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Bringing Real-World Testing To Relative Strength

Numerous academic and practitioner studies have shown relative strength—also known in academia as "momentum"—to be a robust factor that leads to outperformance. However, much of the academic research has been handicapped by testing methodologies that are not at all similar to the way that portfolios are managed in the real world. This white paper discusses our improved testing process, which incorporates two elements that are unique: 1) a continuous portfolio testing protocol that manages portfolios the way they are managed in the real world, and 2) a Monte Carlo process overlaid on the continuous portfolio testing to insure robustness.

Part I: Background

Relative Strength and momentum strategies have been used by market technicians for stock selection for many years. All the way back in the 1950's, George Chestnutt was publishing market letters with stocks and industry groups ranked based on relative strength. Chestnutt also used his research to manage the very successful no-load mutual fund, American Investors Fund.

In the 1960's, computing power became more readily available and Robert Levy published what would be one of, if not the first, tests of using relative strength as a stock selection strategy. His work was published in the 1968 book, The Relative Strength Concept of Common Stock Forecasting. Levy's work was incredible for its time considering the amount of computing available to him. He tested not only relative strength as an investment factor, but also two different portfolio management strategies. His research into "upgrading" versus "replacement" as a portfolio management strategy was well ahead of its time and certainly holds true today. Levy's relative strength calculations were fully disclosed in his research. He compared the current price versus an intermediate-term moving average. This same relative strength formulation is still used by Charlie Kirkpatrick who wrote Beat The Market: Invest by Knowing What Stocks To Buy and What Stocks to Sell in 2008. After almost 50 years, Levy's fully disclosed factor continues to deliver market-beating performance.

The academics began to heavily research the topic of momentum in the early 1990's. In 1993, Jegadeesh and Titman published the paper, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." Their research showed momentum strategies based solely on historical pricing data outperformed over time. This was a serious blow to the Efficient Market Hypothesis because it had been commonly assumed no investment strategy based solely on publicly available data could outperform the market over time. Their work has spawned scores of research papers on the topic of momentum and relative strength. Over time, research has shown that momentum exists over intermediate time horizons. Momentum also exists across asset classes, countries, and in many other areas. There has been so much research showing that momentum works that academics no longer dispute its value as an investment factor.

Part II: Traditional Testing Methods

Relative strength and momentum strategies have traditionally been tested in one of three ways. The first method is to take a predetermined number of securities and hold them in a portfolio for a predetermined time period. The top 50 high relative strength stocks, for example, might be held in a portfolio for 12 months. At the end of the 12 month period, all 50 stocks are sold, and the new 50 highest relative strength stocks are purchased. One of the biggest drawbacks to this strategy is the sensitivity to the start date of the portfolio. Very different results can be achieved if you form your portfolio at the end of June instead of at the end of December. Another major drawback to this method is the very small sample of securities that is included in the portfolio. It is difficult to determine the robustness of the strategy when dealing with such a small sample.

In order to increase sample size, many academic papers separate a large universe into deciles or quartiles. Instead of looking at how a small sample of securities performs, they are looking at how a selection of several hundred securities, for example, is performing. This is a dramatic improvement over looking at a very small sample size. This method, however, suffers from some of the same problems as the previous model. When the portfolio is formed, several hundred securities are purchased and held until a pre-determined sale date. Sometimes portfolios are held 12 months, and some research shows portfolios being rebalanced at more frequent intervals. The tradeoff is a difficult one. Rebalancing on a more frequent schedule reduces the effects of the calendar, but also increases the turnover in the portfolio.

A third testing method used involves buying large numbers of securities in multiple portfolios for a predetermined time period. The goal of this method is to reduce the effect of the formation date, while attempting to limit turnover. Each month, for example, the top decile of securities is purchased and held for 12 months. Because a new portfolio is formed each month, at any given time there are 12 portfolios open. Each month the maturing portfolio is sold and a new one is created. The other 11 portfolios remain untouched. This process can be run over any time period. Another way to run the test would be to run 6 portfolios and hold each one 6 months. As you can imagine, the number of securities held at any given time is quite large. While this method does limit the effects of the calendar, it also involves quite a bit of turnover and operational overhead.

