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.

Journal of Wealth Management, Winter 2015.

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:

- Chong, J. T., Jennings, W. P., and Phillips, G. M. (2014). **Monitoring the five risks: Analytical risk measurement for retail investors and wealth managers.** *Investments & Wealth Monitor, March/April,* 17–19 and 24.
- Chong, J., Jennings, W. P., and Phillips, G. M. (2012). **Five types of risk and a fistful of dollars: Practical risk analysis for investors.** *Journal of Financial Service Professionals, 66*(3), 68–76.
- Chong, J., and Phillips, G. M. (2011). **Beta measures market risk except when it doesn't: Regime-switching alpha and errors in beta.** *Journal of Wealth Management, 14*(3), 67–72.

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!"

http://www.solver.com/optimization-solutions-investment-and-portfolio-management-examples

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…)

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:

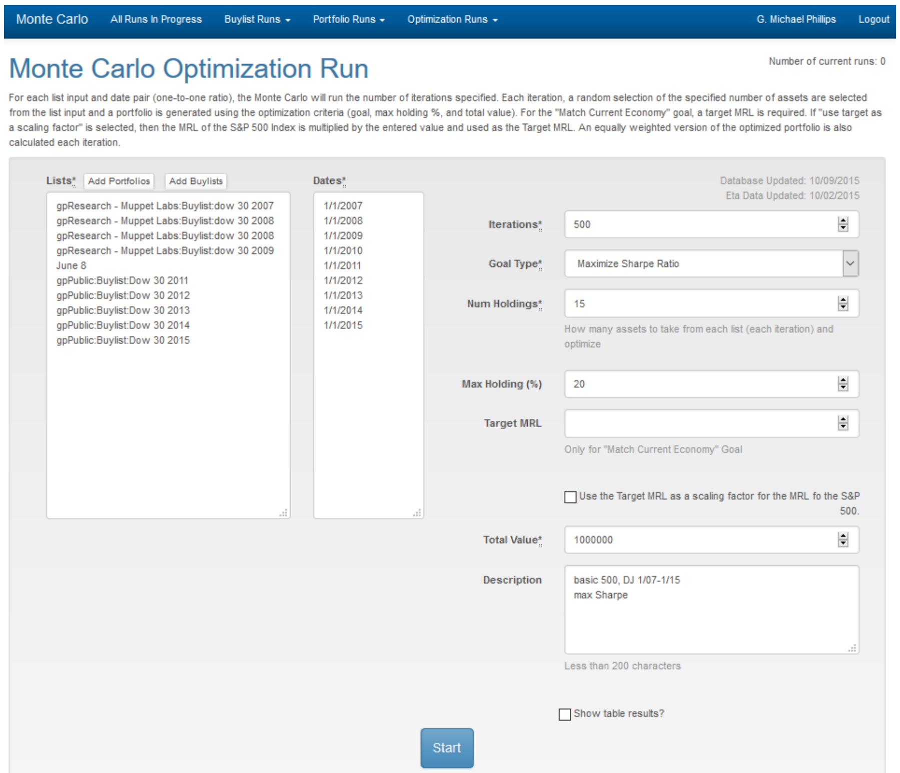
1. Identify the portfolio construction approaches to analyze
2. Using a standard universe of stocks, conduct a Monte Carlo analysis
   I. Identify a subset of the universe
   II. Create a portfolio as of a given date using a chosen method
   III. Assess how that portfolio would perform in subsequent 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:

- Underwood, S. J. (2013). *Optimal financial portfolio selection.* Unpublished master's thesis, California State Polytechnic University, Pomona, Pomona, CA.

- Chong, J., and Phillips, G. M. (2013). **Portfolio size revisited.** *Journal of Wealth Management, 15*(4), 49–60.

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* $\boldsymbol{J} = \mathbf{1}\mathbf{1}'$ *is a square matrix of ones.*

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

$$R(\boldsymbol{w}) = \boldsymbol{R}\boldsymbol{w}$$

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

$$R_A(\boldsymbol{w}) = \frac{260}{n}\mathbf{1}'\boldsymbol{R}\boldsymbol{w} = \frac{260}{n}\mathbf{1}'R(\boldsymbol{w})$$

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, $\sigma^2(\boldsymbol{w})$, is

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

So the target function for maximizing Sharpe Ratio is

$$\text{Maximize } \frac{R_{\mathrm{A}}(\boldsymbol{w}) - r_f}{\sigma(\boldsymbol{w})}$$

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

$$\sigma_{-}^{2}(\boldsymbol{w}) = \frac{260}{n-1} \sum_{i=1}^{n} [\min(R_i(\boldsymbol{w}) - R_{\mathrm{A}}(\boldsymbol{w}), 0)]^2 = \frac{260}{n-1} \big(R_{\delta-}(\boldsymbol{w})\big)' \big(R_{\delta-}(\boldsymbol{w})\big)$$

So the target function for maximizing Sortino Ratio is

$$\text{Maximize } \frac{R_{\mathrm{A}}(\boldsymbol{w}) - \bar{r}_f}{\sigma_{-}(\boldsymbol{w})}$$

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 $\max(\boldsymbol{a}, \boldsymbol{b})$ 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 $R_{\delta+}(\boldsymbol{w}) = \max(R(\boldsymbol{w}) - \mathbf{1}' R_{\mathrm{A}}(\boldsymbol{w}), \mathbf{0})$. Then the portfolio's annualized upper semi-variance is

$$\sigma_+^2(\boldsymbol{w}) = \frac{260}{n-1} \sum_{i=1}^{n} [\max(R_i(\boldsymbol{w}) - R_{\mathrm{A}}(\boldsymbol{w}), 0)]^2 = \frac{260}{n-1} \big(R_{\delta+}(\boldsymbol{w})\big)' \big(R_{\delta+}(\boldsymbol{w})\big)$$

So the target function for maximizing Upside Scaled Return is

$$\text{Maximize } \frac{R_{\mathrm{A}}(\boldsymbol{w}) - \bar{r}_f}{\sigma_+(\boldsymbol{w})}$$

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, $\boldsymbol{e}_i$, of length k. The Eta® Profile of the portfolio is $\mathbf{E}\boldsymbol{w}$, 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

$$\text{Minimize } \frac{1}{2}\boldsymbol{w}'\mathbf{E}'\mathbf{E}\boldsymbol{w}$$

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.

