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PRICE DISTANCE TO MOVING AVERAGES AND SUBSEQUENT RETURNS

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Abstract

This paper is testing the premise that U.S. stocks exhibit mean reversion characteristics in the short to medium term (one week to one year), with the "mean"being the most commonly used moving averages. The analysis indicates that there is a connection between the distance of stock prices to moving averages and subsequent returns: portfolios of stocks with lower prices to moving averages generally outperformed portfolios of stocks with higher prices to moving averages This "overextended" effect is more pronounced when using shorter moving averages of 20 and 50 days, and is especially strong in short-term holding periods like one and two weeks. The highest annual returns are recorded when buying in the range of 0-5% below shorter moving averages of 20/50 days, and 0-10% below longer moving averages of 100/200 days. However, buying very far below almost all moving averages on almost all holding periods produces the lowest returns.

Keywords: Moving averages, mean reversion, U.S. stock market, technical analysis, P/MA ratio, R-squared

INTRODUCTION

When thinking about buying a stock that has recently gone up too much in price probably every investor feels at least a little bit discomforting. Instinctively, they fear the security is now due for a downward correction. On the other hand, investors see a stock that has recently sharply fallen as a potential buying opportunity because they assume it is now ready to rebound.

This kind of thinking comes largely from two sources: psychological conditioning and experience. Most of us have been conditioned from early on not to overpay and always search for bargains or discounts. So, mental shortcuts or heuristics make us deem stocks that have gone up a lot as "expensive" and those that have gone down a lot as "cheap". The other aspect is experience, mostly painful, after witnessing on more than one occasion high-flying stocks getting crushed or beaten-down securities rise from the ashes. While each personal experience is utterly subjective, this can be easily explained by the very nature of the stock movement, which is highly fluctuating on most observable time frames, except the longest ones. Therefore, investors have come to expect adverse price development in securities they follow or put another way, they tag stocks that have strayed too much in any direction as "overextended" and bound to come back to some notional "mid-point" or "true" value. Such reasoning is not without merit, as we will soon see because research shows that stocks do exhibit the tendency to "return to the mean" after periods of over- or undershooting.

From the practitioner's point of view, the concept is relatively straightforward. Fundamental analysis uses discounted cash flows and comparison techniques to determine the "fair" value of a security. If for instance, the "fair" value of a stock is calculated to be \$100 and its price on the exchange is \$120, then the stock is clearly overvalued and due to return to "fair" value in the (not necessarily near-term) future. Technical analysis obviously makes no reference to the fundamental value of a firm but assesses if the stock price is overextended simply by comparing it with its past price. Technicians use a wide array of different indicators to help them with this task, like the relative strength index (RSI), stochastic oscillator, moving average convergence-divergence indicator (MACD), etc. Overbought levels of these indicators flash technical signals that the security, after a run-up in price, is now prone to reverse, while oversold levels indicate the possibility that the stock, after a period of weakness, is now poised for a rebound.

Academics have looked intensely into this matter and found different effects on different time scales. In the short term, Lehman (1990) finds that from 1962 to 1986 portfolios of stocks that had positive returns in one week typically had negative returns in the next week, while those with negative returns in one week typically had positive returns in the next week. This would imply that a "reversal effect" exists in stock investing in the short term. Jegadeesh (1990) draws a similar conclusion for the monthly time interval. From 1934 to 1987 winning stocks from the previous month turned into loser stocks the next month, and vice versa. However, Lo and MacKinley (1987) state that in the period from 1962 to 1985 weekly stock returns exhibit positive serial correlation, meaning that positive returns in one week are more likely to be followed by positive returns in the next week and negative returns in one week are more likely followed by negative returns in the next week. This can be interpreted as to stocks having “momentum” characteristics, which would be quite the opposite from “mean reversion”. More recently, Gray and Vogel (2016) tried to resolve this by examining monthly stock returns from 1927 to 2014. They notice a reversal in returns from month to month: the returns of a monthly rebalanced portfolio of stocks with the worst returns from last month generate a compounded annual growth rate (CAGR)of 13,46%, while the returns of a monthly rebalanced portfolio of stocks with the best returns from last month earn only a CAGR of 3,21%, which was even less than the risk-free rate for this period. This is also observed by Da, Liu, and Schaumburg (2013) for the period from 1982 to 2009 on the monthly time frame, with short-term return reversal in stocks being more pervasive and greater than previously reported.

While the weight of the evidence seems to favor mean reversion of stock returns in the short term (on a weekly and monthly basis), when investigating the medium-term time frame(from 3 to 12 months) studies find the opposite. The landmark paper of Jegadeesh and Titman (1993) showed that stocks that have risen the most in the previous 12 months tend also to outperform in the next 3 to 12 months, while stocks that have fallen the most in the last 12 months tend to keep falling in the next 3 to 12 months as well. The majority of follow-up research in the next decades supported their conclusion, suggesting that trend-following strategies on the mid-term should be applied to exploit this “momentum effect”, as opposed to using reversal strategies on shorter time frames to capture the “return to the mean” phenomenon.

