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Does Momentum Work?

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Given the definition, can active managers outperform?

According to the many advocates of passive investing, if an investor is picking stocks in the public equities markets and gets better than average returns, it doesn't count if the selections represent types of stocks that usually have done better in the past. It doesn't count if upon analysis it is discovered that the positions disproportionately represent smaller or value companies. The common wisdom of the Capital Asset Pricing Model (CAPM) is that one would expect better returns because while these types of stocks have more variation in their returns, overall they perform better over time. Therefore performance is evaluated not in comparison to the overall market, but in comparison to similar indexes such as market cap size or value stocks. The rationale is that one could have obtained similar out-performance merely by buying indexes representing small and/or value stocks.

To extend this logic, if the investor has any systematic screening criteria for selecting outperforming stocks, one could say that it is a form of index investing. Might there not be an index that represents stocks characterized by five different variables, each variable with a range determined by historical quantitative analysis? I believe this is called Smart Beta. The definition that remains of active investor is someone who picks each stock in a purely idiosyncratic way. The challenge for the systematic investor is that the more focused the selection criteria, the more likely that what worked in the past will not work in the future given that markets have multiple unpredictable cycles for what is in favor.

In addition to small cap and value, the investment academic and trade literature adds momentum as a characteristic of outperformance. The assertion is that stocks going up will continue to go up, although in reading some of the academic articles cited to support momentum, the data used is spotty and the statistical evidence is not that strong. Counter evidence is discounted in the narratives. When I have tried buying stocks with nice up trends, it doesn't seem to work. This prompts the question of whether there are known characteristics of a trending stock that precede a reversal in the trend, or an abandonment of the trend in favor of a random walk. Are trends with a tighter and tighter range or variability more likely to break, as expounded by the fractal analysists and also the technical analysts who predict from triangles? Does the slope of the trend matter? Does the duration of the trend matter? Does the straightness of the trendline matter?

Are perceived trends merely random?

Are we seeing momentum and trends when in fact the price movement is random? To look at this, imagine a hypothetical experiment with 3,000 die representing the Russell 3000 index. We roll each dice 25 times to establish a simple moving average (SMA). Statistically we know that the average is going to be 3.5 (average of 1 through 6) and the values will form a normal distribution or bell-shaped curve. Any dice that consistently comes up with fours, fives and sixes is going to cumulatively show returns moving up. I did it on Excel with a random number generator and found one dice with a 6 ten times, a 5 four times, a 4 four times and a 3 seven times. There were no 1's or 2's representing bigger losses. And true to form, the pattern for all 3,000 followed a normal bell-shaped distribution.

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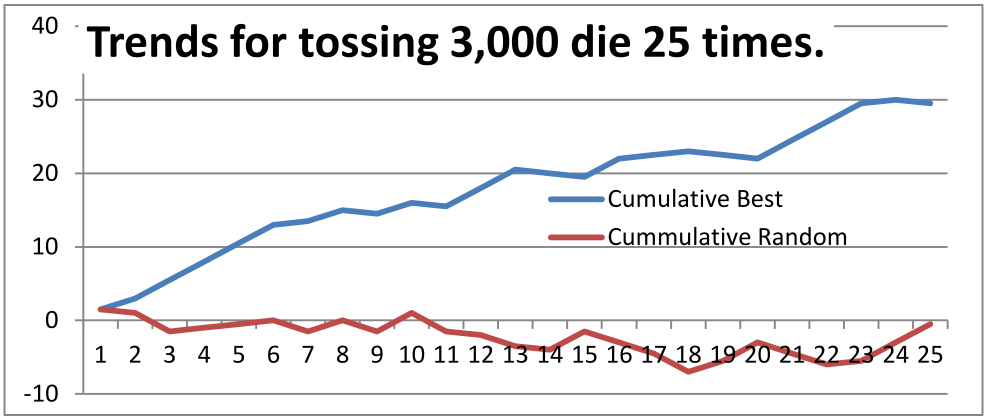


The blue line on the chart shows the dice with the best cumulative return. Note that in spite of appearance, it is still a result of randomness. Is it similar to sorting through charts of the Russell 3000 and picking the stock with the best momentum? Contrary to intuition and appearance, the odds on the next roll or the next day's percent change are still average. This is an example of curve fitting. While the odds of finding that particular pattern and apparent trend were one in 3,000, the odds in the future are still 50:50 between rolling a three or less versus a four or more.