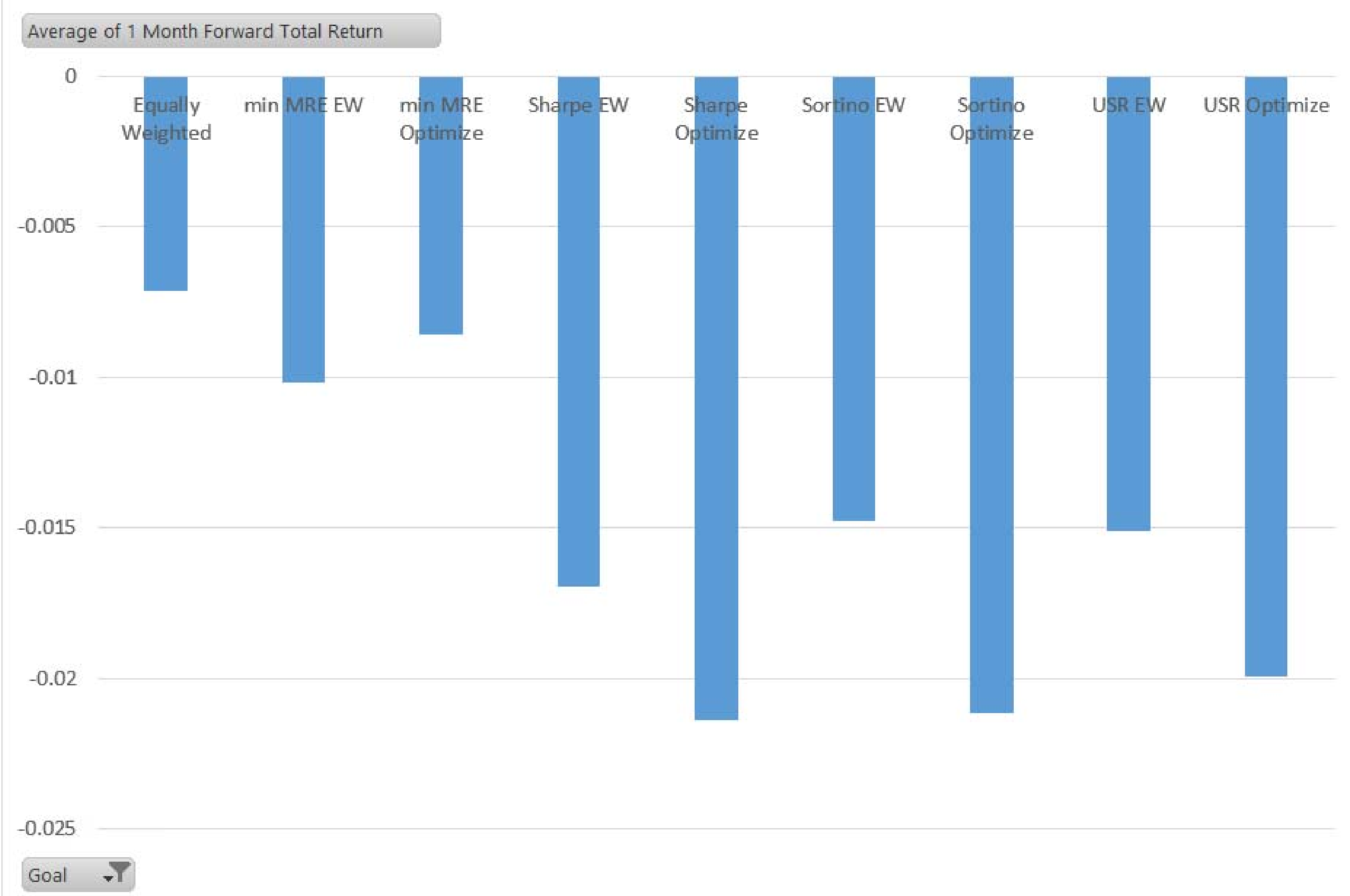
Why pick just 15 stocks of the 30?

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))

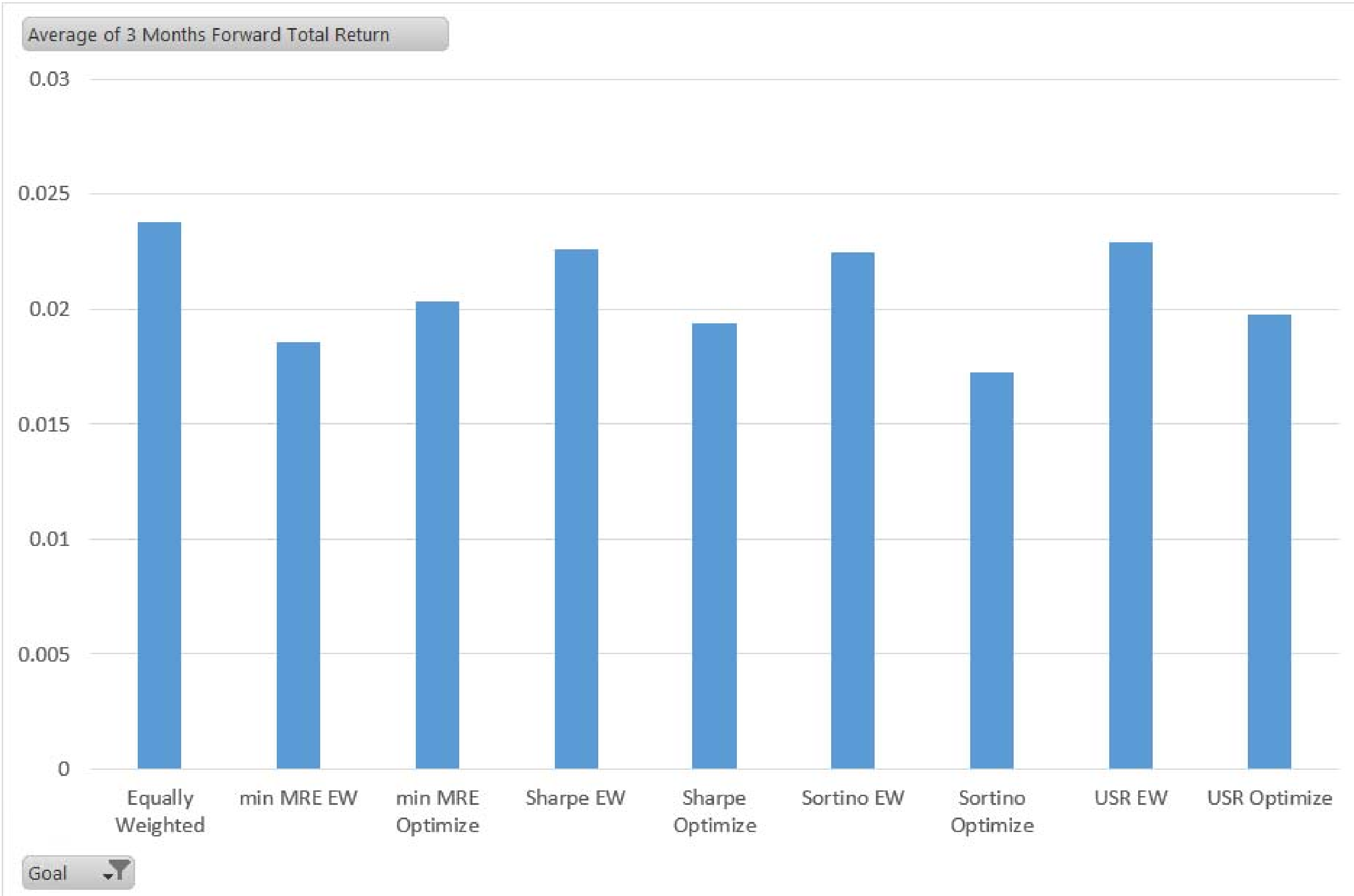
We will eventually extend the research to include different investment universes, including additional stock groups and mutual fund families.

