Comparing Portfolio Performances

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Abstract

The objective of good fund managers is to maximize investor's return while minimizing exposure to risk subject to a client's risk tolerance. Much research has been done on portfolio investment strategies and as a result, we know of several approaches to optimizing a portfolio of assets. Depending on the situation however, each model has its pros and cons. This paper evaluates several portfolio investment strategies.

Keywords: Sharpe Ratio, PCA, Maximum Drawdown, Bootstrapping

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Motivation

With information and computational power easily accessible, there is great incentive for Portfolio managers to leverage these resources to maximize returns. In our paper we construct portfolios by using different approaches. Then, using metrics such as Sharpe Ratios, Maximum Drawdowns and Turn-Over Rates we will determine the best approach to maximize return.

INVESTMENT STRATEGIES

Minimum Variance Portfolio.

The Minimum Variance Portfolio model consists of allocating our investment budget towards our stocks in a manner which minimizes the overall risk of the portfolio. This is done by setting the derivative of the matrix equation for variance to zero and then solving for the weights.

Tangency Portfolio with Risk-free Asset

The Tangency Portfolio with a risk free asset is an unleveraged variation of the Minimum Variance Portfolio which introduces a risk free asset and then optimizes the mean-variance combination to achieve the best risk-reward tradeoff (highest Sharper Ratio) possible.

Capital Asset Pricing Model

The Capital Asset Pricing Model regresses a given portfolio– in our case the Tangency Portfolio with Risk-free Asset—against a benchmark to understand its sensitivity to variations in the benchmark in terms of standard regression metrics. In CAPM model, the portfolio risks (standard deviation of portfolio) are decomposed as market risk (systematic risk, β) and unique risk (unsystematic risk). For CML, we normally use to check the efficiency of the portfolio. For SML, we normally use to pick the undervalued stocks to invest. We use CML model and Sharpe Ratio to review our target return portfolio's efficiency. In our portfolio, the Sharpe Ratio is 1.2617126, which is higher than the market Sharpe Ratio, 1.0432513, calculated by S&P 500 benchmark.

Nonparametric Bootstrap Portfolio

Nonparametric Bootstrapping consists of making no assumption on the distribution of the data, sampling the empirical data with replacement multiple times, and calculating the Tangency Portfolio each time in order to estimate the return and variance of the population. Since the empirical sample approximates the population from which it was drawn, resamples from this sample approximate what we would get if we took many samples from the population. The issue encountered with this method is that there are large outliers in the data which appear multiple times in some of the resamples. This overrepresentation skews the results significantly and robust mean-trimming is needed. Yet even with a 5% trim, results still appear unrealistic.

Target Return Portfolio

The Target Return portfolio is a mean-variance optimization of the Tangency Portfolio where variance is minimized subject to a declared mean (target return) using Lagrange multipliers. Target Return investment is a kind of passive investment. Most of time, the portfolio will be used to meet future spending or debts. The first way of managing Target return is to build the portfolio by hedging the debts risks exposure. The second way of managing target return is to maximizing the return, meeting risks requirements.

Target Return Portfolio with Risk-free Asset

The Target Return Portfolio with Risk-free Asset is equivalent to the Target Return Portfolio described above but also allows for leveraging in the model using a risk free asset.

Principal Component Portfolio

Principal Component Analysis consists in identifying the elements of a dataset which best explain the variance. In the case of portfolio construction, the aim is to identify the linear combination of stocks which contribute to the highest risk. Since our assets within the 25 largest holdings in the S&P 500, they are highly correlated and result in two principal components explaining 91% of the variance in the portfolio. Based on daily returns, we calculated the eigenvectors v_i of the covariance matrix to find the weights $D_1 = v_1'(Z - \mu_Z)$ where v_1 has unit length and is selected to maximize the variance of D_1. This is achieved by setting v_1 equal to the normalized first eigenvector of ΣZ —the eigenvector with the largest eigenvalue. In this case, the variance of D_1 equals that eigenvalue λ_1. The second principal component D_2 is defined as $D_2 = v_2'(Z - \mu_Z)$ where v_2 is selected from the set of all n-dimensional unit vectors that are orthogonal to v_1 in such a manner as to maximize the variance of D_2. This is achieved by setting v_2 equal to the normalized second eigenvector of ΣZ —the eigenvector with the second largest eigenvalue. The variance of D_2 equals that eigenvalue, λ_2. Proceeding in this manner, we define the remaining principal components. There will be m principal components D_i, each one corresponding to a normalized eigenvector v_i of ΣZ. We can represent $Z = \sum_{i=1}^{m} D_i v_i + \mu_Z = vD + \mu_Z$.

