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# When Technical Indicators Predict Short-Term Reversal

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## Abstract

I went through the history of some of the most successful trading rules from the 80s in the US market. Then, combining them, I created a strategy based on picking the best stocks for the next month. It has underperformed the benchmark heavily, generating the worst portfolio of the entire pool of stocks. Therefore, I analyze short-term reversal as explanation. The same could also justify why the worst predicted performer portfolio is the one that does best. This shows that, when too many investors go into the same direction of trades, the outcome is the existence of opportunities to exploit.

## Keywords

Behavioral Finance
Technical Trading
Short-Term Reversal
Alpha Creation

## 1. Introduction

Technical analysis is a technique used to predict future prices through the study of past market data, using mainly historical prices and volumes. Then, Investors develop technical models using regressions, correlations, moving averages and crossovers among the others, in order to make profits. Therefore, I looked for the most popular strategies, which have worked well in the years 1980-2000, after the boom of behavioral finance (Shiller 2003). This investment technique captured the attention of the average investors for the easiness of implementation and for the easier access to information. For example, the production of several papers (Grossman and Shiller 1981), books (The Econometrics of Financial Markets written by Campbell, Lo and MacKinlay in 1996 among others), media and internet. As a consequence, people started investing big amount of money into this type of trading (Barber and Odean 2012). This mass behavior creates big fluctuations in prices, which consequently generates trends and arbitrage opportunities. This aspect is not coherent with the efficient market hypothesis (EMH), developed by Fama (1970). In fact, EMH assumes that prices reflect the true value of an asset, since they incorporate all the available market information. As a result, returns should be largely unpredictable, or, even if patterns exist, they cannot be exploited after transaction costs. This connects to the idea of "no free lunch" from Fama (1970) that refers to circumstances in which investors are not able to consistently make large profits without facing the risks of potential losses. Later studies (Hirshleifer et al. 2012 and Ohlson and Bilinski 2012) explained mispricing occurrences as caused by different risk factors. In fact, they split returns into different risk types, in order to find patterns of predictabilities and market inefficiencies. More specifically, mispricing is due to the risk premium demanded by investor for holding a specific risk. Consequently, the idea of an active investing strategy is to define those patterns to outperform the market, given that we believe that market is inefficient. I like to mention the sentence of So and lee (2014): “market efficiency is a journey, not a destination”, which means that, even though the true price cannot be defined with certainty, its fluctuation will be affected by invertors’ expectations and evaluations. Hence, the basis of a strategy development is to determine how and why the prices adjust to be able to gain a significant advantage to the competitors in the market.

Generally, we can define two types of investors: “Smart Money Investors” and “Noise traders”. The firsts are defined in Black (1986) with the following sentence: “Noise trading is trading on noise as if it were information. People who trade on noise are willing to trade even though from an objective point of view they would be better off not trading”. As a results, this market component is the one that creates inefficiencies and explains the great volume of trading that we see every day. Different, instead, is the “smart investor” type. He demands a premium for making specific investments, placing bets taking into account risk aversion, wealth constraint and others relevant factors. So and Lee (2014) divides its demanded premium into 3 categories. 1) Trading costs, which are related to opening and closing the positions, for example bid-ask spreads, brokerage and government fees etc. 2) Holding costs, which are associated with maintaining a stock, and they are influenced from occurrences like the duration of the arbitrage position and the incremental cost of short-selling a stock. 3) Information costs, which it is simply the cost of obtaining information and the cost of the analysis and monitoring of it.

Barber and Odean (2012) gives an example of poor results of noise investors. They collected the performances of a big variety of average investors’ types, showing clearly inferior returns against the market. In fact, as a rule of thumb for the market, for any winner, you need a loser, and we all gain on average the market returns before transaction costs and taxes (Harris 1993). The most common mistake of the "losers" is the involvement in too many marginal trades and we will see the reasons in detail later.

Literature has extensively focused in documenting price anomalies. Among the first models explaining the expected returns, we find the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966) and the empirical studies by Black et al. (1972) and Fama and MacBeth (1973), which suggested a significant positive cross-sectional relations between performances of stocks and their beta with the market. The subsequent literature, like Fama and French (1993), switched to other risks and factors to explain expected returns. However, the recent studies focused on various behavioral models to explain predictability patterns, like Daniel et al. (1998, 2001), Barberis et al. (1998), and Hong and Stein (1999). Subrahmanyam (2007) made an extensive summary of the behavioral finance work of the antecedent literature on it. Finally, putting those papers together has helped me to clarify and to give order to the various definition and explanation for trends and noise traders' behaviors.

