An overview of technical analysis in systematic trading strategies returns and a novel systematic strategy yielding positive significant returns

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Abstract: This paper contributes to the literature on systematic trading strategies, in particular technical analysis profitability. We measure the profitability and forecasting power of a trend following strategy implemented in Python on a wide perimeter (205 European stocks, 11 industries, 7 major stock exchanges) over 8 years: from 2015 to 2022. The strategy signal is based on 4 moving averages and a trailing stop loss. We also introduce a mechanism based on trailing upper and lower price bounds to avoid false signals and limit transaction costs during lateral movements. We calibrate the iper-parameters to all stocks belonging to the same industry. The returns of the strategy applied to the constituents of the top performing industries provides a total return of 20% net of transaction costs, with an annualized Sharpe ratio of 0.54, in the out of sample time window from 2020 to 2022.

1. Introduction

Our focus is the back-test of a trend following strategy. The scope is to contribute to the literature on systematic trading strategies addressing in particular issues related to referencing a limited sample of assets, strategy settings (iper-parameters) not properly cross-validated, performance measured without considering transaction costs. In this respect, our reference universe of assets consists of 205 European stocks. The time window for our analysis spans 8 years: from 2015 to 2022.

In addition, in our analysis we present the results of a back testing that is both out-of-sample and out-of-time: we recalibrate the strategy iper-parameters on a yearly basis and apply the strategy for the next year. Finally, we take into consideration market impact and transaction costs applying a fixed cost to each trade.

Our work is related to the literature discussing the merits of the technical and fundamental analysis: Antoniou, Doukas, and Subrahmanyam (2013); Brock and Hommes (1998); Brown and Jennings (1989); De Grauwe and Grimaldi (2006); De Long, Shleifer, Summers, and Waldmann (1990); Frankel and Froot (1990); Han, Yang, and Zhou (2013); Hellwig (1982); Hirshleifer (2001); Menkhoff (2010); Mills (1997); Özyeşil (2021); Petrusheva and Jordanoski (2016); Schulmeister (2009); Shiller, Fischer, and Friedman (1984); Shiller (2003); Smith, Wang, Wang, and Zychowicz (2016) and Treynor and Ferguson (1985).

The areas we are addressing in our work are: (i) the overall profitability of systematic trading strategy based on technical analysis across periods, industries and stocks, (ii) identifying a potential subset of industries or stocks for which the strategy yields significant positive returns (iii) verifying that the returns and risks of this strategy are consistent with a continuous growth trend for the cumulative return or just spot returns not easy to always replicate in the future.

In chapter 2 we review the literature discussing the importance of the technical analysis. In chapter 3 we detail the scope of the analysis. In chapter 4 we define in detail the systematic trading strategy and discuss how we split our dataset between training and test samples. The results are in chapter 5. The conclusion with a summary of the findings is in chapter 6.

2. Technical Analysis Literature Review

The literature regarding technical analysis can split between two main historical periods according to Park and Irwin (2007): "Early studies" from 1960 to 1987 and "Modern studies" from 1988 to 2004.

They noticed that there is a relevant number of studies identifying trading profits of technical trading strategies on stock, foreign exchange and futures markets (56), far outnumbering the number of studies that found losses (20).

Regarding the "Early studies", the authors identified a series of articles showing poor profitability of trading strategies based on technical analysis indicators. One of this is Fama and Blume (1966), where they tested a filter rule strategy (buy/sell signal when the closing prices rise/fall above/below their most recent high/low) on the 30 constituents of the Dow Jones Industrial Average (DJIA) from 1956 to 1962, finding only few cases of profitability after transaction costs. Similar studies were conducted by James (1968); Jensen and Benington (1970); Van Horne and Parker (1967) and Van Horne and Parker (1968) on moving averages and relative strength systems confirming the results of Fama and Blume (1966).

An important limitation underlined by Park and Irwin (2007) about the "Early studies" is that these were based on few and very simple technical analysis indicators.

