Portfolio Optimization Strategy: Models & Time Horizons

A presentation to the fi360 Insights 2016 Conference

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Framing the problem:

- There are many approaches to portfolio optimization and construction
- (MacroRisk.com provides at least a dozen methods)
- Does it matter which method is used?
This presentation

• Some background regarding different approaches
• Specific discussion of leading contenders
• Results of a “shoot-out” between different approaches, assessing when various methods are preferred
• A few selected “Real World” examples
A Bit About Our Background for this topic:

• We are professors at CSUN’s David Nazarian College of Business & Economics, which now has over 8000 majors, many taking financial planning & wealth management coursework

• James & Mike co-teach an undergraduate honors seminar there that manages three portfolios for the University Corporation and University Foundation, with about $3.5mm AUM

• The authors advise a small long-only hedge fund and provide additional advice to selected other products

• Going from glib lectures to investing real money provides bracing opportunities to ensure that our reality checks don’t bounce…
Observations:

• What’s in the textbooks doesn’t always square with practice, something which became crystal clear when we started doing things in the “real world”

• Most financial management and investments textbooks focus on CAPM and “traditional” MVO to create portfolios.

• Our student portfolios, like retirement and endowment funds, are not rebalanced or tweaked every day, every week, or even every month. They are adjusted twice a year (once per semester) which is still more frequent than many “low touch” funds.

• Many financial planning clients seek long term capital gains and planners go out of their way to avoid short term gains; our financial planning students are taught this as a management goal.
More observations:

• Many “Wall Street” product managers use variations of Modern Portfolio Theory to create portfolios.

• However, through many hours of conversation with financial planners, it’s clear that many financial planners and portfolio managers focus more on “investment picking” than “portfolio crafting”,

• After which they apply various heuristics to create model portfolios or to make client portfolio decisions; rarely do most financial planners engage in “optimization”
A few popular “non-optimization” heuristic approaches we see as we talk with portfolio managers:

• “Investment Club” approach: Create a “Watchlist” (buylist) of several desirable investments, then vote on how much of available funds should be invested in the best of the new “picks” or “ideas”

• “All In” (old school, pre MPT, approach; still followed by some concentrated hedge funds and private equity funds): Identify a few good investments and put all your money into these, put new money into whichever looks to be the best at the time

• “Copycat”: Look at holdings in popular UITs or filings by wealthy investors and then copy their portfolio weights
Asset-class Based Portfolios are undoubtedly the most popular approach to “optimal” portfolio construction.

- In the basic “risk tolerance” approach, the whole world is viewed as either “growth assets” (equities) or “defensive assets” (bonds) and your optimal portfolio is determined by investing your “risk tolerance” percentage in “growth assets” and the remainder in “safety assets”
- One of the best known is a 60/40 “equity/bonds” portfolio
- (At a recent financial planning conference, various gurus were proposing a 40/60 allocation because of the Fed’s policies)
- Some popular optimization software is just aimed at asset class indexes rather than specific holdings
While there are many “portfolio optimizers” and “model portfolios” available, for the most part these focus on asset class optimization which has numerous potential problems.

• It is difficult to purchase the “entire” asset class
• It is difficult to tailor such portfolios around individual financial traits (including human capital, nontraded investments, real estate, etc)
• It is difficult to create SRI/ESG portfolios at the asset class level
• Selecting individual assets from the class will not generally result in performance equivalent to the asset class
• Some portfolio allocation within the asset class is necessary and portfolio managers will more likely fail, resulting in portfolios that do not have the expected characteristics
Bottom line, asset classes don’t work very well to describe or create portfolios

We address this further in our most recent publication (and last year’s fi360 presentation)

Chong, J., Jennings, W. P., and Phillips, G. M.

**Issues with asset class based portfolio construction: An analysis of mutual fund characteristics.**

Further, over longer periods, “low-frequency” (intrinsic value) changes happen that aren’t captured in returns based models.

We identify five key types of risk that impact longer term investors:

1. Capital market risk (CAPM or downside beta)
2. Behavioral Risk (or momentum risk)
3. Economic Risk
4. Attribution Stability Risk
5. Idiosyncratic (firm specific) Risk
Some of our additional references include:


Q: So, how do we weight our investments?

A: “We all know the solution: mean-variance optimization (MVO) is best, taught in all the books, and you can do it with Excel’s Solver!”