I present below some of the possible causes of stock patterns presented in the literature:

- Ambiguity Aversion: First known as Ellsberg Paradox (Ellsberg 1961), it refers to the fact that people are more prone to take risks on situations where the odds are known, instead of scenarios when the statistical distribution is not certain.

- Attention: Chasing the Action: Higgins (1996) suggests that possibly irrelevant verbal information triggers associations that influence judgments. Hence, individuals who dedicate little amount of time to investing can be affected in two manners. First, not giving enough weight to important information can generate an underreaction. Second, giving too much attention to secondary information can cause an overreaction.

- Confirmation bias: It means that investors give more weight to facts and news that confirm their prior beliefs to take decisions, nonetheless, they may omit relevant more recent information. Edwards (1968) defined this circumstance as conservatism, which means that individuals don't change their beliefs as they should, according to Bayesian theorem, after seeing new evidences.

- Disposition Effect: Shefrin and Statman (1985) describes this anomaly as individual investors tend to sell winners too early and hold on losers too long. In fact, they have the preference of realizing gains and, conversely, to make up losses. This behaviors generate a difficulty for prices to adjust upward for winning stocks, and a slowness to push the prices down for losers, due to few willing sellers available.

- Familiarity: Seasholes and Zhu (2010) claims that individuals invest more in stocks where they have more knowledge about, or closer to where they live, because they are familiar to them. The consequence is under diversification. There is no proof that they generates superior returns, in fact there is debate about whether individual investors have an informational advantage in regards to people far from the company.

- Herding and Feedback trading: Investors tend to chase stocks that have followed a trend for a while, encouraged also from analyst recommendation, earning predictions and strategies taken by institutional investors (Nofsinger and Sias 1999)

- Institutional activities: Another point of Nofsinger and Sias (1999) is that big institutions tend to rebalance their strategic asset allocation weight, according to the change of exchange rates, interest rates and news or performances of stocks (for example, they buy bonds if equity market has outperformed) and this coordinated behavior can influence price movements.

- Overconfidence: Barber and Odean (2009) observed a strong link between self-rated competence and the propensity to trade. Since a trade implies two positions and the reason of a trade should be the profit, one of the two sides is going to lose. However, there should be no trade with asymmetric information, since people should fear that the counterpart is aware of something that he/she is not. All this considered, the rational expectation studies should imply that we should have no trading in individual stocks, nevertheless, every day billion of shares are traded.

- Prospect Theory: Tversky and Kahneman (1992) defined this behavior as people measuring differently gains and losses. While they are risk averse for the former, they are risk lovers for the latter. Put differently, people are more available to gamble for losses than for gains.

- Representativeness: It is complementary to the physiological factor of confirmation bias. Rabin (1999) implies that people are extending occasional occurrences, which are analyzed in a very isolated way, to general rules.

- Sensation Seeking: High trading rate can be explained by the enjoyment of a feeling comparable to other gambles. Barber et al. (2009) discovered that Taiwan assisted to a 25% decrease in trade volume when a legal lottery was launched in April 2002.

Saying that the above mentioned trends are proven to exist and they are still a strong component of the market behavior does not give us any clue whether investing on sentiment can give us more profitable strategies than leaving our money into the market passively. More importantly, very often it is not clear if the outperformance of some strategies is due to skill of technical analysts or they are just temporary outliers from the obvious huge amount of combinations of possible trades. Bajgrowicz and Scalliet (2009) extensively analyzed the historical success of 7,846 trading rules on daily prices of the Dow Jones Industrial Average (DIJA) from 1897 to 2011, and tested for their significance and persistence. They discovered that there were no rules that, after accounting for transaction costs, can consistently generate alpha on a daily trading frequency and in highly liquid markets as the one considered. In fact, they warned people to be wary of common technical indicators presented on investment websites and financial advertising, in fact, no profitability could possibly be guaranteed. Said that, there still are phenomena that may sound puzzling and counterintuitive given the massive amount of daily trades in liquid markets, like the still extensive use of technical analysis investing from the noise investor and the growing number of institutions that develop high frequency trading. Therefore, instead of focusing on how to solve such anomalies, we came out with an idea of finding additional patterns to take advantage of the correction process that those trends can generate, which is also known and studied n literature as short-term reversal.