Jensen (1967) enhanced the analysis robustness introducing the database split between training and test to avoid overfitting.

In the "Modern studies", the academic perception on the technical analysis improved and much more articles were realized. Several authors found out profitability and predictive power of technical analysis, some of them taking into account also transaction costs. Lukac, Brorsen, and Irwin (1988), seen as the pioneer of the "Modern studies", found technical analysis strategies, including moving averages and channel systems, on futures market from 1975 to 1984 showing significant monthly returns net of brokerage fees. Lukac and Brorsen (1990) extended the analysis of Lukac et al. (1988) on more futures assets, more strategies and a longer time window, obtaining the same positive result net of brokerage fees. Brock, Lakonishok, and LeBaron (1992) tested 90 years of DJIA stocks finding positive evidences on the technical analysis forecasting power. Bessembinder and Chan (1998) verified the same trading rules of Brock et al. (1992) on dividend-adjusted DJIA data from 1926 to 1991 with an average annual profit of 4.4% across strategies.

Another evidence of the widespread application of the technical analysis is provided by Menkhoff (2010), a survey on around 700 fund managers in Germany, Italy, Switzerland, Thailand and US; 87% of them considered technical analysis important, and a subset of 18% of them even considered it as the primary source of investment decision.

Menkhoff and Taylor (2007) discovered that all fund managers use technical analysis, most of them in combination with fundamental analysis, and it is the proper method for the short-term horizons.

Technical analysis is widely adopted in the real market, for example Lo and Hasanhodzic (2009) and Schwager (1995) found that many of the top traders and fund managers whom they interviewed suggested and applied technical analysis; Covel (2005) showed instead examples of large and successful hedge funds using only technical analysis.

Smith et al. (2016) confirmed the diffusion of technical analysis among professionals; about 19% of hedge funds use it. They also demonstrated that funds using technical analysis are less likely to fail; among live funds about 22% use technical analysis, in contrast to only 15% among graveyard funds.

Technical analysis can support the investors to profit from prices oscillation given by the incomplete and different levels of information available on the market for different actors. For examples, authors like Blume, Easley, and O'hara (1994); Brown and Jennings (1989); Grundy and McNichols

(1989) and Treynor and Ferguson (1985) dived deep the information diffusion model that recognizes differences in the time for investors to receive information. Under this misalignment, technical analysis is useful for assessing whether information has been fully incorporated into prices and can provide useful information for investors to make better price inferences. Hong and Stein (1999) highlighted that stocks tend to show trending patterns due to the under or over reaction by investors with incomplete information.

Hellwig (1982) pointed out that differences in information can lead to a price discovery process during which technical analysis may be a proper instrument to reveal superior knowledge and thus to partially anticipate price development.

Lo, Mamaysky, and Wang (2000) evaluated the usefulness of ten chart patterns (head-and-shoulders, inverse head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms, double tops and bottoms) in predicting stock prices on different perimeters. For NASDAQ (National Association of Securities Dealers Automated Quotations) stocks all ten strategies are statistically significant. While for NYSE (New York Stock Exchange) and AMEX (American Stock Exchange) stocks five of the ten strategies are not so statistically significantly. The same ten patterns are applied by Dawson and Steeley (2003) to UK stocks without clear profits. Leigh, Paz, and Purvis (2002a) and Leigh, Modani, Purvis, and Roberts (2002b) found that bull flag patterns, another geometric figure of technical analysis, provide positive excess returns, before transaction costs, for the NYSE constituents over a buy & hold strategy.

Özyeşil (2021) measured the performance of some technical and fundamental analysis trading strategies using the back-test method on Borsa Istanbul national stock indexes. The trading strategy based on both Price on Earnings (P/E) and moving average, so a mix of technical and fundamental analysis, provided both maximum positive residual return to the investor and maximum risk-adjusted return when applied to 3 indexes (Bist-30, Bist-50 and Bist-100) and all-time windows considered.