Finally, in the long-term (multiyear periods)the case is again very strong for stocks reversing to the mean. When DeBondt and Thaler (1985) categorized stocks in groups from worst performing to best performing in the last three years and measured subsequent three year returns they found that the worst performing stock portfolio of the previous three years was the best performing portfolio of the next three years, and vice versa. Fama and French (1988) and Poterba and Summers (1988) indicate pronounced negative long-term serial correlation in the performance of the aggregate market, similar to Chopra, Lakonishok and Ritter (1992) who also found that in portfolios formed on the basis of prior five-year returns, extreme prior losers outperform extreme prior winners by 5–10% per year during the subsequent five years. All in all, the current standing in academic literature is a rough consensus that stocks exhibit mean reversion characteristics in the short and long-term while showing momentum attributes in the medium-term.

As mentioned earlier, many investors and trading professionals are preoccupied with the idea of “runaway” security prices and how to properly deal with them. In this study will try to examine one popular technical concept: the moving average (MA) as the unequivocal reference point for “mean” value. The moving average is the average price of a number of specified prior periods that gets “moving” by including the most recent price into the calculation and dropping the oldest one. From the technical perspective, the moving average can be seen as the fair value of a security. Prices too high above the MA or too low below it represent overextended conditions which are likely to be remedied in the future by a reverse price movement. The timeframe in which this reversal should occur depends on the length of the moving average itself. For example, if the price of a stock is significantly above its 200 days moving average, returns are expected to be lower in the long term (months to years), while if the price is significantly higher than the 20 day MA one would expect lower returns in a very short time frame (days to weeks).

Based on this premise popular technical literature is advocating so-called “swing trading”, like for example Elder (2002) and Carr (2008). Elder claims that “prices keep getting away from a moving average but snap back to it as if pulled by a rubber band.” The concept of “swing trading” recognizes three different modes of action. In a clearly established upward trend traders should be buying when prices are near or below the MA line and selling when prices move too far above the MA. Conversely, in downward trend stocks should be shorted when reaching or going above the moving average and covered when they drop too far below the MA line. In a sideways movement “swing traders” are advised to buy if the price is too low below the moving average and sell when it goes too far above it.

In this paper, we are trying to find out whether this particular technical idea has some merit. Does it really matter at what distance to their relevant moving average stocks is bought? Or framed more precisely: are the subsequent returns lower if stocks are bought at levels too far above the MA, and are subsequent returns higher if stocks are bought at levels much lower than the MA line? The focus will be on the U.S. stock market since it is the biggest, most liquid equity market in the world with the longest data series. Also, most research on the reversal and momentum effect is done with U.S. stocks and they are the focus of most popular investing approaches touted by practitioners. Beneficially as well is the fact that information on U.S. stocks is easily accessible and included in many software simulation packages.

METHODOLOGY

All price data in this study was taken from the investment website Portfolio123, which compiles it from the Compustat database. The Compustat database is operated by S&P Global Market Intelligence, one of the biggest data and analytics provider in the world.

The examined time period is January 2nd, 1999 to August 11th, 2017. It is a highly representative time span because it encompasses two bull markets (2003-2007; 2009-2017 and ongoing), two bear markets (2000-2002 and 2007-2009) and a year and a half of sideways movement in 2015/16.

The study only included stocks that in the period in question were members of the S&P 1500 index. The S&P 1500 is comprised of three sub-indices: the large-cap S&P 500 index, the mid-cap S&P 400 and the small-cap S&P 600 index (S&P Dow Jones Indices, 2017). That makes the S&P 1500 an index of “tradable” securities, stocks with sufficient market capitalization and liquidity that they can be bought and sold without significant impact on their prices. Many simulations that test the aggregate U.S. stock market with more than 8000 listed companies tend to come up with results that are strongly influenced by the performance of numerous small and micro-cap securities. Because of the low liquidity and high transaction cost of these stocks, it is generally more difficult to invest any meaningful amounts in them, which would in practice most likely alter the results of the performed analysis. Hence, we only consider stocks that can be easily bought and sold by institutional and individual investors, such as those in the S&P 1500 index.

For the purpose of this study moving averages of four different lengths or lookback periods were chosen, with two different methods of their calculation. Firstly, the length or lookback period of the MA is 20, 50, 100, and 200 days. There is nothing special about the chosen time periods; these MA are simply the ones most commonly used by market practitioners and most often cited in technical analysis literature. Also, they cover the spectrum of time scales needed: from the short term (represented by the 20 dayMA) to medium term (100 day MA) and long-term (200 day MA), with the 50 days MA being somewhere between a short and medium term MA.