A reversal is a change in the direction of a price against the prevailing trend, and a short-term reversal strategy takes advantage of the strong propensity of stocks with heavy gains and stocks with big losses to reverse in a short-term time span, usually up to a month, which is also the frequency that we will use. In particular, we can see in our strategy how a buy signal, expressed in a daily recurrence, can convert an expected uptrend of a stock price, according to technical trading bet on noise, into a downward one, and, conversely, a sell signal can produce interesting profitable buy positions . We take the explanation from  Da, Liu and Schaumburg (2014), which states that "stock returns unexplained by fundamentals, such as cash flow news, are more likely to reverse in the short run than those linked to fundamental news". This aspect has shown historical consistency, in fact, Jegadeesh (1990) showed that a strategy of buying the worst and selling the best performers of the previous month, and then holding them for the following month, over the period 1934-1987, demonstrated a 2% profit per month. Therefore, we found in the literature two rational explanation for that: the first, sentiment driven, was developed by Shiller (1984), Black (1986), Stiglitz (1989), and they explained the short-term reversal profits as the result of investors' overreaction to information or cognitive mistakes from them. The second is liquidity-driven, in fact, Campbell et al. (1993) Avramov (2006) and Pastor and Stambaugh (2003) suggest that this reversal in prices is due to a compensation to the liquidity providers that guarantee temporary needs to uninformed investors. Back to our strategy, this leads to an interesting idea that can explain why our returns became in some way predictable. Indeed, the fact that people trade on noise or non-fundamental news gives us a way to exploit those patterns. All we have to do is to try to predict the positions that the average investors and big players are going to take, and counter them with opposite trades for the next reasonably short-period, which it can range from intraday to monthly frequency with obviously higher transaction costs related to the shorter time frame. In our case, we take advantage of the market flaw that creates prices bubbles from noise, which obviously, as soon as the investors realize that the values are deviating too much from the fundamental one, tends to correct and reverse, giving the chance of trading on those margin of corrections.

To sum up, we put together this two component, the fallacy of technical analysis and the short-term reversal, and we discovered that a strategy that bets on the results of the expected worst performer, according to four historical technical trading rules combined, generates outperformance consistently for 15 year, from 2001 to 2015. The short-term reversal explanation gives us an interesting approach to investing when a huge amount of money start flowing towards the same direction Other examples could be big funds that for internal or external reasons take huge individual position and it is very likely that they are going to attract several imitators among investor for the same trades.

## 2. Portfolio Construction

To build our portfolio, we selected the top 100 stock for market cap of the S&P 500 the last day of each year to be part of the eligible stocks that are going to be traded the following year. The list of eligible stocks is changed every last day of the year according to the new market value of the companies, however they remain in that list only if they are still part of S&P 500. For example, I choose the first pool of stock the 29th of December 2000, then I collected the daily data of the stocks starting the 1st of January 2000 until the 31st of December 2001 to generate the signal to sort my stocks in 5 sub-portfolios (20 stocks each). The time period, when the performance of those stocks have been evaluated, is from January 2001 to December 2001. I measured it monthly, due to the monthly rebalancing rule of the portfolio for guaranteeing reasonably low transaction costs. I repeated this exercise for the following 15 year to simulate the performance of a portfolio launched in January 2001 and active until December 2015. The four daily data are the closing price (1), high (2), low (3) and volume (4), which are used to generated the following 4 common technical indicators:

1) <u>Trend indicator: Moving Average Crossover</u>

Moving Average is the rolling average of a value for a given period of time. It is a technique that helps to smooth out the value taken into account. Translated into our scope, it is aimed to find the rolling moving average of the price considered.

$$\text{Moving Average Closing Price (P, t)} = \frac{\text{Sum of x days closing price}}{x\ days}$$

In the formula above, x represents the amount of days chosen, which is 13 for the fast moving average and 48 days for the slow one, and the reason for us to choose this 2 values will be explained next in the paragraph.