Implementation

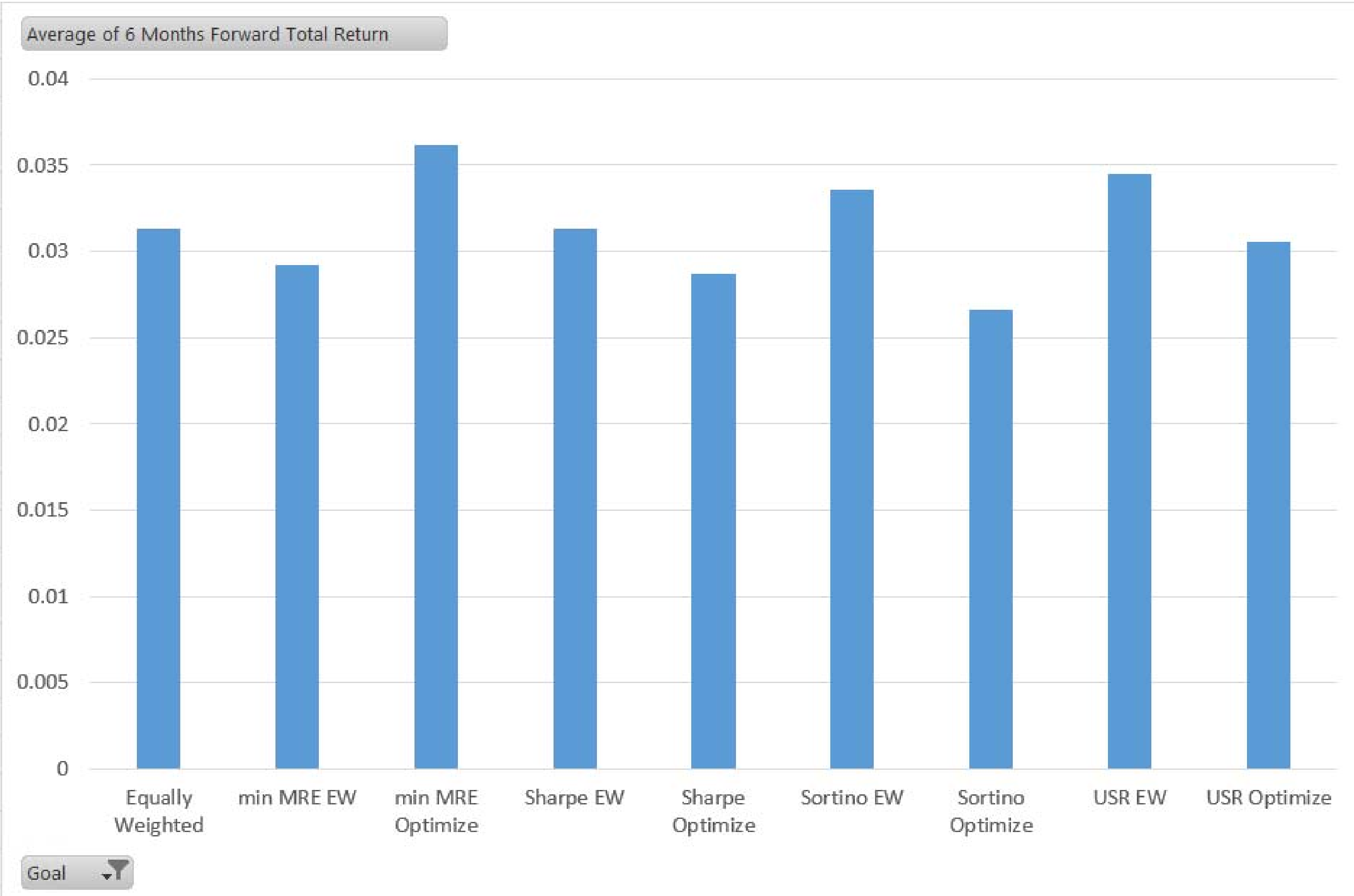
- Using our Monte Carlo platform we constructed 22,500 (=5 methods x 9 years x 500 iterations) buylists of 15 stocks selected from the appropriate DJIA 30
- For each buylist, we constructed an optimized portfolio and the corresponding equally weighted portfolio
- For each buylist, we estimated the forward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