Petrusheva and Jordanoski (2016) compared technical and fundamental analysis underlining their pros and cons. The authors pointed out how fundamental analysis is important to understand the sector and company prospect and status even if it is time consuming, while technical analysis is simple and fast to apply but it has not a strong scientific and academic confirmation. They also pointed out that fundamental analysis investors use also technical analysis for the market timing, while technical analysis investors use fundamental analysis to understand if that stock is overall a good investment to pick.

3. Premises and Perimeter

We performed our analysis in Python. The perimeter of the study are all the European stocks belonging to the following stock indexes:

- FTSEMIB (Financial Times Stock Exchange Milano Indice di Borsa) in Italy.
- CAC40 (Cotation Assistée en Continu) in France.
- DAX40 (Deutscher Aktienindex) in Germany.
- AEX25 (Amsterdam Exchange index) in Holland.
- BEL20 (BEL index on Euronext Brussels) in Belgium.
- FTSE100 (Financial Times Stock Exchange 100 Share Index) in England and
- IBEX35 (Iberian Index) in Spain.

We retrieved the list of tickers from the official Stock Exchanges websites using the Python library *"pytickersymbols"*.

The total number of stocks collected are 283, we had to remove several stocks because data was not retrievable from Yahoo Finance through Python: the final number of stocks is 205. The daily information collected for each asset are: adjusted closing price, volumes, industry, stock exchange and market daily simple return. We retrieved the data using the Python libraries *"yfinance"*, *"yahoofinancials"* and *"yahoo_fin.stock_info"*.

We split the whole dataset into training (in sample) and test (out of sample), as pioneered by Jensen (1967), to avoid the issues overfitting common in technical analysis. The considered period goes from 2015 to 2022. We applied a rolling triple split of the database into training and test as outlined in Table 1.

Table 1.
Database triple split in training and test.

2015	2016	2017	2018	2019	2020	2021	2022
Training					Test	/	/
/	Training					Test	/
/		Training					Test

For simplicity, we neglected the risk-free interest rate in the Sharpe ratio computation because over the analysed period it is very close to zero. We included a brokerage fee of 10 basis points for each transaction, 5 bps for the opening and 5 bps for the closure of each trade.

4. Algorithm and Outcomes
4.1. Description of the Trading Strategy
The strategy is based on 4 exponential moving averages (MA) with different half-life to be calibrated on the training sample: MA1 the fastest (for example 5 days), MA2 the fast (for example 10 days), MA3 the medium (for example 15 days) and MA4 the slowest (for example 20 days).

We opened a long position when MA1>MA2>MA3>MA4 and we closed it when MA1<MA4. Conversely, we opened a short position when MA1<MA2<MA3<MA4 and we closed it when MA1>MA4. This trading strategy is along the lines of Özyeşil (2021). By definition, the 4 moving averages must have different and increasing time spans. The time spans of the moving averages are parameters to be optimized in the training sample. To limit false signals, the condition to open a trade must be fulfilled for 3 days in a row. To avoid lateral movements, we introduced an additional condition to open the trades that is based on the upper and lower bounds. Both long and short positions cannot be opened when the stock price is within the bounds' range. Their definition is the following:

- When closing long positions, we defined U as the maximum closing price reached during the life of the trade just closed. U is then the upper bound and the lower bound (L) is symmetrically below the closing price (L = 2*S - U) where S is the price of the stock when closing the trade.
- When closing short positions, we defined L as the minimum closing price reached during the life of the trade. L is then the lower bound and the upper bound (U) is symmetrically above the closing price (U = 2*S - L).
- A coefficient (α) is applied to increase or reduce the width of the original bands from the closing price (S); this is a parameter to be optimized.
- The value of the bounds defining the no-trade area is kept until the opening of a new trade (long or short).

Lastly, we introduced a trailing stop loss; this parameter is also to optimize in the training sample.