Secondly, two different moving averages were used based on their method of calculation: the simple moving average (SMA) and the exponential moving average (EMA). Again, both dominate market practice and literature. The SMA is the simple mean of the previous period’s closing prices. The “moving” part of the SMA comes from dropping the oldest price from the calculation of the mean in favor of the most recent one.

The formula for the SMA is:

$$SMA = \frac{p_t + p_{t-1} + \cdots + p_{t-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{t-i}$$

Where, p_t is today's closing price and n is number of periods (Wikipedia, 2017).

While simple moving averages give all prices the same weight, exponential moving averages are calculated as follows:

$$EMA_t = p_t K + EMA_{t-1}(1-K)$$

$$K = \frac{2}{(n+1)}$$

Where, p_t is today's price, n the number of periods and K the weight of the most recent observation (Elder, 2002).

EMA is weighted; the most recent price has the biggest weight in calculating the average while the oldest price has the least impact. Therefore, EMA is more biased towards the current market situation than SMA and will respond more quickly to new price changes. To the knowledge of the authors, no study has so far convincingly proved that the use of one MA calculation method is superior to the other. The SMA is slower than the EMA which sometimes can be beneficial to traders and other times not. It is predominantly a matter of personal preferences which one to use in technical trading. Two different moving average calculation methods are applied to the data in order to assess whether the obtained results are sufficiently consistent to draw meaningful conclusions. Since the concept of moving average application is very similar in both versions there is no valid reason why the results should be markedly different when using SMA or EMA. By employing two different MA on the data an additional layer of verification is established.

The aim of the paper is to find out if the price distance of the stock to the respective MA has any relation to its subsequent returns. The price distance for every stock to the MA is calculated by dividing the current price (P) with the appropriate moving average (MA) to obtain the P/MA ratio:

$$P/MA = \frac{Current\ price\ P}{SMA/EMA\ of\ n\ periods}$$

For every S&P 1500stock in the investigated period from 1999 to 2017 the P/MA ratio was calculated and the stock was put into the corresponding decile category, from 1 (lowest P/MA ratio, i.e., lowest price in regard to the MA) to 10 (highest P/MA ratio, i.e., highest price in relation to the MA). These decile portfolios are then held for the specified holding period, after which they are continuously rebalanced until the end of the simulation. The holding periods of the constructed stock portfolios are chosen to cover the short-term (1, 2 and 4 weeks), medium term (3 and 6 months) and the long-term (12 months).For example, if the holding period is one week, stocks are sorted into corresponding deciles according to their P/MA ratio every week, from January 2nd, 1999 to August 11th, 2017, which amounts to976 rebalances. On the other hand, for a holding period of 12 months, the portfolio was rebalanced only 19 times.

The annualized total return (the compounded annual growth rate of price appreciation/depreciation plus dividends) for every SMA and EMA length and every holding period was calculated and compared across deciles. For example, holding stock portfolios with the lowest P/MA, i.e., those with the lowest price to the SMA 20 for 4 weeks would have resulted in a CAGR of 10,3% in the period 1999 to 2017, while holding stocks with the highest P/MA, i.e., those with the highest price to the SMA 20 for the same holding period of 4 weeks would have yielded a CAGR of 8,8% (see Table 1). The calculation of the P/MA ratio and annualized returns was done with the Portfolio123 build-in simulation software. Transaction cost and slippage were not accounted for.

After calculating annual returns across deciles for every MA and every holding perioda simple regression of these returns was performed. A simple linear regression is a method for describing and evaluating the relationship between a given (dependent) variable *y* and one explanatory variable (or independent variable) *x*. The formula is:

$$\hat{y}_t = \hat{\alpha} + \hat{\beta} x_t$$

Where, α is the intercept and β the slope (Brooks, 2008).

Also, the coefficient of determination or R^2(R-squared) is calculated. R^2 is the square of the sample correlation coefficient or the Pearson's correlation coefficient. Pearson's correlation coefficient is a measure of the linear correlation between variables *x* and *y*. It is the covariance of the two variables divided by the product of their standard deviations (Šošić, 2004):

$$\rho_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y}$$

R^2 is often interpreted as the proportion of the variation in variable *y* explained by the variation in variable *x*. Thus, $R^2 = 1$ indicates that the model explains all variability in *y*, while $R^2 = 0$ indicates no linear relationship between the response variable *y* and the explanatory variable *x*. A value of R^2 between 1 and 0, for example, 0.815 as found in the third column of Table 1,can be interpreted as follows: 81,5% of the variability in the annual returns of stock portfolios with a holding period of two weeks can be attributed to the distance stock prices have to the SMA 20. The remaining 18,5%can be credited to other, unknown variables. Higher R^2would, therefore, indicate a stronger relationship between the distance prices have to their respective MA and subsequent returns, while lower R^2would suggest a weaker connection. The R^2 of all moving averages and holding periods will be summarized in tables and compared.