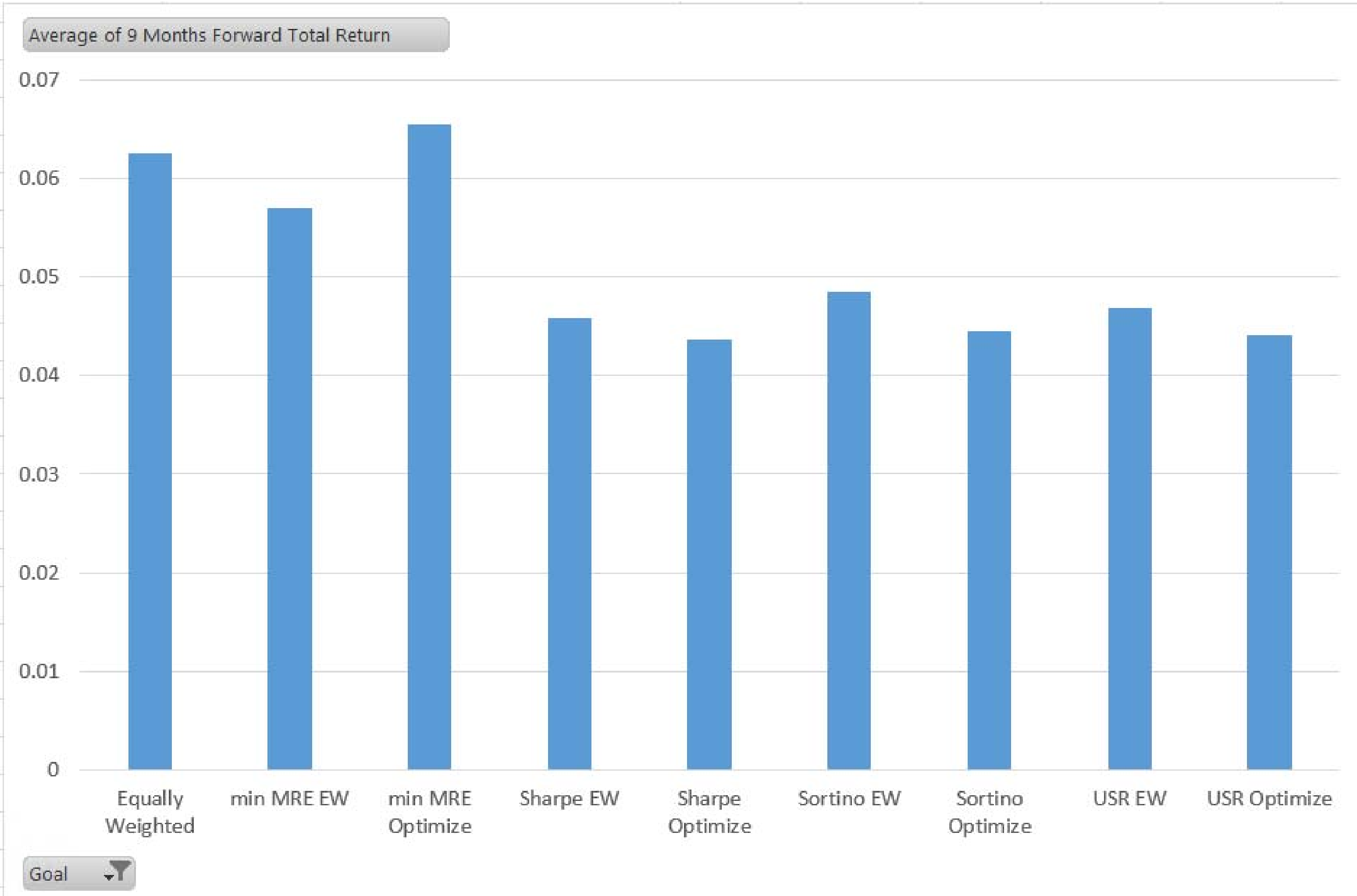


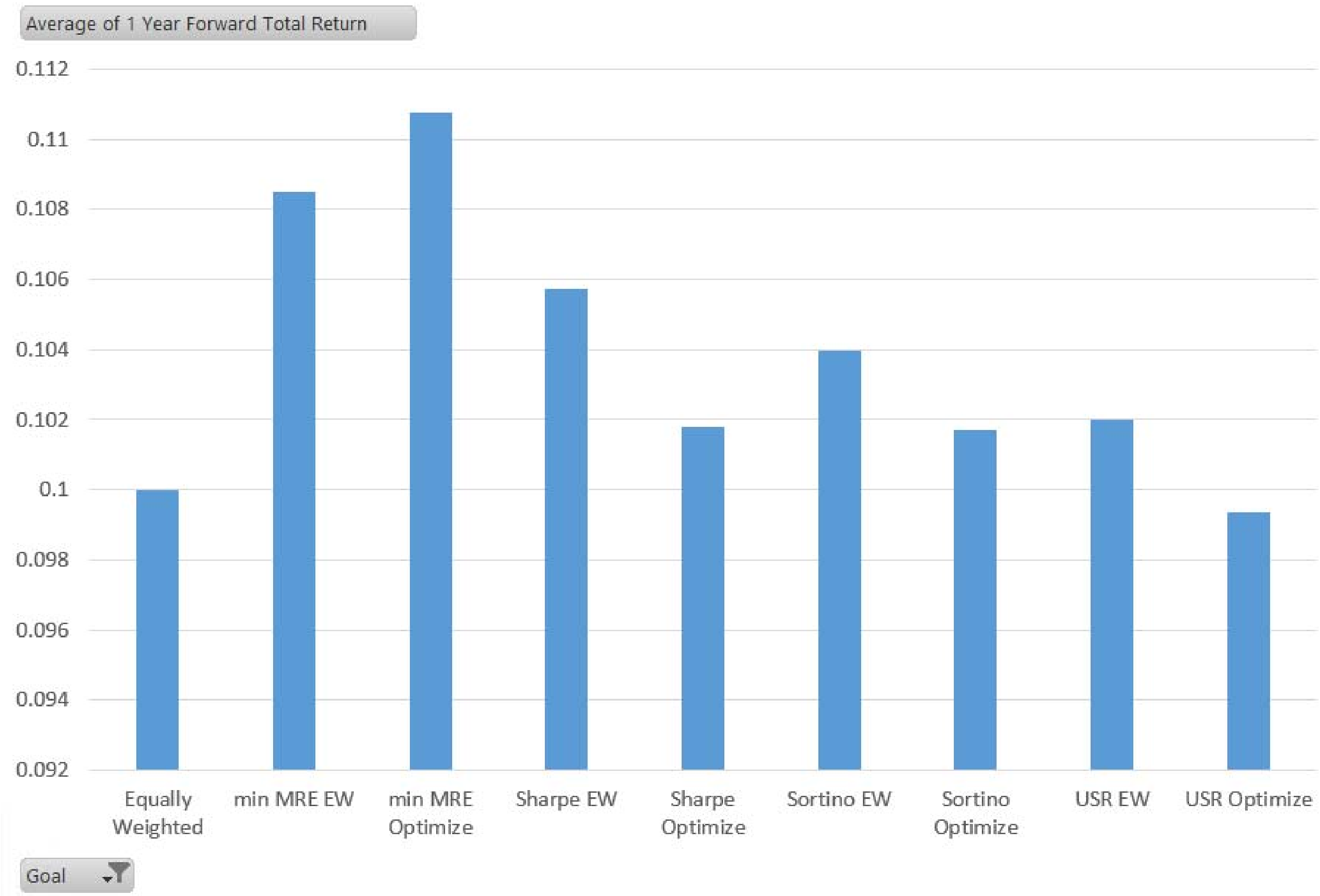
Average of 1 Month Forward Total Return
0
-0.005
-0.01
-0.015
-0.02
-0.025
Equally Weighted
min MRE EW
min MRE Optimize
Sharpe EW
Sharpe Optimize
Sortino EW
Sortino Optimize
USR EW
USR Optimize
Goal

