

**Portfolio Risk Management**  
**Econ 353 - Computational Economics**  
**Final project, Submitted to Dr. Alan Mehlenbacher**

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**Introduction**

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Investors in equity markets are besieged by risk. At times, in fact, it seems as though equity investors are more likely to lose money than gain it. In order to address the perceived risk associated with investing, portfolio risk management was developed. Portfolio risk management is a field of economics, finance and statistics that seeks to help investors manage the risk associated with the investments they make. Portfolio risk management is largely predicated on the idea that there is some trade-off between risk and return. Equities with higher levels of risk must also carry higher returns, in order to compensate owners for undertaking an elevated level of uncertainty. Portfolio risk management attempts to quantify and manage this risk so as to better match investments to the needs of investors.

This project begins with an examination of the economic nature of the metrics being examined. The examination of the economic model is followed by a brief overview of the computational model being used. These sections are primarily meant to provide a background for the experiments that follow, but are written to also be didactic. The experiment section outlines the experiments that will be undertaken. This section also provides a background for how the source data was collected and prepared for the purposes of the experiments. The experiments fall mainly in two categories: portfolio optimization and risk management. Since the portfolio optimization model maximizes a particular kind of risk-adjusted return, this project can be holistically viewed as an exercise in risk management. The results of the experiment are then examined, followed by a discussion section. An appendix that includes code and output is then followed by references.

## **Economic Model**

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### **Portfolio Optimization**

This portfolio optimization model builds on the Monte-Carlo simulation model used by Kendrick, Mercado and Amman (2006). While the Kendrick model maximizes returns subject to a subjectively weighted variance function, the model proposed here maximizes the alpha that would have been obtained given the historic results. Alpha, in this case, refers to the returns in the portfolio in excess of what the Capital Asset Pricing Model would have predicted. For a more thorough examination of this criterion function, refer to the later examination of Jensen's Alpha, keeping in mind that Jensen's alpha is an ex-post measure, while the alpha being used in the criterion function is an ex-ante measure. The Kendrick model is also extended to include a larger number of assets and to be based on statistics pertaining to actual equities.

It should be noted that the results provided by this method of portfolio optimization could easily be improved by a skillful portfolio manager. One of the stocks examined, for instance, is that of Microsoft. Over the period of returns being examined, Microsoft experienced phenomenal growth. Given the fact that Microsoft is already one of the largest corporations in the world, it is unlikely that such phenomenal growth rates will continue. A portfolio manager could therefore stand a good chance of improving on the results of this model, by adjusting the Monte-Carlo simulation's results in order to take into account real-world limits to growth.

### **Treynor ratio**

The Treynor ratio is "a ratio, developed by Jack L. Treynor, to measure excess return per unit of risk, based on systematic risk (the beta of a portfolio versus the benchmark)" (Russell Investments, 2008). This ratio is used to rank portfolios based on their risk premium (return in excess of the risk-free rate), when weighted by the degree of risk required to obtain this return.

The Treynor ratio is equal to:

$$T = (r_p - r_f) / \beta_p \quad (1)$$

(Russell Investments, 2008), where  $r_p$  is the return of the portfolio in question,  $r_f$  is the risk-free rate of return, and  $\beta_p$  is the CAPM beta of the portfolio in question (Sharpe, 1964). As a portfolio gets riskier relative to the market,  $\beta_p$  increases, causing the Treynor ratio to drop. Similarly, if the portfolio's return increases or the risk-free rate decreases, the Treynor ratio will increase. It is therefore clear that when ranking portfolios by their Treynor ratio, the portfolio with the highest Treynor ratio should entail the best risk-return trade-off. In this case, we are using the simple Treynor ratio, as we are only considering one portfolio. In the case where one portfolio is being examined, the simple Treynor ratio is equal to the generalized Treynor ratio, a robust counterpart to the simple Treynor ratio being examined here (Hubner, 2003).

### **Sharpe ratio**

The Sharpe ratio is a ratio of the risk premium to the standard deviation of the risk premium. Reminiscent of a Student t-test, this ratio attempts to measure the risk premium per unit of risk taken to acquire this premium.

The Sharpe Ratio is equal to:

$$S = (r_p - r_f)/\sigma_e \quad (2)$$

(Sharpe, 1994), where  $r_p$  is the return of the portfolio in question,  $r_f$  is the risk-free rate of return, and  $\sigma_e$  is the standard deviation of  $r_p - r_f$ . As a simplifying assumption, and to reflect the fact that  $r_p$  and  $r_f$  are unknown on an ex-ante basis, it will be assumed that  $\sigma_e$  is equal to  $\sigma_p$ , the standard deviation of  $r_p$ . Effectively, this assumes that the risk-free rate will be a constant throughout the life of the portfolio.

### **Jensen's Alpha**

Jensen's Alpha quantifies the return of an asset or portfolio in excess of what the Capital Asset Pricing Model would have predicted. In doing this, Jensen's Alpha attempts to measure the degree to which the returns obtained by a portfolio manager are a result of their ability to select superior stocks and not simply a result of a riskier portfolio.

Jensen's Alpha is equal to:

$$\alpha_p = r_p - (r_f + \beta_p(r_m - r_f)) \quad (3)$$

(Private Banking, 2008), where  $r_p$  is the return of the portfolio in question,  $r_f$  is the risk-free rate of return,  $r_m$  is the rate of return for the market, and  $\beta_p$  is the beta of the portfolio in question. For a portfolio manager to maximize their 'alpha,' they must choose stocks they expect to outperform what would be historically expected of them (since the CAPM prediction is based on past performance).

### **Value-at-Risk**

Value-at-Risk (VaR) measures the risk of loss in a specific portfolio, given a particular probability. In statistical terms, VaR is a measure of tail risk at a given significance level. The smaller the level significance being considered, the greater the value being put at risk.

Though VaR is a widely used measure of risk, it is very flawed. First, VaR measures typically depend on returns following a normal distribution. This is clearly not the case for financial data, which is typically skewed and leptokurtic. Next, "[t]he crux of being able to provide an accurate estimate for the Value-at-Risk is in being able to accurately estimate the expected return  $R^*$  associated with the portfolio value

$W^*$ . Value-at-Risk estimation therefore requires knowing the probability distribution of the expected returns, which of course is unknown. Hence the various methods for estimating VaR depend on the assumption made about the probability distribution of the expected returns."

While it is not possible to avoid making some assumption about the probability distribution of returns, it is possible to make a more accurate assumption than normality. Huisman, Koedijk and Pownall (1998) suggest an extreme-value methodology for determining tail risk. VaR-x models the tail risk associated with the returns of a distribution by examining the most extreme observations and through the usage of a Student's t-distribution. VaR-x is implemented first by creating an index of tail observations based on the absolute value of returns, ranked by size. The estimator of this tail index is:

$$\gamma(k) = \frac{1}{k} \sum_{j=1}^k \ln x_{n-j+1} - \ln x_{n-k} \quad (4)$$

(Huisman, Koedijk and Pownall, 1998), where  $k$  is the number of tail observations and  $x_i$  refers to the  $i$ -th tail observation. Using a modified version of this estimator, we can correct for sampling-size bias by setting  $k$  to the sample size and then calculating the tail index as:

$$\gamma(k) = \beta_0 + \beta_1 k + \varepsilon(k) \quad (5)$$

(Huisman, Koedijk and Pownall, 1998). Alpha is determined by taking the inverse of the intercept produced from this regression. Next, a parameter, theta, is determined by:

$$\theta = \sigma / (\alpha/(\alpha-2))^{0.5} \quad (6)$$

Finally, the measure for VaR-x is calculated as:

$$\text{VaR-x} = W_0 \theta S^* \quad (7)$$

(Huisman, Koedijk and Pownall, 1998), where  $W_0$  is the dollar value of the portfolio,  $\theta$  is the parameter described in the previous steps, and  $S^*$  is the t-statistic associated with a Student t-distribution with  $\alpha$  degrees of freedom. VaR-x will be equal to the dollar value at risk, given the probability level being taken into account and the particular nature of the extreme-values in the distribution of returns.

## Computational Model

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The computational model spans three programs: Microsoft Excel, Quantitative Micro Software's EViews and MathWorks' MATLAB. First, data is collected from Yahoo! Finance, then sorted and interpreted while various statistics are calculated. The Yahoo! Finance data and some of the calculated statistics are then put into EViews where several regressions are performed. The Excel statistics and EViews regression outputs are then inputted into MATLAB. Using a Monte-Carlo simulation, the optimal portfolio is then determined. The Monte-Carlo simulation begins with a portfolio composed of ten percent of each of the ten available equities. The simulation then creates several portfolios with slightly different compositions. The portfolio that best meets the criterion function is then used as the starting point in the next iteration. As numerous iterations are run, the portfolio will close in on the optimal portfolio.

