Mutual Funds and Segregated Funds: A Comparison

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<u>Mutual Funds and Segregated Funds: A Comparison</u>

<u>Comparing Risks and Returns of Mutual Funds and Segregated Funds</u>

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I. Introduction

To play any game of chance in exchange for money or other stakes; to take a risk in the hope of gaining some advantage; these define the word gamble. The idea of gambling is visible in many aspects of our everyday world, in particular, its financial aspect. The financial world has always been rather risky, and recently the risks have increased in number and size.

There is much more going on in our world today which causes risk to be categorized into many specific types, such as market risk, credit risk, liquidity risk and so on. Due to the numerous risks that surround the financial world, risk measurement has especially become a concept of great importance.

Many early attempts to measure risk were very limited to only certain types. More recently, a risk measure known as value-at-risk (VaR) emerged that has proven successful in its flexibility and ease with regards to how and when it can be applied. Also, numerous other measures, based on the VaR concept, such as cVaR (Conditional Value-at-Risk) and ES (Expected Shortfall) have emerged. Overall, these risk measures have allowed us to better deal with the important issue of risk.

The most common type of risk is Market Risk, which occurs mainly due to changes in the price of a financial asset. All one must do is observe any financial source and realize that prices of financial assets are ever changing, leading to the presence of market risk.

A. Mutual Funds and Segregated Funds

Many types of financial assets exist, and now with the boom in the derivatives market, investment possibilities are endless. The most commonly purchased financial assets by households are Mutual Funds. They are pooled investments from individuals (or organizations) used to purchase, stocks, bonds and other securities. Therefore, investors are part owners of the overall portfolio. An eventual spin-off to the common mutual fund was the segregated fund.

Segregated funds combine the investment advantages of mutual funds – potential for growth, outstanding money management, diversification, choice and flexibility – and the security of insurance (CI). Essentially, they are mutual funds that include some aspects of an insurance policy. The main additional aspect is a guarantee on the initial principal invested, usually anywhere from 75% up to 100% of the initial investment. So, should the markets take a turn for the worse, your initial investment, or most of it, will be guaranteed.

Another feature of a segregated fund is a reset option, which gives one the option to reset their initial investment amount to the current value of their investment. For example, if the investor starts with an initial investment of $10,000 and the market value of his mutual fund portfolio increases to $16,000, then the guarantee of recovering his initial principal is unlikely to seem very valuable because the investment is currently worth much more than the guarantee level. If a reset provision is offered, the investor can lock in a new guarantee set at the current market value [1].

B. Key Questions and Goals of this paper

This paper intends to bring up two topics of interest, one more important than the other. Firstly, a simple empirical analysis and comparison of mutual funds returns to segregated funds returns, in terms of risk and return, as well as some other useful descriptive statistics. Secondly, an analysis of the VaR of the segregated fund returns and the mutual fund returns, which is of great interest. There are two main methodologies behind estimating the VaR; the historical approach and parametric estimation. Once the results of both the descriptive statistics and the VaR analysis are obtained and observed, one can begin to think about how best to model the segregated funds data and the mutual funds data to obtain an optimal estimate for the VaR, given the probability distribution results.

The reason that the VaR analysis and comparison between the mutual funds and the segregated funds would be of interest is the simple fact of how they are different. They are essentially the same but for two major differences; as previously mentioned, segregated funds offer a guarantee of anywhere from 75% to 100% of the initial investment and they offer a reset feature. These two features of a segregated fund might make it less risky and should result in lower returns, theoretically.

In the first section of the paper, we have given an important introduction about the focal points of this paper. In section II, we focus on the actual calculations and analysis, with subsection A showing the descriptive statistics and subsections B and C going over the historical and parametric VaR estimations, respectively. Section III of the paper offers the results of our investigations from section II, while section IV gives some additional comments and insights we can get from these results. Section V of the paper concludes with all results and comments.

II. Statistical and VaR Analyses

VaR calculations are an important part of any risk management course, job and relevant risk-based literature and/or analysis. They play a key role in any of those areas because VaR is a benchmark for assessing one's risk, for individual or corporate investments. In general, VaR measures are very important because they allow one to prepare for potential losses that may occur when investing by using a common statistical distribution to model the data. Despite the fact that a Normal distribution is the standard used in estimating these losses, it still isn't the optimal one for all scenarios that can occur, thus it is important to understand certain scenarios and which distributions give optimal VaR estimates. For this paper, the situation of interest is the VaR calculation for investments in mutual funds and segregated funds and how they compare.

A. Descriptive Statistics

A simple empirical analysis can allow one to better understand how the returns of each of these types of assets differ and what similarities they share, as well as giving us an idea of what distribution they follow for modeling, and eventual forecasting purposes. The information on the distributions will be of great use when trying to calculate the VaR.

The datasets used in these analyses consist of 5 mutual funds and 5 segregated funds. Mostly funds of the equity type were chosen for both mutual and segregated funds because equity funds are the most commonly purchased funds in the financial markets. The data consists of the monthly prices, starting January 31st 2000 and continuing up until February 28th, 2007. The five mutual funds each come from one of the 5 major Canadian banks (CIBC, Scotia Bank, TD, BMO and RBC), and to stay consistent with the selecting of different institutions, each of the five segregated funds come from 5 different institutions (CI, Clarica, Maritime/Manulife, Mackenzie, and AIC).

The 5 mutual funds selected are CIBC Canadian Equity Fund, Scotia Bank Canadian Stock Index Fund, BMO Equity Fund, TD Canadian Equity Index Fund and RBC Canadian Equity Fund. As mentioned, all data sets for these funds are monthly prices ranging from January 31st, 2000, to February 28th, 2007. The returns are thus calculated from the prices using the basic returns formula, (A1) in Appendix A.