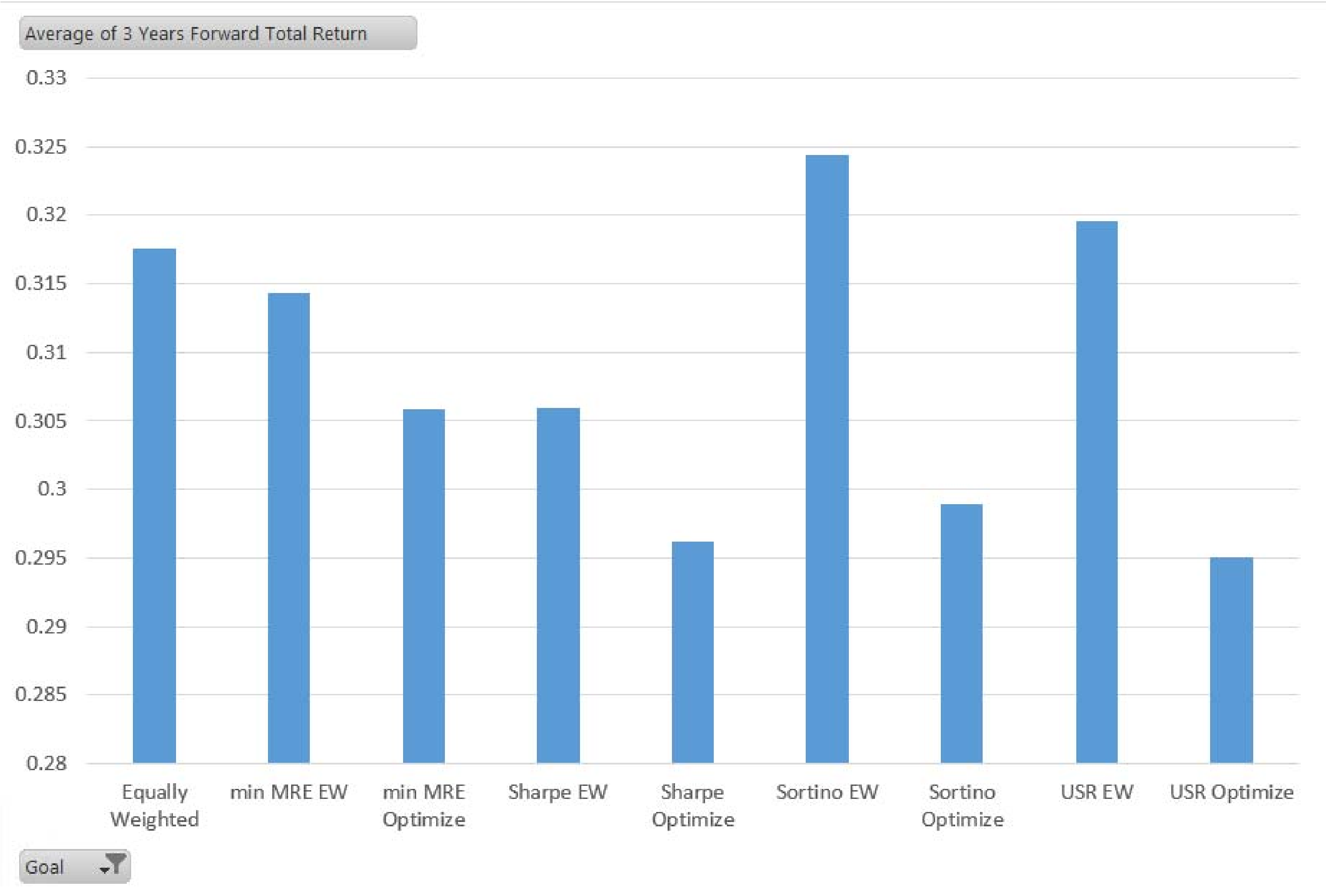


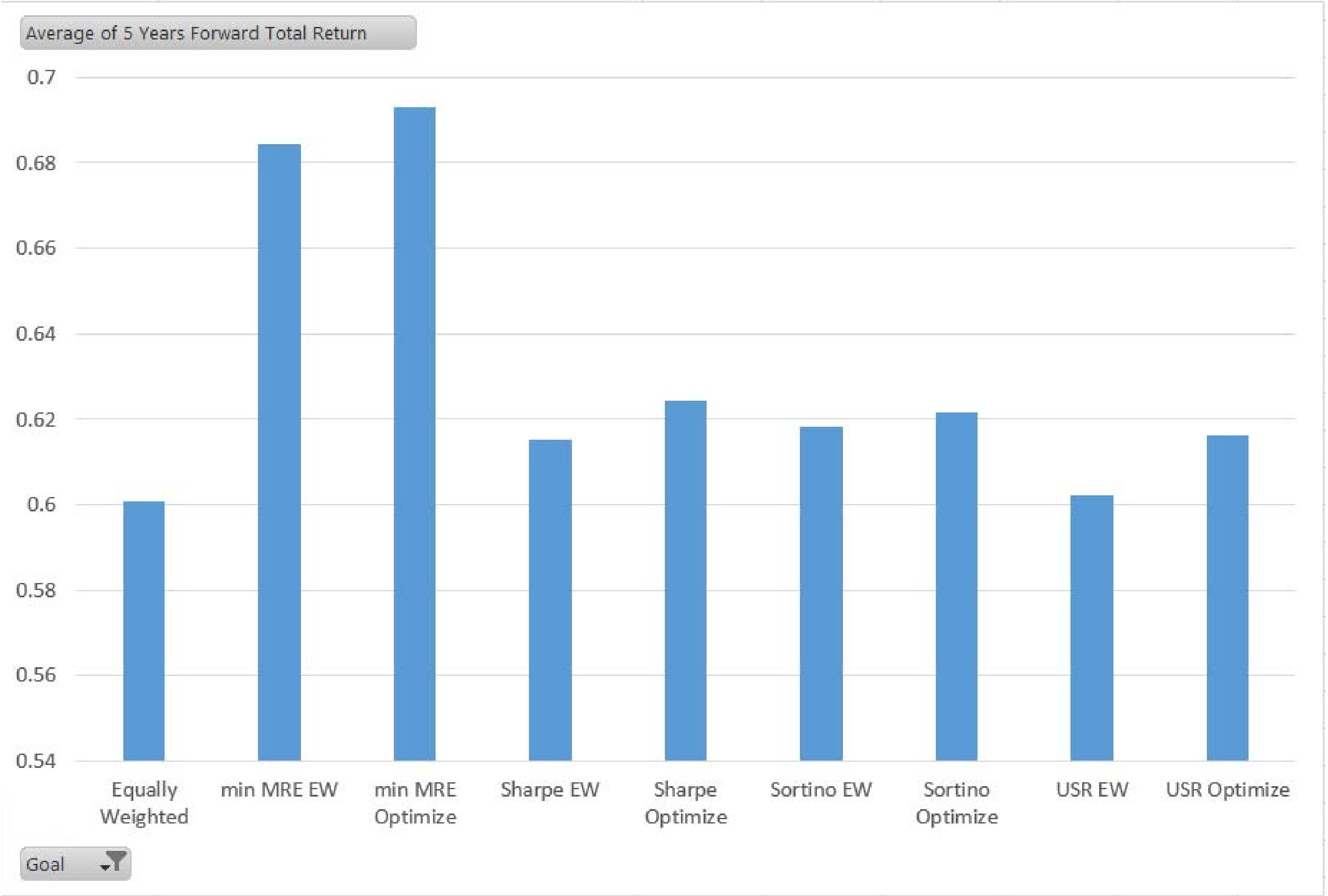
Average of 3 Months Forward Total Return
0.03
0.025
0.02
0.015
0.01
0.005
0
Equally Weighted
min MRE EW
min MRE Optimize
Sharpe EW
Sharpe Optimize
Sortino EW
Sortino Optimize
USR EW
USR Optimize
Goal


