04	9.021E-05	2.749E-04	0.000E+00	0.000E+00	USDNZD	6.103E-05	6.174E-05	-2.591E-06	1.280E-04	5.600E-02	5.537E-01
XLB	2.279E-04	2.267E-04	1.333E-04	3.203E-04	0.000E+00	0.000E+00	AUDUSD	1.159E-04	1.158E-04	4.295E-05	1.959E-04	0.000E+00	0.000E+00
XLU	2.072E-04	2.075E-04	1.313E-04	2.867E-04	0.000E+00	0.000E+00	AUDNZD	1.087E-05	1.132E-05	-2.518E-05	4.826E-05	5.440E-01	1.000E+00
IYZ	2.115E-04	2.137E-04	1.243E-04	3.114E-04	0.000E+00	0.000E+00	EURCAD	2.490E-05	2.443E-05	-2.108E-05	7.237E-05	3.140E-01	9.949E-01
IYR	2.508E-04	2.508E-04	1.395E-04	3.642E-04	0.000E+00	0.000E+00	EURNZD	5.061E-05	5.093E-05	3.113E-07	1.136E-04	4.600E-02	4.828E-01
SPY	2.717E-04	2.722E-04	1.810E-04	3.678E-04	0.000E+00	0.000E+00	NZDUSD	5.993E-05	5.997E-05	-1.083E-05	1.315E-04	8.400E-02	7.072E-01
DIA	1.890E-04	1.900E-04	1.120E-04	2.703E-04	0.000E+00	0.000E+00	EURAUD	4.597E-05	4.585E-05	-3.075E-06	9.495E-05	6.000E-02	5.795E-01
IEF	7.728E-05	7.708E-05	4.457E-05	1.120E-04	0.000E+00	0.000E+00	USDTRY	1.863E-04	1.868E-04	1.086E-04	2.602E-04	0.000E+00	0.000E+00
TLT	1.777E-04	1.754E-04	9.886E-05	2.531E-04	0.000E+00	0.000E+00							
GLD	3.706E-04	3.731E-04	2.712E-04	4.790E-04	0.000E+00	0.000E+00							
QQQ	2.333E-04	2.335E-04	1.425E-04	3.338E-04	0.000E+00	0.000E+00							

Table 21. Holy Grail strategy bootstrap confidence intervals and p-values

	Holy Grail (two-tail bootstrap)							Holy Grail FOREX (two-tail bootstrap)					
	sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak		sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak
XLP	1.667E-04	1.680E-04	9.898E-05	2.544E-04	0.000E+00	0.000E+00	EURUSD	5.556E-05	5.568E-05	1.219E-05	1.021E-04	6.000E-03	8.080E-02
XLY	2.004E-04	1.988E-04	1.200E-04	2.891E-04	0.000E+00	0.000E+00	GBPUSD	5.720E-05	5.753E-05	2.554E-05	9.663E-05	0.000E+00	0.000E+00
XLE	2.047E-04	2.086E-04	1.164E-04	3.171E-04	0.000E+00	0.000E+00	EURGBP	5.301E-05	5.325E-05	2.077E-05	8.841E-05	0.000E+00	0.000E+00
XLV	1.064E-04	1.075E-04	4.562E-05	1.847E-04	0.000E+00	0.000E+00	USDCHF	8.415E-05	8.335E-05	4.411E-05	1.363E-04	0.000E+00	0.000E+00
XLF	2.009E-04	2.012E-04	7.959E-05	3.358E-04	0.000E+00	0.000E+00	USDJPY	1.155E-04	1.148E-04	6.449E-05	1.723E-04	0.000E+00	0.000E+00
XLI	2.014E-04	1.991E-04	1.053E-04	3.054E-04	0.000E+00	0.000E+00	USDCAD	6.262E-05	6.310E-05	2.305E-05	1.142E-04	0.000E+00	0.000E+00
XLK	3.225E-04	3.242E-04	2.034E-04	4.730E-04	0.000E+00	0.000E+00	USDNZD	4.576E-05	4.625E-05	4.059E-06	9.128E-05	2.800E-02	3.281E-01
XLB	1.956E-04	1.947E-04	8.836E-05	3.134E-04	0.000E+00	0.000E+00	AUDUSD	1.020E-04	1.020E-04	5.841E-05	1.508E-04	0.000E+00	0.000E+00
XLU	1.350E-04	1.360E-04	5.365E-05	2.456E-04	0.000E+00	0.000E+00	AUDNZD	6.397E-05	6.329E-05	2.825E-05	1.042E-04	0.000E+00	0.000E+00
IYZ	2.571E-04	2.594E-04	1.704E-04	3.529E-04	0.000E+00	0.000E+00	EURCAD	4.971E-05	5.048E-05	1.825E-05	8.770E-05	4.000E-03	5.457E-02
IYR	1.339E-04	1.356E-04	4.995E-05	2.339E-04	0.000E+00	0.000E+00	EURNZD	9.979E-05	1.009E-04	3.830E-05	1.716E-04	0.000E+00	0.000E+00
SPY	2.341E-04	2.355E-04	1.351E-04	3.632E-04	0.000E+00	0.000E+00	NZDUSD	1.264E-04	1.260E-04	6.989E-05	1.927E-04	0.000E+00	0.000E+00
DIA	1.139E-04	1.140E-04	4.860E-05	1.981E-04	0.000E+00	0.000E+00	EURAUD	9.521E-05	9.476E-05	4.902E-05	1.516E-04	0.000E+00	0.000E+00
IEF	4.612E-05	4.697E-05	2.157E-05	7.455E-05	0.000E+00	0.000E+00	USDTRY	1.125E-04	1.115E-04	4.606E-05	1.714E-04	0.000E+00	0.000E+00
TLT	1.134E-04	1.121E-04	4.714E-05	1.898E-04	0.000E+00	0.000E+00							
GLD	8.455E-05	8.527E-05	3.052E-05	1.454E-04	0.000E+00	0.000E+00							
QQQ	2.026E-04	2.016E-04	1.188E-04	3.050E-04	0.000E+00	0.000E+00							

Table 22. Anti strategy bootstrap confidence intervals and p-values

	Anti (two-tail bootstrap)							Anti FOREX (two-tail bootstrap)					
	sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak		sample mean	boot mean	ci lower	ci upper	p-value	p-value Sidak
XLP	1.528E-04	1.523E-04	9.369E-05	2.139E-04	0.000E+00	0.000E+00	EURUSD	7.597E-05	7.693E-05	4.025E-05	1.141E-04	0.000E+00	0.000E+00
XLY	2.435E-04	2.431E-04	1.736E-04	3.219E-04	0.000E+00	0.000E+00	GBPUSD	8.496E-05	8.623E-05	4.408E-05	1.264E-04	0.000E+00	0.000E+00
XLE	3.029E-04	3.021E-04	2.014E-04	4.323E-04	0.000E+00	0.000E+00	EURGBP	7.024E-05	7.086E-05	3.694E-05	1.097E-04	0.000E+00	0.000E+00
XLV	1.316E-04	1.318E-04	7.635E-05	1.919E-04	0.000E+00	0.000E+00	USDCHF	1.147E-04	1.158E-04	7.769E-05	1.564E-04	0.000E+00	0.000E+00
XLF	3.229E-04	3.264E-04	2.404E-04	4.159E-04	0.000E+00	0.000E+00	USDJPY	9.496E-05	9.381E-05	5.484E-05	1.329E-04	0.000E+00	0.000E+00
XLI	2.398E-04	2.395E-04	1.646E-04	3.165E-04	0.000E+00	0.000E+00	USDCAD	9.537E-05	9.604E-05	5.680E-05	1.365E-04	0.000E+00	0.000E+00
XLK	2.340E-04	2.347E-04	1.504E-04	3.314E-04	0.000E+00	0.000E+00	USDNZD	7.677E-05	7.624E-05	2.987E-05	1.228E-04	0.000E+00	0.000E+00
XLB	2.754E-04	2.771E-04	2.030E-04	3.536E-04	0.000E+00	0.000E+00	AUDUSD	1.127E-04	1.126E-04	6.532E-05	1.611E-04	0.000E+00	0.000E+00
XLU	1.060E-04	1.069E-04	5.091E-05	1.638E-04	0.000E+00	0.000E+00	AUDNZD	1.985E-05	2.009E-05	-7.482E-06	4.951E-05	1.680E-01	9.238E-01
IYZ	2.267E-04	2.269E-04	1.649E-04	2.900E-04	0.000E+00	0.000E+00	EURCAD	3.741E-05	3.692E-05	-2.310E-06	7.650E-05	5.600E-02	5.537E-01
IYR	2.644E-04	2.620E-04	1.863E-04	3.322E-04	0.000E+00	0.000E+00	EURNZD	7.404E-05	7.448E-05	3.440E-05	1.128E-04	0.000E+00	0.000E+00
SPY	1.823E-04	1.821E-04	1.157E-04	2.478E-04	0.000E+00	0.000E+00	NZDUSD	1.353E-04	1.346E-04	8.872E-05	1.813E-04	0.000E+00	0.000E+00
DIA	1.435E-04	1.455E-04	8.491E-05	2.041E-04	0.000E+00	0.000E+00	EURAUD	9.274E-05	9.378E-05	4.883E-05	1.367E-04	0.000E+00	0.000E+00
IEF	9.057E-05	9.158E-05	5.504E-05	1.305E-04	0.000E+00	0.000E+00	USDTRY	1.440E-04	1.440E-04	9.908E-05	1.915E-04	0.000E+00	0.000E+00
TLT	2.021E-04	2.019E-04	1.457E-04	2.581E-04	0.000E+00	0.000E+00							
GLD	2.151E-04	2.161E-04	1.479E-04	2.844E-04	0.000E+00	0.000E+00							
QQQ	2.064E-04	2.068E-04	1.289E-04	2.919E-04	0.000E+00	0.000E+00							

Order Flow Analysis

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What Is Order Flow Analysis and Its Importance?

Order flow analysis (OFA) is a tool that helps to analyze the strength of bulls or bears in the market—in other words, who is in control, buyers or sellers? Markets are driven by what we call “smart money”, and if traders are able to get a hint of what the big institutions are doing, then the analysis would help them to align their trades with the trend. Most indicators are lagging in nature and will only trigger a buy/sell signal after part of the trend is over, but data, on the other hand, is a leading indicator, which gives an edge to retail traders.

Another significant use of this tool is to identify whether breakouts/breakdowns are real or fake. The tool will also help to point out the exhaustion levels for trending up moves or down moves in intraday.

What Are Some of the Important Parameters to Be Considered in OFA and When Should They Be Monitored?

Big orders are normally executed through limit orders or market orders. OFA talks about aggressive market buy/sell orders and the data needs to be analyzed only at reference points. These reference levels could be previous day high/low, weekly high/low, and higher timeframe swing highs/lows, which act as resistances or supports. Refer to Figure 1 for all the parameters described below. The numbers in green on the right side of every candle show the aggressive buyers, while the numbers in red on the left side of every candle show the aggressive sellers during that timeframe. The table at the bottom in the picture shows the four parameters that have been described below.

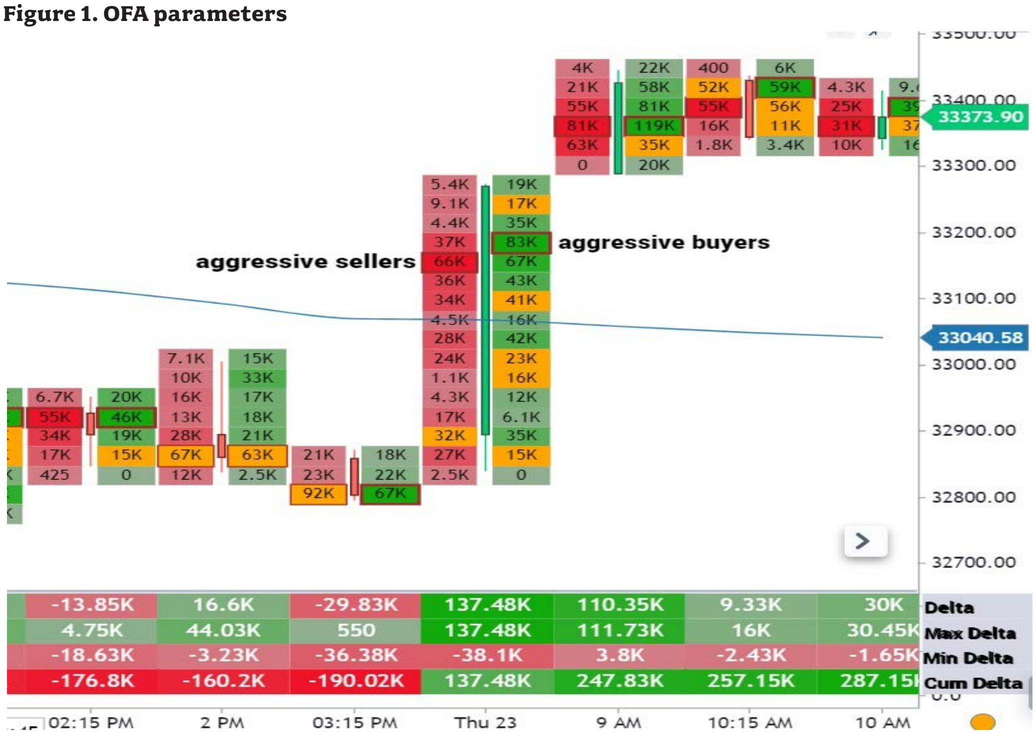
Delta: The sum of aggressive market buy orders and aggressive market sell orders. If Delta is positive, buyers are strong. So, a big positive Delta value above a resistance would be a buying indication, and a big negative Delta below a support would be a selling indication.

Max Delta: The maximum value of Delta during the selected timeframe. Similar to Delta, Max Delta has to be observed only above a resistance, and a combination of Delta and Max Delta indicate whether buying pressure is going to sustain or not.

Min Delta: The minimum value of Delta during a selected timeframe. This parameter is observed below a support, and the combination of Delta and Min Delta indicate whether selling pressure is going to increase or not.

Cumulative Delta: The sum of Delta from the first minute of the day to the last minute.

Figure 1. OFA parameters



How to Identify Momentum

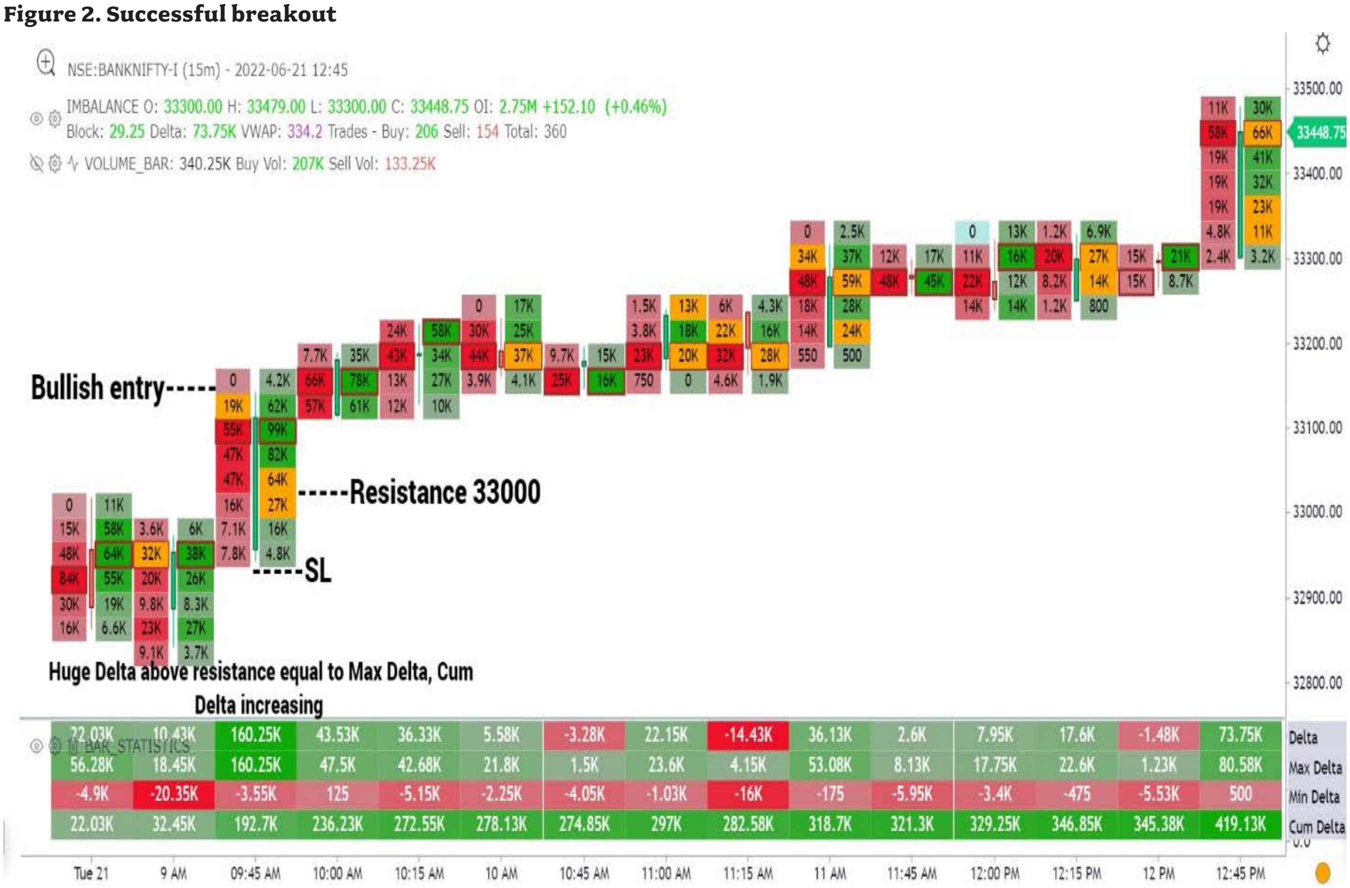
When the market is moving higher, the cumulative Delta needs to be increasingly positive and above a reference point; if the Delta and Max Delta have big values, then a bullish momentum is likely. The Delta for every subsequent candle above a resistance should keep increasing, suggesting a continuation of the up orientation.

On the other hand, for a bearish momentum, the cumulative Delta preferably needs to be increasingly negative, and a break below a support should be accompanied with big negative values for Min Delta and Delta.

Breakout

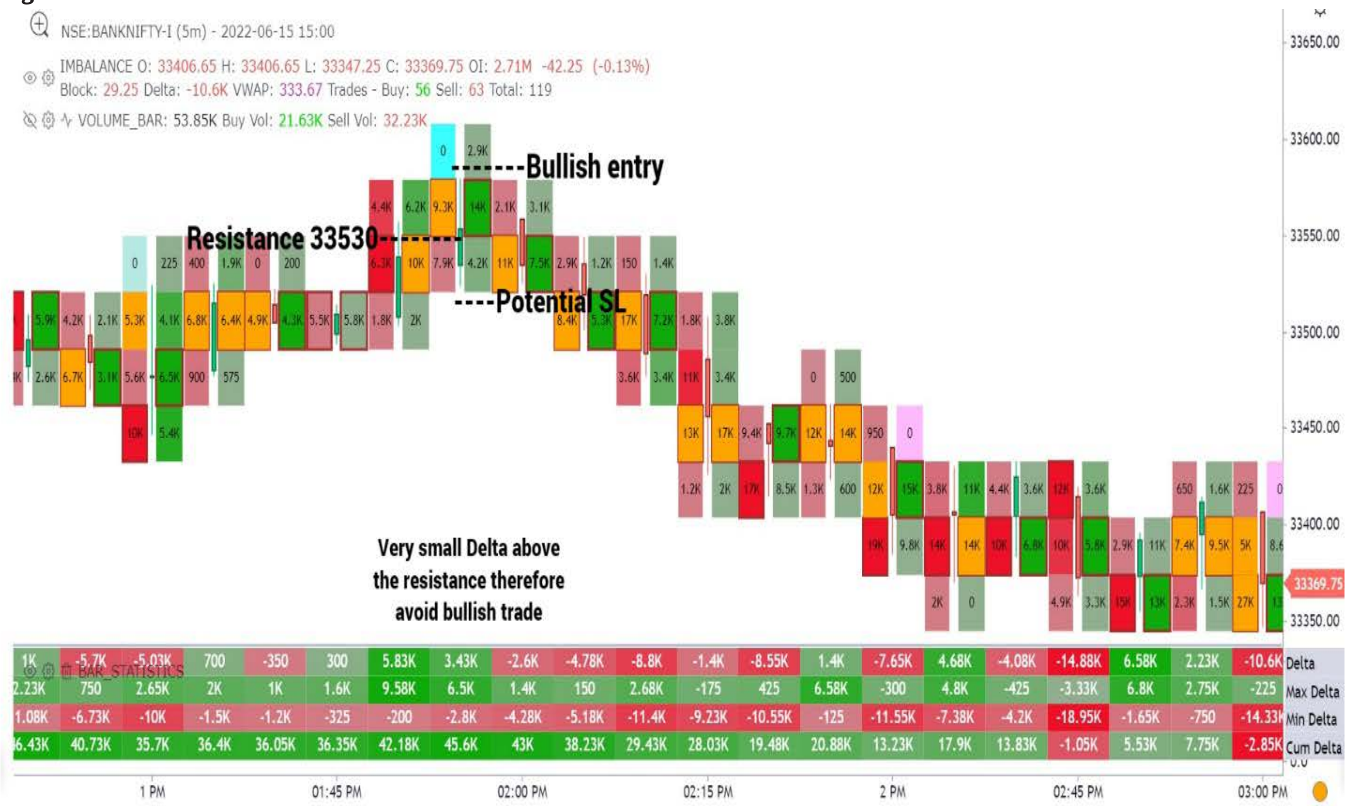
Once reference levels are identified, the Delta and Max Delta above a resistance need to be observed. For a successful bullish breakout, Delta needs to be at least 65% of Max Delta above a resistance (a Delta value closer to Max Delta indicates that buyers are still in control at the end of the candle). If the momentum condition and breakout condition are met, there is a higher probability that the up move would sustain. In such a case, a bullish trade can be initiated with a stop-loss below the breakout candle and a 1:2 risk reward ratio. Refer to Figure 2 for an example of a successful breakout. The Cum Delta had been increasing, and the 15 min candle closed above the resistance at 33,000 with a huge Delta (160.25k). A bullish entry is made above the high of the breakout candle.

Figure 2. Successful breakout



On the other hand, when the positive Delta above a support is not big enough (3.4K as shown in Figure 3), there is a good possibility that the breakdown will fail and the market would eventually move lower. A small positive Delta value indicates that the buyers are not strong enough to take the price higher. Refer to Figure 3 for an example of a failed breakout. The bullish entry itself wasn't triggered, and the market headed lower even after it crossed the resistance.

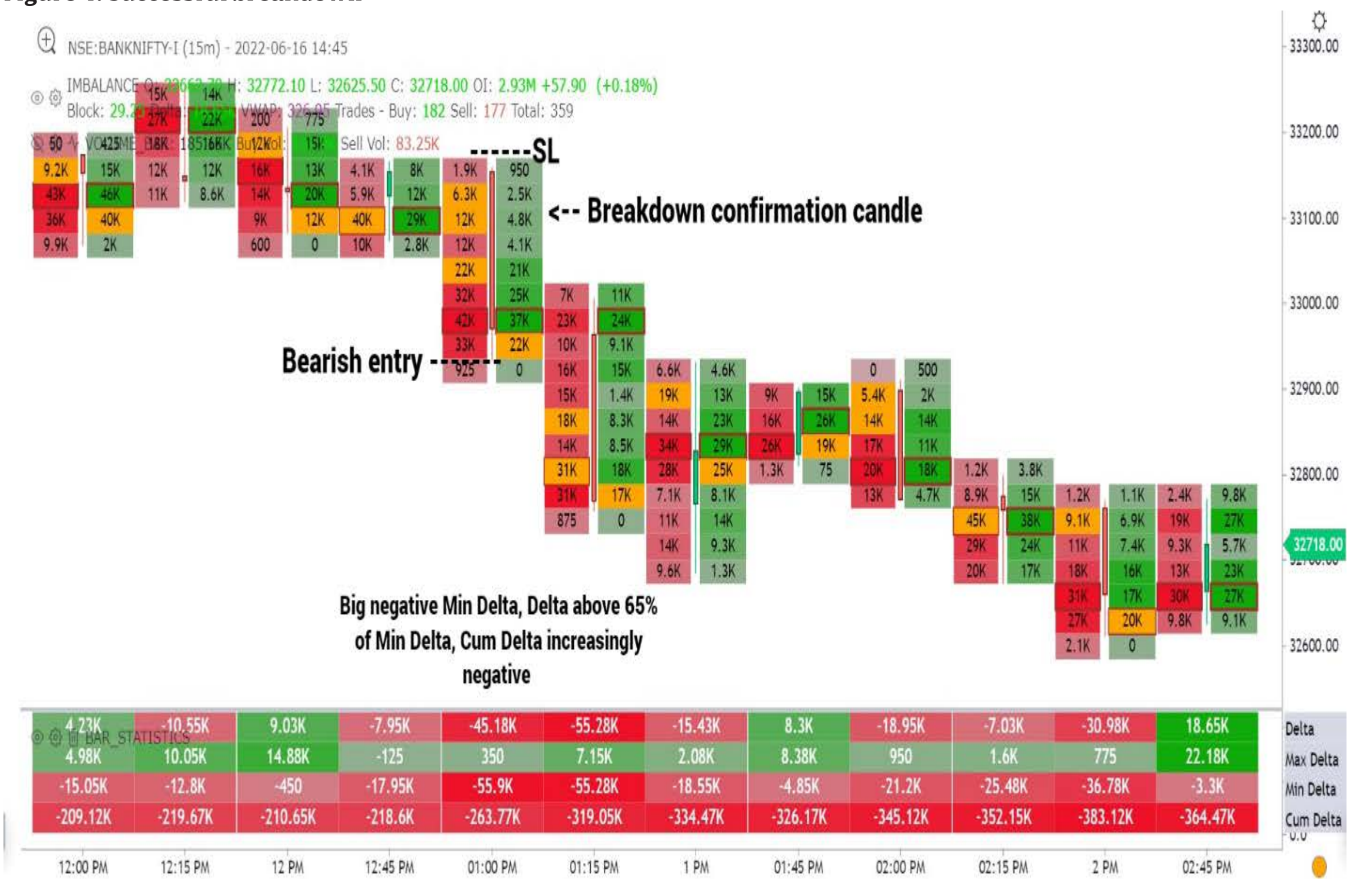
Figure 3. Failed breakout



Breakdown

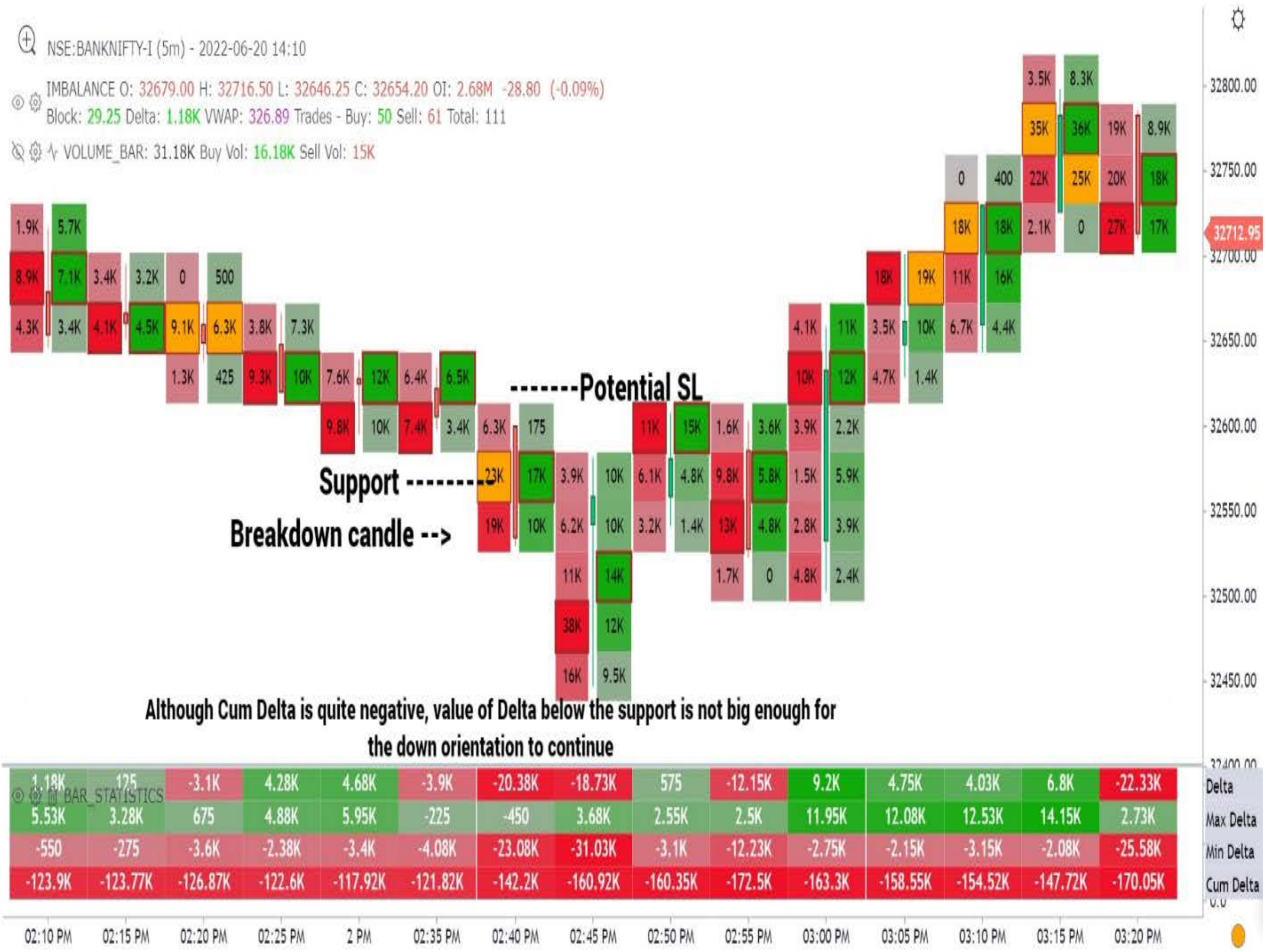
Delta and Min Delta below a support are observed. Both need to have big values with Delta value at least 65% of Min Delta below a support (a Delta value close to Min Delta indicates that sellers are still in control). The momentum condition and bearish breakdown conditions together are necessary for a down move. A bearish trade can be initiated with minimum 1:2 risk-reward ratio and stop-loss above the breakdown candle. Refer to Figure 4 for a successful breakdown example. Although the support was at 33,260, once the price moved below it, there wasn't any indication of major selling in prior candles, and the down move was gradual. When buyers finally gave up, sellers took control below 32,950 (Delta -45.18K and Max Delta -55.9K), which can be seen in the breakdown candle. A bearish momentum followed suit with only a few retracements.

Figure 4. Successful breakdown



On the other hand, when the negative Delta below a support is not big enough, there is a good possibility that the breakdown will fail, and the market would eventually move higher. A small negative Delta value indicates that the sellers do not have full control, and the operator is able to take the price high enough to trigger most of the SLs in the system. Refer to Figure 5 for an example of a failed breakdown.

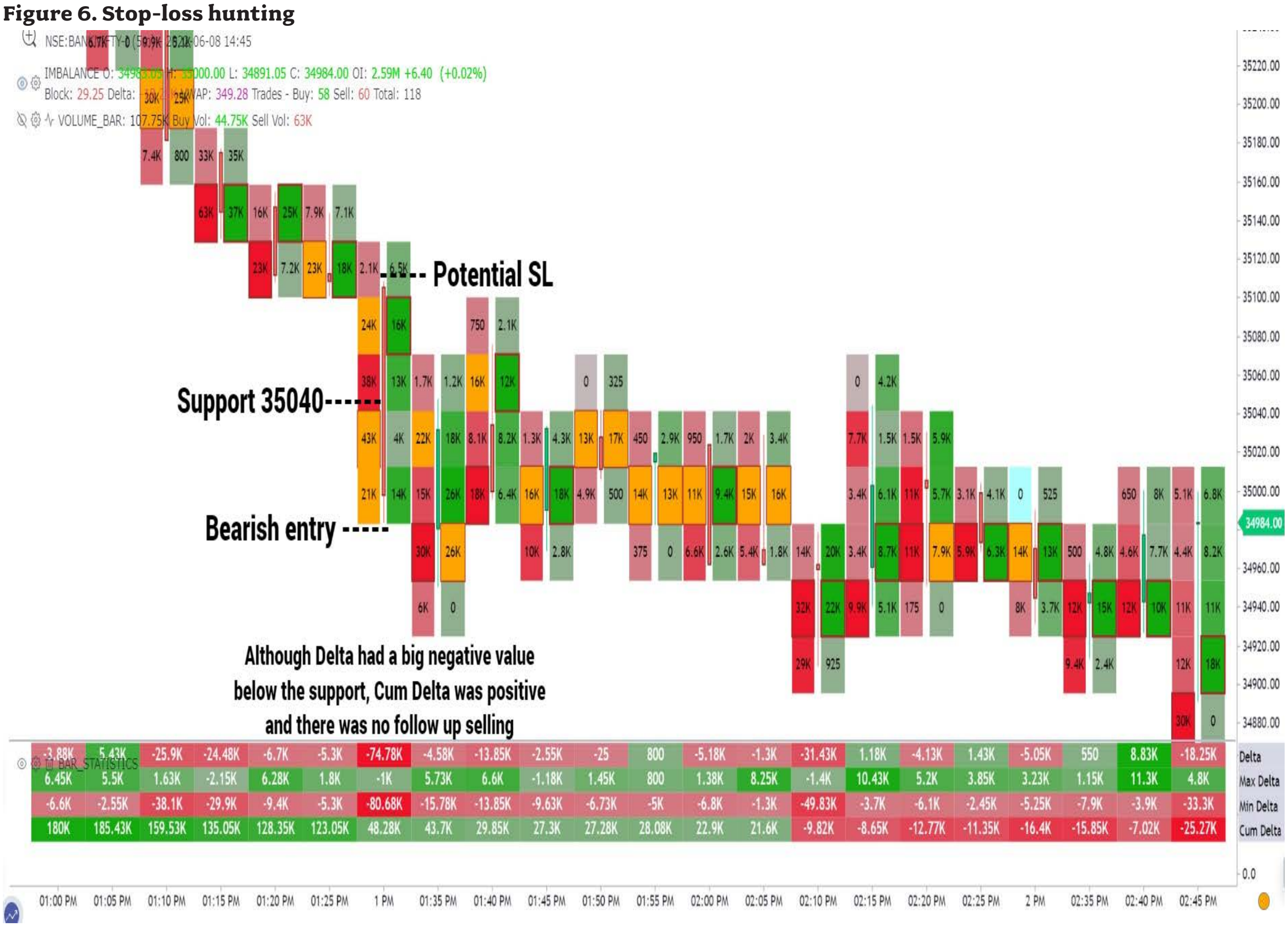
Figure 5. Failed breakdown



Stop-Loss Hunting

Stop-loss hunting can happen if buyers are not in control above a resistance or sellers are not in control below a support. The strength of the buyers or sellers has to be gauged by using OFA. Refer to Figure 6, which shows an example of stop-loss hunting. The market was strong throughout the day, which is shown by the positive Cum Delta (120K), before a candle suddenly closes below the support at 35,040. The big negative Delta (74K) in this case indicates that the SLs of buyers got triggered, owing to the big value. No follow-up big negative Delta confirmed the view that the down move was only a stop-loss hunting one. The market did not move down significantly, and a bearish trade can be avoided.

Figure 6. Stop-loss hunting



Summary

OFA is a great tool to gauge the strength of buyers or sellers in the market. Some important points to be kept in mind are as follows:

1. The OFA parameters have to be observed only at reference points. They do not hold much importance in a consolidation zone.
2. OFA shows the presence of aggressive buyers/sellers in the market, and this helps to differentiate between a trending and a nontrending day.
3. The most important use of OFA is to identify a successful bullish breakout or a bearish breakdown and avoid stop-loss hunting moves by the operators.

Plotting Market Dependencies

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Abstract

"The trick is to take risks and be paid for taking those risks, but to take a diversified basket of risks in a portfolio."
—Jeffrey Gundlach, DoubleLine

Diversification is the key to successful portfolio construction for every trader or investor. But it is not sufficient just to split the portfolio into several positions. The positions themselves should be least dependent to gain the optimal risk reduction. In institutional risk management, the dependencies between the assets are often measured by correlations and those are used to estimate the risk of a certain portfolio. But for a discretionary trader, such a correlation matrix is just a mess of numbers and not really helpful to construct a well-diversified portfolio.

This paper presents methods to construct a plot of the correlation matrix based on so called "force-directed graph drawing." The result is a graph showing the instruments to trade and these instruments are laid out in such a way that higher correlated assets are closer together and less correlated assets have a larger distance in the plot. Hence, for a good risk management the trader picks the assets which fit to the individual trading strategy and are far away in this market dependency plot.

Introduction

This paper demonstrates how to plot the dependencies in the market, which are usually expressed by correlations of the assets. A plot of the assets is provided in such a manner that highly correlated assets lie closer together and less dependent assets are plotted more away from each other. Three methods to construct such market dependency plots are provided and, even if they look quite different, their interpretation is always the same: A trader should pick promising assets which are far apart on these plots in order to increase the diversification in the portfolio.

The construction of these plots is based on the technique of "force-directed graph drawing," which are, for example, used to visualize relationships obtained from the analysis of big data (Kobourov, 2013). One traditional force-directed graph drawing approach is based on the work of (Eades, 1984) and is used in this paper. The idea is quite simple: Assume that each asset is a particle and there are two forces interacting on the particles:

1. A repulsive force driving all particles apart.
2. An attracting force pulling each pair of particles together. This force depends on the correlation of the two assets (particles) and is stronger if the correlation is higher.

These particles are laid out on the two-dimensional plane and the core idea is that this physical system should attain a state of minimal energy.

This paper starts with a first market dependency plot and an explanation of how to use it for trading or investment. A simple algorithm for the construction of this first example is presented thereafter. Throughout this paper, all examples are based on the stocks contained in the Dow Jones Industrial Average Index; hence, we assume that the portfolio is composed by some of these stocks and the reader is free to choose the actual trading strategy for the single stocks.

Even if the correlation is quite popular to measure dependencies, correlations work fine in general only for certain distributions (Embrechts et al, 1999). A warning example is provided and therefore another mathematical concept should be considered to measure dependencies: The Gaussian copula.

The first example uses a heuristic to formulate the attracting force. In the second example, the attracting force is modified such that it is based on a metric, a proper mathematical way to describe distances. The resulting plot looks different at first glance, but the general interpretation of this plot remains the same.

The third and last example is based on the idea of (Kamada and Kawai, 1989). In their approach, a metric is needed and there is only one kind of force: The particles are linked by springs which have individual spring constants and rest lengths.