Another option is to use the log returns. This, however, will yield similar results as the basic returns, so one opts for the basic returns. From these returns, one can calculate some basic descriptive statistics and plot histograms to get a better idea of the behaviour of these returns and the distribution they tend to follow. Table B1 in Appendix B shows the descriptive statistics and additional values for the Mutual Funds.

The best performing mutual fund based solely on expected returns is the RBC Equity Fund at 0.7%, which is rather impressive considering it also has the lowest standard deviation at 3%, implying the lowest risk involved.

The 5 segregated funds selected are CI Global Equity Seg Fund, Clarica MVP Equity Fund, Maritime Life Canadian Equity-B Fund, Mackenzie Ivy Canadian Equity Seg Fund and AIC Canadian Balanced Seg Fund. Again, all data sets for these funds are monthly prices ranging from January 31st, 2000 to February 28th, 2007 and the returns are, again, calculated from the prices. The descriptive statistics for the segregated funds, found in Table B2 in Appendix B, show that the best performing segregated fund, based solely on expected returns, is the Clarica fund, which is odd because it does not follow the idea of highest returns implying highest risk, Perhaps it has to do with lower management fees, better guarantee and reset features, or better investment distribution, all factors that come up on a normal basis. The main oddity of this data is the CI fund, which has the second highest risk (standard deviation) of the lot, yet offers a negative return.

B. VaR Analysis: Historical Approach

The historical approach of VaR deals with collecting historical data based on previously determined time intervals. For the purposes of this analysis, the monthly returns are used and estimating is done using sample quantiles. Use of sample quantiles is only feasible if the sample size is large. For example, if we based the analysis on quarterly data as opposed to daily or monthly data, we would have far less observations and would require more years to be included in our data which could bias our estimates.

The data in this analysis gives a rough idea of how to tackle the historical approach, however, the sample may still not be large enough to be as effective as one would desire. For example, testing with 99% confidence, there is only one value.

From the results in Table B3 in Appendix B, we can say that perhaps the VaR values with 99% confidence can be discarded, and more focus can be given to those of 95% confidence and, in particular, those of 90% confidence. As can be observed, for the most part, the idea that with segregated funds you incur less risk is evident. This observation may be attributed to the extra features of a segregated fund that were discussed in section I, or perhaps it could be that segregated funds have better fund managers.

Despite these findings, one should always note the sample size issue that comes with a historical approach to VaR, and should then consider other approaches, such as the various ways to calculate VaR under the parametric estimation method.

C. VaR Analysis: Parametric Estimation Approach

The parametric estimation approach involves assuming that the data takes on a certain probability distribution; most commonly Normal distribution is used. What distribution the data takes on can be observed graphically through histograms, QQ-Plots and so on, but also through observing particular descriptive statistics obtained in the initial part of the analysis as well as other key statistical tests such as those testing for normality of the data set. The main tests for normality used in this paper will be the Kolmogorov-Smirnov test, which will be supplemented by the Anderson-Darling test and some basic observations of QQ-Plots.

The usual parametric estimation of the VaR assumes a normally distributed set of data, whether the data are the returns or log returns. The VaR formula (A3) is based on, the α–quantile of a Normal distribution with mean, μ, and variance, σ^2; the S in the formula represents an initial investment amount. The α–quantile in the formula is representative of the percentage of the initial investment that risks being lost. The results for the VaR under the parametric estimation method using a Normal distribution found in Table B4 in Appendix B give a significant amount of insight.

Once again, it is important to note that in general, the segregated funds tend to have lower VaR values than the Mutual Funds, with a few exceptions. Also, it is important to see how these results are more accurate than those of the historical because the values for 95% confidence and especially 99% confidence seem more realistic and representative of the data. This is mainly due to the fact that sample size is not an issue with this type of estimation.

One can also observe the Histograms of the data, shown in Figure B5 for the Mutual Funds and B6 for the Segregated Funds within Appendix B, to get an idea of how the data behaves. The histograms include a fitted Normal Distribution curve to easily compare the normal distribution with the real data distribution.

From the Histograms, the information obtained from the summary statistics pertaining to skewness and kurtosis is confirmed. One can see the clear negative skewness, which implies longer left tails. Also, most of the histograms confirm the presence of higher kurtosis levels than the Normal distribution, which was also a fact derived from the descriptive statistics. The RBC data stands out as having a somewhat significant measure of negative kurtosis, or a flatter mound than the normal distribution, while the CI data is the only one to have a very slight positive skewness (or slightly longer right tail). Despite these small anomalies on the overall trends, from observing the histograms alone, the fact that heavy tails are present, for some more than others, becomes very important and becomes clearer.

Finally, to conclude the normality analyses, it is important to observe the Normal Probability plots as well as perform normality tests. As mentioned before, this paper uses the Kolmogorov-Smirnov (KS) test and also will include the Anderson-Darling (AD) test of normality for completeness. Within Appendix B, we find Figures B6 and B7 which contain these plots for Mutual Funds and Segregated Funds, respectively. They are plotted with a normality line and confidence bounds of 95% ($\alpha = 0.05$). This level of a holds for the normality tests (both KS and AD).

From the Normal Probability Plots, it can be seen how the majority of the plotted data lie within the bound for both mutual and segregated fund returns data. However, some of the funds show signs of being heavy tailed data by the way the ends of the plotted line of data gradually curve outward falling outside the confidence bounds. This matches the idea that higher kurtosis implies heavier tails, as the funds that exhibit heavier tails through the Normal Probability plots. Maritime, TD, AIC, Scotia and RBC, also happen to be those funds which have the highest kurtosis values.