Average of 6 Months Forward Total Return
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Equally Weighted
min MRE EW
min MRE Optimize
Sharpe EW
Sharpe Optimize
Sortino EW
Sortino Optimize
USR EW
USR Optimize
Goal


Average of 9 Months Forward Total Return
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Equally Weighted
min MRE EW
min MRE Optimize
Sharpe EW
Sharpe Optimize
Sortino EW
Sortino Optimize
USR EW
USR Optimize
Goal


Average of 1 Year Forward Total Return
0.112
0.11
0.108
0.106
0.104
0.102
0.1
0.098
0.096
0.094
0.092
Equally Weighted
min MRE EW
min MRE Optimize
Sharpe EW
Sharpe Optimize
Sortino EW
Sortino Optimize
USR EW
USR Optimize
Goal


Average of 3 Years Forward Total Return
0.33
0.325
0.32
0.315
0.31
0.305
0.3
0.295
0.29
0.285
0.28
Equally Weighted
min 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
0.6
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

goal	stat	1mo	3mo	6mo	9mo	1yr	3yr	5yr
Equally Weighte	Mean	-0.0071	0.0238	0.0313	0.0625	0.1000	0.3176	0.6007
min MRE EW	Mean	-0.0102	0.0186	0.0292	0.0570	0.1085	0.3143	0.6843
min MRE Optimiz	Mean	-0.0086	0.0203	0.0362	0.0655	0.1108	0.3059	0.6930
Sharpe EW	Mean	-0.0170	0.0226	0.0313	0.0458	0.1057	0.3059	0.6152
Sharpe Optimize	Mean	-0.0214	0.0194	0.0287	0.0436	0.1018	0.2962	0.6245
Sortino EW	Mean	-0.0148	0.0225	0.0336	0.0485	0.1039	0.3244	0.6184
Sortino Optimiz	Mean	-0.0211	0.0173	0.0266	0.0446	0.1017	0.2989	0.6218
USR EW	Mean	-0.0151	0.0229	0.0345	0.0469	0.1020	0.3195	0.6021
USR Optimize	Mean	-0.0199	0.0198	0.0306	0.0441	0.0993	0.2951	0.6164

goal	stat	1mo	3mo	6mo	9mo	1yr	3yr	5yr
Equally Weighte	Median	0.0026	0.0286	0.0577	0.0874	0.1266	0.3660	0.5155
min MRE EW	Median	-0.0096	0.0148	0.0438	0.0731	0.1210	0.4002	0.5798
min MRE Optimiz	Median	-0.0041	0.0176	0.0405	0.0628	0.1146	0.4151	0.6256
Sharpe EW	Median	-0.0222	0.0226	0.0507	0.0475	0.1301	0.3348	0.6058
Sharpe Optimize	Median	-0.0289	0.0209	0.0506	0.0320	0.1266	0.2944	0.6192
Sortino EW	Median	-0.0207	0.0170	0.0473	0.0493	0.1236	0.3699	0.5796
Sortino Optimiz	Median	-0.0287	0.0187	0.0429	0.0289	0.1226	0.3049	0.6144
USR EW	Median	-0.0230	0.0163	0.0504	0.0513	0.1224	0.3680	0.5973
USR Optimize	Median	-0.0269	0.0202	0.0494	0.0344	0.1202	0.2982	0.6118

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

goal	stat	rank 1mo	rank 3mo	rank 6mo	rank 9mo	rank 1yr	rank 3yr	rank 5yr	Avg Rank	Avg. Short Rank	Avg. Long Rank
Equally Weighte	Mean	1	1	5	2	8	3	9	4.14	2.25	6.67
min MRE EW	Mean	3	8	7	3	2	4	2	4.14	5.25	2.67
min MRE Optimize	Mean	2	5	1	1	1	6	1	2.43	2.25	2.67
Sharpe EW	Mean	6	3	4	6	3	5	7	4.86	4.75	5.00
Sharpe Optimize	Mean	9	7	8	9	6	8	3	7.14	8.25	5.67
Sortino EW	Mean	4	4	3	4	4	1	5	3.57	3.75	3.33
Sortino Optimiz	Mean	8	9	9	7	7	7	4	7.29	8.25	6.00
USR EW	Mean	5	2	2	5	5	2	8	4.14	3.50	5.00
USR Optimize	Mean	7	6	6	8	9	9	6	7.29	6.75	8.00

goal	stat	rank 1mo	rank 3mo	rank 6mo	rank 9mo	rank 1yr	rank 3yr	rank 5yr	Avg Rank	Avg. Short Rank	Avg. Long Rank
Equally Weighte	Median	1	1	1	1	2	5	9	2.86	1.00	5.33
min MRE EW	Median	3	9	7	2	7	2	7	5.29	5.25	5.33
min MRE Optimize	Median	2	6	9	3	9	1	1	4.43	5.00	3.67
Sharpe EW	Median	5	2	2	6	1	6	5	3.86	3.75	4.00
Sharpe Optimize	Median	9	3	3	8	2	9	2	5.14	5.75	4.33
Sortino EW	Median	4	7	6	5	4	3	8	5.29	5.50	5.00
Sortino Optimiz	Median	8	5	8	9	5	7	3	6.43	7.50	5.00
USR EW	Median	6	8	4	4	6	4	6	5.43	5.50	5.33
USR Optimize	Median	7	4	5	7	8	8	4	6.14	5.75	6.67

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:

Chong, J., and Phillips, G. M. (2015). Sector rotation with macroeconomic factors. *The Journal of Wealth Management, 18*(1), 54-68.