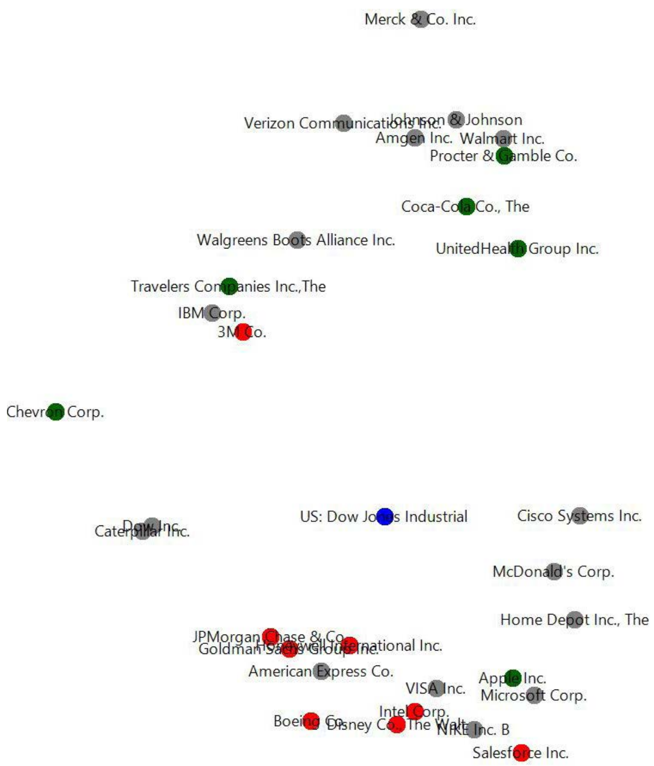
In the final conclusion, the three different market dependency plots are reviewed. Regarding the purpose to compose a portfolio with reduced risks due to a rather high diversification, all three methods provide similar results. Hence the usage of force-directed graph drawing to display market dependencies is rather independent from the concrete definition. Hence choose your favorite layout to find less dependent assets for your portfolio!

A First Market Dependency Plot

How to Use the Market Dependency Plot

To get an impression of a market dependency plot, an example based on the stocks of the Dow Jones Industrial Average Index is provided in Figure 1. The index is printed in blue and each stock is presented in a color based on a certain trading strategy: Green for buying, red for selling, and gray for stocks without a signal. In all examples of this paper, these signals are based on a trend following strategy, but any trading system can be used to define the colors of the stocks.

Figure 1. The first example of a market dependency plot



The closer the stocks lie together, the higher the correlation between them. So, without surprise, some stocks are plotted closely together:

- The financial stocks: J.P. Morgan, Goldman Sachs, American Express, Visa
- The pharmaceutical companies: Merck, Johnson & Johnson, Amgen
- The software companies: Apple, Microsoft, Salesforce

These groups, based on the same industry of the companies, are well known to all traders and that these lie together in the chart indicates how this plot works. But, at first glance, a portfolio of Visa, Microsoft, and Nike may look diversified from the sector point of view, but the plot shows that these stocks are also highly correlated.

Let's assume a trader wants to construct a portfolio with three positions from the Dow Jones constituents. In a first step, the trader applies the favorite trading system on each stock and gets, for example, the three results for each stock: Buy (Green), Sell (Red), or Neutral (Gray). Hence, only the Green plotted equites are relevant for the long-only portfolio.

In the second step, the trader choses the green equites which lie most apart in Figure 1. In this example, this results obviously in buying Chevron, Procter & Gamble, and Apple.

A short-seller on the other hand would focus on red dots and would diversify the short portfolio with 3M, Salesforce, and either J.P. Morgan or Boeing. Maybe the short investor will reconsider in this example to construct the portfolio of four shorts instead of three.

The concrete trading system used to color the equities in the plot is not relevant. For any successful trading system, regardless of short-term or long-term, regardless of trend following or mean reversion, a well-diversified portfolio will reduce the risks of the portfolio. The lower the correlation of the assets, the higher the effect of the diversification, and the most suitable positions for a portfolio can be obtained in the market dependency plot by the dots of the right color which lie most apart from each other.

The Model Behind This Plot

The model is inspired by (Eades 1984) and consists of repulsive and attracting forces between particles which represent the assets. Let p_i be the position of the particle i with $i = 0$ being the Dow Jones Index and $i = 1 \dots n$ the single stocks. The repulsive force for each stock is defined by a constant force pushing the particle away from the center c of all particles. The center is defined by:

$$c = \frac{1}{n+1} \sum_{i=0}^{n} p_i$$

There is no repulsive force for the index ($i = 0$) and the repulsive force F_i^r for the stocks ($i = 1 \dots n$) is given by:

$$F_i^r = \begin{cases} \dfrac{p_i - c}{\|p_i - c\|} & p_i \neq c \text{ and } i > 0 \\ 0 & p_i = c \text{ or } \ i = 0 \end{cases}$$

Since $\|p\|$ denotes the Euclidian Norm, $\|p\| = \sqrt{p_x^2 + p_y^2}$, so the absolute value of this force is either 1 (in the first case) or 0 (if the particle is in the center or the particle is the index). The energy related to the repulsive forces is given by

$$E^r = -\sum_{i=1}^{n} \|p_i - c\|$$

To link the particles together, an attracting spring force between the particles is established. The spring constant is higher if the particles (assets) are higher correlated. If two assets are uncorrelated, there is no spring at all. If assets are perfectly anti-correlated, these assets would also not contribute to some diversification, hence it is reasonable to define the model by spring constants $k_{i,j}$ which depend on the correlation $\rho_{i,j}$ between the two assets.

$$k_{i,j} = -\frac{1}{\ln(|\rho_{i,j}|)}$$

Hence for a correlation of almost ±1, the spring constant is very high. For a correlation of 0, the spring constant is 0. The force acting on particle i induced by the spring to particle j is given by:

$$F_{i,j}^a = k_{i,j}(p_j - p_i)$$

The energy of the attracting springs is given by:

$$E^a = \sum_{i=0}^{n} \sum_{j=i+1}^{n} k_{i,j} \|p_i - p_j\|^2$$

The total energy of the system is given by $E = E^r + E^a$ and for the plot, the particles should be located such that the energy of the system is minimal. The bad news is that optimal solution may not obtained. But the good news is that a rather good approximation is fine for this application.

The construction of the forces implies that there is some energy minimum. If all particles are on the same spot, hence the center of the system, the total energy is obviously zero. If the particles move only a small distance away from the center, the total energy is approximated by the linear repulsive energy term E^r and hence negative if the distances are quite big. The positive attracting energy E^a dominates the total energy due to its quadratic behavior with respect to the distances.

The solution will not be unique since any rotation or mirroring of a solution provides another solution with the same energy. Therefore, there is a freedom to rotate or mirror the result. For the purpose of this paper, all plots are oriented such that the finance stocks are at the bottom and Chevron is on the left. Also, a proper scaling of the result for the plot must be considered.

The Steepest Descent Algorithm to Minimize the Energy

The algorithm to find an approximate solution is based on a steepest descend algorithm, which is also used to train neutral networks. The idea behind this algorithm is quite simple. For the initialization, let all particles be randomly placed on the two-dimensional plain. Then the force of the system drives all particles for a small moment (called learning-rate in the context of neural networks) into a certain direction and then the system is frozen again, hence all particles are fixed at the new position. If the energy of the new system got smaller, the step is repeated. If the energy of the system increased, then the learning-rate is decreased.

Here is the algorithm in pseudo-code based on the formulas presented above, especially the formulas for the forces and energy are not stated explicitly again. The forces and positions are two-dimensional vectors. The learning rate λ, the energies, and the small constant ε are numeric values. The final positions are the result of the algorithm and can be plotted after rescaling (and possible rotation).

Algorithm 1. The steepest descent algorithm

```
for i:=0 to n
        position_i := RandomLocation
        lastPosition_i := position_i
next i
λ := 1
lastEnergy := ComputeEnergy(lastPosition)
while (λ > ε) do
        for i:=0 to n
                position_i := lastPosition_i + λ (F_i^r + Σ_{j=0}^n F_{i,j}^a)
        next i
        energy := ComputeEnergy(position)
        if (energy < lastEnergy) then
                lastEnergy := energy
                for i:=0 to n
                        lastPosition_i := position_i
                next i
        else
                λ := λ/2
        end if
end while
```

How to Measure Dependencies: Correlation or Gaussian Copula

If everything behaves benignly, the correlation is a good measure for dependencies. But as (Embrechts 1999) pointed out, there are several pitfalls. For a warning example that correlation may be a bad measure for dependency, let A_i be some drawings of a standard-normal variable and define $B_i = \exp(A_i)$ and $C_i = \exp(5 A_i)$. Then B and C are perfectly dependent, since from any value of B_i one can compute the corresponding value of C_i. But note, the correlation of B and C is just around 66%!

To describe general dependencies of stochastic variables, Abe Sklar introduced the concept of copulas, see (McNeil 2005 and the references therein). A special case of copula dependency is the Gaussian copula. Each random variable is transformed into a standard normal distributed random number and then the correlation between these transformed random variables is measured. Hence the Gaussian copula is a correlation again and, in the warning example above, the Gaussian copula will be 100%. To clarify this procedure, the calculation of the Gauss copula of two stocks is explained.

Let X_t and Y_t with $t = 0...T$ the close quotes of the stocks. The log-returns of the stocks are given by $\Delta X_t = \ln(X_t) - \ln(X_{t-1})$ and $\Delta Y_t = \ln(Y_t) - \ln(Y_{t-1})$ with $t = 1 \dots T$. The data ΔX_t and ΔY_t will be used to estimate the usual Person correlation ρ. Using the notation and $\mu_X = \frac{1}{T}\sum_{t=1}^{T} \Delta X_t$ and $\mu_Y = \frac{1}{T}\sum_{t=1}^{T} \Delta Y_t$ the formula for the correlation is given by:

$$\rho = \frac{\sum_{t=1}^{T}(\Delta X_t - \mu_X)(\Delta Y_t - \mu_Y)}{\sqrt{\sum_{t=1}^{T}(\Delta X_t - \mu_X)^2 \sum_{t=1}^{T}(\Delta Y_t - \mu_Y)^2}}$$

In order to compute the Gaussian copula, the values of ΔX_t need to be ranked. Hence for the value of t where ΔX_t is the smallest value $R_t^X = 0$, for the value of t of which ΔX_t attains the second smallest value $R_t^X = 1$, and so on up to $R_t^X = T - 1$, for the t where ΔX_t is maximal. Let $N()$ be the cumulative normal distribution function and $N^{-1}()$ its inverse, then we define:

$$\hat{X}_t = N^{-1}\left(\frac{R_t^X + \frac{1}{2}}{T}\right)$$

Since R_t^X obtains each integer value from 0 to $T - 1$, $\hat{X}_t$ is approximately standard normal distributed. The similar transformation can be performed with the data ΔY_t to obtain $\widehat{Y_t}$. The correlation based on the Pearson correlation formula between $\hat{X}_t$ and $\widehat{Y_t}$ is the Gaussian copula. Note that the mean of and $\hat{X}_t$ and $\widehat{Y_t}$ is zero by construction:

$$\hat{\rho} = \frac{\sum_{t=1}^{T}(\Delta\hat{X}_t)(\Delta\hat{Y}_t)}{\sqrt{\sum_{t=1}^{T}(\Delta\hat{X}_t)^2 \sum_{t=1}^{T}(\Delta\hat{Y}_t)^2}}$$

Of course, if the distribution of the random variables is close to the normal distribution, the correlation and the Gaussian copula will be quite similar. For the results in this paper, the Gaussian copula based on the daily returns over a one-year horizon is used as correlation. So even if the stock returns are not as benign as expected, the measure of their dependency is based on a robust mathematical foundation.

A Second Market Dependency Plot

In the first example, the heuristic distance $-\ln(\rho)$ between two assets has been used based on their correlation (or Gaussian copula) ρ. Even if the results are reasonable, this kind of distance does not fit to the mathematical concept of a metric. So, it's worthwhile to introduce a distance which fulfills the axioms of a metric and to review a market dependency plot based on a metric.

A Mathematical Distance Between the Assets

In mathematics, a well-defined distance d(A,B) between A and B is called a metric if it fulfills three axioms.

1. $d(A,B) \geq 0$ and $d(A,B)$ is zero if and only if A = B
2. $d(A,B) = d(B,A)$
3. $d(A,B) < d(A,C) + d(C,B)$

The third and last axiom is called the triangular inequality and states that any detour via point C is never shorter than the direct way.

For this discussion, A, B, and C are the random variables which may represent the returns of the stocks. Working within the framework of Gaussian copulas, we now assume that A, B, and C are standard normal distributed random variables. Hence the transformed equity returns. The distance shall be expressed by their correlation, which is again commutative—hence the second axiom holds:

$$d(A,B) = d(\rho_{B,A})$$

To find a suitable expression for the distance of A and B expressed by their correlation, basic stochastics and geometry is combined. The idea of the following discussion is that the standard normal distributions (A, B, C) can be identified by points (A, B, C) on the unit-sphere.

Let K_1, K_2 and K_3 be the orthogonal coordinates in the geometric interpretation and independent standard normal distributed random variables in the stochastics view. Define three points on the unit sphere:

$$A = a_1\,K_1 + a_2\,K_2 + a_3\,K_3 \quad \text{with } a_1^2 + a_2^2 + a_3^2 = 1$$
$$B = b_1\,K_1 + b_2\,K_2 + b_3\,K_3 \quad \text{with } b_1^2 + b_2^2 + b_3^2 = 1$$
$$C = c_1\,K_1 + c_2\,K_2 + c_3\,K_3 \quad \text{with } c_1^2 + c_2^2 + c_3^2 = 1$$

From the stochastics point of view, A, B, and C are standard normal distributed random variables since they are a sum of normal distributed random variables and have again a mean of 0 and a variance of 1.

The squared Euclidian metric between the points A and B can be expressed by:

$$\|A-B\|^2 = \|A\|^2 + \|B\|^2 - 2\langle A|B\rangle = 2 - 2\langle A|B\rangle$$

where $\langle A|B\rangle = a_1b_1 + a_2b_2 + a_3b_3$ denotes the scalar product and for the last equality recall that $\|A\|^2 = \|B\|^2 = 1$ holds by definition.

In the stochastics view, the correlation between A and B is given by its covariance since the expectation of A and B is 0 and their variance is 1. As a result, the correlation of A and B is just the scalar product due to the linearity of the covariance and the fact that K_1, K_2 and K_3 are independent standard normal distributed:

$$\rho_{A,B} = \mathrm{Cov}(a_1K_1 + a_2K_2 + a_3K_3,\, b_1K_1 + b_2K_2 + b_3K_3) = a_1b_1 + a_2b_2 + a_3b_3$$

Since the discussion started with the Euclidian metric, the term $\sqrt{2 - 2\rho_{A,B}}$ is a metric for the stochastic variables expressed by their correlation. The multiplication of the metric with any positive number fulfills the axioms, as well. Hence a simplified expression for a metric expressed by the correlation is given by:

$$d(A,B) = \sqrt{1 - \rho_{A,B}}$$

In our application, the distance of anti-correlated assets should be small too since anti-correlated assets do not contribute to diversification. Therefore, this distance is modified to bring anti-correlated assets close together by taking the absolute value of the correlation:

$$\hat{d}(A,B) = \sqrt{1 - |\rho_{A,B}|}$$

To show that $\hat{d}(A,B)$ still fulfills the triangular inequality, a discussion of eight possible cases regarding the signs of $\rho_{A,B}$, $\rho_{B,C}$ and $\rho_{A,C}$ must be performed. Such a proof of the triangular inequality of $\hat{d}(A,B)$ is provided in the appendix of (Chen et al. 2019).

The Model

This second model is quite analogous to the first model. Only the attracting force between two particles (stocks) is defined based on the previously introduced metric. The spring constant used in this model between stock i and stock j is given by the inverse of the metric

$$\hat{k}_{i,j} = \frac{1}{\sqrt{1 - |\rho_{i,j}|}}$$

and the attracting force is again given by Hook's law:

$$F_{i,j}^{a} = \hat{k}_{i,j}(p_j - p_i)$$

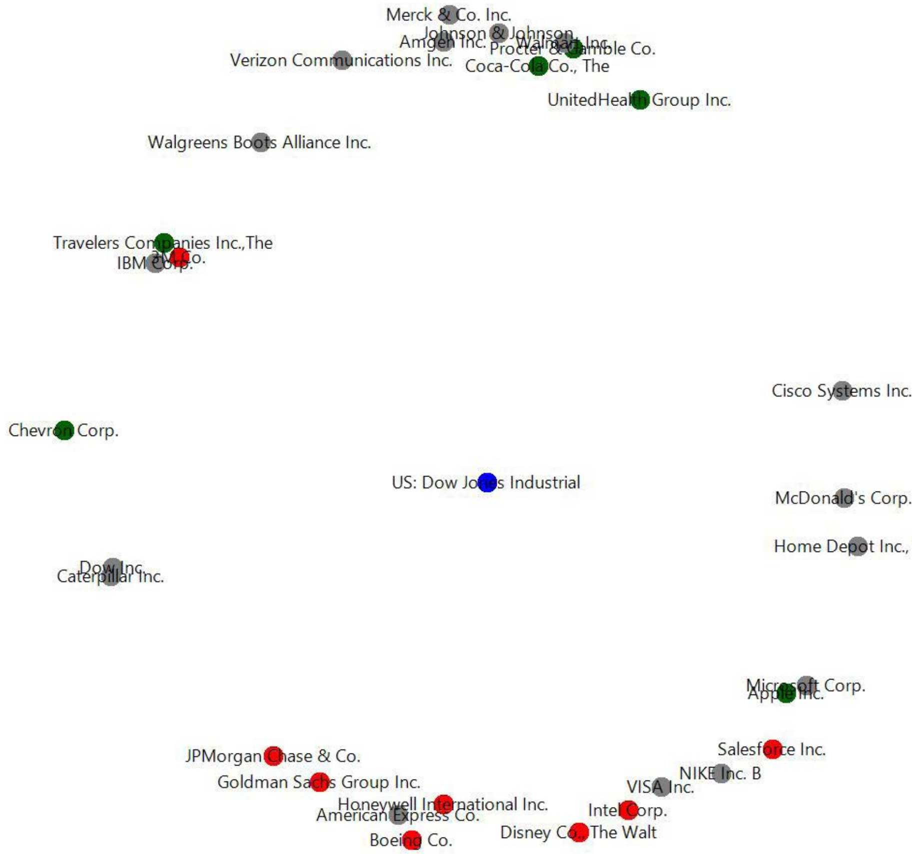
Hence the attracting energy is given by

$$E^a = \sum_{i=0}^{n} \sum_{j=i+1}^{n} \hat{k}_{i,j}\, \|p_i - p_j\|^2$$

These are the only modifications to the first model and the repulsive forces are unchanged. This model can also be solved with the steepest descend Algorithm 1.

The Resulting Plot

Figure 2. The second example of a market dependency plot



The result shown in Figure 2 arranges the single stocks almost on a circle. As in the first plot, the stocks of certain sectors are again arranged closely together:

- The financial stocks: J.P. Morgan, Goldman Sachs, American Express, Visa
- The pharmaceutical companies: Merck, Johnson & Johnson, Amgen
- The software companies: Apple, Microsoft, Salesforce

To compare the usage of this plot to the first plot, we look for the decision a trader makes who wants to pick three most far apart but green stocks from the graph. The result from the second plot will be Apple, Chevron, and Procter & Gamble, as in the decision based on the first plot.

Also, the short seller would prefer to build a portfolio based on the same short positions as in the first plot (3M, Salesforce, J.P. Morgan, or Boeing). Hence even if the forces to create the plot are changed and the plot looks different, the resulting portfolio build from the positions most apart from each other do not differ.

A Third Market Dependency Plot

The Model

The third model is based on the idea of (Kamada and Kawai, 1989) and this model consists of spring forces only. Hence there is no general repulsing force and there is no special treatment of the Dow Jones Index particle anymore. In order to push the particles apart, the rest length of the springs is greater than 0. In general, the rest length should be proportional to the metric and the spring constant should be proportional to the inverse of the squared metric. Using the previously introduced metric, the spring constant $\tilde{k}_{i,j}$ and the rest length $\tilde{l}_{i,j}$ of the spring between particles i and j are given by:

$$\tilde{l}_{i,j} = \sqrt{1 - |\rho_{ij}|}$$

$$\tilde{k}_{i,j} = \frac{1}{1 - |\rho_{ij}|}$$

The force $\tilde{F}_{i,j}$ on particle i induced by the spring to particle j is dependent on the position of the particles p_j, p_i:

$$\tilde{F}_{i,j} = \tilde{k}_{i,j} \left(\|p_j - p_i\| - \tilde{l}_{i,j} \right) \frac{p_j - p_i}{\|p_j - p_i\|} = -\tilde{F}_{j,i}$$

And the energy of spring between particles i and j is given by:

$$\tilde{E}_{i,j} = \frac{1}{2} \tilde{k}_{i,j} \left(\|p_j - p_i\| - \tilde{l}_{i,j} \right)^2$$

The Algorithm to Solve This Model

To solve for a solution of this model, the steepest descend algorithm fails due to too much local minima. But there is a simple way to modify the steepest descend algorithm such that it will yield proper results. Instead of moving all particles at the same time, only the particle which is exposed to the largest force will be moved until it attains a position of rest. Then the next particle, which is then exposed to the highest force, is chosen to relocate while all other particles are fixed. Since only one particle is moving in every step, the computational effort is higher than for the steepest descend algorithm.

Algorithm 2 presents the Kamada and Kawai algorithm in pseudo-code based on the formulas presented above. Please note that the formulas for the forces $\tilde{F}$ and energy $\tilde{E}$ depend on the positions of the particles and their value changes if any particle is moved. The index of the particle to move is an integer value denoted by m. The forces and positions are two-dimensional vectors. The learning rate λ, the energies, and the small constant ε are numeric values and the variable isimproving is Boolean.

Algorithm 2. The algorithm of Kamada and Kawai

for i:=0 to n
    $position_i \coloneqq RandomLocation$
next i
do
    $m \coloneqq \operatorname{argmax}_{i\in[0,\dots,n]} \left\| \sum_{j=0}^{n} \tilde{F}_{i,j} \right\|$
    $\lambda \coloneqq 1$
    $isImproving \coloneqq false$
    $lastEnergy \coloneqq \sum_{j=0}^{n} \tilde{E}_{m,j}$
    while $(\lambda > \varepsilon)$ do
        $lastPosition \coloneqq position_m$
        $position_m \coloneqq position_m + \lambda \sum_{j=0}^{n} \tilde{F}_{m,j}$
        $energy \coloneqq \sum_{j=0}^{n} \tilde{E}_{m,j}$
        if $(energy < lastEnergy)$ then
            $lastEnergy = energy$
            $isImproving \coloneqq true$
        else
            $position_m \coloneqq$ last$Position$
            $\lambda \coloneqq \lambda/2$
        end if
    end while
loop while $(isImproving)$

The Resulting Plot

Figure 3. The third example of a market dependency plot

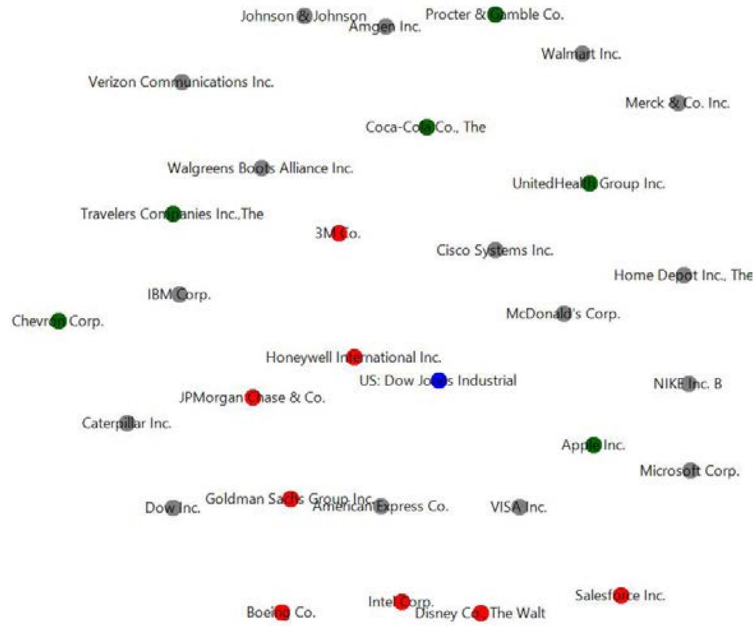


Figure 3 spreads the particles (stocks) over the whole plane without a circular structure anymore. Even if there is no special treatment of the index, it is placed in the center of the plot. As in the previous plots, stocks of the same industry (e.g., financial, pharmaceutical, software) are placed closely together.

The market dependency plot will be used by the same manner as before. The long-investor is spotting for the green stocks most far apart and the selection will again yield to a portfolio of Apple, Chevron, and Procter & Gamble. Hence the portfolio consisting of three long positions is again unchanged.

For a portfolio consisting of three short positions, this plot is more clear than the previous one and the selected stocks would be 3M, Salesforce, and Boeing. In the previous plots, the selection of either Boeing or J.P. Morgan was considered and there was a tendency to use four stocks in a short portfolio. But if a fourth short position should be added based on this plot, it would certainly be J.P. Morgan.

Conclusion

While it is quite simple to identify stocks which are highly dependent, for example by acting in the same industry, it is inconvenient to imagine which stocks are least dependent. But this task is important to construct a portfolio which gains most from the effect of diversification. To visualize the dependencies of the stocks, some market dependency plots have been provided.

The technique behind plotting of these dependencies is known as "force-directed graph drawing" and three models have been analyzed. The core idea is to embed the correlation or Gaussian copula into the attracting forces. This can be done either by some heuristic approach (first model) or by an approach which utilizes a metric (second and third model). Even if the resulting plots look different at first glance, the application to build a portfolio of a few mostly independent stocks based on these plots yield mostly to the same (or at least quite similar) portfolio. Even if the list of models can easily be extended, their results in the application to construct a portfolio will almost have the same outcome. That seems likely from the portfolio discussions of the three models in this paper.

The degree of dependency is often expressed by the correlation, but keep the warning example in mind: correlation may be misleading. To cover the dependence of stochastic variables, a general approach of copulas exists and the special case of a Gaussian copula is presented. The Gaussian copula differs mathematically from the usual correlation but can be treated like a correlation again. Hence, one should easily get used to it.

The presented algorithms to search for an energy minimum will work for this purpose, but they are just basic and may be trapped in a local minima without finding a better global minimum. To overcome this issue, there are algorithms containing some stochastic components based on the idea of "Simulated annealing" (Press et. al., 1992) and which are recommended to improve the minimization task.

The market dependency plots provide the freedom to color each stock based on a signal of your favorite trading system and the construction of the market dependency plot does not depend on a certain trading strategy. You are also free to choose your convenient time frame to measure the dependencies of the financial instruments. Therefore, market dependency plots provide a general tool to reduce the portfolio risk as well for the short-term trader as for the long-term investor.

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Software and Data

The market data used for this research has been obtained by the software TAI-PAN End-of-Day from the provider Lenz+Partner GmbH (www.lp-software.com), which is part of Infront ASA (www.infrontfinance.com).

Modelling Financial Time Series by Generative Adversarial Networks: With Applications to the Nasdaq Composite Index

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Introduction

This study aims to introduce TimeGANs to the field of financial modelling or more generally to the field of artificial intelligence (AI) in finance. TimeGANs belong to the family of GANs (Generative Adversarial Networks), which are a neural networks architecture developed for generating images. They are increasingly used for generating time series and other types of financial data. The purpose of this study is to give an introduction to the modelling problem in finance, to describe the architecture of TimeGANs and how they are implemented in the language Python, to assess the quality of the generated synthetic time series data, to present some stylized facts about financial time series and to verify whether synthetic data can reproduce them and to conclude with an outlook of future developments and limitations of this technique. The overall finding is that GANs are able to produce solid results with respect to synthetic time series data generation and modelling.

The Modelling Problem in Finance

The finance industry is one of the most influential fields impacted by new developments in AI. Machine learning (ML) tools have been used for forecasting, risk management, fraud detection, and portfolio management. ML tools are by their very nature data intensive, and a lack of (financial) data due to regulations and privacy laws may limit their potential. In this respect, GANs are useful for generating synthetic data where real data is scarce. In addition to this, GANs are used for data-driven modelling, and their application can improve the modelling of complex and unknown statistical dynamics present in financial data. Before the advent of ML, financial modelling was mainly based on families of models (i.e., ARCH/GARCH for modelling and forecasting volatility and stochastic models such as Black Scholes [1973], Merton [1976], and Heston [1993]). ARCH/GARCH models describe the variance as time-varying (heteroskedastic) and as a function of current and past (squared) error terms. They do not have a stochastic component since volatility is completely dependent on previous values. On the other hand, stochastic volatility models introduce (as their name suggests) stochastic components in the form of Brownian motions to the modelling of volatility and ultimately to logarithmic return series and options pricing. The limitation of Black Scholes, for example, is that it produces (by its model assumptions) constant (implied) volatilities where, in practice, implied volatilities are not constant (in practice, implied volatilities may be described by a U-shape called "volatility smile"). More advanced stochastic models like the Merton model introduce so-called random jumps following a Poisson process to allow for discontinuities beside (standard) Brownian motions for modelling return series and to capture the stylized facts of implied volatilities.

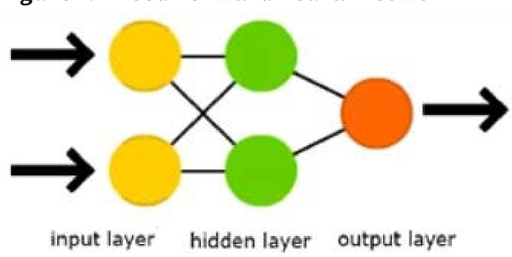
In sum, these models rely on assumptions, whereas ML models are much more empirical (i.e., data driven). Thus, a great risk in financial modelling, model risk, which is the risk of using an inappropriate model, can be mitigated.

Machine Learning Versus Deep Learning

ML is an area within the fields of AI and computer science that enables computers to learn by using data and advanced statistical methods. In short, ML consists of the creation of learning algorithms that receive data (e.g., training data) as an input and return a classification—a label of a prediction related to this input. The traditional tasks that ML models perform are regression, classification, clustering, and prediction. A closely related field is deep learning with more innovative solutions.

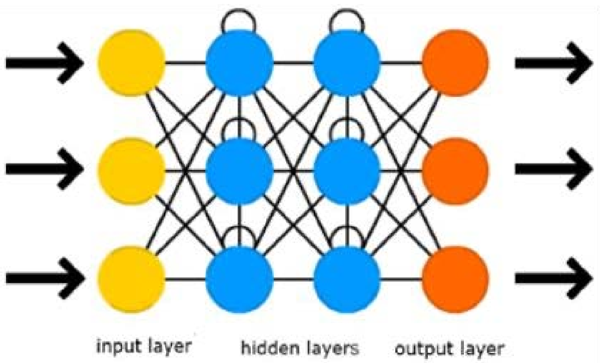
Deep learning algorithms are based on so called artificial neural networks, which are networks of connected layers of nodes (neurons) inspired by the biological neural networks of brains. These networks are called "deep" because they are composed of more than two layers: an input layer, an output layer, and at least one hidden layer that enables the network to learn complex nonlinear functions that are required to carry out complicated tasks of AI. The simplest neural network is the feed-forward network since data flows from the input layer to the output layer.

Figure 1. A feed-forward neural network



A more sophisticated type of neural network is the Recurrent Neural Network (RNN). An RNN not only has neurons with connections from the input layer to the output layer but also neurons with connections from the output layer back to the input layer. This additional connection enables the RNN to store information over time, which is called dynamic memory. RNNs are particularly useful for time series predictions.

Figure 2. A recurrent neural network



One important distinction is between generative models and discriminative models, and another is between supervised learning and unsupervised learning. Learning means "learning from data," and it is called "supervised" because of the presence of the outcome variable to guide the learning process (one example of supervised learning is linear regression analysis, where the linear model learns from the input ($X_1,\ldots,X_p$) on which it is trained to predict an output ($Y_1,\ldots,Y_m$). In the "unsupervised learning problem" or "learning without a teacher", only the features or inputs are observed while there is no measurement of the output. The task is rather to describe how the data is organized or clustered. Most discriminative models fall in the category of supervised learning, while most generative models are labeled as unsupervised.

GANs

GANs were introduced in 2014. Goodfellow et al. proposed a model made up of two components: a generator (G) and a discriminator (D). Their tasks can be described as follows. The G captures the data distribution and generates new data. The second model is a classifier, the D, which estimates the probability that a sample came from the training data and not from G. The training process of the G is to maximize the probability of its output being misclassified by the D. The D has the task of assessing the quality of the generated data and providing feedback to the G. These neural networks are optimized under game-theoretic aspects: the G is optimized to generate data to fool the D, and the D is optimized to detect the source of the input, namely the G or the real data set. The overall aim is to generate data that is indistinguishable from the real data in key aspects, in which case we do not need the D anymore. This means that both models are competing against each other in a game called adversarial in Game Theory, and they are playing a zero-sum game. This means that when the D successfully identifies a sample, it is rewarded or no update is done to the model parameters, whereas the G is penalized with large changes to model parameters. From the other perspective, when the G tricks the D, it is rewarded, or no update is done to its parameters, but the D is penalized, and its model parameters are changed.

The GAN training process uses loss functions that measure the distance between the distributions of the generated data and the real data to assess their similarity. There are many methods that can be used to solve this task. In the original "vanilla" GAN, a so-called minimax function was introduced:

$$min_G \, max_D \, V(D,G)= E_x \,[\log D(x)] + E_z \,[\log(1-D(G(z)))]$$

- D(x) is the Discriminator's estimate of the probability that the real data instance x is real.
- E_x is the expected value over all data instances.
- G(z) is the Generator's output given noise z or given the fake instance.
- D(G(z)) is the Discriminator's estimate of the probability that a fake instance is real.
- E_z is the expected value over all generated fake instances G(z).

Thus, the G minimizes the loss, which is equivalent to log (1-$D(G(z))$ since it cannot directly affect the D(x) term in the function. As the G distribution approaches the real data distribution, the D distribution will be unable to distinguish them and stabilizes at $D(x) = ½$.

The GAN Family

A number of GANs can be divided into two categories, namely by Architecture and by the design of the Loss function. TimeGANs, for example, use the Kullback-Leibler divergence as Loss function, WGANs (WassersteinGANs) use the Wasserstein distance as an alternative to the originally proposed Loss function. FIN-GANs could successfully produce synthetic time series that replicate the main stylized facts of financial time series. What makes GANs particularly useful is their ability to learn the properties of data without requiring explicit assumptions or mathematical formulations, something that stochastic processes cannot do without non-trivial assumptions.

The TimeGAN Architecture and the Scope of This Study

The scope of this study is to use the Nasdaq Composite Index as the quantity of interest and apply TimeGANs to it in order to ultimately create synthetic financial data. The quality of the created synthetic financial data is evaluated by three criteria:

1. Diversity: The distribution of the synthetic samples should roughly match that of the real data.
2. Fidelity: The sample series should be indistinguishable from the real data.
3. Usefulness: The synthetic data should as useful as its real counterparts for solving a predictive task.

Furthermore, it should be verified if synthetic data created by TimeGANs represent the main stylized facts of financial time-series:

- Linear unpredictability or absence of linear autocorrelation: Except for short intraday time scales, it is expected that asset returns show minimal linear autocorrelations.
- Fat-tailed distribution: The distribution of returns exhibits fat tails, which means that the probability of extreme returns, either positive or negative, is much higher than under the Gaussian distribution.
- Volatility clustering: Volatility displays a positive autocorrelation over several days. This means that large price changes tend to be followed by large price changes and small price changes tend to be followed by small price changes.

- Gain/loss asymmetry: Large plunges in asset prices do not share equally large upward movements.
- Aggregational gaussitanity: Over large time scales, the distribution of returns looks like a normal distribution.

The data for this study is EOD (End of Day) and comprises 20 years, from April 18, 2002, until April 18, 2022. It uses six features, namely open, high, low, close, adjusted close, and volume.

Figure 3. 20 years of daily data of the Nasdaq Composite Index, 2002–2022

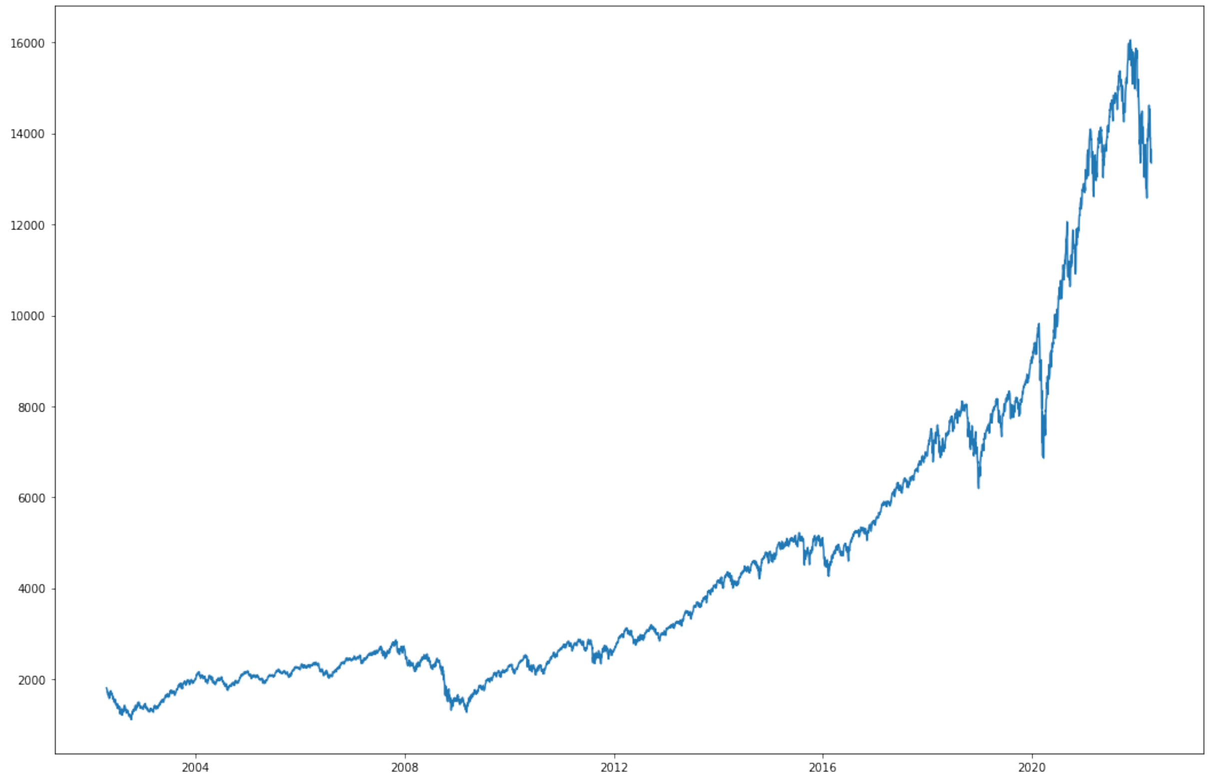
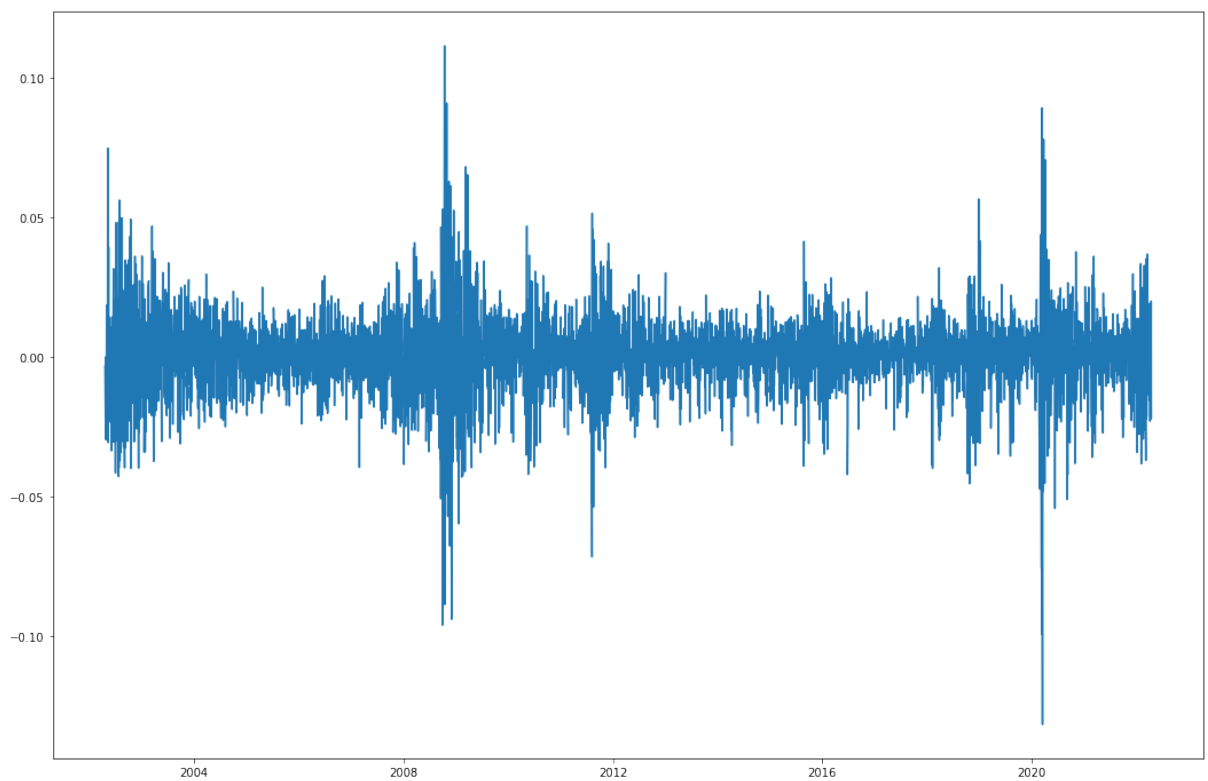


Figure 4. The Logarithmic return series of the Nasdaq Composite Index, 2002–2022



Figures 3 and 4 show different pictures of the same quantity of interest. Figure 3 depicts the Nasdaq Composite Index in levels, whereas Figure 4 depicts its logarithmic return series. While the former is called a nonstationary or trending process, the latter is called a stationary or nontrending process. The phenomenon of volatility clustering is easily detectable, particularly around the years 2008 and 2020.