Also, one can see from these plots evidence of negative skewness because the ends of the plotted data lines that curve outside the confidence bounds, the bottom end tends to curve out the most, and one can also observe that for all the funds there is slight curvature signaling some sort of skewness. Another thing to take note of is the funds that exhibit skewness and excess kurtosis values closest to 0 (that of a Normal distribution) are also those which have the Normal Probability plots most normally distributed; AIC and especially, Mac Ivy Segregated funds.

All of the observations that came from these basic plots can be derived from and confirmed by certain statistical tests of normality. The two of interest here are the Kolmogorov-Smirov test and the Anderson-Darling test. Clearly from Table B9 in Appendix B, one can observe that, with α = 0.1 (or 90% confidence), there are discrepancies between the two tests when it comes to normality of most of the mutual funds. The exceptions are CIBC, where the results state an obvious non-normality for both tests and BMO, where the results state clear normality on both tests as well. The results seem more straightforward for the segregated funds because for all the funds both tests agree on normality. The only exception here is the result for both tests on the Maritime fund, which show strong signs of non-normality.

III. Results

It seems that the normality assumption does not always hold true. It also seems the true issue here is not if the differences in what defines mutual and segregated funds translate over to differences in modeling and estimating the VaR of each. The true issue has now become whether or not the Normal distribution is necessarily the optimal distribution for estimating the VaR through the parametric approach.

Through the many tests and analyses, it was found that there were slight differences in the way the mutual fund and segregated fund data were distributed but these differences were not significant enough to allow one to categorize them into two different distribution groups. The returns, for both mutual funds and segregated funds, have varying characteristics which makes it difficult to pinpoint a direct difference. That does not allow for one to be able to classify all, or most, of the segregated funds under one particular distribution and all, or most, of the mutual funds under another. Despite this, it does not stop one from trying to find which distribution may be optimal in each case brought up in this paper. Especially since it was found that clearly there were some slight and some more major deviations from normality for each of the individual data sets, which brings up the next logical question; is there another distribution? Is there a better way to model VaR?

IV. Additional Insight

Section III, despite having offered a sufficient solution to our initial issue, left some questions for one to think about. This section will attempt to give some additional insight into answering these remaining problems as well as taking the initial goals of our analysis a step further.

As mentioned in the previous sections, some deviations from the Normality assumption were found through the summary statistics data for each and supplemented by similar results given in the respective plots. The main deviations from Normality shown by the data can be clearly seen from the Normal Probability Plots for each of the funds, and also the slight deviations in skewness and excess kurtosis from the normal skewness and excess kurtosis measures suggests, for the most part, slight negative skewness (longer left tails) and a somewhat higher kurtosis which implies heavier tails. Therefore, a distribution must be found that can accurately model the heavier tails. Figure B10 of Appendix B gives an illustration, from *[2]*, which depicts the differences between a Normal distribution and a Heavy-tailed distribution. As we can see, some of the deviations from Normality follow closely to those seen in the illustration. The next logical step would be to examine and test with different distributions, which tend to be classified as a heavier tailed distribution.

One interesting option would the t-student distribution, which although similar to the Normal, has a slightly higher kurtosis and thus exhibits heavier tails. The one issue with t-student lies in that it is a symmetric distribution, which goes against our finding of slight negative skewness of data.

By use of a modified version of the parametric estimation of VaR under Normality formula, a similar formula for the t-distribution can be applied and the results it yields for the VaR can be found in Table B11 within Appendix B. The t-distribution offers a good alternative to the Normal distribution when calculating VaR because it has the slightly heavier tails and as can be seen from the findings, the calculations for VaR under the t-distribution do offer bigger estimates, eliminating the risk of under-estimating the VaR, should the Normal distribution method be employed. The findings state that the deviations from normality for those funds that differ are not drastic. Therefore, it would be safe to assume that the t-distribution measures could be more accurate then those for the Normal distribution.

Another option, which is a common alternative to the Normal distribution, is the idea of distributions with Pareto tails. Pareto tails tend be quite heavy so they are often preferred when dealing with most types of financial data. This fact about Pareto tailed distributions can be seen in the illustration from *[2]* found in Appendix B, Figure B12.

The estimation of VaR using Pareto tails requires the calculation of the tail index, in which first you find an estimator known as the Hill Estimator (formula given in (A6)) and then everything is applied to a formula for finding the Pareto VaR estimate (A5). From the data and applying (A6), we obtain a Hill Estimator for each fund as seen in Table B13 in Appendix B. These Hill Estimators allow for the estimation of the tail index so that (A5) can be put in use to obtain the respective VaR results under the Pareto distribution for both the Mutual and Segregated Funds. The final results, as found in (B14) of Appendix B, of assuming that the funds data follows a Pareto tailed distribution seems to lead to some results that could be clearly identified as overestimating the VaR, especially when one recalls the historical data and the summary statistics.

The kurtosis, QQ-Plots and histograms do suggest heavy tails, but not to the extent of these particular VaR estimations. The overestimations are present for values of $\alpha = 0.01$ and $\alpha = 0.025$ because the estimates, when assuming a Pareto tail, become much larger than the parametric estimates (under both Normal and t) as the a value gets small due to the fact that the Pareto tail is heavier than that of Normal or t-distributions.

Based on this concept, one could simply discard the estimations for $\alpha = 0.01$ and $\alpha = 0.025$ and focus solely on the estimates for $\alpha = 0.05$ as they seem the most realistic and the most consistent with the previous results and data. However, one cannot help but feel that these VaR estimates are still high when compared with the rest of the results. One could also say that the use of Pareto tails in this particular analysis would not be advisable.