Which recently received

The William F. Sharpe Indexing Achievement Awards, ETF/Indexing Paper of the Year across all Institutional Investor Journals (2015).

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 12-2-2015 FINAL

Type: Portfolio | Notes

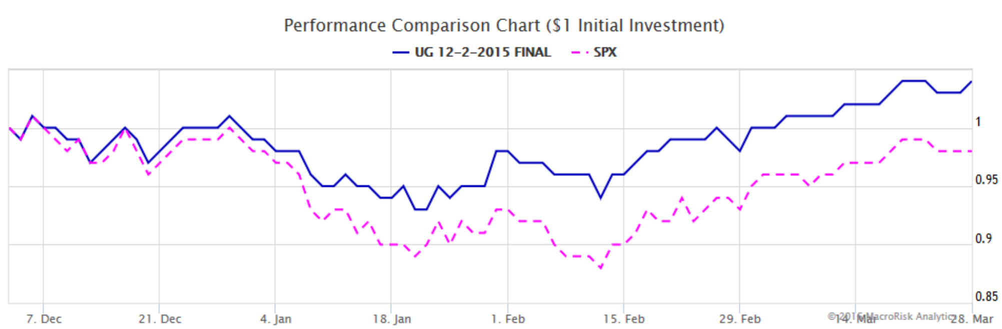
Performance Report Dates:
12/02/2015 — 03/28/2016
using dividend & split adjusted series

Compare: CBOE S&P 500 INDEX S&P 500

Type: Market Index | Symbol: SPX

Historic Returns Measures	UG 12-2-2015 FINAL	SPX
Total Return	3.62%	-2.04%
Annualized Ret.	11.73%	-6.24%
TT Month Ret.	7.04%	-1.16%
Avg. Daily Ret.	0.05%	-0.02%
Annualized Mean Ret.	12.27%	-4.79%
Std. Dev of Returns	0.1517	0.1840
Upper SemiDev of Returns	0.1503	0.1741
Lower SemiDev of Returns	0.1549	0.1980

Scaled Values	UG 12-2-2015 FINAL	SPX
Start Value	$1.00	1.00
End Value	$1.04	0.98
Max Value	$1.04	1.01
Min Value	$0.93	0.88
Average Value	$0.99	0.95



UG Sustainable {CSUN} (EW optimization, from Responsible, Sustainable, stocks)

UG S 12-2-2015 FINAL

Type: Portfolio | Client: CSUN | Notes

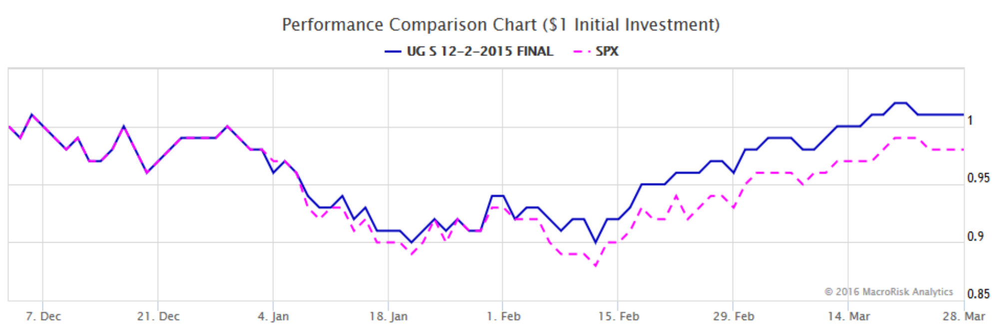
Performance Report Dates:
12/02/2015 — 03/28/2016
using dividend & split adjusted series