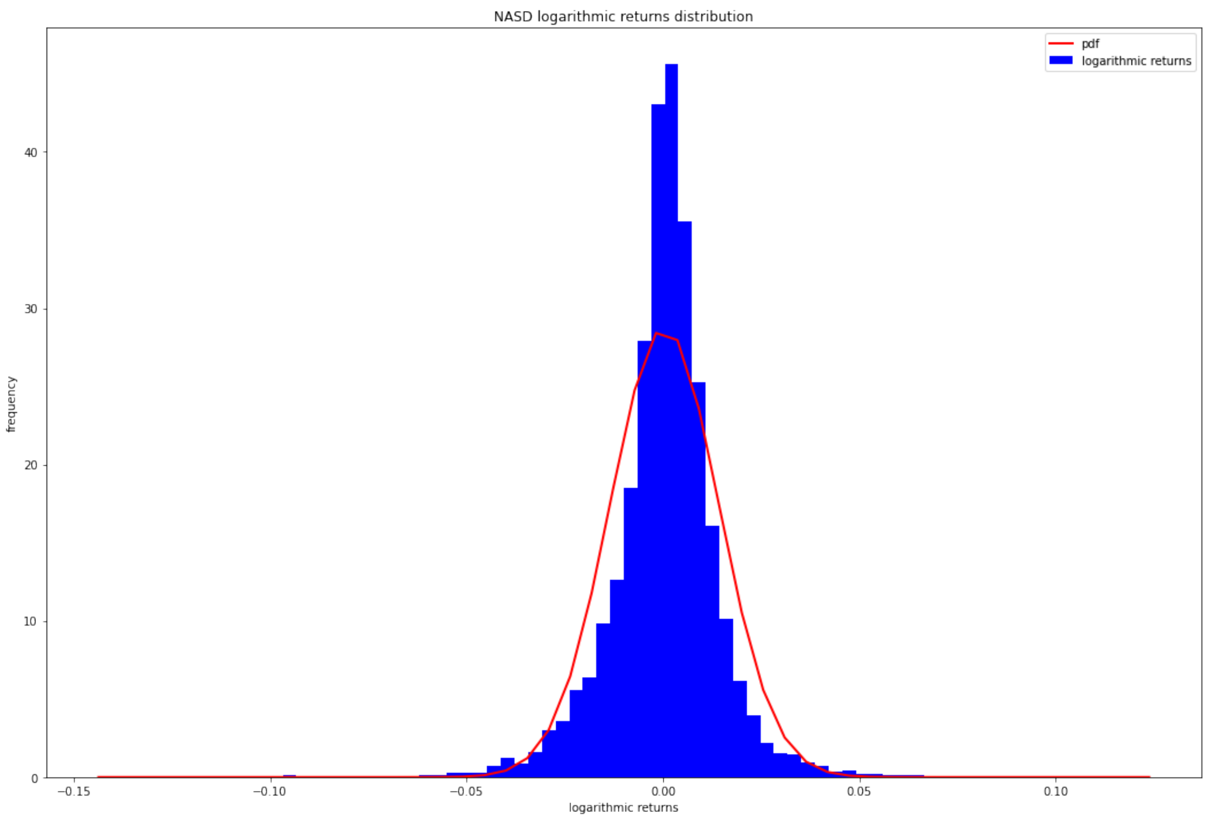
Figure 5 shows the distribution of the logarithmic returns of the Nasdaq Composite Index. It can be easily seen that the distribution is leptokurtic (i.e., there is a large excess kurtosis) (3 being the Gaussian distribution).

Table 1. Some descriptive statistics of the Nasdaq logarithmic returns distribution

Kurtosis	10.209
Skewness	-0.325
Min	-0.131
Max	0.111

Table 1 shows some descriptive statistics of the Nasdaq logarithmic returns distribution. The kurtosis is much greater than 3 (3 being the value characterizing a Gaussian distribution), and the skewness is negative (0 being the Gaussian distribution), suggesting more weight on the right tail of the distribution. Together, kurtosis and skewness suggest a fat-tailed distribution. The absolute minimum of the logarithmic return series was -13.1%, whereas the absolute maximum was 11.1%.

Figure 5. The Nasdaq logarithmic returns distribution (blue) and the Gaussian PDF (red)



The TimeGAN architecture is comprised of two main categories with a total of four components. The two main categories are:

- The Autoencoder: It comprises the embedding and recovery networks.
- The Adversarial network: It comprises the generator and discriminator.

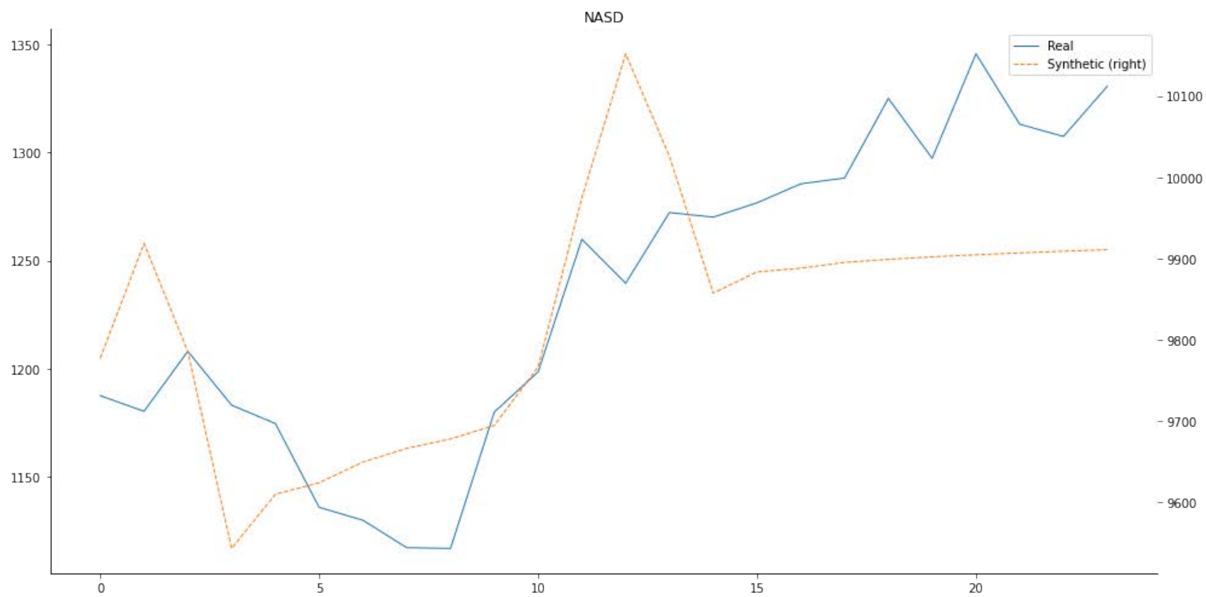
The embedding and recovery networks of the autoencoder map the feature space into the latent space and vice versa. The latent space is simply a representation of compressed data. Compressed data is obtained by transforming complex forms of data into simpler representations (e.g., dimensionality reduction from 3D to 2D). This is done because it is more convenient for a deep learning algorithm to process and analyze compressed data.

One of the specific characteristics of the TimeGAN architecture is the joint training of the autoencoder and adversarial networks by means of three different loss functions: the reconstruction loss optimizes the autoencoder, the unsupervised loss trains the adversarial network ,and the supervised loss is responsible for the temporal dynamics. Consequently, the TimeGAN simultaneously learns to encode features, generate representations, and iterate across time.

Assessing the Quality of the Synthetic Time-Series Data

Having outlined the broad architecture of TimeGANs, the next step is to create synthetic time-series data. A total of 24 observations were created by the TimeGAN framework.

Figure 6. Synthetic time-series data (yellow) versus real time-series data (blue)

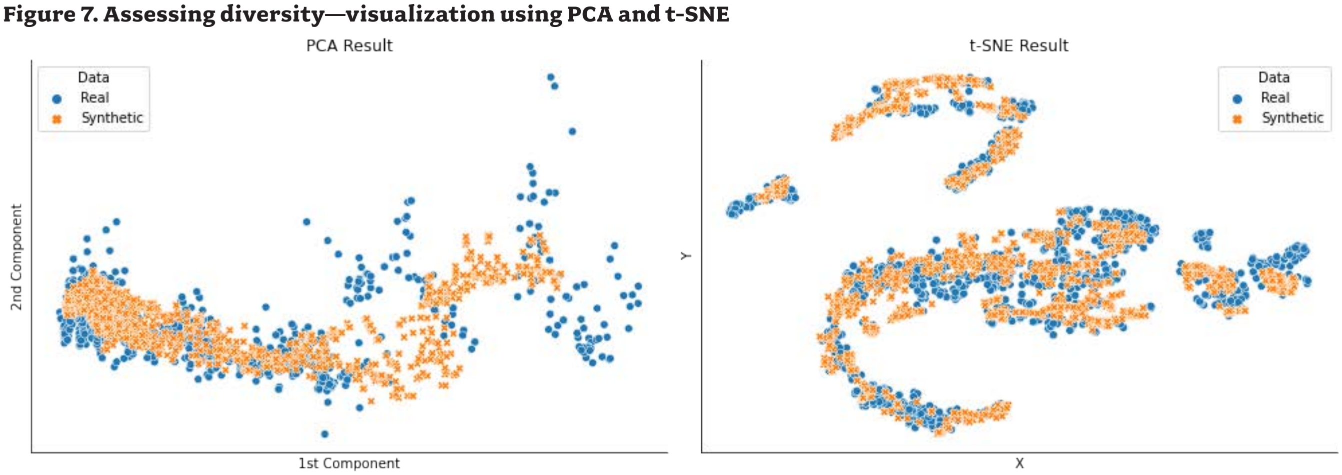


As can be seen from Figure 6, the yellow graph (synthetic data) replicated the blue graph (real data) reasonably well. However, it is necessary to take a closer look at the quality of the synthetic data. For this task, the three aforementioned criteria (diversity, fidelity, and usefulness) are employed.

Diversity

For a qualitative assessment of diversity, I use two methods of dimensionality reduction (in order to plot them in 2D), principal component analysis (PCA) and t-SNE (t-distributed Stochastic Neighbor Embedding) to visually inspect how closely the distribution of the synthetic samples resembles that of the original data. PCA is a linear method that is applied when many of the variables are highly correlated, and it is desirable to reduce their number to an independent set while preserving as much of the data's variation as possible. t-SNE is a nonlinear method for dimensionality reduction and is used when data is not linearly separable.

Figure 7. Assessing diversity—visualization using PCA and t-SNE



As can be seen from Figure 7, both methods reveal strikingly similar patterns and significant overlap, suggesting that the synthetic data captures important aspects of the real data characteristics. Upon closer examination, it is interesting to note that the t-SNE result is better than the PCA result, suggesting the existence of nonlinearities in the data.

Fidelity

For this task, I trained a time-series classifier to distinguish between real and fake data and evaluate its performance on a held-out test set. Therefore, the first 80% of the data was selected for training and the last 20% was selected as a test set. A simple RNN with six units that receives mini batches of real and synthetic data is used. It is optimized using binary cross-entropy loss and the Adam optimizer, while the AUC (Area Under the Curve; the curve in this case is the receiver operating characteristics [ROC]) and other accuracy metrics are tracked. The higher the AUC, the better the performance of the model at distinguishing between real and synthetic data.

Figure 8. Assessing fidelity—time-series classification performance

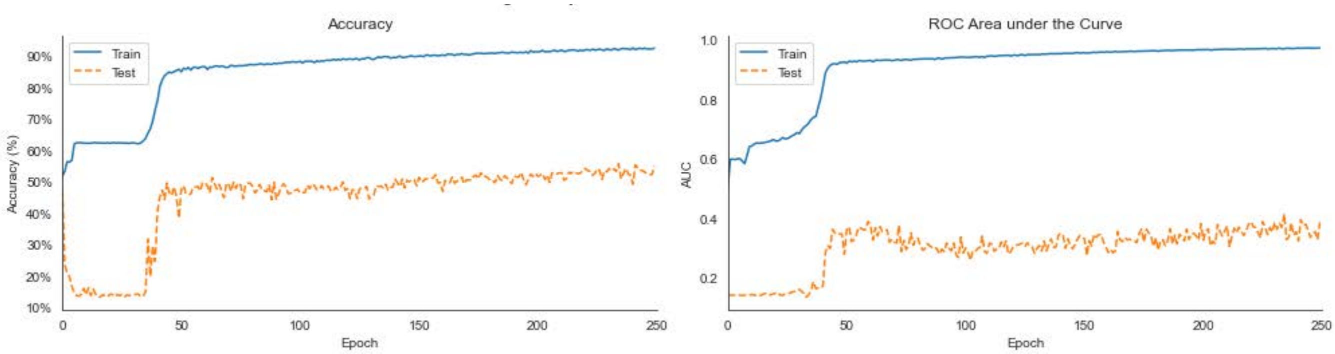


Figure 8 (right panel) suggests that the model is able to distinguish between real and synthetic data quite well on the train set (high AUC) but this does not generalize to the test set (low AUC). This result suggests that the quality of the synthetic data meets the fidelity standard.

Usefulness

The last step involves a prediction task (one step ahead prediction) and assesses whether real data or synthetic data are more useful for accomplishing this. Specifically, the first 23 observations of each sequence are selected as input to a one-layer RNN with 12 GRU (gated recurrent units) and the last observation as output. I trained the RNN model twice—on synthetic data and on real data for training, and the out-of-sample performance is evaluated by the MAE (mean absolute error). The MAE is a statistical measure of accuracy that averages the sum of the absolute errors, which are the absolute difference between a prediction and the true value. The lower this value, the more accurate the model is.

Figure 9. Assessing usefulness—time series prediction performance

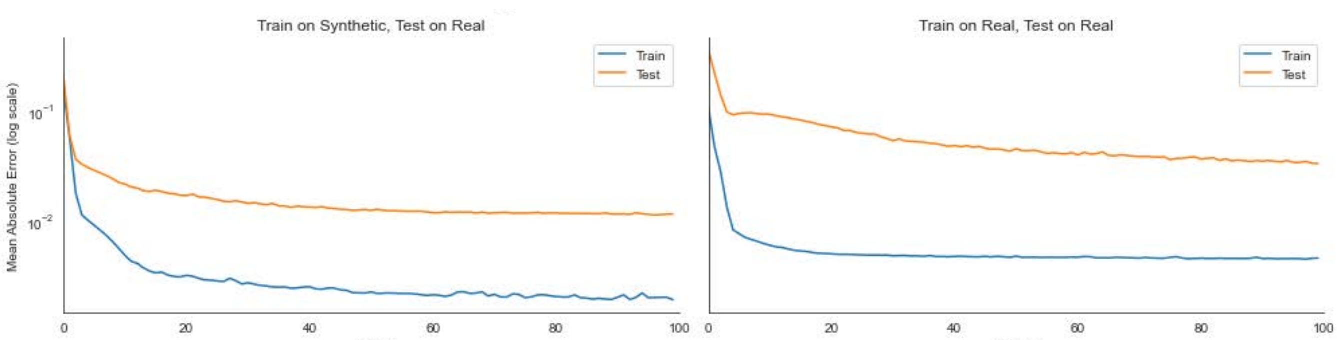


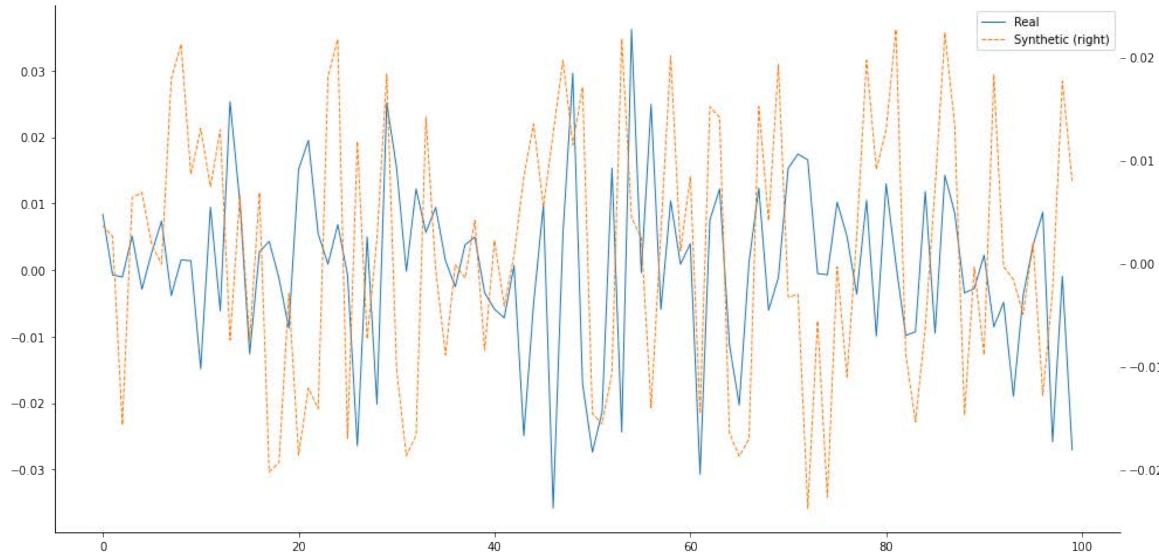
Figure 9 suggests that the MAE is lower after training on the synthetic dataset. This means that training a simple model (e.g., an RNN) on synthetic TimeGAN data delivers equal or better performance than training on real data.

In conclusion, the three evaluation criteria show that TimeGANs are able to produce high-quality synthetic data that resembles the real data in important characteristics.

Stylized Facts of Financial Time Series

The last section of this study aims to reproduce some of the stylized facts mentioned in the section on TimeGAN architecture by TimeGAN synthetic data. For this purpose, the focus lies on logarithmic returns and not on level data, as in the preceding sections. A sample of 100 observations of TimeGAN synthetic data has been generated. At this point, it is worth mentioning that generating synthetic data is a computationally intensive process. Working on a MacBook Pro with a 1.4 GHz Quad-Core Intel Core i5 processor took approximately four hours for this task to be completed. Consequently, it was not possible to prove all stylized facts, especially volatility clustering and aggregational gaussitanity, due to the relatively small sample of synthetic data.

Figure 10. Synthetic (yellow) and real (blue) logarithmic returns



The above figure shows that synthetically generated logarithmic returns are able to reproduce the time series of real logarithmic returns. The synthetic returns series is centered around zero, but it exhibits greater oscillations. Due to the small sample size, it is not possible to check whether the phenomenon of volatility clustering could be satisfactorily reproduced. In conclusion, there is some doubt about this finding.

Figure 11. PDF of the real return series (blue) versus PDF of the Gaussian distribution (red)

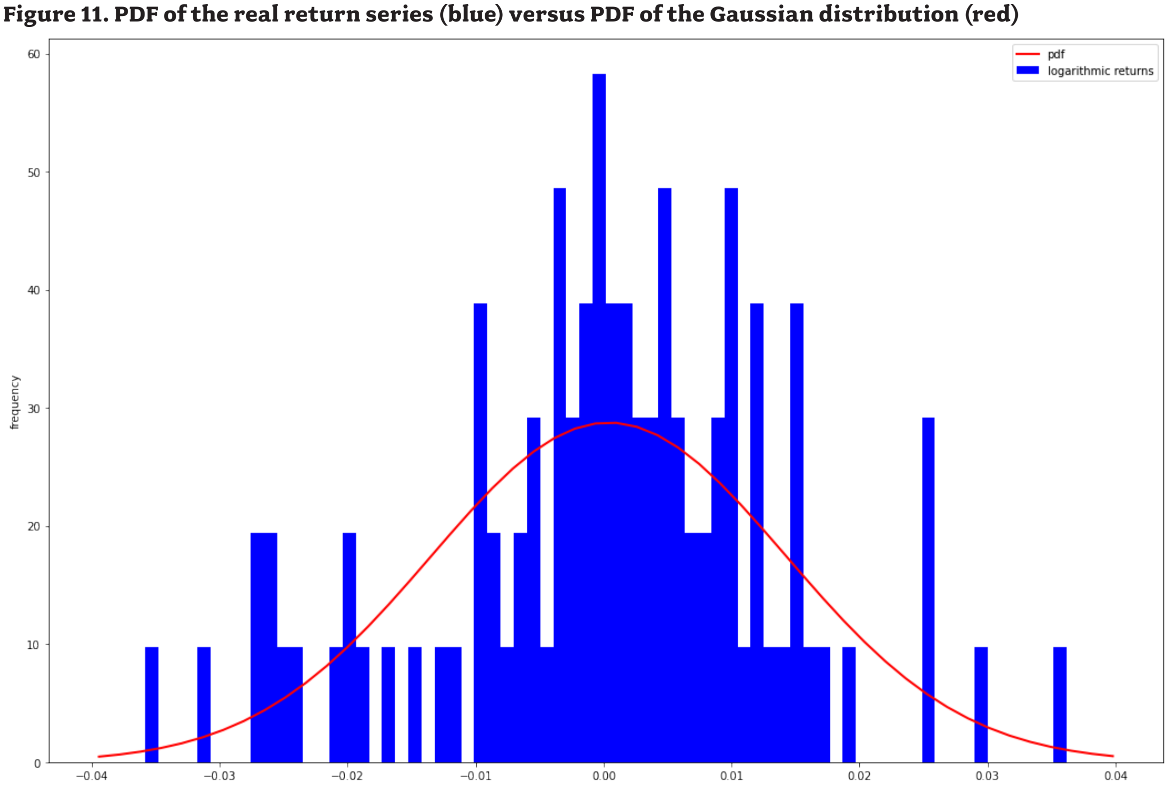


Figure 11 depicts the distribution of the sample of the real logarithmic return series. The distribution is asymmetric with a kurtosis of 3.363 and a skewness of -0.304. The sample exhibits the same properties as the its larger counterpart containing 20 years of daily observations.

Figure 12. PDF of the synthetic return series (blue) versus PDF of the Gaussian distribution (red)

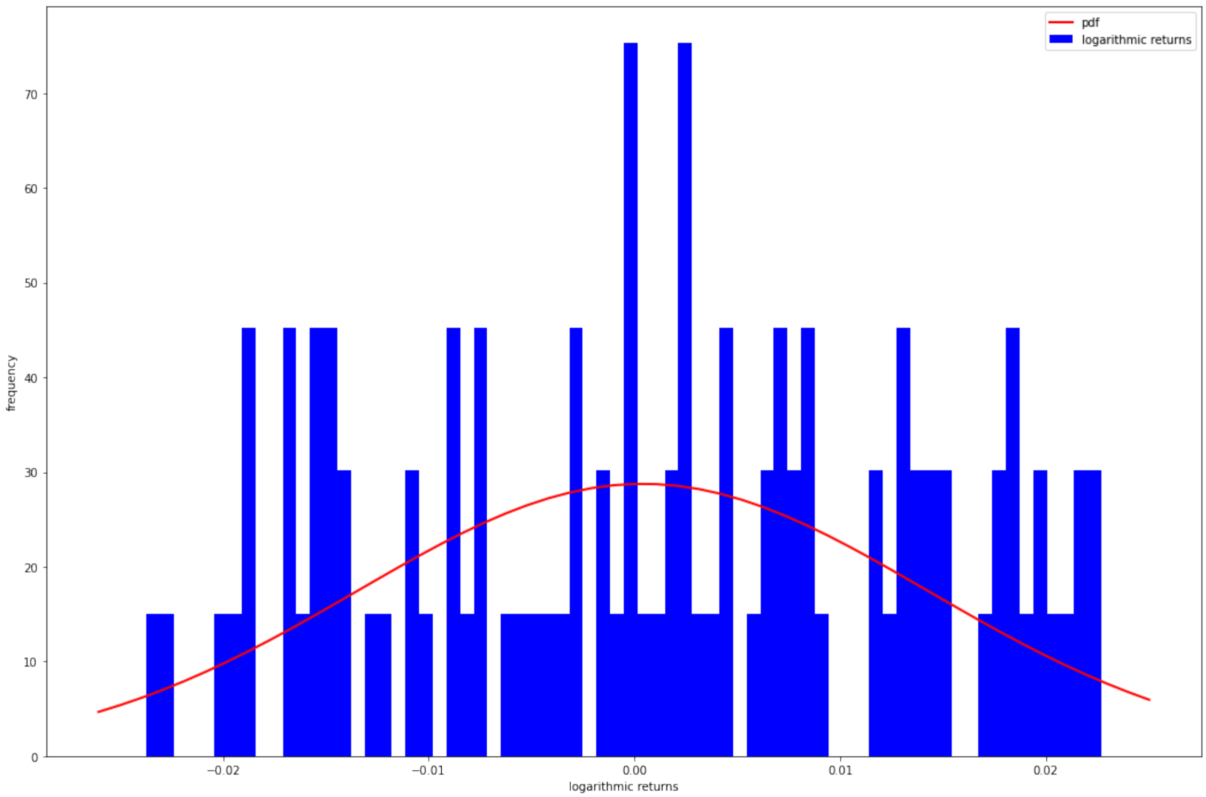
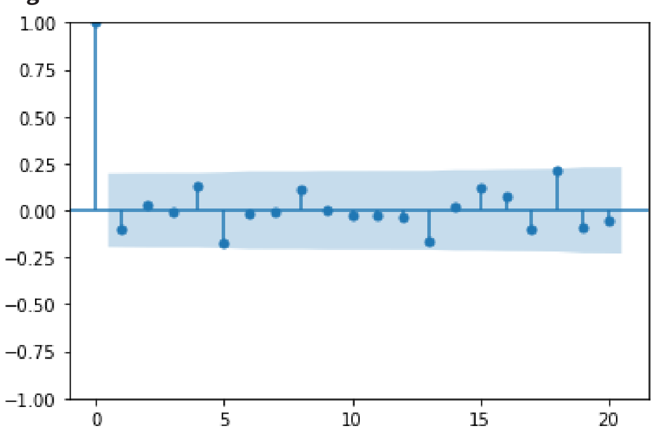


Figure 12 depicts the distribution of the sample of the synthetic logarithmic returns. In this case, the kurtosis is 1.949 and the skewness is -0.070. The distribution is platykurtic and approximately symmetric with a skewness parameter close to zero. It therefore fails to reproduce the fat tails that are a characteristic of financial time series data.

Figure 13. Autocorrection function (ACF) of the real logarithmic return series



For financial returns, the autocorrelation is expected to be very low, given the stylized fact of linear unpredictability. Figure 13 depicts this stylized fact for the real logarithmic return series.

Figure 14. ACF of the synthetic logarithmic return series

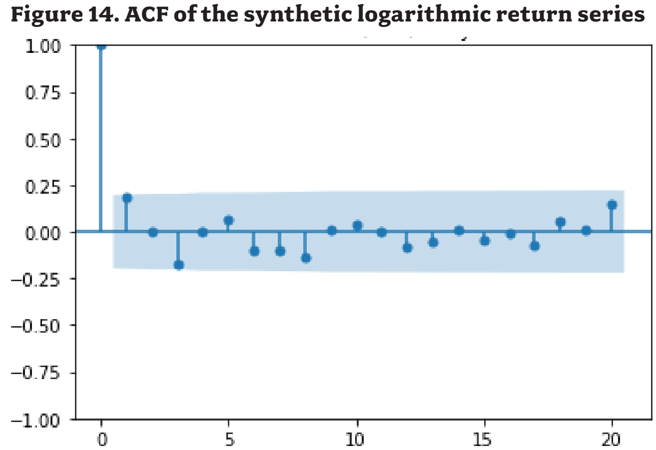


Figure 14 is very similar to Figure 13, which means that synthetically generated logarithmic returns are mostly linearly unpredictable, as are their real counterparts.

Conclusion

This study introduced one version of Generative Adversarial Networks, namely TimeGANs. Starting the conclusion backwards, an attempt was made to show how TimeGAN synthetic data reproduces some of the stylized facts of financial time series. This attempt was made to show that there are no unified quantitative metrics by which to assess the performance of synthetic financial data. Some of the results were satisfactory and some were not, partially due to the small sample size of the synthetic data. Maybe one of the present limitations for individual practicioners of this tool is the immense computational power needed for generating a large enough sample of synthetic data. Another caveat is that this study dealt with daily data. Assessing diversity, it was shown that there are nonlinearities present in financial time series as the t-SNE performed better than the PCA. Working with high-frequency data (e.g., tick data, generally intraday data) would presumably make temporal dynamics more complex and require adjustments to be made to the TimeGAN architecture.

On the other hand, this study attempted to highlight or rather to suggest a set of quantitative metrics, namely diversity, fidelity, and usefulness, for assessing the quality of the generated financial data—and consequently to provide unified metrics. Thus, it forms a contrast to the previous literature, which is basically summarized in the Stylized Facts of Financial Time Series section of this study.

By their very nature, GANs generate synthetic data that can also be used for training deep learning models when real data is scarce due to privacy laws. Seen this way, GANs are an indispensable component of deep learning and machine learning tools. In addition to this, it was also shown that predictions based on synthetic data are at least as good as those based on real data.

In sum, GANs are a promising new tool for modelling purposes and add new possibilities to the challenging world of quantitative finance.

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Using Deep Learning Models for Stock Market Predictions: An Application of Long Short-Term Memory Algorithms to Micron Technology, Inc.

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Micron Technology, Inc.

This study examines the chart of Micron Technology (MU), a stock listed on the Nasdaq Global Select (GS) for the purpose of financial predictions. This particular stock has been selected by the author of this study because it is a big player in the semiconductor industry. The company is headquartered in Boise, Idaho, in the United States and has approximately 43,000 employees. Its market capitalization is at about $78 billion US, and its EPS (earnings per share) are at $5.14 US per share, which means the company is profitable. Furthermore, the stock has been chosen because, according to financial news media, it was a favorite short of David Einhorn of Greenlight Capital Management, a famous U.S. hedge fund.

About This Study

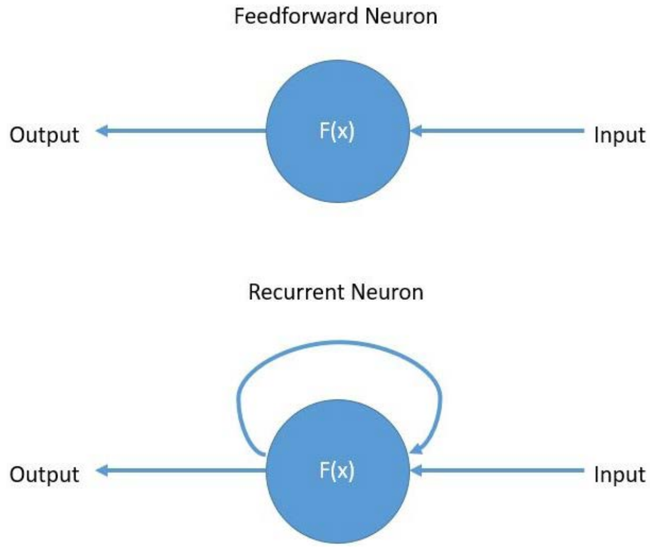
This study employs deep learning algorithms for predicting the stock price of Micron Technology. The analysis is regression-style (i.e., the aim is to model the chart/time series of Micron Technology). Therefore, the root mean square error (RMSE) as well as the R-squared statistic have been used as performance metrics. The reason for this style of analysis is straightforward: Long short-term memory (LSTM) algorithms are atheoretical models that learn from historical data. The advantage of using such models is that no theoretical models (i.e., models that use the fundamental determinants of Micron Technology's stock price as regressors) are necessary. This fact alone is a tremendous simplification. Furthermore, the aim of the study is the comparison between LSTM models and Gated Recurrent Unit models that are the modern variant of plain vanilla LSTMs. Both types of models are run over three different time spans of historical data—one long-term and two short-term. The study concludes with 1-step ahead predictions of Micron Technology's stock price.

LSTM Algorithms—A Special Kind of RNNs

LSTM constitutes a special case of recurrent neural networks (RNNs), which were originally proposed to model both short-term and long-term dependencies. As the name suggests, a RNN contains, in addition to a feedforward, a recurrent connection.

The main difference between a feedforward neuron and a recurrent neuron is shown in Figure 1. The feedforward neuron possesses only connections from its input to its output. In contrast, a recurrent neuron has an additional connection from its output to its input. This extra connection is called "feedback connection"; thus, the information can flow around in a loop.

Figure 1. Difference between a feedforward neuron and a recurrent neuron

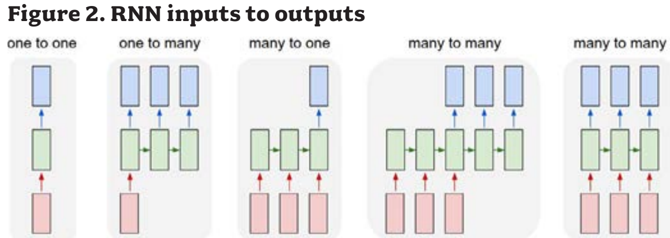


In conclusion, an RNN is formed by the combination/connection of many feedforward and recurrent neurons.

An RNN offers two main advantages:

1. *Store Information*
   The RNN can take advantage of its feedback connection in order to store information over time. Therefore, an RNN has some form of memory.
2. *Learn Sequential Data*
   The RNN is able to handle sequential data. This means that a simple feedforward network can compute one fixed size input to one fixed size output (similar to a linear function). The RNN instead can handle one to many, many to one, or many to many inputs to outputs (similar to a nonlinear function). See Figure 2.

Figure 2. RNN inputs to outputs



Note: RNNs were first introduced in 1982 by J.J. Hopfield.

However, one significant drawback of RNNs is their inability to learn to store information over extended time intervals. This problem is called "vanishing gradient problem" or "exploding gradient problem". When the network is learning to bridge long time lags, the network takes either too much time or it stops working (vanishing gradient problem). On the other hand, the exploding gradient leads to oscillating weights, which is another drawback.

Therefore, the solution to this problem was presented in 1997 by Hochreiter and Schmidhuber in the form of LSTM algorithms. LSTMs are able to model both short-term and long-term dependencies. The major novelties in a LSTM network are the memory block and the adaptive gate units. More specifically, the structure of the memory cell C_t is composed by three gates: the input gate, the forget gate, and the output gate. At every time step t, the input gate x_t determines which information is added to the cell state C_t (memory); the forget gate f_t determines which information is thrown away from the cell state; the output gate σ_t determines which information from the cell state will be used as output.

First, the forget gate looks at h_{t-1} (output at time step t-1) and x_t (input at time step t) to compute f_t which is a number between 0 and 1. This is multiplied by the cell state C_{t-1} (i.e., $C_{t-1} * f_t$). If f_t takes on a value of 1, the cell keeps all information, and at a value of 0, the cell forgets all information.

Second, the outputs i_t and $\tilde{C}_t$ are multiplied, which constitutes an update of the cell. This update is then added to the previous input $C_{t-1} * f_t$.

Finally, the output value h_t is computed by the multiplication of o_t with the tanh of the result of the second step (i.e., $h_t = o_t *$ tanh (C_t), where $o_t = \sigma*(W_0\,[h_{t-1},x_t\,]+b_0)$), tanh being the hyperbolic tangent function and W_0 and b_0 being the weighting matrix and a bias vector, respectively.

Gated Recurrent Unit

The Gated Recurrent Unit (GRU) was introduced in 2014. Whereas a LSTM has three gates, a GRU has two gates. GRUs do not have a memory cell C_t. Instead, GRUs use the hidden state to transfer information.

In many tasks, both models yield comparable performance. Therefore, tuning hyperparameters like layer size is important. GRUs have fewer parameters and thus may train a bit faster or need less data to generalize. On the other hand, LSTMs work better with more data. Thus, GRUs are parsimonious in nature when compared to LSTMs; they have fewer parameters and are presumably able to work with less data. These are the main advantages of GRUs.

Data Analysis and Tests of Normality

The scope of this section is to inspect the data for Micron Technology, first, visually, by the means of a histogram and a probability—probability plot (P-P plot), and secondly, quantitatively, by employing specific tests for evaluating the null hypothesis of normality of the distribution of the logarithmic returns. The significance level for these tests is set at 5%. Therefore, a pValue of less than 5% or 0.05 means that the null hypothesis of a normal distribution is rejected. The following tests were used: Jarque-Bera and Shapiro-Wilk.

The first dataset for Micron Technology was chosen to encompass its whole history (i.e., since its IPO). The time span ranges from June 1984 to October 2021. 80% of the data has been reserved for training the models, and the remaining 20% was used for model validation. The data has been normalized using the MinMaxScaler, and the data frequency is EOD (End of Day). Using a scaler should boost the predictive performance of the models.

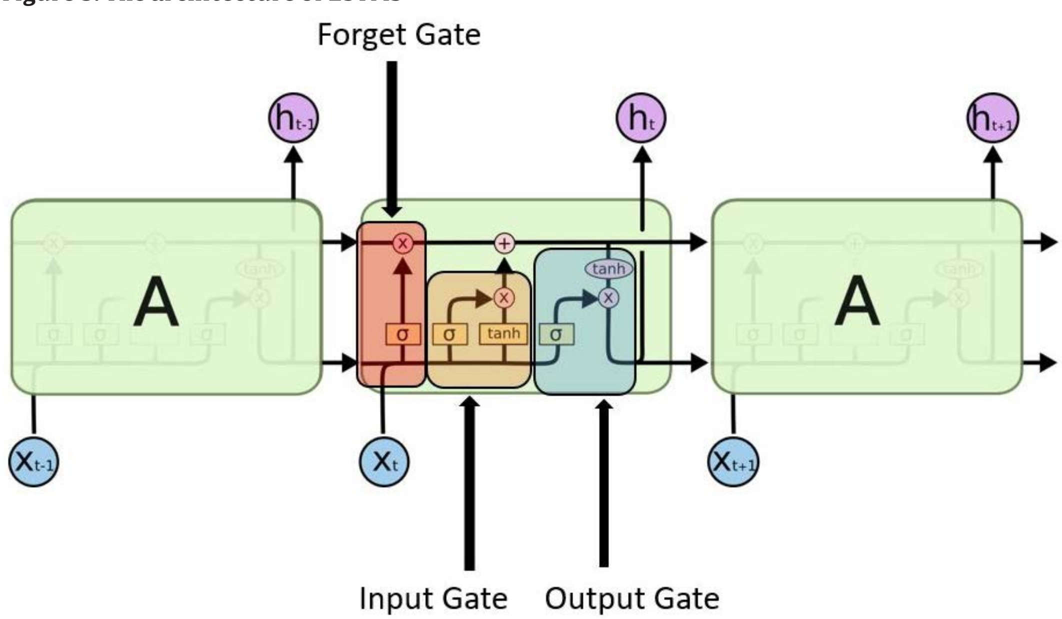
The second and third datasets encompass three years and one year, respectively, and should purposefully test whether GRU models perform better than LSTM models when the availability of data is scarce.