There remain countless other possible ways to model financial data, estimate VaR and estimate risk in general, for example, use of the stable distributions. However, they can be rather complicated to work with and this makes them unpopular. The parametric estimation under the Normal distribution seems to still remain as the most commonly used method, but using the t-distribution and Pareto tails are excellent alternatives that usually can give more accurate results.

V. Conclusions

This paper began discussing the differences between mutual and segregated funds, the idea behind VaR and how it applies to investing and, in particular, how it applies to investing in mutual and segregated funds. The question was whether the differences between these two investment types carry over to the returns distributions and successively to the estimation of VaR.

From the results of the various analyses, it can be concluded that, although the differences exist and they do result in similar differences with regards to mean and risk values, the distribution results for each individual fund vary and there is no particular pattern that allow one to conclude that segregated funds belong to one distribution and mutual funds to another.

It was more a case of each individual fund having an optimal distribution and knowing why this was the case. This involves further study in regards to what investment types the funds focus on and how they are distributed. For example, within the mutual funds, the Scotia and TD funds were primarily index funds and had the strongest signs of heavy tails while CIBC was an equity fund and had near normal tails. Also, within the segregated funds, the CI fund is a Global equity fund and had the second heaviest tails, while the Mac Ivy fund is a Canadian equity fund and was essentially normally distributed. Table B15 of Appendix B contains some valuable information which gives us some insight as to which would be the optimal distribution to model each individual fund -mutual or segregated. Although this paper concludes that the additional features of a segregated fund does not do much in terms of affecting how the returns data is modeled, it does tell us that we need to look deeper and think in smaller terms to get down to what exactly affects the differing modeling choices.

From these results it would be easy to say that Canadian equity funds, whether mutual or segregated, are best modeled by a Normal distribution and, thus, VaR should be estimated using the parametric Normal method (or historical depending on sample sizes), while Index funds and Global equity funds will tend to have heavier tails and, obviously one could implement a heavier tailed distribution such as t-student or Pareto tailed to model the data. To know which exact distribution would be optimal for each individual fund would require further study.

There are some things to consider about these analyses that could have led to somewhat different or even better results. Firstly, the sample size issue; this would have given the historical method more validity and could have increased the accuracy of some other results. Secondly, the type of investments selected and the number of different investment types used. Thirdly, other variables that were not taken into consideration such as taxation, management and other fees would be important to reflect on.

Investing has always been risky and these risks have only increased in recent years. It is important to give risk measurement and management techniques sufficient priority, especially when investing great sums of money. Tail loss estimation is an issue which has not received the sufficient amount of attention it deserves since they result with low probabilities. VaR estimation has become a standard in risk management and helps give more focus to these issues. However, despite this, one should not focus solely on a single risk measure and VaR should be complimented with other measures. The importance of risk management cannot be stressed enough. Not even a betting man would make a blind wager.

Appendix A – Formulas

[A1] Returns from Prices

$$r_t = \frac{P_{t+1} - P_t}{P_t}$$

[A2] VaR using Historical Data:

$$VaR(\alpha) = -S \times R_{(K)}$$

[A3] VaR using Normal Distribution

$$VaR(\alpha) = -S \times \{\overline{X} + \Phi^{-1}(\alpha)s\}$$

[A4] VaR using t-Distribution

$$VaR(\alpha) = -S \times \{\overline{X} + t_{v-1}(\alpha)s\}$$

[A5] VaR using Pareto tails

$$VaR(\alpha) = VaR(\alpha_0)\left(\frac{\alpha_0}{\alpha}\right)^{\frac{1}{\hat{a}_{hill}}}$$

[A6] Hill Estimator

$$\hat{a}_{Hill}(c) = \frac{n(c)}{\sum_{-R_i \geq c} \log\left(-R_i / c\right)}$$

Appendix B – Graphs and Tables

(B1) Summary Statistics Table of the Mutual Funds

Mutual Funds					
	CIBC	**Scotia**	**BMO**	**TD**	**RBC**
Mean	0.004078848	0.00588378	0.00507753	0.00251496	0.007471407
Std. Deviation	0.038924772	0.04141526	0.03458776	0.04968607	0.034143265
Min	-0.101569054	-0.13216146	-0.0804827	-0.15651916	-0.070836605
Max	0.0898971	0.10421995	0.07651897	0.11148148	0.071217597
Skewness	-0.596302367	-0.57852213	-0.3656941	-0.72753046	-0.440085054
Kurtosis	0.141195485	0.60455162	-0.3572672	1.23591621	-0.558681094

(B2) Summary Statistics Table of the Segregated Funds

Segregated Funds					
	CI	**Clarica**	**Maritime**	**Mac Ivy**	**AIC**
Mean	-0.004535939	0.00654941	0.0038002	0.00587149	0.00456437
Std. Deviation	0.042073177	0.0388387	0.04273333	0.02120204	0.028432143
Max	0.14106225	0.08329477	0.08289971	0.06099616	0.073770492
Min	-0.096436059	-0.08961984	-0.1442492	-0.04536781	-0.067961165
Skewness	0.213540702	-0.39066618	-0.9611494	-0.01427057	-0.199301579
Kurtosis	0.72268274	-0.17539149	1.58472652	-0.16834967	0.152879562