APPROACH

In order to evaluate the different investment strategies, we picked 20 stocks from the Standard & Poor's 500 (S&P 500) American stock market index and analyzed their returns over a seven year period (January 1, 2007 to December, 1 2014). The 20 stocks chosen were the top holdings which have been part of the index for the entire period of evaluation. We use the same assets in each portfolio strategy evaluated. Our portfolio consist of the following set of fairly diversified large-cap stocks: Apple (AAPL), Exxon Mobil (XOM), Microsoft (MSFT), Johnson & Johnson (JNJ), General Electric (GE), Wells Fargo Company (WFC), Proctor & Gamble (PG), JP Morgan Chase (JPM), Chevron Corp. (CVX), Verizon (VZ), Pfizer (PFE), Intel (INTC), Bank of America (BAC), AT&T (T), Merck & Co (MRK), Coca Cola (KO), Citigroup (C), International Business Machines (IBM), Google (GOOGL), Gilead Sciences (GILD).

Portfolio Performances

During the period in review, the S&P500 had a 9.2% return with a standard deviation of 22.2% and 0.504 Sharpe ratio (Table 1). Yet in spite of this positive return, each investment strategy outperformed the benchmark with bootstrapping yielding the highest return and Sharpe ratio of

71% and 1.11 respectively, and Principal Component Analysis yielding the lowest risk with a 13.1% standard deviation.

Risk Management

The results for Value-at-Risk and Expected Shortfall using a $10,000,000 initial investment became essentially a ranking of standard deviations. The higher the standard deviation the more value was at risk and the greater the expected shortfall. Hence, Principal Component Analysis gave the lowest VaR and ES, while bootstrapping gave the highest.

Take Away and Further Study

Having the same investments across each portfolio, performance depended less on the stocks but rather the investment strategy and its underlying subtleties, in our analysis it became evident that each strategy had its benefits and drawbacks. With this in mind it is possible to tailor portfolios to meet clients’ long and short term goals whether they are risk averse or not. In our study, Bootstrap Tangent Portfolio promised the highest return while our Principal Component Portfolio was the least risky. This bit of information can help to improve returns. The plan would consist of alternating approaches as the market’s behavior changed over time, pushing for conservative portfolios when market variability is high and less conservative approach when variability goes down. Leveraging predictive analytics tools, identifying the when to favor a strategy may be a possibility.

Tables Performance Summary

Table 1

Period

- *start = "2007-01-01"*
- *end = "2014-12-01"*

S&P500 Index (Benchmark)

- *Mean = 0.09166378*
- *Standard Deviation = 0.2224576*
- *Sharpe Ratio = 0.3221458*
- *Maximum Draw Down = 1.852949*

Minimum Variance Portfolio

- *Mean = 0.09305468*
- *Standard Deviation = 0.1450562*
- *Sharpe Ratio = 0.5036302*
- *Maximum Draw Down = 2.968063*

Tangency Portfolio with Risk Free Asset

- *Mean = 0.34323781*
- *Standard Deviation = 0.3051219*
- *Sharpe Ratio = 1.0593728*

- *Maximum Draw Down = 1.794105*

Capital Asset Pricing Model

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.29336	0.09965	2.944	0.00328 **
t(R_SPY)	0.54413	0.02822	19.284	< 2e-16 ***

*Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Residual standard error: 4.447 on 1991 degrees of freedom

Multiple R-squared: 0.1574, Adjusted R-squared: 0.157

F-statistic: 371.9 on 1 and 1991 DF, p-value: < 2.2e-16

Nonparametric Bootstrap Tangent Portfolio

- *Resamples = 10^5*
- *Time @ 1.8 GHz = 10.46968 mins*
- *Robust Mean (0.05 Trim) = 0.71230152*
    - *Outlier Returns in Dataset*
    - *[1] 0.5782493 8.7699115*
    - *[1] -0.5066259 -0.5012057 -0.5030242 -0.4965201 -0.8548569*
- *Standard Deviation = 0.5486998*
- *Sharpe Ratio = 1.2617126*
- *Maximum Draw Down = 3.056742*