The Jarcque-Bera statistic is a measure of whether the data has the skewness and kurtosis matching a normal distribution. The test statistic is defined as follows:

$$JB = \frac{n}{6} * (S^2 + \frac{1}{4} * (K-3)^2)$$

where n is the sample size, S is the sample skewness (the third moment), and K is the sample kurtosis (the fourth moment; a

Figure 3. The architecture of LSTMs



kurtosis greater than 3 means leptokurtosis [i.e., a higher peak than the normal distribution, which is quite representative for most financial data]).

The Shapiro-Wilk test is another test for normality of the data. The test statistic is defined as follows:

$$SW = \frac{(\sum_i a_i x_i)^2}{\sum_i (x_i - \bar{x})^2}$$

where x_i is the ith order statistic (i.e., the ith smallest number in the sample), $\bar{x}$ is the sample mean, the coefficients a_i are given by $(a_i \ldots, a_i) = \frac{m' V^{-1}}{C}$, where C is a vector norm: $C = ||V^{-1} * m|| = (m' V^{-1} V^{-1} m)^{1/2}$, and the vector m (transposed) = $(m_1 \ldots, m_n)'$ is made of the expected values of the order statistics of identically and independently distributed (IID) random variables sampled from the standard normal distribution. V is the covariance matrix of these normal order statistics.

Figure 4. Price chart of Micron Technology, Inc. (MU)

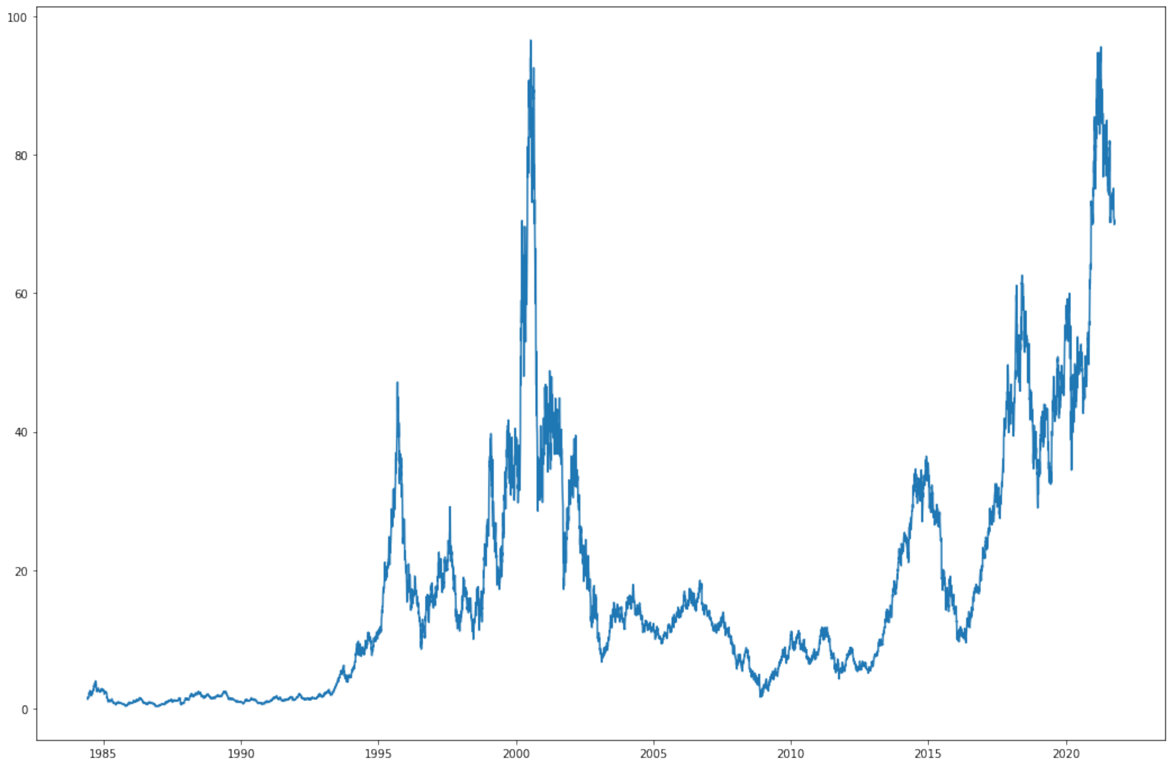


Figure 4 shows the price chart of MU. There are some strong trends, particularly from 1995 to 2000, when the dot.com bubble had its full strength. After 2000, the bubble burst and prices declined to pre-1995 levels. Then, 2012–2013 was the beginning of another bull run, and MU reached the level of the dot.com climax. Since then, prices have been declining.

Figure 5. Chart of the logarithmic returns

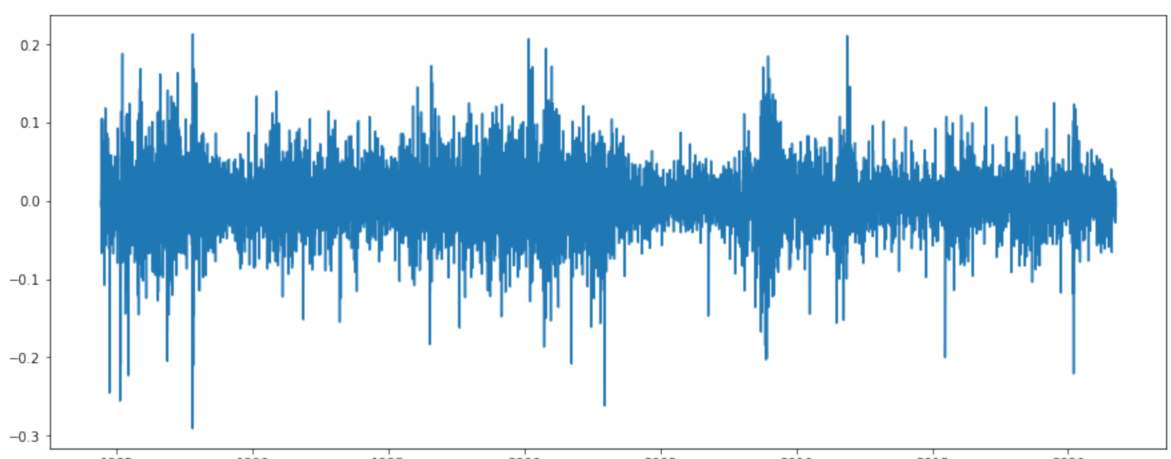


Figure 5 shows the logarithmic returns of MU. For their calculation, the close has been used, as this is traditionally the most important price of the day when compared to the other features, such as open, high, and low.

As expected, this time series is stationary. There are frequent instances when the logarithmic returns oscillated strongly either up or down, with a maximum of 20% to the upside and nearly -30% to the downside.

Figure 6. Logarithmic returns distribution

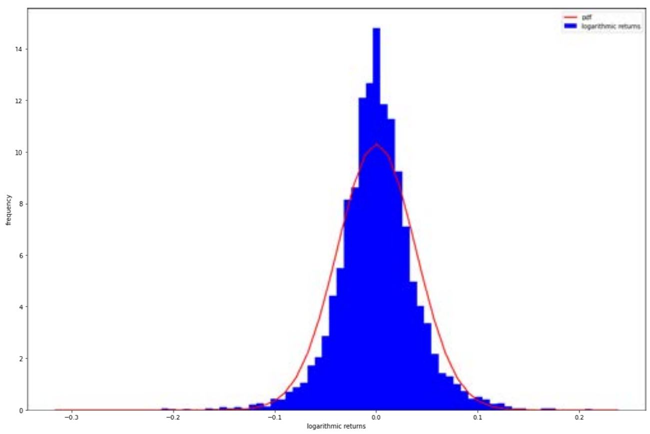


Figure 6, which shows the distribution of the logarithmic returns of MU, suggests that the distribution is not Gaussian. The first visual impression is that the distribution is leptokurtic. The red-colored distribution is the probability density function of the Gaussian distribution.

Figure 7. Probability plot of the logarithmic returns

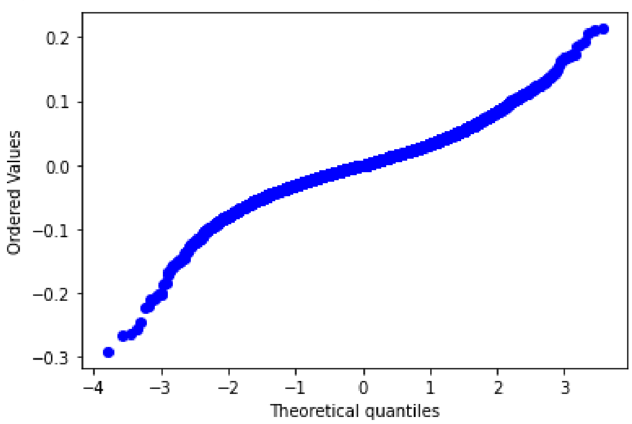


Figure 7 shows the probability plot of the logarithmic returns. It can be seen that the logarithmic returns exhibit fat tails, which means that extreme returns (either positive or negative) are more likely than under the assumption of a Gaussian distribution.

The results of the normality tests can be seen in the Table 1.

Table 1. Test results of two normality tests

	Test Statistic	pValue
Jarcque-Bera	5836.72	0.0
Shapiro-Wilk	0.9609	1.5e-44

Employing a significance level of 5%, a pValue less than 0.05 rejects the null hypothesis of a Gaussian distribution. This is true for both tests.

LSTM Architecture

This section describes a selection of relevant hyperparameters of the LSTM and GRU models theoretically and numerically.

Number of Hidden Layers and Dropout: The employed LSTM and GRU models are so-called stacked models. This means that there are multiple hidden layers stacked one on top of another. A hidden layer is the connection between inputs and outputs. For this study, the first LSTM layer has hidden units varying from 64 to 128 to 256. This LSTM layer is followed by a dropout layer with a keep probability of 70% (or a dropout of 30%). A dropout layer mitigates overfitting in training by bypassing randomly selected neurons. These are followed by a second LSTM layer with hidden units varying from 32 to 64 to 128. Again, these are followed by a second dropout layer with a keep probability of 70%. The same holds true for the GRUs.

Optimization: Adam (Adaptive Moment Estimation) optimization was chosen for all models. Adam optimization is a stochastic gradient method that is based on adaptive estimation of first-order and second-order moments.

Dense Layers: A dense layer is a layer where each neuron receives input from all neurons in the previous layer. Dense layers improve overall accuracy. For the models, one dense layer was used.

Activation Function: As an activation function, the Rectified Activation Function (ReLU) was chosen. An activation function defines the output of a node as either being on or off. These functions are used to introduce nonlinearities to models, thus allowing deep learning models to learn nonlinear prediction boundaries. The ReLU function can be described by a simple if-statement:

```
if input>0:
  return input
else:
  return 0
```

or mathematically: $g(x)=\max\{0, x\}$.

Number of Epochs: An epoch is how many iterations of the dataset are to be run. The number of epochs has been set at 100.

Batch Size: The batch size defines the number of samples to work on before the internal parameters of the model are updated. The batch size was chosen to be 32.

Results

As outlined before, the dataset was split into 80% training data and 20% test data. This corresponds approximately to using 2014 as the cutoff. The blue time series represents the training set whereas the orange dataset represents the test set (i.e., the dataset used for regression). The aim is to model this dataset as accurately as possible. For this purpose, two metrics were used to describe the goodness of the fit: RMSE and the R-squared statistic. A low RMSE as well as a high R-squared (i.e., an R-squared close to 1) describe a good fit. The data has been normalized by using the MinMaxScaler. This last step should boost the performance of the models.

Figure 8. Splitting the dataset Into 80% training and 20% testing

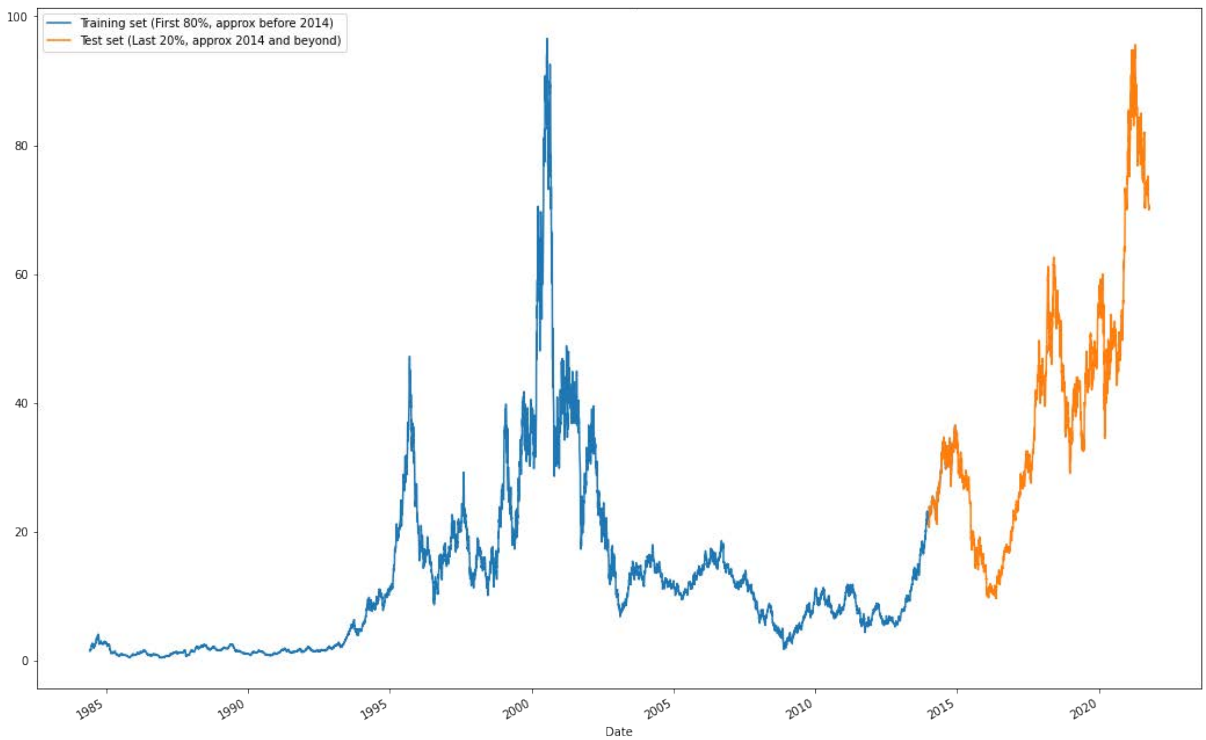


Figure 9. The actual (blue) vs. predicted (orange) test set

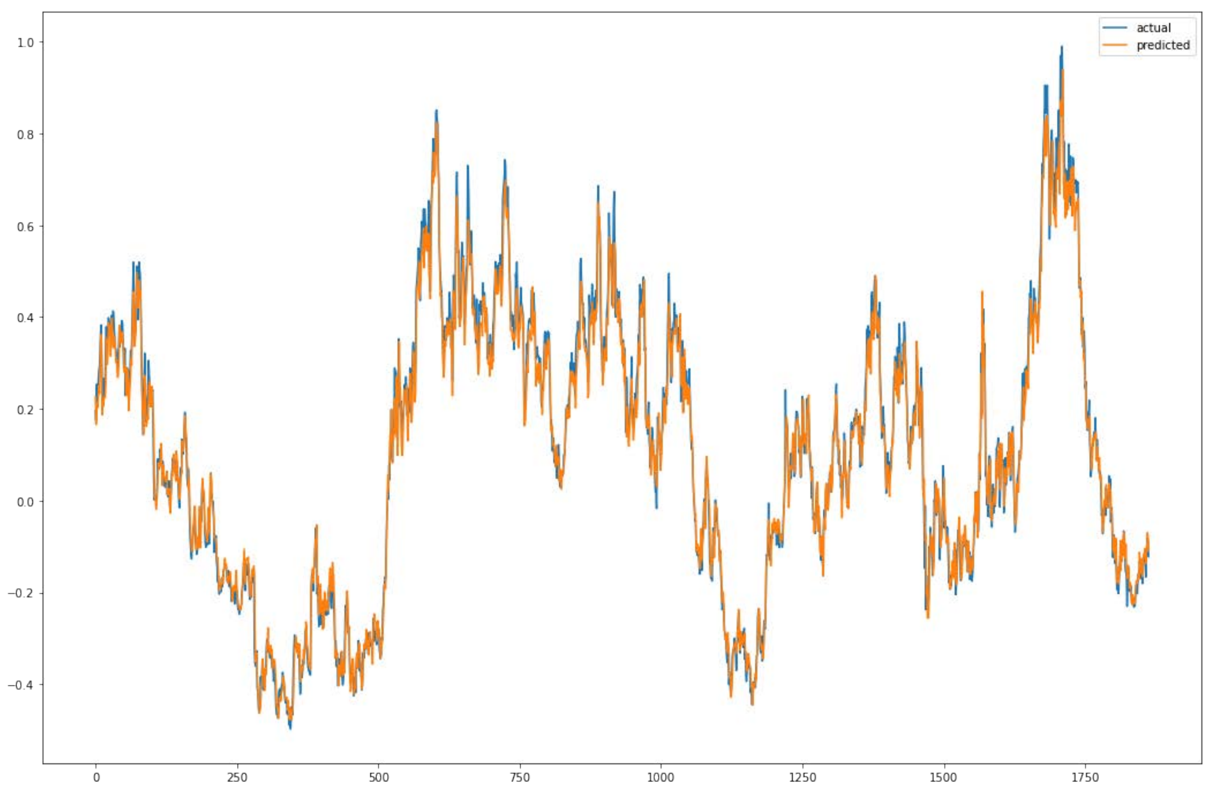


Figure 9 shows an accurate modeling/regression of the test dataset. As can be seen, the LSTM model learns from the training data to reproduce the test data. Figure 9 is representative for all models. Table 2 summarizes the test results by means of RMSE and R-squared statistic.

Table 2. Test results of LSTMs and GRUs

	RMSE	R-squared
LSTM 64x32	0.03614	0.98587
LSTM 128x64	0.03374	0.98768
LSTM 256x128	0.03263	0.98848
GRU 64x32	0.03410	0.98742
GRU 128x64	0.03467	0.98700
GRU 256x128	0.03288	0.98830

As can be seen from Table 2, the most complex LSTMs and GRUs in terms of hidden layers perform best. The best model is the LSTM 256x128 with a RMSE of 0.03263 and a R-squared statistic of 0.98848, which means that the model describes over 98% of the variation of the test data. The second-best model is the GRU 256x128, with a nearly equal RMSE of 0.03288 and a R-squared statistic of 0.98830.

The next area of analysis is determining whether LSTMs or GRUs perform better when financial data is scarce. For this purpose, the two strongest models (i.e., LSTM 256x128 and GRU 256x128) have been tested on three-year and one-year data, respectively. Table 3 summarizes the results.

Table 3. Test results for 3-year and 1-year data

3-Year Data	RMSE
LSTM 256x128	0.02619
GRU 256x128	0.03650
1-Year Data	
LSTM 256x128	0.02216
GRU 256x128	0.01331

For answering this question, only the RMSE was used. As can be seen, the LSTM performs better than the GRU on the 3-Year dataset, whereas the GRU performs better than the LSTM on the 1-Year dataset.

1-Step Ahead Predictions

For this last area of analysis, the last 100 data points from the full dataset of MU are used to make 1-step ahead predictions into the future and compare the predictions with the actual trend direction of the test set. This means that 100 last data points are used to predict number 101, the next point (number 102) is predicted by 98 last data points, number 103 is predicted by 97 last data points, and so on. I repeat these steps 60 times for every model out of the set of six models. The results are shown in Figure 10.

Figure 10. Rolling 1-step ahead predictions: LSTM 64x32

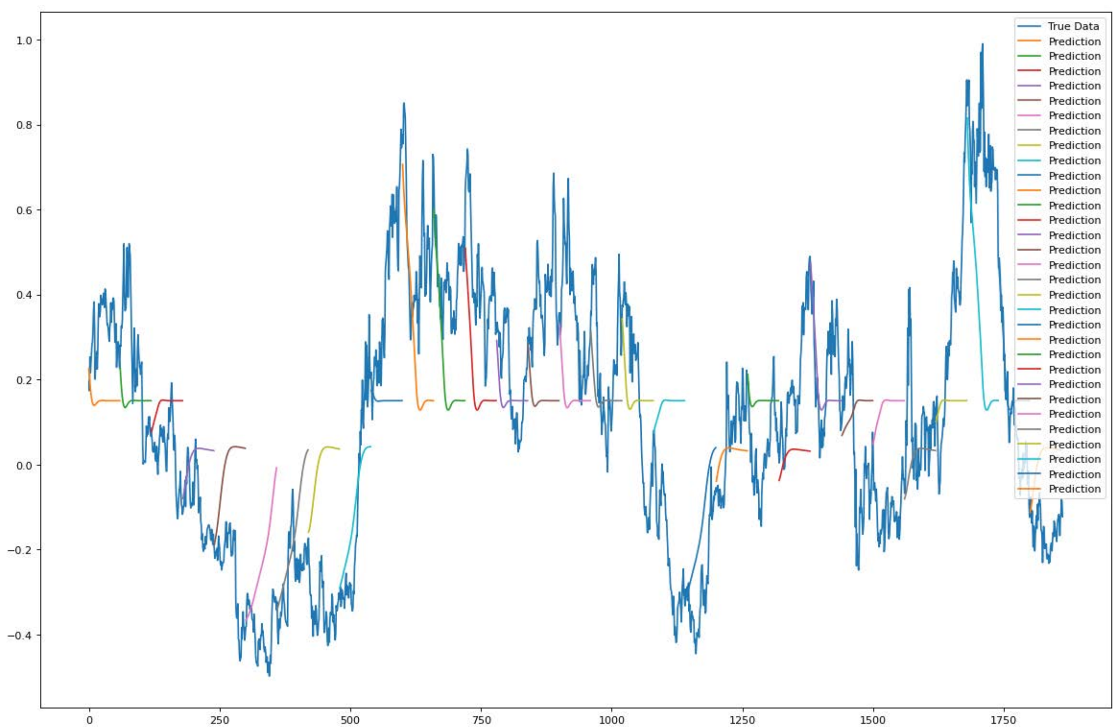


Figure 11. Rolling 1-step ahead predictions: LSTM 128x64

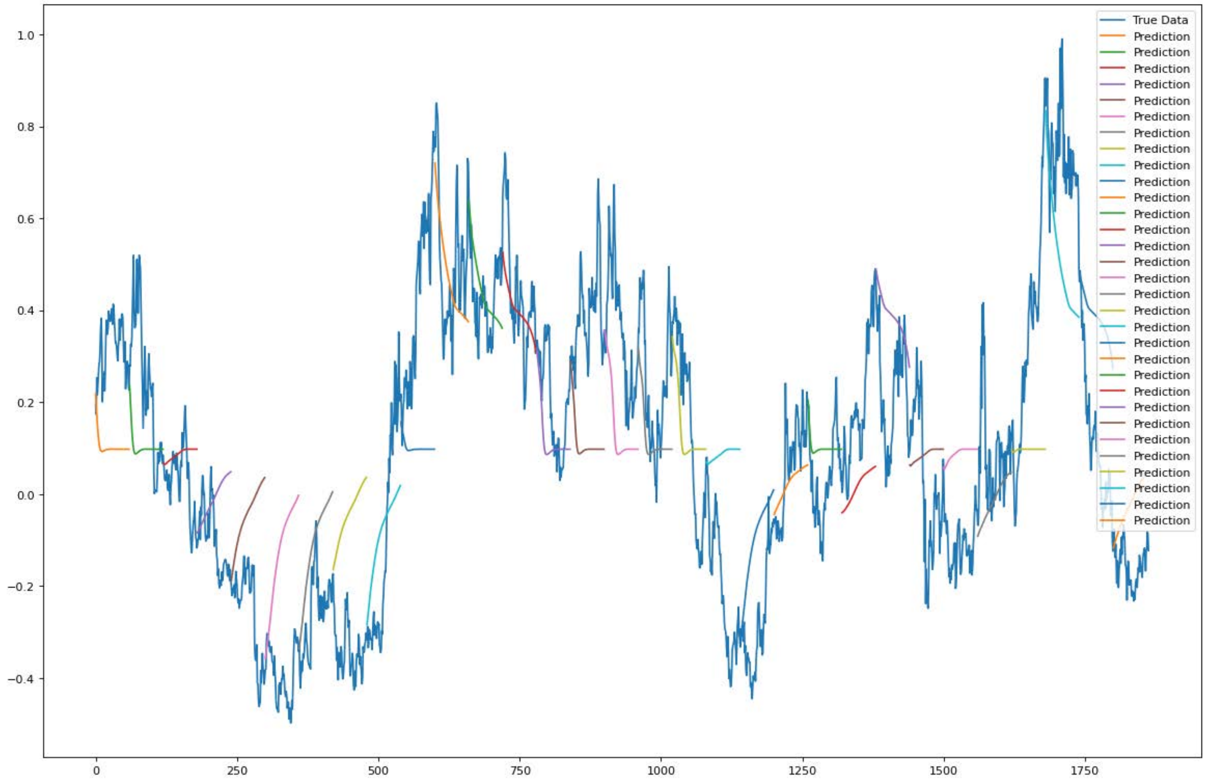


Figure 12. Rolling 1-step ahead predictions: LSTM 256x128

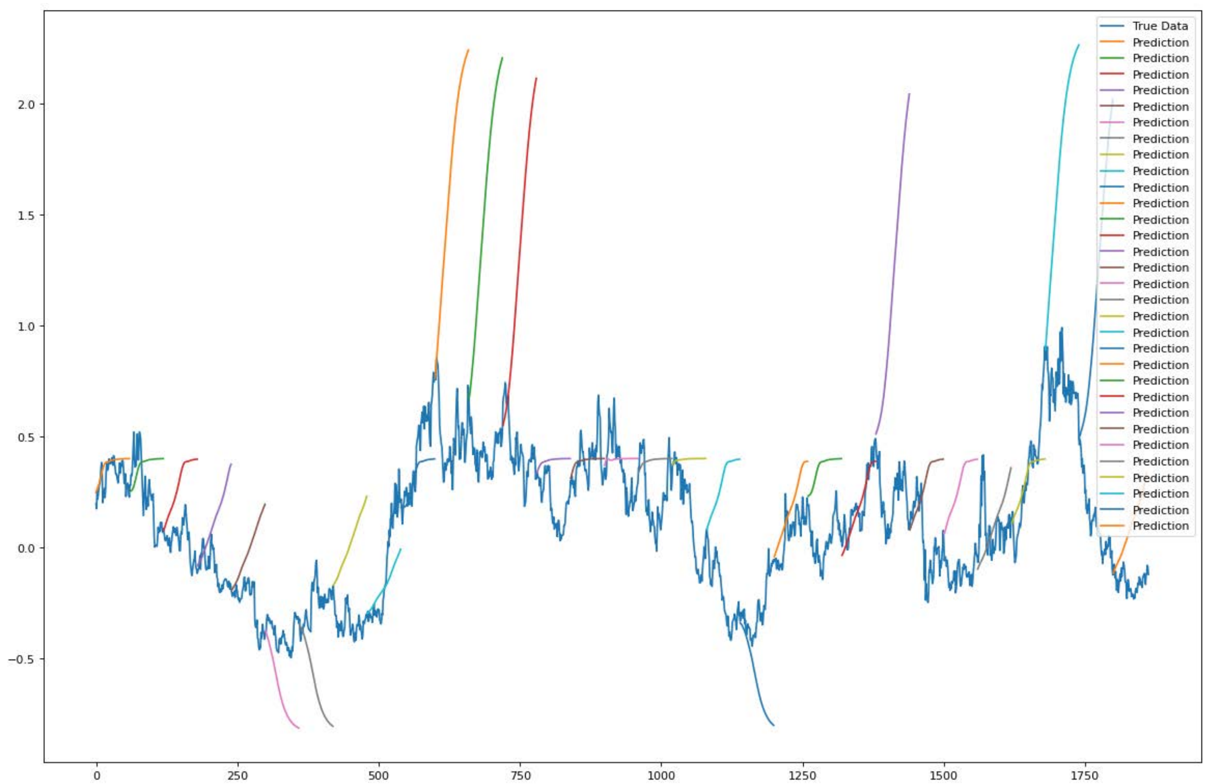


Figure 13. Rolling 1-step ahead predictions: GRU 64x32

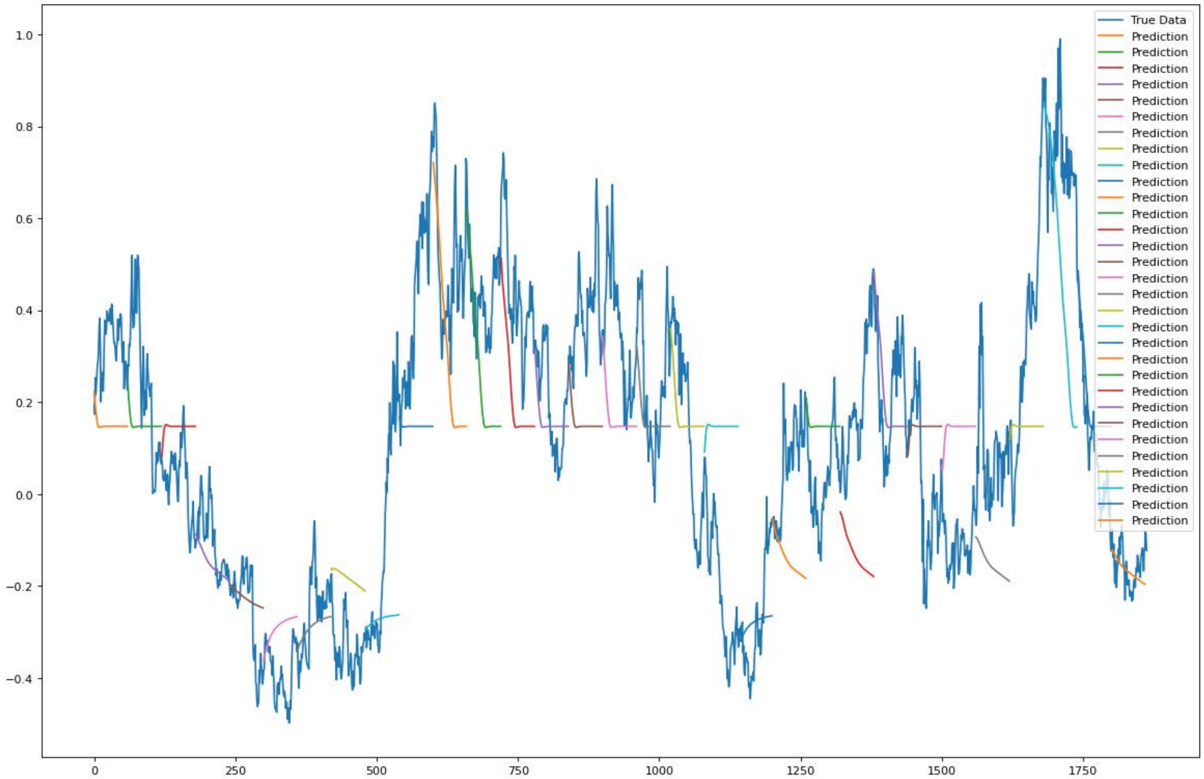


Figure 14. Rolling 1-step ahead predictions: GRU 128x64

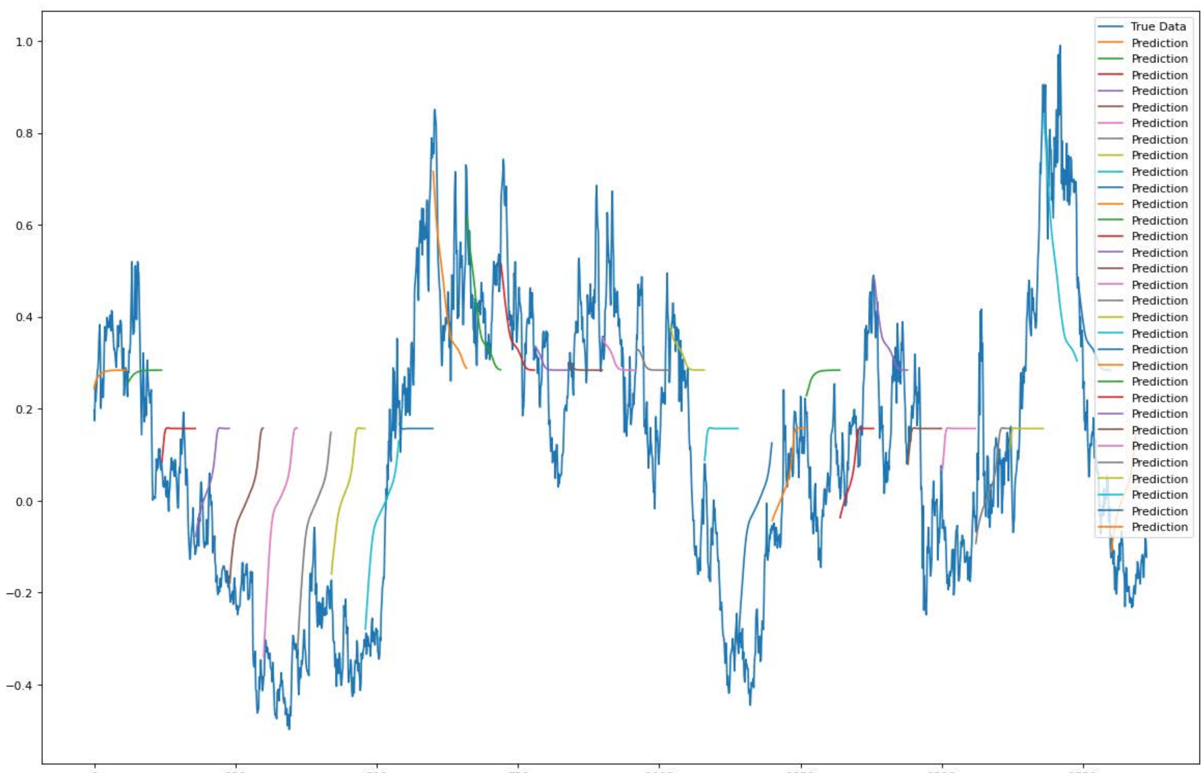
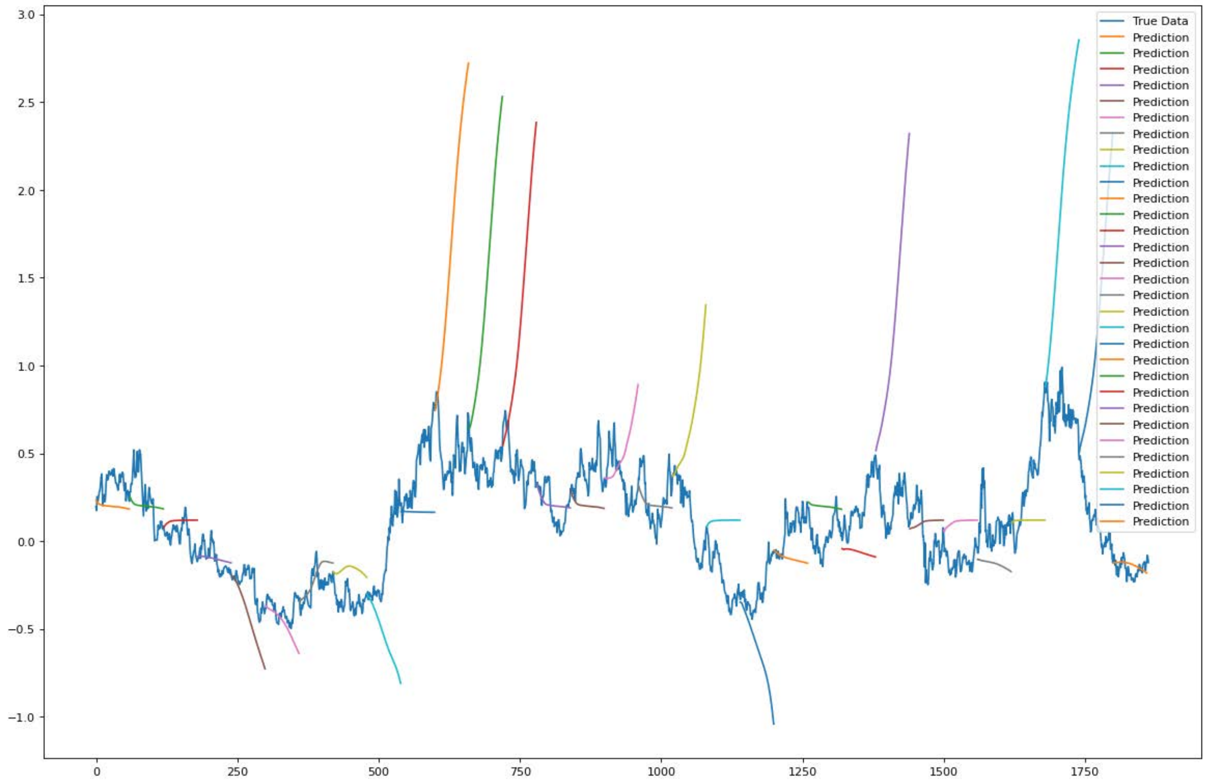


Figure 15. Rolling 1-step ahead predictions: GRU 256x128



The conclusion of the rolling predictions is that most models do not get the predictions right all the time. Quite to the contrary, the more complex the model, the worse the predictions, especially at the very tops and the very bottoms (see Figure 15 for example). Nevertheless, GRU 64x32 performs quite well, getting the majority of predictions right, or at least the big moves, which is the holy grail recipe for every trader.

Conclusion

This study was about analyzing deep learning models, namely LSTMs and GRUs. The chosen style of analysis was regression type. The last part of the study ventures some predictions, which, according to the author of this study, is the most relevant part.

There is no real performance difference between LSTMs and GRUs. In fact, LSTMs perform slightly better the more historical data is available, and GRUs presumably perform better the less historical data is available. However, GRUs are to be preferred, as they have fewer parameters and train faster. As a comparison, the most complex LSTM (LSTM 256x128) has a total of 461,441 parameters, while the GRU 256x128 has 347,265 parameters in total. The run time for these two models on the full dataset is 1h 5min 15s and 52min 48s, respectively. (Calculations were performed on a MacBook Pro with a 1.4 GHz Quad-Core Intel i5 CPU with 8 GB 2133 MHz LPDDR3 memory.)

Furthermore, one has to use many different LSTMs and/or GRUs when doing predictions, as not all models perform well. In fact, most models get the big moves wrong, which translates into financial losses for the trader. Only one model (GRU 64x32) showed an adequate prediction capacity.

As far as stocks and the stock market are concerned, many factors (macroeconomic factors such as inflation expectations, interest rates and bond yields, and consumer sentiment, but also company specific events such as earnings and earning outlooks) play a relevant role. Whereas it is true that the price of a stock is the most important variable and it should incorporate all relevant factors (in accordance with the EMH), other sources of information besides the price could be used with deep learning models.

Another point is that no trader should only rely on one model or one tool for making predictions. Other tools are technical analysis and fundamental analysis, which is a combination of macroeconomic and company-specific variables. I think that these tools should be used as complements to deep learning models.

Last but not least, deep learning or, more broadly, AI, is a fairly new scientific discipline that is expected to progress at a fast pace. Therefore, there is a good reason why traders, investors, and financial institutions should study these models, as they may become the foundation for more complex and accurate models in the future.

