Thursday, March 08, 2018

Quarterly Review and Commentary

Earlier this year, we highlighted the rising popularity of "quant strategies" among asset managers. In our most recent commentary, we discussed factor investing and its application to portfolio management. In this piece, we would like to close out the "quant" discussion by providing an overview of how fundamental multifactor models can be developed and backtested using widely-available financial data vendors as well as their application to stock picking.

There are several ways in which a multifactor model can be developed. Common approaches use regression utilities in statistical packages which estimate factor coefficients and premiums. The process we will discuss today leverages similar statistical methods but is more "user friendly". While the process is complicated in practice and involves controlling for various statistical biases and errors, we attempt to provide a straightforward conceptual overview.

Choosing and Testing Factors

An investor must begin by using his/her intuition regarding the market and the factors which drive individual stock performance to establish a list of factors to backtest. These factors may include valuation, efficiency, solvency, technical, and/or growth potential factors among others. The initial goal in assembling this list is to identify those factors which have historically provided material outperformance at reasonable high confidence (significance) levels within a relevant universe over multiple time periods.

Factor backtesting software can calculate performance summary statistics of quartile, quintile, decile, or any other number of "bucketed" portfolios ranked according to a fundamental factor. For example, in a test with five buckets (or quintiles), the best scoring stocks are assigned to the first quintile and the lowest-scoring stocks are assigned to the fifth quintile for each rebalance period. Factors with favorable performance and statistical significance typically display a clear pattern of positive spread returns, with higher-scoring quintiles outperforming lower-scoring quintiles.

The following table displays quintile annualized active (excess) returns for four widely-recognized valuation factors, Price-Earnings to Growth (PEG) ratio, Free Cash Flow Yield, Enterprise Value to EBITDA, and Dividend Yield.



Clearly, the quintile active returns of the PEG ratio display a clearer pattern of quintile return-spread outperformance while the results for Dividend Yield do not provide an indication that it alone can contribute to outperformance since the 1st quintile fails to outperform all of the other quintiles. This conclusion is consistent with each factor's level of significance measured by their information coefficients ("IC"- an information coefficient is a measure of significance calculated as the correlation between expected excess return and subsequent realized excess return).

The following table depicts the ICs of our four valuation factors.



Select Valuation Factors' Information Coefficents

Anecdotally, we consider an IC in excess of 0.05 sufficient to confirm an assumption of strong significance and an IC below 0.03 sufficient to warrant doubt.

Identifying the Best Factors

In our simplistic example factor backtest, we can see that PEG Ratio, FCF Yield and EV/EBITDA exhibit positive quintile spread returns and relatively-high ICs. While it is tempting to select these factors and use them in our factor model, we must first look at how well they complement one another. While there are numerous considerations, two of the most important are the factors' Interaction Effects and Factor Correlations.

Interaction Effects

When evaluating factor interaction, we can use a bivariant matrix (in this case, a table containing excess returns which are "double-sorted" by quintiles with lower quintiles representing higher factor scores) to determine if holding stocks in the higher quintiles of both metrics provides higher active returns than those of either in isolation. Factors which display favorable interaction effects typically tend to have higher active returns for stocks that rank in higher quintiles of both factors than those that rank in the lower quintiles of both factors.



The following table depicts favorable interaction effects in a bivariant matrix. For illustrative purposes, we focus on the PEG ratio and FCF Yield factors (In practice we would evaluate each factor pair). Although not perfect, the table demonstrates a generally favorable interaction relationship, illustrated by the excess returns of "squares" 1:1 relative to 5:5 and those in between.