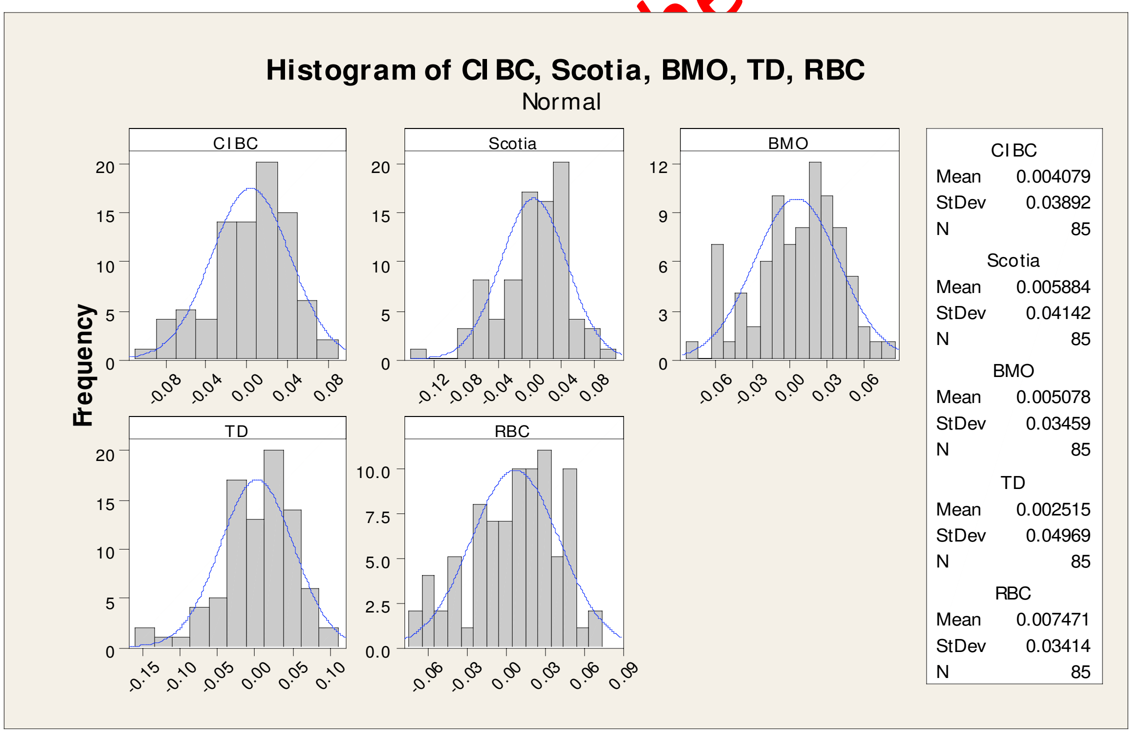
(B3) Historical VaR Calculations for all funds; 90%, 95%, and 99% confidence, resp.

VaR (α = 0.01) ~ Historical		VaR (α = 0.05) ~ Historical		VaR (α = 0.1) ~ Historical	
CIBC	-0.101569054	**CIBC**	-0.074148768	**CIBC**	-0.056387018
Scotia	-0.132161458	**Scotia**	-0.064529844	**Scotia**	-0.056643727
BMO	-0.080482678	**BMO**	-0.058556403	**BMO**	-0.051308702
TD	-0.156519157	**TD**	-0.075434439	**TD**	-0.06076166
RBC	-0.070836605	**RBC**	-0.058447276	**RBC**	-0.042387572
CI	-0.096436059	**CI**	-0.076164875	**CI**	-0.06088993
Clarica	-0.089619835	**Clarica**	-0.063009623	**Clarica**	-0.048347613
Maritime	-0.144249169	**Maritime**	-0.078339143	**Maritime**	-0.054555165
Mac Ivy	-0.045367812	**Mac Ivy**	-0.032036352	**Mac Ivy**	-0.022147037
AIC	-0.067961165	**AIC**	-0.045889101	**AIC**	-0.032085561

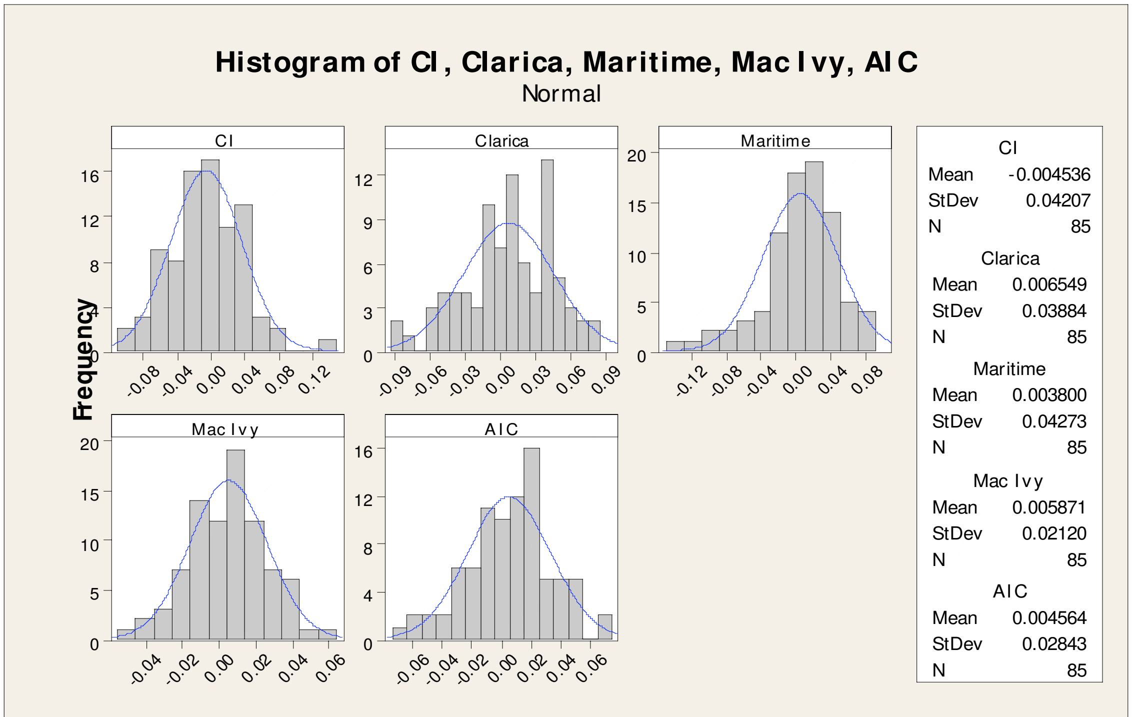
<u>(B4) Parametric VaR Calculations for all funds under the Normal Distribution; 90%, 95%, and 99% confidence, resp.</u>