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Price Monitoring of Stock Portfolio—Software Development in Lazarus

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Introduction

In my MFTA thesis from 2021, I have shown by using the programming language Lazarus (Object-Pascal, similar to Delphi, cross-platform development) that it is possible to produce software for the observation of intraday stock developments and to include insights of Fibonacci trading. This does not produce a compelling result for a buy or sell decision, but this supplementary view of the price development can help to make such a decision. Forecasting is not possible, but the development can be upgraded with probability estimation. In doing so, the separation between observation and trading has to be taken care of in order to take a consciously active role and to execute a trading action only after careful consideration and, if necessary, with the help of further information. High frequency trading is of course not possible.

Finally, the focus is on the presentation of one's own portfolio. In particular, stock developments that do not correspond to the desired course must be observed. Currently (i.e., at the end of February 2022), the stock market developments show dramatically negative due to the Ukraine crisis as a result of the invasion of Russian troop units with Belarusian support in the context of the violation of international law. Provided that one does not sell in panic, but holds, it is purposeful to observe the deficit stock developments in one's own portfolio both intraday and over several months. Of course, now is not a time to trade with special strategies; every strategy is influenced by the war and current market movements. There are winners and losers every day, but this is not due to the common parameters of the enterprises. However, the current volatile markets with extreme movements are purposeful for the demonstration of certain effects.

In the following article, the development of a small administration software in Lazarus for 10 stock titles to be observed is represented. The system can be extended at any time. I added example data to simulate a possible loss risk identification. The basis portfolio lies exemplarily with approximately 15,000 EUR evaluation sum, the current loss risk with approximately -3,900 EUR. The values can be extrapolated analogously.

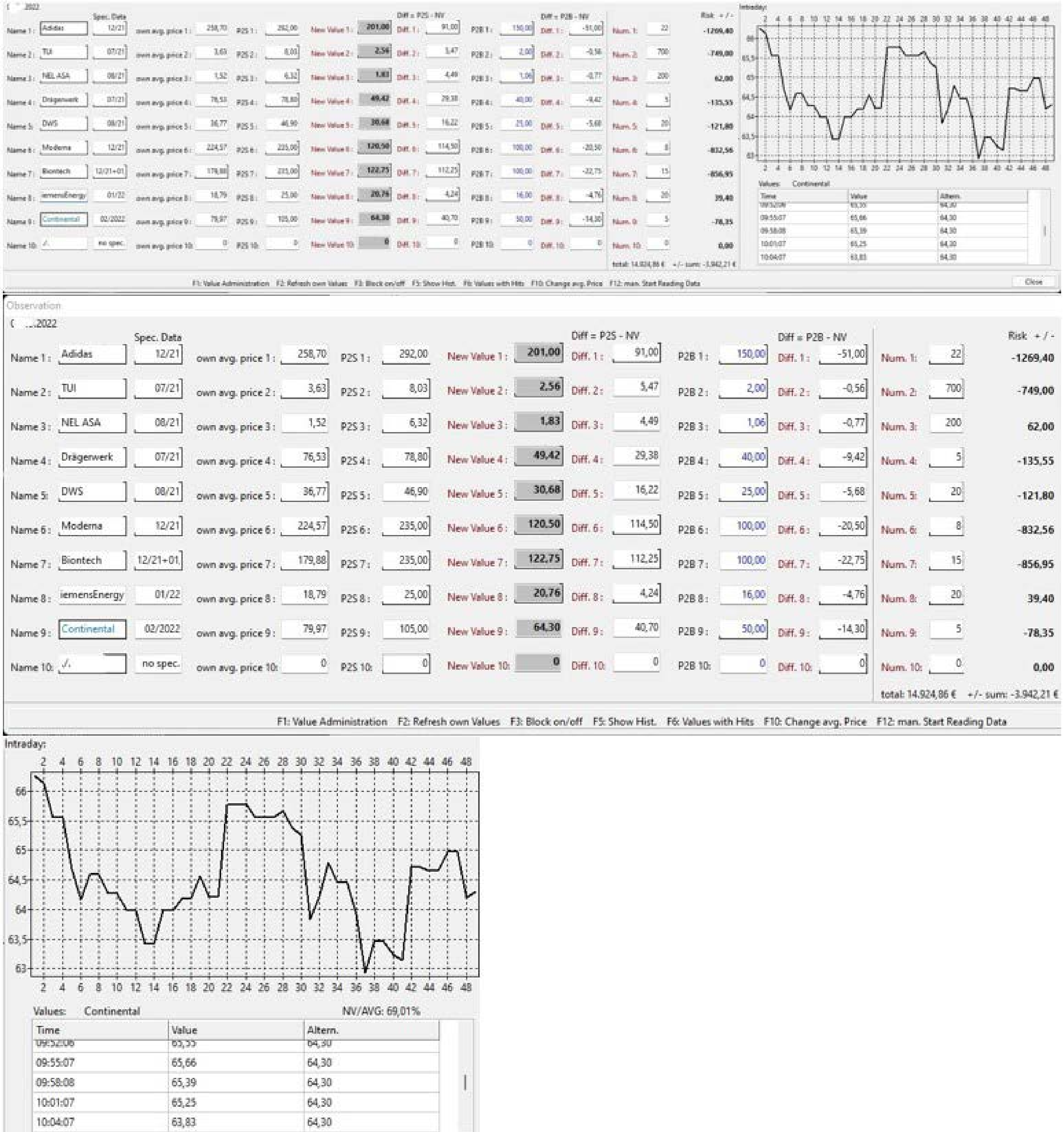
IT System Development

As in the master's thesis, the IT system is based on reading the prices for all the titles to be monitored via website (https://www.finanzen.net), and this is done every two minutes. In this way, 30 values per title are generated per hour. If a price cannot be read, the last correct price is used as an alternative value. To get an overview of the portfolio and its development, certain values must be held and mirrored against the current development. Essential points can be, for example:

- "own avg. price" — average price, including all fees of a stock title.
- "P2S" — target price at which a number of stocks is to be sold
- "New Value" — current market value (NV, „new value")
- "P2B" — price at which a subsequent purchase is being considered
- "Num." — number of stocks in the portfolio.

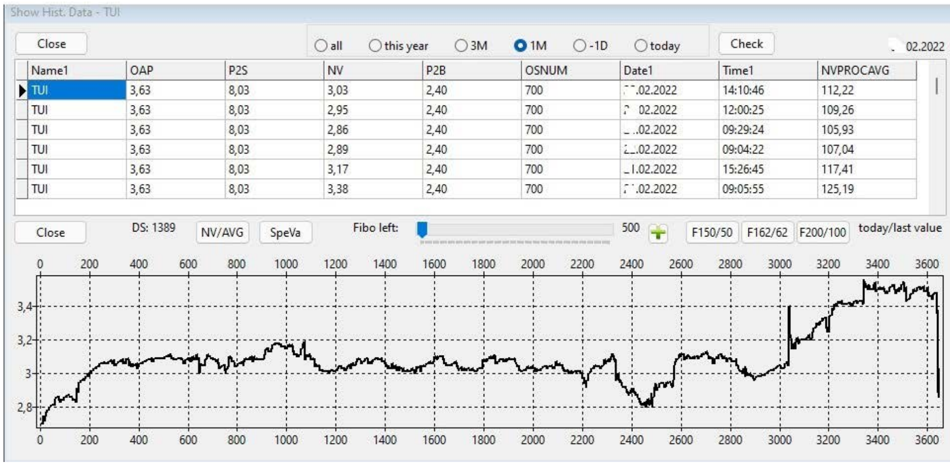
This can be used to map both the development and the user's own preferences. If the software is connected to a database, the values can be stored over a long period of time. The software saves permanently but copies all values [year - 1] into a historical table after one year so that the productive table does not expand unnecessarily.

Figure 1. Main form



On the left to just above the center, the above-mentioned values are held for the 10 stock titles in Figure 1. In addition, certain difference values (P2S - NV and P2B - NV) are calculated. If the threshold values are exceeded and/or fallen below, the system produces a beep so that the user receives a reference to look at the values. This way, he can run the software in the background during the day and does not miss important points of the intraday development. On the right side, the price development intraday is displayed both in tabular form and visually, provided that a fast view for every title is selected with a mouse click.

Figure 2. Show hist-data, here from TUI



In Figure 2, the previous developments of the stock can be viewed (F5). Several time ranges can be activated, such as today, yesterday (-1D), last month (1M), the last three months (3M), the entire year (this year) and all existing values. The button „Check" is used to narrow down the development. "DS" shows the number of records that fit into the narrowing down. On the right side, as usual, are the last values of the series.

Inclusion of Fibonacci

Fibonacci inclusion means that a right and left point in the trend view of the stock performance is used to create a difference of the left and right value. This is used to generate the Fibonacci support lines. In such a view, the right-hand value is only marginally removed from the latest price value, while the left-hand value may well be several hundred points away, depending on the will to know. In my original work, I used only the change points of the intraday development, only to see with the intraday change performance, constant prices were ignored, so the distance of the left and right secant value was not so large.

Here, however, I bring in each new price value so that the secant values are located with long distancy. The trackbar (i.e., the slide, sets this distance and of course cannot be larger than the total number of existing records. The buttons F150/50, F162/62, and F200/100 create the support lines according to Figure 3.

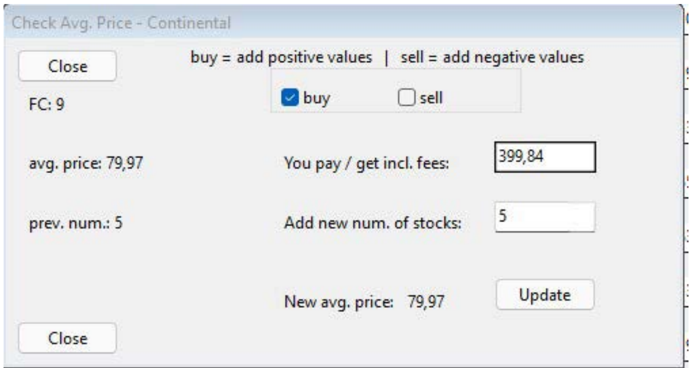
Figure 3. Development with support lines

The price of the TUI share, for example, fell back from almost EUR 3.60 to near EUR 2.80 on this day. Accordingly, the lower support line struck. The other support line definitions also showed an identical result.

Import of New Values

Of course, it must be possible to insert new values, including fees, automatically adjusting the average price. This can be seen in Figure 4.

Figure 4. Add new value

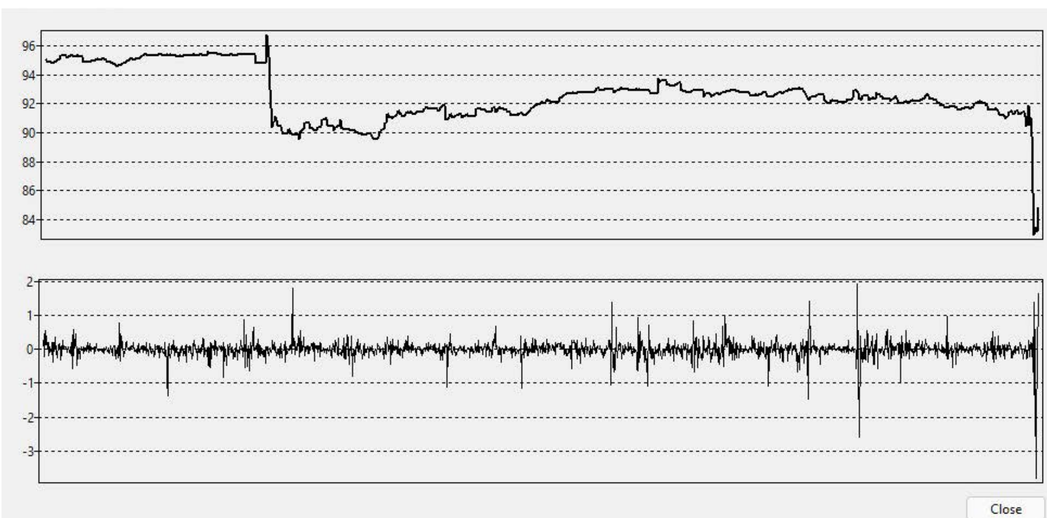


Further Analytics

First of all, any analyses can be run with regard to the existing values stored in the database. These are limited only by the stored raw data itself. The speed is hardly burdening since the keeping of historical data larger than one year is not permanently needed. The raw data width can be extended as desired with additional fields and then saved to the new price value with more complex calculated attribute values.

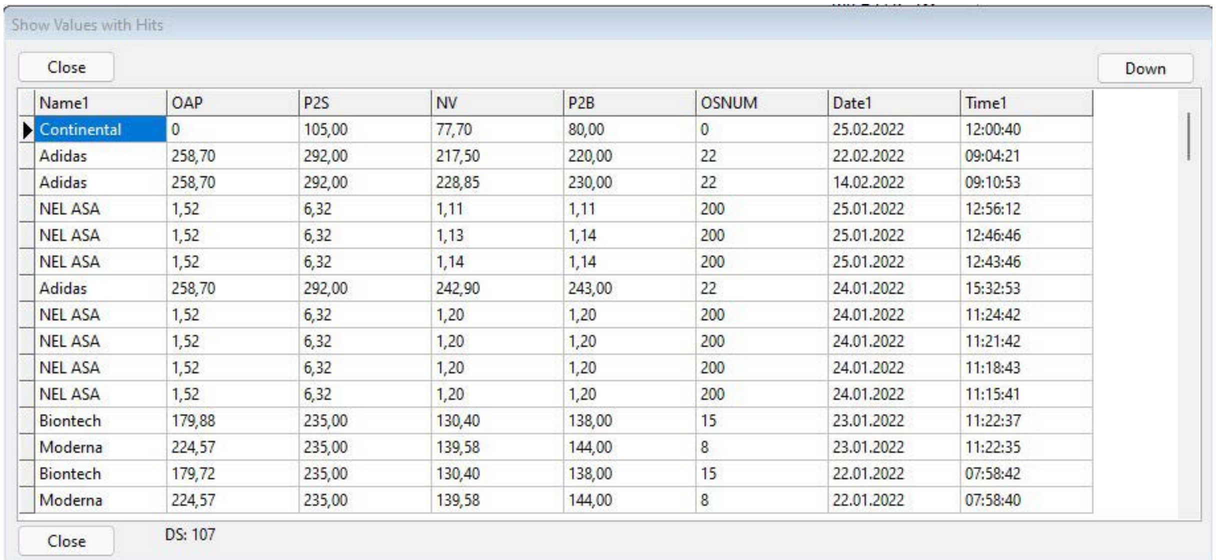
An example is the relationship between the current and average price value (upper graph from Figure 5). This is solved by calculating the average value of the selected stock title. Another example in Figure 5 is the ratio of the last to the newly read price value (lower graph).

Figure 5. Examples of different data views



It can also be useful to see if there were records that exceeded or fell below previous defaults. This is shown in Figure 6. The corresponding SQL statement is 'SELECT Name1, OAP, P2S, NV, P2B, OSNUM, Date1, Time1 FROM 10Stocks WHERE ((CDbl(NV) - CDbl(P2S) >= 0) OR (CDbl(NV) - CDbl(P2B) <= 0)) ORDER BY ID DESC'.

Figure 6. Exceeding or falling below favored values



Show Values with Hits

Close | Down

Name1	OAP	P2S	NV	P2B	OSNUM	Date1	Time1
Continental	0	105,00	77,70	80,00	0	25.02.2022	12:00:40
Adidas	258,70	292,00	217,50	220,00	22	22.02.2022	09:04:21
Adidas	258,70	292,00	228,85	230,00	22	14.02.2022	09:10:53
NEL ASA	1,52	6,32	1,11	1,11	200	25.01.2022	12:56:12
NEL ASA	1,52	6,32	1,13	1,14	200	25.01.2022	12:46:46
NEL ASA	1,52	6,32	1,14	1,14	200	25.01.2022	12:43:46
Adidas	258,70	292,00	242,90	243,00	22	24.01.2022	15:32:53
NEL ASA	1,52	6,32	1,20	1,20	200	24.01.2022	11:24:42
NEL ASA	1,52	6,32	1,20	1,20	200	24.01.2022	11:21:42
NEL ASA	1,52	6,32	1,20	1,20	200	24.01.2022	11:18:43
NEL ASA	1,52	6,32	1,20	1,20	200	24.01.2022	11:15:41
Biontech	179,88	235,00	130,40	138,00	15	23.01.2022	11:22:37
Moderna	224,57	235,00	139,58	144,00	8	23.01.2022	11:22:35
Biontech	179,72	235,00	130,40	138,00	15	22.01.2022	07:58:42
Moderna	224,57	235,00	139,58	144,00	8	22.01.2022	07:58:40

Close DS: 107

At the calculation point shown in Figure 3, it is possible to implement any additional calculation model, e.g., univariate ARMA, GARCH ..., possibly via Python or MATLAB integration. The results can be conveyed in a new Form like Figure 5, perhaps shown with a probable range of future value. This is difficult and tricky but can be done quite well. I extracted the generation of a value prediction to a DLL. Therefore, in the case of a calculation change, only the DLL has to be changed, not the main component; ArrayPred[1..2]: Double = DLL (ArrayVal[]: Double; numberofval:integer; ArrayModelParam[]: Variant). The result is a range of a value prediction.

Note

The default values are fictitious, the price values were read in March 2022.

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Data and Software

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Appendix

Selected Sample Source Code // Delphi - Lazarus

```
[...]
 for i:=1 to anzds do // number of records selected
  begin
 // New Value
   try
    q:=DBGridShowData.DataSourceReadData.DataSet.
FieldByName('NV').AsString;
   except
    q:='0';
   end;
 // NV*100/AVG
   try
    t:=DBGridShowData.DataSourceReadData.DataSet.
FieldByName('NVPROCAVG').AsString;
 // nv / avg is stored in Database every reading of new value
   except
    t:='0';
   end;
   try
    ArrayNumNV[i]:=StrToFloat(q);
   except
```

```
      //
     end;
     try
      ArrayNVAVG6[i]:=StrToFloat(t);
     except
      //
     end;
   // add. calculations (here you can implement any calculation
you want, put an array
   // in a form, initialize it at [1..200000] to 0 and implement any
calc here). Maybe with
   // Python4Delphi / Lazarus or Matlab integration; Forecast
model with probability calc
   // implementation, display; ...then ...
     if (i > 1) then
      begin
       try
        if (buyprice = 0) then // diff. calc, when own avg. price equal
or unequal 0
         begin
          ArrayNVQ6[i]:=(-100*((ArrayNumNV[i]-
ArrayNumNV[i-1]))/ArrayNumNV[i]);
         end
         else
         begin
          ArrayNVQ6[i]:=(-100*((ArrayNumNV[i]-
ArrayNumNV[i-1]))/buyprice);
         end;
       except
        //
       end;
      end;
   // ***
    [...]


   CreateAVGStock(StockName1, selected_stockid, NewValue);
   procedure TForm1.CreateAVGStock(Name1: String; stid:
integer; nv: Double);
   var
    anzds1: integer; i: integer; q: String; p: Double; sum1: Double;
sum2: Double; proc1: Double;
   begin
    anzds1:=0; i:=0; q:=''; sum1:=0; sum2:=0; proc1:=0; p:=0;
    try
     SQLTransactionReadData1.Active := true;
     SQLQueryReadData1.UsePrimaryKeyAsKey := false;
     SQLQueryReadData1.SQL.Text :=
   ,SELECT Name1, OAP, P2S, NV, P2B, OSNUM,
   Date1, Time1, NVPROCAVG FROM 10Stocks
   WHERE Name1 = '+QuotedStr(Name1);
     SQLQueryReadData1.Open;
     SQLQueryReadData1.Last;
     anzds1:=SQLQueryReadData1.RecNo; // number of records
     SQLQueryReadData1.First;
    except
     //
    end;
    if (anzds1 > 1) then
     begin
      for i:=anzds1 downto 1 do
       begin
        try
         q:=DataSourceReadData1.DataSet.FieldByName('NV').
AsString;
        except
         q:='0';
        end;
        try
         p:=StrToFloat(q);
        except
         p:=0;
        end;
        sum1:=sum1+p; // sum of all Values
       end;
      sum2:=sum1/anzds1; // sum of all values / number of records
      proc1:=(nv*100)/sum2; // new value in relation to sum2
     end;
    avgv1[stid]:=FloatToStrF(proc1, ffixed, 8,2);
   // array with proc1 for all time stamps
   end;
```

Active/Passive Blending Based on the Liquidity Premium: A Practical Study

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Abstract

The merits of active and passive investing have been explored extensively in volumes of academic research where the superiority of each approach has been debated at length. We acknowledge the advantages of each by preferring a blended portfolio approach that includes both active and passive strategies to achieve our objectives.

Our study is conducted from a practical perspective. It relies on widely available information, accessible real investments, and operationally feasible processes. We propose the liquidity premium described by the spread between the yield of U.S. Treasury 10-Year and 3-Month securities as an indicator for allocating to active or passive strategies. Our proposal is tested by simulating an active/passive blended portfolio allocating regular bimonthly new money contributions through a 14-year period of wealth accumulation. Our total blended portfolio includes a passive strategy represented by an unmanaged buy-and-hold portfolio of an equally weighted S&P 500 ETF, and an active strategy represented by a Cap Weighted S&P 500 ETF & Cash portfolio that tactically manages its equity allocation according to the NAAIM Exposure Index. Our proposed allocation method, the Liquidity Premium Blend, allocates its new money portfolio contributions to the active strategy in periods of low liquidity premium and to the passive strategy in periods of high liquidity premium. The intent is to achieve enhanced portfolio efficiency through risk management while minimizing its opportunity cost to returns. Investment performance presentation includes total returns with reinvested dividends. Our final analysis uses internal rate of return as its performance measure to evaluate alternative active/passive allocation sequences. We draw conclusions primarily based on risk-adjusted portfolio efficiency.

As background for our strategy simulation, the study begins with a review of the U.S. Treasury 10-Year Minus 3-Month spread data. We explore the performance of the S&P 500 through periods of high and low liquidity premium. The chosen ETFs are also examined through these periods for perspective. Our active strategy is defined after a review of the NAAIM Exposure Index historical data.

Ultimately, the simulation results supported our proposal, suggesting liquidity premium serves as an effective indicator for efficiently blending active and passive management through portfolio contribution allocations. The rate of return for our Liquidity Premium Blend outperformed all other blended portfolio methods we tested. Its portfolio efficiency described by our modified Sharpe ratio was second only to the active strategy. It beat its comparable randomized allocation method's rate of return by 50 bps and was more efficient. The most significant implications for wealth management and financial planning practitioners are:

In all simulations, blending the active strategy: NAAIM Tactical Risk Managed with the passive strategy improved portfolio efficiency and reduced drawdowns versus the passive-only methodologies.

Liquidity premium measured by the spread between the U.S. Treasury 10-Year and

3-Month serves as an effective indicator for efficiently allocating between the active and passive strategies.

This Liquidity Premium Blend method can be customized for client objectives and risk tolerance.

Introduction

The merits of active and passive investing have been explored extensively in volumes of academic research where the superiority of each approach has been debated at length. We acknowledge the advantages of each by preferring a blended portfolio approach that includes both active and passive strategies to achieve our objectives.

In this paper, we will explore liquidity premium as an indicator for blending active and passive strategies through allocations of regular new-money portfolio contributions. We will consider a passive strategy represented by an unmanaged buy-and-hold exposure to equity beta, and an active strategy represented by an equity/cash portfolio that tactically manages its equity beta level. Our proposed method, the Liquidity Premium Blend, allocates its new money portfolio contributions to the active strategy in periods of low liquidity premium and to the passive strategy in periods of high liquidity premium. The intent is to achieve enhanced portfolio efficiency through risk management while minimizing its opportunity cost to returns.

Our study is conducted from a practical perspective. It relies on widely available information and accessible real investments and aims for operational feasibility. We will simulate our proposed blending method through a wealth accumulation pattern of regular, bimonthly contributions made by the typical investor saving for retirement. Investment performance presentation will account for total returns, including the compounding effect of reinvested dividends. Our final analysis uses internal rate of return as its performance measure to evaluate alternative active/passive allocation sequences. We draw conclusions primarily based on risk-adjusted portfolio efficiency.

The liquidity premium occurred as a natural fit for our indicator, owing in part to its pattern of cyclicality and our acceptance of The Liquidity Preference Theory.[1,2] While there are many measures of liquidity premium, some directly derived from U.S. equity market data, we selected U.S. Treasury yield spreads as our strategy's indicator. From a practical perspective, yield spread data is readily available. From a philosophical perspective, as "risk-free" assets, we believe treasuries are a purer indication of broad liquidity premium and are less susceptible to "noise". We accept this broader measure of liquidity premium, believing that capital flows freely between public markets.

Background

Studying the Law Yield Spread Data: 1/4/1982–2/23/2021

In preparation for this study, we considered a variety of U.S. Treasury yield spreads and settled on the 10-Year Minus 3-Month to define our liquidity premium periods. This spread was selected for its relatively smooth cycles over decades of our observation. This would allow our proposed methodology to be practical for real-world implementation. Additionally, we felt these durations best match the durations of the assets included in the study: equities carrying a long duration while "cash" assets are fairly represented by the 3-Month maturity. This information is readily available on the Federal Reserve Bank of St. Louis economic research website[3] in a constant maturity format that is free and easy to access.

Figure 1. U.S. Treasury 10-year minus 3-month constant maturity

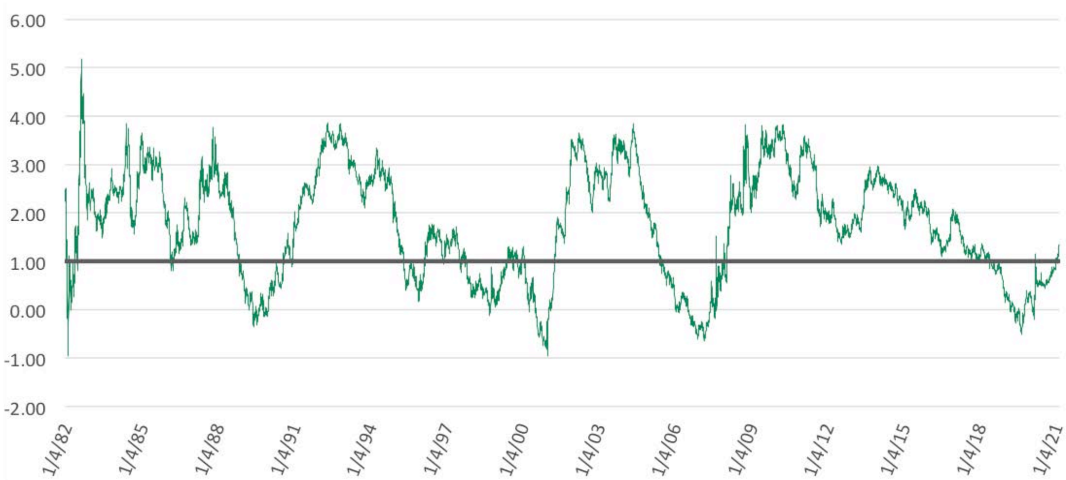

Table 1. U.S. Treasury 10-year minus 3-month constant maturity statistics

1/4/1982–2/23/2021	
Total observations	9,787
Maximum Value	5.18
Minimum Value	-0.96
Average	1.74096761
Median	1.8
Mode	1.92
Standard Dev	1.120893684
Kurtosis	-0.957030843
Skew	-0.10971558
Days greater than .999	6,986.00
Avg consecutive Days	136.98
Days Less than 1	2,800.00
Average Consecutive Days	56.00

This data led us to designate 1% as the threshold to define periods of low liquidity risk premium and high liquidity risk premium, which determine the active/passive allocation of new money contributions to our blended portfolio. We intentionally sought a level that led to longer high premium periods while avoiding frequent signal changes. This was because our Liquidity Premium Blend strategy is intended to be applied over long periods of wealth accumulation, and we believe that equity prices rise over time. The 1% level achieved both of these objectives, with days at or above 1% representing approximately 70% of observations, and days below 1% representing approximately 30% of all observations. After selecting the 1% level as our threshold we defined start and stop dates for high premium and low premium periods by requiring 15 consecutive days at a new level (above or below the 1% threshold) to confirm a period change. Fifteen days was chosen as the smoothing number because no transitionary period exceeded this timeframe, and the study does not include new money contributions more frequently than 15 days.

Table 2. Smoothed liquidity premium periods

HIGH PREMIUM PERIODS: 1% +			LOW PREMIUM PERIODS: LESS THAN 1%		
Beginning Date	Ending Date	Number of Days	Beginning Date	Ending Date	Number of Days
1/8/21	2/23/21	31	6/15/18	1/7/21	640
1/22/08	6/14/18	2,604	6/22/05	1/18/08	646
4/9/01	6/21/05	1,049	1/31/00	4/6/01	299
12/28/99	1/28/00	23	10/29/99	12/27/99	39
6/1/99	10/28/99	105	10/22/97	5/28/99	401
2/20/96	10/21/97	421	5/5/95	2/16/96	198
8/6/90	5/4/95	1,186	11/14/88	8/3/90	432
5/19/82	11/10/88	1,619	3/2/82	5/18/82	55
1/4/82	3/1/82	39			
	Total	7,046	338.75 235.8812 27.78%		2710
	Average Days in Period	880.75			
	StD	917.5686			
	Percent of Time	72.22%			

S&P 500 Through Our Defined Liquidity Premium Periods

With Liquidity Premium Periods defined, we observed the S&P 500 through these timeframes to better understand how the broad equity market performed and anticipate any impact to our proposed methodology. This would provide an initial indication if the strategy could achieve its intended objectives and potentially explain future results. Cumulative returns for each liquidity premium period were annualized, along with standard deviation of daily returns. A weighted average was then applied to compare returns and price volatility between periods of high liquidity premium and low liquidity premium.

Figure 2. S&P 500 through liquidity premium periods

Table 3. S&P 500 performance by liquidity premium periods

Liquidity Premium Environment	Period	Cumulative Return	Annualized Return	StDev of Daily Returns	Annualized StD of Daily Returns
Low	6/15/18 - 1/07/21	36.84%	19.59%	0.0152	0.2460
High	1/22/08 - 6/14/18	112.30%	11.13%	0.0128	0.2061
Low	6/22/05 - 1/18/08	9.17%	5.08%	0.0082	0.1328
High	4/09/01 - 6/21/05	6.68%	2.28%	0.0116	0.1875
Low	1/31/00 - 4/06/01	-19.08%	-22.77%	0.0145	0.2342
High	12/28/99 - 1/28/00	-6.69%	-66.67%	0.0142	0.2286
Low	10/29/99 - 12/27/99	6.91%	86.89%	0.0081	0.1303
High	6/01/99 - 10/28/99	3.72%	13.54%	0.0116	0.1871
Low	10/22/97 - 5/28/99	34.42%	30.90%	0.0132	0.2131
High	2/20/96 - 10/21/97	51.76%	43.57%	0.0087	0.1402
Low	5/05/95 - 2/16/96	24.58%	49.95%	0.0057	0.0917
High	8/06/90 - 5/04/95	55.65%	14.59%	0.0073	0.1177
Low	11/14/88 - 8/03/90	28.81%	23.85%	0.0081	0.1315
High	5/19/82 - 11/10/88	138.20%	21.61%	0.0116	0.1881
Low	3/02/82 - 5/18/82	2.80%	20.11%	0.0082	0.1319
High	1/04/82 - 3/01/82	7.14%	90.69%	0.0109	0.1754
		Avg Annualized Return		Avg Annualized StD of Daily Returns	
Average for Low Liquidity Premium Periods		17.01%		0.1793	
Average for High Liquidity Premium Periods		14.96%		0.1800	

The results were interesting and likely carry implications for additional research beyond the scope of this study. Risk, or price volatility, was nearly identical for the high- and low-premium periods. Returns, on the other hand, were approximately 2% annualized higher in our low liquidity premium periods. Considering that low liquidity premium is typical in later stages of the business cycle, we assume this is the result of strong price momentum. This was interesting to observe because our Liquidity Premium Blend method will allocate new money contributions to the active strategy during these low premium periods when momentum is strong and likely to cause an increase in the passive strategy's proportional share of the total blended portfolio. The original motivation of our Liquidity Premium Blend was to have new money contributions actively allocated between equity and cash when there is little premium being paid for the illiquidity risk of long duration assets. This analysis of S&P 500 performance through our liquidity premium periods shows that our methodology should also strategically help maintain balance between active and passive allocations.

Methods

Defining Investments and Their Performance Measures

For practicality, this study uses a couple of the largest and most tenured Exchange Traded Funds (ETFs) to simulate investment results. They are available on most no-transaction fee trading platforms and are increasingly available in fractional shares, adding to their accessibility. All performance presentation of investment results for our active and passive strategies, including final simulations, are calculated using the Total Return Price (Forward Adjusted) available through YCharts.[4] The Total Return Price (Forward Adjusted) allows us to simulate dividend reinvestment, a key component of long-term investing. Its formula is:

Total Return Level = Actual Price x Split Factor x Dividend Adjustment Factor

Split factor = 0.5 for a 2 for 1 split, 0.33 for a 3 for 1 split, etc.

Dividend Adjustment Factor = (1 + Value of Dividend/Previous Day's Close Price)

Risk is presented as standard deviation of daily returns calculated as a weighted average of portfolio components' daily returns.

Transaction costs and taxes were intentionally omitted from the calculation, assuming no transaction fees for our ETF trading and a qualified account for wealth accumulation. Expense ratios of the ETFs are reflected in their performance, with no other hypothetical fees applied.

Active Strategy: NAAIM Tactical Risk Managed

The active strategy: NAAIM Tactical Risk Managed or NAAIM TRM implements the National Association of Active Investment Manager's (NAAIM) Exposure Index[5] as an equity/cash allocation strategy. This indicator represents the average level of exposure to U.S. equity markets reported by the group's membership. The NAAIM Exposure Index is a very credible indication of professional risk manager's sentiment, widely cited by major financial press.[6-10] It provides over 14 years of live data spanning four of our most recent liquidity premium periods.

"NAAIM member firms who are active money managers are asked each week to provide a number which represents their overall equity exposure at the market close on a specific day of the week, currently Wednesdays. Responses can vary widely as indicated below. Responses are tallied and averaged to provide the average long (or short) position of all NAAIM managers, as a group.

Range of Responses: 200% Leveraged Short, 100% Fully Short, 0% (100% Cash or Hedged to Market Neutral), 100% Fully Invested, 200% Leveraged Long."[5]

Figure 3. NAAIM exposure index

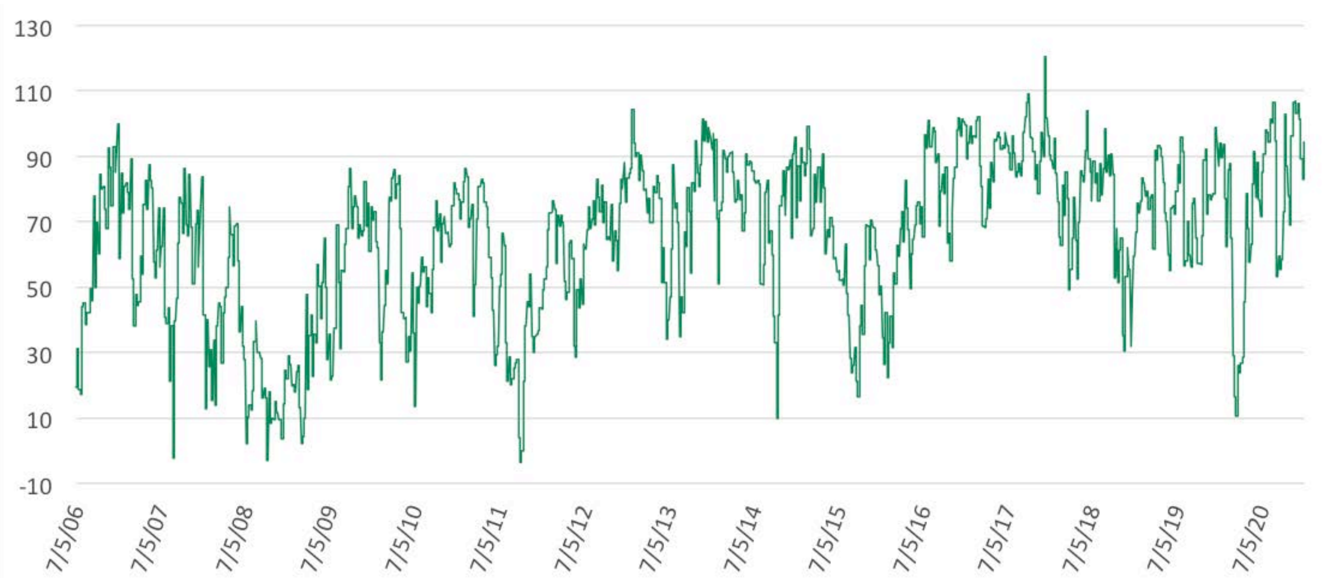

Table 4. NAAIM exposure index simple statistics

Number of Observations	764	
Maximum Allocation	120.56	
Minimum Allocation	-3.56	
Mean	65.3270	
Median	69.665	
Mode	97.44	
Standard Deviation	24.2367	
Skew	-0.6016	
Kurtosis	-0.3224	
Number of Observations Above 100, percentage of total	28	3.66%
Number of Observations Below 0, percentage of total	3	0.39%

We modeled the NAAIM Tactical Risk Managed Portfolio by applying the Exposure Index numbers since its inception as a percentage of exposure to the daily performance of SPY—State Street SPDR S&P 500 ETF Trust. SPY was selected as the most common, longest tenured ETF available as broad representation of "the market". Any unallocated cash received the daily yield of the 3-Month U.S. Treasury. Exposure levels were not constrained, so market exposures less than 0% and greater than 100% were allowed. Although many practitioners are limited in their ability to implement leverage or short exposure especially in qualified accounts, these instances were not extreme, with -4% being the "shortest" observation and 121% the most "levered". We assume these levels could be creatively replicated with no observable impact, given that the occurrences of "short" and "levered" observations were rare at 0.39% and 3.66% of total observations, respectively. The NAAIM TRM portfolio's equity/cash allocation was held constant for each day between reported changes in the exposure number.

Passive Strategy

The passive strategy is represented as a buy-and-hold accumulation of RSP—Invesco S&P 500 Equal Weight ETF, which holds the S&P 500 constituents in equal proportions and rebalances quarterly. While it can be fairly argued that quarterly rebalancing and annual reconstitution is not purely passive ownership, this investment was selected as our passive strategy for a few reasons. Our study includes regular contributions to the portfolio, and RSP's quarterly rebalancing ensures that contributions to the passive strategy will be made nearly equally among its stocks. Additionally, our proposed Liquidity Premium Blend is intended to be easily implemented for wealth management practitioners. As fiduciaries, none would actually hold an investment completely unmanaged (even allowing it to fall to $0.00). As a result, we felt RSP is as philosophically close to passive ownership as is practical.

Market Cap Weight Versus Equal Weight

The decision to implement the active and passive strategies using investments that weigh the S&P 500 stocks differently was made for philosophical reasons, fully aware this results in tilting towards different factor risk premia. The SPY cap weighted index is expected to provide a higher exposure towards the momentum factor, whereas the equally weighted RSP tilts towards (small) size and value factors. Knowing these risk factors tend to be rewarded differently through the course of a business cycle, we observed performance of the cap weighted SPY and equal weight RSP through our periods of high and low liquidity premium.