		Active Return (PEG RATIO)						
		1	2	3	4	5		
Active Return (FCF Yield)	1	5.51	9.16	2.05	3.64	0.02		
	2	8.49	2.16	1.82	2.73	1.34		
	3	-0.38	3.42	1.10	2.75	-3.63		
	4	0.69	1.98	-2.62	-0.98	-0.51		
	5	2.99	-1.13	-0.92	-3.08	-3.51		

Factor Correlations

A tenant of modern finance is that asset classes which exhibit less-than-perfect correlations (those less than one) can provide diversification benefits. The same is true with fundamental equity factors. The following factor correlation matrix provides factor data correlations for the three better-performing factors in our example backtest. The data suggests that these factors are generally uncorrelated with the PEG Ratio exhibiting slightly negative correlations with FCF Yield and EV/EBITDA.

	PEG Ratio	FCF Yield	EV / EBITDA
PEG Ratio	1.000	-0.051	-0.105
FCF Yield	-0.051	1.000	0.291
EV/EBITDA	-0.105	0.291	1.000

Source: Factset Data*

Putting the Factors Together in a Multifactor Model

At this point we have tested numerous factors and identified PEG ratio, FCF Yield, and EV/EBITDA as those which have favorable historic performance and relatively high significance (represented by Information Coefficients). We then evaluated each of three paired factor relationships for interaction and correlation characteristics, which we determined are satisfactory. We must now combine the three valuation factors in a scoring model (which we will refer to as "Multifactor Model Value" or "MFM Value") and test the model to see if it provides and incremental improvement in performance and/or significance.

To do so, we will create an equally-weighted model scored based on factor percentiles of each factor and run another backtest using the same parameters as the first (for illustrative purposes- we may want to test over other periods and/or universes otherwise in order to confirm robustness). We then interpret the results by comparing the quintile returns of the new MFM Value with those of the three valuation factors from which it is comprised.





By comparing the quintile performance of MFM Value with those of the valuation factors we can see that, while PEG Ratio has a higher return in the top quintile, the MFM Value displays attractive quintile active return performance, which is supported by the MFM Value's annualized Spread Returns relative to those of the other test factors (depicted to the right).



Source: Factset Data*

While top-quintile factor performance is important, we must pay particularly close attention to significance levels before drawing any conclusions since we are basing the validity of our results on significance levels. The following chart shows that, by combining the three test factors in the MFM Value, we have improved the significance of the MFM, expressed by a superior IC relative to the other Test Factors (illustrated below).



MFM and Select Valuation Factors' Information Coefficients

A review of the factor test's statistical summary provides further support for the MFM Value relative to the Test Factors in isolation.



Factor	F1-FN Return	Avg IC	Avg IC T-Stat	Std Dev of ICs
MFM	6.642	0.085	2.100	0.080
G/P/E	6.074	0.077	1.835	0.090
FCF Yield	3.084	0.067	1.650	0.083
EV/EBITDA 1	3.393	0.053	1.159	0.110

The first two columns of the table above summarize the Spread Returns and Average ICs that we've previously discussed. The following two columns, however, provide new information that we can use to evaluate the validity of the average ICs for each factor. The Avg IC T-Stat column provides us with a measure of how much relative confidence we may place on the accuracy of the Avg. IC value (higher is better). Finally, the last column, Std Dev of ICs provides us with a measure of how volatile the ICs across periods are for each factor (lower is better). The information in the table above supports our earlier assertion that the MFM Value is more robust (and thus useful in selecting stocks) than any of the factors in isolation.

Applying Multifactor Models to Portfolio Management – Our Approach

Once we are satisfied with the historic performance of our multifactor model, we can use vendor stock screening engines to sort and score the stocks of any specified equity universe according to our model. The results from the screening engine can then be used to not only determine which stocks are attractive to purchase, but also serve as a tool for identifying stocks for replacement. The following graphic summarizes how we apply multifactor models to the portfolio management process.



As always, we welcome your questions/comments and are available at your convenience to discuss the Strategies.

Thank you for investing with us!

***DISCLOSURE:** The information in this document is provided solely for illustrative purposes. While Gyroscope Capital believes this information to be accurate, the firm cannot guarantee its accuracy or the validity of the results presented.