Note that the red line appears to be trending down but is also random. It was the first one selected arbitrarily from those with a value of 87 or at the middle of the bell-shaped curve.

So it is easy to sort 3,000 stocks and find a few with strong up trends that promptly go nowhere after being purchased. Of course if we rolled the same 3,000 die again, and again, and each time the same dice came up with similar results, then we might have something such as a weighted dice or a stock with reason to excel. So is a longer trend going to be more persistent into the future, or merely more likely to have its luck run out? The naked eye looking at a chart has trouble distinguishing a trend from a random movement. Using a Fractal Dimension Indicator I have found that most but not all charts are random most of the time.

Does the perception of trend and momentum by many investors or speculators in itself create a trend? Are markets influenced by market makers? (Definitely, that is their job.) Are markets influenced by fund flows in and out impacting buying pressure in the balance between buyers and sellers? If so, what is the role of money supply? What is the influence of a third of the market being comprised by indexed products buying every stock within the index regardless of merit, however defined? And how about another third of the market comprised of the benchmarked active managers buying up enough of the stocks in an index to at least come close to matching their benchmarks?

I had selected a list of twenty or so stocks with very nice looking trends when I decided that, against this backdrop, I would run some tests before actually buying. Could I learn anything about the shape of the trends (tightness, slope, straightness, length) that would help me in knowing what trends would hold and which would reverse? It is easy to theorize most anything. What would the data tell me?

Methodology

I arbitrarily decided to review weekly price-change data on the current 3,000 largest market cap stocks beginning in August of 2009. Using twenty-five weeks as my measure of trend gave a starting point at the beginning of the current bull market. I measured percent change returns at intervals going forward of one week, two weeks, three weeks, four weeks, eight weeks and twelve weeks, and converted all of these to an annual rate for purposes of comparison. Starting with trends at the end of the first twenty-five weeks and ending with allowance for twelve-week returns going forward, I had 310 weeks of data. After taking account of stocks that existed for only part of this period, 768,462 rows of data remained for my first analysis.

Price data was obtained from Yahoo using the XLQ add-on in Excel. Data were not available from historical Yahoo data for stocks no longer listed, so we are dealing with retrospective results. We have no way of knowing survivorship bias from delisted stocks. Did they go bankrupt and the value go to zero? Were they acquired at a premium? Did they merely reorganize with little impact on total value?

The variables thus available and constructed were:

1. Price.
2. Standard deviation of percent change in price over the previous 25 weeks.
3. Simple moving average (SMA) of percent change in price over the previous 25 weeks.
4. Coefficient of variation or the standard deviation divided by the SMA over the previous 25 weeks.
5. Fractal Dimension Indicator. This is a measure I had XLQ program for me that measures the degree to which the price pattern is linear or one-dimensional and the extent to which the price pattern is all over the chart or two-dimensional.
6. I included the current market cap and price/sales but didn't find that it had much value since it lacked historical perspective.
7. On the first set of data I did not use correlation of each row to the average of all stocks for that week. I repeated the analysis with a slightly different set of data and then included correlation, plus SMA and standard deviation for just the previous four weeks, the eight weeks prior to that, and then the twelve week prior to that. The purpose of dividing up the prior periods was to determine if there were excess returns from stocks moving consistently up or down, followed by a basing or flat period, followed by a more recent trend up.