Figure 4. RSP and SPY performance

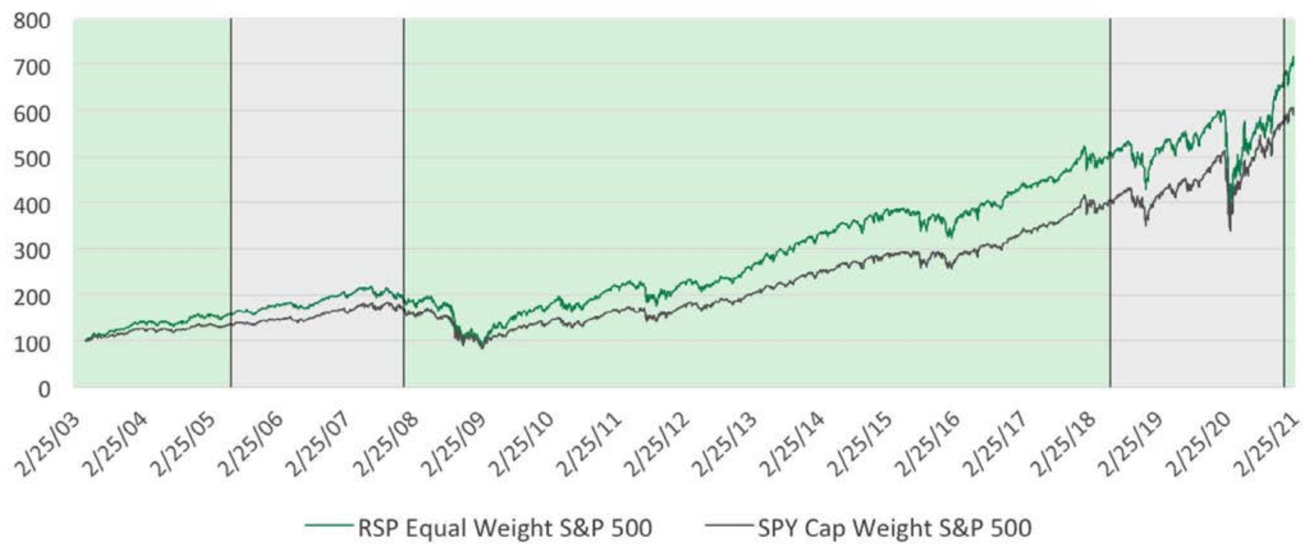

Table 5. RSP and SPY performance through liquidity premium periods

Liquidity Premium	Period	Annualized Return		Annualized StD	
		SPY	RSP	SPY	RSP
Low	6/15/18 - 1/07/21	22.89%	17.56%	0.2421	0.2654
High	1/22/08 - 6/14/18	14.57%	16.10%	0.2057	0.2251
Low	6/22/05 - 1/18/08	7.55%	5.50%	0.1315	0.1400
High	4/30/03(inception) - 6/21/05	24.44%	37.28%	0.1196	0.1333

The equally weighted RSP is more volatile than the market cap weighted SPY through all periods, unsurprising given its tilt towards the (small) size and value factors. However, it was interesting to discover the cap-weighted portfolio outperforms in our periods of low liquidity premium while the equally weighted portfolio outperformed in periods of high liquidity premium. This is noteworthy since our proposed Liquidity Premium Blend allocates its contributions to the active strategy using SPY in the low liquidity premium periods and to the passive RSP strategy in high liquidity, and is likely to have a favorable impact on performance while also potentially helping to maintain balance in our blended portfolio.

Simulation Methods

Simulations spanning 14.5 years were conducted to compare the effects of blending our active and passive strategies through allocations of regular bimonthly new money contributions to the portfolio. The intent is to replicate the typical wealth accumulation pattern of an average investor saving for retirement. The beginning date of 7/5/2006 coincides with the inception of the NAAIM Exposure Index while the end date of 1/7/2021 marks our most recent change of liquidity premium periods.

Each simulation begins with a total portfolio value of $200,000. All active/passive blending methods begin with the total portfolio divided equally: $100,000 allocated to active, and $100,000 allocated to passive. The active NAAIM TRM Only, Passive Only, and SPY Only simulations begin with the full $200,000 allocation to their respective single investment portfolios. Regular bimonthly contributions of $1,000 are made through the course of the study on the same dates in each method simulation.

Liquidity Premium Blend

Our proposed method for active/passive blending allocates its $1,000 new money portfolio contributions to the active strategy in periods of low liquidity premium and to the passive strategy in periods of high liquidity premium.

Passive Only

Holds and allocates to RSP exclusively.

NAAIM TRM Only

Holds and allocates to the active strategy exclusively.

SPY Only

Holds and allocates to SPY exclusively.

50–50 Contribution

Equally divides each $1,000 bimonthly contribution with $500 allocated to the active strategy and $500 to the passive strategy.

1:1 Random Contribution

Randomized contributions with a simulated "coin flip" determining the allocation of the $1,000 contributions to the active or passive strategy.

Reverse Contribution

Reverse Contribution allocates the $1,000 contribution to the active strategy in periods of high liquidity premium and the passive strategy in periods of low liquidity premium. This is the opposite of our proposed Liquidity Premium Blend.

2:1 Random Contribution

Randomized allocation of the $1,000 contribution to the passive strategy in 2/3 of instances, active in 1/3 of instances. This was intended to compare directly with our proposed Liquidity Premium Blend by approximating the historical amount of time in each liquidity regime.

Simulation Analysis

Because our study explores the effects of new money allocation sequences through a common timeframe, we chose to analyze the simulation results using their Internal Rate of Return. For each simulated method, the total annual new money contributions were subtracted from the gross change in portfolio value for each calendar year to represent net "cash flows". For example:

> *Cf0 = -$200,000, Cf1 = (2006 ending value – $200,000 – 2006 contributions), Cf2 = (2007 ending value – 2007 beginning value – 2007 contributions), Cf3 = (2008 ending value – 2008 beginning value – 2008 contributions), etc.*

Portfolio efficiency is presented with a modified Sharpe ratio (Rp – Rf)/ StDp:

> *Rp = the portfolio's IRR*
>
> *Rf = The 10-Year U.S. Treasury Inflation-Indexed Security, Constant Maturity rate on our 7/5/2006 inception*
>
> *StD = The portfolio's annualized standard deviation of daily returns*

An analysis of annual drawdowns was calculated to determine the maximum drawdown for each simulation. All occurred through the 2008–2009 financial crisis. The 2020 drawdown was also included in the study's results, as it was the second greatest drawdown for all simulations.

Figure 5. Liquidity premium blend, NAAIM TRM only and passive only

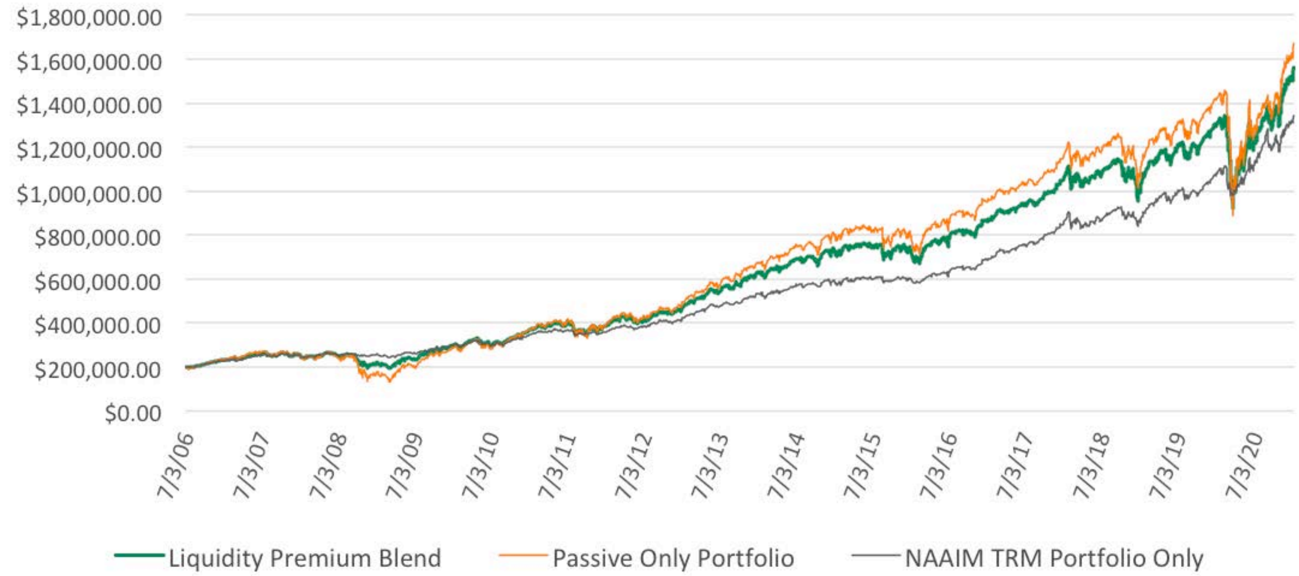

Figure 6. Liquidity premium blend vs. others

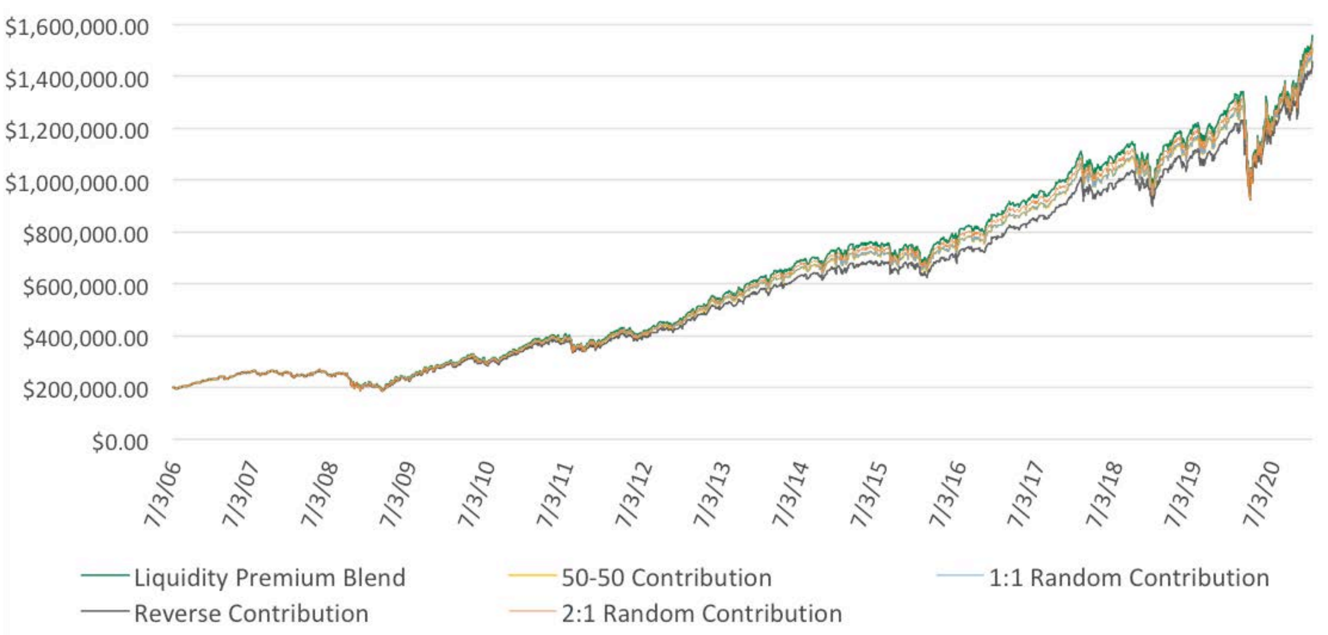

Table 6. Final simulation results

Portfolio	Ending Portfolio Value	Internal Rate of Return	Annualized StD	Modified Sharpe	Max Drawdown: '08-'09	2020 Drawdown	% Contributions Passive	% Contributions Active
Liquidity Premium Blend	$1,560,579.28	15.080%	0.1578	0.79	-30.83%	-30.09%	63.5%	36.5%
Passive Only	$1,672,786.31	16.348%	0.2260	0.61	-55.19%	-38.43%	100.0%	0.0%
NAAIM TRM Only	$1,344,154.47	11.744%	0.0956	0.95	-13.43%	-11.71%	0.0%	100.0%
SPY Only Portfolio	$1,758,883.25	15.813%	0.2067	0.64	-52.66%	-30.43%	NA	NA
50–50 Contribution	$1,508,470.39	14.197%	0.1502	0.77	-32.32%	-26.05%	50.0%	50.0%
1–1 Random Contribution	$1,511,648.38	14.252%	0.1500	0.77	-32.19%	-25.71%	48.7%	51.3%
Reverse Contribution	$1,420,104.33	13.298%	0.1434	0.74	-33.25%	-21.81%	36.5%	63.5%
2–1 Random Contribution	$1,534,154.44	14.573%	0.1585	0.75	-33.60%	-28.61%	61.7%	38.3%

Conclusion

The Liquidity Premium Blend results support our proposal, suggesting liquidity premium serves as an effective indicator for efficiently blending active and passive management through portfolio contribution allocations. Our overall rate of return for the Liquidity Premium Blend was 15.08%, outperforming all other blended methods and the active-only strategy. Its portfolio efficiency described by our modified Sharpe ratio of 0.79 is second only to the active-only strategy.

The active-only strategy: NAAIM Tactical Risk Managed produced impressive portfolio efficiency, handedly outperforming all other strategies with its modified Sharpe ratio of 0.95. Its max drawdown was less than 1/3 of the SPY Only Portfolio. However, its superior efficiency and downside protection comes at the expense of returns; nothing is free in this world. The purely passive strategies including SPY Only finished with the highest portfolio values and rates of return but were soundly the worst from a risk-adjusted efficiency perspective.

In most blended portfolio methods, we observed an improvement in portfolio efficiency as more new money contributions were allocated to the risk managed active strategy. The major exception is our Reverse Contribution methodology, which posted the worst modified Sharpe ratio of all active/passive blended portfolios despite allocating 64% of contributions to the active risk-managed strategy, more than any other blending method. The Reverse Contribution results support our proposal, indicating that allocating contributions between active and passive strategy according to the liquidity premium has significant impact on the blended portfolio's efficiency.

Further evidence is apparent when comparing the Liquidity Premium Blend to its 2:1 Random Contribution counterpart. These methods allocated roughly the same amount of new money to their active and passive strategies but in different sequences. Our proposed Liquidity Premium Blend method prevailed with 50 bps greater rate of return and superior portfolio efficiency.

Implications for Practitioners

Our proposed Liquidity Premium Blend strategy was designed for real-world implementation. It relies on readily available information and includes widely accessible investments for operational feasibility. The most significant implications for wealth management and financial planning practitioners are:

1. In all simulations, blending the active strategy: NAAIM Tactical Risk Managed with the passive strategy improved portfolio efficiency and reduced drawdowns vs. the passive-only methodologies.
2. Liquidity premium measured by the spread between the U.S. Treasury 10-Year and 3-Month serves as an effective indicator for efficiently allocating between the active and passive strategies.
3. This Liquidity Premium Blend method can be customized for client objectives and risk tolerance.

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MACD-V: Volatility Normalised Momentum

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Introduction

What Is This Topic About?

This paper will focus on the study of momentum using a very popular technical analysis indicator, the Moving Average Convergence Divergence (MACD), created by one of the most respected analysts of our time—Gerald Appel.[1]

This paper is comprised of six parts.

In the first section, we will focus on the MACD itself. We will do a brief description of its construction, the most elementary ways to use it, and then a review of the five limitations it has. This is a section that is familiar territory to all technicians.

In the second section, we will show a widely known suggestion to deal with these limitations that does improve one, but does not solve all of them.

In the third and fourth sections, we will present our own solution, which remedies the shortcomings while creating unique advantages (edges) that would not be possible to obtain via the classic MACD.

In the last two sections, we will use our framework to improve existing tools in TA literature and explore new techniques.

Why Does This Topic Matter to Us?

Most price-based momentum indicators fall into roughly two camps:

Range Bound Oscillators

These operate within a finite range of values, usually 0–100 (e.g., RSI, Stochastics, Williams %R, etc.). They offer the advantage of having objectively defined momentum readings, while at the same time making these readings uniform across securities for cross market comparison purposes. On the other hand, the very fact that these tools can only obtain a limited range of values presents problems during extended price trends, as their extreme readings (aka "overbought/overbought") remain at high (or low) levels for a prolonged period of time, thereby giving many false signals. In fact, some analysts have created some counterintuitive techniques, based on this phenomenon, whereby "overbought" is a sign of future strength and "oversold" is a sign of future weakness.[2] Oscillators are not trend-friendly and one could argue that these are not *truly* momentum measuring yardsticks, but range identification indicators. For example, a 14 period stochastic oscillator states where you are as a % in a 14 period Donchian channel and does not measure price momentum per se. Thus, the terms "overbought, oversold" become a bit of a misnomer.

Trend-following Indicators

These measure price change over some period of time and usually are boundless indicators (but not exclusively), as their readings can be increasing (or decreasing) along with price trends (e.g., RoC, MACD, etc.). Their very freedom makes it almost impossible to have objectively defined "overbought" "oversold" levels or have meaningful momentum comparisons between different asset classes (e.g., individual equites vs. currencies).

Of course, the aforementioned categorization of indicators is not a fully detailed taxonomy, but a rather broad distinction for definitional purposes…

Irrespective of which family (category) of momentum tool is used, it would appear that in technical analysis literature there is certainly no shortage of indicators. One could even argue that there are more indicators than traders…

So, why attempt to build another tool?

It is not the author's intention to simply design yet "another" indicator that would provide approximately the same informational value as numerous ones already do, thus resulting in a tool that exacerbates the already existent issue of indicator multicollinearity.

Our goal is to improve an existing tool (MACD) so that, by eliminating its shortcomings, we will be creating a unique type of hybrid **"***boundless oscillator***,"** that opens the doors for several pattern recognition opportunities which would not be definable using the classic MACD.

We are big believers in creating new techniques rather than new tools, thus we will use the improved MACD to define a general Momentum Lifecycle RoadMap (framework), new entry and exit techniques, and versatile cross asset (intermarket) strategies, among other uses, that would not be achievable via the venerable MACD.

MACD: A Measure of Momentum

Construction

One of the available tools to define momentum is the Moving Average Convergence Divergence (MACD) indicator. The MACD was created by Gerald Appel in the late 1970s. It is a trend-following momentum indicator that shows the relationship between two moving averages of prices.

The MACD is constructed in four steps :

1. Calculate a 12 bar Exponential Moving Average
2. Calculate a 26 bar Exponential Moving Average
3. MACD Line = 12 bar EMA – 26 bar EMA
4. Signal Line = 9 bar EMA of the MACD Line

What is momentum?

Momentum is closely tied to physics and is the rate (speed) that prices change (velocity = d/t, where d = distance, t = time).

Momentum in market prices is a direct challenge to the Efficient Market Hypothesis (EMH), as it implies that prices trend and are not randomly distributed, thus it is possible to outperform the broad market.

Momentum Strategies are broadly distinguished between (i) Time Series (absolute) Momentum—establish long (short) positions by determining the trend of each asset individually (e.g., go long positive 12-month price return).

(ii) Cross Sectional (Relative) Momentum Strategies—ranking assets and going long top and shorting bottom performers.

Further to the MACD, Thomas Aspray in 1986 created the MACD Histogram, which is constructed as follows:

5. MACD Histogram = Signal Line – MACD Line

Thus in essence:

- The 12 & 26 EMAs are the 1st derivative of price.
- The MACD Line is the 2nd derivative of price.
- The Signal Line is the 3rd derivative of price.
- The MACD-H is the 4th derivative of price.

The MACD is a versatile tool with many non-conventional uses, but it nevertheless has five key shortcomings. Three of them are regarding the MACD values themselves and two have to do with signal line crossovers. Let's see these in detail.

Limitation 1: The MACD Across Time

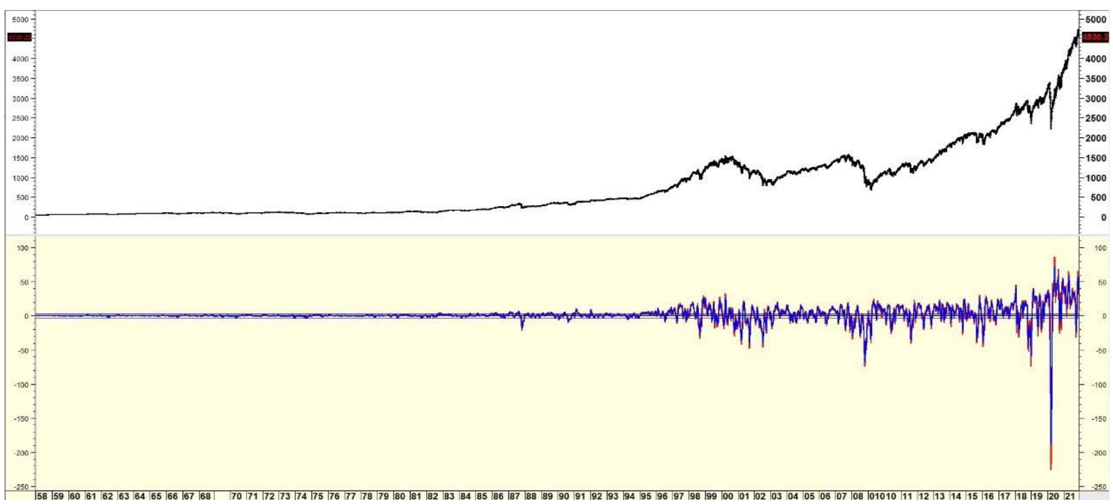
By way of design, the MACD is an "absolute price indicator" as it takes absolute price inputs (price MAs) and produces an output (spread of raw price MAs) without any kind of normalisation. This creates the following situation:
Although the MACD in 2020 has a bigger value than in 1957, that does not imply that the market has more momentum. That was simply a function of the underlying security having a larger absolute value when it was calculated in the second instance (2020) than the first (1978). The problem is exacerbated the further one goes back in time.

Table 1. MACD ranges

S&P 500	1957–1971	2019–2021
MACD Maximum	1.56	86.31
MACD Minimum	-3.3	-225.40

The implication of this is that MACD (and MACD Histogram) readings are not comparable across time for the same security, especially if the market in question has had substantial price appreciation or depreciation.

Figure 1. S&P 500 & MACD (1957–2021)



The MACD is not time stable (comparable across time).

Limitation 2: The MACD Across Markets

The second limitation of the MACD and MACD Histogram are that they are not comparable across securities. Any differences in the indicator readings are attributable to comparing securities that have different absolute values, rather than depicting varying levels of momentum strength.

For example, the MACD for the S&P 500 at the time of writing is 65 and for the euro currency is -0.0070.

Again, this does not mean that the S&P has more momentum than the euro, but its bigger MACD reading is a function of the bigger absolute price of the underlying security.

Cross market momentum comparisons are not possible, as it would be the case with say using a (0–100) scaled indicator. The RSI for the S&P and euro in this instance would be directly comparable, but not for the MACD.

The MACD is not comparable across securities.

Limitation 3: MACD Momentum Lifecycle

The MACD is an improved version of a moving average crossover system.

When a market is trending in a particular direction, the shorter term EMA responds quicker to price than the longer term EMA, moving away from (closer to) it and consequently their difference/spread increases (decreases). Thus, the MACD indicates the *direction of momentum* (bullish if above the signal line or bearish if below the signal line). When this is viewed against the prevailing trend, it highlights momentum *acceleration* or *deceleration* and the beginning and end of this process can be identified via signal line cross overs. Moreover, the further away the MACD is from the equilibrium line, the stronger momentum is (please refer to Figure 4, bottom panel).

However, since MACD values are not comparable across time and across securities, it is impossible to standardize the *intensity (strength)* of (MACD-defined) momentum into an objectively and quantitatively defined framework, where “High (fast) vs Low (slow)” and/or “overbought vs. oversold” levels would exist.

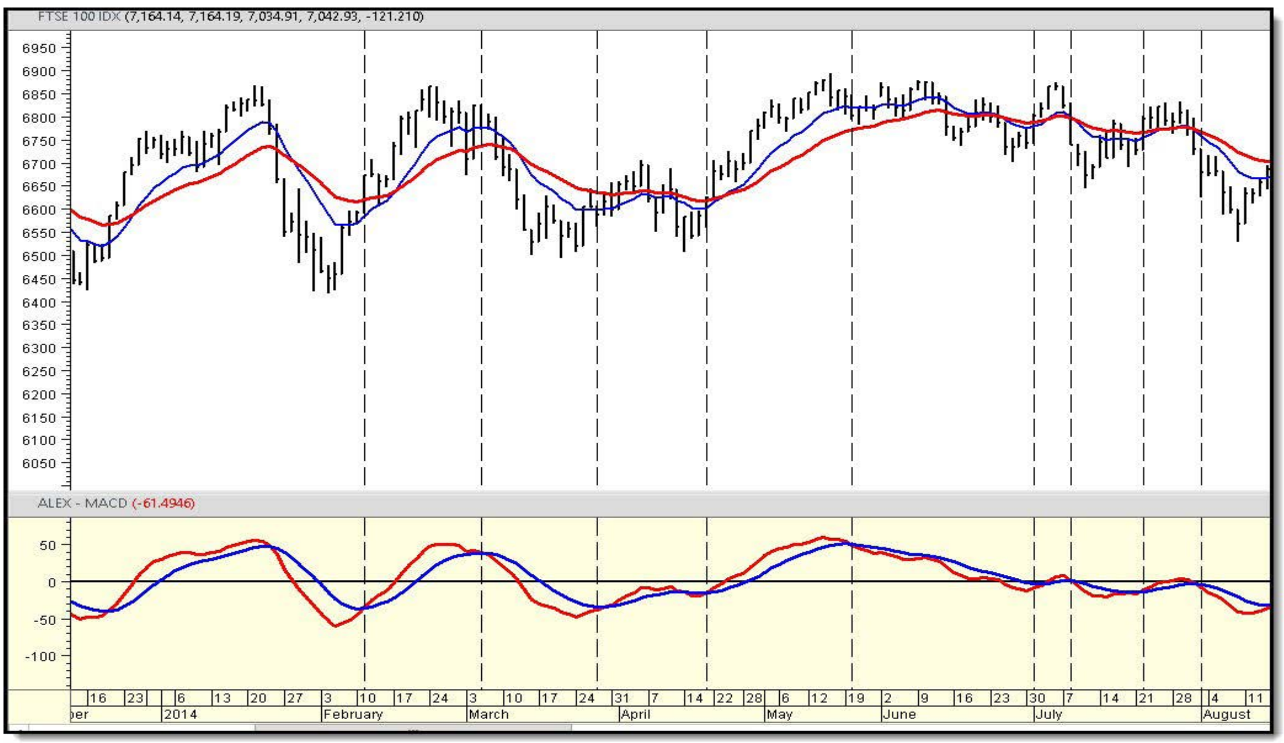
The MACD momentum readings cannot be objectively scaled.

Limitation 4: Signal Line Accuracy

When directional strength is low, the MACD will be near the equilibrium line and/or close to the signal line. As such, signal line crossovers will be frequent, giving many (false) signals. This phenomenon is one of the “Achilles' heels” of trend-following system behavior in low momentum environments in general. The MACD is no exception.

In Figure 5, this is easily observed during the May to August 2016 period, where six loss producing crossovers signals occurred in a range bound, low momentum environment. As a consequence of limitation #3 (lack of momentum level scaling), these cannot be avoided by way of rejecting the signals that occur within an objectively and quantitatively defined low momentum environment.

Figure 2. MACD behavior in low momentum - FTSE 100 (February—August 2014)



MACD signal line crossovers are unreliable in low momentum environments.

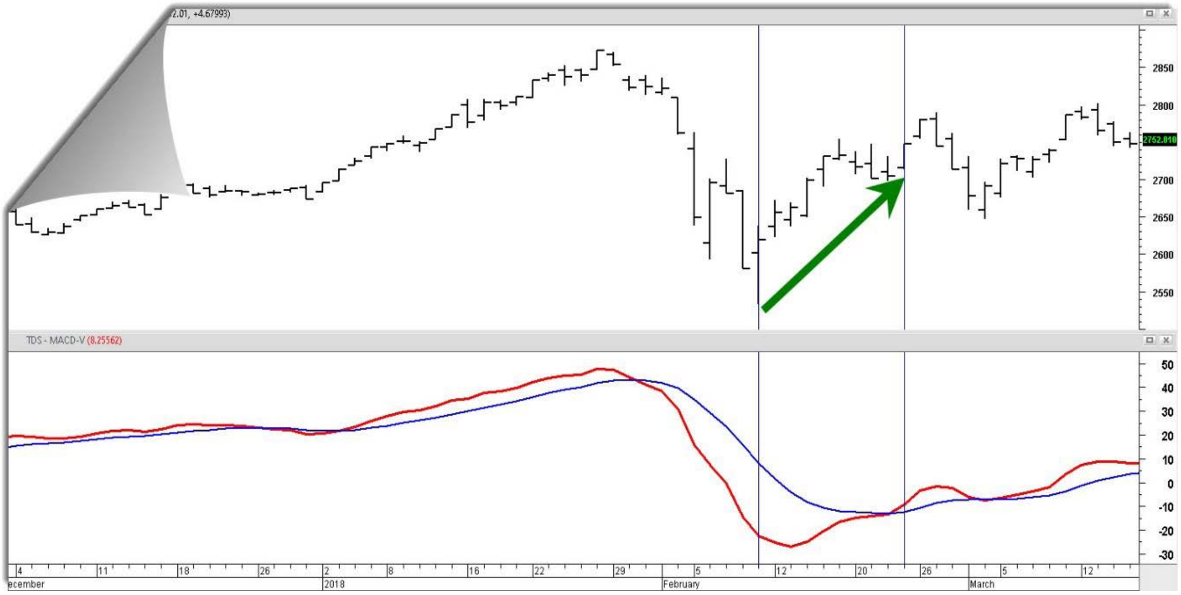
Limitation 5: Signal Line Timing

When momentum is high, MACD signal accuracy is (one) of its main strengths. However, when the market is pushing higher (lower) with too much force, to the point where the MACD line has built significant distance from the signal line but then changes its trend to the downside (upside) *abruptly,* it takes some time before the lagging MAs catch up to the new data (raw price), which translates into a directionally correct (accurate) but late (from a timing point of view) signal.

This phenomenon is more often observed in fast bearish trends, which then proceed to form a V-shaped bottom (when a counter-trend bounce occurs). Given the trend following nature of the MACD, it is guaranteed that it will signal the turn, but it will produce a signal line cross over that may be some distance away from the actual price bottom itself.

For example, the S&P 500 bottomed at 2532.69 on the February 9, 2018, but the MACD signaled the turn at 2747.30 on February 23, which means it was “late” by 8.47%!!

Figure 3. MACD in high momentum trend reversal—S&P 500 (February 2018)



Again, as a direct consequence of limitation #3 (and the lagging nature of the signal line), it is impossible to improve signal timing by first identifying a high momentum environment.

MACD crossover signals are late in high momentum trend reversals.

PPO: An Improvement, But Not a Solution

Construction

A solution to deal with limitations #1 and #2 is to normalize the readings of the MACD, so as to become comparable across time and securities. A well-known suggestion is to place the raw MA spread as a function of the absolute price of the underlying security so that momentum (MACD) is placed in context. This is then multiplied by 100 to obtain the output on a percent (%) basis.

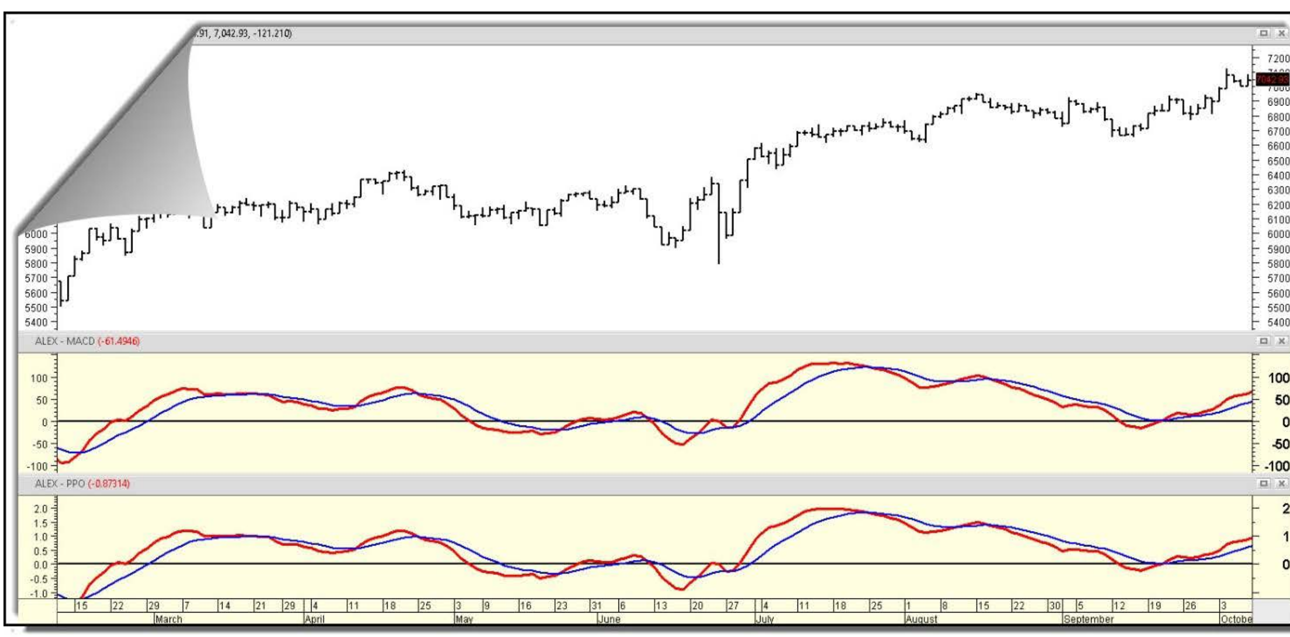
Thus, the formula for the MACD Line now becomes:

[(12 period EMA - 26 period EMA) / (close)] x 100 or [(12 period EMA - 26 period EMA) / (26 period EMA)] x 100

This resulting indicator is commonly known as the PPO (percent price oscillator).

Let's see what the effect of the PPO on the MACD limitations is.

Figure 4: MACD & PPO—FTSE 100 (February to October 2016)



Limitation 1: The PPO Across Time

Since the PPO readings are expressed on a percent basis, that means that they should be comparable across time for the same security on an "apples to apples" basis. Let's confirm this by revisiting the S&P 500.

Figure 5: S&P 500 & PPO (1970–2021)

Although specific stationarity tests could be employed to prove the point, we can easily observe that the range of fluctuation (variables dispersion around zero) is more stable as the MA spread is normalized on a percentage basis. In fact, if we set lower and upper boundaries in such a way that it contains 95% of the observations, since the February 3, 1975, the PPO has oscillated within 2% and -2%.

Table 2: PPO Ranges (S&P 500)

PPO Ranges	> 2%	2% to -2%	< - 2%
% of time	2.2%	94.3%	3.5%

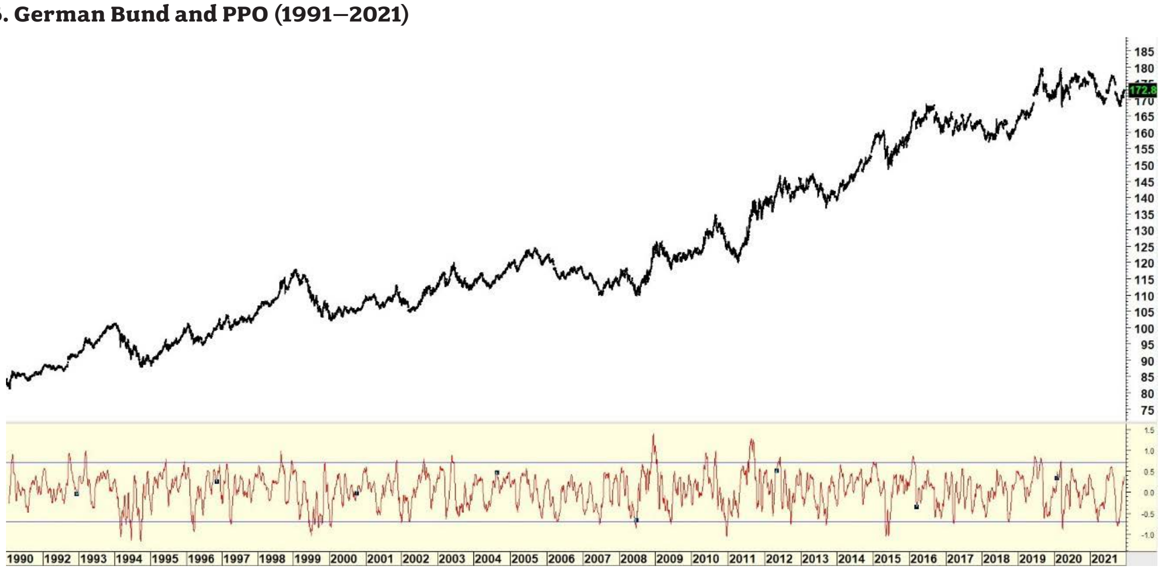
The PPO retains all of the advantages that the MACD has but also adds reading uniformity across time for the same security. It would appear that limitation #1 is solved.

PPO readings are time stable (comparable across time).

Limitation 2: The PPO Across Markets

One would be tempted to assume that since the PPO is expressed on a percent (%) basis and is comparable across time, then cross market comparisons would also be feasible. However, upon closer inspection it would appear that the PPO fails the test. Let's see this via an example:

Figure 6. German Bund and PPO (1991–2021)



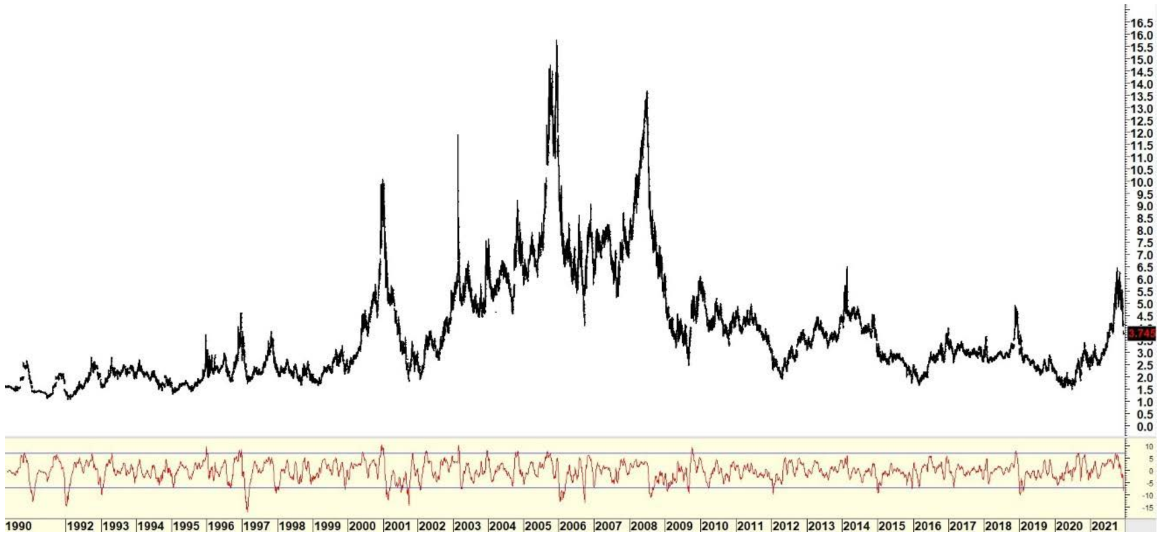
Using the aforementioned upper/lower boundaries used for the S&P 500, it would appear that the Bund has never traded above the upper level of 2% and never below the lower -2% level in its entire history. It is evident that there is considerable variation in the data and in order to see where 95% of the PPO values for the Bund reside we would need to establish different levels.

Table 3. PPO Ranges (German Bund futures)

PPO Ranges	> 0.7%	0.7% to -0.7%	< - 0.7%
% of time	3.5%	93.6%	2.9%

Thus, a PPO reading higher than 0.5% for the Bund would constitute a strongly trending environment. The same reading for the S&P would be indicative of an almost range bound market. What constitutes "high momentum" in one market may very well be classified as "low momentum" in another.

