WHITEPAPER

SECURITIES SELECTION & PORTFOLIO OPTIMIZATION: IS MONEY BEING LEFT ON THE TABLE?

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ABSTRACT

In this report we ask the question, can fund managers form better-performing portfolios of stocks or bonds? In particular, can they take advantage of: 1) the Single-index Capital Asset Pricing Models (CAPM), 2) Multi-factor models, or 3) Generalized CAPM (GCAPM) to improve stock and bond mutual fund performance?

We found that: 1) Using CAPM can increase gross annual returns by 70 basis points to 80 basis points, 2) Using multi-factor models gross annual returns typically increased by 95 basis points, and 3) Using G-CAPM typically increases gross annual returns by 170 basis points.

INTRODUCTION

The main reason for the increase in returns noted in the abstract is not because optimization improves security selection, something we found portfolio managers (PMs) do well, but rather the use of optimization itself after securities have been selected, i.e., optimization can help PMs decide **how much** of the chosen stocks or bonds will produce the best portfolio.

DATA & METHODOLOGY

Our study of portfolio optimization was done in three parts: (1) We optimized 600 U.S. stock funds whose holdings we have on a monthly basis from January 2004 through December 2008, (2) 171 bond funds whose holdings we have on a quarterly basis from January 2002 through September 2008, and (3) We optimized the Thomson Reuters (TR) U.S. Equity Index, the TR UK Equity Index, and the TR Jefferies CRB Index from January 2004 through December 2008.

Of the 600 U.S. stock portfolios covered, there were 420 U.S. Diversified Equity (USDE) portfolios, 168 core funds, 150 growth funds, and 102 value funds. 180 portfolios were Sector Equity funds, with a fairly even split between fund types. The typical security span for these equity portfolios was between 125 – 250 stocks.

Our bond coverage was not as deep as our stock coverage. Using Lipper data, we were able to get a good quarterly sampling of investment-grade bond funds and general U.S. Treasury funds. We were also able to span a similar period: January 2004 to December 2008. We used 38 Corporate A-Rated Debt portfolios, 33 Corporate BBB Rated Debt portfolios, 10 General U.S. Treasury portfolios, and 90 Intermediate Investment-Grade Debt portfolios. The portfolios had a range of 75 to 200 securities in them.

All the required stock data was pulled from Datascope each month, as was all the required bond data.

Index data came from Thomson Reuters. Ken French's Web site (**http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html**) was the source of the multifactor data used. All the CAPM calculations were done in R with a Python script for the data layer. The multi-factor portfolios used R as did GCAPM and both used Python script for the data layer.

OPTIMIZATION TECHNIQUES

CAPM

The work of Markowitz, Sharpe and others can be utilized to determine an optimal portfolio (set of security holdings) given estimates of risk, relevant constraints and expected returns

For the purposes of this paper, it was assumed each month (or quarter if it's a bond fund) that:

- Risk as measured by last month's realized standard deviation will be next month's risk
- Observed constraints such as no security being greater than 5% of the portfolio and no security is smaller than 0.01% are be used
- Expected returns for next month will equal last month's realized returns

MULTI-FACTOR MODELS

Fama and French developed a three factor model to explain stock returns. Their model included:

- A beta related to the market
- A beta related to a sort of stocks based on capitalization
- And a beta related to a sort of stocks based on their book-value-to-price ratio

The Carhart 4-factor model adds momentum as a 4^{th} factor (or beta) in explaining stock returns.

To form stock portfolios using the method of Fama & French:

- An investor's optimal holdings include an active portfolio of individual stock selections and a passive factor portfolio are formed
- The optimal weights for the stocks in the active portfolio are determined by the product of the vector of $\boldsymbol{\alpha}$'s, i.e. the intercepts of the regression equations for each of the stocks and the inverse of the covariance matrix of the residuals

Since the individual stock selections contribute factor risk to the overall portfolio, the optimal weights for the factor portfolio reflect a compensating adjustment for the factor risk of the active portfolio. Forming portfolios in this way should get us to the maximum Sharpe ratio.

The optimal portfolio weights methodology for the active portfolio may mean going long or short stocks as no constraints based on short-selling are introduced. Unfortunately, restrictions on short selling prevent most mutual funds from directly utilizing simple portfolio weighting schemes such as those described above. However, the assumption that residual returns are uncorrelated allows us to establish the following corollary which will provide the foundation for our portfolio construction strategy

Corollary: When the residual returns from a linear factor model are uncorrelated across individual securities, the maximum Sharpe ratio for a portfolio subject to short selling constraints is obtained by assigning weights of zero to those stocks having negative alphas and weighting each stock having a positive alpha in proportion to the ratio α_i / σ_i^2

(This corollary is proven in Day et al.)