In summary, the parameters to be optimized are the 4 exponential moving averages, the coefficient α defining the no-trade area and the trailing stop loss. In this article, we tested for each calibration sample 1620 combinations of these parameters to determine the optimal one. The total number of combinations is given by three different values for each of the four moving averages, five values for α parameter and four values for the trailing stop loss.

- MA1 $\in$ {15, 20, 25}, MA2 $\in$ {30, 35, 37}, MA3 $\in$ {40, 45, 50} and MA4 $\in$ {55, 60, 65}.
- α $\in$ {1, 2, 3, 4, 5}.
- Trailing stop loss $\in$ {-5%, -10%, -20%, -30%}.

As outlined above in Table 1, each training period is calibrated on the last five available years and then the best strategy combination by industry is applied to the test dataset, i.e., over the next year.

For each industry, the target function to maximize in the training sample is the cumulative return of an equally weighted portfolio of the strategy applied to the single stock within each industry.

To activate the strategy on a given industry in the test sample, we set the following condition to be fulfilled in the training dataset: a growing and possibly linear Cumulated Return Trend (later also called CRT) without particular peaks.
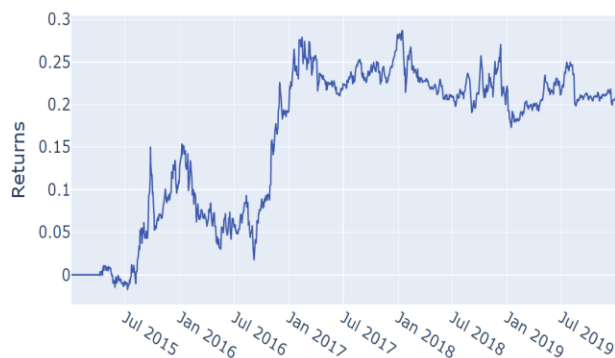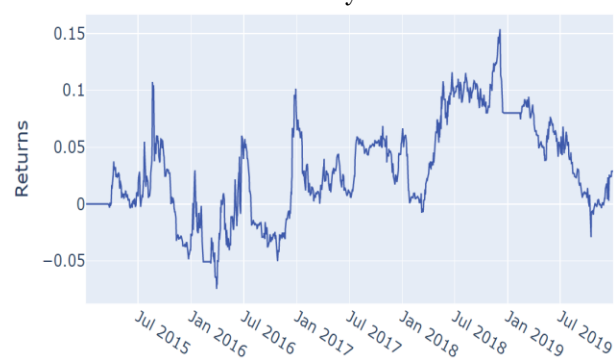