The crossover signal is very straightforward. A buy (1) signal is created when the fast moving average is greater than the slow one, and it suggests than an upward trend of the price is probable. Conversely, if the slow moving average crosses the fast one, a sell (-1) signal is generated.

$$\text{Moving Average Crossover (P, t)} \begin{cases} \text{Buy if:} \quad \text{MA 13 Days} > \text{MA 48 Days} \\ \text{Sell if:} \quad \text{MA13 Days} < \text{MA 48 Days} \end{cases}$$

The critical part is to assess the correct lookback period (the optimal combination of both fast and slow moving average for the type of strategy wanted, which in our case is monthly) to spot favorable trading opportunities. ETF HQ, which is a small firm based in New Zealand, tested 1750 different moving averages combinations of for 300 years of data in 16 different markets and it came out that the most profitable combination is a 13-48 days rule for a monthly investment strategy. Therefore, I opted for this lookback period to be consistent with the fact that I am looking for successful rules that looked to be profitable in the past and there may have been a huge crowds of investors ready to follow it.

Additionally, W. Brock, J, Lakonishok, B. LeBaron (1992) analyzed the historical profitability of the crossover rule, covering the period 1897-1986, 90 years of daily data, of the Dow Jones Industrial Average(DJIA), and they proved outperformance for a different varieties of combination of lookback periods. Han, Yang and Zhou (2011) focused on the time-frame 1963-2009 using Fama-French factors to prove abnormal returns provided by a Moving Average strategy. However, even though we can find evidences supporting the success of this strategy, Zakamulin (2016) rejects the above mention conclusion due to data mining. In fact, he shows that no Moving average strategy rewards an investor of more than a marginally better return given by a buy-hold strategy. To sum up, even if the successfulness is still debated, the key thing is that there is a lot of noise on it, and therefore it is likely for people to over rely on it.

2) <u>Momentum Indicator: Stochastic Oscillator</u>

This indicator was developed by a group of dedicated analysts in the 1950s and claimed soon later by G. Lane. It uses support and resistance level to determine when the stock price is going to stop a trend and reverse. In particular, he noticed that, if the closing price is near to the top of the price range for the past 14 days, it suggests that the security is overbought, hence we can expect a downward price trend. Conversely, if the closing price is near to the bottom range for the same period of time, it implies that it is oversold, and it can trigger an upward price movement. Additionally, we picked a 14 days' time frame, which is suggested by Murphy (1999) in his very influential technical analysis's book. As a consequence, it is very likely that many investor took this line. Hence, here we define a range of prices between the highest and the lowest price in a specific period of time of 14 days to find the so called K% value.

$$\text{K\%} = \frac{(Last\ Closing\ Price - \ Low\ of\ the\ previous\ x\ days)}{(high\ of\ the\ Previous\ x\ days - Low\ of\ the\ previous\ x\ days)}$$

After that, we obtain the moving average of the last 3 values of K%, in the form of:

D% = Moving Average of the last three K %

It is useful to define when this stochastic indicator is close to the upper end of the price curve and it means that it is overbought, hence a sell (-1) signal is generated. Conversely, if my D% is close to the lower end, a buy (1) signal is created, due to the implied overbuying trend. The remaining values suggest us a neutral position on the stock. I chose the thresholds that are suggested by Murphy (1999), which are 20% for the buying signal and 80% for the selling one.

$$\text{Stochastic Oscillator (Ps, t)} \begin{cases} \text{Buy}(1)\text{if } \%\text{D}(\text{t} - 1) < 20\% \\ \text{Sell}(-1)\text{if } \%\text{D}(\text{t} - 1) > 80\% \\ \text{Hold}(0) \text{ otherwise} \end{cases}$$

3) Volatility Indicator: Bollinger Band.

This concept was introduced by John Bollinger in the 1980s and the copyright was deposited in 2011, giving to it the official name of Bollinger Band. The purpose is to define a band, where the price of the stock is supposed to fluctuate. The band is computed by defining an arbitrary number of standard deviations and days. In our work, we used 2 standard deviation and 21 days of prices as Murphy (1999) suggests to apply. That value is later added to the moving average of the same amount of 21 days.

(21 Days MA – 2 Standard Deviations) < Bollinger Band < (21 days MA + 2 Standard Deviation)

This is aimed to identify when the closing prices cross the band and it suggests that a reversal is likely to happen, therefore, we should sell a stock(-1), if it crosses the upper band, conversely if it goes below the lower band, a buy(1) signal is created. In the remaining scenario, inside the band, we have a neutral position for the stock.

$$\text{Bollinger Band Indicator:} \begin{cases} \text{Buy}(1) \text{ if Closing price} < \text{Lower Band} \\ \text{Sell}(-1) \text{ if Closing Price} > \text{Upper Band} \\ \text{Hold}(0) \text{ otherwise} \end{cases}$$

The effectiveness has been extensively described from Fang, Jacobsen, Qin (2014), in fact they demonstrated a return of 2.96% monthly across 14 main markets during the period 1983-2001.