It is also important to note that most academic studies (methods 2 and 3) focus on the spread between

Disadvantages Of Current Methods

Top X Securities	Top Decile	Top Decile / Multi-Port
• Sensitive To Start Date	• Sensitive To Start Date	• Huge Number Of Holdings
• Small Sample Of Securities	• Large Number Of Holdings	• Large Number Of Transactions
• Pre-Defined Rebalance	• Pre-Defined Rebalance	• Pre-Defined Rebalance

high relative strength securities and low relative strength securities. When portfolios are formed, a low RS portfolio is formed and sold short, while the high RS portfolio is held long. These two portfolios form a "zero cost" long/short portfolio. This method does a good job testing whether ranking securities by relative strength provides a performance edge between the high- and low-ranked securities. However, in practice, most portfolios are not run in this fashion. The short side of the market has operational difficulties and is much less efficient to trade than the long side. In addition, many portfolios don't even attempt to participate on the short side; they have long-only mandates.

Part III: Improved Testing Process

In order to account for many of the deficiencies we have identified in existing testing protocols, we developed a unique testing process to quantify the impact of implementing different relative strength factors in real-world portfolio situations. We developed our continuous, Monte Carlo-based testing process from the ground up, and no part of it is commercially available. It is truly unique to us. When we developed the process, we wanted to move our testing from the realm of factor testing to real-world implementation. While no testing process is perfect, we feel our unique method allows us to get a better view of how different portfolios and factors perform over time in different markets than many of the more widely used processes.

Our testing methodology allows us to do continuous portfolio testing rather than being limited to the fixed holding period testing used in other protocols. Actively managed portfolios are not necessarily rebalanced on a fixed schedule. We designed our process to trade the portfolios on an "as needed" basis. Each holding's relative strength rank is examined weekly (or whatever time period we specify – it can be as frequently as daily), and if it needs to be sold that one holding is sold. Everything that still qualifies for inclusion remains in the portfolio. Sometimes a test will go weeks (and occasionally, months) without a trade. Other weeks, there will be a flurry of trades. But the main thing to remember is that the portfolios are being traded exactly like an actual account would be traded. We feel this is a dramatic improvement on the fixed holding period models that are used in almost all of the research we have seen. Our continuous process allows us to eliminate the calendar problems associated with fixed time period rebalancing, while also allowing turnover to remain at an acceptable level.

Advantages Of Our Testing Methods

- Not sensitive to start date or calendar effects
- Continuous portfolio testing
- Realistic number of holdings
- More optimal holding periods
- Monte Carlo process to ensure robustness

The second testing deficiency we wanted to improve on was the large number of holdings that result from many testing methodologies, particularly those favored in the academic community. The universe of eligible securities can often number several thousand. If you are looking at the top decile of relative strength ranks, for example, you can easily wind up with several hundred securities in the portfolio. This can be implemented in an institutional setting, but is very cumbersome. Research also shows that concentrated portfolios, while often more volatile, deliver better performance over time. Our Monte Carlo process restricts the portfolio to a smaller number of securities (usually 25 or 50) that is more easily implemented in real life, and that has the potential to overweight the real winners.

Because we don't hold every highly ranked security, and we trade on an "as needed" basis, we designed our testing process to determine if our tests were robust over time. Normally when you take a sub-set of highly ranked securities you just take, for example, the top 25 out of the top 100. The problem with this is that you never know if your back-tested results are the result of luck. What if just a handful of securities are driving the return? Going forward, what if you don't select one of those securities? Your actual results will never match the historical results. You can't be sure if your historical results are the result of a superior investment process or simply the good luck of picking a couple of stocks that are substantial winners.

Our Monte Carlo process was developed to answer all of these questions and solve the problems we identified in traditional testing methods. The goal of the process is simple: to create multiple portfolios and run them through time to identify superior RS factors and also test the robustness of those factors. The process is very simple in theory (not so simple to program and implement however!). We define portfolio parameters before the test is run. These parameters include: the RS calculation method, number of holdings in the portfolio, buy rank threshold, and sell rank threshold. For this example, assume the number of portfolio holdings is 25, the buy threshold is the top decile of our ranks, and securities are sold when they fall out of the top half of our ranks. On the first day, there might be 100 securities in the top decile of ranks, but we only need 25. Our process selects 25 securities <u>at random</u> from the top decile and adds them to the portfolio. As the program moves to the next trading day it looks to see if any of the stocks in the portfolio has a rank below the top half. If so, that <u>one</u> security is sold, and another security is drawn <u>at random</u> from the top decile of ranks. This process is repeated on each trading day through the end of the test. Once we reach the end of the test, we archive all of the portfolio information and run another test with the exact same parameters. We generally run 100 simulations over the entire test period.