After an optimal portfolio is obtained, it is entered into Excel and EViews where additional statistics are calculated. Finally, the results from the portfolio optimization and the statistics calculated thereafter are inputted into a MATLAB model that calculates the risk metrics discussed in the Economic Model section. Each step of the process is described in greater detail in the experiments section that follows.

The portfolio optimization model has been significantly altered from the Kendrick model. First, the criterion function has been entirely changed. As mentioned in the Economic Model section, rather than using a subjectively weighted measure of risk to determine the particular portfolio weightings, the new criterion function maximizes the 'alpha' obtained by the portfolio manager. The model has also been extended to encompass a larger number of firms. As a result of this extension, the scope of the model has also been increased to include a larger number of iterations and test portfolios. This was necessary to obtain stable portfolio weights.

## Experiments

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### Data Collection & Conditioning

In order to set up the following experiments, historic stock prices must be obtained and properly prepared. This data is obtained from Yahoo! Finance's historic prices (Yahoo! Finance, 2009). For the sake of simplicity, the stocks of ten large-capitalization corporations are examined: 3M, Coca-Cola, Exxon-Mobil, Kellogg, General Electric, MacDonalds, Microsoft, Proctor & Gamble, Southwestern Energy and Union Pacific. Stock prices are examined for the period January 1, 1990 to January 1, 2009. To avoid the conditioning problems associated with using daily returns, weekly returns are used. This step will also help the model better reflect the problems faced by long-term buy-and-hold investors.

From these stock prices, weekly returns are then calculated, as is a variance-covariance matrix between the returns of the stocks. Stock prices are then regressed against the weekly prices of the S&P 500, to determine the CAPM  $\beta$ -values of each individual stock.

### Portfolio Optimization

In order to obtain a portfolio that maximizes returns, subject to the risk taken to get this return, a Monte Carlo simulation is performed using statistics from the stocks being examined. The particular details behind Monte Carlo optimization are detailed in Kendrick, Mercado and Amman (2006). The criterion function being examined in this experiment is:

$$\alpha = r_p - (r_f + \beta_p(r_m - r_f)) \quad (8)$$

Where  $r_p$  is the effective weekly return of a portfolio of stocks:

$$E(r_p) = \sum_{i=1}^{10} w_i E(r_i) \quad (9)$$

(Bodie, Kane, Marcus, Perrakis & Ryan, 2005). The return on each individual equity is denoted by  $r_i$ . For the sake of this experiment we assume that the expected values of the individual stock returns and the portfolio are equal to the true values. Additional parameters are  $r_f$  is the risk-free rate of return,  $r_m$  is the rate of return for the market, and  $\beta_p$  is the beta of the portfolio in question. Equation (8) therefore

maximizes the portfolio's return in excess of the risk-free rate, relative to the portfolio's beta times the market's return in excess of the risk-free rate.

## **Risk Management**

Using the portfolio weights determined in the previous step, another MATLAB program determines the values of a number of different risk-to-return and risk metrics discussed in the Economic Model section. The unified goal of the following four experiments is to compare and contrast the risk metrics that follow and to build an understanding of the risk behaviour of the optimal portfolio relative to the individual stocks.

### **1- Treynor Ratio**

This experiment determines the Treynor ratio associated both with the optimal portfolio and single-equity portfolios consisting of each of the ten input stocks. This experiment will determine the amount of return obtained in excess of the risk-free rate, per unit of systematic risk. This experiment relies on the portfolio  $\beta$ , which is calculated as:

$$\beta_p = \sum_{i=1}^{10} w_i \beta_i \quad (10)$$

(Bodie, Kane, Marcus, Perrakis & Ryan, 2005), where the portfolio's beta is equal to the square root of  $\sigma_p^2$  and  $i = (1, \dots, 10)$  refers to the ten stocks being modelled. The portfolio with the highest Treynor ratio should be considered superior.

### **2- Sharpe Ratio**

This experiment determines the Sharpe ratio associated both with the optimal portfolio and single-equity portfolios consisting of each of the ten input stocks. This experiment will determine the return obtained in excess of the risk free rate, per unit of volatility, as measured by the standard deviation of returns. To calculate this ratio, the portfolio's standard deviation must be determined. It is calculated as:

$$\sigma_p^2 = \sum_{i=1}^{10} w_i^2 \sigma_i^2 + \sum_{i=1}^{10} \sum_{j=1}^{10} w_i w_j \text{Cov}(r_i, r_j) \quad (11)$$

(Bodie, Kane, Marcus, Perrakis & Ryan, 2005), where the portfolio's standard deviation is equal to the square root of  $\sigma_p^2$  and  $i = (1, \dots, 10)$  refers to the ten stocks being modelled. The Sharpe ratio of the optimal portfolio should be higher than the Sharpe ratios calculated for each individual stock portfolio.

### 3- Jensen's Alpha

This experiment determines the Jensen's alpha associated both with the optimal portfolio and single-equity portfolios consisting of each of the ten input stocks. As discussed, Jensen's alpha is a measure of the return of a portfolio in excess of what would be expected, given that assets systematic risk. The portfolio with the highest Jensen's Alpha should be considered superior.

### 4- VaR-x

This experiment determines the VaR-x associated both with the optimal portfolio and single-equity portfolios consisting of each of the ten input stocks. Since VaR-x measures the potential dollar loss associated with a given portfolio and significance level, the optimal portfolio hopefully has a lower VaR-x value than the individual stock portfolios. If so, this would imply that the portfolio optimization process is implicitly minimizing the tail risk associated with the portfolio.

The execution of this experiment involves numerous important steps. First, the absolute value of percentage changes in stock prices is calculated. These changes are then ranked by size, from largest to smallest. Equation (4) is then determined for  $k$ -values that range from 1 to the sample size divided by two. The resulting  $\gamma(k)$  values are then regressed against a constant and  $k$ , as per equation (5). The resulting intercept is the inverse of the alpha value used to calculate theta in equation (6). Finally, VaR-x is calculated by equation (7). The result is a numerical estimate of the dollars put at risk, given an equity's historic volatility characteristics.

## Results

### Data Collection & Conditioning

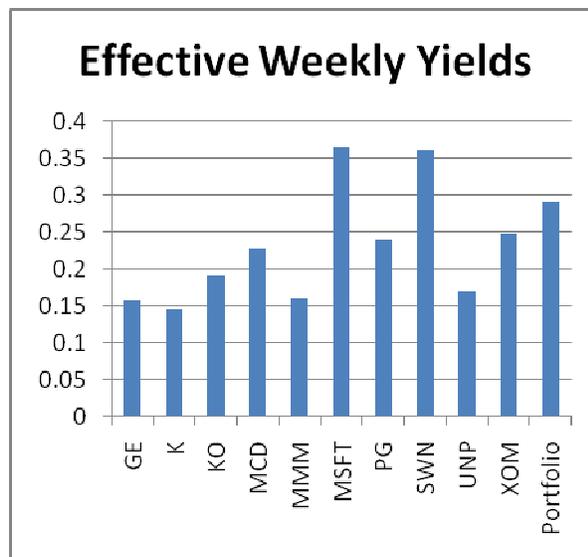
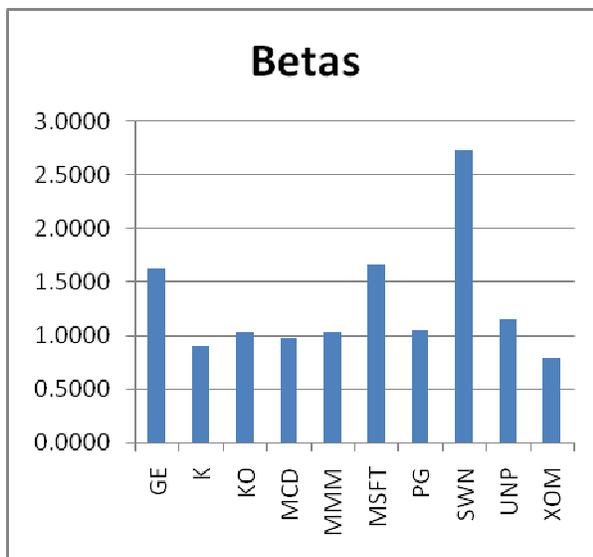
The data collection phase began by acquiring the historic returns of the equities being examined. The historic prices of ten equities and the Standard and Poors 500 index over the period January 1, 1990 through January 1, 2009 were acquired. Weekly percentage returns, a variance-covariance matrix, and the effectively weekly yield were then calculated.

