



***Predicting Sector Performance  
Using Momentum and  
Volatility***

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In a recent article, I proposed a conceptual model for thinking about momentum investing. The main point of that article was that there are two essentially competing forces at work in determining the persistence of out-performance of an asset class. One of these forces is momentum—the fact that asset classes that have been out-performing tend to continue to out-perform for some period of time. The other force is the tendency of markets to balance risk with return. An asset class that has dramatically out-performed the range of risk-adjusted returns that are typically available in capital markets will tend to correct downwards. This is the function of capital markets. I have run across some additional resources that pertain to this issue, and I decided to expand upon this theme.

I recently ran across a summary of research on fund performance by James Davis at *Dimensional Fund Advisors* that is as good as I have seen anywhere:

[http://www.dfaus.com/library/articles/informational\\_efficiency\\_of\\_stock\\_prices/](http://www.dfaus.com/library/articles/informational_efficiency_of_stock_prices/)

A compilation of studies of thirty years generally supports the idea that out-performing funds will continue to out-perform for some period of time and vice versa. While this study focuses on fund performance, a number of the studies conclude that the momentum effects observed were principally due to momentum in the stocks that made up the fund rather than manager skill. Overall, there is evidence for persistence at the stock and fund level, but most observable momentum effects appear to be driven by individual stocks or asset classes. This type of momentum effect is exactly what I discussed in a recent article. In that article, I showed that there appeared to be momentum effects in a cross-section of Exchange Traded Funds (ETF's) over the past six years.

While momentum effects appear to exist, we also know that a single asset or asset class will not out-perform its peers on a risk-adjusted basis forever unless the capital markets are very inefficient or there is some major structural shift going on. In general, the evidence is that markets are actually fairly good at providing higher returns to investors who are willing to carry higher risk. It is the rational balance of risk and return that must ultimately limit momentum effects. In our recent article on this topic, we showed that using the observed risk level (in the form of trailing volatility in returns) of the ETF's in our sample to predict future return generated an advantage in average return similar to

betting on momentum. Notably, the momentum effects and trailing volatility effects were found to contribute independent information to the estimation of future returns: combining them improved the advantage over using either one individually. After writing this article, a friend directed my attention to the so-called ‘periodic table of asset classes’ as compiled by *Dimensional Fund Advisors* (<http://www.dfaus.com>). This table simply shows the absolute and relative performance of a series of asset classes by year—from 1991 through 2005 in the current version. The asset classes included are:

- US Large Companies
- US Small Companies
- US Micro Cap Companies
- US Large Value Companies
- US Small Value Companies
- REIT Securities
- International Large Companies
- International Small Companies
- International Value Companies
- Emerging Markets Companies
- US One-Month T-Bills
- Intermediate Fixed Income

These tables show the ranking of asset classes by annual return as they vary from year to year. I believe that this table may be available only through financial advisors or from DFA directly, so I cannot reproduce it here. With fourteen years of data and twelve asset classes, this is a more significant set of data in which to look for momentum effects. In each year, the asset class with the highest return for that year gets a rank of 1, the second highest gets a rank of 2, etc. We then assume that we will invest equally in the six asset classes with the highest ranking annual returns in the previous year (i.e. the top half). If there are momentum effects, it seems reasonable that they should show up in the performance of such a portfolio from 1994 through 2005 (the reason that we did not start with 1992 will be clear shortly).

	Average Annual Return	SD in Annual Return
Equal Weight	11.7%	14.4%
Momentum	13.0%	14.8%

***Equal weight in all 12 classes vs. the six with highest trailing return (momentum)***

The portfolio that is rotated between the six asset classes with the highest trailing annual return in the previous year generates 1.3% more in return per year than the portfolio invested equally in all asset classes. Further, even though the portfolio invested based on momentum has fewer asset classes represented, there is only slightly more risk (i.e. slightly higher Standard Deviation, SD) in the annual returns generated by the momentum strategy. These results suggest a modest benefit to using relative momentum to create an asset allocation. It would be possible to vary the weights based on the relative returns but this would be quite susceptible to over-fitting of the data.