What we wind up with are 100 different return streams using the exact same parameters. Some of the portfolios perform better than others—that is simply the luck of the draw. What we <u>can</u> determine is the probability of outperforming a benchmark over time. Over short time periods such as a quarter or even a year, the returns can exhibit large variation. But after a 14-year simulation we can see how many of the 100 trials outperform. If 100% of the trials outperform, we know we have a robust process that isn't reliant on just a small number of lucky trades. It really speaks to the power of relative strength when we can draw stocks at random for a portfolio and have 100% of the trials outperform over time.

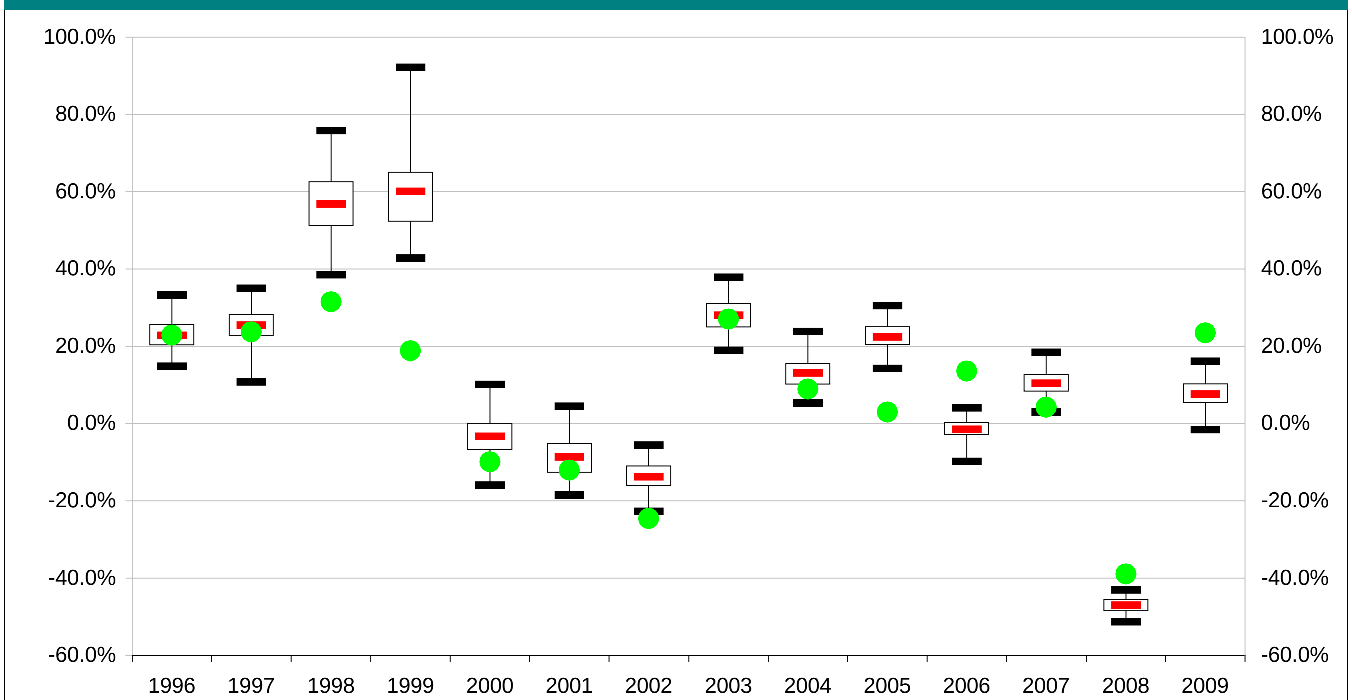
Part IV: Example Of The Process

Table 1: Summary Data (Cumulative Returns)	
12/29/95—12/31/09	
# of Trials	100
Average Return	227.1%
Median Return	214.8%
Max Return	446.4%
Top Quartile	263.4%
Bottom Quartile	181.0%
Min Return	94.2%
S&P 500 Return	81.0%
% Trials Outperform	100%