Variance-Covariance Matrix:

All values are scaled up by 1000 for presentation purposes, and are in the units %<sup>2</sup>.

Ticker	GE	K	KO	MCD	MMM	MSFT	PG	SWN	UNP	XOM
GE	1.28	0.26	0.41	0.43	0.50	0.55	0.40	0.23	0.46	0.34
K	0.26	0.94	0.38	0.22	0.29	0.20	0.37	0.26	0.28	0.24
KO	0.41	0.38	1.19	0.40	0.40	0.31	0.57	0.36	0.29	0.35
MCD	0.43	0.22	0.40	1.22	0.29	0.38	0.39	0.18	0.30	0.25
MMM	0.50	0.29	0.40	0.29	0.99	0.28	0.38	0.48	0.44	0.36
MSFT	0.55	0.20	0.31	0.38	0.28	2.01	0.23	0.24	0.32	0.27
PG	0.40	0.37	0.57	0.39	0.38	0.23	1.25	0.23	0.29	0.26
SWN	0.23	0.26	0.36	0.18	0.48	0.24	0.23	3.66	0.48	0.56
UNP	0.46	0.28	0.29	0.30	0.44	0.32	0.29	0.48	1.31	0.32
XOM	0.34	0.24	0.35	0.25	0.36	0.27	0.26	0.56	0.32	0.85

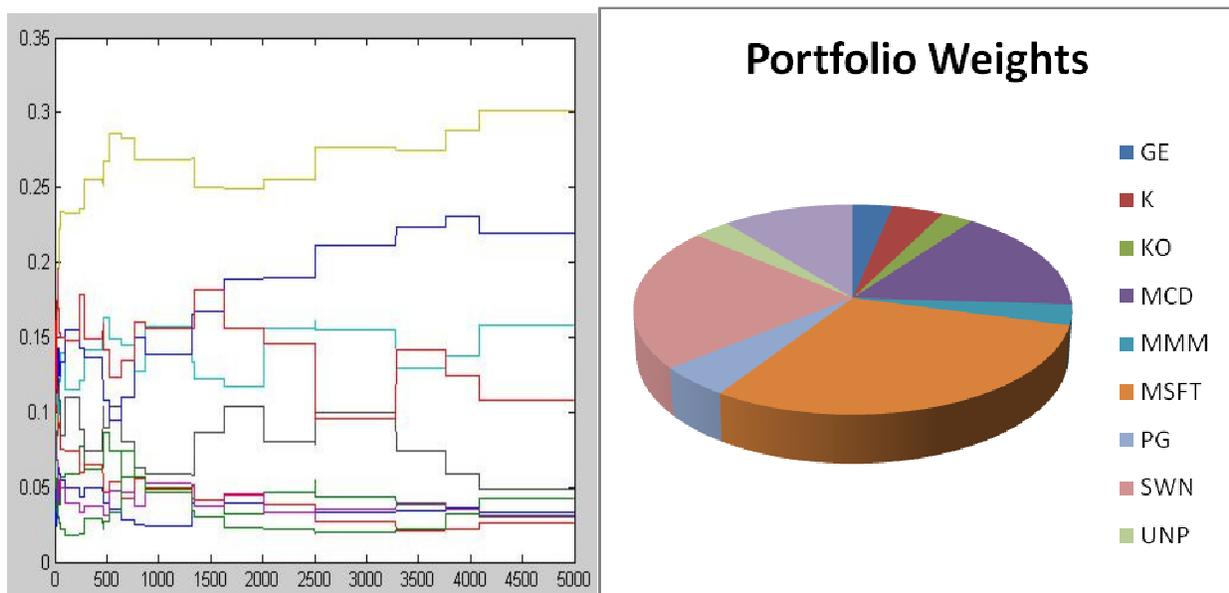
Individual stock betas and effective weekly yields:



These betas were calculated by regressing the stock returns against the returns from the S&P 500.

### Portfolio Optimization

Next, the betas calculated in the previous step, along with the weekly returns are added to MATLAB. A Monte-Carlo simulation is then performed in order to determine the percentage of the portfolio placed that composed of by each equity.



The left-hand MATLAB output shows the Monte-Carlo simulation as it iteratively alters the portfolio so as to obtain the highest risk-weighted return. The right-hand pie-chart displays the results of this simulation. It should be noted that the legend on the pie chart only applies to the pie chart. It is not immediately obvious from the output, but all equities began with an equal 10% portfolio weighting.

```
wnew =
    0.0328
    0.0423
    0.0262
    0.1585
    0.0316
    0.3016
    0.0485
    0.2200
    0.0305
    0.1079

top =
    0.1607

    0.2914
```

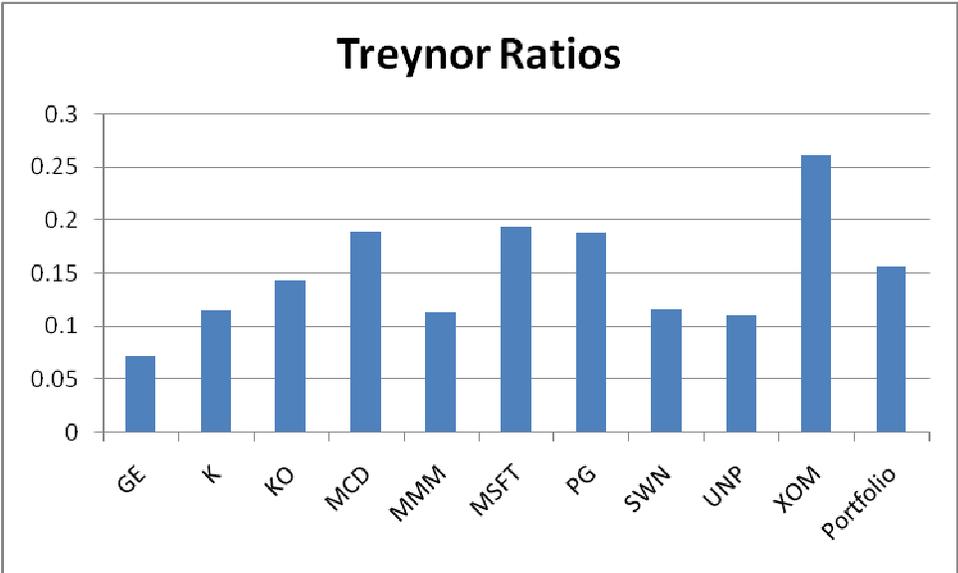
Above is the MATLAB output from the Monte-Carlo simulation. Wnew refers to the portfolio weights of GE, K, KO, MCD, MMM, MSFT, PG, SWN, UNP, and XOM, respectively. Top refers to the risk-adjusted return and the actual percentage return of the portfolio, respectively. These figures are weekly percentage gains. The estimated effective weekly yield on the portfolio is 0.2914%, whereas the risk adjusted return is a weekly yield of 0.1607%.

## Risk Management

Risk analysis metrics were calculated using data from the data collection and conditioning phase. Brief descriptions are given alongside the computational results from the Treynor Ratio, Sharpe Ratio and Jensen's alpha. A cohesive, in-depth discussion of these ratios can be found at the end of the discussion section. VaR-x is given a slightly longer analysis both here and in the discussion section, reflecting the added complexity involved in calculating and interpreting VaR-x.

### 1- Treynor Ratio

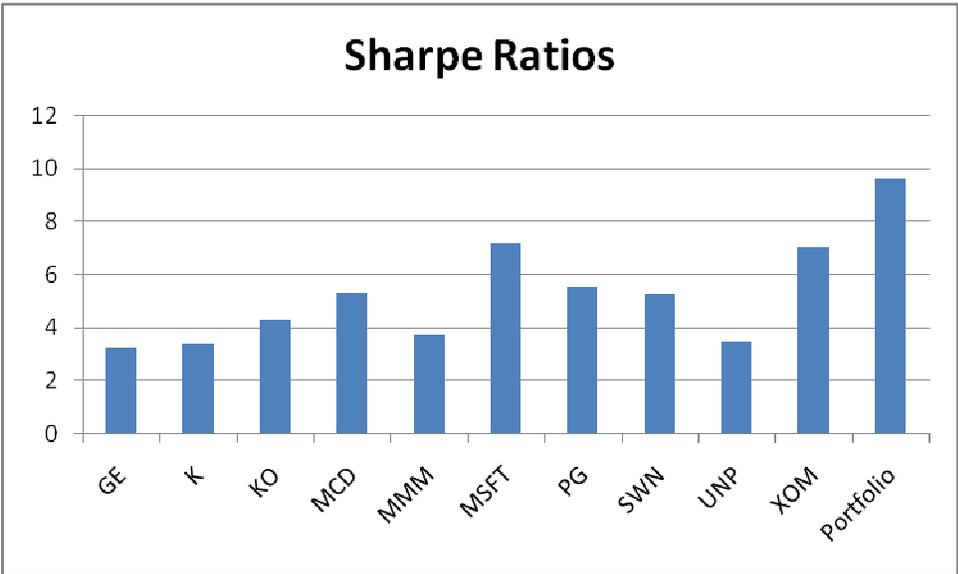
Treynor ratios were calculated for ten theoretical portfolios consisting of 100% of each individual equity, as well as the overall portfolio.