GENERALIZED CAPM (GCAPM)

Generalized CAPM is a recent tool that exploits the understanding that extreme events are important in portfolio construction. It does so by offering a dual approach:

- Transforming what is often non-Normal data in something very close to the Normal
- A full way of dealing with non-Normal data via a family of Weibull distributions

GCAPM uses a family of modified Weibull distributions to either transform the original probability distribution function (pdf) into a good approximation of the Normal distribution (a good approximation as it keeps the tail thickness of the original pdf intact) or by using family members of the Weibull distributions - the Exponential and what is called the Sub-exponential – directly, ie as the pdfs of the assets in question.

Via GCAPM it is possible to parameterize the marginal distributions of asset returns and their natural multivariate generalizations. In GCAPM extreme values are examined and modeled as Weibull distributions which allows the number of extreme events in each asset examined to vary based upon the "thickness" and/or the "length" of the tail of the distribution being fit.

Using combinatorial and hypergeometric functions, GCAPM can generate results where the exponents of the Weibull distributions are different from asset to asset and when there is correlation between assets.

The use of combinatorial and hypergeometric methods allows different Weibull distributions to be fit to different assets. These different parameterizations allow the modeler to:

- Transform the original distribution of asset returns to a distribution that is very close to a Normal
- Or stay in Weibull space and potentially develop a better performing portfolio

With the parameterization of returns, risk minimization using two different measures of risk (cumulants or value-at-risk) can be constructed. One of the advantages of GCAPM it that it allows risk minimization across a variety of moments or cumulants:

- Return vs Variance
- Return vs Skewness
- Return vs Kurtosis (tail length or thickness)
- Return vs any combination of the moments above

as well as VaR.

The Weibull parameterization allows for a more precise modeling of extreme events whether one uses copulas or GEV (Generalized Extreme Value theory). In the works of GCAPM's authors, GCAPM "formulas enable us to determine analytically the conditions under which it is possible to ``have your cake and eat it too'', i.e., to construct a portfolio with both larger return and smaller ``large risks.''

This paper will use the version of GCAPM that transforms the asset's returns in to a very good approximation of the Normal. By doing so, the paper will stay in Normal space and use all the well developed and analytically tractable tools that exist for Normal distributions. The results that follow will trade off return and kurtosis.

USE OF OPTIMIZATION TECHNIQUES

The portfolios were optimized in the following way:
For stock funds:

- Each month three optimized portfolios (one each for CAPM, multi-factor, and GCAPM) were formed, using the prior month end's stocks as a starting point.
- The optimized holdings, i.e., what they held and what percentage of each security they held after the optimization, were kept constant during the month. No intra-month optimizations were done.
- Returns were computed each month-end for the actual stock fund and its optimized counterpart.
- A total of 60 monthly periods were tested (January 2004 to December 2008).

For bond funds:

- At the start of each quarter-end two optimized portfolios (one each for CAPM and G-CAPM) were formed, using the prior quarter-end's bonds (currently no multi-factors models such as Fama-French or Carhart exist for bonds).
- The optimized holdings, i.e., what they held and what percentage of each security they held, were kept constant during the quarter.

- Returns were computed each quarter-end for the actual bond fund and the optimized portfolios.
- A total of 15 quarters were tested (January 2004 to January 2008).

RESULTS

Our results section is in two parts. The first part provides a look at the 600-odd stock portfolios and the 150 or so bond portfolios, while the second part looks at optimized stock indices.

INDIVIDUAL PORTFOLIOS

The results of the CAPM tests were:

- The average annual increase in gross returns, i.e., the amount by which the CAPM-optimized portfolios bested the actual funds gross was 70 basis points to 80 basis points.
- Across capitalization, except for optimized small-caps, there was not much variability.
- Across styles there was variability: growth funds tended to benefit the most (up 170 basis points per annum). Value funds had mixed benefits (some positive, some negative).
- We think the disparity between growth and value fund results was due to turnover ratios, i.e., higher turnover funds tended to have higher benefits.
- Sector funds as a group did well, with the caveat that higher-turnover funds benefited more than lower-turnover funds, i.e., Science and Technology funds tended to do better with optimization than Finance funds.
- Though gross returns increased using CAPM, risk adjusted returns did not. This signifies that on average portfolio managers know how to pick stocks but could potentially improve portfolio-forming skills by using CAPM.