Compare: CBOE S&P 500 INDEX S&P 500

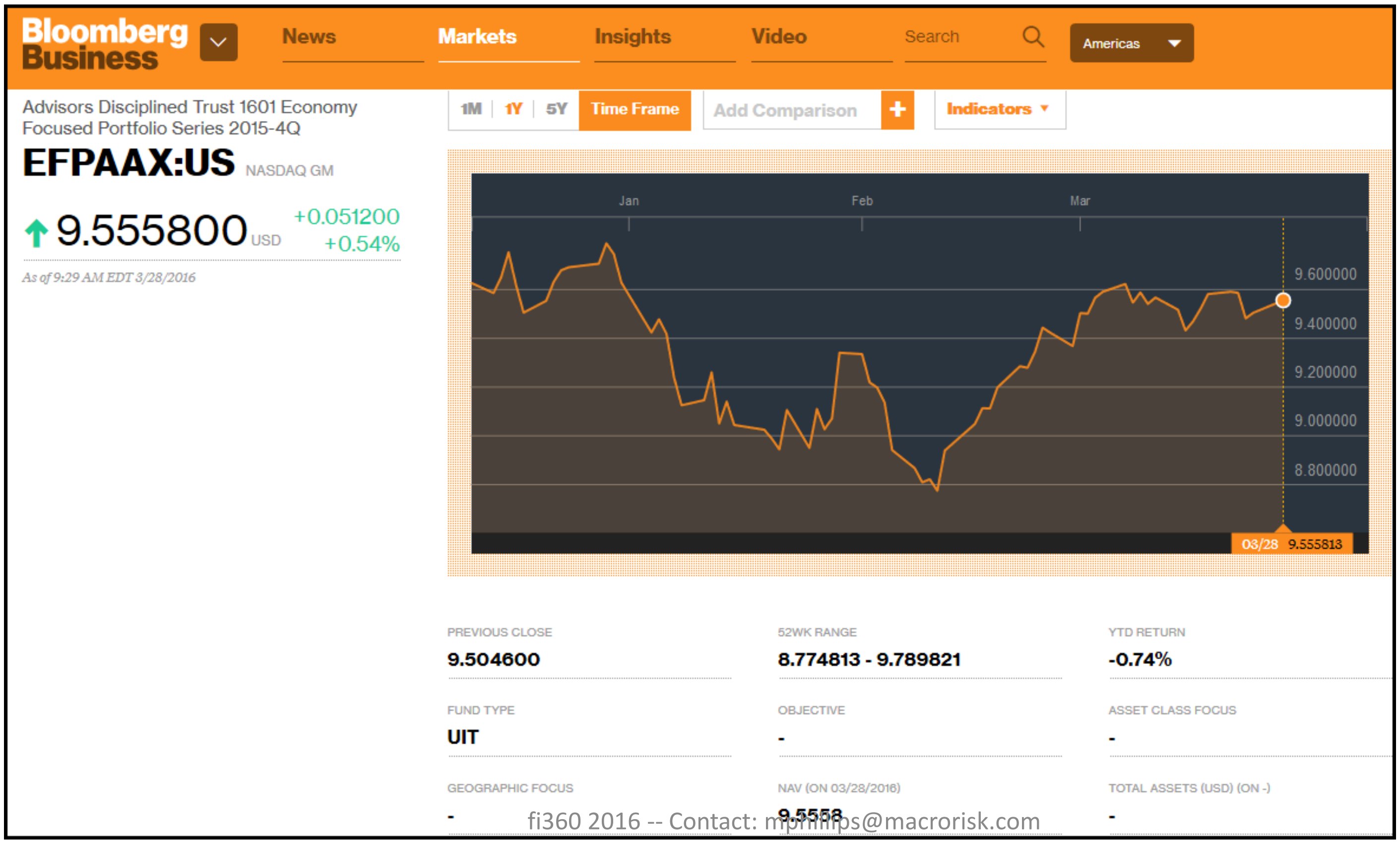
Type: Market Index | Symbol: SPX

Historic Returns Measures	UG S 12-2-2015 FINAL	SPX
Total Return	1.11%	-2.04%
Annualized Ret.	3.50%	-6.24%
TT Month Ret.	3.70%	-1.16%
Avg. Daily Ret.	0.02%	-0.02%
Annualized Mean Ret.	4.83%	-4.79%
Std. Dev of Returns	0.1670	0.1840
Upper SemiDev of Returns	0.1656	0.1741
Lower SemiDev of Returns	0.1706	0.1980

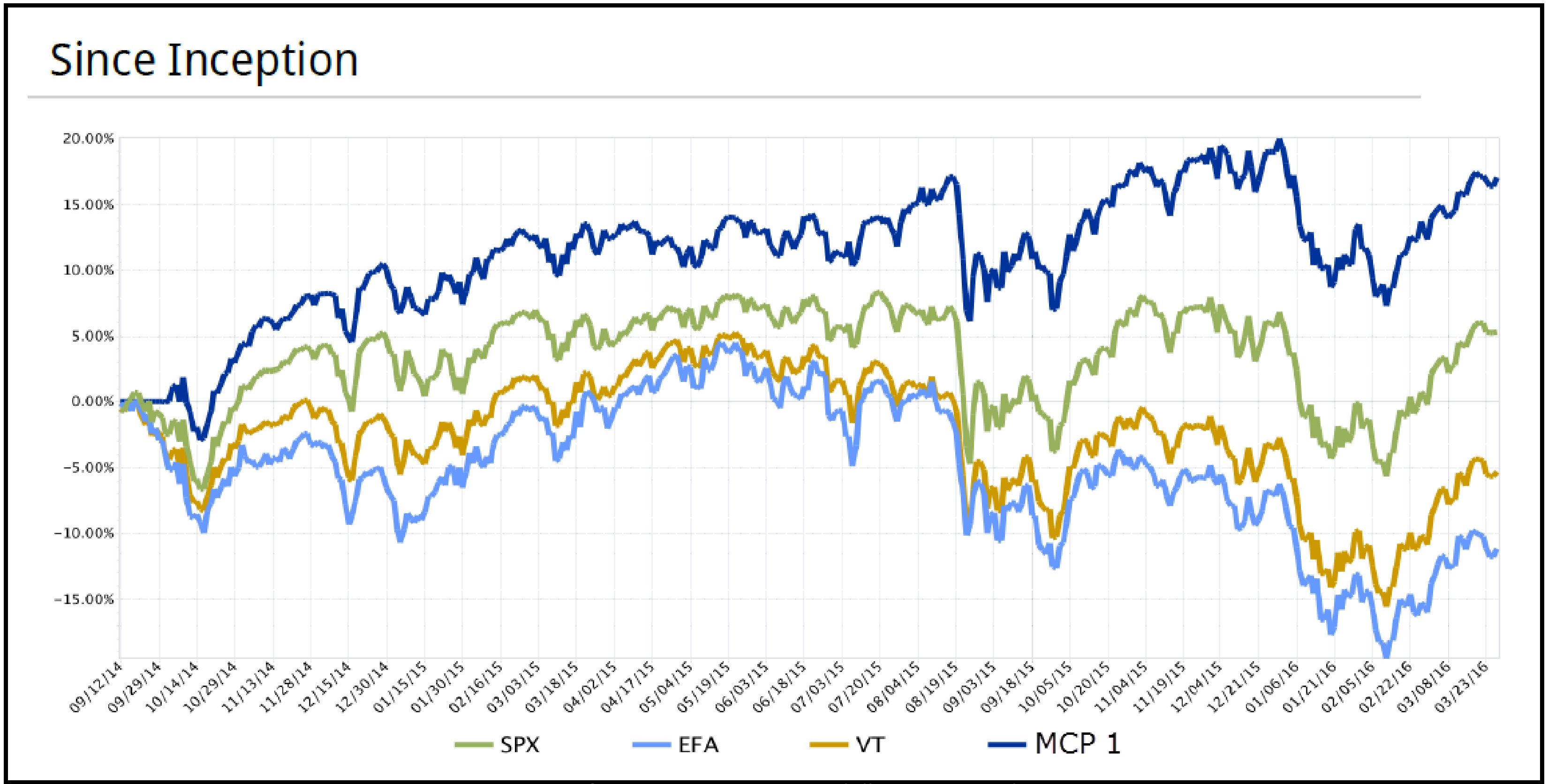
Scaled Values	UG S 12-2-2015 FINAL	SPX
Start Value	$1.00	1.00
End Value	$1.01	0.98
Max Value	$1.02	1.01
Min Value	$0.90	0.88
Average Value	$0.96	0.95



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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