The portfolio with the highest Treynor ratio is generally considered to be the superior portfolio. From the above graph it is clear that not only is the portfolio's Treynor ratio not higher than some of the single-equity portfolios, it is only the fifth highest ratio.

**2- Sharpe Ratio**

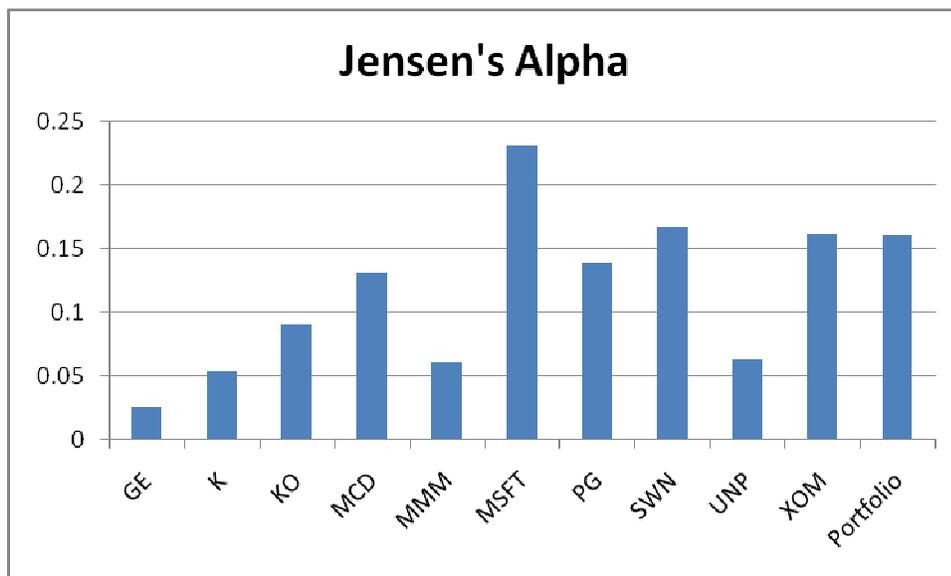
Sharpe ratios were calculated for ten theoretical portfolios consisting of 100% of each individual equity, as well as the overall portfolio.



The portfolio with the highest Sharpe ratio is generally considered to be the superior portfolio. The above graph suggests that the portfolio handily beats the all-equity portfolios.

### 3- Jensen's Alpha

Jensen's alphas were calculated for ten theoretical portfolios consisting of 100% of each individual equity, as well as the overall portfolio.



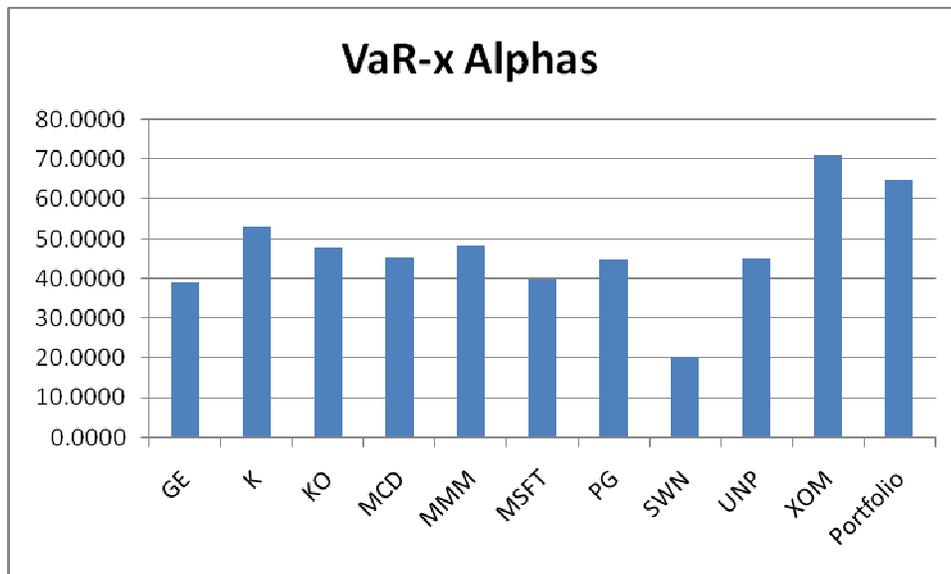
The portfolio with the highest Jensen's alpha is generally considered to be superior. As the above graph shows, the portfolio's Jensen's alpha, though above average, is not the highest.

### 4- VaR-x

The VaR-x calculation began with a series of regressions whose results can be viewed in Appendix 2. When viewing these regressions it is important to note that the coefficients of determination in these regressions are very low. This is an expected result of the regressions, as they regress values determined by stock values against the constants  $k = (1, \dots, n/2)$ , where  $n$  is the sample size. It should not be expected that a constant will do a particularly effective job at reducing the sum of squares relative to the mean model. It is more important, however, that the p-values for each individual

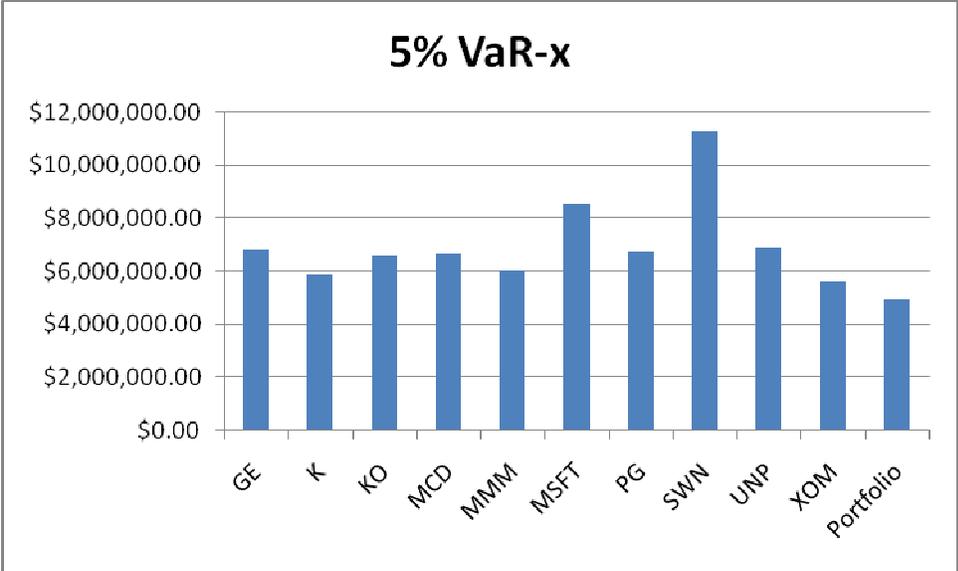
parameter estimate and the overall equations are significant. Since all of the equations and parameter estimates are statistically significant at very low significance levels, these values should be viewed as statistically significant.

The following alpha values refer to the inverse of the intercepts produced by the regressions. These values are calculated using Microsoft Excel.



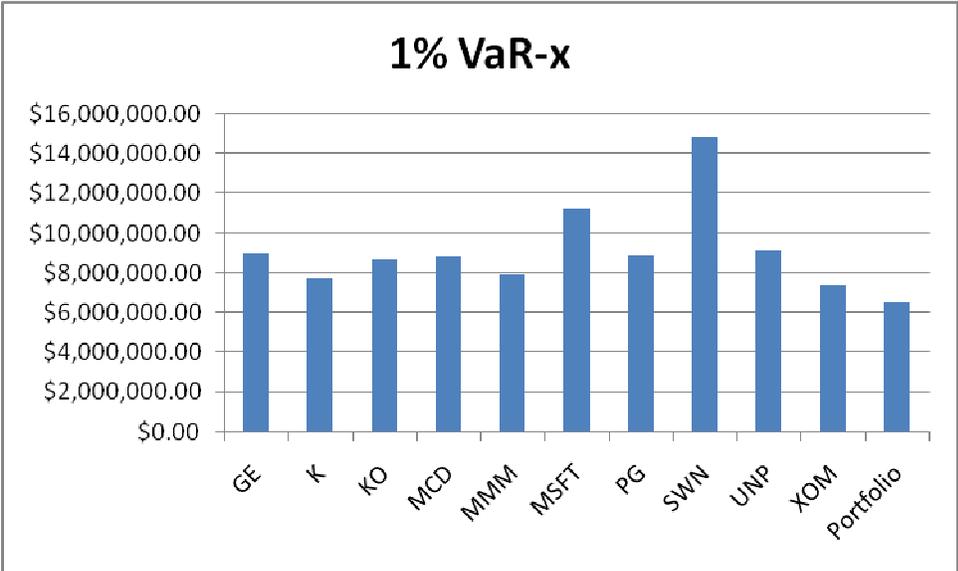
The highest alpha value occurs from Exxon-Mobil, followed by the portfolio. Nothing, however, can be inferred from this step, yet.