Then, its predictability had lost power, due to the several publications on it, which will be useful for my purpose of supporting the short term reversal theory.

4) <u>Volume Indicator: On Balance Volume (OBV)</u>

This indicator was developed by Joe Granville (1963) and it was aimed to determine a positive or negative volume trend, depending on the price change. Volume should be higher when the price follows the trend, in fact, if the trend is upward, I am expecting more volume on up days than on down days, and vice versa.

OBV is not an absolute number, in fact, taken individually, it is meaningless. The starting value is arbitrary and it is usually chosen the volume of the first day of data and then, by summing and subtracting the following daily values, the volume trend is built.

$$OBV_t = OBV_{t-1} + \begin{cases} \text{VOLUME} & \text{if Closing Price today} > \text{Closing Price Yesterday} \\ 0 & \text{if Closing Price today} = \text{Closing Price Yesterday} \\ -\text{VOLUME} & \text{if Closing Price today} < \text{Closing Price Yesterday} \end{cases}$$

This value are used in the same fashion as the trend indicator, which means that we apply the moving average crossover rule. More specifically, we will have the fast moving average including the last 7 days minus the slow one for the last 14 days. The reason why we chose this indicator is totally arbitrary, in fact, we wanted to represent a short term slope increase, if the fast moving average is greater than the short one, or a decrease, if smaller, according to the formula:

$$\text{Moving Average OBV Crossover (P, t)} \begin{cases} \text{Buy if:} & \text{MA 7 Days} > \text{MA 14 Days} \\ \text{Sell if:} & \text{MA 7 Days} < \text{MA 14 Days} \end{cases}$$

TRADING RULE

After obtaining a daily score for each stock in my portfolio from those indicators, we took into account the scores from the first trading day of December of the previous year until the last day of November, when the stocks are eligible. Continuing the example of the first year to make it more clear, the information considered are from $1^{St}$ December 2000 to $30^{th}$ November 2001, in order to predict the monthly performance from January 2001 to December 2001. The four different daily indicators score are summed together, generating only 9 possible values each day [-4,-3,-2,-1, 0, 1, 2, 3, 4] and this result will be used to generate a weighted average monthly score (WAS), which gives more weight to the last days of the month, since it is expected to affect most the next month returns. This method allowed us to rank our stocks from the best predicted performer to the worst, according to the formula:

$$WAS_m = W_1 \text{ x } S_1 + W_2 \text{ x } S_2 + W_n \text{ x } S_n$$

Where S represents the daily score, n is the number of days of the month and W is the weight given to each day, and we gave, as weight, the actual day divided by the sum of the days of the months. The best possible value could potentially be 4 and the worst possible value -4.

Then, we formed 5 quintiles of stocks, each portfolio including 20 stocks, where portfolio”1” is the best expected performer and “5” is supposed to be the worst. Put differently, we assigned the highest score to the first quintile of stocks and, then, we created the second, and so on until the last one.

we made some assumption for the academic purposes of this research. we utilized an equally weighted portfolios, where each stock’s position is 5% of the portfolio at any point in time, and it is also applied a monthly rebalancing rule, in fact, every stock is brought back to the original weight of 5% the last day of each month. Additionally, we have 100% of the capital allocated in the portfolio at any moment. This means that we assume our money is entirely invested in the stock market and there is no capital available for other purposes. Put differently, we exclude the capital allocation component. We only consider risk free rate to compute the premium that we obtain from our risky investment.

