Determining VaR using Filtered Historical Simulations for Representative Balanced Funds in South Africa

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Abstract

Value at Risk (VaR) is a commonly used statistic for analysing the downside risk attached to certain assets and investment portfolios. (Brandolini and Colucci 2012). This paper introduces an alternative method of calculating the VaR for an investment by using Filtered Historical Simulations (FHS). According to Barone-Adesi, Giannopoulos, and Vosper (2000), the FHS technique addresses many of the shortcomings of traditional methods in determining VaR and thus more reliable. An empirical analysis using data of representative balanced funds is conducted in this paper. It finds that FHS has strong predictive strength in determining the VaR of future investments for a two-week period and less accuracy for shorter periods.

Keywords: VaR, Filtered Historical Simulation, Univariate GARCH

JEL classification C01, C58, G17

1. Introduction

Value at Risk (VaR) is a commonly used statistic for analysing the risk attached to certain assets and investment portfolios. It is popular for its relatively simple methodology to measure risk, although these methods have also been criticised for being too simplistic and are blamed for contributing towards the 2008 Global Financial Crisis (Brandolini and Colucci 2012). Thus, risk managers have made efforts to revisit these methods in attempt to improve them and obtain a more accurate measurements of risk.

Kuester, Mittnik, and Paolella (2006) discussed that many approaches to VaR have been developed, with some being more adequate than others. These variations of VaR all estimate the probable losses of a portfolio using different methods of calculating the probability distribution functions of those losses. The most basic form of VaR analyses historical data and uses a parametric approach that imposes theoretical assumptions on the distribution of the return series. However, this approach struggles to be implemented into real world conditions and are rendered inefficient. Barone-Adesi, Giannopoulos, and Vosper (2000) developed a semi-nonparametric approach to determine VaR, which refines many of

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the shortcomings of the conventional methods. This approach involves generating simulations of many scenarios based on the historical returns. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are used in this method to control for volatility clusters. This method is referred to as Filtered Historical Simulation (FHS) and is argued to be a highly effective way of determining VaR for future investments(Gurrola-Perez and Murphy 2015).

This article will discuss the theory behind VaR measurements as well as FHS, followed by an empirical analysis of the VaR for representative balanced funds in South Africa. The VaR for different time periods will be calculated using the FHS technique and then compared to the VaR of the actual data corresponding to those time periods. Thus, highlighting any predictive accuracy of using FHS to determine the VaR of an investment going into the future.

2. Theory

2.1. VaR

The VaR of any portfolio is given as a single estimate of the amount in which the position of an investor could decline over a specific time frame (i.e. One month). It must be noted that this potential decline in an individual's/institutions investment position would be a result of general market movements and not from significant events (Tsay 2014).

Barone-Adesi, Giannopoulos, and Vosper (2002) indicated how all versions VaR models consist of the same aim, in that they attempt to measure the scale of a future possible losses at a predetermined probability and confidence level. The potential losses are derived from a density function of the return series. Piroozfar (2009) defines the confidence level and the VaR formula respectively as the following:

$$Confidence.Level = (1 - \alpha)100\% \tag{2.1}$$

$$VaR_\alpha = inf[L : Prob(Loss > L) \leq 1 - \alpha] \tag{2.2}$$

> Where lower threshold of loss is defined by L, meaning that the probability of loosing more than L in a specific time period (e.g.one month) is equivalent to or greater than $1 - \alpha$.

It must be noted that the means to achieve these measurements vary in between VaR models. As mentioned in section 1, each of these models differ in their approaches in determining the density functions of potential profits and losses an investor could achieve over a given investment period. According to Barone-Adesi, Giannopoulos, and Vosper (2000), traditional versions of the VaR models involves linear models that use variance-covariance of historical returns. These contain strong theoretical assumptions such as returns being normally distributed. However, such assumptions conflicts with empirical results, which show non-normality of returns in real life. The violations of such assumptions give room to generate large biases in the VaR results, especially for longer investment horizons (Gurrola-Perez and Murphy 2015).

According to Kuester, Mittnik, and Paolella (2006), one of the biggest challenges faced by conventional methods, is that the VaR estimates which are produced, portray more information about the past than the future. For example, if someone wanted to know the VaR of an investment for the month by using a traditional approach, the distribution of returns from the last month would usually be used to determine the VaR directly. However, this estimate reflects the downside risk from past market conditions of the last month and does not capture current market conditions and the downside risk that one could experience in the future. Hence, why there has been some criticism of using VaR as a meaningful measure of risk going into the future. However, despite the challenges faced in determining VaR from historical data, it is still a widely used measurement for risk analysis in many investment firms Angelidis and Benos (2015).

2.2. FHS

According to Barone-Adesi, Giannopoulos, and Vosper (2002), the challenges presented by the linear models discussed in section 2.1 can be overcome by fitting a conditional volatility model to the historical returns and then filtering the standardized residuals to become i.i.d stationary. These filtered residuals are then used to simulate multiple pathways of future possible returns which are used to determine the VaR. This FHS technique is able to overcome the limitation of the variance-covariance model by allowing past and future volatility of the returns to vary over time, as well as being able to generate scenarios that conform to the historical gains and losses of the investment. Brandolini and Colucci (2012) discussed that FHS uses a combination of nonlinear econometric models and historical returns to generate probability distributions of potential returns in these future scenarios.

Barone-Adesi, Giannopoulos, and Vosper (2000) explained that this method is referred to as semi-parametric, since assumptions of theoretical distributions are not necessary to generate the simulations. In this procedure, GARCH models are attached to an ARIMA (Autoregressive Integrated Moving Average) models, which are fitted to the data to produce the i.i.d stationary standardized residuals.

The typical ARIMA(1, 0, 1) (equation 2.3) and GARCH(1, 1) (equation 2.4) models are represented below:

$$r_t = \mu r_{t-1} + \theta\epsilon_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(0, h_t) \tag{2.3}$$
$$h_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{2.4}$$

Where, r_t is the conditional mean of the series, μ is the AR(1) term, θ is the MA(1) term, h_t^2 is the conditional variance of the return series, ω is a constant, ϵ_t is the random error residual.

The residuals from the fitted ARIMA and GARCH models are then brought close to stationary i.i.d. once they are divided by the contemporaneous volatility estimate:

$$e_t = \frac{\epsilon_t}{\sqrt{h_t}} \tag{2.5}$$

The standardized residuals are then filtered by the deterministic volatility values one period ahead to become suitable for simulation:

$$z_{t+1}^* = e_t^* \sqrt{h_{t+1}} \tag{2.6}$$
$$Where: \sqrt{h_{t+1}^*} = \sqrt{\omega + \alpha(z_t^*)^2 + \beta h_t^*} \tag{2.7}$$

Finally, the pathways for the return series can be simmulated as follows:

$$r_{t+1}^* = \mu r_t + \theta z_t^* + z_{t+1} \tag{2.8}$$

It is evident that simulated returns are not based directly off the historical data, but the i.i.d standardized residuals instead. Therefore, theoretical distributions do not need to be assumed as long as the correct GARCH and ARIMA models are calibrated (Gurrola-Perez and Murphy 2015).

According to Piroozfar (2009), the simulated returns depend on the historical distribution captured by the GARCH model, hence the VaR for the chosen time horizon is then calculated from the distribution of simulated return pathways. FHS excels in the ability in scaling past returns to match current market volatility, which traditional VaR methods fail to do. Furthermore, the benefits of using FHS for calculating VaR is that it is possible to generate a high number of pathways over a certain time interval for a specific investment. While calculating VaR purely from historical data is just from one potential pathway. Furthermore, the higher the number of pathways allows for a more accurate distribution of potential returns. Thus, the calculated VaR should tend towards the true value of the VaR for that investment as the number of simulations increases (Roy 2011).

When VaR is calculated from computer generated simulations, given α, by varying L so the probability is below $1 - \alpha$, it is possible to find the value L as the VaR (Piroozfar 2009). Therefore, the VaR calculation for simulated pathways can be given by:

$$Prob(Loss > L) = \frac{No.of.simulations.with.value < P - L}{N} \tag{2.9}$$

Where N is the number of simulations generated using the FHS method, and P is the initial amount of investment.

3. Data

The nature of this analysis and the use of GARCH models to model volatility of the returns required a reasonably large data set. Ghalanos (2017) suggested having a sample size of at least 100 observations. Furthermore, volatility clusters in long periods as well as short periods need to be captured in the models for successful simulations. Therefore, daily data spanning more than 2 years was necessary. Hence, daily fund prices from 1 February 2016 to 13 September 2018 (655 observations) were collected and used as the main sample.

The underlying aim of this analysis was to investigate predictive strength of the FHS method in determining the VaR for an investment in the future. While future values are uncertain in reality, this investigation required a comparison of 'simulated future data' with 'actual future data'. Therefore, prices from 14 September 2018 to 15 November 2018 were collected to represent the future time period to allow for an efficient analysis. All data was obtained from Bloomberg ("Bloomberg" 2018).