Basic materials

Communication services

Consumer cyclical
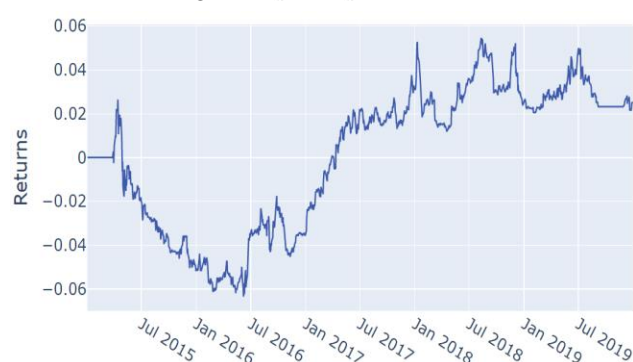
Consumer defensive

Energy

Financial services

Figure 1.
Cumulated return trend by industry in the training dataset 2015-2019.
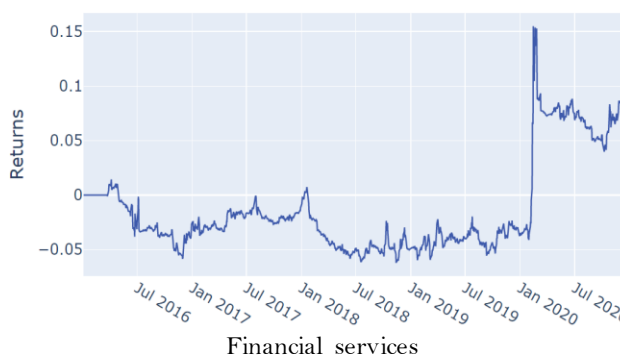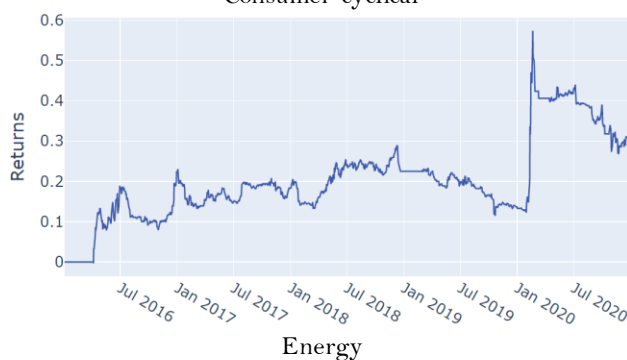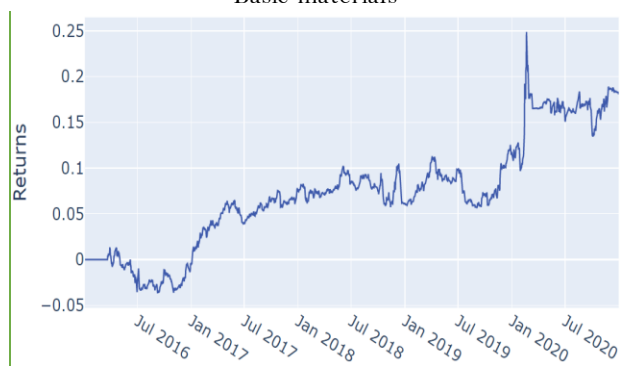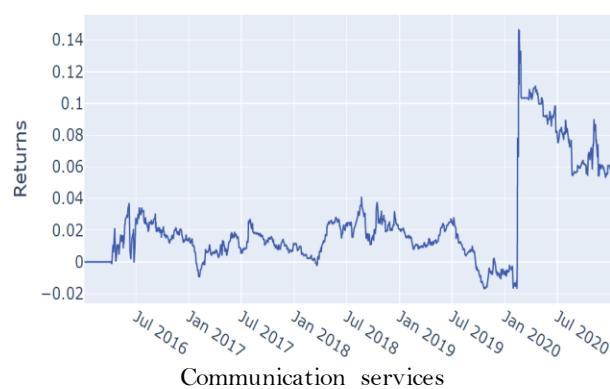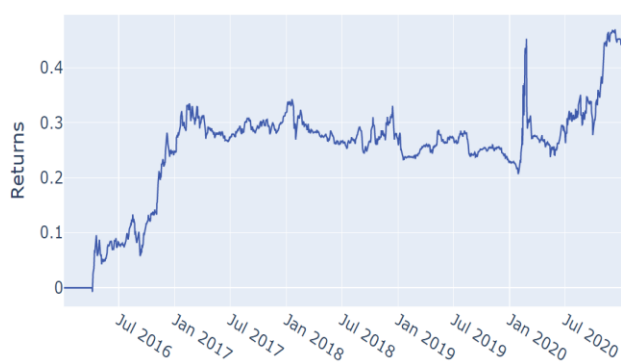
4.2. Training Dataset 2015-2019

Based on the cumulated return trend condition, from the training dataset 2015-2019 outcomes in Figure 1, we have selected Consumer Cyclical, Healthcare and Industrials to include in the next test dataset (2020).

4.3. Test Dataset 2020

Considering the optimal parameters from the 2015-2019 training dataset, in Table 2 there are the outcomes for the 2020 test dataset split by industry.

Table 2.
Test dataset 2020 outcomes by industry.