The VaR-x calculations for the overall portfolios at the 5% probability level appears below. The lower the VaR-x value, the less money is at risk at the 5% probability level.



The optimized portfolio has a far lower VaR-x than the other portfolios. This suggests that the portfolio has a lower tail-risk than any of the individual stocks.

Below is the VaR-x calculation for a 1% significance level.



Although all of the VaR-x values are higher, the portfolio's VaR-x is still the lowest.

## Discussion

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### Portfolio Optimization

The portfolio optimization process produced a portfolio that was heavy weighted in Microsoft, MacDonalds, Southwestern Energy and Exxon Mobil. This is a sensible result, as over the period in question, these companies experienced phenomenal growth with relatively little volatility. In fact, as is determined in the risk management section, these four stocks have the highest Jensen's alpha of the stocks being examined. Since the portfolio's goal is to maximize alpha, this should be an intuitive result.

It is questionable, however, whether the stocks picked by this portfolio will be the best stocks going forward. Although opportunities for global expansion are presenting themselves, it is not clear that Microsoft, for instance, will be able to continue to grow at the pace they have historically grown at. In fact, Microsoft has to increasingly compete not only with direct competitors like Apple and Linux, but with old editions of their old products. Although far from perfect, Microsoft's software is, in many cases, already 'good enough' for consumers. Additional features or upgrades may add features or stability, but this may not necessarily draw in new customers. The recommendations made by the Monte Carlo simulation may therefore be questionable. This is not a flaw unique to this particular model, however, as any portfolio model making forward-looking predictions based on past results will share similar deficiencies. As an aside, this directly implies that it is incumbent on any portfolio manager using an optimization program to select portfolio components to adjust this output according to real-world limits on future growth.

This portfolio's weekly yield is approximately 0.2914%, or 16.3% per year. The risk-adjusted yield is approximately 0.1607% per week, or 8.7% per year. In comparison, the Standard and Poors 500 yielded approximately 5.2% per year over this period. It should be noted that this difference in returns is based on historic data, and may change going forward.

### Risk Management

The risk management experiments sought to find a way to quantify the amount of risk the portfolio and the individual stocks entailed. Following brief discussions on the four metrics, there is a discussion on

how these ratios provide contradictory results, and what these contradictions mean in terms of portfolio risk management.

### **1- Treynor Ratio**

The Treynor ratio for the portfolio suggests that it is not the best portfolio in terms of excess return per unit of systematic risk. In fact, the portfolio's performance is about average.

### **2- Sharpe Ratio**

The Sharpe ratio of the optimal portfolio was far larger than the Sharpe ratios of the all-single equity portfolios.

### **3- Jensen's Alpha**

The Jensen's Alpha for the portfolio is not the largest. Similar to the results from the Treynor ratio, several individual equity portfolios have higher Jensen's alphas than the optimal portfolio.

### **4- VaR-x**

The VaR-x for the portfolio is far smaller than the VaR-x values for the all-equity portfolios, at both the 1% and 5% probability level. This suggests that the portfolio has less tail risk than the individual equity portfolios. This is a sensible result, given Markowitz Portfolio Theory(MPT).

A portfolio manager trying to interpret these four ratios will be faced with a dilemma: half of the ratios suggest the portfolio is inferior, half will suggest that the portfolio is superior. This problem would be easily resolved if it was clear that some of the metrics were superior measures. However, this is not the case. More generally, in fact, the difficulties associated with conflicting metrics and ratios is one typically faced by not only portfolio managers, but individual investors. Finance and financial economics are rife with ratios, and these ratios often tell different stories. As with these other cases in economics in finance, a careful examination can often help explain the contradictory risk metrics.

In the case of this portfolio, it should first be noted that none of these ratios are intended to be used for the examination of single stock portfolios. This is especially true for the Treynor Ratio and Jensen's alpha. These two metrics are similar in that they rely on a stocks CAPM  $\beta$  as a way to measure risk. To optimize this kind of portfolio in the absence of short selling, one simply has to buy a portfolio containing only the equity with the highest Treynor Ratio or Jensen's alpha. This clearly would not produce an optimal result. The Sharpe ratio and VaR-x measure of the portfolio, on the other hand, prefer portfolios that consist of a mix of different equities. This will occur because one of the key benefits of diversification is a lower portfolio variance. Since the Sharpe ratio and VaR-x depend on the standard deviation of the portfolio in question, and a portfolio's variance can be lower than the variance of its components, it is sensible that a portfolio's Sharpe ratio or VaR-x can be superior to its components.

It is therefore clear that for the sake of comparison with component equities, the Sharpe ratio and VaR-x values should be viewed as relevant measures of risk, whereas the Treynor ratios and Jensen's alpha should be largely ignored in this instance. When comparing against other mixed-equity portfolios, these two metrics will provide relevant benchmarks, so their calculation is therefore still important.

## Appendix

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**Appendix 1: portfoliomax.m**

**Appendix 2: EViews Output**

**Appendix 3: riskmeasures.m**

**Appendix 4: riskmeasures.m Output**

**Appendix 5: Weekly Stock Returns**

A copy of portfoliomax.m can be found at:  
<http://www.thomasthorn.com/portfoliomax.m>

A copy of riskmeasures.m can be found at:  
<http://www.thomasthorn.com/riskmeasures.m>

A copy of the Excel file used to tabulate stock prices and prepare the data can be found at:  
<http://www.thomasthorn.com/353final.xlsx>

A copy of the EViews file used for this project can be found at:  
<http://www.thomasthorn.com/353final.wf1>

## Appendix 1: portfoliomax.m

```
%Monte Carlo portfolio program;
%Program name: mcportfol.m
%Developed by Ruben Mercado with modifications by Scott Schwaitzberg,
%David Kendrick and Thomas Thorn

%number of runs and population size
nruns = 5000; popsize = 20;

%Stating the risk free rate, the market rate of return (S&P 500 over
%the period in question)
rf = 0.042610623;
rp = 0.098322952;

%Individual stock returns and betas
mu = [0.159 0.147 0.191 0.228 0.161 0.366 0.240 0.362 0.170
0.249]';
betas = [1.6267 0.9092 1.0310 0.9790 1.0377 1.6616 1.0456 2.7332
1.1498 0.7899]';

%declaring starting values, constants, and vectors of constants
const = 0.1;
pwm = (1/10) * ones(10,popsize);
pbr = rf * ones(1,popsize);
rfarray = rf * ones(1,10);

%Markets return in excess of the risk-free rate and the CAPM risk
%compensation for individual equities
riskprem = rp - rf;
inriskprem = riskprem * betas;

for k = 1:nruns;
    % generation of vectors of returns, variance cost and criterion function
    %setting pret to equal the alpha generated from the portfolio
    pret = pwm' * (mu - (rfarray + inriskprem'))';

    pcrit = pret';

    % selection of the best portfolio;
    [top topi] = max(pcrit);
    wnew = pwm(:,topi);
    pwm
    wnew

    % store the best portfolio and the optimal criterion value for each run
    wbest(:,k) = wnew;
    pcritvec(:,k) = top;

    % random generation of popsize minus one new porfolios;
    for i = 1:popsize-1;
        w1 = wnew(1) + rand * const;
        w2 = wnew(2) + rand * const;
```

```

w3 = wnew(3) + rand * const;
w4 = wnew(4) + rand * const;
w5 = wnew(5) + rand * const;
w6 = wnew(6) + rand * const;
w7 = wnew(7) + rand * const;
w8 = wnew(8) + rand * const;
w9 = wnew(9) + rand * const;
w10 = wnew(10) + rand * const;

temp = w1 + w2 + w3 + w4 + w5 + w6 + w7 + w8 + w9 + w10;
w1 = w1/temp;
w2 = w2/temp;
w3 = w3/temp;
w4 = w4/temp;
w5 = w5/temp;
w6 = w6/temp;
w7 = w7/temp;
w8 = w8/temp;
w9 = w9/temp;
w10 = w10/temp;

pwnew(:, i) = [w1;w2;w3;w4;w5;w6;w7;w8;w9;w10];
end

% put the best portfolio for the run in the last column of the matrix
pwnew(:, popsize) = wnew ;
pwm = pwnew;

end

wnew
top

disp(mu' * wnew);
%print and graph optimal weights and criterion value
%wbest

xaxis = [1:1:nruns]';

plot(xaxis, wbest(:, :));
%plot(xaxis, pcritvec(:, :));