TIME LAGS

Pedersen (2015) puts emphasis on back testing the trading strategies. In particular, one important aspect is to guarantee that the strategy is implementable, in fact, we have to make sure that the data and all the information required are available at any point in time for completing the trades. Therefore, we selected the stocks with the highest market cap every year from the S&P 500 every last day of the year. For example, I picked the list the 31st of December 2014 and these stocks will remain the only eligible for the portfolio until the next 31st of December. I start trading the 2nd of January 2015, indeed we do not have any problem of missing information about which stock to choose that day. From those 100 stocks, I retrieved four daily data every day after the closing time of the US market. The data are Closing Price, Daily High, Daily Low and Volume, which are readily available at closing market hour. Then, I used the daily score of the previous month to generate a ranking of stocks from the highest expected performer quintile to the lowest, in order to make the trades the first day of every month from January to December with the same original pool of 100 stocks, which is then changing every year as explained. For example, I took APPL US Equity from 1st December 2014 to 31st November 2015. Then, the accumulation of daily signal for December 2014 gives me the score of that stock, and the position in the ranking of stocks, and consequently the belonging to one of the 5 sub-portfolios. The first order is placed the 2nd of January. Since then, every trade, which can be a buy, sell or hold, takes place the first day of every month from February to December 2015, according to the changes in the score value of any stock of the portfolio. Finally, one important assumption that we make is that a security is bought at the closing price of the previous day when the markets open. This is not true in reality, in fact, it is a rare occurrence that we are able to achieve that price, also due to the after-market and derivatives trades. However, it is a trick commonly used from academics to compute performances and also it is suggested by Pedersen (2015), since I can expect that on average the expected deviation from the closing price for all the securities for a long-time frame when the markets open should be zero, and, as a consequence, it should cancel out the disparities from the observed closing value.

## PERFORMANCE MEASUREMENT

It is important the evaluation of a strategy in order to define the alpha generated in regard with the risk taken, and also to identify the compensation obtained from the different risk that any portfolio can face.

More specifically for our portfolio, we decided to use five factors to evaluate it. All the factors are taken from Fama and French online database. The first one is the value-weighted return of the stocks listed in the main US markets. Put differently, it shows the extra amount gained by investing in our portfolio than leaving our money into the market. The second one is the High-Minus-Low (HML) factor, which controls for the higher expected returns given by stocks having high Book-to-Value as opposed to poorer performances of low Book-to-Value Stocks. Third, we have the Small-Minus-Big (SMB), which takes into account the better performances of small stocks vs bigger ones according to Market Cap, where the difference in size on average has historically shown outperformances for the small ones. The final two factors are Momentum and Short-Term Reversal. The reason to add these two extra factors to the usual three Fama and

French is that our work tries to connect technical analysis to short-term reversal, therefore, I want to find the impact that these factors, which are a key component for technical analysts, have on my portfolio. Put differently, I want to know if I create extra value or this premium is already captured by a portfolio that invests in these risk factors. More specifically, Momentum (WML) is the difference between the returns of the high prior (2-12 months) return portfolios and the low prior return portfolios. Short Term Reversal (STR) is the average return on the low prior (1 month) return portfolios minus the average return on the high prior return portfolios.

It is important to mention that my data can give slightly better results due to survivorship bias. In fact, for convenience, I removed the stocks that were eligible in the current year but they were delisted in the same period from the S&P 500 (which are 3 to 5 every year usually), leaving in the portfolio stocks that on average have performed slightly better than the market overall. The reason of not making such stocks part of the overall performances is that it would go further the objective of my research, and it is definitely one thing that could be analyzed deeper. Anyway, this information timing problem, which is that I would not know at the end of any year if a stock would be delisted the following one, could be overcome by creating a "waiting list" of stocks aside from the eligible ones, and immediately substituting them for the no longer present stocks into the portfolio, giving similar performances results, and removing the problem of acting on information not available at that time.

The final important information taken into account to compute my results is the risk free monthly value, which is taken from Fama and French online database. It is deducted from the all portfolio returns, in fact, all the portfolio results are net of the risk free in order to capture the value added by investing into the market, instead of limiting the own investment into the non-risky market.

## 3. Results

In Table 1, we can see the summary of the five different sub-portfolio performances according to our strategy and we obtained very interesting results. The main result to notice is the comparison between Portfolio “1” and Portfolio”5”, where the former includes the best predicted performer and the latter is made of the worst according to the technical forecast. Portfolio “5” produced an annualized return of 9.59%, which is 3.26% higher than the benchmark of the top 100 market cap stocks every year, and Portfolio “1” generated an annual return of 3.93%, which is 2.4% lower than the benchmark. Additionally, the volatility is also very similar, but still the portfolio 5 gives better results, in fact portfolio “5” shows a lower annual standard deviation of 16.14% than the compared portfolio “1”, which has 17.4%. As a consequence, the portfolio “5” having greatly higher returns and slightly lower standard deviation, generates a Sharpe Ratio, which is a common measure used to compute the amount of premium returns per unit of risk, more than 3 times higher than portfolio “5”, which is 0.5045 against 0.1427.