Representative balanced funds under high and medium risk profiles were selected for this investigation. At the end of the sample period, funds with the median value of cumulative returns in each risk profile was chosen. Furthermore, two funds with cumulative returns above the median, along with one fund below the median were also selected as representative funds. Therefore, there were four representative funds in each risk category.

- High Risk:

- STANLIB Global Balanced Feeder Fund B.
  - Analytics Ci Moderate Fund of Funds.
  - Momentum International Balanced Feeder Fund A.
  - Oasis Crescent Balanced High Equity Fund of Funds D

- Medium Risk:
  - Allan Gray Tax-Free Balanced Fund A.
  - Coronation Balanced Plus Fund A.
  - Kagiso Islamic Balanced Fund A.
  - Old Mutual Balanced Fund A.

The historical returns of the representative balanced funds under the high and medium risk categories are depicted in figures 3.1 and 3.2 respectively:

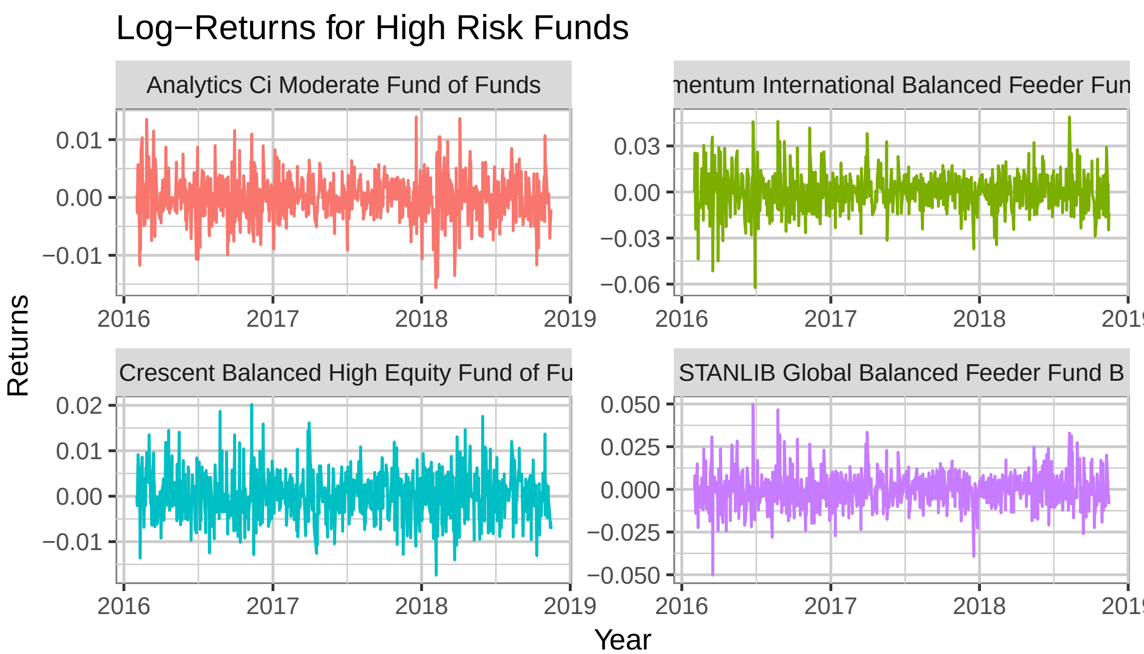

Figure 3.1: Log-Returns of Representative High Risk Balanced Funds

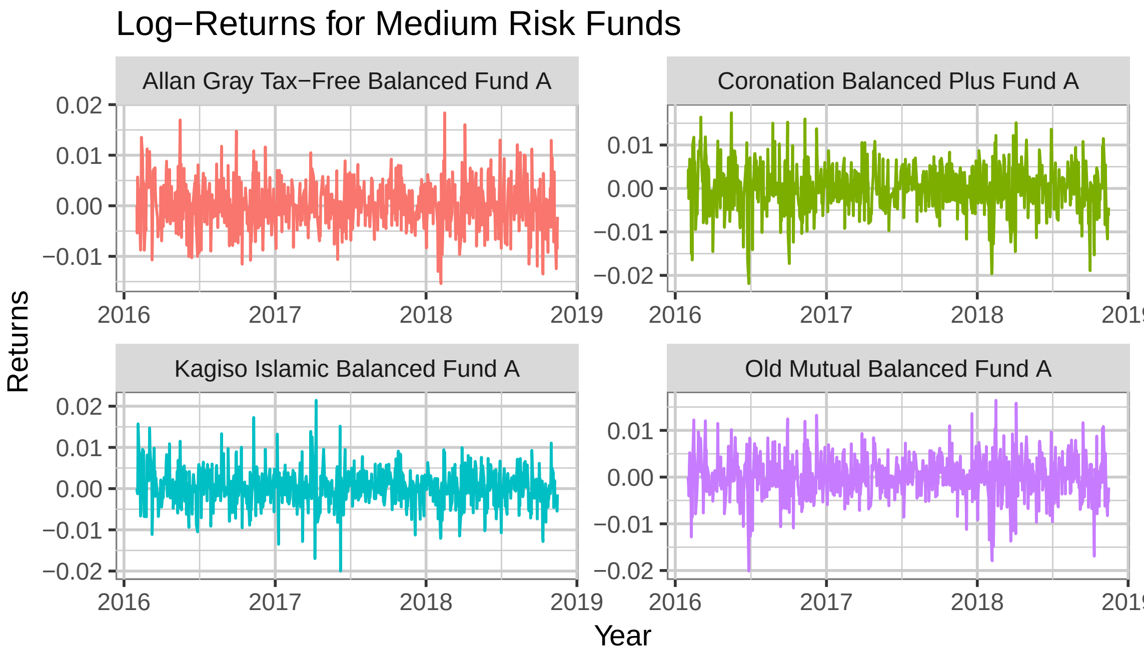

Figure 3.2: Log-Returns of Representative Medium Risk Balanced Funds

4. Methodology

Firstly, the daily prices of the funds were converted to log returns. The methodology then followed the FHS process discussed by Barone-Adesi, Giannopoulos, and Vosper (2000) in section 2.2. Using the rugarch package by Ghalanos (2017) in R Studio. The cumulative log returns for representative funds were fitted with the appropriate ARIMA and GARCH models by minimizing the AIC (Akaike Information Criterion)[1]. The basic GARCH model (equation 2.4) along with the EGARCH (equation 4.1) and GJR-GARCH (equation 4.2)[2] were all investigated to allow for best fit and for the standardized residuals to become i.i.d stationary.[3]

$$ln(h_t^2) = \omega + \alpha \frac{\epsilon_{t-1}^2}{h_t} + \gamma \left[\left| \frac{\epsilon_{t-1}^2}{h_t} \right| - \sqrt{\frac{2}{\pi}} \right] + \beta ln(h_{t-1}^2) \tag{4.1}$$

[1]The models were calibrated using the data from 2 February 2016 to 15 October 2018
[2]As suggested by Barone-Adesi, Giannopoulos, and Vosper (2002) and Brandolini and Colucci (2012)
[3]The fit of the ARIMA and GARCH models for all representative funds can be viewed in the appendix in Section 8.3

$$
\begin{aligned}
h_t^2 = \omega + \alpha\epsilon_{t-1} + \gamma I_{t-1}\epsilon_{t-1}^2 + \beta h_{t-1}^2 \\
Where : I = 1 \quad if \quad \epsilon_{t-1} < 0 \\
0 \quad if \quad \epsilon_{t-1} \geq 1
\end{aligned}
\tag{4.2}
$$

Where, I is the asymmetric indicator function for positive and negative shocks.

Once filtered and i.i.d stationary, the standardized residuals were used to simulate 100 pathways, one week (5 business days) forward from 14 September 2018 to 20 September 2018. The distributions of simulated future returns were then used to determine the VaR of the funds for the simulated future period. All of the VaR Calculations were done using the PerformanceAnalytics package by Peterson et al. (2015). The same process was repeated twice, except simulating one month (22 business days) forward from 14 September 2018 to 15 October 2018, and two months (45 business days) forward from 14 September 2018 to 15 November 2018.

Finally, the actual historical returns for the three sets of dates were used to calculate the VaR for the one-week, one month and two-month term investment periods. Since these values represent the true returns of the 'future time period', they provided a solid basis to compare the predictive strength of the FHS approach in calculating VaR of future investments.