To analyze the data I used a tool called KnowlegeSEEKER which divides the results for each variable into clusters. I usually start with the default 10 and may checkout results for 20 clusters. If adjoining clusters have similar results, they are combined. The required level of statistical significance is set at .01, although most results are greater than .0000001 because of the relatively high N. Results for each cluster can be further refined in a hierarchical fashion using other variables. The minimum size for each cluster is set in order to preclude spurious results for a small set that would not be replicated in the future. It is a good tool but more art that science in terms of adapting for curve fitting. It has a built in Bonferoni adjustment to correct for the fact that if one searches long enough and deep enough, one will always find something of interest.

Findings and Elaboration of Table Data

What I judged to be the best returns are given in Screen 7 (column 7) of the table on the next page. The returns after four weeks are in the box. The average percent change over four weeks is taken times 13 to give an annual rate for making comparisons to the rates of return on other timer periods going forward from the presumed purchase. **In this case the overall rate of 16% for all 3,000 stocks has been improved to 104% or by a factor of about 6 times**. The Coefficient of Variation (standard deviation divided by average) gives a measure of how consistent the findings are within each cluster. Adding the correlation variable significantly improves the consistency of findings. **The selected screen is also 6 times more consistent than the market's COV of 13.4** over a four-week period.

The findings in column seven utilize only two variables, the simple moving average of the rate of return and the correlation of a stock's percent change each of twenty five weeks correlated to the average for all stocks. The particular parameters (SMA-RR > -0.009 and correlation >0.822) produced an expected count of 13 stocks each week. If I want a larger count, I could choose Screen (column) 6 or even 5. If I want a smaller count, I could choose column 8 or even column 9.

All of the variables are linear in the sense that each cell with a higher or lower parameter value produced progressively higher or lower returns. The impact is typically much greater near the end of the scale. For the past week, screen 7 produced only six stocks instead of the expected 13. I want to diversify with at least ten. Since the greater the correlation, the greater the returns and the greater the consistency of returns, for this first week I chose to go with Screen 6 and then take the ten selections with the highest correlations.