```

## Appendix 2: EViews Output

### Var-X Gamma calculations (C = $\gamma$ ):

Dependent Variable: GE  
Method: Least Squares  
Date: 03/29/09 Time: 14:07  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.025657	0.000732	35.05745	0.0000
K	-1.28E-05	2.59E-06	-4.930443	0.0000
R-squared	0.047543	Mean dependent var	0.022531	
Adjusted R-squared	0.045587	S.D. dependent var	0.008270	
S.E. of regression	0.008080	Akaike info criterion	-6.794870	
Sum squared resid	0.031791	Schwarz criterion	-6.777724	
Log likelihood	1663.346	Hannan-Quinn criter.	-6.788136	
F-statistic	24.30927	Durbin-Watson stat	0.235408	
Prob(F-statistic)	0.000001			

Dependent Variable: KO  
Method: Least Squares  
Date: 03/29/09 Time: 14:09  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020813	0.000526	39.57101	0.0000
K	3.52E-06	1.86E-06	1.891882	0.0591
R-squared	0.007296	Mean dependent var	0.021676	
Adjusted R-squared	0.005257	S.D. dependent var	0.005822	
S.E. of regression	0.005807	Akaike info criterion	-7.455546	
Sum squared resid	0.016420	Schwarz criterion	-7.438399	
Log likelihood	1824.881	Hannan-Quinn criter.	-7.448811	
F-statistic	3.579219	Durbin-Watson stat	0.304054	
Prob(F-statistic)	0.059100			

Dependent Variable: MMM  
Method: Least Squares  
Date: 03/29/09 Time: 14:03  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020633	0.000478	43.16725	0.0000
K	-4.95E-06	1.69E-06	-2.929212	0.0036
R-squared	0.017314	Mean dependent var	0.019420	
Adjusted R-squared	0.015296	S.D. dependent var	0.005318	
S.E. of regression	0.005277	Akaike info criterion	-7.646897	
Sum squared resid	0.013561	Schwarz criterion	-7.629750	
Log likelihood	1871.666	Hannan-Quinn criter.	-7.640162	
F-statistic	8.580286	Durbin-Watson stat	0.317054	
Prob(F-statistic)	0.003558			

Dependent Variable: PG  
Method: Least Squares  
Date: 03/29/09 Time: 14:04  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022398	0.000464	48.28559	0.0000
K	-9.62E-06	1.64E-06	-5.864834	0.0000
R-squared	0.065970	Mean dependent var	0.020041	
Adjusted R-squared	0.064052	S.D. dependent var	0.005293	
S.E. of regression	0.005121	Akaike info criterion	-7.706867	
Sum squared resid	0.012771	Schwarz criterion	-7.689721	
Log likelihood	1886.329	Hannan-Quinn criter.	-7.700133	
F-statistic	34.39628	Durbin-Watson stat	0.303976	
Prob(F-statistic)	0.000000			

Dependent Variable: KK  
Method: Least Squares  
Date: 03/29/09 Time: 14:06  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018773	0.000439	42.80231	0.0000
K	1.75E-06	1.55E-06	1.125458	0.2609
R-squared	0.002594	Mean dependent var	0.019201	
Adjusted R-squared	0.000546	S.D. dependent var	0.004843	
S.E. of regression	0.004842	Akaike info criterion	-7.818909	
Sum squared resid	0.011418	Schwarz criterion	-7.801762	
Log likelihood	1913.723	Hannan-Quinn criter.	-7.812174	
F-statistic	1.266655	Durbin-Watson stat	0.246864	
Prob(F-statistic)	0.260949			

Dependent Variable: MCD  
Method: Least Squares  
Date: 03/29/09 Time: 14:06  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.021986	0.000462	47.56312	0.0000
K	-4.04E-06	1.63E-06	-2.471651	0.0138
R-squared	0.012389	Mean dependent var	0.020996	
Adjusted R-squared	0.010361	S.D. dependent var	0.005130	
S.E. of regression	0.005103	Akaike info criterion	-7.713874	
Sum squared resid	0.012682	Schwarz criterion	-7.696727	
Log likelihood	1888.042	Hannan-Quinn criter.	-7.707139	
F-statistic	6.109058	Durbin-Watson stat	0.311696	
Prob(F-statistic)	0.013790			

Dependent Variable: MSFT  
Method: Least Squares  
Date: 03/29/09 Time: 13:11  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.024915	0.000813	30.65567	0.0000
K	5.83E-06	2.87E-06	2.027963	0.0431
R-squared	0.008374	Mean dependent var	0.026343	
Adjusted R-squared	0.006338	S.D. dependent var	0.009001	
S.E. of regression	0.008972	Akaike info criterion	-6.585231	
Sum squared resid	0.039206	Schwarz criterion	-6.568085	
Log likelihood	1612.089	Hannan-Quinn criter.	-6.578497	
F-statistic	4.112632	Durbin-Watson stat	0.273264	
Prob(F-statistic)	0.043108			

Dependent Variable: SWN  
Method: Least Squares  
Date: 03/29/09 Time: 14:10  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.048955	0.001211	40.41474	0.0000
K	-3.11E-05	4.28E-06	-7.262614	0.0000
R-squared	0.097723	Mean dependent var	0.041332	
Adjusted R-squared	0.095870	S.D. dependent var	0.014064	
S.E. of regression	0.013372	Akaike info criterion	-5.787155	
Sum squared resid	0.087087	Schwarz criterion	-5.770008	
Log likelihood	1416.959	Hannan-Quinn criter.	-5.780420	
F-statistic	52.74556	Durbin-Watson stat	0.176699	
Prob(F-statistic)	0.000000			

Dependent Variable: UNP  
 Method: Least Squares  
 Date: 03/29/09 Time: 14:10  
 Sample: 1 489  
 Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022215	0.000541	41.06683	0.0000
K	-1.34E-06	1.91E-06	-0.700176	0.4842
R-squared	0.001006	Mean dependent var	0.021887	
Adjusted R-squared	-0.001046	S.D. dependent var	0.005969	
S.E. of regression	0.005972	Akaike info criterion	-7.399398	
Sum squared resid	0.017369	Schwarz criterion	-7.382251	
Log likelihood	1811.153	Hannan-Quinn criter.	-7.392663	
F-statistic	0.490246	Durbin-Watson stat	0.303145	
Prob(F-statistic)	0.484152			

Dependent Variable: XOM  
 Method: Least Squares  
 Date: 03/29/09 Time: 14:05  
 Sample: 1 489  
 Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.014084	0.000411	34.23713	0.0000
K	7.64E-06	1.45E-06	5.254508	0.0000
R-squared	0.053652	Mean dependent var	0.015957	
Adjusted R-squared	0.051709	S.D. dependent var	0.004663	
S.E. of regression	0.004541	Akaike info criterion	-7.947138	
Sum squared resid	0.010043	Schwarz criterion	-7.929991	
Log likelihood	1945.075	Hannan-Quinn criter.	-7.940403	
F-statistic	27.60985	Durbin-Watson stat	0.228337	
Prob(F-statistic)	0.000000			

### S&P 500 and Optimal Portfolio Gamma Values:

Dependent Variable: SP500  
 Method: Least Squares  
 Date: 04/10/09 Time: 15:44  
 Sample: 1 489  
 Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016400	0.000436	37.65314	0.0000
K	-9.13E-06	1.54E-06	-5.928808	0.0000
R-squared	0.067319	Mean dependent var	0.014162	
Adjusted R-squared	0.065404	S.D. dependent var	0.004974	
S.E. of regression	0.004808	Akaike info criterion	-7.832882	
Sum squared resid	0.011259	Schwarz criterion	-7.815735	
Log likelihood	1917.140	Hannan-Quinn criter.	-7.826147	
F-statistic	35.15077	Durbin-Watson stat	0.207406	
Prob(F-statistic)	0.000000			