Figure 7. Natural gas futures and PPO (1990–2021)



The aforementioned differences become more pronounced as we examine a very volatile market, such as natural gas futures. Figure 7 depicts the PPO ranging most of the time (94.2%) from +7% to -7%.

Table 4. PPO ranges (across markets)

NG - PPO Ranges	> 7%	7% to -7%	< - 7%
% of time	1.4%	94.2%	4.4%
SP 500 - PPO Ranges	> 2%	2% to -2%	< - 2%
% of time	2.2%	94.3%	3.5%
BUND - PPO Ranges	> 0.7%	0.7% to -0.7%	< - 0.7%
% of time	3.5%	93.6%	2.9%

Thus, it appears that the PPO is not a **truly** normalized momentum comparison tool for cross market purposes as it fails to provide uniform benchmarks levels due to fact that markets may have significantly different volatility structures.

The PPO is not comparable across securities.

Limitation 3: PPO Momentum Framework

Since the PPO cannot be standardized both across time AND securities, it is then not possible to deal with momentum level definition in a uniform framework.

It would be perhaps feasible on a *per individual market* basis to create levels where historically each market in question is deemed as "overstretched" or with adequate levels of trend strength, but this would not be practical as it would require massive amounts of optimization for an almost limitless universe of securities and the findings for each market would not be transferable to another.

Limitations 4 and 5: PPO Signal Line Accuracy and Timing

Consequently, the lack of a uniform "high/low" momentum definition renders limitations #4 and #5 unsolved under the PPO as well, as cross over signal filtering is not feasible.

The PPO improves some but not all of the MACD shortcomings.

MACD-V: Volatility Normalised Momentum

Construction

Since "normalization by price" results in cross market momentum valuation discrepancies due to differences in volatility, then it would be preferable to *normalize by volatility itself.*

We will be using Welles Wilder's Average True Range (ATR) as the tool for the measurement of volatility.

Thus, the MACD line formula now becomes:

[(12 bar EMA - 26 bar EMA) / ATR(26)] * 100

The output of the indicator is the amount of momentum a security has that is in excess of its average volatility expressed as a percentage.
We are measuring directional strength "purified" from volatility fluctuations.

What is ATR ?

Average true range (ATR) is a technical analysis volatility indicator originally developed by J. Welles Wilder Jr. for commodities.

The true range indicator is taken as the greatest of the following: current high less the current low; the absolute value of the current high less the previous close; and the absolute value of the current low less the previous close.

The indicator does not provide an indication of price trend, simply the degree of price fluctuation.

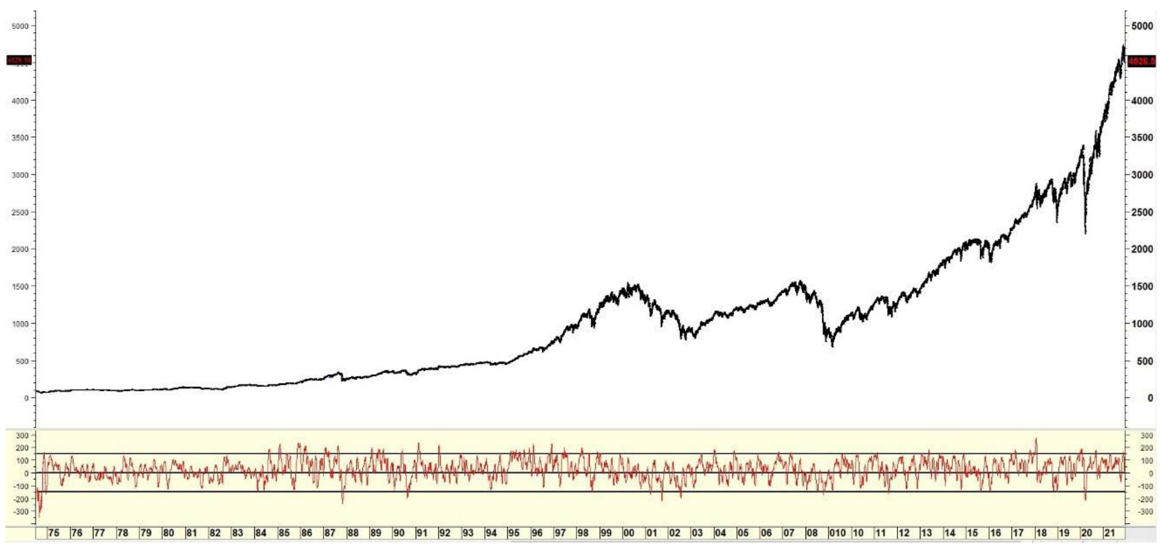
The average true range is an N-period smoothed moving average (SMMA) of the true range values.

In order to distinguish the new indicator from the classic MACD I will name it by adding a "V" at the end of the original name ("MACD-V") and refrain from creating a completely new name altogether, so as to honour the original inventor.
Let's examine now how MACD-V measures against the five shortcomings of the classic MACD.

The MACD-V Across Time

We will first be checking how MACD-V behaves across time for the S&P 500.

Figure 8. S&P 500 and the MACD-V (1975–2021)



It is easily observable that MACD-V fluctuates within a finite range of a values around its equilibrium line (similar to the PPOs behaviour). Any indicator reading discrepancies across time have been eliminated due to normalization.

If we try to find the range where 95% of the data fluctuate and define the rest as "extremes," then since February 1975 for the S&P 500 the MACD-V oscillates between 150 and -150.

Table 5. MACD-V ranges (S&P 500)

MACD-V Ranges	> 150	150 to -150	< - 150
% of time	4.4%	95%	0.6%

MACD-V readings are time stable (comparable across time).

The MACD-V Across Markets

Will the MACD-V succeed where the PPO failed? Does the range of 150 to -150 also hold 95% of the MACD-V values for other markets? Below we feature the figures of the German Bund and natural gas futures and the levels.

The range of fluctuations for the two MACD-Vs is considerably more uniform than when comparing the equivalent ones for the two PPOs. They essentially oscillate the same amount around the equilibrium line as differences in volatility have been eliminated.

Slight and sporadic extremes are strictly attributable to strong momentum (prolonged moves in a particular direction), since the MACD at its core is a boundless indicator.

Figure 9. German Bund and the MACD-V (1990–2021)

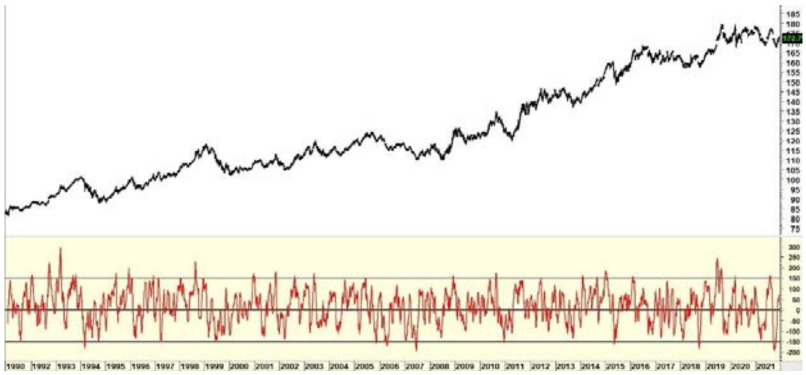


Figure 10. Natural gas and the MACD-V (1990–2021)

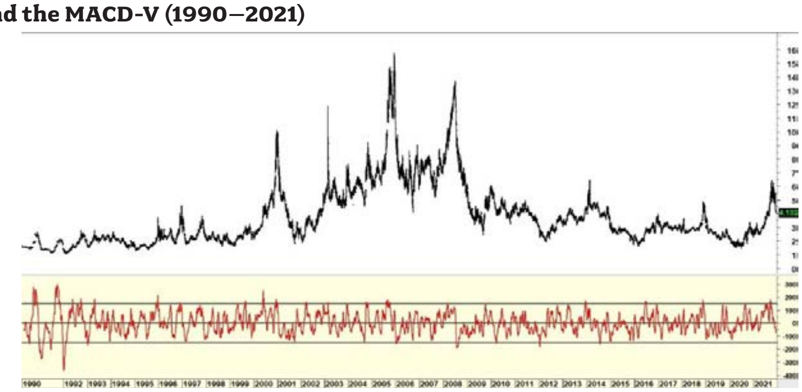


Table 6. MACD-V extreme ranges (S&P 500, 1975–2021)

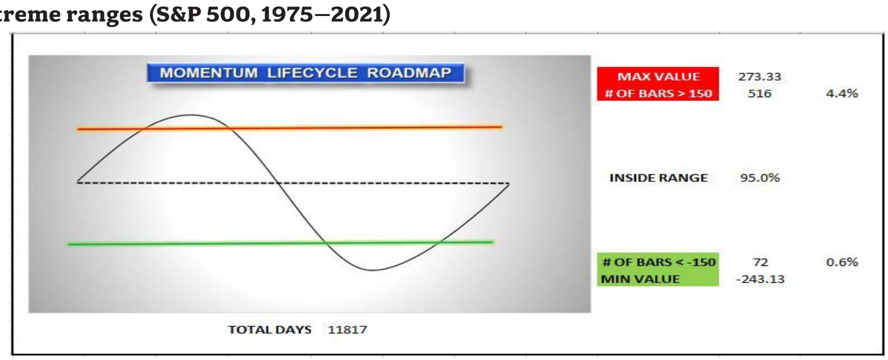


Table 7. MACD-V extreme ranges (Bund, 1991–2021)

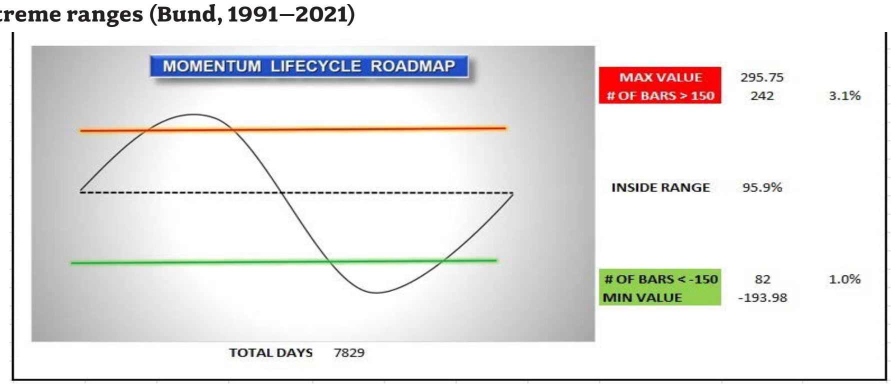
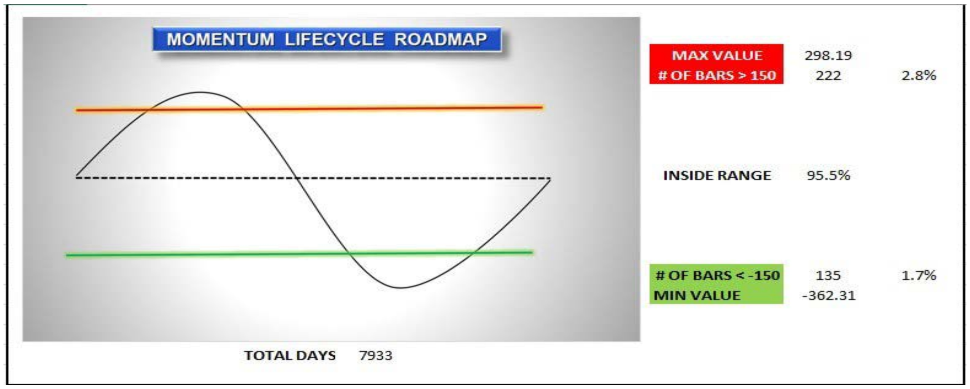


Table 8. MACD-V extreme ranges (natural gas, 1990–2021)



All three markets share similar exhaustion levels (when momentum is 1.5 times its volatility), despite the fact that they have completely different absolute volatilities in general. In addition, the min and max values differ for each market since the MACD-V is a boundless indicator and not constrained by a 0 to 100 scale.

MACD-V values are comparable across securities.

MACD-V Ranges

Since MACD-V readings are comparable across time and markets, that means that we can create a Momentum Lifecycle RoadMap that will rank both the momentum's direction ("bullish" or "bearish") and strength, as well as "low" vs. "high" momentum and "overbought" vs. "oversold". However, since the MACD-V is an unbounded indicator it will have the added advantage that it will not be limited by the scaling boundaries (0–100) of conventional oscillators and will avoid the problem of "pegging" at high levels.

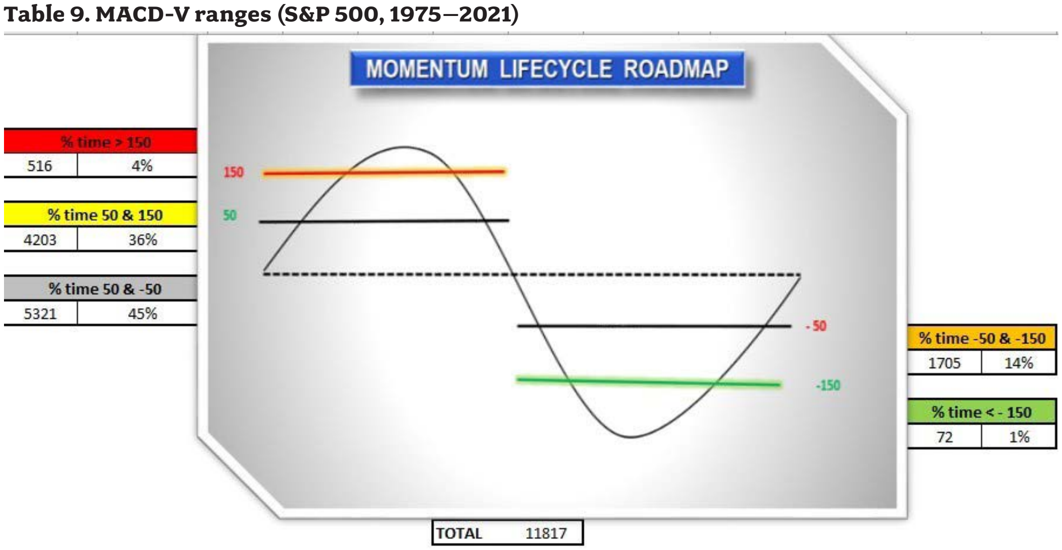
OBOS (Extreme) Momentum: When the market has advanced too far and too fast the EMA spread will have reached a point where historically it becomes unstainable to progress any further in the short to intermediate term. This should be around 5% of the data and is located when momentum is 1.5 or -1.5 times its volatility.

Strong (High) Momentum: When the market begins to gain some directional strength, then distance between the two EMAs (12 and 26) begins to increase as the shorter EMA is being driven away from the longer one and thus the MACD-V would move significantly away from the equilibrium line. This should be around 35%–40% of the data and is located when momentum is over +0.5 or -0.5 times its volatility.

Weak (Low) Momentum Range: When there is little directional conviction (low momentum), the MAs (12 and 26) should be relatively close and thus their spread (MACD-V) should be close to zero, the equilibrium line. This should be around 45%–50% of the data and is when momentum is between 0.5 or -0.5 times its volatility

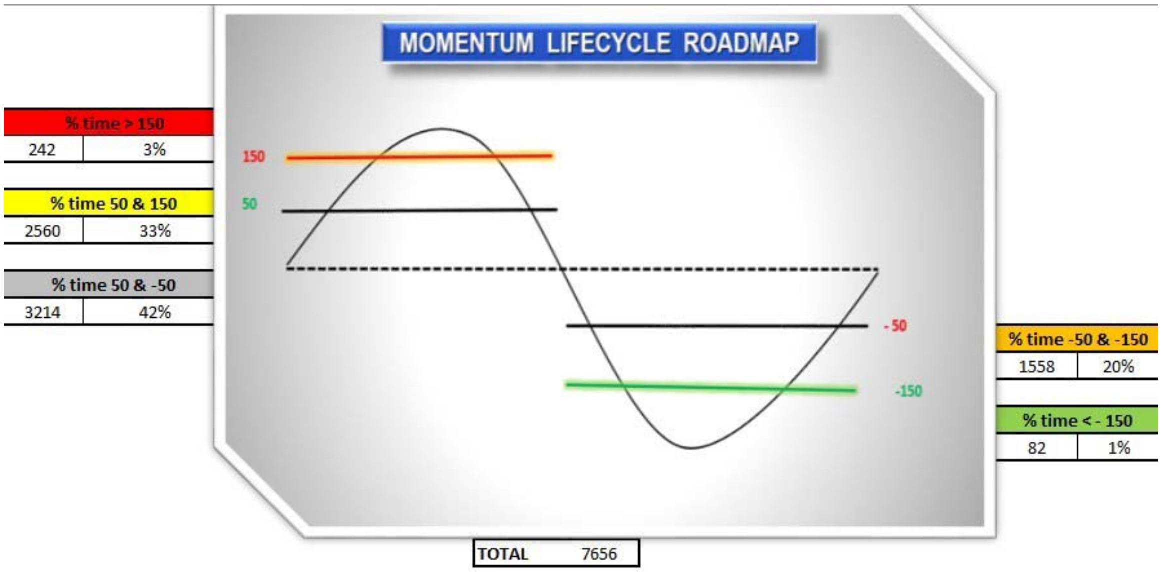
Based on this framework, we can test the objective momentum levels that would hold across securities using the MACD-V.

Table 9. MACD-V ranges (S&P 500, 1975–2021)



Using data since 1975 (11,817 days) for the S&P 500, we observe that the index has been above the overbought benchmark (>150) around 4% of the time and below the oversold level (-150) around -1% of the time, reflecting the "upward drift" (bullish bias) of the market. The time spent between the "neutral zone" that is close to the equilibrium line (50 to -50) is around 45% of the time. Finally, time spent on the strong momentum zone (50<x<150 and -150<x<-50) is respectively 36% and 14%, reflecting the bullish bias for the S&P 500.

Table 10. MACD-V ranges (Bund, 1991–2021)



Using data on the German Bund (a fixed income market with different volatility characteristics), we observe that the data that falls into the aforementioned brackets is roughly the same with the S&P 500.

Table 11. MACD-V ranges (natural gas, 1991–2021)

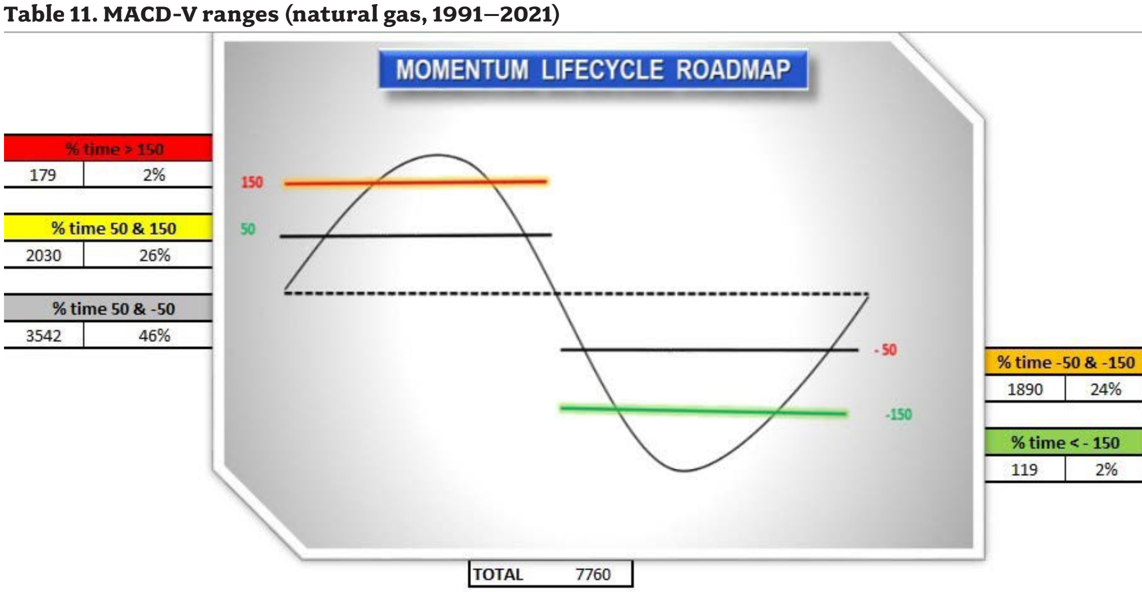


Table 11 reflects the data for natural gas, a market with completely different trend and volatility DNA. However, the data supports that again we have achieved a unified definition of "fast vs. slow" vs. "overbought/oversold" without having presented boundaries to the values that the indicators can have (e.g., RSI, etc.).

The extreme levels (>150 and <-150) capture roughly 5% of the data in the market again, while the "fast" range (50–150 and -50–-150) is around 50% of the data.

Based on this framework, we can test the objective momentum levels under different trend regimes and across markets.

Figure 11. MACD-V ranges and trend regime filter v.1

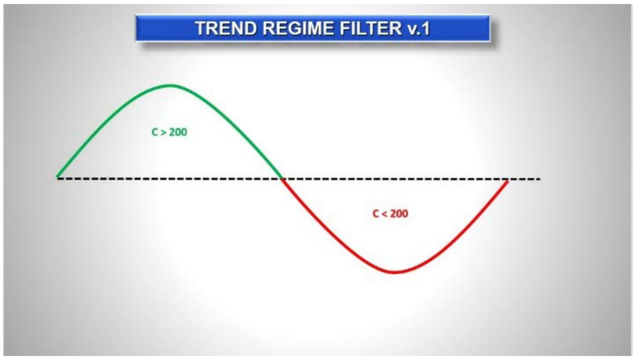


Table 12. MACD-V ranges and trend regime filter v.1 (S&P 500, 1975–2021)

% C > 200 EMA	9006	76%	of total time	% C < 200 EMA	2811	24%	of total time
% MACD-V > 150	516	**100%**	of total occurences	% MACD-V > 150	0	**0%**	of total occurences
% MACD-V 150 > x > 50	4021	45%	of the total time in this Stage	% MACD-V 150 > x > 50	182	6%	of the total time in this Stage
% MACD-V 50 > x > -50	4007	44%	of the total time in this Stage	% MACD-V 50 > x > -50	1314	47%	of the total time in this Stage
% MACD-V -50 > x > -150	462	**5%**	of the total time in this Stage	% MACD-V -50 > x > -150	1243	**44%**	of the total time in this Stage
% MACD-V < -150	0	**0%**	of total occurences	% MACD-V < -150	72	**100%**	of total occurences
% MACD-V x >- 100	8951	**99.4%**	of the total time in this Stage	% MACD-V x < 100	2806	**99.8%**	of the total time in this Stage

If we were to dissect the MACD-V data by a basic trend rule (above or below a 200 EMA), we would see that the S&P 500 stands above the EMA 76% of the time (i.e., having an "upward drift," bullish bias) and 24% below. Let's examine how the MACD-V behaves in each of these conditions. A similar concept (observation) has been suggested by Andrew Cardwell (RSI range rules). Thus, I will keep the same term (range rules) to study the behavior of the MACD-V.

All of the occurrences (100%) of the MACD-V reaching the overbought range have been recorded in the bullish stage and it has never reached the oversold level while over the 200 EMA. While in the bullish stage, **99.4%** of market action is contained with readings of the MACD-V > -100. If we observe the data more closely, 5% of the data on the downside are captured within the -50 to -150 range, thus becoming the "new" oversold level while the market stands above the 200 EMA. As long as the market stays above the 200 EMA, we would not expect it to fall below the – 100 range of the MACD-V.

Analogous behavior is observed on the bearish stage (< 200 EMA) as there are zero occurrences of the indicator reaching the overbought range (>150) and 100% readings of the oversold range. While in the bearish stage, 99.8% of market action is contained with readings of the MACD-V < 100, which is a quite similar number to the bulls (99.4%).

Thus, while the market is bearish (< 200 EMA) we would expect a maximum stretch until the MACD-V reaches the 100 level (bear market rally).

Table 13. MACD-V ranges and trend regime filter v.1 (Bund, 1991–2021)

% C > 200 EMA	5156	67%	of total time	% C < 200 EMA	2500	33%	of total time
% MACD-V > 150	242	**100%**	of total occurences	% MACD-V > 150	0	**0%**	of total occurences
% MACD-V 150 > x > 50	2384	46%	of the total time in this Stage	% MACD-V 150 > x > 50	176	7%	of the total time in this Stage
% MACD-V 50 > x > -50	2151	42%	of the total time in this Stage	% MACD-V 50 > x > -50	1063	43%	of the total time in this Stage
% MACD-V -50 > x > -150	379	**7%**	of the total time in this Stage	% MACD-V -50 > x > -150	1179	**47%**	of the total time in this Stage
% MACD-V < -150	0	**0%**	of total occurences	% MACD-V < -150	82	**100%**	of total occurences
% MACD-V x >- 100	5097	**98.9%**	of the total time in this Stage	% MACD-V x < 100	2496	**99.8%**	of the total time in this Stage

Table 13 displays the data for the Bund, a market with different trend characteristics (i.e., > 200 EMA 67% of the time vs. 76% of the time for the S&P 500) and certainly different volatility DNA. However, the same observations (range rules) can be made.

While the market is in the bullish stage (> 200 EMA), it has 100% of the occurrences of overbought readings (>150), 0% of the oversold readings (<-150), and **98.9%** of the data is captured by the >-100 level. Thus, similarly to the S&P 500, any bull market decline can be expected to stop at the -100 MACD-V level (if the market is to stay above the 200 EMA).

Symmetrically for the bearish stage, it has 100% of the occurrences of oversold readings (<-150), 0% of the overbought readings (>150), and **99.8%** of the data are captured by the <100 level. Thus, similarly to the S&P 500, any bear market rally can be reasonably expected to stop at the 100 MACD-V level (if the market is to stay below the 200 EMA).

Figure 12: Bund and cxtreme MACD-V readings (1994–2021)

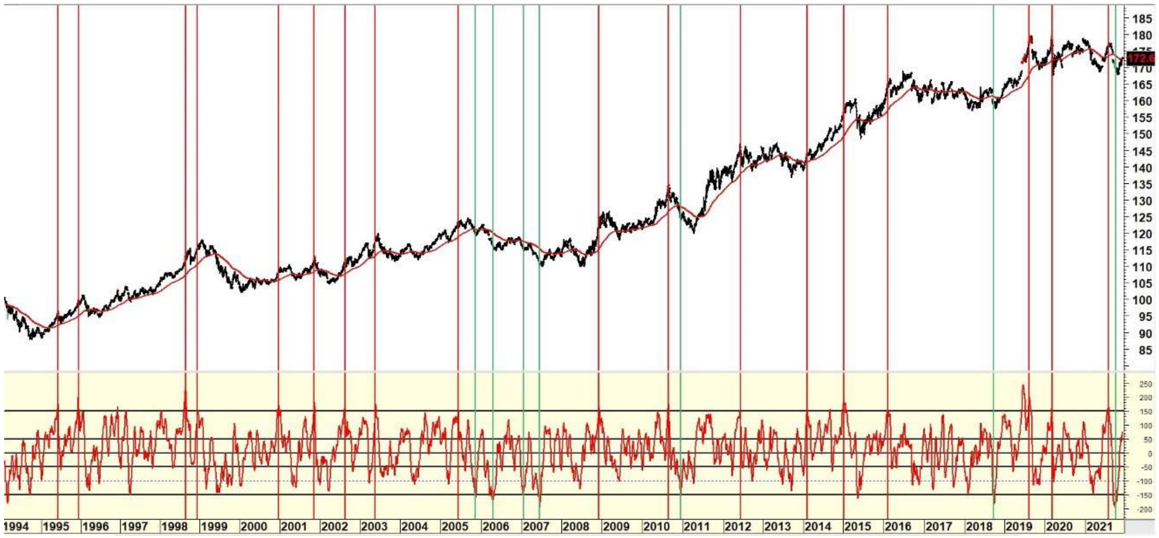


Table 14. MACD-V ranges and trend regime filter v.1 (natural gas, 1991–2021)

% C > 200 EMA	3878	50%	of total time
% MACD-V > 150	179	**100%**	of total occurences
% MACD-V 150 > x > 50	1835	47%	of the total time in this Stage
% MACD-V 50 > x > -50	1679	43%	of the total time in this Stage
% MACD-V -50 > x > -150	185	5%	of the total time in this Stage
% MACD-V < -150	0	**0%**	of total occurences
% MACD-V x >- 100	3869	**99.8%**	of the total time in this Stage

% C < 200 EMA	3882	50%	of total time
% MACD-V > 150	0	**0%**	of total occurences
% MACD-V 150 > x > 50	195	5%	of the total time in this Stage
% MACD-V 50 > x > -50	1863	48%	of the total time in this Stage
% MACD-V -50 > x > -150	1705	**44%**	of the total time in this Stage
% MACD-V < -150	119	**100%**	of total occurences
% MACD-V x < 100	3861	**99.5%**	of the total time in this Stage

The data for NG are even more compelling, as this market has completely different trend characteristics (spends an equal amount of time in bullish/bearish stages, each one is 50% of the data) and is considerably more volatile than the aforementioned ones. However, the exact same observations (range rules) can be made.

While the market is in the bullish stage (> 200 EMA), it has 100% of the occurrences of overbought readings (>150), 0% of the oversold readings (<-150), and **99.8%** of the data is captured by the >-100 level. Thus, similarly to the S&P 500, any bull market decline can be expected to stop at the -100 MACD-V level (if the market is to stay above the 200 EMA).

Symmetrically for the bearish stage, it has 100% of the occurrences of oversold readings (<-150), 0% of the overbought readings (>150), and **99.5%** of the data is captured by the < 100 level. Thus, similarly to the S&P 500, any bear market rally can be reasonably expected to stop at the 100 MACD-V level (if the market is to stay below the 200 EMA).

Figure 13. Natural gas and the bear market rallies (2014–2016)

MACD-V Ranges and Trend Regime Filter v.1 and Swing Filters

Another way to help study the data even further would be to create a swing line as an additional price filter and then observe where market tops and bottoms occur.

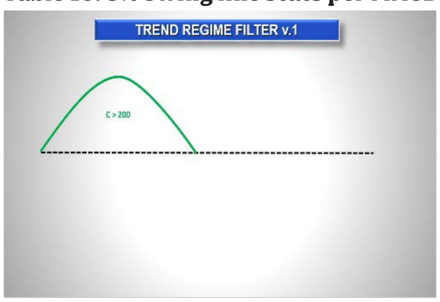
For the S&P 500, we will use a 3% swing line. Our personal preference for this type of filtering work is using swing based on ATR (not percents), but for this study we will use percentage calculations to keep things relatively simpler.

Table 15 records where these swing highs/lows are placed within the Trend Regime Filter v.1 . Since 1975, the S&P 500 has made 651 swings that had a magnitude of 3% or more. 233 swing highs were recorded in the bullish stage and 93 in the bearish stage.

Table 15. 3% Swing line stats per stage (S&P 500, 1975–2021)

We will provide more context to the total number of highs and lows per stage by relating them to the MACD-V.

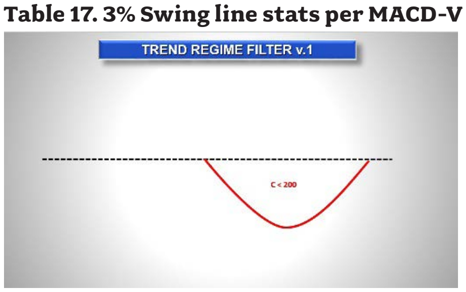
Table 16. 3% Swing line stats per MACD-V ranges (S&P 500, 1975–2021)



# of 3% SWING HIGHS	93	28.5%	of total occurences	# of 3% SWING LOWS	193	59.4%	of total occurences
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	10	10.8%	of the total time in this Stage	% MACD-V 150 > x > 50	5	2.6%	of the total time in this Stage
% MACD-V 50 > x > -50	39	41.9%	of the total time in this Stage	% MACD-V 50 > x > -50	58	30.1%	of the total time in this Stage
% MACD-V -50 > x > -150	38	40.9%	of the total time in this Stage	% MACD-V -50 > x > -150	116	60.1%	of the total time in this Stage
% MACD-V < -150	6	6.5%	of total occurences	% MACD-V < -150	14	7.3%	of total occurences
% MACD-V x < 100	92	98.9%	of the total time in this Stage	% MACD-V x < 100	193	100.0%	of the total time in this Stage

Table 16 sheds more light. When the market is in the bullish stage, almost **60%** of swing highs occur in the "Strong Momentum" Range (50 to 150) and almost all (**99.1%**) above the -100 range of the MACD-V. Similarly, **72%** of swing lows in the bullish stage occur in the weak momentum range (50 to -50), while almost all (**99.7%**) are above the -100 level for the MACD-V. This confirms the findings of tables 11–13 that should the market stay above the 200 EMA, then the "maximum" decline it can have should be around -100 of the MACD-V.

Table 17. 3% Swing line stats per MACD-V ranges (S&P 500, 1975–2021)

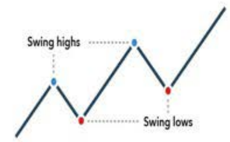


# of 3% SWING HIGHS	93	28.5%	of total occurences	# of 3% SWING LOWS	193	59.4%	of total occurences
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	10	10.8%	of the total time in this Stage	% MACD-V 150 > x > 50	5	2.6%	of the total time in this Stage
% MACD-V 50 > x > -50	39	41.9%	of the total time in this Stage	% MACD-V 50 > x > -50	58	30.1%	of the total time in this Stage
% MACD-V -50 > x > -150	38	40.9%	of the total time in this Stage	% MACD-V -50 > x > -150	116	60.1%	of the total time in this Stage
% MACD-V < -150	6	6.5%	of total occurences	% MACD-V < -150	14	7.3%	of total occurences
% MACD-V x < 100	92	98.9%	of the total time in this Stage	% MACD-V x < 100	193	100.0%	of the total time in this Stage

Table 16 shows the data for the bearish stage and they are analogous to the bulls.

Table 18. Trend regime filter v.1, swing line (1%), and MACD-V stats (Bund, 1991–2021)

407 1% SWINGS	204 SWING HIGHS	168 SWING HIGHS > 200 EMA
		36 SWING HIGHS < 200 EMA
	203 SWING LOWS	92 SWING LOWS > 200 EMA
		111 SWING LOWS < 200 EMA



% C > 200 EMA	5156	67.3%	of total time
% MACD-V > 150	242	**100.0%**	of total occurences
% MACD-V 150 > x > 50	2384	46.2%	of the total time in this Stage
% MACD-V 50 > x > -50	2151	41.7%	of the total time in this Stage
% MACD-V -50 > x > -150	379	**7.4%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x >- 100	5097	**98.9%**	of the total time in this Stage

# of 3% SWING HIGHS	168	82.4%	of total occurences	# of 3% SWING LOWS	92	45.3%	of total occurences
% MACD-V > 150	17	10.1%	of total occurences	% MACD-V > 150	1	1.1%	of total occurences
% MACD-V 150 > x > 50	94	56.0%	of the total time in this Stage	% MACD-V 150 > x > 50	23	25.0%	of the total time in this Stage
% MACD-V 50 > x > -50	46	27.4%	of the total time in this Stage	% MACD-V 50 > x > -50	52	**56.5%**	**of the total time in this Stage**
% MACD-V -50 > x > -150	11	6.5%	of the total time in this Stage	% MACD-V -50 > x > -150	16	17.4%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x >- 100	167	99.4%	of the total time in this Stage	% MACD-V x > -100	90	97.8%	of the total time in this Stage

% C < 200 EMA	2500	32.7%	of total time
% MACD-V > 150	0	**0.0%**	of total occurences
% MACD-V 150 > x > 50	176	7.0%	of the total time in this Stage
% MACD-V 50 > x > -50	1063	42.5%	of the total time in this Stage
% MACD-V -50 > x > -150	1179	**47.2%**	of the total time in this Stage
% MACD-V < -150	82	**100.0%**	of total occurences
% MACD-V x < 100	2496	**99.8%**	of the total time in this Stage

# of 3% SWING HIGHS	36	17.6%	of total occurences	# of 3% SWING LOWS	111	55%	of total occurences
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0%	of total occurences
% MACD-V 150 > x > 50	4	11.1%	of the total time in this Stage	% MACD-V 150 > x > 50	2	2%	of the total time in this Stage
% MACD-V 50 > x > -50	19	52.8%	of the total time in this Stage	% MACD-V 50 > x > -50	34	31%	of the total time in this Stage
% MACD-V -50 > x > -150	13	36.1%	of the total time in this Stage	% MACD-V -50 > x > -150	69	62%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	6	5%	of total occurences
% MACD-V x < 100	35	97.2%	of the total time in this Stage	% MACD-V x < 100	111	100%	of the total time in this Stage

To study the Bund, we will use a 1% swing line since the volatility for fixed income markets is considerably less than for their equity counterparts. However, the results are very similar to the ones presented for the S&P 500. The range rules for one market are applicable across other markets as well.

Table 19. Trend regime filter v.1, swing line (5%), and MACD-V stats (NG, 1991–2021)

% C > 200 EMA	3878	50%	of total time
% MACD-V > 150	179	**100%**	of total occurences
% MACD-V 150 > x > 50	1835	47%	of the total time in this Stage
% MACD-V 50 > x > -50	1679	43%	of the total time in this Stage
% MACD-V -50 > x > -150	185	**5%**	of the total time in this Stage
% MACD-V < -150	0	**0%**	of total occurences
% MACD-V x >- 100	3869	**99.8%**	of the total time in this Stage

# of 3% SWING HIGHS	281	61%	of total occurences	# of 3% SWING LOWS	160	35%	of total occurences
% MACD-V > 150	28	10%	of total occurences	% MACD-V > 150	7	4%	of total occurences
% MACD-V 150 > x > 50	147	52%	of the total time in this Stage	% MACD-V 150 > x > 50	76	48%	of the total time in this Stage
% MACD-V 50 > x > -50	94	33%	of the total time in this Stage	% MACD-V 50 > x > -50	66	**41%**	**of the total time in this Stage**
% MACD-V -50 > x > -150	12	4%	of the total time in this Stage	% MACD-V -50 > x > -150	11	7%	of the total time in this Stage
% MACD-V < -150	0	0%	of total occurences	% MACD-V < -150	0	0%	of total occurences
% MACD-V x >- 100	281	100%	of the total time in this Stage	% MACD-V x >- 100	160	100%	of the total time in this Stage

% C < 200 EMA	3882	50.0%	of total time
% MACD-V > 150	0	**0.0%**	of total occurences
% MACD-V 150 > x > 50	195	5.0%	of the total time in this Stage
% MACD-V 50 > x > -50	1863	48.0%	of the total time in this Stage
% MACD-V -50 > x > -150	1705	**43.9%**	of the total time in this Stage
% MACD-V < -150	119	**100.0%**	of total occurences
% MACD-V x < 100	3861	**99.5%**	of the total time in this Stage

# of 3% SWING HIGHS	179	38.9%	of total occurences	# of 3% SWING LOWS	301.0	65%	of total occurences
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0.0	0%	of total occurences
% MACD-V 150 > x > 50	11	6.1%	of the total time in this Stage	% MACD-V 150 > x > 50	13.0	4%	of the total time in this Stage
% MACD-V 50 > x > -50	95	53.1%	of the total time in this Stage	% MACD-V 50 > x > -50	125.0	42%	of the total time in this Stage
% MACD-V -50 > x > -150	71	39.7%	of the total time in this Stage	% MACD-V -50 > x > -150	154.0	51%	of the total time in this Stage
% MACD-V < -150	2	1.1%	of total occurences	% MACD-V < -150	9.0	3%	of total occurences
% MACD-V x < 100	176	98.3%	of the total time in this Stage	% MACD-V x < 100	301.0	100%	of the total time in this Stage

In order to complete our cross-market validation, we will present the same study for natural gas. The difference is with the swing line again. In this instance, we employ a 5% swing filter in order to deal with the elevated inherent volatility of this market.

The rest of the data leads to the same results, which we will leave to the reader to validate and explore further.