Industry	Return	Sharpe ratio	Moving averages	Trailing stop loss	Band coefficient
Basic materials	0.336	1.219	(25, 30, 40, 65)	-0.300	1,000
Communication services	0.010	0.088	(25, 30, 45, 55)	-0.200	4,000
Consumer cyclical	0.091	0.846	(15, 30, 50, 65)	-0.200	2,000
Consumer defensive	0.100	1.218	(15, 35, 45, 60)	-0.100	2,000
Energy	0.239	0.760	(25, 30, 40, 55)	-0.100	1,000
Financial services	0.068	0.823	(25, 30, 40, 55)	-0.100	5,000
Healthcare	-0.064	-0.953	(25, 30, 40, 55)	-0.300	4,000
Industrials	0.117	0.963	(15, 37, 40, 60)	-0.200	3,000
Real estate	-0.032	-0.379	(15, 30, 40, 55)	-0.100	2,000
Technology	-0.020	-0.113	(25, 30, 40, 65)	-0.300	1,000
Utilities	-0.203	-1.691	(20, 30, 40, 60)	-0.200	1,000

Basic materials

Communication services

Consumer cyclical

Consumer defensive

Energy

Financial services

Figure 2.
Cumulated return trend by industry in the training dataset 2016-2020.

Table 3.
Test dataset 2021 outcomes by industry.

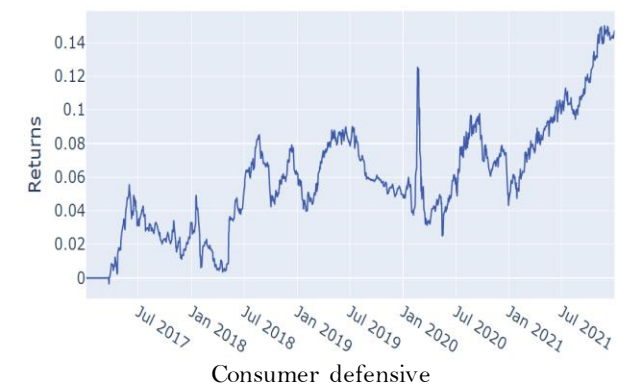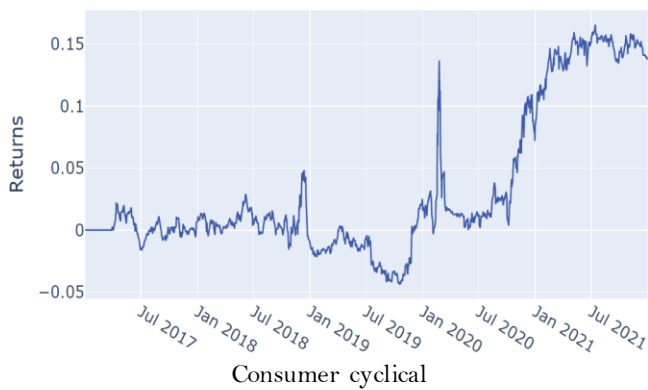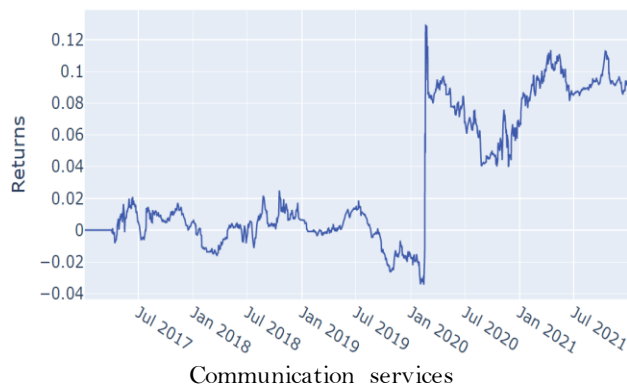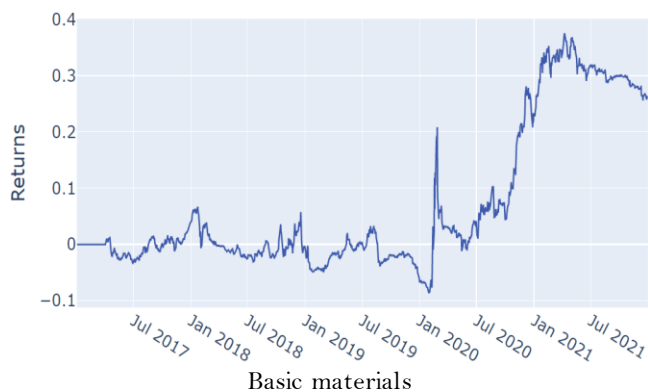| Industry	Return	Sharpe ratio	Moving averages	Trailing stop loss	Band coefficient
Basic materials	0.105	0.796	(25, 30, 40, 65)	−0.200	1,000
Communication services	0.018	0.330	(20, 37, 45, 65)	−0.100	2,000
Consumer cyclical	0.013	0.183	(25, 30, 40, 55)	−0.100	1,000
Consumer defensive	0.016	0.290	(25, 30, 40, 55)	−0.100	1,000
Energy	0.111	0.858	(25, 30, 40, 65)	−0.100	1,000
Financial services	−0.017	−0.294	(20, 30, 40, 55)	−0.050	1,000
Healthcare	−0.005	−0.088	(15, 30, 40, 60)	−0.100	1,000
Industrials	0.138	1.756	(25, 30, 40, 60)	−0.200	1,000
Real estate	0.069	1.142	(25, 35, 40, 55)	−0.100	4,000
Technology	−0.005	−0.044	(20, 30, 40, 55)	−0.200	1,000
Utilities	0.005	0.136	(25, 30, 40, 55)	−0.100	5,000