VaR (α = 0.01) ~ N		VaR (α = 0.05) ~ N		VaR (α = 0.1) ~ N	
CIBC	-0.086460172	**CIBC**	-0.059952402	**CIBC**	-0.04582271
Scotia	-0.090448118	**Scotia**	-0.062244325	**Scotia**	-0.047210584
BMO	-0.075373597	**BMO**	-0.051819335	**BMO**	-0.039263979
TD	-0.113054841	**TD**	-0.079218626	**TD**	-0.061182582
RBC	-0.071945828	**RBC**	-0.048694264	**RBC**	-0.036300259
CI	-0.102398148	**CI**	-0.073746315	**CI**	-0.058473752
Clarica	-0.0837894	**Clarica**	-0.057340247	**Clarica**	-0.0432418
Maritime	-0.095597535	**Maritime**	-0.066496134	**Maritime**	-0.050983934
Mac Ivy	-0.04344445	**Mac Ivy**	-0.029005862	**Mac Ivy**	-0.021309522
AIC	-0.061568794	**AIC**	-0.042206504	**AIC**	-0.031885637

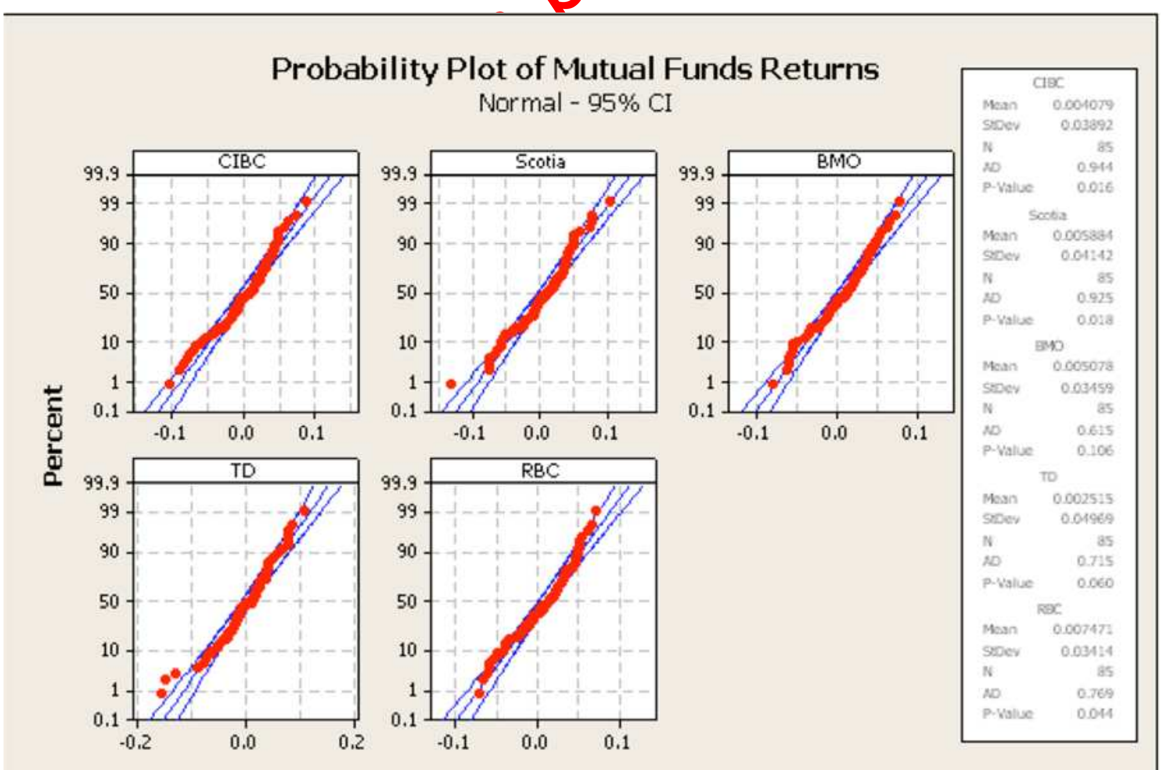
<u>(B5) Histograms of Mutual Fund Returns (plotted with Normal Distribution curve)</u>