Dependent Variable: PORTFOLIO  
 Method: Least Squares  
 Date: 04/11/09 Time: 16:08  
 Sample: 1 489  
 Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.015417	0.000396	38.93319	0.0000
K	-4.82E-06	1.40E-06	-3.438872	0.0006
R-squared	0.023707	Mean dependent var	0.014237	
Adjusted R-squared	0.021703	S.D. dependent var	0.004420	
S.E. of regression	0.004372	Akaike info criterion	-8.023289	
Sum squared resid	0.009307	Schwarz criterion	-8.006143	
Log likelihood	1963.694	Hannan-Quinn criter.	-8.016555	
F-statistic	11.82584	Durbin-Watson stat	0.214975	
Prob(F-statistic)	0.000634			

### CAPM $\beta$ -values:

Dependent Variable: GE  
 Method: Least Squares  
 Date: 04/10/09 Time: 17:08  
 Sample: 1 489  
 Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000507	0.000234	-2.164074	0.0309
SP500	1.626728	0.015614	104.1861	0.0000
R-squared	0.957061	Mean dependent var	0.022531	
Adjusted R-squared	0.956973	S.D. dependent var	0.008270	
S.E. of regression	0.001716	Akaike info criterion	-9.894141	
Sum squared resid	0.001433	Schwarz criterion	-9.876994	
Log likelihood	2421.117	Hannan-Quinn criter.	-9.887406	
F-statistic	10854.74	Durbin-Watson stat	0.436966	
Prob(F-statistic)	0.000000			

Dependent Variable: KK  
 Method: Least Squares  
 Date: 04/10/09 Time: 17:08  
 Sample: 1 489  
 Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006325	0.000237	26.65876	0.0000
SP500	0.909152	0.015809	57.50978	0.0000
R-squared	0.871652	Mean dependent var	0.019201	
Adjusted R-squared	0.871389	S.D. dependent var	0.004843	
S.E. of regression	0.001737	Akaike info criterion	-9.869322	
Sum squared resid	0.001469	Schwarz criterion	-9.852176	
Log likelihood	2415.049	Hannan-Quinn criter.	-9.862588	
F-statistic	3307.375	Durbin-Watson stat	0.098094	
Prob(F-statistic)	0.000000			

Dependent Variable: KO  
Method: Least Squares  
Date: 04/10/09 Time: 17:25  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007074	0.000377	18.76687	0.0000
SP500	1.031015	0.025117	41.04912	0.0000
R-squared	0.775786	Mean dependent var	0.021676	
Adjusted R-squared	0.775325	S.D. dependent var	0.005822	
S.E. of regression	0.002760	Akaike info criterion	-8.943376	
Sum squared resid	0.003709	Schwarz criterion	-8.926230	
Log likelihood	2188.656	Hannan-Quinn criter.	-8.936642	
F-statistic	1685.030	Durbin-Watson stat	0.144257	
Prob(F-statistic)	0.000000			

Dependent Variable: MCD  
Method: Least Squares  
Date: 04/10/09 Time: 17:26  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007132	0.000221	32.30433	0.0000
SP500	0.978956	0.014710	66.55163	0.0000
R-squared	0.900938	Mean dependent var	0.020996	
Adjusted R-squared	0.900735	S.D. dependent var	0.005130	
S.E. of regression	0.001616	Akaike info criterion	-10.01342	
Sum squared resid	0.001272	Schwarz criterion	-9.996271	
Log likelihood	2450.281	Hannan-Quinn criter.	-10.00668	
F-statistic	4429.119	Durbin-Watson stat	0.258443	
Prob(F-statistic)	0.000000			

Dependent Variable: MMM  
Method: Least Squares  
Date: 04/10/09 Time: 17:26  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004724	0.000175	26.98780	0.0000
SP500	1.037727	0.011663	88.97930	0.0000
R-squared	0.942054	Mean dependent var	0.019420	
Adjusted R-squared	0.941935	S.D. dependent var	0.005318	
S.E. of regression	0.001281	Akaike info criterion	-10.47767	
Sum squared resid	0.000800	Schwarz criterion	-10.46052	
Log likelihood	2563.790	Hannan-Quinn criter.	-10.47093	
F-statistic	7917.316	Durbin-Watson stat	0.437814	
Prob(F-statistic)	0.000000			

Dependent Variable: MSFT  
Method: Least Squares  
Date: 04/10/09 Time: 17:26  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002812	0.000488	5.765050	0.0000
SP500	1.661594	0.032496	51.13228	0.0000
R-squared	0.842980	Mean dependent var	0.026343	
Adjusted R-squared	0.842657	S.D. dependent var	0.009001	
S.E. of regression	0.003570	Akaike info criterion	-8.428202	
Sum squared resid	0.006208	Schwarz criterion	-8.411056	
Log likelihood	2062.695	Hannan-Quinn criter.	-8.421468	
F-statistic	2614.510	Durbin-Watson stat	0.118507	
Prob(F-statistic)	0.000000			

Dependent Variable: PG  
Method: Least Squares  
Date: 04/10/09 Time: 17:26  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005232	0.000135	38.80711	0.0000
SP500	1.045636	0.008984	116.3905	0.0000
R-squared	0.965298	Mean dependent var	0.020041	
Adjusted R-squared	0.965227	S.D. dependent var	0.005293	
S.E. of regression	0.000987	Akaike info criterion	-10.99958	
Sum squared resid	0.000474	Schwarz criterion	-10.98243	
Log likelihood	2691.397	Hannan-Quinn criter.	-10.99284	
F-statistic	13546.75	Durbin-Watson stat	0.573215	
Prob(F-statistic)	0.000000			

Dependent Variable: SWN  
Method: Least Squares  
Date: 04/10/09 Time: 17:27  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002624	0.000493	5.325258	0.0000
SP500	2.733242	0.032827	83.26164	0.0000
R-squared	0.934362	Mean dependent var	0.041332	
Adjusted R-squared	0.934227	S.D. dependent var	0.014064	
S.E. of regression	0.003607	Akaike info criterion	-8.407924	
Sum squared resid	0.006335	Schwarz criterion	-8.390777	
Log likelihood	2057.737	Hannan-Quinn criter.	-8.401189	
F-statistic	6932.500	Durbin-Watson stat	0.142631	
Prob(F-statistic)	0.000000			

Dependent Variable: UNP  
Method: Least Squares  
Date: 04/10/09 Time: 17:27  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005603	0.000234	23.96745	0.0000
SP500	1.149803	0.015578	73.81164	0.0000
R-squared	0.917947	Mean dependent var	0.021887	
Adjusted R-squared	0.917778	S.D. dependent var	0.005969	
S.E. of regression	0.001712	Akaike info criterion	-9.898777	
Sum squared resid	0.001427	Schwarz criterion	-9.881630	
Log likelihood	2422.251	Hannan-Quinn criter.	-9.892042	
F-statistic	5448.159	Durbin-Watson stat	0.284767	
Prob(F-statistic)	0.000000			

Dependent Variable: XOM  
Method: Least Squares  
Date: 04/10/09 Time: 17:28  
Sample: 1 489  
Included observations: 489

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004770	0.000344	13.88341	0.0000
SP500	0.789874	0.022894	34.50192	0.0000
R-squared	0.709667	Mean dependent var	0.015957	
Adjusted R-squared	0.709071	S.D. dependent var	0.004663	
S.E. of regression	0.002515	Akaike info criterion	-9.128719	
Sum squared resid	0.003081	Schwarz criterion	-9.111572	
Log likelihood	2233.972	Hannan-Quinn criter.	-9.121984	
F-statistic	1190.382	Durbin-Watson stat	0.043335	
Prob(F-statistic)	0.000000			