4.4. Training Dataset 2016-2020

Based on the cumulated return trend condition, from the training dataset 2016-2020 outcomes in Figure 2, we have selected Consumer Cyclical, Industrials and Technology to include in the next test dataset (2021).

4.5. Test Dataset 2021

Considering the optimal parameters from the 2016-2020 training dataset, in Table 3 there are the outcomes for the 2021 test dataset split by industry.

Basic materials

Communication services

Consumer cyclical

Consumer defensive

Energy

Financial services
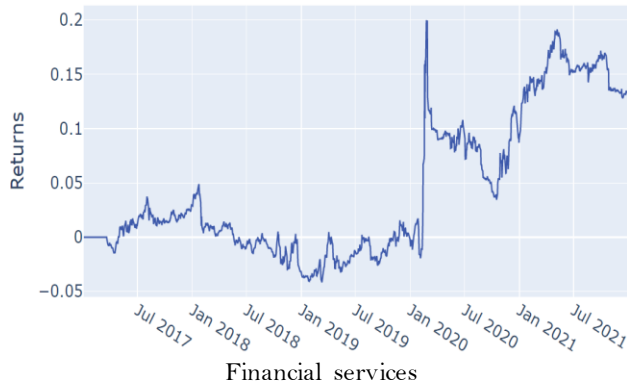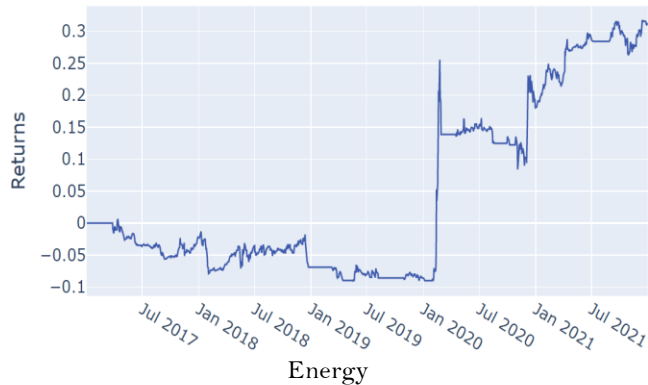
Figure 3.
Cumulated return trend by industry in the training dataset 2017-2021.