On the bond fund side:

- The average annual increase to gross returns was 60 basis points to 70 basis points.
- Across bond groups, there was not much variability.
- Corporate bond funds benefited a bit more than Treasury funds (by about 10 basis points per annum).
- And, as with stock funds returns, risk-adjusted returns did not increase, signifying again that on average portfolio managers do know how to pick stocks but could potentially improve portfolio-forming skills.

As mentioned above, the multi-factor model we used is available only for equities, so the results summarized below do not cover bonds:

- We had a much better and smoother response with the multi-factor model.
- The average increase in annual gross returns was 92 basis points.
- Value funds were consistently positive (about 80 basis points per year).
- And while there was still a difference between growth and value; growth funds benefited just 14 basis points more on average.
- And again, we found on average risk-adjusted returns to be the same pre- and post optimization.

Finally, the results of our GCAPM model were:

- There was a large difference between growth and value: growth funds returns were 270 basis points higher versus value funds 130 basis points.
- There was a smaller difference between Sector funds.
- Even small-caps benefited (+60 basis points).
- Some growth funds saw a 400-basis point per annum improvement in returns.

Significant improvements were also seen in bond funds:

- Corporate funds saw 150 basis points to 175 basis points in improvement of returns.
- Treasury funds saw about a 100-basis point improvement.
- However, risk-adjusted returns on average for the optimized portfolios were sometimes better, sometimes the same, and sometimes worse than for the original portfolios.
- Why?

GCAPM works with the tails of the distribution, i.e., the kurtosis or fourth moment, not the variance or the second moment as the CAPM or the Fama-French multi-factor models do.

When we adapt the Sharpe ratio to include the higher moments, the optimized portfolios on a risk adjusted basis do not outperform the unoptimized portfolios on average.

INDICES & PORTFOLIOS

Our treatment for the three indices (the TR U.S. and U.K. equity indices the TRJ CRB index) was the same as for the stock funds above, i.e., an optimized CAPM, multi-factor, and GCAPM portfolio was formed every month and its performance was compared to the unoptimized holdings of the index. Table 1 summarizes in dollars and percentages the optimized indices versus their unoptimized form:

Table 1 Cumulative Outperformance of Optimized Indices Versus Unoptimized Indices: Return on $10,000, December 31, 2003, through December 31, 2008

Model Type	TRJ CRB $	TRJ CRB %	TR U.S. $	TR U.S. %	TR U.K. $	TR U.K. %
Original Performance	30	3	-100	-10	198	20
CAPM	30	3	0	0	210	21
Fama-French	31	3	430	4.3	380	3.8
GCAPM	120	12	650	6.5	540	5.4

For the TR/J CRB, GCAPM's ability to work to trade-off return and kurtosis is the major reason why GCAPM is the only one of the 3 techniques that improved the CRB performance over the test period.

For the 2 equity indices, as would be expected, Fama-French easily outperforms classic CAPM optimization and GCAPM easily bests Fama-French as it appears to be choosing the correct cumulant to trade return off with.

CONCLUSION

1. Portfolio managers do know how to pick stocks; on average risk-adjusted returns pre- and post-optimization were approximately the same.
2. However, optimization techniques such as CAPM, multi-factor models, or GCAPM could help in the assembly of portfolios from scratch, i.e., they could be used once the securities have been selected and need to be assembled. They could also be used as fine tuning tool for asset allocation.
3. In terms of security selection, two methodologies not mentioned in this paper, ultrametrics and random matrix theory (RMT) are strongly suggested to interested readers. The author has used both methods in a single instance where he constructed a hypothetical fund-of-funds by first filtering equity and bond funds using three Lipper Leader measures (Total Return, Consistent Return, and Preservation) and then choosing the best of the stock and bond funds by using ultrametrics and RMT. He then constructed the fund-of-funds portfolio using GCAPM and found that over a two year test period this combination of techniques yielded a fund

with a 0.75 annualized Sharpe ratio and anywhere from 300bp – 700bp annualized return over LIBOR based upon the Value-at-Risk (VAR) target of the portfolio.

On a final note, we leave our readers with the following question: could it be that the observed underperformance of fund managers versus their benchmark is due to portfolio construction skills and not to stock-picking skills as so many have claimed?

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FOR MORE INFORMATION

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