### Appendix 3: riskmeasures.m

```
%Risk Measurement Program
%Program name: riskmeasures.m
%Developed by Thomas Thorn

%individual stock returns and their portfolio weights
mu = [0.159 0.147 0.191 0.228 0.161 0.366 0.240 0.362 0.170
0.249]';
pweights = [0.0328 0.0423 0.0262 0.1585 0.0316 0.3016 0.0485 0.22
0.0305 0.1079];

%individual stock betas and portfolio beta
betas = [1.6267 0.9092 1.0310 0.9790 1.0377 1.6616 1.0456 2.7332
1.1498 0.7899]';
pbeta = pweights * betas;

%dollar value of portfolio and the t-value to be used for VaR-x calculation
dollarval = 100000000.00;
tval = 1.96;

%alpha values calculated as input to VaR-x calculation
alphas = [38.97571813 53.26799126 48.04689377 45.48348949 48.46604953
40.13646398 44.64684347 20.4269 45.01462975 71.00255609];
palpha = 64.86346241;

%Variance-covariance matrix
sigma = [0.00128 0.00026 0.00041 0.00043 0.00050 0.00055 0.00040 0.00023
0.00046 0.00034;
0.00026 0.00094 0.00038 0.00022 0.00029 0.00020 0.00037 0.00026 0.00028
0.00024;
0.00041 0.00038 0.00119 0.00040 0.00040 0.00031 0.00057 0.00036 0.00029
0.00035;
0.00043 0.00022 0.00040 0.00122 0.00029 0.00038 0.00039 0.00018 0.00030
0.00025;
0.00050 0.00029 0.00040 0.00029 0.00099 0.00028 0.00038 0.00048 0.00044
0.00036;
0.00055 0.00020 0.00031 0.00038 0.00028 0.00201 0.00023 0.00024 0.00032
0.00027;
0.00040 0.00037 0.00057 0.00039 0.00038 0.00023 0.00125 0.00023 0.00029
0.00026;
0.00023 0.00026 0.00036 0.00018 0.00048 0.00024 0.00023 0.00366 0.00048
0.00056;
0.00046 0.00028 0.00029 0.00030 0.00044 0.00032 0.00029 0.00048 0.00131
0.00032;
0.00034 0.00024 0.00035 0.00025 0.00036 0.00027 0.00026 0.00056 0.00032
0.00085];

%calculating portfolio standard deviation
tempvar = zeros(1,10);
for i = 1:10;
    for j = 1:10;
        tempvar(i) = tempvar(i) + pweights(i)*pweights(j)*sigma(i,j);
    end
end
pvar = tempvar * ones(10,1);
pstdev = sqrt(pvar);
```

```

%Creating a vector containing the standard deviations of individual stocks
stdevarray = ones(1,10);
    for i = 1:10;
        stdevarray(i) = sqrt(sigma(i,i));
    end

%Stating the risk free rate, the market rate of return (S&P 500 over
%the period in question) and calculating the portfolio return
rf = 0.042610623;
rp = 0.098322952;
pret = pweights * mu;

%Individual stock returns in excess of the risk-free rate
excessret = zeros(1,10);
    for i = 1:10;
        excessret(i) = mu(i) - rf;
    end

rfarray = rf * ones(1,10);

%Calculating the Treynor ratios for individual stocks, then the overall
%portfolio
itreynor = zeros(1,10);
    for i = 1:10;
        itreynor(i) = excessret(i) / betas(i);
    end

ptreynor = (pret - rf) / pbeta;

%Calculating the Sharpe ratios for individual stocks, then the overall
%portfolio
isharpe = zeros(1,10);
    for i = 1:10;
        isharpe(i) = excessret(i) / stdevarray(i);
    end

psharpe = (pret - rf) / pstdev;

%Calculating Jensen's alpha for individual stocks, then the overall
%portfolio
ijensens = zeros(1,10);
    for i = 1:10;
        ijensens(i) = mu(i) - (rf + (betas(i) * (rp - rf)));
    end
pjensens = pret - (rf + (pbeta * (rp - rf)));

%Calculating VaR-x for individual stocks and overall portfolio
thetaport = pstdev / sqrt(palpha / (palpha - 2));
thetastocks = zeros(1,10);
    for i = 1:10;
        thetastocks(i) = sqrt(sigma(i,i)) / sqrt(alphas(i) / (alphas(i) - 2));
    end

varxstocks = zeros(1,10);
    for i = 1:10;

```

```

        varxstocks(i) = dollarval * tval * thetastocks(i);
    end

varxport = dollarval * tval * thetaport;

```

```

%Output
disp('XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX');
disp('Statistics: ');
disp('XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX');
disp('Stock standard deviations: ');
disp(stdevarray');
disp('Portfolio standard deviation: ');
disp(pstdev);
disp('Individual stock betas: ');
disp(betas);
disp('Portfolio beta: ');
disp(pbeta);
disp('Individual stock returns: ');
disp(mu);
disp('Portfolio return: ');
disp(pret);
disp('XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX');
disp(' ');
disp('Risk/Return measures: ');
disp('Individual stock Treynor ratios: ');
disp(itreynor');
disp('Portfolio Treynor Ratio: ');
disp(ptreynor);
disp('Individual stock Sharpe Ratio: ');
disp(isharpe');
disp('Portfolio Sharpe ratio: ');
disp(psharpe);
disp('Jensens Alpha for individual stocks: ');
disp(ijensens');
disp('Jensens Alpha for overall portfolio : ');
disp(pjensens);
disp('XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX');
disp(' ');
disp('Risk quantification:')
disp('Individual stock betas:');
disp(betas);
disp('Portfolio beta:');
disp(pbeta);
disp('Individual stock VaR-x: ');
disp(varxstocks');
disp('Portfolio Var-X: ');
disp(varxport);

```

#### Appendix 4: riskmeasures.m Output

XX

Statistics:

XX

Stock standard deviations:

0.0358  
0.0307  
0.0345  
0.0349  
0.0315  
0.0448  
0.0354  
0.0605  
0.0362  
0.0292

Portfolio standard deviation:

0.0257

Individual stock betas:

1.6267  
0.9092  
1.0310  
0.9790  
1.0377  
1.6616  
1.0456  
2.7332  
1.1498  
0.7899

Portfolio beta:

1.5802

Individual stock returns:

0.1590  
0.1470  
0.1910  
0.2280  
0.1610  
0.3660  
0.2400  
0.3620  
0.1700  
0.2490

Portfolio return:

0.2914

XX

Risk/Return measures:

Individual stock Treynor ratios:

- 0.0715
- 0.1148
- 0.1439
- 0.1894
- 0.1141
- 0.1946
- 0.1888
- 0.1169
- 0.1108
- 0.2613

Portfolio Treynor Ratio:

0.1574

Individual stock Sharpe Ratio:

- 3.2532
- 3.4048
- 4.3016
- 5.3077
- 3.7627
- 7.2132
- 5.5830
- 5.2793
- 3.5196
- 7.0791

Portfolio Sharpe ratio:

9.6649

Jensens Alpha for individual stocks:

- 0.0258
- 0.0537
- 0.0909
- 0.1308
- 0.0606
- 0.2308
- 0.1391
- 0.1671
- 0.0633
- 0.1624

Jensens Alpha for overall portfolio :

0.1607

XX

Risk quantification:

Individual stock betas:

1.6267

0.9092

1.0310

0.9790

1.0377

1.6616

1.0456

2.7332

1.1498

0.7899

Portfolio beta:

1.5802

Individual stock VaR-x:

1.0e+007 \*

0.6830

0.5895

0.6619

0.6694

0.6038

0.8566

0.6773

1.1262

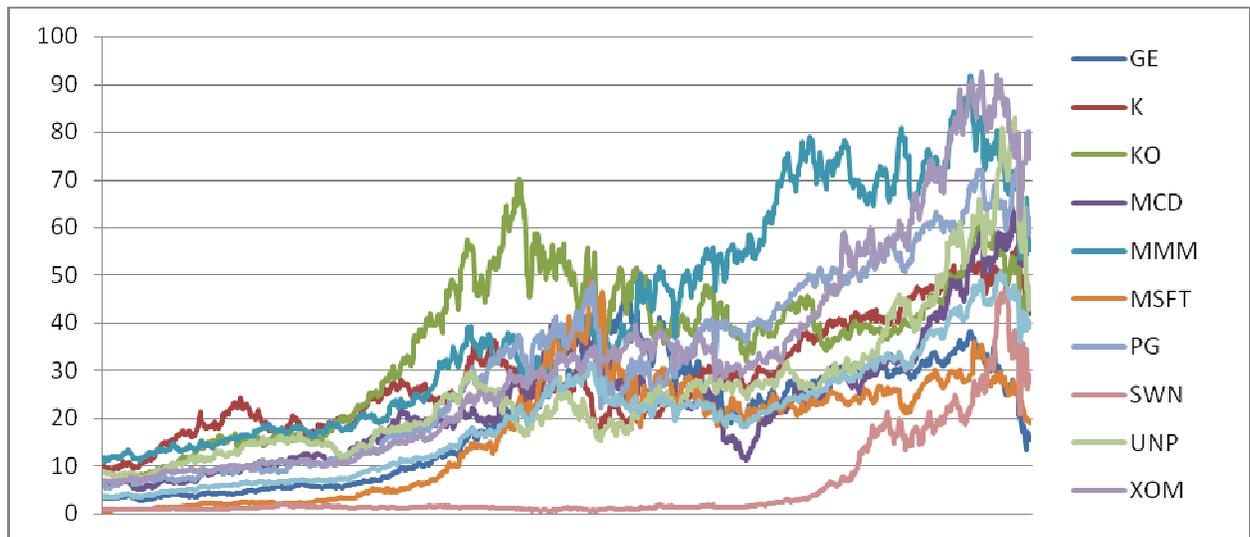
0.6935

0.5633

Portfolio Var-X:

4.9666e+006

## Appendix 5: Weekly Stock Returns



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