In my earlier article on this topic, I used Quantext Portfolio Planner's (QPP) predicted expected returns as the basis for determining which assets are likely to have higher returns over a future period. That was for a single period (as noted earlier). QPP predicts expected future return largely on the basis of trailing volatility. More volatile (riskier) investments should generate higher expected future returns. In a rational market, investors must have the expectation of higher returns for taking on more volatile assets. If this assumption is correct, we should see higher returns (on average) for investing in more volatile assets. To examine this effect further, I took the DFA table of returns mentioned above and looked at whether the standard deviation in the annual returns over the trailing three years would have any predictive value in determining future performance. To (potentially) predict the return in 1994, for example, I simply calculated the standard deviation in the annual return from 1991, 1992, and 1993. The standard deviation is a measure of spread around the average. My purpose here is simply to identify assets in which the returns over the trailing three years have varied more or less from year to year. In each year, I created a ranking of trailing three year standard deviation in annual return. I then assumed a strategy in which you invest equally in the six asset classes with the highest trailing volatilities. It should now be clear why I started with 1994: I needed 1991-1993 to calculate the trailing volatility for 1994. The average return and volatility results are shown below (along with the earlier results) for applying this strategy from 1994-2005 are shown below:

	Average Annual Return	SD in Annual Return
Equal Weight	11.7%	14.4%
Momentum	13.0%	14.8%
Volatility	13.9%	18.6%

***Equal weight vs. momentum vs. portfolio of six assets with the highest trailing 3 year SD in annual return (Volatility)***

These results show that the asset allocation based on a high degree of variability in trailing three year returns does indeed predict asset classes with higher future return than average (13.9% vs. 11.7%). This higher return is accompanied by higher risk—i.e. higher standard deviation in annual returns from year to year. This is exactly what we would expect in a generally efficient market and these results are consistent with how QPP projects future returns.

What does all of this suggest from the perspective of asset allocation? First, trying to use relative ranking of returns (i.e. momentum) as a determinant in asset allocation does, in general, seem to yield a benefit in terms of average annual return. This benefit has a cost—and that cost is higher volatility. An asset allocation strategy that conditions expected future returns using trailing volatility, in the belief that higher volatility will yield higher returns, is also borne out. This is consistent with the idea that capital markets are at fairly efficient and the underlying dynamics of QPP. While these results do show some variability based on how many portfolio components are specified, the results shown here are representative of most choices.

There is one final question that is of interest. It is quite common when analyzing a portfolio using QPP or other portfolio tools to find an asset class which has dramatically out-performed over several years. I often look at this out-performance in terms of average return relative to the standard deviation in annual return (SD). It is natural that a stock with a very high standard deviation in annual return (high risk) has the potential to generate very high average returns. When an asset or portfolio has generated average returns *relative to the standard deviation* that are much higher than the long-term balance of risk and return established in capital markets, it is rational to expect that the future

average returns will be lower. This is how QPP’s Risk-Return Balancing works in generating outlooks for an asset. To explore whether this effect shows up in the DFA data, I created historical ranks of the ratio of the average annual return to the standard deviation of annual return over the trailing three years. I then created a portfolio that is equally allocated between the six asset classes with the highest values for this ratio. I expected to see a mean reversion effect in which the assets that had out-performed on a risk-adjusted basis would generate lower future returns—and this is what is found:

	Average Annual Return	SD in Annual Return
Equal Weight	11.7%	14.4%
Momentum	13.0%	14.8%
Volatility	13.9%	18.6%
High Return/SD	10.5%	14.2%

***Comparison of earlier results to a portfolio made up of the top six ranked assets in terms of the ratio of three-year trailing average annual return to SD***

If you had built a portfolio out of assets that generated the highest trailing ratio of average return to volatility (i.e. average return divided by SD in annual return), you would have under-performed all other strategies. This portfolio strategy generated an average annual return of 10.5% per year (1.2% less than the equal weight portfolio), with 0.2% per year less in standard deviation than a portfolio than the equal weight portfolio.

Overall, these results support the concept of risk-return balancing in generating an outlook of future risk and return. The results show some evidence for momentum, consistent with many far more exhaustive analyses. The conclusions to be drawn here are similar to our recent article on this topic. There is a case to be made for the value of momentum investing. That said, if you are going to look at recent returns as a guide for investment decisions, it is a very good idea to also examine the volatility in returns. Markets are far from perfectly efficient, but they are reasonably efficient. When an asset has out-performed relative to its volatility level, it is reasonable to plan for the future with the assumption that the balance of risk and return will tend to revert to the mean.

*More information on Quantext portfolio planning tools, as well as a free trial, is available at: <http://www.quantext.com/gpage3.html>*