However, even knowing that a strong correlation exists between the price distances to their MA with subsequent stock returns is not always precise enough for market participants. If it is indeed more profitable to buy stocks with lower prices in comparison with their MA than practitioners usually want to know what lower levels are those: 1%, 5%, 20% or some other percentage below the MA? In order to solve for this, stocks will be regrouped in categories according to their actual percentage distance to the relevant MA. The calculation methodology is the same as before, stock portfolios are held across the whole spectrum of moving averages and time frames (from 1 week to 12 months) and their respective CAGR is calculated (including dividends). The purpose is to find out if there are common areas of outperformance/ underperformance in terms of percentage levels around the moving averages.

ANALYSIS AND RESULTS

Table 1contains the annual returns for the stock portfolios constructed on the basis of price distance to the 20, 50, 100 and 200 day SMA (the P/SMA ratio) across all investigated holding periods, as well as the respective R^2.Most eye-catching are the very high R^2 of around 80-90% for the shorter moving averages SMA 20 and 50 in the shortest holding periods of one and two weeks. Lower P/SMA decile portfolios outperform higher P/SMA decile portfolios in these time frames, with the difference in returns almost completely (80-90%) explained by the distance the stock price has to its SMA 20 and 50. In practice, this means that short-term traders can expect to outperform in a one or two week time window if buying stocks with lower prices compared to their 20 and 50 SMA as opposed to buying stocks with higher prices in relation to these MA. The higher the stock price to the MA, the lower the returns traders can expect. When the investment horizon moves beyond the two-week time frame, lower decile portfolios by and large still outperform higher decile portfolios, but the R^2 noticeably drops, indicating that the correlation between the P/SMA 20 and 50 and subsequent returns is getting weaker with the expansion of holding periods.

The longer moving averages SMA 100 and SMA 200 demonstrate somewhat different characteristics. Here, only the one week holding period for the SMA 100, with a very high R^2 of 92,5%, is consistent with the above finding. Other R^2 on different lengths and holding periods vary considerably, especially for the SMA 200, suggesting more randomness. Although lower P/SMA portfolios generally outperform higher P/SMA portfolios here as well, the relationship between the distance prices have to their longer SMA and subsequent results are not as strong as the relationship between prices and their shorter SMA 20 and 50.

To verify above assertions the same procedure was undertaken with the other widely used moving average, the EMA. Results are presented in Table 2.

Table 1: P/SMA annual returns and R^2 in %

SMA lenght	Holding period	Deciles										R^2
		1	2	3	4	5	6	7	8	9	10	
20	1 week	14,1	13,9	12,3	12,9	11,3	11,0	9,6	9,2	7,6	3,8	88,8
	2 weeks	11,9	12,4	11,8	13,3	10,6	10,7	8,9	9,3	7,7	7,3	81,5
	4 weeks	10,3	11,6	11,6	12,9	11,4	10,8	10,3	8,3	7,8	8,8	53,3
	3 months	11,2	13,4	12,9	11,2	9,9	10,6	9,2	9,7	9,0	5,6	73,1
	6 months	9,9	12,1	12,0	12,0	9,5	10,3	10,0	9,8	9,5	7,0	51,3
	12 months	8,5	11,1	12,6	11,9	10,3	11,1	10,3	9,7	9,0	8,8	16,9
50	1 week	13,6	12,7	11,9	10,9	11,1	10,6	10,7	8,9	8,3	6,6	92,5
	2 weeks	11,6	12,8	12,5	10,5	10,9	10,1	9,7	8,5	8,4	8,5	86,0
	4 weeks	10,7	13,5	13,1	11,6	10,8	10,2	9,3	8,5	8,7	7,1	75,9
	3 months	9,4	11,3	15,0	11,3	11,1	10,0	9,8	8,3	8,0	8,0	42,0
	6 months	10,0	10,7	13,1	12,2	10,0	10,2	9,3	9,1	8,3	8,9	46,0
	12 months	10,0	12,1	13,0	11,5	9,5	9,5	10,0	10,3	8,7	8,2	50,0
100	1 week	13,5	12,0	11,3	11,2	10,5	10,1	9,5	10,1	8,6	7,9	92,5
	2 weeks	11,0	11,6	12,6	10,6	9,6	10,0	9,1	10,5	9,1	8,6	62,7
	4 weeks	10,4	12,4	13,0	10,3	10,0	9,6	9,5	9,5	9,2	8,9	57,2
	3 months	7,5	12,3	11,9	11,3	11,9	9,8	9,4	9,9	8,9	8,8	11,7
	6 months	9,2	11,8	11,3	10,6	10,9	9,2	10,4	9,8	8,6	9,9	22,0
	12 months	10,4	12,2	11,8	11,9	10,8	10,7	9,3	9,6	8,0	7,9	71,1
200	1 week	11,1	10,8	12,1	10,7	10,7	11,7	10,5	8,7	9,3	8,7	58,0
	2 week	10,0	10,2	11,9	11,1	10,8	10,4	9,9	8,1	10,4	9,8	18,9
	4 weeks	9,2	11,5	11,8	11,1	11,1	10,6	9,6	8,0	10,0	10,1	17,3
	3 months	7,2	11,9	12,9	10,1	10,7	9,9	10,6	8,8	9,8	9,9	1,4
	6 months	7,9	11,0	12,5	10,3	11,6	10,5	10,0	9,1	9,4	8,9	8,1
	12 months	9,5	12,5	11,9	10,9	13,3	10,4	10,3	8,7	8,8	5,9	45,6