MACD-V Ranges and Trend Regime Filter v.2

The numbers in tables 11–13 could be more insightful by using a more detailed Trend Regime Filter. The rules for Trend Regime Filter v.2 (Figure 14) were created, to our knowledge, by Chuck Dukas.3 We will examine the bullish stages (1,2,3).

The swing line percentages will remain the same for each market.

Figure 13. MACD-V ranges and trend regime filter v.2

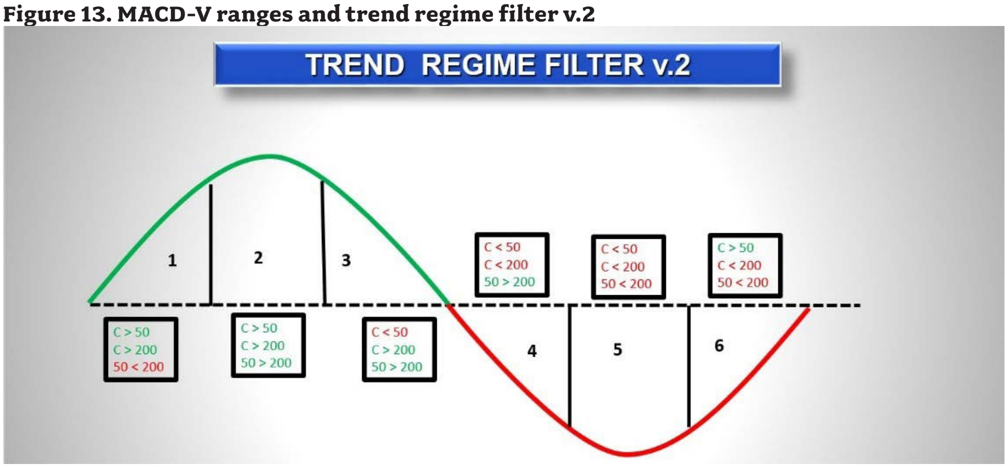


Table 20. MACD-V ranges and trend regime filter v.2, stage 2 (S&P 500, 1975—2021)

% C > 50 EMA > 200 EMA	6894	58.3%	of total time
% MACD-V > 150	507	**98.3%**	of total occurences
% MACD-V 150 > x > 50	3695	53.6%	of the total time in this Stage
% MACD-V 50 > x > -50	2675	38.8%	of the total time in this Stage
% MACD-V -50 > x > -150	17	**0.2%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -50	6877	**99.8%**	of the total time in this Stage

These are the relevant numbers for the S&P 500 in Stage 2 (i.e., C >50>200). This time the maximum downside stretch of the MACD-V is **-50**, as the range 150 to -50 contains **99.8%** of the data.

Thus, if one thinks that on any pullback the market will not break the 50 EMA, then any dive that would cause the MACD-V > -50 would provide a definition of a stage-specific oversold level.

Table 21. MACD-V ranges, trend regime filter v.2 (stage 2), and 3% swings (S&P 500, 1975—2021)

# of 3% SWING HIGHS	203	87.1%	of total occurences in this Stage	# of 3% SWING LOWS	29	22.0%	of total occurences in this Stage
% MACD-V > 150	19	9.4%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	121	59.6%	of the total time in this Stage	% MACD-V 150 > x > 50	17	58.6%	of the total time in this Stage
% MACD-V 50 > x > -50	62	30.5%	of the total time in this Stage	% MACD-V 50 > x > -50	12	41.4%	of the total time in this Stage
% MACD-V -50 > x > -150	1	0.5%	of the total time in this Stage	% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	202	99.5%	of the total time in this Stage	% MACD-V x > -50	29	100.0%	of the total time in this Stage

The table above shows that out of the 233 swing highs above the 200 EMA, **87.1%** of these (203) have occurred in Stage 2 (C > 50 EMA > 200 EMA). The vast majority of these (**59.6%**) were in the 50—150 range of the MACD-V, while around 10% occurred while in the overbought range. Almost all of the highs (**99.5%**) were over the -50 range of the MACD-V.

Turning our attention to swing lows in Stage 2, these are really rare events as we have seen 29 occurrences in the past 46 years. 100% of these were over the -50 range of the MACD-V.

It would seem that if one expects a larger than 3% correction that would not extend below the 200 EMA, then the odds greatly favour that the S&P 500 would breach the 50 EMA (Stage 3) and the MACD-V to be in the -50 to -50 range (or -50 to -100 in the case of stronger corrections).

Table 22. MACD-V ranges and trend regime filter v.2, stage 3 (S&P 500, 1975—2021)

% 50 EMA > C > 200 EMA	**1646**	13.9%	of total time
% MACD-V > 150	0	**0.0%**	of total occurences
% MACD-V 150 > x > 50	10	0.6%	of the total time in this Stage
% MACD-V 50 > x > -50	1191	72.4%	of the total time in this Stage
% MACD-V -50 > x > -150	445	**27.0%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -100	1591	**96.7%**	of the total time in this Stage

When the market has progressed into Stage 3, the vast majority of times (**72.4%**) the MACD-V is in the neutral range (50 to -50). In quite rare occurrences we may have a dip below the -100 level, but it would be an exception as **96.7%** of the values in the stage are above that.

Table 23. MACD-V ranges, trend regime filter v.2 (stage 3), and 3% swings (S&P 500, 1975—2021)

# of 3% SWING HIGHS	11	4.7%	of total occurences in this Stage	# of 3% SWING LOWS	101	76.5%	of total occurences in this Stage
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	0	0.0%	of the total time in this Stage	% MACD-V 150 > x > 50	3	3.0%	of the total time in this Stage
% MACD-V 50 > x > -50	5	45.5%	of the total time in this Stage	% MACD-V 50 > x > -50	**83**	**82.2%**	of the total time in this Stage
% MACD-V -50 > x > -150	6	54.5%	of the total time in this Stage	% MACD-V -50 > x > -150	15	14.9%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -100	9	81.8%	of the total time in this Stage	% MACD-V x > -100	98	97.0%	of the total time in this Stage

When the market has slid below the 50 EMA, in the vast majority of cases, the reversal swings associated in the stage are lows (101) vs. highs (11). A notable statistic is that **82.2%** of the swing lows that occur in this stage are in the "neutral zone" of 50 to -50 and a few extend to the -50 to -150 range. In total, **97%** of swing lows in Stage 3 occur over the -100 range of the MACD-V.

Thus, pullbacks into this stage could end in the aforementioned ranges for a possible resumption of the trend.

Table 24. MACD-V ranges and trend regime filter v.2, stage 1 (S&P 500, 1975–2021)

% C > 200 EMA > 50 EMA	465	3.9%	of total time
% MACD-V > 150	9	1.7%	of total occurences
% MACD-V 150 > x > 50	316	68.0%	of the total time in this Stage
% MACD-V 50 > x > -50	140	30.1%	of the total time in this Stage
% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	465	100.0%	of the total time in this Stage

Stage 1 does not occur very often or rather does not register for long. It is usually an explosive move to the upside coming off of a low. Hence, it is the only stage (except 2) that manages to drive the market into the overbought zone (>150). In the vast majority of cases, the market is in the "fast" range of the MACD-V (50 to 150) and in **100%** of the cases the MACD-V stays above -50

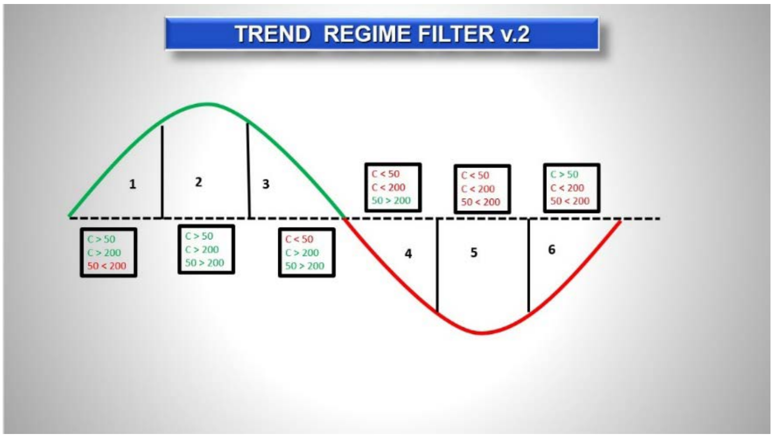
Table 25. MACD-V ranges, trend regime filter v.2 (stage 1), and 3% swings (S&P 500, 1975–2021)

# of 3% SWING HIGHS	19	8.2%	of total occurences in this Stage	# of 3% SWING LOWS	2	1.5%	of total occurences in this Stage
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	14	73.7%	of the total time in this Stage	% MACD-V 150 > x > 50	2	100.0%	of the total time in this Stage
% MACD-V 50 > x > -50	5	26.3%	of the total time in this Stage	% MACD-V 50 > x > -50	0	0.0%	of the total time in this Stage
% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage	% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	19	100.0%	of the total time in this Stage	% MACD-V x > -50	2	100.0%	of the total time in this Stage

There aren't many reversals (swings) occurring in this stage and **almost all** are high (19) vs. lows (2) in the 46-year history of the data. Notable stats are that these aforementioned highs occur in the 50 to 150 range of the MACD-V (73.7% of the occurrences).

Note: The following pages will display the same studies for the Bund and natural gas markets. They exhibit similar behavior thus we will leave it up to the readers to dive deeper into the data without our commentary. Please note that we used a 1% swing line for the Bund and a 5% swing line for natural gas to account for different volatility levels. Moreover, in our private work we use ATR-based swing lines and more sophisticated Trend Regime Filters.

Table 26. Trend regime filter v.2 Key statistics (Bund, 1991–2021)



% C > 50 EMA > 200 EMA	3647	47.6%	of total time
% MACD-V > 150	237	**97.9%**	of total occurences
% MACD-V 150 > x > 50	2075	56.9%	of the total time in this Stage
% MACD-V 50 > x > -50	1322	36.2%	of the total time in this Stage
% MACD-V -50 > x > -150	13	**0.4%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -50	3634	**99.6%**	of the total time in this Stage

# of 3% SWING HIGHS	137	81.5%	of total occurences in this Stage	# of 3% SWING LOWS	30	32.6%	of total occurences in this Stage
% MACD-V > 150	17	12.4%	of total occurences	% MACD-V > 150	1	3.3%	of total occurences
% MACD-V 150 > x > 50	78	56.9%	of the total time in this Stage	% MACD-V 150 > x > 50	19	63.3%	of the total time in this Stage
% MACD-V 50 > x > -50	39	28.5%	of the total time in this Stage	% MACD-V 50 > x > -50	10	33.3%	of the total time in this Stage
% MACD-V -50 > x > -150	3	2.2%	of the total time in this Stage	% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	134	97.8%	of the total time in this Stage	% MACD-V x > -50	30	100.0%	of the total time in this Stage

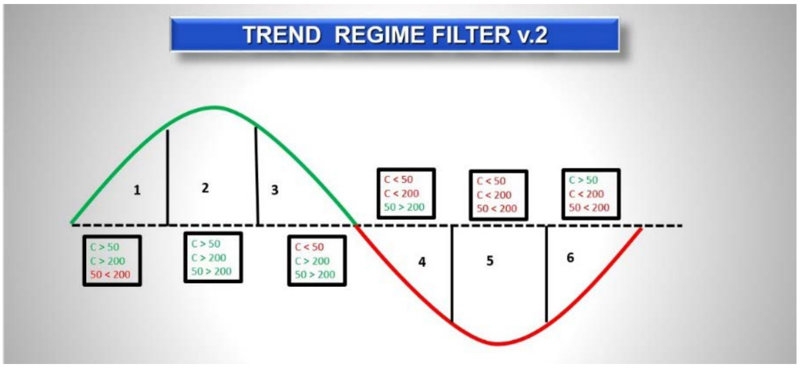
% 50 EMA > C > 200 EMA	1019	13.3%	of total time
% MACD-V > 150	0	**0.0%**	of total occurences
% MACD-V 150 > x > 50	12	1.2%	of the total time in this Stage
% MACD-V 50 > x > -50	641	62.9%	of the total time in this Stage
% MACD-V -50 > x > -150	366	**35.9%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -100	960	**94.2%**	of the total time in this Stage

# of 3% SWING HIGHS	11	6.5%	of total occurences in this Stage	# of 3% SWING LOWS	61	66.3%	of total occurences in this Stage
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	0	0.0%	of the total time in this Stage	% MACD-V 150 > x > 50	3	4.9%	of the total time in this Stage
% MACD-V 50 > x > -50	3	27.3%	of the total time in this Stage	% MACD-V 50 > x > -50	**42**	**68.9%**	of the total time in this Stage
% MACD-V -50 > x > -150	8	72.7%	of the total time in this Stage	% MACD-V -50 > x > -150	16	26.2%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -100	10	90.9%	of the total time in this Stage	% MACD-V x > -100	59	96.7%	of the total time in this Stage

% C > 200 EMA > 50 EMA	490	6.4%	of total time
% MACD-V > 150	5	**2.1%**	of total occurences
% MACD-V 150 > x > 50	297	60.6%	of the total time in this Stage
% MACD-V 50 > x > -50	188	38.4%	of the total time in this Stage
% MACD-V -50 > x > -150	0	**0.0%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -50	490	**100.0%**	of the total time in this Stage

# of 3% SWING HIGHS	20	11.9%	of total occurences in this Stage	# of 3% SWING LOWS	1	1.1%	of total occurences in this Stage
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	16	80.0%	of the total time in this Stage	% MACD-V 150 > x > 50	1	100.0%	of the total time in this Stage
% MACD-V 50 > x > -50	4	20.0%	of the total time in this Stage	% MACD-V 50 > x > -50	**0**	**0.0%**	**of the total time in this Stage**
% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage	% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	20	100.0%	of the total time in this Stage	% MACD-V x > -50	1	100.0%	of the total time in this Stage

Table 27. Trend regime filter v.2 key statistics (natural gas, 1991–2021)



% C > 50 EMA > 200 EMA	2405	31.0%	of total time
% MACD-V > 150	148	**82.7%**	of total occurences
% MACD-V 150 > x > 50	1393	57.9%	of the total time in this Stage
% MACD-V 50 > x > -50	860	35.8%	of the total time in this Stage
% MACD-V -50 > x > -150	4	**0.2%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -50	2401	**99.8%**	of the total time in this Stage

# of 3% SWING HIGHS	188	66.9%	of total occurences in this Stage	# of 3% SWING LOWS	77	48.1%	of total occurences in this Stage
% MACD-V > 150	25	13.3%	of total occurences	% MACD-V > 150	5	6.5%	of total occurences
% MACD-V 150 > x > 50	100	53.2%	of the total time in this Stage	% MACD-V 150 > x > 50	62	80.5%	of the total time in this Stage
% MACD-V 50 > x > -50	61	32.4%	of the total time in this Stage	% MACD-V 50 > x > -50	10	13.0%	of the total time in this Stage
% MACD-V -50 > x > -150	2	1.1%	of the total time in this Stage	% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	186	98.9%	of the total time in this Stage	% MACD-V x > -50	77	100.0%	of the total time in this Stage

% 50 EMA > C > 200 EMA	803	10.3%	of total time
% MACD-V > 150	0	**0.0%**	of total occurences
% MACD-V 150 > x > 50	6	0.7%	of the total time in this Stage
% MACD-V 50 > x > -50	616	76.7%	of the total time in this Stage
% MACD-V -50 > x > -150	181	**22.5%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -100	794	**98.9%**	of the total time in this Stage

# of 3% SWING HIGHS	25	8.9%	of total occurences in this Stage	# of 3% SWING LOWS	68	42.5%	of total occurences in this Stage
% MACD-V > 150	0	0.0%	of total occurences	% MACD-V > 150	0	0.0%	of total occurences
% MACD-V 150 > x > 50	0	0.0%	of the total time in this Stage	% MACD-V 150 > x > 50	2	2.9%	of the total time in this Stage
% MACD-V 50 > x > -50	15	60.0%	of the total time in this Stage	% MACD-V 50 > x > -50	55	**80.9%**	of the total time in this Stage
% MACD-V -50 > x > -150	10	40.0%	of the total time in this Stage	% MACD-V -50 > x > -150	11	16.2%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -100	25	100.0%	of the total time in this Stage	% MACD-V x > -100	68	100.0%	of the total time in this Stage

% C > 200 EMA > 50 EMA	670	8.6%	of total time
% MACD-V > 150	31	**17.3%**	of total occurences
% MACD-V 150 > x > 50	436	65.1%	of the total time in this Stage
% MACD-V 50 > x > -50	203	30.3%	of the total time in this Stage
% MACD-V -50 > x > -150	0	**0.0%**	of the total time in this Stage
% MACD-V < -150	0	**0.0%**	of total occurences
% MACD-V x > -50	670	**100.0%**	of the total time in this Stage

# of 3% SWING HIGHS	68	24.2%	of total occurences in this Stage	# of 3% SWING LOWS	15	9.4%	of total occurences in this Stage
% MACD-V > 150	3	4.4%	of total occurences	% MACD-V > 150	2	13.3%	of total occurences
% MACD-V 150 > x > 50	47	69.1%	of the total time in this Stage	% MACD-V 150 > x > 50	12	80.0%	of the total time in this Stage
% MACD-V 50 > x > -50	18	26.5%	of the total time in this Stage	% MACD-V 50 > x > -50	**1**	**6.7%**	**of the total time in this Stage**
% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage	% MACD-V -50 > x > -150	0	0.0%	of the total time in this Stage
% MACD-V < -150	0	0.0%	of total occurences	% MACD-V < -150	0	0.0%	of total occurences
% MACD-V x > -50	68	100.0%	of the total time in this Stage	% MACD-V x > -50	15	100.0%	of the total time in this Stage

MACD-V Momentum Lifecycle RoadMap

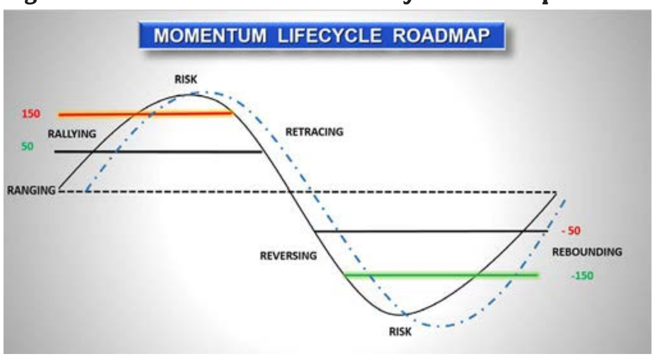
At this stage we can introduce the signal line (9 period EMA of the MACD line), as it is the tool that signals changes in momentum. The signal line is guaranteed to highlight momentum shifts, but its lagging nature does so at the expense of accuracy and timing sometimes (please refer to "Limitation 4: Signal Line Accuracy" and "Limitation 5: Signal Line Timing"). Thus, we chose to replace it with another tool that deals (to some extent) with the aforementioned issues. However, we made a conscious choice not to present the modifications we have made on the signal line and just focus on the MACD line, as the length of this paper would increase significantly. Therefore, henceforth any mention of the signal line assumes that we would use the 9 period EMA.

Table 28 presents the ranges and how the MACD-V line relates to the signal line. There are in total eight ranges that the MACD-V can take, which of course can be easily programmed in any language of your choice (Python, AmiBroker AFL, etc.).

Table 28. MACD-V and signal line combinations

RANGE	ABOVE SIGNAL LINE	BELOW SIGNAL LINE
> 150	Risk	
50 < x < 150	Rallying	Retracing (in price or time)
-50 < x < 50	Ranging	Ranging
-150 < x < -50	Rebounding	Reversing
-150 <	Risk	

Figure 15. MACD-V momentum lifecycle roadmap



This opens up new and unexplored opportunities to use the MACD. Up until today, the MACD could be used in two ways: either above/below the signal line and/or above/below the 0-line. The MACD-V now presents us with eight different scenarios to explore and of course these are multiplied in the case of cross asset comparisons.

MACD-VH: Volatility Normalised Histogram

Further to the MACD, Thomas Aspray in 1986 created the MACD Histogram, which is constructed as follows:

MACD Histogram = Signal Line – MACD Line.

Since the MACD line has now been normalized, similar properties should also be shared by the 4th derivative of price, the MACD-V Histogram (MACD-VH). That means that it is possible to detect indicator levels which are associated with short term extreme price levels. This is a unique property of the MACD-VH, as thus far the applications of the MACD Histogram were confined to comparisons of the height of each bar of the histogram relative to the preceding ones (higher vs. lower) and not relative to the absolute level that each bar has.

It appears that when the MACD-VH is above 40 (or below –40) that would imply that the market is mildly stretched to the upside (downside).

Figure 16. MACD-VH Momentum Lifecycle RoadMap

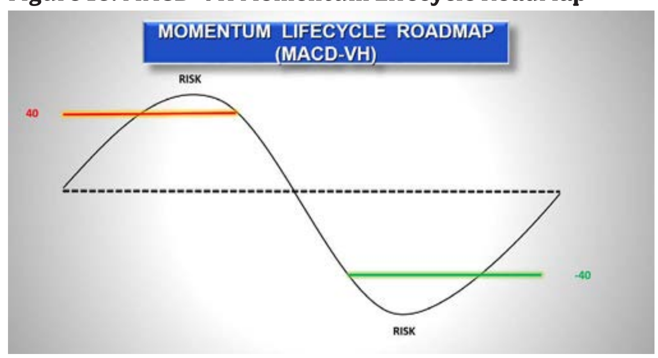


Table 29. MACD-VH Extreme Levels for Three Markets

	S&P 500		NATURAL GAS		BUND	
% time > 40	349	3%	296	4%	196	3%
% time < - 40	502	4%	250	3%	346	5%

Figure 17. MACD-VH Mildly Overbought/Oversold (>40, <-40) (FTSE 100, 2014–2015)

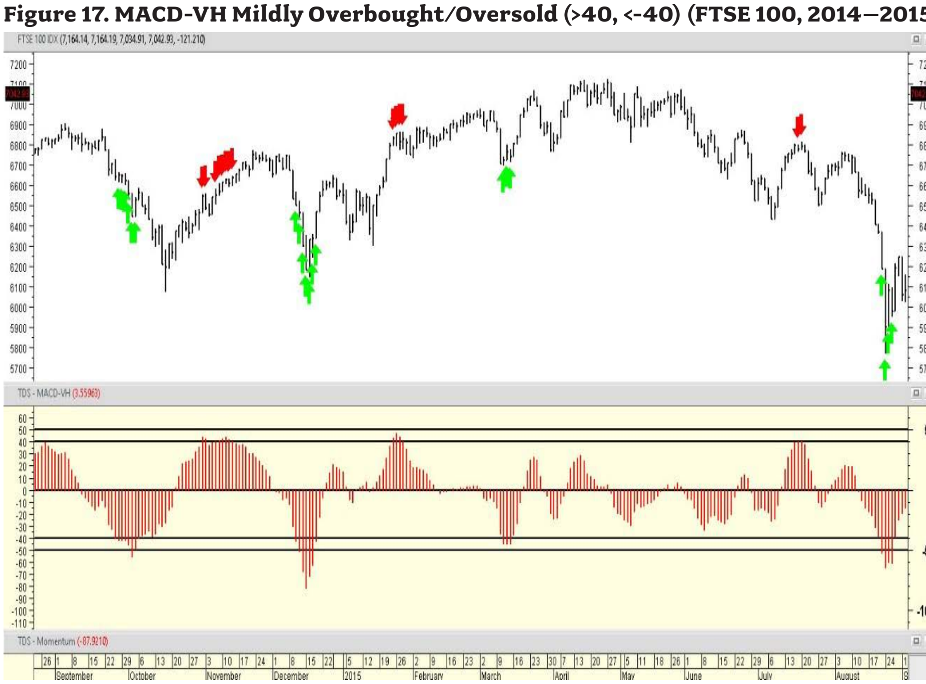
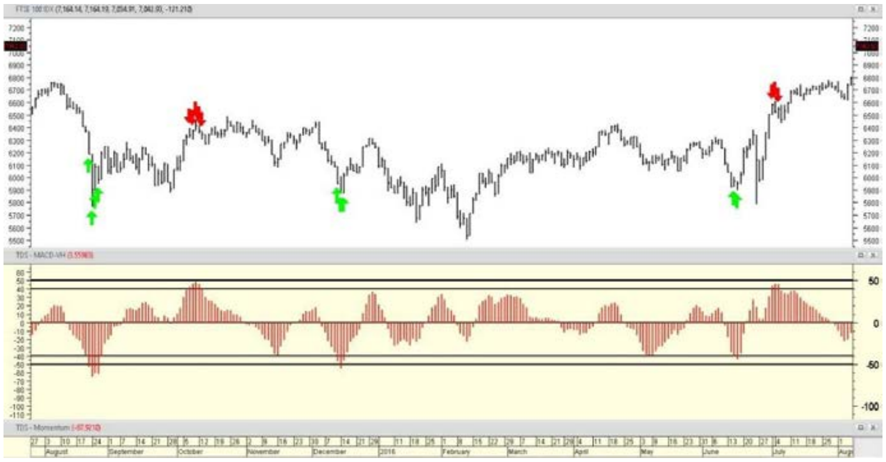


Figure 18. MACD-VH mildly overbought/oversold (>40, <-40) (FTSE 100, 2015–2016)



Teaching New Tricks to Old "Tools"

At the final part of the paper, I would like to apply the concept of volatility normalization to other well-known indicators, thus expanding their informational value.

LBR 3/10 Oscillator "Sardine"[4]

The first tool would be the LBR 3/10 oscillator by the esteemed trader Linda Bradford Raschke. Linda has publically disclosed many trading setups using this tool ("Anti" setup, divergences, new momentum highs/lows). The oscillator is a MACD(3,10), thus it would be easy to create range rules for this indicator as well. The new formula would be:

[EMA(3,C) – EMA(10,C)] / ATR(10).

The data in table 30 behaves in a similar fashion as do the MACD-V and MACD-VH.

Figure 19. LBR 3/10 oscillator & 100/125, -100/-125 levels (S&P 500)

Table 30. LBR 3/10 oscillator extreme levels for three markets

S&P 500		NATURAL GAS		BUND	
% time > 125		% time > 125		% time > 125	
431	4%	220	3%	197	3%
% time < - 125		% time < - 125		% time < - 125	
187	2%	150	2%	151	2%

Alex Elder Impulse "Plus" System

The "Elder Impulse System" was designed by Alexander Elder.[5] The system, according to its creator, *"identifies inflection points where a trend speeds up or slows down."*

The price bars are color coded as follows:

- Green: EMA(13,C) > previous (EMA(13,C) and (MACD-H> previous MACD-H)
- Red: EMA(13,C) < previous (EMA(13,C) and (MACD-H< previous MACD-H)
- Blue: In all other cases

In this particular case, additional rules could be added so as to warn the trader when the market has been overstretched in the short term. Thus, the rules could look like:

Green: EMA(13,C) > previous (EMA(13,C) and (MACD-VH> previous MACD-VH)

Red: EMA(13,C) > previous (EMA(13,C) and (MACD-VH> previous MACD-VH) and MACD-VH > 40

Blue: In all other cases

Red: EMA(13,C) < previous (EMA(13,C) and (MACD-VH< previous MACD-VH)

Green: EMA(13,C) < previous (EMA(13,C) and (MACD-VH< previous MACD-VH) and MACD-VH < - 40

Blue: In all other cases

There are certainly more possibilities to explore, but the point is to exhibit the additional value that volatility normalized momentum presents to the existing toolset.

Chuck Dukas Diamond "Refined"

Figure 13 presented in brief the rules for the "Chuck Dukas Diamond," a trend classification system. Using volatility normalization, this can be improved in a few ways.

One possible solution to "refine" the diamond would be the following:

1. Each of the EMAs would be expressed as a MACD-V—i.e., the 50 EMA would be MACD-V(1,50), the 200 EMA would be MACD-V(1,200), and the 50 EMA/200 EMA crossover rules would be MACD-V(50,200).
2. Create extreme levels for each of the MACD-Vs—i.e., for the MACD-V(1,50) we would use +/- 4, for the MACD-V(1,200) we would use +/- 8, and for the MACD-V(50,200) we would use +/-5.
3. Create a weighted condition scoring system that would serve as a warning for overbought/oversold conditions within each of the six stages— i.e., MACD-V(1,50) > 4, 1 point; MACD-V(1,200) > 8, 2 points; and MACD-V(50,200) > 5, 3 points.

In addition to an OBOS warning system, another possible solution would be then to use the readings of the MACD-V(50,200) as a relative strength ranking tool for the universe of the markets classified by the system. Thus, one would not just classify securities in a stage, but also within that stage. The higher (lower) the reading, the stronger (weaker) the market would be.

The 70 & 77 System (Strong Momentum Range Rules)

As mentioned in "Momentum Lifecycle RoadMap," the MACD-V Momentum Lifecycle RoadMap opens up opportunities that would not exist with the simple MACD.

One simple example would be to filter buy signals when a market enters high in the strong momentum range. The following equity curve was created by buying one DAX futures contract (long only) when the MACD-V is above 70 (market entry order) and selling at target exit of 2.85% (next bar limit) or after 15 days if in profit (but the target exit had not been reached) or after 77 days if neither of these conditions held true. (€25 per roundtrip trade were deducted for slippage and commissions.)

Figure 20. 70 & 77 System equity curve (DAX, 1991–2021)

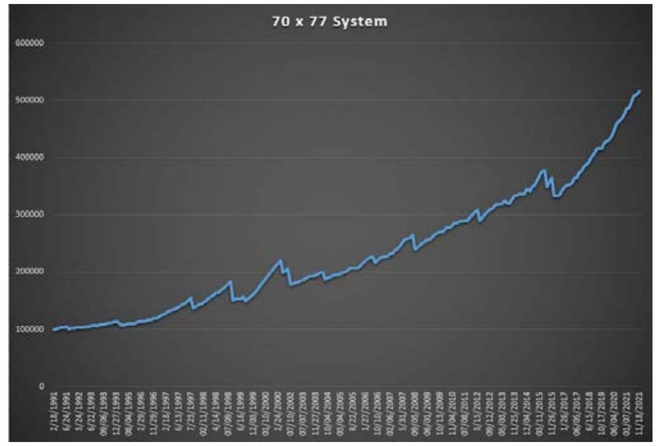


Table 31. 70 & 77 System key stats (DAX, 1991–2021)

Starting Account	€ 100,000
Closed Trade Net Profit	€ 410,370.5
Profit Factor	2.58
Closed Trades	234
Winning	201
Losing	33
% Profitable	85.90%
Worst Drawdown	32.79%

Of the 201 profitable trades, 95 trades managed to reach their target exit price (77.23% of all winning trades). Of course this is not a tradeable system on its own, but serves as inspiration for further strategy idea development.

Epilogue

This paper is the definition of "standing on the shoulders of giants," as it would not have been possible without the knowledge shared by esteemed technicians past and present. I sincerely hope that we have added a small brick on the huge wall of the Body of Knowledge of Technical Analysis.

Notes

[1] Gerald Appel, "Technical Analysis: Power tools for active investors," FT Press; Reprint edition (21 Mar. 2005).

[2] Tom Demark, "The New Science of Technical Analysis," Wiley; 1st edition (10 Dec. 2007).

[3] Chuck Dukas, "The TrendAdvisor Guide to Breakthrough profits," John Wiley & Sons; 1st edition (16 Mar. 2006).

[4] Linda Raschke, "Trading Sardines," Self-published (2018).

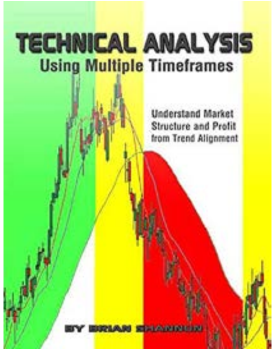
[5] Alex Elder, "Come Into My Trading Room," Wiley; 1st edition (16 May 2002).

Acknowledgements

This research paper is dedicated to my wife and parents and in memory of Gerald Appel (June 2, 1933–February 13, 2020).

Technical Analysis Using Multiple Timeframes *by Brian Shannon*

Reviewed by Regina Meani, CFTe



Brian Shannon's Preface focuses on the passions in our life and questions whether we are passionate enough about the markets. He expresses this as the *mental challenge and the sense of satisfaction … knowing that I have attained success on my own terms.*[1] It is Shannon's passion that fills this book with a goal to help us understand and be able to recognize market structure, and from there, to discover our own trading edge. An edge that will allow us to identify low-risk, high-profit trades with a planned risk management strategy.

Chapter 1 deals with technical analysis and examines whether it works. Shannon, from his observations, concludes that it does work and that *the market speaks the language of supply and demand, and that message is broadcast on price charts.*[2]

In Chapters 2 through to 6, Shannon outlines the four stages for stocks, which he terms Accumulation, Markup, Distribution, and Decline. These stages are present in all timeframes, and he believes that the ability to recognize them allows one to keep our analysis unbiased and objective.

The author uses very clear and simple language with pertinent examples to explain the concepts of support and resistance, trend following, volume, and the use of moving averages. He suggests that support and resistance may help us to uncover potential turning points, but he goes further to propose that they help us to objectively work out conceivable risk/reward ratios.

Volume is dealt with in Chapter 9, and Shannon believes that after price, it is the next most important analysis to add. It allows us a window into market psychology as a measure of the emotional intensity level of the market participants.

We are introduced to "trend alignment" in Chapter 11. The concept deals with the use of multiple timeframes to analyze the risk/reward relationship. He looks at how short-term traders and longer term investors hold different objectives and views of the value for an entity and how quickly that value may change—hence, the need for trends in multiple timeframes. We are provided with the example of when a short-term trader may well be best served by entering a position when the short-term trend confirms the longer term trend. *Regardless of whether you are an investor, swing trader or day trader, a minimum of three timeframes should be studied before you commit capital to a trade.*[3]

The last chapters take a look at stock selection both from the long and short side, how to integrate news and fundamentals, and most importantly, risk management techniques. Shannon gives us a guide to the different types of stop losses and where to place them with chart examples. Finally, we end up with some *Trading tips and truisms to think about*[4] and how to plan our trades and put it all together. Included are two wall charts—on the market structure and truisms.

Overall, Shannon has given us a very easy-to-read adventure into technical analysis for the beginner, and for the more advanced among us, perhaps a refresher and a reminder that our techniques can be used across all timeframes.

Notes

1 Shannon, B., *Technical Analysis, Using Multiple Timeframes,* Alphatrends Publishing, LLC, Canada, 2008 p. vi.

2 Ibid. p. 4

3 Ibid. p. 101

4 Ibid. p. 165

Author Profiles

Anand Behere

Anand Behere graduated from EDHEC Business School with a master's degree in finance. He currently works as a technical market analyst in the energy sector at a large German utilities company. He has previously been involved in option trading by analyzing order flow and market depth.

Garrett H. Brookes, CFA

Garrett Brookes has worked in the financial industry for more than 20 years, serving in a marketing and sales capacity to registered investment advisors, independent financial advisors, and money management firms throughout the United States on behalf of major investment companies and small boutique investment providers. In January 2021, he formed Slingshot Financial to partner with the "hidden gems" of money managers focused on quantitative strategies, alternatives, strategic income, and innovative fintech, offering strategic guidance on wholesale product development and marketing as well as tactical execution through Slingshot Financial's turnkey wholesaler program (https://slingshotfin.com).

Cezar-Valerian Lupusor, MSc, CFTe

Cezar-Valerian Lupusor, MSc, CFTe, is an avid follower of financial markets and has been trading them systematically for many years. He holds a degree in economics from Vienna University of Economics and Business in Austria and an MSc in quantitative finance from Bayes Business School, London, UK. Lately, he has become involved with the fascinating field of machine learning for algorithmic trading, where he explores financial time series data by utilizing sophisticated machine learning algorithms. He uses these tools as a complement to technical analysis. Currently, he is based in Austria.

Regina Meani, CFTe

Regina Meani, CFTe, covered world markets as a technical analyst and associate director for Deutsche Bank prior to freelancing. She is an author in the area of technical analysis and is a sought-after presenter both internationally and locally, lecturing for various financial bodies and universities as well as the Australian Stock Exchange. Regina is a founding member and former president of the Australian Professional Technical Analysts and a past *Journal* director for IFTA, carrying the CFTe designation and the Australian AMT (Accredited Market Technician). She has regular columns in the financial press and appears in other media forums. Her freelance work includes market analysis, webinars, and larger seminars; advising and training investors and traders in market psychology; CFD; and share trading and technical analysis. She is also a former director of the Australian Technical Analysts Association and has belonged to the Society of Technical Analysts, UK for over 30 years.

Davide Pandini, Ph.D., CFTe, MFTA, CMT

Davide Pandini, Ph.D., CFTe, MFTA, CMT, joined STMicroelectronics in Agrate Brianza, Italy, in 1995, where he is a technical director and a fellow of ST technical staff. He was previously a research intern at Philips Research Labs in Eindhoven, the Netherlands, and at Digital Equipment Corp., Western Research Labs, in Palo Alto, California. He holds a Ph.D. in electrical and computer engineering from Carnegie Mellon University. Davide has authored or co-authored more than 50 papers in international journals and conference proceedings and served on the program committee of several premiere international conferences. He received the STMicroelectronics Corporate STAR Gold Award in 2008 and 2020 for R&D excellence. Since June 2015, he has been the chair of the ST Italy Technical Staff Steering Committee. Davide is a professional member of SIAT (Societa' Italiana Analisi Tecnica). In 2021, he was the recipient of the prestigious XII SIAT Technical Analyst Award in the Open category. He was a speaker at SIAT Trading Campus in May 2022 and at the Investing and Trading Forum in June 2022. He served as a volunteer at the Universal Exhibition Expo2015—*Feeding the Planet, Energy for Life*—in Milano, Italy.

Dr. Oliver Reiss, CFTe, MFTA

Dr. Oliver Reiss, CFTe, MFTA, received a master's degree in physics from the University of Osnabrueck (1998) and a Ph.D. in mathematics from the University of Kaiserslautern (2003)—the latter for his research on financial mathematics performed at the Weierstrass Institute in Berlin. Since then, he has worked in the banking industry and today is a self-employed consultant for financial institutions, with a focus on risk controlling, derivatives pricing (quant), and related IT implementations. As a private investor, Oliver is interested in technical analysis, and, due to his mathematical and programming expertise, he is now focused on developing and back-testing midterm trading strategies based on more sophisticated algorithms. He joined the VTAD in 2011, when he became a freelancer, and currently serves as deputy manager of the VTAD's regional group in Dusseldorf, Germany.

Oliver received his MFTA for his thesis on the application of the Empirical Mode Decomposition to technical analysis, for which he was recognized with the John Brooks Memorial Award in 2019. As a frequent attendee of IFTA's conferences, he also presented the results of his MFTA research at the IFTA Conference in Cairo.

Alex Spiroglou, DipTA (ATAA), CFTe

Alex Spiroglou, DipTA (ATAA), CFTe, is a quasi-systematic, cross-asset proprietary futures trader, currently trading his own book. He is active in all major liquid futures markets and across all major asset classes (equity, interest rates, FX, commodities). Spiroglou has worked with various proprietary trading and investment management firms in the UK and Greece. Based in the United Kingdom, he is founder and CEO of SMART Trader Systems Ltd, London, a firm focused on the training, support, and development of institutional traders. Visit www.AlexSpiroglou.com for more information on Alex.

Christoph T. Wildensee, Ph.D., MFTA

Christoph Wildensee, Ph.D., MFTA, is a well-known auditor and data/process analyst at enercity AG in Hannover, Germany. Christoph's special focus is on finding errors and optimization potential in IT systems relevant to accounting, including, in particular, the Energy Trade and Risk Management system, which is used to handle all energy trading activities at enercity. He was also a member of the team evaluating the new Pioneer/Hitachi-ABB ETRM system.

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To Register

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Cost

IFTA Member Colleagues	Non-Members
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Paper submission deadline	**October 15**
SESSION 2	
"Alternative Path" application deadline	**July 31**
Application, outline and fees deadline	**October 2**
Paper submission deadline	**March 15 (of the following year)**

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