5. Results

The future returns generated from FHS of the three time periods for STANLIB Global Balanced Feeder Fund B are illustrated in figure's 5.1, 5.2 and 5.3 respectively[4]:

[4]The simulated returns for the rest of the representative funds can be viewed in the appendix

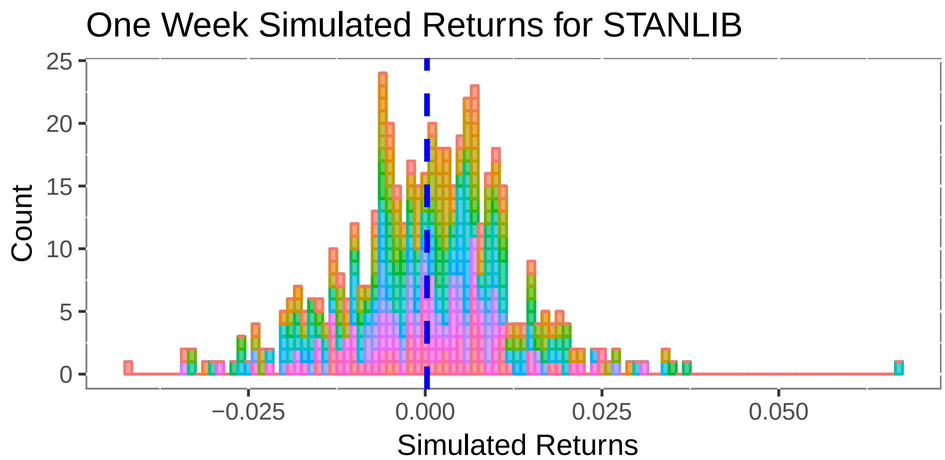

Figure 5.1: One Week Simulated Returns for STANLIB Global Balanced Feeder Fund B

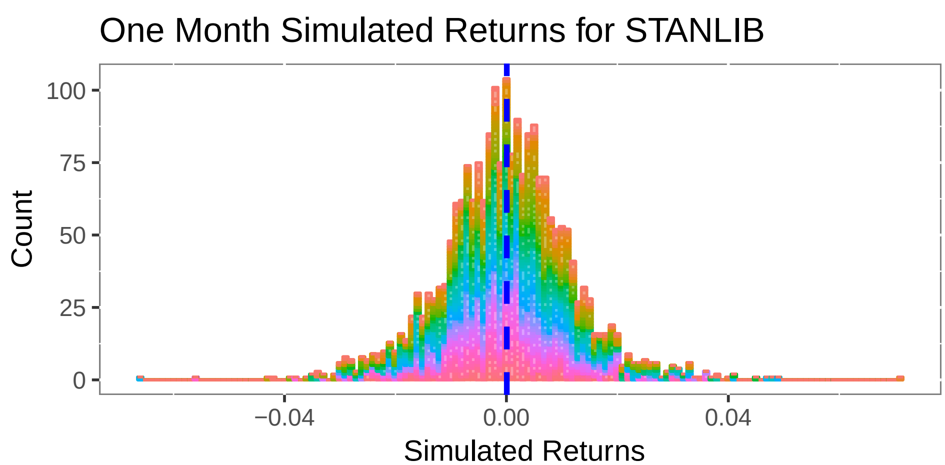

Figure 5.2: One Month Simulated Returns for STANLIB Global Balanced Feeder Fund B

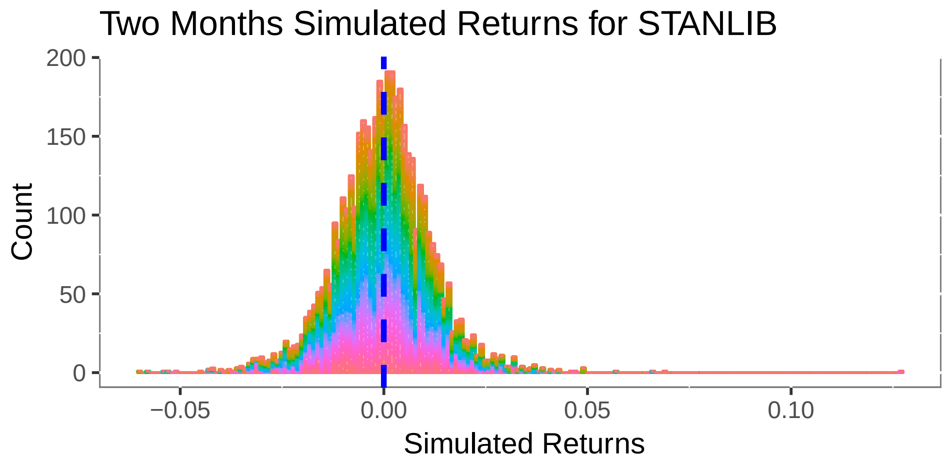

Figure 5.3: Two Months Simulated Returns for STANLIB Global Balanced Feeder Fund B

The accuracy of the simulated returns depended on how well the ARIMA and GARCH models were fitted to the data and how close the filtered residuals are brought to stationary. It is evident from the figures that the distributions of returns become more defined as the time period increases, due to the increasing amount of observations. The distributions are also noticeably wider for the one-month and two-month periods than the one-week period. This would be due to the fact that the larger, uncommon outliers and higher variances are captured by the GARCH model and projected in the simulations. Furthermore, with more time passing, new market conditions and trends begin to take form. Therefore, there is a higher probability that returns will vary to a larger extent in longer periods than shorter one. These trends are consistent with the rest of the representative balanced funds.

Table 5.1 compares the VaR estimates calculated for STANLIB Global Balanced Feeder Fund B from the FHS and the actual historical returns for the three time periods. Furthermore, the third row of table 5.1 includes the difference (in absolute values) between the FHS VaR estimates and the true historical VaR estimates for those periods. Thus, the predictive accuracy of the FHS VaR estimates depends on how close the absolute difference is to zero. The VaR comparisons for all of the representative funds are displayed in the appendix under tables 8.1 to 8.8.

	One-Week	One-Month	Two-Months
FHS	-0.02283	-0.01923	-0.01885
Historical	-0.01554	-0.01629	-0.01593
Difference	0.00728	0.00295	0.00292

Table 5.1: Comparrison of VaR estimates between FHS and Historical Returns for the three time periods, for STANLIB Global Balanced Feeder Fund B

From analysing the tables, the one-week VaR estimates of the FHS appear much lower than the VaR estimates determined from the historical values of that period. This result indicates that the FHS method overestimated the probable amount an investor might have lost over that investment period. The absolute differences between the two VaR estimates ranged from 0.00360 to 0.00810, with an average of 0.00573. However, as soon as the time period was extended, the absolute difference between the two VaR estimates decreased substantially. In all tables, the difference between the VaR estimates was lowest for the two-month horizon (14 September 2018 to 15 November 2018). In the two-month period, the absolute difference between the FHS VaR estimates and the historical returns Var estimates ranged from 0.00007 to 0.00408 and had an average of 0.00166. These trends were consistent with all representative funds, indicating that the FHS approach increased its predictive strength in determining VaR as the investment horizon increased.

A possible reason for the improved accuracy in the VaR estimates is the exponentially increasing number of observations produced by simulating the next time period. The results support the literature of Gurrola-Perez and Murphy (2015) and suggest that the FHS VaR estimates tends towards the true estimates of VaR for future time periods as the number of observations increases. Therefore, using FHS to determine VaR is more efficient over medium term investment of a couple of months rather than short term periods of a week of less.

6. Conclusion

In conclusion, this paper set out to investigate and demonstrate the benefits of using FHS to determine the VaR for a future investment. The weaknesses of traditional methods to calculate VaR were discussed while the strengths of using FHS were highlighted. As the challenge with all future forecasts, it is impossible to always predict true events. However, the use of FHS was able to scale past returns to match current market conditions allowed for the simulations into the future to be more dependable. Furthermore, fitting and filtering the data allowed for no need for theoretical assumptions about the distribution of returns, as this was a semi-parametric approach.

The empirical analysis demonstrated how FHS in determining VaR was more accurate in the two-month horizon than the one-month one-week horizons respectively. Therefore, the FHS technique appears to have stronger reliability for medium term investment periods than shorter term horizons. The absolute differences between the VaR estimates indicate that FHS can predict the VaR of a future investment over two months to a high degree of accuracy. The increasing number of observations produced by the simulations allow the VaR estimates tend towards the true values in the near future. However, it must be reminded that VaR cannot see 'Black Swan' events. Therefore, simulating further into the future poses risk of such events happening, which would result in highly inaccurate VaR estimates. Hence, why this paper suggested that using FHS to determine VaR should ideally be applied to medium term periods of two months.

Finally, is suggested that future avenues of research should apply the methodology of the analysis to longer time periods of six months to year. This will investigate predictive strength of the FHS method and how accurate it is in determining the VaR of longer term investments.