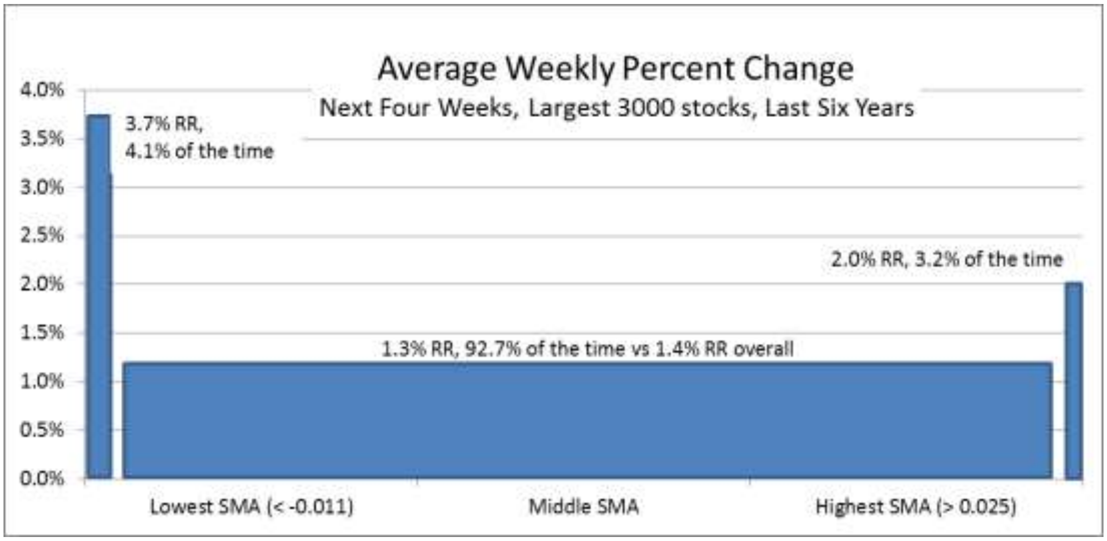
Findings		First Set of data			Second set of data						
	Screen	1	2	3		4	5	6	7	8	9
Variables (Subsets)		SD-RR	SMA-RR	Pr-Wk	All	SMA-RR	Correl	SD-RR	Correl	Prior4wk	SD-4wk
Parameters	>	0.065					0.734	0.061	0.822		0.081
	<		-0.011	11.87		-0.009				-0.049	
Count per 3,000 stocks		548	70	42	3000	186	32	18	13	7	5
Annualized RR	Rate of Return Weeks Forward										
	1	41%		62%	17%	42%	90%	111%	114%	161%	198%
	2	38%	67%	80%	16%	39%	84%	103%	109%	140%	161%
	3	36%	65%	77%	17%	42%	88%	102%	113%	137%	154%
	4	36%	61%	74%	16%	39%	81%	93%	104%	129%	160%
	8	34%	49%	61%	16%	31%	60%	72%	70%	79%	90%
	12	33%	45%	58%	16%	24%	41%	47%	45%	47%	53%
	Avg	36%	58%	69%	16%	36%	74%	88%	92%	116%	136%
	St Dev	3%	10%	10%	0%	7%	19%	24%	29%	43%	54%
	Deterioration	-19%		-8%	-4%	-42%	-54%	-58%	-61%	-71%	-73%
Coefficient of Variation (StDev/Avg) Lower is better.	COV Weeks Forward										
	1	35.6		33.2	16.4	10.9	4.7	4.2	3.7	2.5	2.3
	2	22.3	6.9	6.5	11.7	8.0	3.3	2.9	2.5	1.9	1.8
	3	2.0	5.5	5.1	15.3	6.3	2.5	2.4	1.9	1.6	1.6
	4	18.5	5.0	4.6	13.4	5.9	2.4	2.3	1.9	1.6	1.4
	8	15.8	4.2	3.9	10.4	5.1	1.9	1.8	1.6	1.5	1.4
	12	12.9	3.3	2.9	5.0	3.7	1.9	1.7	1.9	1.8	1.6
	Avg	17.9	5.0	9.3	12.0	6.6	2.8	2.6	2.3	1.8	1.7
	StDev	11.1	1.3	11.7	4.1	2.5	1.1	0.9	0.8	0.4	0.3

The rather precise numbers should not be presumed to be replicated going forward, but rather represent broad patterns. While they might be as good a number to use as any, the parameter values for example are merely where the initial cluster divisions happen to fall. Expected returns will not match the numbers here in part because of extrapolating annual returns from brief time periods, and in part because of the way the data are skewed by a few stocks gapping up or down which will not likely be replicated.

The findings posted in the table have been selected from a much broader range of explorations. The extent of accidental curve fitting represented will only be determined by future explorations with other populations. I plan to do a similar study of monthly percent change over a ten-year period.

Additional Summary of Findings

1. At least for this period of time with the current 3,000 largest stocks, upward momentum did not produce nearly the amount of gains as did downward trends. In science it is easier to prove something false than to prove something true. Momentum may work over long historical time periods, as is obvious if one looks at a long historical chart of the market, or over very short periods, but it hasn't worked on a weekly timeframe over the past six years for most domestic stocks. A reversal of trend was more frequent than a continuation of trend.



a. In the first dataset, the strongest percent change of 3.7% over four weeks was found in the 4.1% of stocks with the lowest SMA.

b. The next best returns at 2.0% over four weeks were found in the 3.2% of stocks with the highest SMA.

c. The vast 92.7% of stocks in between had the lowest returns at 1.3% over four weeks compared to the overall average of 1.4%. While the returns for this group may not be a random walk, in this case they are not predictable by trend behavior.