Target Return Portfolio

- *Mean = 0.5*
- *Standard Deviation = 0.4601001*
- *Sharpe Ratio = 1.0432513*
- *Maximum Draw Down = 1.765257*

Target Return Portfolio with Risk-free Asset

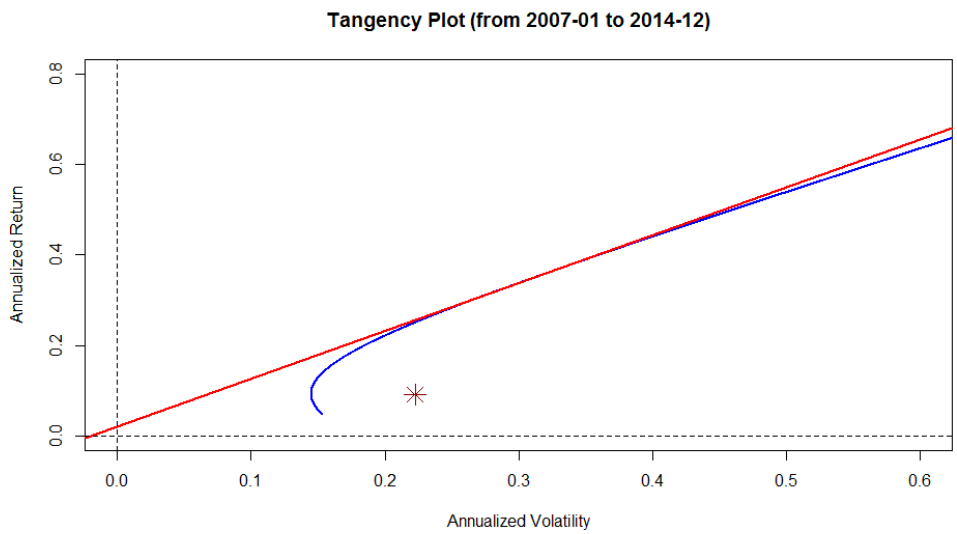
- *Mean = 0.5*
- *Standard Deviation = 0.4530983*
- *Sharpe Ratio = 1.0593728*
- *Maximum Draw Down = 1.765257*

Principal Component Portfolio

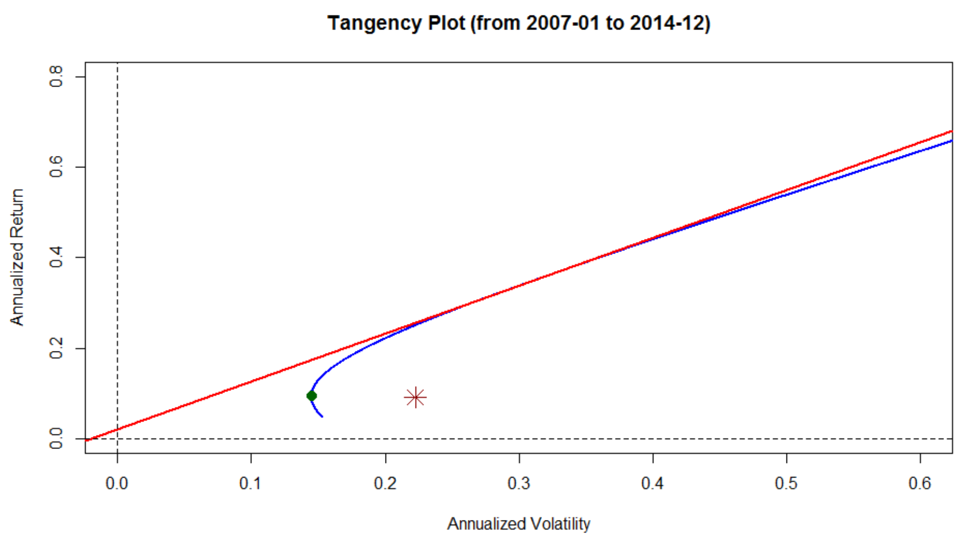
- *Mean = 0.16556244*
- *Standard Deviation = 0.1307560*
- *Sharpe Ratio = 1.1132370*
- *Maximum Draw Down = 1.615135*