7. References

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8. Appendix

8.1. Simulated Log-Returns for the Representative Funds:

8.1.1. High Risk Balanced Funds:

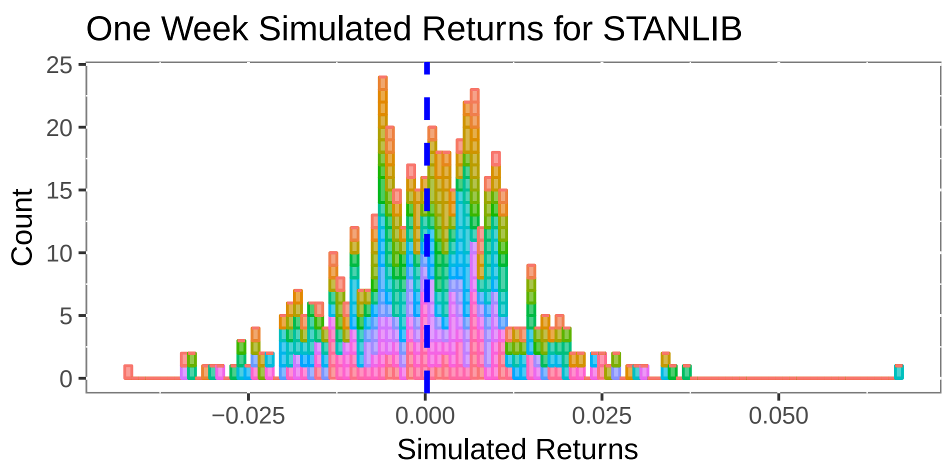

Figure 8.1: One Week Simulated Returns for STANLIB Global Balanced Feeder Fund B

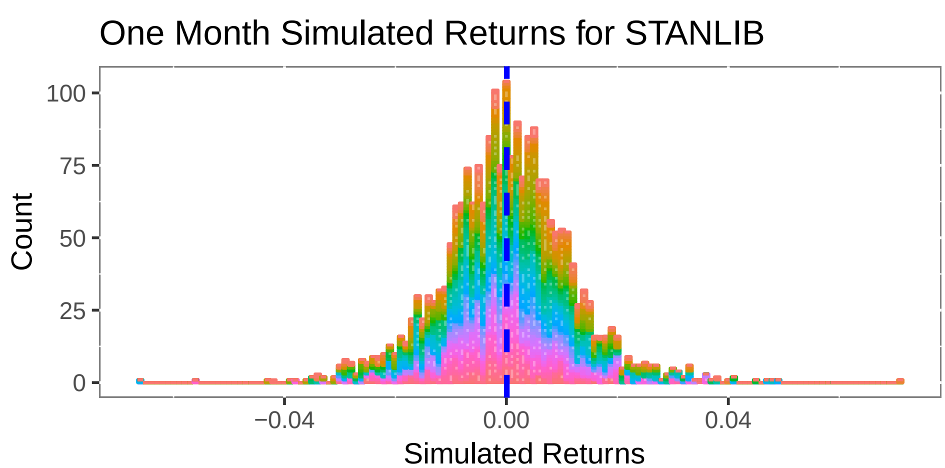

Figure 8.2: One Month Simulated Returns for STANLIB Global Balanced Feeder Fund B

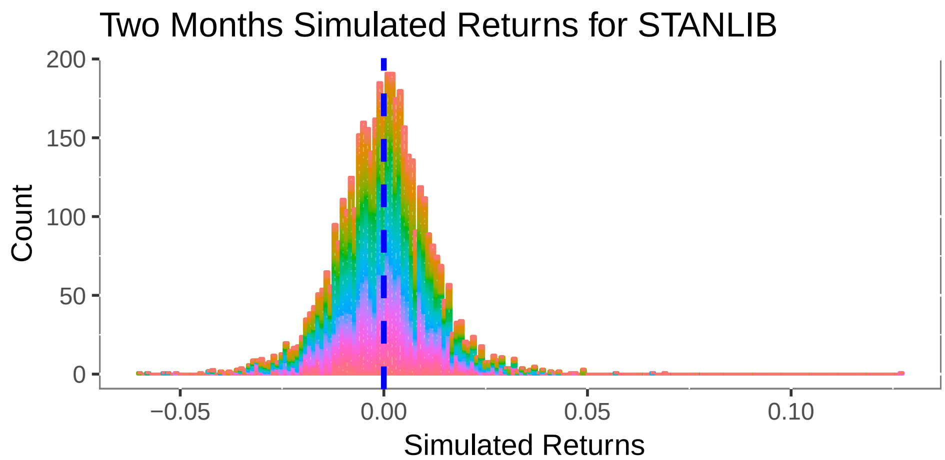

Figure 8.3: Two Months Simulated Returns for STANLIB Global Balanced Feeder Fund B

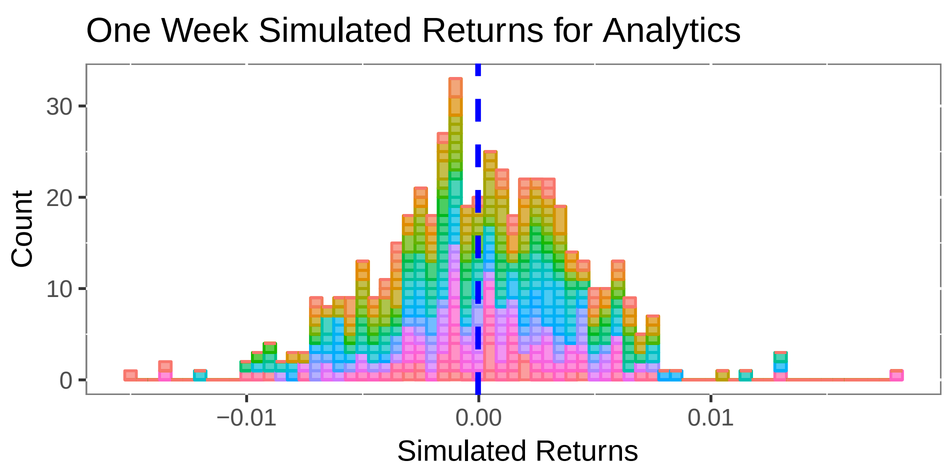

Figure 8.4: One Week Simulated Returns for Analytics Ci Moderate Fund of Funds

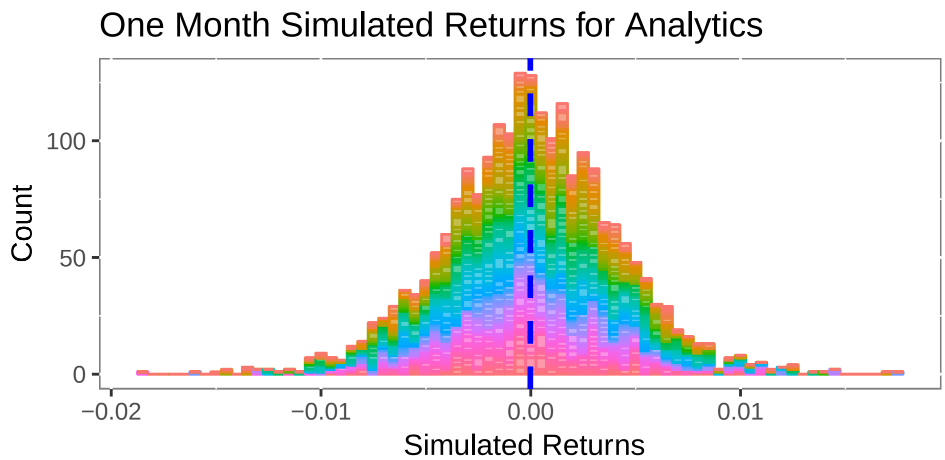

Figure 8.5: One Month Simulated Returns for Analytics Ci Moderate Fund of Funds

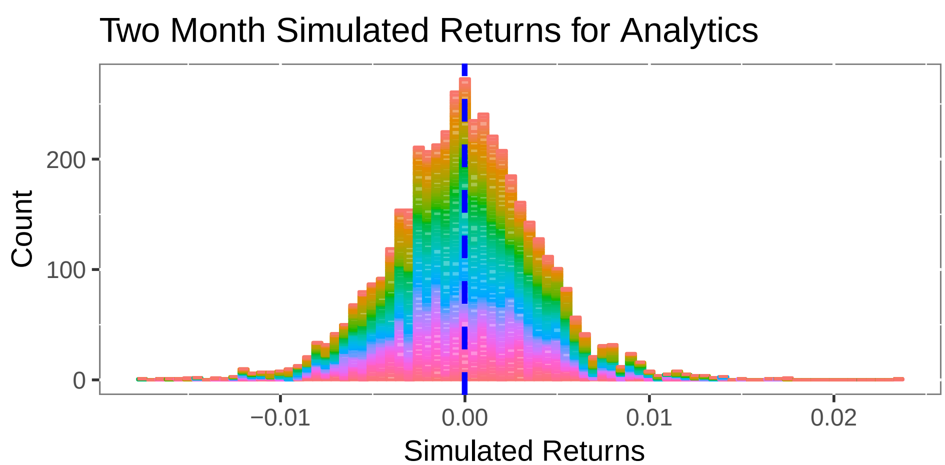

Figure 8.6: Two Months Simulated Returns for Analytics Ci Moderate Fund of Funds

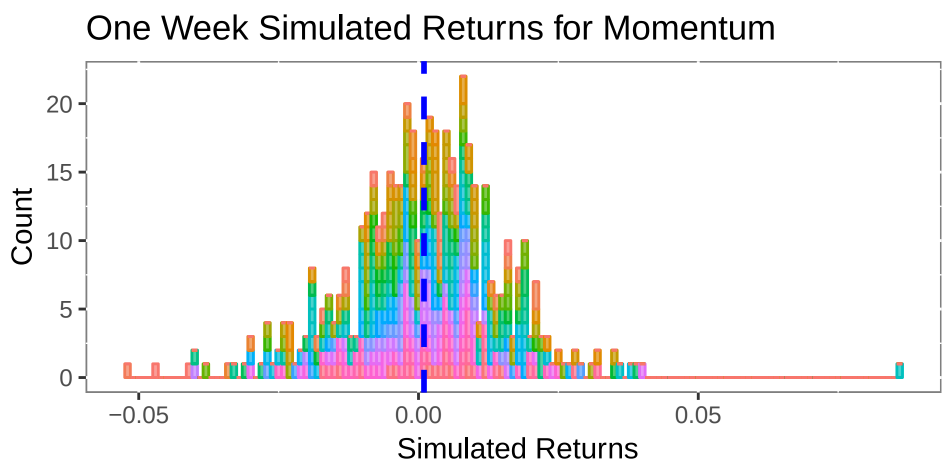

Figure 8.7: One Week Simulated Returns for Momentum International Balanced Feeder Fund A