2. While relatively few stocks meet trend criteria, the 50% of stocks priced under $23.63 improve returns by 36%. However, price did not interact with other variables well enough so as to include it in the chosen screening criteria.
3. Anything that works based on trends deteriorates significantly over time. Expect the rate of return over 12 weeks to be 60% less than proportional returns the first week for the best screen. Therefore, the strategy is to buy and hold for only four weeks.
4. The higher the returns, the greater deterioration from the first week's returns to the overall twelve week returns. (Correlation -.73)
5. The trend measurements of Coefficient of Variation (COV) of price change over the 25 weeks and Fractal Dimension Indicator (FDI) did not identify clusters of consistent out-performance.
6. The best variables of merit are the simple moving average (SMA) and correlation with the market.
7. Statistically the most significant variable is standard deviation or volatility over the 25 weeks, with greater volatility producing greater gains. However, the results within each range of values for standard deviation are highly variable, and the variable doesn't readily interact well with other variables.
8. The simple moving average (SMA) measures the slope of the trend. We are not measuring turns or crossings of moving averages. The steeper slopes down precede the best returns.
9. The selected screen works better over more recent periods than it did for earlier weeks.
10. I created the appropriate indicators for standard deviation (SD) and simple moving average (SMA) in TC2000. On any given chart, when I look back over time and compare the charted lines for SD and

SMA to the value identified in this exploration, the chart lines generally correspond to when stocks reached their low and turned up.

11. The actual periodic selection of stocks to buy is done with a smaller spreadsheet that calculates the variables and filters the stocks.

Questions and Discussion

The overall question was whether patterns of price variation have predictive value for future price variation. At this point it would appear that they do, but in support of the contrarian downtrends rather than the assumed momentum. It is not unusual for there to be more opportunity for profits in going opposite the crowd. In a way, the findings here are to be expected if value stocks have better returns, since value stocks usually become value stocks by price declines. I recall reading a book from the early Twentieth Century that advocated buying stocks after a long decline, followed by a flat period of basing, and then starting to turn up. That was not confirmed here with the parameters selected.

The big variation that we cannot get at is survivorship bias. How many of the stocks in steep decline continued to decline and disappeared as bankrupt? I'm not able to find any research that would give an indication, or a practical way to assemble enough relevant data to answer the question. Even if a stock has declined from say $30 per share to $2 per share and continues down or down and out, the loss is limited to 100% of that stock while stocks that bounce can increase 100% and continue going back up. Even if it didn't go back up to $30, if it went up to $12 that is a 600% return.

Intuitively, there is such a fear of loss that one might expect gains by buying large numbers of down-trending stocks, since that is an opportunity which most speculators avoid. We know from behavioral finance that fear of loss is stronger than greed for gain. If a stock is going down, most investors fear continuing losses. If a stock is going up, at some point the fear of a reversal takes over, especially upon a small lurch down.

We know from the Black Scholes formula that undergirds the options markets that volatility is more predictable than price. This is not merely academic theory but used in everyday price determinations. Therefore it should not be surprising that volatility corresponds to changes in price movement going forward. Without price movement there is no room for gains. So if other variables can foretell the direction, the volatility foretells the likelihood of a change and the amount.

To understand why correlation might be such an important variable one must think about why high correlation between stocks and markets exist. Why do so many diverse stocks move in synchronized harmony second by second all day long? Is there some ether in the news that causes all these investors to trade together? The best explanation I know is that indexed buying is buying or selling all these stocks at the same time. Stocks with greater correlations to the market might be presumed to have a e greater impact from index buying.

My interpretation of the significant impact that correlation with the market has on improving returns and consistency is that stocks fall based on factors such as company news, fundamentals or merely the fear that every investor has in buying a falling knife. Declining stocks turn around at some point because of the buying pressure coming from the index products and buying which buys all stocks in an index regardless of price. Some indexes continuously rebalance the positions in the index, some do so annually. If the cap weighting of the positions held in an index is not automatically adjusted as a stock's price falls, the more the price declines the greater the relative influence of the index buying. At some point the strength of the high proportion of index buying for a specific stock reverses the downward trend. If my findings are indeed predictive and my interpretation is correct, it poses a way for an active investor to capitalize on the prevalence of passive investing.