Maybe that’s the answer, but maybe not...

• One can do MVO with Excel, but to do so requires nontrivial data analysis and powerful spreadsheet optimization that, in our experience, exceeds the current abilities of typical financial planners.

• Further, while MVO may work when there is regular inflow or outflow into the AUM being optimized, over time the underlying returns correlations tend to change.

• For actively managed mutual funds or corporate treasury operations, regular re-optimization is less of a problem. However, for “low transactions costs” portfolios, volatile correlations can be problematic.
There are lots of other approaches being discussed when thinking about MVO...

• Fat Tails (e.g., Mandelbrot and the Stable Paretian Distribution; Mixtures of Distributions)

• Morningstar’s researchers promoting “Truncated Levy-Flight” modeling of returns distributions (a transitional distribution between the Normal and the Stable Paretian distributions)

• Copulas

• Monte Carlo based efficient frontiers

• (and there are a few other approaches discussed below...)

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Conventional wisdom, “street knowledge”, and the previous points suggest:

• Different approaches might be better depending on the anticipated holding period for the portfolio

• Different approaches might be better depending on the desired characteristics of the portfolio

• Different approaches might be better depending on the acceptable asset mix
So, finally, our research goal:

What are some guidelines for choosing a portfolio optimization approach? How do they actually work in practice?

Our approach will be an empirical experiment using Monte Carlo sampling and simulation methods.
Outline of the experiment:

1. Identify the portfolio construction approaches to analyze

2. Using a standard universe of stocks, conduct a Monte Carlo analysis
   I. Identify a subset of the universe
   II. Create a portfolio as of a given date using a chosen method
   III. Assess how that portfolio would perform in subsequent periods
   IV. Repeat at other dates
   V. Repeat with a different subset
   VI. Repeat with different methods
   VII. Summarize various experiments and see if there are any clear patterns or results
Our methods used here are based in part on:


We used our own proprietary “cloud-based” program for this paper which allowed Monte Carlo simulations to be performed. *(This is NOT commercially available software.)*

**Inputs needed include**

- Buylists
- Portfolio formation dates
- Number of MC iterations
- Portfolio Construction Method
- Number of assets to be sampled
- Max holding percentage
- Other parameters depending on method being studied
1. Identify the portfolio construction approaches to study

- Maximum Sharpe Ratio (MVO)
- Maximum Sortino Ratio
- Maximum Upside Scaled Return
- Minimum MacroRisk Exposure
- Equally Weighted (from entire buylist)
- Various Equally Weighted (from various buylist subsets)
Preliminary Definitions

Define \( \mathbf{1} \) as a vertical vector of ones, so \( \mathbf{J} = \mathbf{1} \mathbf{1}' \) is a square matrix of ones.

For a portfolio with \( n \) holdings, let the vertical vector \( \mathbf{w} \) represent the weights of the holdings in the portfolio. So vector \( \mathbf{w} \) has the shape \( 1 \times n \). Let the matrix \( \mathbf{R} \) be a \( m \times n \) matrix of asset daily returns over \( m \) days. So the function for the portfolio daily returns, \( R(\mathbf{w}) \), is (Underwood, 2013, p. 9)

\[
R(\mathbf{w}) = \mathbf{Rw}
\]

The annualized expected return of the portfolio, \( R_A(\mathbf{w}) \), is (Underwood, 2013, p. 12)

\[
R_A(\mathbf{w}) = \frac{260}{n} \mathbf{1}' \mathbf{Rw} = \frac{260}{n} \mathbf{1}' \mathbf{R(w)}
\]

Let \( r_f \) represent the annualized risk-free rate.
Maximize Sharpe Ratio

The Sharpe Ratio is the annualized expected return, less the risk-free rate, divided by the standard deviations of return.

The annualized portfolio variance, $\sigma^2(w)$, is

$$
\sigma^2(w) = \frac{260}{n-1} w' R' \left( I - \frac{1}{n} J \right) R w = \frac{260}{n-1} (R(w))' \left( I - \frac{1}{n} J \right) R(w)
$$

So the target function for maximizing Sharpe Ratio is

$$
\text{Maximize} \quad \frac{R_A(w) - r_f}{\sigma(w)}
$$
Maximize Sortino Ratio

The Sortino Ratio is the portfolio expected return, less the risk-free rate, divided by downside risk instead of the standard deviation of returns. We define downside risk as the lower semi-deviation of portfolio returns.