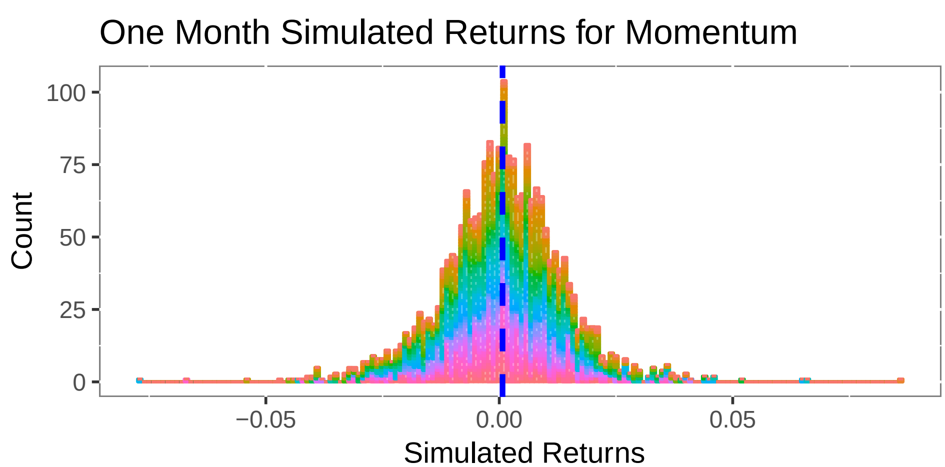

Figure 8.8: One Month Simulated Returns for Momentum International Balanced Feeder Fund A

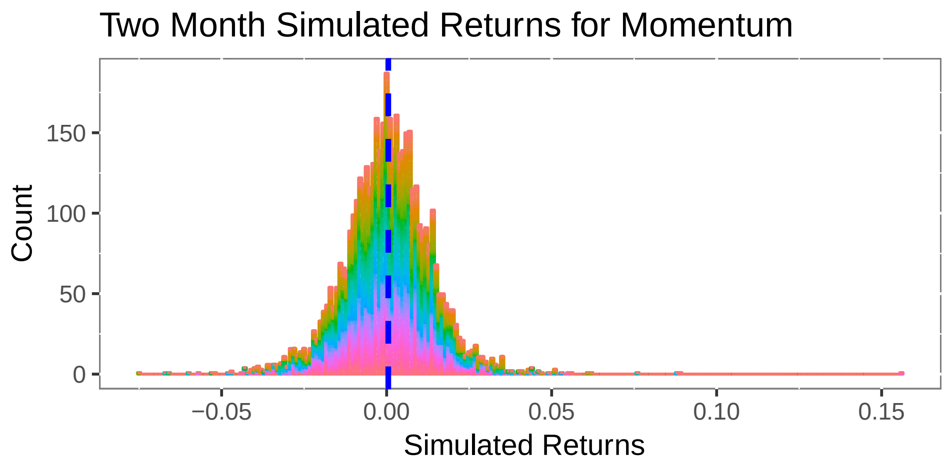

Figure 8.9: Two Months Simulated Returns for Momentum International Balanced Feeder Fund A

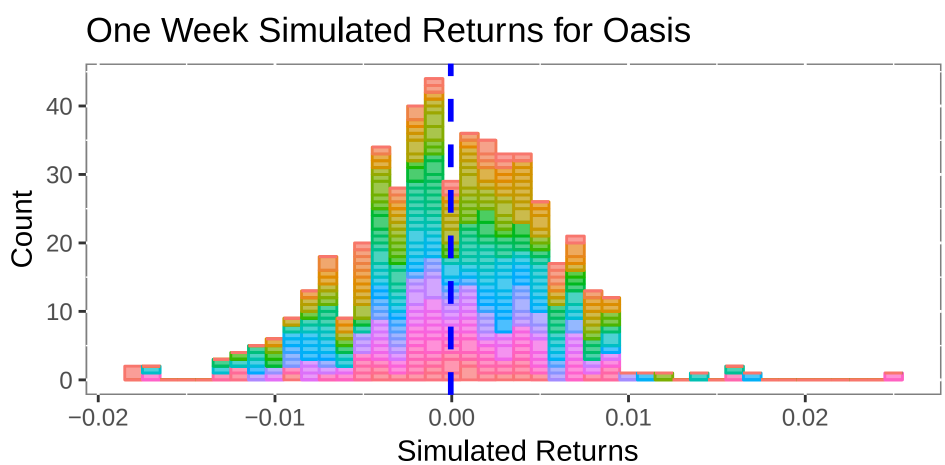

Figure 8.10: One Week Simulated Returns for Oasis Crescent Balanced High Equity Fund of Funds D

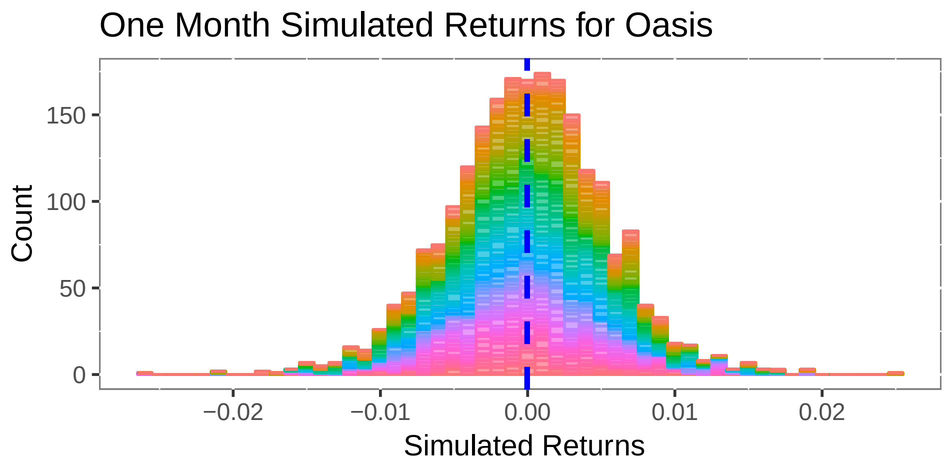

Figure 8.11: One Month Simulated Returns for Oasis Crescent Balanced High Equity Fund of Funds D

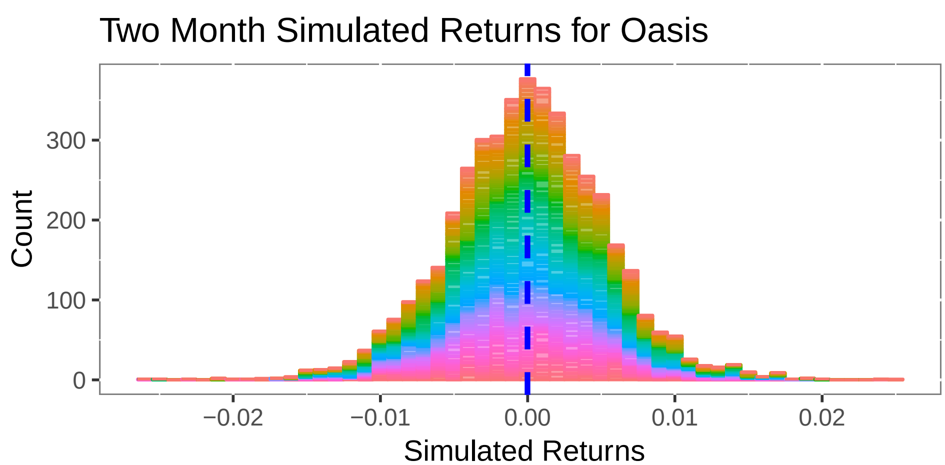

Figure 8.12: Two Months Simulated Returns for Oasis Crescent Balanced High Equity Fund of Funds D