Source: Portfolio123 backtesting software & authors' calculations

Table 2: P/EMA annual returns and R^2 in %

EMA lenght	Holding period	Deciles										R^2
		1	2	3	4	5	6	7	8	9	10	
20	1 week	14,3	13,5	12,4	11,6	11,8	10,7	10,1	8,3	8,4	4,3	89,7
	2 weeks	11,9	12,4	12,0	11,9	11,1	10,1	9,6	9,0	7,9	7,9	92,6
	4 weeks	10,1	12,3	12,4	12,0	11,1	10,2	10,9	8,8	7,3	8,9	55,0
	3 months	11,9	14,0	12,9	11,9	9,5	11,0	9,2	8,8	8,2	5,1	81,8
	6 months	10,0	13,3	11,7	11,9	9,0	10,6	9,5	9,5	9,7	6,9	51,6
	12 months	9,5	13,2	10,7	11,4	10,0	10,6	10,4	10,4	8,7	8,4	37,1
50	1 week	14,7	12,6	11,3	11,7	11,4	9,9	10,4	8,6	9,3	5,5	85,3
	2 weeks	11,6	12,4	12,1	11,1	10,3	10,1	9,7	8,9	8,4	8,7	90,9
	4 weeks	10,4	13,4	13,0	11,0	11,1	9,5	9,7	8,0	9,1	8,3	64,4
	3 months	9,9	12,2	13,3	11,3	11,5	9,8	10,8	7,8	7,0	8,5	53,5
	6 months	9,8	12,1	12,8	10,5	10,4	9,9	9,9	8,7	8,5	9,0	53,1
	12 months	9,7	13,4	13,2	11,0	10,1	9,1	10,1	8,8	9,3	8,0	50,9
100	1 week	13,7	13,2	11,0	10,8	10,6	10,6	10,1	9,4	8,2	7,2	91,8
	2 weeks	11,6	12,7	11,3	11,2	9,7	9,4	9,9	10,0	8,5	8,9	79,2
	4 weeks	10,4	14,3	11,8	10,1	10,3	9,1	10,8	8,7	8,1	9,6	46,2
	3 months	7,9	12,4	12,4	11,8	10,7	10,1	9,9	8,8	8,9	8,8	21,4
	6 months	8,6	11,9	12,5	10,3	10,7	10,6	9,2	10,1	8,3	9,3	21,5
	12 months	9,4	13,3	12,2	11,7	10,4	10,3	9,7	9,6	8,2	7,5	55,1
200	1 week	11,7	13,5	11,3	12,1	11,5	10,4	8,8	9,3	8,0	8,0	82,9
	2 weeks	10,3	12,5	11,8	11,5	10,6	9,9	8,7	9,8	8,3	9,4	59,2
	4 weeks	9,5	13,5	11,9	11,4	9,9	10,5	9,0	8,9	8,4	9,9	39,2
	3 months	7,2	13,0	12,2	10,6	11,2	9,4	10,3	9,1	8,5	9,9	7,3
	6 months	7,5	11,6	12,4	11,8	11,0	9,9	10,6	8,9	7,9	9,2	12,9
	12 months	8,7	12,1	12,8	11,5	12,2	10,1	10,5	9,0	8,3	6,8	39,8

Source: Portfolio123 backtesting software & authors' calculations

Here again, the shorter length EMA of 20 and 50 in the shortest holding periods of one to two weeks display the same features like their SMA cousins, with an even higher R^2 of around 90%. Interestingly, this relationship transfers almost in full scale to the EMA 100 in the one and two weeks holding period, as well as to the one week period of the EMA 200.Otherwise, we see the same pattern developing as with the simple moving averages before; with the expansion of the holding time horizon correlations not only drop but evolve in a more random manner. Traders can still expect to outperform when buying lower P/EMA portfolios as opposed to higher ones, but the probability of doing so decreases with the expansion of the holding period above one and two weeks.