Define \( \min(a, b) \) as an element-wise vector function that takes two vectors of length \( n \) and, for \( i = 1, \ldots, n \), compares \( a_i \) to \( b_i \), selecting the one with the smallest value. Define \( R_{\delta-}(w) = \min(R(w) - 1'R_A(w), 0) \). Then the portfolio’s annualized lower semi-variance is

\[
\sigma^2_-(w) = \frac{260}{n-1} \sum_{i=1}^{n} \left[ \min(R_i(w) - R_A(w), 0) \right]^2 = \frac{260}{n-1} \left( R_{\delta-}(w) \right)' \left( R_{\delta-}(w) \right)
\]

So the target function for maximizing Sortino Ratio is

\[
\text{Maximize } \frac{R_A(w) - \bar{r}_f}{\sigma_-(w)}
\]
Maximize Upside Scaled Return

We define the upside scaled return as the expected portfolio return, less the risk-free rate, divided by the upper semi-deviation of portfolio returns. Define \( \max(a, b) \) as an element-wise vector function that takes two vectors of length \( n \) and, for \( i = 1, \ldots, n \), compares \( a_i \) to \( b_i \), selecting the one with the smallest value. Define \( R_{\delta+}(w) = \max(R(w) - 1'R_A(w), 0) \). Then the portfolio’s annualized upper semi-variance is

\[
\sigma^2_+(w) = \frac{260}{n-1} \sum_{i=1}^{n} [\max(R_i(w) - R_A(w), 0)]^2 = \frac{260}{n-1} (R_{\delta+}(w))'(R_{\delta+}(w))
\]

So the target function for maximizing Upside Scaled Return is

\[
\text{Maximize } \frac{R_A(w) - \bar{r}_f}{\sigma_+(w)}
\]
Minimize MacroRisk Exposure

MacroRisk Exposure is measured using the squared sum of the portfolio’s MacroRisk Eta® Profile.

Define the Eta® Profile of asset $i$ as a vertical vector, $\mathbf{e}_i$, of length $k$. The Eta® Profile of the portfolio is $\mathbf{Ew}$, where $\mathbf{E}$ is a $k \times n$ matrix containing the Eta® Profile vectors of the holdings of the portfolio.

So the target function for Minimum MacroRisk Exposure is

$$\text{Minimize } \frac{1}{2} \mathbf{w}'\mathbf{E}'\mathbf{E}\mathbf{w}$$
Equally Weighted Portfolios (a benchmark for comparison)

1. Across all assets randomly selected in an iteration
   • This provides a constant size benchmark for comparison across techniques

2. Across the subset of assets selected through the optimization
   • By computing a corresponding equally weighted portfolio for each iteration of each optimization, we obtain benchmarks that work for each randomly selected portfolio
   • When the METHOD_EW is compared to the METHOD_OPT, we are able to check for the differential effects of selection vs. weighting with respect to the METHOD approach
2. Using a standard universe of stocks, conduct a Monte Carlo analysis

• The research being presented today used the Dow Jones Industrial Average (Dow 30) as the universe for analysis. We used index constituents as of January 1 for each year 2007 – 2015.

• For each iteration, 15 stocks were randomly selected
Why the Dow 30 to start with?

The Dow 30 are perhaps the closest to stocks trading in an academic “efficient market” that we know of.

As a result, we believe that experiments conducted with data from the Dow 30 are powerful because they aren’t just exploiting the results of thin markets or inadequately monitored stocks.
Why pick just 15 stocks of the 30?

