Wenzel Analytics Inc

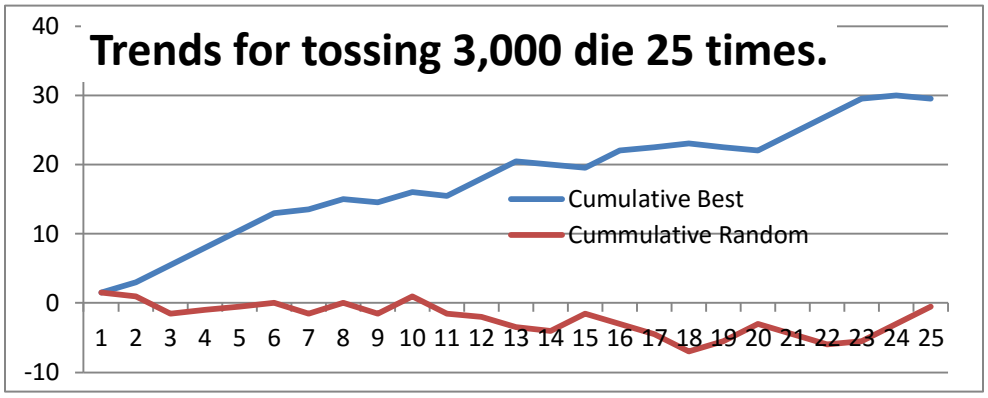
Does Momentum Work?

11/17/15

If an investor is picking stocks in the public equities markets and gets better than average returns, it doesn't count if upon analysis it is discovered that the positions disproportionately represent smaller companies according to the total value of their shares, or represent value rather than growth, meaning that the price was relatively cheap given factors such as earnings, sales and book value as determined by accounting standards. (Is the research supporting value stocks done prospectively or retrospectively on the stocks that survive?) The common wisdom 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 of 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? The definition of active investor is someone who picks each stock in a purely idiosyncratic way. However 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. When I have tried this it doesn't seem to work. This prompts the question of whether there are other 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 the technical analysts describe with triangles? Does the slope of the trend matter? Does the duration of the trend matter? Does the straightness of the trendline matter?

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 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.



The blue line on the chart shows the dice

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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. So is a longer trend going to be more persistent into the future, or merely more likely to have its luck run out?

Maybe markets are not random. Does such perception 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. The arbitrary twenty-five weeks as my measure of trend gave an arbitrary 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.

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 constructed or available 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. I wish I had used correlation of each row to the average of all stocks for that week. Maybe next time.

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 one searches long enough and deep enough, one will always find something of interest.

Findings

		Parameters		**N per**	**Annualized RR**								
Scrn		>	<	**3,000**	**Wks: 1**	**2**	**3**	**4**	**8**	**12**	Avg	St Dev	Deterio ration
	1 Wk RR, All			3,000	20.8%	19.5%	19.1%	18.2%	17.9%	18.1%	19%	1.1%	-13%
1	SD-RR	0.065	0.127	498	33.8%	32.2%	31.2%	30.8%	29.9%	30.1%	31%	1.5%	-11%
2	SMA- RR		-0.011	63	64.0%	59.3%	58.9%	55.3%	43.6%	42.3%	54%	8.9%	-34%
3	SD-RR	0.127		50	113.4%	91.8%	86.3%	85.8%	73.0%	67.6%	86%	16.0%	-40%
*	SD-RR	0.189		14	241.3%	178.1%	173.2%	173.2%	144.1%	125.5%	173%	39.4%	-48%
*	SD-RR	0.096		140	68.6%	59.0%	56.0%	55.4%	51.0%	48.8%	56%	7.0%	-29%
*	Pr-Wk		11.87	87				81.6%	74.7%	71.2%	76%	5.3%	
*	SD-RR	0.065		548	41.1%	37.7%	36.2%	35.8%	33.8%	33.5%	36%	2.8%	-19%
*	SMA-RR		-0.011	70		67.3%	65.0%	61.2%	48.9%	45.3%	58%	9.9%	
*	Pr-Wk		11.87	42	62.4%	79.6%	77.5%	73.7%	60.5%	57.5%	69%	9.5%	-8%
4	SMA-RR		-0.011	123	56.7%	50.4%	50.8%	48.1%	36.2%	35.8%	46%	8.5%	-37%
5	SD-RR	0.065		70	73.8%	67.3%	65.0%	61.2%	48.9%	45.3%	60%	11.0%	-39%
6	SMA-RR	-0.011	0.025	2,780	18.7%	17.7%	17.3%	17.3%	16.9%	16.9%	17%	0.7%	-9%
7	SMA-RR	0.025		97	36.9%	29.9%	26.0%	25.9%	26.3%	29.8%	29%	4.2%	-19%
8	SD-RR	0.127		26	57.2%	51.7%	41.8%	39.5%	37.2%	44.3%	45%	7.7%	-23%
9	Pr-Wk		23.63	1,502	28.1%	26.3%	25.7%	26.0%	24.2%	24.4%	26%	1.4%	-13%
10	SD-RR	0.127		43	137.8%	111.3%	105.2%	104.0%	90.0%	82.6%	105%	19.2%	-40%
11	SMA-RR		-0.011	99	61.4%	54.9%	54.6%	50.7%	40.8%	40.8%	51%	8.3%	-34%
12	COV (F)	43.64	87.39	34	84.2%	69.9%	74.5%	75.4%	67.9%	59.7%	72%	8.3%	-29%
*	20 cells or clusters instead of 10												

The table above gives the average annualized percent change or rate of return. The table on the next page gives the consistency of these returns, measured as the coefficient of variation or standard deviation divided by the average within each cluster.