Tangency Plot

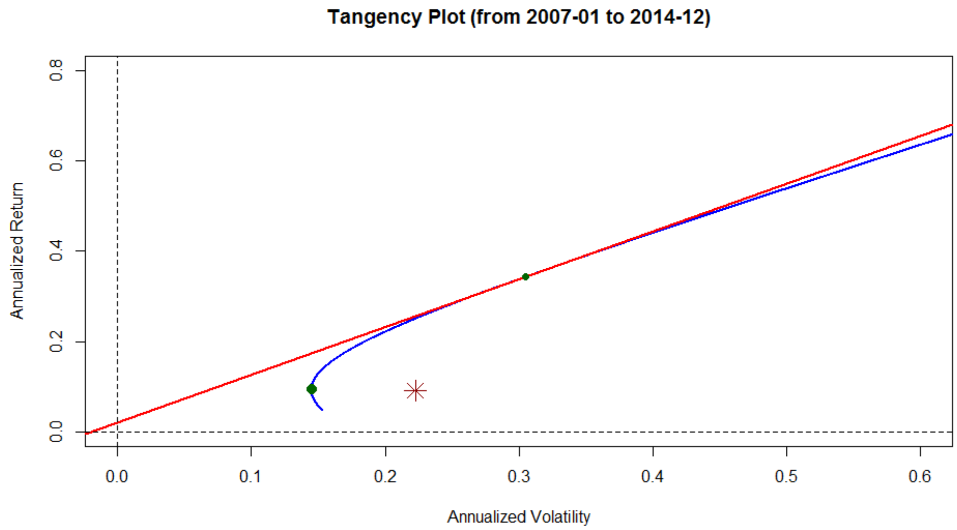
Benchmark



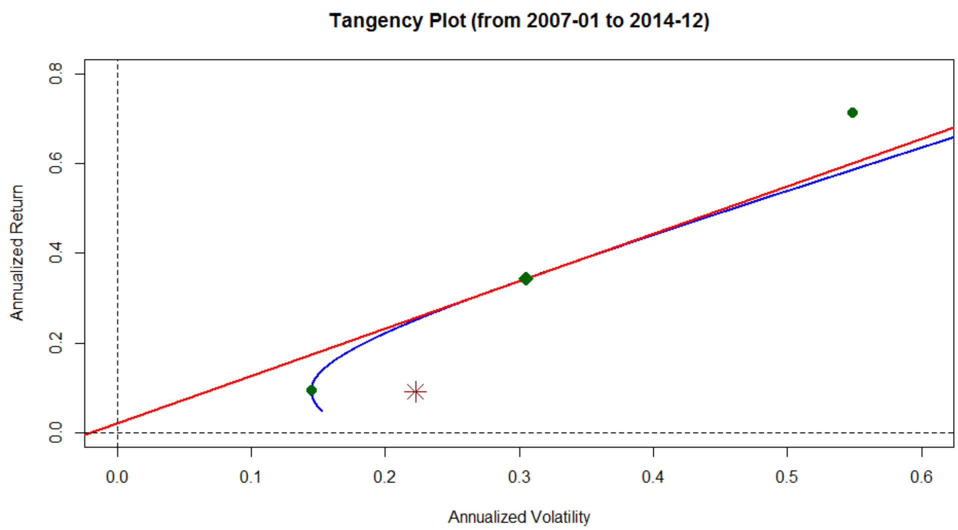
Minimum Variance Portfolio



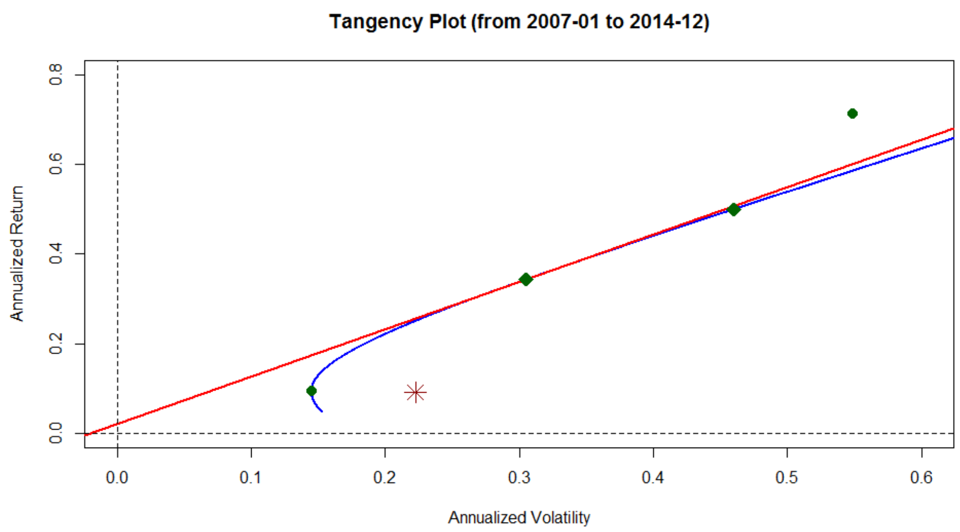
Tangency Portfolio



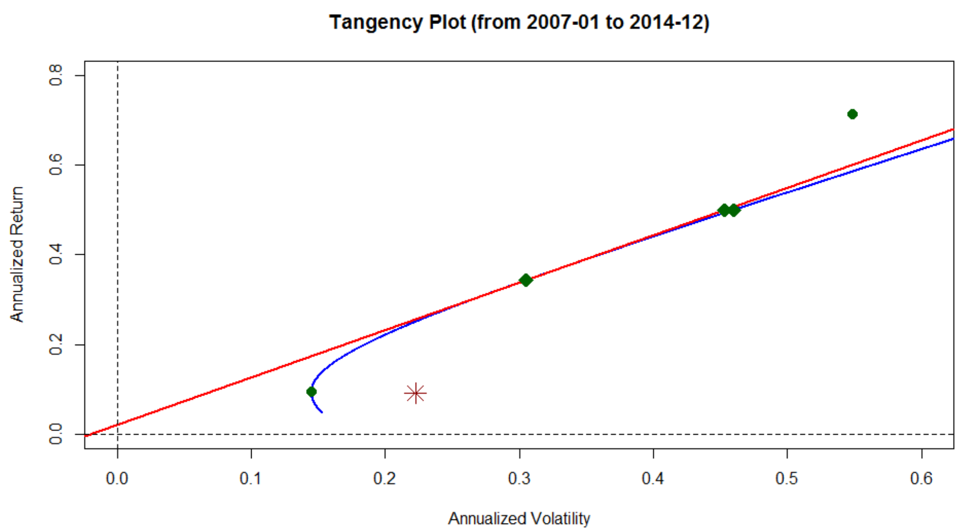