**Table 1. Performance 5 sub-portfolio January 2001 – December 2015**

| | **1** | **2** | **3** | **4** | **5** | **100** | **“5 – 1”** |
|---|---|---|---|---|---|---|---|
| Mean | 3.93% | 6.81% | 5.08% | 6.23% | **9.59%** | 6.33% | 5.66% |
| SD | 17.40% | 19.49% | 20.34% | 17.59% | 16.14% | 17.00% | **8.77%** |
| Sharpe Ratio | 0.1427 | 0.2750 | 0.1785 | 0.2722 | **0.5045** | 0.2871 | 0.4806 |
| Skewness | -0.60 | -0.55 | -0.46 | -0.47 | -0.58 | -0.59 | **0.26** |
| Kurtosis | **1.14** | 2.47 | 1.93 | 1.47 | 2.67 | 1.27 | 1.29 |
| Quartile 1 | 3.28% | 3.81% | 3.34% | 3.27% | 3.78% | 3.67% | 1.95% |
| Median | 0.94% | 0.92% | 1.18% | 1.35% | 1.11% | 1.06% | 0.34% |
| Quartile 3 | -2.27% | -2.15% | -2.09% | -1.74% | -1.93% | -1.85% | -1.02% |

This gives us two interesting investment options:

Long only in portfolio "5"

This strategy consists in simply buying the stocks that belong to the portfolio "5" starting in January 2001. Then, changing position every month according to the updated ranking, we would invest until December 2015. It would reward the highest returns of 9.59% and the highest Sharpe Ratio of 0.5045 of the all sub-portfolios, including a standard deviation of 16.14%, which is the lowest excluding long-short strategies. To measure the goodness of a long-only strategy, investors usually define an alpha, which represents the excess return of the own investment strategy compared to a benchmark, which can be one index and/or one or more factors. For more details about the factors chosen, I refer to the paragraph 2. Our alpha is taken according to the formula:

$$R_5 - R_{f} = \alpha_5 + \beta_{MKT} \text{ x } MKT + \beta_{HML} \text{ x } HML + \beta_{SMB} \text{ x } SMB + \beta_{WML} \text{ x } WML + \beta_{STR} \text{ x } STR$$

Betas are the correlation of the factors chosen with our portfolio. MKT is the performance of the main US markets, discounting the risk free. HML is High-Minus-Low, where high Book-to-Value stocks outperforms. SMB is the Small-Minus-Big with low stock performing best. WML is Winner minus Loser, which stands for momentum. STR is the Short-Term reversal indicator.
We refer to the results displayed in the table 2 of the appendix. The monthly alpha is 0.2932%, which annualized became 3.52%. The significance is considerably high, in fact, the adjusted $R^2$ of the observations is 0.7461 and the t statistic of alpha is 1.64, significant for a 10% confidence level.
Furthermore, it is interesting to notice the 2.67 value of excess kurtosis, which represents the likelihood that future returns will be either extremely large or small, which for our portfolio means that the probability of strong outliers is way higher than the other portfolios. Instead, -0.58

of  Skewness, which represents the asymmetry compared to a normal distribution, is in line with the comparable sub-portfolios and it indicates a small higher chance of negative returns.

<u>Long-Short "5-1"</u>

This strategy suggests to buy the stocks that belong to the Portfolio "5" and to sell the ones belonging to portfolio"1". The intuition behind is that in this way we can create a zero-investment portfolio with no money spent beforehand. In fact, we use the money collected from the short sales of the portfolio "1" to buy the stocks of portfolio "5". In reality, the money invested cannot be zero because to sell short the stock I need to borrow it first from someone else, and that procedure is usually few basis point expensive, depending on the liquidity of the stock. For the same time horizon, the realized returns would have been 5.66%, but with a greatly lower standard deviation than any other long-only portfolio of 8.66%, producing a Sharpe Ratio very similar to the long-only strategy in portfolio "5" of 0.4806.

To evaluate this strategy, we compare it to the same benchmark explained above and our aim to find again the alpha generated. According this time to the formula:

$$R_5 - R_1 = \alpha_5 + \beta_{MKT} \times MKT + \beta_{HML} \times HML + \beta_{SMB} \times SMB + \beta_{WML} \times WML + \beta_{STR} \times STR$$

It only changes our Y variables, which becomes the difference between the long and short leg of the portfolio.

We find the results in the table 3. The monthly alpha is 0.5083%, which annualized became 6.1% and its significance of the observation is very high according to a t statistic of 2.69.