To get an even better perspective of the correlations, every calculated $R^2$is listed separately in Tables 3 and 4 along with their median value across different MA lengths and holding periods.

Table 3: R^2 (%) for SMA and holding periods

MA lenght	Holding period						Median
	1 week	2 weeks	4 weeks	3 months	6 months	12 months	
SMA 20	88,75	81,5	53,27	73,05	51,33	16,92	63,16
SMA 50	92,47	85,96	75,85	41,97	46,04	49,98	62,92
SMA 100	92,5	62,68	57,19	11,67	21,95	71,1	59,94
SMA 200	57,95	18,85	17,34	1,44	8,11	45,55	18,10
Median	90,61	72,09	55,23	26,82	34,00	47,77	

Source: authors' calculations

Table 4: R^2 (%) for EMA and holding periods

MA lenght	Holding period						Median
	1 week	2 weeks	4 weeks	3 months	6 months	12 months	
EMA 20	89,73	92,62	55,04	81,76	51,64	37,06	68,40
EMA 50	85,28	90,91	64,39	53,46	53,05	50,9	58,93
EMA 100	91,78	79,16	46,21	21,38	21,52	55,08	50,65
EMA 200	82,94	59,21	39,24	7,29	12,85	39,78	39,51
Median	87,505	85,035	50,625	37,42	36,58	45,34	

Source: authors' calculations

Tables 3 and 4 confirm our previous observations about the stronger relationship between price distance to moving averages and subsequent returns in the very short term. The median R^2 in the one to two-week holding periods is quite high, ranging from 72,09% to 90,61% for the SMA and 85,03% to 87,5% for the EMA. It can be reasonably assumed that within holding periods of one to two weeks there is a higher probability for portfolios of stocks with lower P/MA ratios (lower prices in regard to their MA) to outperform portfolios with higher P/MA ratios (higher prices relative to their MA). This most likely implies a certain short-term “reverse to the mean” feature, where the “mean” in this case would be the respective MA. This is especially true for shorter moving averages like the EMA and SMA of 20 and 50 and probably holds as well for the mid-term SMA and EMA 100, although with a bit lower R^2. On the other hand, the 200-day moving averages show a relatively high R^2 only in the one week holding period for the EMA 200 (82,94%), which cannot be verified with the SMA 200 (57,95%). Since the results for the holding periods of one and two weeks differ quite substantially (57,95%and 18,85% for the SMA 200 and 82,94% and 59,21% for the EMA 200), while other moving averages in these holding periods display more clustered results, the outcome for the MA of 200 are to be taken with some reservation. Observed on both moving average types is the fact that with the expansion of holding periods beyond the one and two-week horizon the median R^2gets evidently smaller and evolves more randomly, pointing to weakening relationships between price distance to MA and future returns.

The other part of data analysis in Tables 3 and 4 is the comparison of the median $R^2$of moving averages of different lengths. Here, it stands out that the median R^2 is generally higher for shorter moving averages. As we move from the 20 day MA towards the 200 MA the median R^2drops from 63% to 18% for the simple and from 68% to 39% for the exponential moving average. The shorter-term SMA and EMA 20 and 50 consistently show higher R^2 across the board on almost any holding period than the SMA and EMA of 100 and 200. Whatever correlation may exist for the price distance to MA and subsequent results, it seems to be stronger not only for shorter holding periods but also for shorter moving averages as well. Traders should be aware of that.

If it can be reasonably considered that it is more profitable to buy stocks that have lower prices in regard to their MA (especially in the short term) than a logical question would be what lower levels in percentage terms are those? To answer this question stocks have been regrouped in categories according to their percentage distance to the respective MA. Results for the SMA are found in Tables 5 and 6. Cells that are shaded green represent the highest annual return in each holding period, light green the second best return, and red shaded cells stand for the lowest return.

Table 5: Price distance to 20 and 50 SMA and annual returns (%)

Distance to MA	Holding period											
	1 week		2 weeks		4 weeks		3 months		6 months		12 months	
	SMA 20	SMA 50	SMA 20	SMA 50	SMA 20	SMA 50	SMA 20	SMA 50	SMA 20	SMA 50	SMA 20	SMA 50
> 10%	0,77	5,18	7,21	8,24	7,73	7,49	4,44	9,08	4,52	10,08	5,14	8,91
5% < 10%	3,76	7,39	5,34	6,89	6,47	7,28	7,71	7,38	7,18	6,93	7,82	9,06
2,5% < 5%	8,46	10,73	9,75	9,77	7,25	9,11	8,99	9,24	8,91	8,51	10,78	10,33
0 < 2,5%	10,50	11,30	10,93	11,56	10,89	9,51	10,86	10,57	10,83	10,90	10,80	9,87
-2,5% < 0	12,23	11,07	12,53	11,85	12,48	11,75	11,68	11,52	11,87	12,96	11,60	13,34
-2,5% > -5%	13,84	11,37	13,66	11,34	11,10	11,24	11,16	11,48	11,53	11,87	12,31	12,70
-5% > -10%	13,90	13,74	11,61	12,28	8,40	9,98	8,22	9,87	9,24	11,07	11,35	10,54
< -10%	7,51	10,98	1,96	6,62	-0,37	4,81	-0,29	1,80	-4,32	2,70	1,02	6,28