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 these tables 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. The findings are probably more relevant in what they prove to be false than in what they prove to be true.

Scrn		Parameters >	Parameters <	N per 3,000	Coefficient of Variation (StDev/Avg) Wks: 1	2	3	4	8	12	Avg	StDev
	1 Wk RR, All			3,000	31.5	19.7	17.5	16.5	13.3	10.6	18.2	7.3
1	SD-RR	0.065	0.127	498	12.3	9.0	7.6	6.6	4.9	4.0	7.4	3.0
2	SMA- | RR		-0.011	63	8.0	6.0	4.9	4.5	3.9	3.2	5.1	1.7
3	SD-RR	0.127		50	41.2	28.7	27.1	24.5	23.5	20.4	27.6	7.3
*	SD-RR	0.189		14	36.6	27.8	25.4	23.0	22.6	20.8	26.0	5.7
*	SD-RR	0.096		140	40.9	27.0	25.2	22.9	20.2	17.0	25.5	8.3
*	Pr-Wk		11.87	87				19.5	17.4	14.7	17.2	2.4
*	SD-RR	0.065		548	35.6	22.3	2.0	18.5	15.8	12.9	17.9	11.1
*	SMA-RR		-0.011	70		6.9	5.5	5.0	4.2	3.3	5.0	1.3
*	Pr-Wk		11.87	42	33.2	6.5	5.1	4.6	3.9	2.9	9.3	11.7
4	SMA-RR		-0.011	123	10.3	7.7	5.9	5.4	4.8	3.6	6.3	2.4
5	SD-RR	0.065		70	9.5	6.9	5.5	5.0	4.2	3.3	5.7	2.2
6	SMA-RR	-0.011	0.025	2,780	35.3	21.8	19.5	17.5	14.3	11.6	20.0	8.3
7	SMA-RR	0.025		97	15.4	13.0	11.9	10.4	7.1	5.3	10.5	3.8
8	SD-RR	0.127		26	15.2	11.5	11.2	10.1	7.4	5.2	10.1	3.5
9	Pr-Wk		23.63	1,502	31.9	19.8	17.8	15.8	13.6	10.9	18.3	7.4
10	SD-RR	0.127		43	36.5	25.4	23.9	21.8	20.5	17.9	24.3	6.5
11	SMA-RR		-0.011	99	9.9	7.3	5.7	5.3	4.5	3.3	6.0	2.3
12	COV (F)	43.64	87.39	34	65.7	44.3	37.2	33.2	30.2	27.6	39.7	14.0
*	20 cells or clusters instead of 10											

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 gains as did downward trends. A reversal of trend was more frequent than a continuation of trend.
    a. The strongest percent change of 3.7% over four weeks was found in the 4% of stocks with the lowest SMA.
    b. The next best returns at 2% over four weeks were found in the 3% of stocks with the highest SMA.
    c. The vast 93% 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%.
3. Price moving down with significant variation in weekly price change had the most consistent returns balanced with the strongest returns at 60% annualized. Consistency is measured by an average coefficient of variation of 5.7 with relatively little variation of return by duration going forward. See Screen 5 in the tables above.
4. Anything that works based on trends deteriorates significantly over time. Expect the rate of return over 12 weeks to be 40% less than proportional return the first week.
5. The higher the returns, the greater deterioration from the first week's returns to the overall twelve week returns. (Correlation -.73) Even so, returns for the full twelve weeks are considerably above average.
6. The trend measurements of Coefficient of Variation (COV) and Fractal Dimension Indicator (FDI) did not identify clusters of consistent out-performance.
7. The three variables of merit are the standard deviation (SD) of percent price change over the preceding twenty-five weeks, the simple moving average (SMA) and price. Until I went from ten

clusters to twenty clusters, I couldn't find a statistically significant use of all three variables that would produce a satisfactory sample size. Combinations of any two of the three variables work well.

8. Standing alone or with the other two variables, greater standard deviation within the trend is the strongest variable. In a linear relationship, the more the volatility, the better the returns. The most consistent 81.7% in weekly price change had price change of 1.2% over four weeks. The next 16.6% had price change of 2.4% over weeks, surpassing the average 1.4%. The next most volatile 1.2% had price change of 4.0% over four weeks and the final 0.5% had price change of 13.3% over the next four weeks.
9. The simple moving average (SMA) measures the slope of the trend. We are not measuring recent changes, turns or crossings of moving averages. The steeper slopes down precede the best returns, followed by steeper slopes up.
10. Moving from the numbers to looking at actual stocks and charts selected by the findings, I found that in the current market the momentum criteria selected only four stocks, and they were all in the same sector (healthcare). I created the appropriate indicators for SD and SMA in TC2000 and selected stocks using the screening criteria. I found it easy to thus find promising looking charts. 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.

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 may well be true. Our methodology here is not refined enough to tease out the parameters. With some work, one might be able to separate the delisted stocks into those that followed a steep down trend and those that did not. That would give a hint, but not a definitive answer.

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.