8.1.2. Medium Risk Balanced Funds

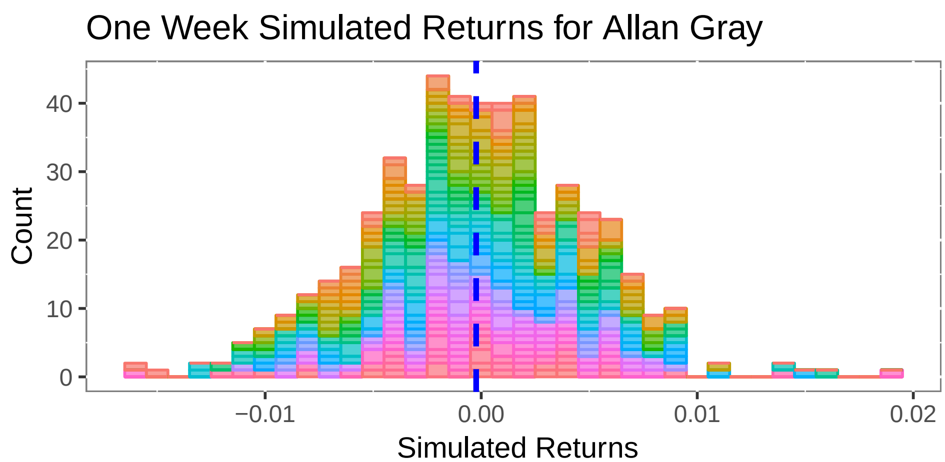

Figure 8.13: One Week Simulated Returns for Allan Gray Tax-Free Balanced Fund A

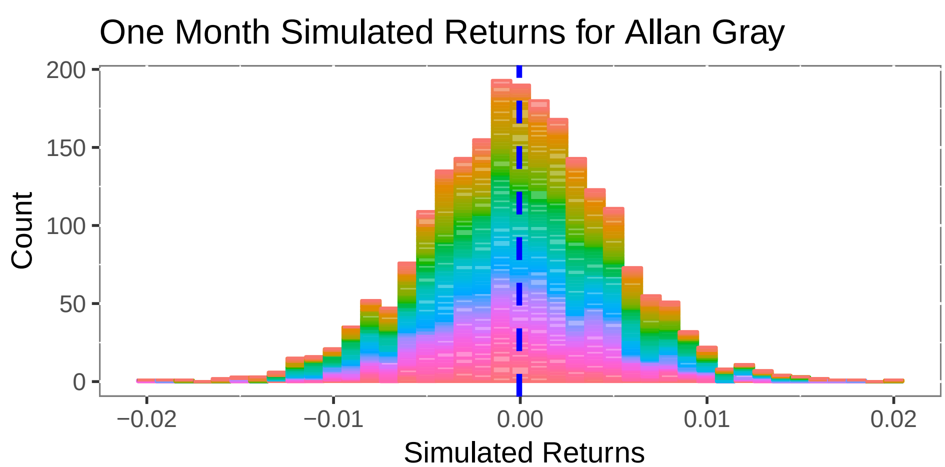

Figure 8.14: One Month Simulated Returns for Allan Gray Tax-Free Balanced Fund A

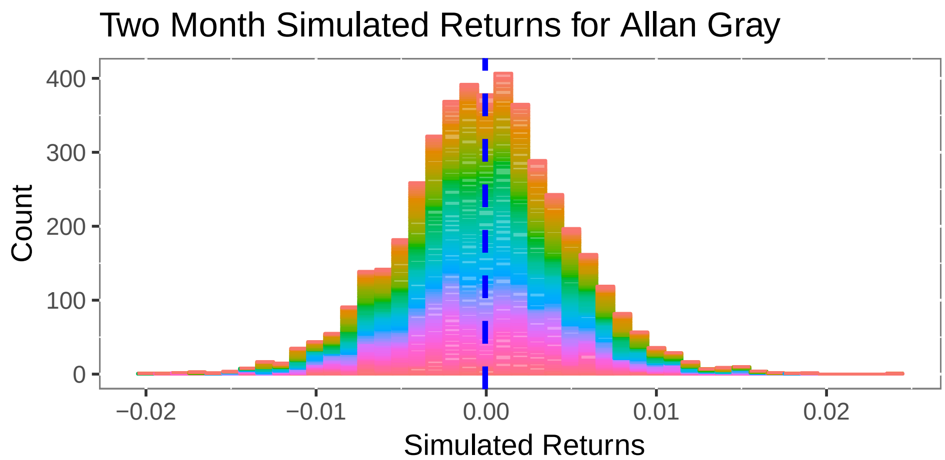

Figure 8.15: Two Months Simulated Returns for Allan Gray Tax-Free Balanced Fund A