Nonparametric Bootstrap Tangency Portfolio



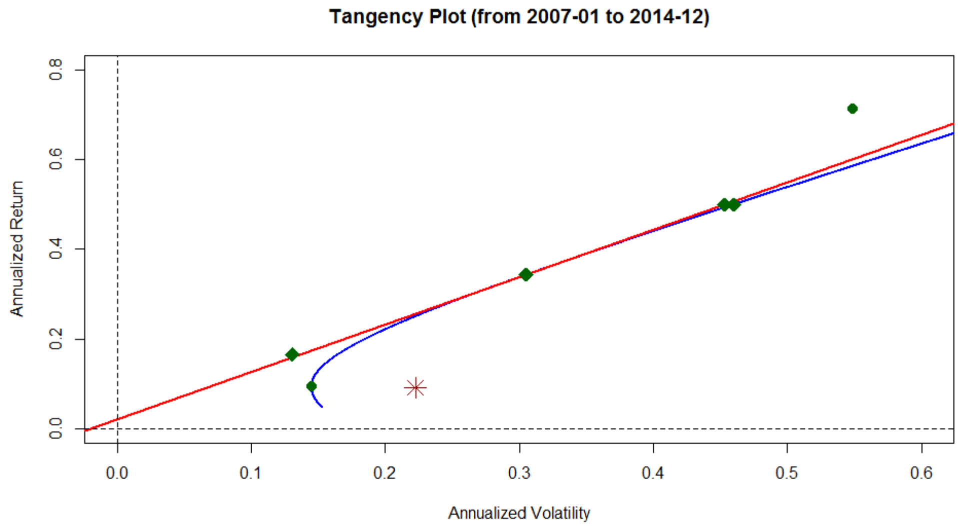
Target Return Portfolio



Target Return Portfolio with Risk Free Asset



Principal Component Analysis



In Memory

of

Timothy Richman

11/22/1982 – 11/28/2014