Source: Portfolio123 backtesting software

Table 6: Price distance to 100 and 200 SMA and annual returns (%)

Distance to MA	Holding period											
	1 week		2 weeks		4 weeks		3 months		6 months		12 months	
	SMA 100	SMA 200	SMA 100	SMA 200	SMA 100	SMA 200	SMA 100	SMA 200	SMA 100	SMA 200	SMA 100	SMA 200
> 20%	6,42	8,76	10,32	10,68	10,22	11,87	9,62	9,51	11,73	9,11	7,01	6,14
10% < 20%	8,36	8,49	7,54	8,11	8,93	7,21	7,81	8,43	7,46	8,50	7,49	7,98
5% < 10%	9,18	9,21	8,12	8,92	6,81	8,02	8,22	7,06	9,20	7,80	8,70	8,29
0 < 5%	9,95	8,54	11,45	8,02	10,76	8,06	10,04	8,65	9,86	9,69	10,01	8,92
-5% < 0	11,10	10,07	10,01	9,70	10,01	10,26	10,95	10,08	11,40	10,88	10,54	10,57
-5% > -10%	13,75	11,65	11,38	11,56	10,79	9,25	9,38	9,16	10,58	10,79	9,44	9,32
-10% > -20%	10,28	10,78	7,65	8,27	5,73	7,01	6,90	5,42	8,88	8,26	9,26	6,62
< -20%	4,64	2,57	1,23	0,32	-2,61	-2,60	-6,64	-3,04	-5,21	-0,87	0,16	4,47

Source: Portfolio123 backtesting software

There are two takeaways from this analysis. First, the best results for the SMA 20 and 50, on average, are concentrated in the region of 0-5% below the MA for the majority of holding periods. The pattern of returns for the longer SMA 100 and 200 is not so clear-cut but the area 0-10% below the MA generally dominates on most holding periods.

Second, while portfolios of stocks below their MA perform on average better than those above, buying stocks that are furthest below their respective MA is not the optimal choice. Far from it, almost unanimously, on almost all moving average lengths and almost all holding periods, those portfolios turn out to be strongest underperformers. It looks like that stocks very far below their MA do not exhibit mean reversion but momentum characteristics since they continue to significantly underperform other portfolios in holding periods of one week to one year.

To see if this finding holds for the EMA as well the same calculations will be applied. Results are shown in tables 7 and 8.

Table 7: Price distance to 20 and 50 EMA and annual returns (%)

Distance to MA	Holding period											
	1 week		2 weeks		4 weeks		3 months		6 months		12 months	
	EMA 20	EMA 50	EMA 20	EMA 50	EMA 20	EMA 50	EMA 20	EMA 50	EMA 20	EMA 50	EMA 20	EMA 50
> 10%	-2,51	5,27	2,97	10,85	6,28	10,10	4,87	9,57	5,99	9,72	6,01	7,44
5% < 10%	4,27	7,37	6,34	7,34	7,36	6,55	6,47	6,57	6,78	6,66	7,52	8,81
2,5% < 5%	6,58	8,54	6,99	8,83	7,30	8,62	8,83	8,71	8,11	8,94	10,22	9,42
0 < 2,5%	9,96	9,90	10,46	9,93	10,11	9,83	10,85	10,49	10,53	10,89	10,32	10,06
-2,5% < 0	12,89	11,87	12,24	12,27	12,32	12,07	11,53	12,04	11,98	12,70	12,70	12,69
-2,5% > -5%	16,41	13,95	15,08	10,97	11,91	10,84	11,66	11,72	12,13	12,23	12,67	12,68
-5% > -10%	15,60	15,15	12,22	12,67	10,07	10,47	8,96	8,45	7,88	10,16	11,12	9,83
< -10%	6,58	11,87	-0,52	7,11	-4,03	3,53	-8,94	-0,94	-6,78	1,15	-1,84	6,43

Source: Portfolio123 backtesting software

Table 8: Price distance to 100 and 200 EMA and annual returns (%)