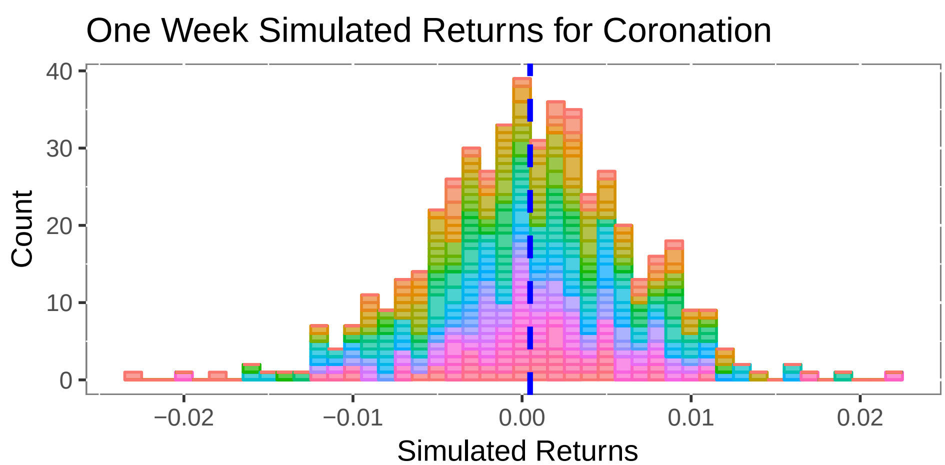

Figure 8.16: One Week Simulated Returns for Coronation Balanced Plus Fund A

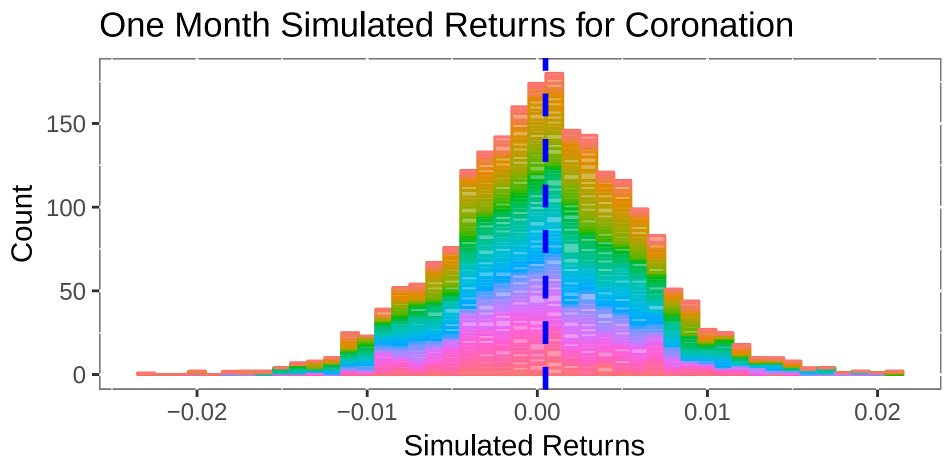

Figure 8.17: One Month Simulated Returns for Coronation Balanced Plus Fund A

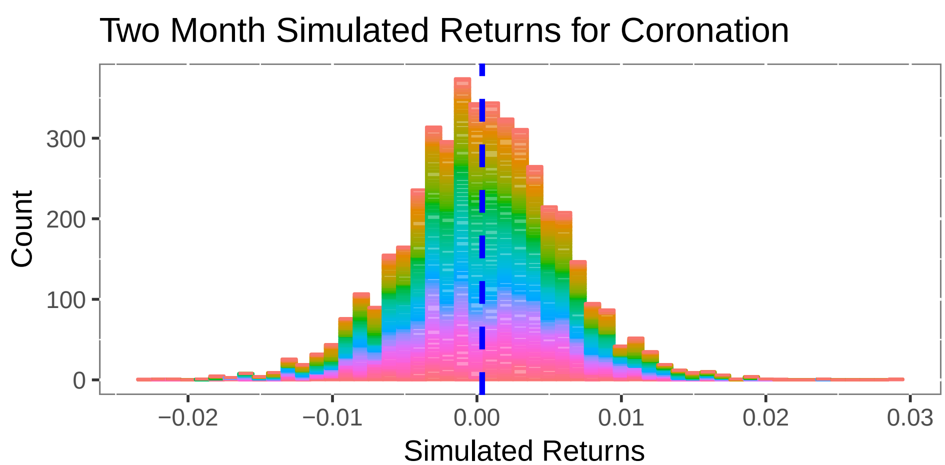

Figure 8.18: Two Months Simulated Returns for Coronation Balanced Plus Fund A

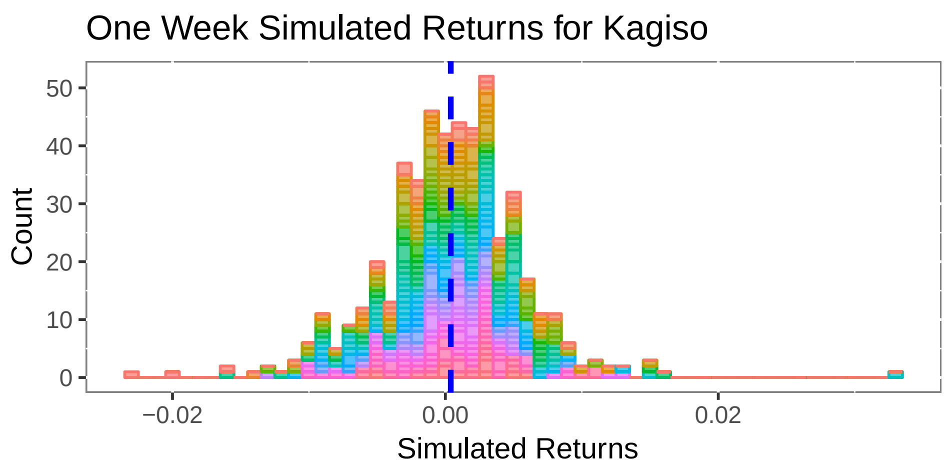

Figure 8.19: One Week Simulated Returns for Kagiso Islamic Balanced Fund A

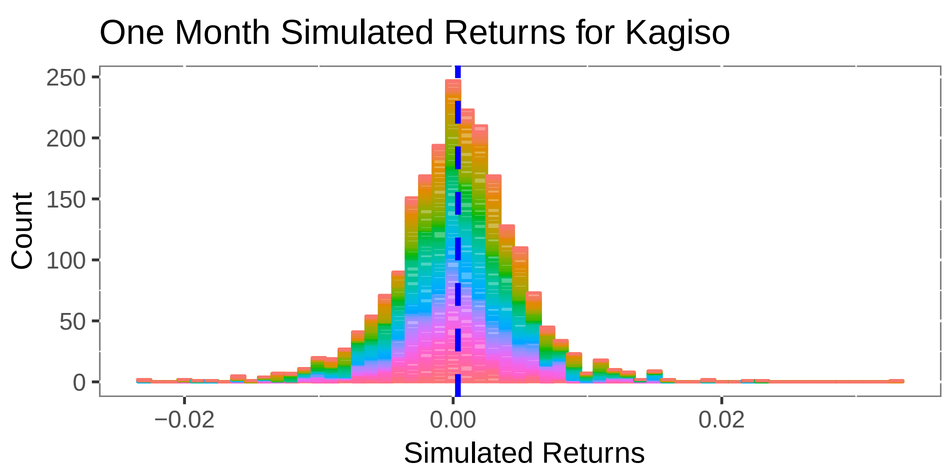

Figure 8.20: One Month Simulated Returns for Kagiso Islamic Balanced Fund A

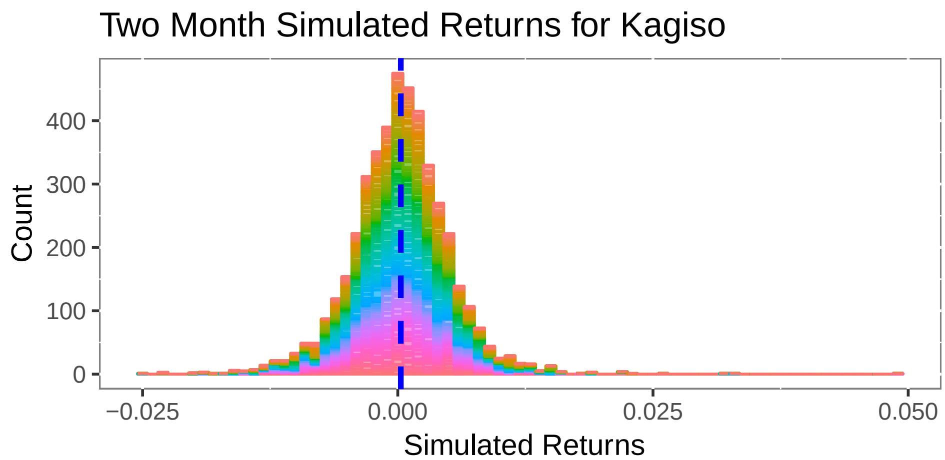

Figure 8.21: Two Months Simulated Returns for Kagiso Islamic Balanced Fund A

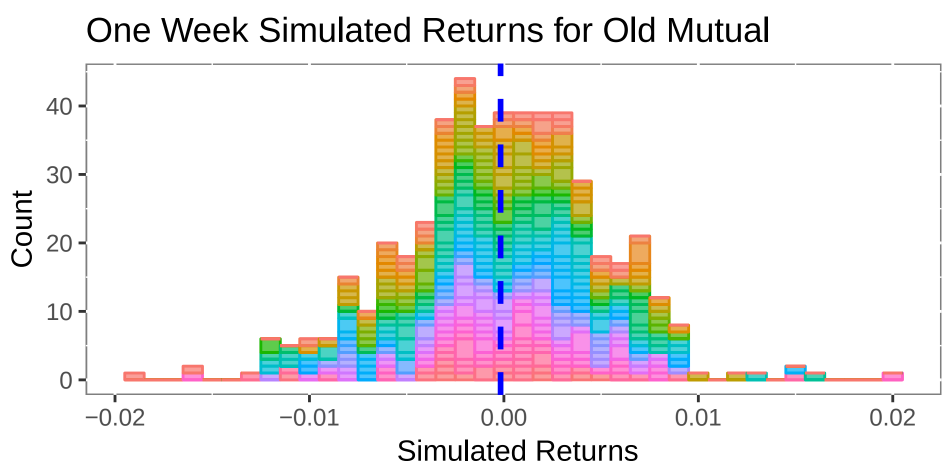

Figure 8.22: One Week Simulated Returns for Old Mutual Balanced Fund A

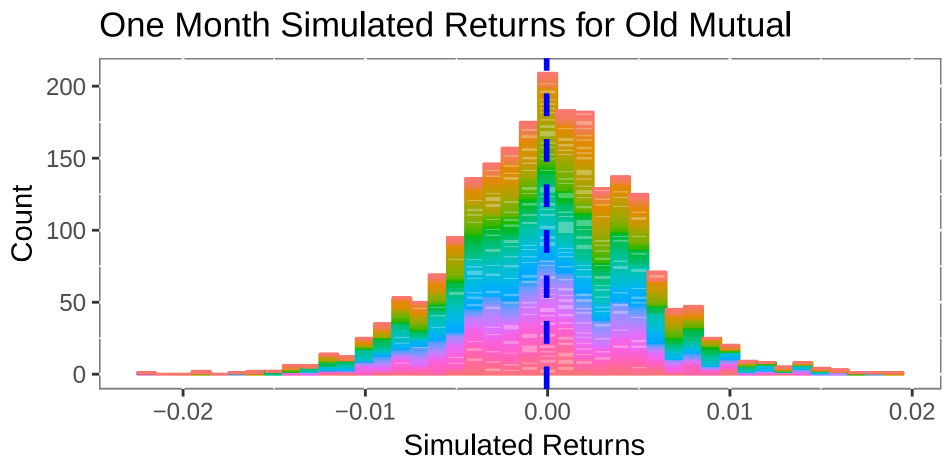

Figure 8.23: One Month Simulated Returns for Old Mutual Balanced Fund A

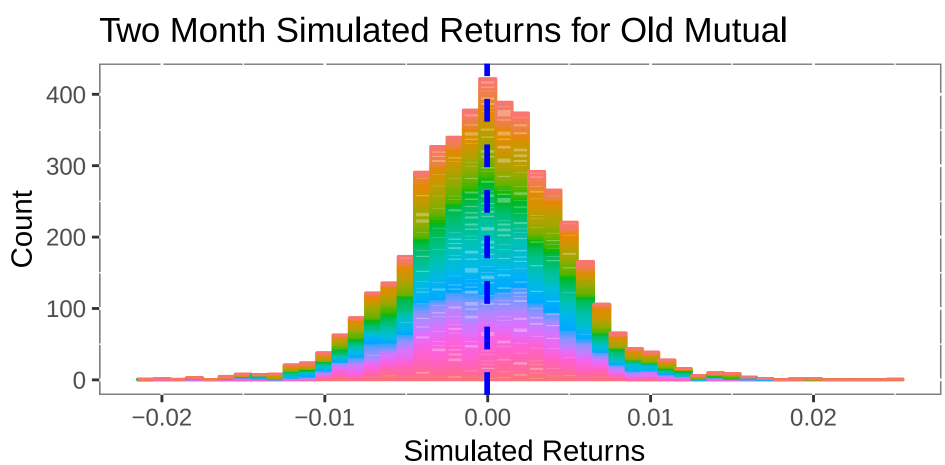

Figure 8.24: Two Months Simulated Returns for Old Mutual Balanced Fund A

8.2. Tables comparing VaR Estimates between FHS and Historical Returns for the three time periods:

8.2.1. High Risk Balanced Funds

	One-Week	One-Month	Two-Months
FHS	-0.02283	-0.01923	-0.01885
Historical	-0.01554	-0.01629	-0.01593
Difference	0.00728	0.00295	0.00292