The following example uses a simple 12-month price return to rank securities over the period 12/29/95-12/31/09. The investment universe is the S&P 900, which includes domestic large cap stocks (S&P 500) and domestic mid-cap stocks (S&P 400). To be eligible for inclusion in the portfolio, a stock's rank must be in top decile. Stocks are sold when their rank falls out of the top quartile of ranks. Fifty securities are held in the portfolio. A summary of the return data for all 100 trials is shown in Table 1. Over the test period the lowest return of the 100 trials was 94.2% versus the return of the broad market (S&P 500) of 81.0%. So even drawing securities <u>at random</u> out of the top decile produces outperformance in 100% of the trials over the entire test period. Table 1 shows a summary of the total returns for all 100 trials. Many of the trials are significantly above the return of the broad market.

Figure 1 shows a breakdown of returns year by year over the test period. The green dot represents the return of the benchmark, and the red line represents the average return of all 100 trials. Some years, such as 1998, 1999, and 2005, relative strength performs so well that all of the trials perform better than the market. Other years, such as 2006 and 2008, relative strength performs poorly and all 100 trials underperform the market. The most common scenario is to have some trials performing better than the market and some trials performing below the

Figure 1: Trial Returns By Year



market. The large dispersion in returns within each individual year is also evident. Each of the 100 trials uses the same investment factor applied exactly the same way, but there is random chance involved when each security is selected. That element of chance can result in some trials outperforming and some trials underperforming over short time periods. We have found this is very common when testing relative strength strategies.

Even with all of the short-term variation, it's important not to lose sight of the big picture. Looking back to Table 1, all 100 trials outperformed over the entire 14-year period. This illustrates the need for patience when using relative strength. Investors are generally their own worst enemies. Research has shown that when choosing investments investors place too much emphasis on recent performance and actually wind up performing, in aggregate, worse than inflation (not just worse than a benchmark).

Relative strength is an intermediate-term factor. Most research has found that relative strength is a viable strategy over a 3-to 12-month formation period. At shorter and longer time periods there is significant mean reversion. Our testing process is also flexible enough to test random portfolios using different relative strength factors. Table 2 shows a summary of returns using different lookback periods for various relative strength ranking factors. Once again, the robust nature of relative strength is shown by the ability of multiple random trials to outperform using a variety of factors. Some of the intermediate-term factors work better than others, but they all exhibit a significant ability to outperform over time. It is also evident that relative strength is not a viable strategy over very short-term and very long-term time horizons.

Relative strength and momentum strategies have delivered market-beating returns for many years. There has been a great deal of research in this area by both practitioners and academics. However, despite this public disclosure of information, these strategies continue to outperform over time. Many of the testing methodologies used over the years are not consistent with real-world portfolio construction and do not address the possible range of outcomes when implementing a relative strength strategy. Our continuous, Monte Carlo testing process corrects for both of these deficien-

Table 2: Factor Summary

Factor	Hldgs	Avg *	Max *	Min *	Index *	% Outperf	Est Turn
1 Mo Price Return	50	3.4%	6.1%	0.3%	4.3%	21%	1385.6%
3 Mo Price Return	50	7.8%	10.8%	5.2%	4.3%	**100%**	564.7%
6 Mo Price Return	50	11.9%	15.8%	8.6%	4.3%	**100%**	304.3%
9 Mo Price Return	50	11.6%	13.9%	8.8%	4.3%	**100%**	210.9%
12 Mo Price Return	50	8.8%	12.9%	4.9%	4.3%	**100%**	158.0%
18 Mo Price Return	50	5.6%	9.8%	2.3%	4.3%	74%	108.7%
2 Year Price Return	50	5.4%	8.5%	2.0%	4.3%	84%	85.1%
3 Year Price Return	50	4.3%	7.6%	1.7%	4.3%	47%	58.6%
5 Year Price Return	50	4.1%	7.3%	0.4%	4.3%	42%	42.0%

** Annualized Returns*

cies. Similar to other research, our process shows simple relative strength factors to be extremely robust over intermediate horizon formation periods, and weak over very short-term and long-term horizons. We also find there can be great variation in portfolio returns over short time periods, but over long holding periods the portfolios perform exceptionally well.

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