Distance to MA	Holding period											
	1 week		2 weeks		4 weeks		3 months		6 months		12 months	
	EMA 100	EMA 200	EMA 100	EMA 200	EMA 100	EMA 200	EMA 100	EMA 200	EMA 100	EMA 200	EMA 100	EMA 200
> 20%	9,55	8,40	15,81	10,22	16,28	11,44	8,45	9,29	11,20	7,91	6,96	6,03
10% < 20%	6,27	7,13	7,42	7,76	8,40	7,61	7,48	7,16	7,49	7,67	6,93	7,76
5% < 10%	8,03	8,35	7,56	7,78	7,17	7,28	8,24	8,76	8,29	8,95	9,05	8,50
0 < 5%	9,69	8,29	10,07	7,61	9,50	8,06	9,97	8,47	10,39	9,70	9,28	9,40
-5% < 0	11,05	11,17	11,14	11,56	11,12	10,69	9,57	8,44	11,14	10,36	10,92	10,00
-5% > -10%	15,01	12,35	12,23	10,65	10,02	9,87	9,61	7,88	10,40	10,58	9,13	7,93
-10% > -20%	11,63	12,28	6,87	9,55	3,95	6,64	4,72	5,97	6,67	5,68	8,14	5,20
< -20%	0,46	1,57	-1,56	-0,40	-4,71	-3,58	-10,67	-5,96	-5,73	-1,54	1,29	3,83

Source: Portfolio123 backtesting software

Again, we see the same pattern emerging when using exponential moving averages. The shorter EMA 20 and 50 produce, on average, the best results 0-5% below the MA, which is mirroring the outcomes obtained from the shorter SMA. The returns of the longer EMA 100 and EMA 200 are more randomly distributed than their SMA counterparts, but here as well investors are more likely to outperform if they concentrate their buying in the range of 0-10% below the MA. The same strong underperformance, though, is noted with stock portfolios furthest below the MA, backing up the identical finding in the SMA segment.

CONCLUSION

The analysis performed in this study indicates that there is a connection between the distance of stock prices to their respective moving averages and subsequent returns. Like in the cited academic research, prices tend to exhibit “reversal to the mean” attributes, with the mean, in this case, being the relevant MA: portfolios of stocks with lower prices to moving averages (low

P/MA portfolios) generally outperformed portfolios of stocks with higher prices to moving averages (high P/MA portfolios).Still, this assertion cannot be indiscriminately applied to all examined MA and holding periods. The “overextended” effect is more pronounced when using shorter moving averages like the SMA and EMA of 20 and 50days, and is especially strong in short-term holding periods like one and two weeks. While in this timeframe the same conclusion could probably be drawn for the intermediate SMA and EMA of 100 as well, this cannot be positively confirmed for the long-term moving averages of 200 days.

Additionally, when searching for so-called “sweet buying spots”, i.e. the percentage distance of prices from moving averages where the highest annual returns can be achieved, the range of 0-5% below shorter term MA of 20 and 50 comes up as the winner; and somewhat less convincingly, the range of 0-10% below the intermediate and long-term MA of 100 and 200. But, perhaps more interestingly and unexpectedly, buying very far below almost all MA in almost all holding periods turns out to be the worst possible option. In other words, it is more likely that a trader can outperform if he/she buys below the MA but not extremely below the MA, concretely not lower than 10% below the 20 and 50 MA, and not lower than 20% below the 100 and 200 MA. When the stock price is very far below the MA it seems that instead of mean reversion, momentum takes over and keeps pushing those prices even further down, at least in the investigated time periods of one week to one year.

It must again be stated that since no transaction cost and slippage were considered, this strategy cannot be recommended per se. Returns would probably be much lower (especially on shorter time horizons which require frequent rebalancing) when these costs are taken into account, and that would certainly reduce its practical efficacy. Still, it can be regarded as a supplement tool to an existing investing/trading methodology wherein, for example, a new position can be entered only upon prices coming down to “value”, i.e. near or below their MA. In such a set-up, traders/investors could count on a higher expectancy of outperformance in contrast to buying stocks that are very far above their MA. This is especially true if the moving averages in question are the SMA and EMA of 20 and 50 and the investment/trading horizon is the next couple of weeks.

The examined time period of 1999 to 2017 is very representative because it covers more than one stock market cycle, but further research could concentrate on different eras of the past when trying to verify the findings of this paper. If the relation of stock prices to moving averages is truly a factor in determining subsequent returns, then there is no sound reason why this should not also be observed in the decades before the tested period. Additionally, it would probably be interesting to note if the results of this study hold when going beyond the one year holding horizon. We found that the relationship between the P/MA ratio and subsequent returns is weakening when moving from one week to one year holding periods, as evidenced in the decreasing R^2, but what happens if the holding period is extended to 3 or 5 years? Finally, a conclusion that is valid for only one market, albeit being the biggest and the most liquid one, is inherently fragile. Further insight is needed of the development of stock prices, moving averages and investor returns on a global level. More far-reaching conclusions could only be drawn if similar results were to be found on other national stock markets as well.

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