It’s a good number to start, allowing for variation in the portfolio compositions, and matches the smallest portfolio sizes needed to attain diversification (see Chong & Phillips (2013))

We will eventually extend the research to include different investment universes, including additional stock groups and mutual fund families.
Implementation

• Using our Monte Carlo platform we constructed 22,500 (=5 methods x 9 years x 500 iterations) buylists of 15 stocks selected from the appropriate DJIA 30
• For each buylist, we constructed an optimized portfolio and the corresponding equally weighted portfolio
• For each buylist, we estimated the forward returns (as available) for
  • 1 month
  • 3 month
  • 6 month
  • 9 month
  • 1 year
  • 3 years
  • 5 years
Average of 9 Months Forward Total Return

- Equally Weighted
- min MRE EW
- min MRE Optimize
- Sharpe EW
- Sharpe Optimize
- Sortino EW
- Sortino Optimize
- USR EW
- USR Optimize

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Average of 3 Years Forward Total Return

Equally Weighted  MRE EW  min MRE Optimize  Sharpe EW  Sharpe Optimize  Sortino EW  Sortino Optimize  USR EW  USR Optimize

Goal
Average of 5 Years Forward Total Return

0.7

0.68

0.66

0.64

0.62

0.60

0.58

0.56

0.54

Equally Weighted

min MRE EW

min MRE Optimize

Sharpe EW

Sharpe Optimize

Sortino EW

Sortino Optimize

USR EW

USR Optimize

Goal

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- Avg Rank: 1,3,6,9 mo + 1,3,5 yr
- Short Term Rank: 1,3,6,9 mo
- Long Term Rank: 1,3,5 yr
Some observations:

1. The traditional Sharpe and Sortino optimizations did not do best.
2. Equally weighting the results from the returns based optimization (Sharpe, Sortino, USR) did better than their respective optimization weights. (This suggests a new use of optimizers as part of the asset selection, rather than weighting, process.)
3. Equally weighting the entire candidate list did better early in the short run. Sharpe EW does consistently well in the first year.
4. “Black Swan” optimization (min MRE) did better in the longer run.
Additional observations:

• For our portfolios with shorter term rebalancing, we would likely use EW if reasonable, or Sharpe EW if a smaller portfolio size is desired.

• For intermediate to longer term rebalancing, we would likely use the “Black Swan” (min MRE) optimization.
These results, in conjunction with some of our other research, allow us to offer some comments on our “favorite practices”

Our favorites are also based on our recent publication:


Which recently received

The following are some of our favorite practices for construction of “nice” portfolios

1. Are asset risk characteristics used as the primary filter criteria for buylist construction? (e.g., fi360 ratings, MacroRisk Stoplights, “Five-Risks Screening”, downside-beta)

   Short Term (e.g., quarterly rebalancing): Optimize with MVO, then equally weight the assets selected

   Longer Term (e.g., annual or longer): Equally weight the assets
(some of our favorite practices, continued)

2. Are asset performance (not risk) characteristics, SRI/ESG/Sustainability, accounting, or non-risk “Smart Beta” criteria used as the primary filters for buylist construction?

   Shorter term: Filter by “Attribution Stability” then use MVO (e.g., maximum Sharpe Ratio optimization) to construct portfolio weights

   Longer term: Filter by “Attribution Stability” then minimize exposure to economic risk (a.k.a. “Black Swan” Optimization)
Additional lessons:

• Optimize over investible assets (including funds & ETFs), not indexes

• Distinguish between the goals of the buylist construction and the portfolio weighting steps (e.g., if using risk criteria for selection, don’t use risk based optimization for weighting)

• Many “Wall Street” portfolio construction methods (including most MPT-based methods) may work in the very short-run but they are not adequately robust for longer term portfolio holding periods.
Finally:

• Prudent buylist construction and portfolio optimization can help meet income goals without requiring taking excessive risks
• Increased portfolio risk is NOT necessarily associated with higher returns long run
• Similarly, zero portfolio risk is NOT necessarily associated with higher returns long run (think “cash under a mattress”)
• There is a Goldilocks solution that allows returns but still demonstrates reduced volatility and investor risk
• This is our investing “sweet spot”
Some “Real World” Examples

• UG (CSUN Undergraduate Portfolio)
• UG S (CSUN Undergraduate “Sustainable Investing” Portfolio)
• EFPAAX (a Unit Investment Trust managed by Steve Case, CFP, AIF)
• MCP 1 (a long only investment fund managed by Walnut Oak Capital)
UG {CSUN} (Min. MacroRisk Exposure, generally from large cap dividend paying stocks)
UG Sustainable {CSUN} (EW optimization, from Responsible, Sustainable, stocks)
EFPAAX (uses EW Sharpe optimization, generally from the Russell 2000 universe)
MCP 1 (uses EW optimization with Sharpe overlay, exclusively from S&P 500 constituents)
Questions/comments?

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