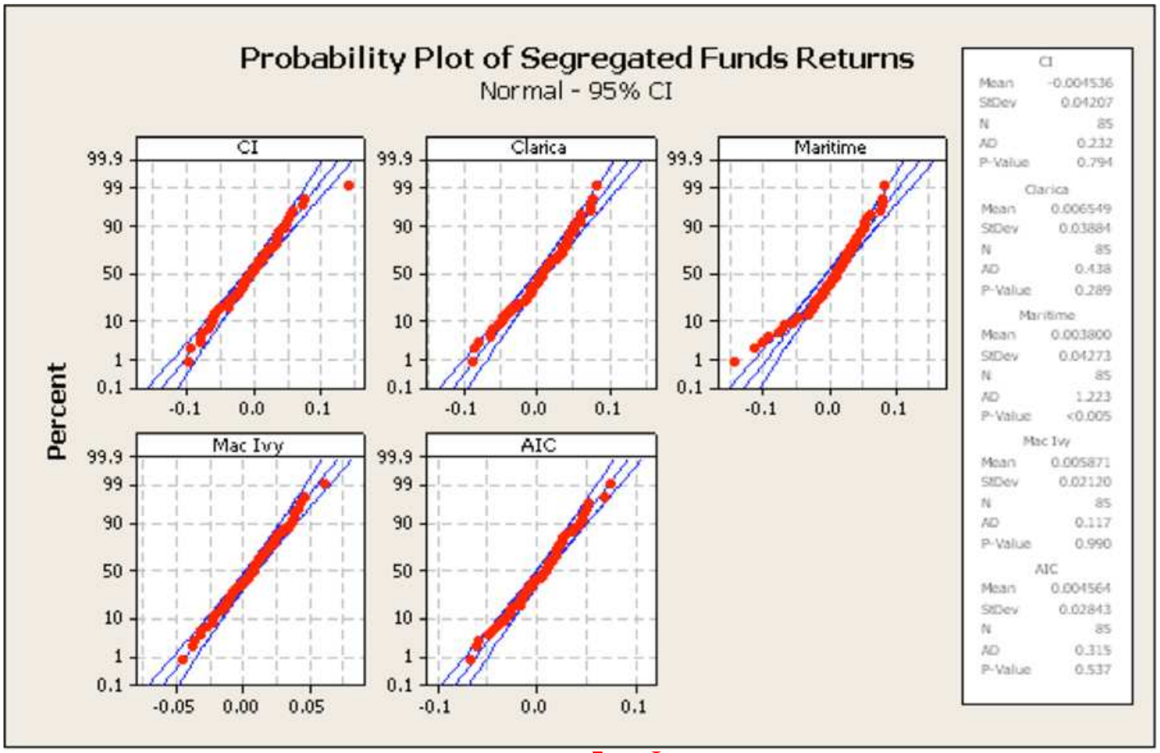
(B6) Histograms of Segregated Fund Returns (plotted with Normal Distribution curve)



(B7) Individual Normal Probability Plots for the Mutual Funds Returns



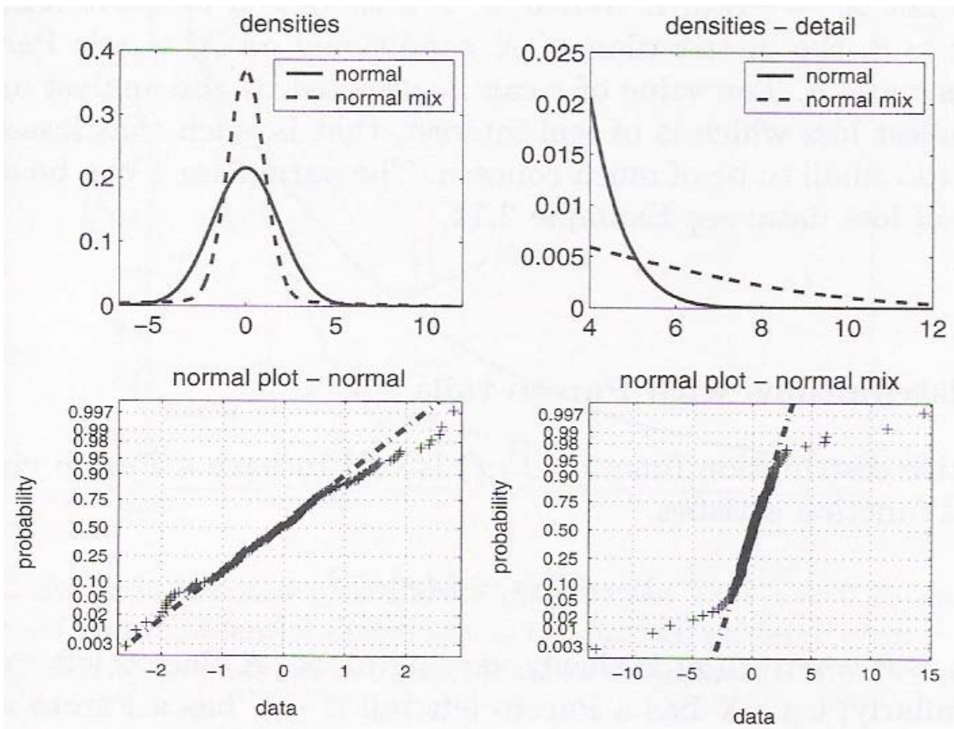
(B8) Individual Normal Probability Plots for the Segregated Funds Returns



(B9) Tests of Normality for both Mutual and Segregated Funds (p-values)

Tests of Normality p-values					
Mutual Funds					
	CIBC	Scotia	BMO	TD	RBC
KS test p-value	0.073	0.138	>0.15	>0.15	0.104
AD test p-value	0.016	0.018	0.106	0.06	0.044
Segregated Funds					
	CI	Clarica	Maritime	Mac Ivy	AIC
KS test p-value	>0.15	>0.15	0.084	>0.15	>0.15
AD test p-value	0.794	0.289	<0.005	0.99	0.289