Finally, beside a higher alpha, this portfolio compared to the previous one has another significant advantage, which is the excess kurtosis of 1.29, which gives much safer tail of the return distribution, as a consequence, it guarantees less amount of capital to keep aside for risk management purposes, in fact its Value at Risk should be consistently lower.

## 4. Conclusion

In this paper, we observe that, even though in the past there were strategies that have produced outstanding returns, the same ones applied looking forward do not guarantee positive returns compared to benchmarks. The reason could be that investors' beliefs and expectations keep evolving over time, therefore, any trading strategy should be flexible and adapt to market changes over time. In particular, we noticed the power of technical analysis due to the behavioral flaw of noise traders. More specifically, Moving averages dates back 1954 (Holt 1954); Stochastic Oscillator became very popular after G. Lane highlighted the predictive power; Bollinger Band showed profit of 2.96% monthly in the period 1983-2001 (Fang, Jacobsen and Qin 2014); On-Balance Volume has been extensively utilized after Joe Granville (1963). It cannot be proved that people used exactly these indicators, however, behavioral finance literature suggests that those signals have been incorporated into many individual strategies. In fact, we demonstrated how a long-only portfolio of stocks, which is supposed to underperform on a daily time frame according to our 4 indicators, generated a 3.52% of alpha yearly, and a long-short one rewarded 6.1%, compared to proper benchmarks, considering the following month's return. The lesson to take is that, if we expect crowds following popular strategies passively, we can assume that they are going to inflate a component of the prices, and a reversal in the next reasonable short term period is probable. Nonetheless, we do not say anything about the successfulness of the technical analysis itself, since we use it as a trigger for the decision process of many investors. To sum up, we can achieve winning strategies by picking good past strategies that can catch the attention of noise investors, who ignore the evolution of the markets and investors' expectations, therefore they generate trends that can be exposed to a short-term reversal.

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# 6. Appendix

Table 2: Long Only Portfolio

Dependent Variable: _5_RF
Method: Least Squares
Date: 12/28/16 Time: 13:39
Sample: 1 180
Included observations: 180

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.002932 | 0.001787 | 1.640236 | 0.1028 |
| MKT_RF | 0.944603 | 0.047511 | 19.88183 | 0.0000 |
| HML | 0.049202 | 0.064143 | 0.767063 | 0.4441 |
| SMB | -0.132996 | 0.073501 | -1.809438 | 0.0721 |
| STR | 0.025431 | 0.051901 | 0.489990 | 0.6248 |
| WML | 0.037614 | 0.037068 | 1.014730 | 0.3116 |

| | | | |
|---|---|---|---|
| R-squared | 0.753192 | Mean dependent var | 0.006786 |
| Adjusted R-squared | 0.746100 | S.D. dependent var | 0.046779 |
| S.E. of regression | 0.023571 | Akaike info criterion | -4.624816 |
| Sum squared resid | 0.096675 | Schwarz criterion | -4.518385 |
| Log likelihood | 422.2335 | Hannan-Quinn criter. | -4.581663 |
| F-statistic | 106.2005 | Durbin-Watson stat | 2.424736 |
| Prob(F-statistic) | 0.000000 | | |

Table 3: Long-Short Portfolio

Dependent Variable: _5_1_
Method: Least Squares
Date: 12/28/16 Time: 13:39
Sample: 1 180
Included observations: 180

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.005083 | 0.001891 | 2.687599 | 0.0079 |
| MKT_RF | -0.040927 | 0.050279 | -0.814001 | 0.4168 |
| HML | -0.011870 | 0.067880 | -0.174862 | 0.8614 |
| SMB | 0.031183 | 0.077784 | 0.400897 | 0.6890 |
| STR | -0.099295 | 0.054925 | -1.807838 | 0.0724 |
| WML | 0.051046 | 0.039227 | 1.301289 | 0.1949 |

| | | | |
|---|---|---|---|
| R-squared | 0.056929 | Mean dependent var | 0.004718 |
| Adjusted R-squared | 0.029829 | S.D. dependent var | 0.025325 |
| S.E. of regression | 0.024945 | Akaike info criterion | -4.511561 |
| Sum squared resid | 0.108268 | Schwarz criterion | -4.405129 |
| Log likelihood | 412.0405 | Hannan-Quinn criter. | -4.468408 |
| F-statistic | 2.100711 | Durbin-Watson stat | 1.978553 |
| Prob(F-statistic) | 0.067527 | | |