4.6. Training Dataset 2017-2021

Based on the cumulated return trend condition, from the training dataset 2017-2021 outcomes in Figure 3, we have selected only Technology to include in the next test dataset (2022).

4.7. Test Dataset 2022

Considering the optimal parameters from the 2017-2021 training dataset, in Table 4 there are the outcomes for the 2022 test dataset split by industry.

The cumulated return trends of all the 11 industries in 2022 show a clear negative result for the second half of the year across industries, this underlines that the main reason is not a bad behaviour of the strategy but more some external factors like for example the remarkable inflation levels and the related increase of interest rates by European Central Bank to handle it.

Table 4.
Test dataset 2022 outcomes by industry.

Industry	Return	Sharpe ratio	Moving averages	Trailing stop loss	Band coefficient
Basic materials	-0.063	-0.482	(15, 30, 40, 65)	-0.200	1,000
Communication services	-0.033	-0.620	(20, 37, 45, 65)	-0.100	2,000
Consumer cyclical	-0.051	-0.394	(15, 30, 40, 60)	-0.200	1,000
Consumer defensive	-0.036	-0.328	(25, 30, 40, 55)	-0.200	1,000
Energy	-0.078	-0.823	(15, 30, 50, 60)	-0.100	2,000
Financial services	-0.156	-2.091	(25, 30, 40, 55)	-0.100	1,000
Healthcare	-0.073	-0.930	(15, 30, 40, 55)	-0.100	1,000
Industrials	-0.024	-0.267	(25, 30, 40, 60)	-0.200	1,000
Real estate	-0.117	-1.229	(15, 30, 40, 60)	-0.300	3,000
Technology	0.058	0.297	(20, 30, 40, 55)	-0.200	1,000
Utilities	-0.086	-1.550	(15, 30, 50, 60)	-0.100	2,000

Figure 4.
Best industries by trend equity line cumulated return (2020-2022 test).

5. Results and Comments

5.1. Top Industries by Cumulated Return Trend

In Figure 4 is the cumulative return of the 3 sample tests, i.e. the last three years in our sample, based on the industries selected according to the criteria cumulated return trend; this criteria consists in selecting the industries showing a clear increasing trend, preferably linear and constant, over most of the time window.

It is interesting to notice that the industries consumer cyclical and industrials repeat for the first two years of the test datasets, while technology is a constant for the last two years of the test datasets.

The return of this method is 20% in the 3 years of out of sample, while the annualized Sharpe ratio is 0.54.

5.2. Equity Line Over Three Years for the Out of Sample

If instead of selecting the best industries by cumulated return trend, we select all the available 205 stocks, equally weighted, the strategy provides just 2% of total yield and a small annualized Sharpe ratio of 0.12.

5.3. Top 20 Assets by Volume

If instead of selecting the best industries by cumulated return trend, we select the top 20 stocks by volume on the market, the strategy provides a total return of 20% and an annualized Sharpe ratio of 0.51. However, all the positive returns are concentrated in the first year of the test dataset (2020).

6. Conclusion

In this article, we addressed some of the most recurring critiques to the literature on the technical analysis. In particular:

- Inclusion of transaction costs in the analysis: 5 bps for each trade, so a total of 10 bps for each transaction.
- Broad reference used for the analysis: 205 stocks spanning 11 industries and the 7 main European countries over a time window of 8 years.
- Cross validation of the strategy iper-parameters splitting the whole database into training (five years) and test (one year) on three rolling blocks, resulting in an out of sample dataset of 3 years.

The strategy selects the top industries based on the cumulative returns showing a clear trend in the training datasets, for example the linearity, the continuous growth, the absence or smallness of lateral movements. Its total return is 20% in three years of test with an annualized Sharpe ratio of 0.54.

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Authors' Contributions:
Both authors contributed equally to the conception and design of the study.

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