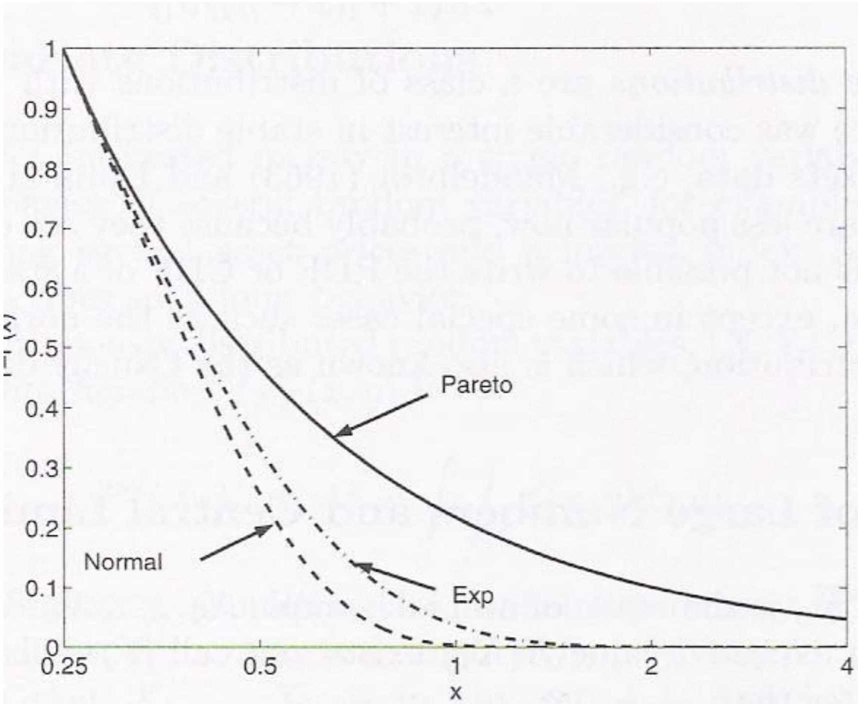
(B10) Comparison between Normal and Heavy-Tailed Distributions (*Ruppert*)



(B11) Parametric VaR Calculations for all funds under the t-student Distribution; 90%, 95%, and 99% confidence, resp.

VaR (α = 0.01) ~ t		VaR (α = 0.05) ~ t		VaR (α = 0.1) ~ t	
CIBC	-0.088172862	**CIBC**	-0.060925522	**CIBC**	-0.046134108
Scotia	-0.09227039	**Scotia**	-0.063279706	**Scotia**	-0.047541907
BMO	-0.076895458	**BMO**	-0.052684028	**BMO**	-0.039540681
TD	-0.115241028	**TD**	-0.080460778	**TD**	-0.061580071
RBC	-0.073448131	**RBC**	-0.049547846	**RBC**	-0.036573405
CI	-0.104249368	**CI**	-0.074798144	**CI**	-0.058810337
Clarica	-0.085498302	**Clarica**	-0.058311214	**Clarica**	-0.04355251
Maritime	-0.097477801	**Maritime**	-0.067564468	**Maritime**	-0.051325801
Mac Ivy	-0.04437734	**Mac Ivy**	-0.029535913	**Mac Ivy**	-0.021479138
AIC	-0.062819808	**AIC**	-0.042917308	**AIC**	-0.032113094

(B12) Illustration comparing Normal, Exponential & Pareto Distributions tails (*Ruppert*)



(B13) Hill Estimator Values for both Mutual and Segregated Funds Returns

Hill Estimators (for estimating Pareto tails)					
Mutual Funds					
	CIBC	Scotia	BMO	TD	RBC
a_{hill}	2.731080914	1.40590069	3.02144897	1.60001014	3.725457077
Segregated Funds					
	CI	Clarica	Maritime	Mac Ivy	AIC
a_{hill}	3.517672828	2.74943329	1.61201364	2.12213164	2.260981898

(B14) Parametric VaR Calculations for all funds under a Pareto tailed Distribution; 90%, 95%, and 99% confidence, resp.

VaR (α = 0.01) ~ Pareto		VaR (α = 0.025) ~ Pareto		VaR (α = 0.05) ~ Pareto	
CIBC	-0.131019072	**CIBC**	-0.093675634	**CIBC**	-0.072677986
Scotia	-0.290046027	**Scotia**	-0.151153097	**Scotia**	-0.092320487
BMO	-0.120822039	**BMO**	-0.089215669	**BMO**	-0.070926762
TD	-0.237779916	**TD**	-0.13411095	**TD**	-0.086960431
RBC	-0.104617073	**RBC**	-0.081806185	**RBC**	-0.067917647
CI	-0.108507056	**CI**	-0.083624215	**CI**	-0.068668188
Clarica	-0.130283808	**Clarica**	-0.093358778	**Clarica**	-0.072554966
Maritime	-0.235245473	**Maritime**	-0.133248496	**Maritime**	-0.086680363
Mac Ivy	-0.166879669	**Mac Ivy**	-0.10836385	**Mac Ivy**	-0.0781685
AIC	-0.156122266	**AIC**	-0.104102621	**AIC**	-0.076616162

(B15) Optimal Distribution results for each fund individually

Suggested Optimal Distribution per Fund				
Fund	**Distribution**		**Fund**	**Distribution**
CIBC	Normal/t		**CI**	t/Pareto
Scotia	t/Pareto		**Clarica**	Normal/t
BMO	Normal		**Maritime**	t/Pareto
TD	t/Pareto		**Mac Ivy**	Normal
RBC	t/Pareto		**AIC**	Normal/t