Table 8.1: Comparrison of VaR estimates for STANLIB Global Balanced Feeder Fund B

	One-Week	One-Month	Two-Months
FHS	-0.00727	-0.00663	-0.00682
Historical	-0.00367	-0.00878	-0.00796
Difference	0.00360	0.00215	0.00114

Table 8.2: Comparrison of VaR estimates for Analytics Ci Moderate Fund of Funds

	One-Week	One-Month	Two-Months
FHS	-0.02134	-0.02148	-0.02092
Historical	-0.01325	-0.01884	-0.01918
Difference	0.00810	0.00264	0.00174

Table 8.3: Comparrison of VaR estimates for Momentum International Balanced Feeder Fund A

	One-Week	One-Month	Two-Months
FHS	-0.00948	-0.00869	-0.00891
Historical	-0.00511	-0.00958	-0.00920
Difference	0.00437	0.00090	0.00034

Table 8.4: Comparrison of VaR estimates for Oasis Crescent Balanced High Equity Fund of Funds D

8.2.2. Medium Risk Balanced Funds

	One-Week	One-Month	Two-Months
FHS	-0.00911	-0.00818	-0.00830
Historical	-0.00405	-0.01317	-0.01238
Difference	0.00506	0.00500	0.00408

Table 8.5: Comparrison of VaR estimates for Allan Gray Tax-Free Balanced Fund A

	One-Week	One-Month	Two-Months
FHS	-0.01014	-0.00867	-0.00885
Historical	-0.00379	-0.01531	-0.01128
Difference	0.00634	0.00664	0.00243

Table 8.6: Comparrison of VaR estimates for Coronation Balanced Plus Fund A

	One-Week	One-Month	Two-Months
FHS	-0.00811	-0.00729	-0.00751
Historical	-0.00228	-0.01091	-0.00803
Difference	0.00582	0.00362	0.00052

Table 8.7: Comparrison of VaR estimates for Kagiso Islamic Balanced Fund A

	One-Week	One-Month	Two-Months
FHS	-0.00905	-0.00813	-0.00827
Historical	-0.00375	-0.00972	-0.00819
Difference	0.00530	0.00159	0.00007

Table 8.8: Comparrison of VaR estimates for Old Mutual Balanced Fund A

8.3. Fitted ARIMA and GARCH Models for Representative Funds:

8.3.1. STANLIB Global Balanced Feeder Fund B

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(2,0,2)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error   t value Pr(>|t|)
## ar1     0.849297    0.009435   90.0170 0.000000
## ar2    -0.969316    0.003538 -273.9495 0.000000
## ma1    -0.863902    0.002126 -406.2826 0.000000
## ma2     1.001261    0.000238 4200.6420 0.000000
## omega   0.000001    0.000000    3.6984 0.000217
## alpha1  0.017724    0.005554    3.1914 0.001416
## beta1   0.970716    0.007587  127.9391 0.000000
```

```
## shape   6.869180    1.669103    4.1155 0.000039
##
## Robust Standard Errors:
##         Estimate  Std. Error    t value Pr(>|t|)
## ar1     0.849297    0.008640   98.29837 0.000000
## ar2    -0.969316    0.003674 -263.80106 0.000000
## ma1    -0.863902    0.002660 -324.71409 0.000000
## ma2     1.001261    0.000339 2950.63826 0.000000
## omega   0.000001    0.000001    1.24447 0.213328
## alpha1  0.017724    0.027705    0.63972 0.522351
## beta1   0.970716    0.028451   34.11877 0.000000
## shape   6.869180    1.971982    3.48339 0.000495
##
## LogLikelihood : 2077.756
##
## Information Criteria
## ------------------------------------
##
## Akaike       -6.3199
## Bayes        -6.2651
## Shibata      -6.3202
## Hannan-Quinn -6.2986
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic p-value
## Lag[1]                      0.2214  0.6379
## Lag[2*(p+q)+(p+q)-1][11]    2.5705  1.0000
## Lag[4*(p+q)+(p+q)-1][19]    6.1855  0.9627
## d.o.f=4
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                    0.05852  0.8088
## Lag[2*(p+q)+(p+q)-1][5]   4.28429  0.2207
## Lag[4*(p+q)+(p+q)-1][9]   5.64604  0.3409
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]     5.144 0.500 2.000 0.02333
## ARCH Lag[5]     5.657 1.440 1.667 0.07228
## ARCH Lag[7]     5.787 2.315 1.543 0.15622
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  139.0561
## Individual Statistics:
## ar1     0.06105
## ar2     0.10252
## ma1     0.11350
## ma2     0.07253
## omega  12.60169
## alpha1  0.19102
## beta1   0.16698
## shape   0.44515
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.89 2.11 2.59
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          0.95586 0.3395
## Negative Sign Bias 0.03954 0.9685
## Positive Sign Bias 1.38081 0.1678
## Joint Effect       2.08060 0.5558
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     11.47       0.9069
## 2    30     21.99       0.8205
```

```
## 3    40     32.33       0.7663
## 4    50     36.68       0.9030
##
##
## Elapsed time : 0.5827842
```

8.3.2. Analytics Ci Moderate Fund of Funds

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(2,0,2)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## ar1      1.15754    0.038152  30.3401 0.000000
## ar2     -0.83159    0.094787  -8.7733 0.000000
## ma1     -1.14897    0.050396 -22.7990 0.000000
## ma2      0.78470    0.092438   8.4889 0.000000
## omega   -0.58890    0.010739 -54.8352 0.000000
## alpha1  -0.10006    0.022196  -4.5079 0.000007
## beta1    0.94715    0.001094 865.4809 0.000000
## gamma1   0.13802    0.008844  15.6050 0.000000
## shape   13.79160    6.558261   2.1029 0.035471
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## ar1      1.15754    0.026018  44.4894 0.000000
## ar2     -0.83159    0.100894  -8.2422 0.000000
## ma1     -1.14897    0.040599 -28.3002 0.000000
## ma2      0.78470    0.101062   7.7646 0.000000
## omega   -0.58890    0.015386 -38.2760 0.000000
```

```
## alpha1  -0.10006    0.023093  -4.3327 0.000015
## beta1    0.94715    0.001165 813.2472 0.000000
## gamma1   0.13802    0.009470  14.5746 0.000000
## shape   13.79160    5.087323   2.7110 0.006709
##
## LogLikelihood : 2747.301
##
## Information Criteria
## ------------------------------------
##
## Akaike       -8.3612
## Bayes        -8.2996
## Shibata      -8.3616
## Hannan-Quinn -8.3373
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      1.741  0.1870
## Lag[2*(p+q)+(p+q)-1][11]    6.054  0.4510
## Lag[4*(p+q)+(p+q)-1][19]   10.531  0.3828
## d.o.f=4
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.4926  0.4828
## Lag[2*(p+q)+(p+q)-1][5]    1.5973  0.7159
## Lag[4*(p+q)+(p+q)-1][9]    2.9993  0.7591
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]  0.009523 0.500 2.000  0.9223
## ARCH Lag[5]  1.792546 1.440 1.667  0.5189
## ARCH Lag[7]  2.502147 2.315 1.543  0.6120
##
```

```
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  0.9977
## Individual Statistics:
## ar1    0.07914
## ar2    0.06560
## ma1    0.05987
## ma2    0.04487
## omega  0.12901
## alpha1 0.11007
## beta1  0.13115
## gamma1 0.09716
## shape  0.03663
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.1 2.32 2.82
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           0.8676 0.3859
## Negative Sign Bias  0.1514 0.8797
## Positive Sign Bias  1.1494 0.2508
## Joint Effect        1.5934 0.6609
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     11.53       0.9046
## 2    30     27.95       0.5208
## 3    40     33.79       0.7059
## 4    50     48.13       0.5083
##
##
## Elapsed time : 0.5091119
```

8.3.3. Momentum International Balanced Feeder Fund A

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(2,0,2)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error     t value Pr(>|t|)
## mu      0.000479    0.000198     2.42062 0.015494
## ar1     0.325082    0.047242     6.88117 0.000000
## ar2     0.474015    0.052941     8.95367 0.000000
## ma1    -0.248302    0.039612    -6.26840 0.000000
## ma2    -0.625415    0.044746   -13.97702 0.000000
## omega  -0.053693    0.001703   -31.52951 0.000000
## alpha1  0.005803    0.014379     0.40358 0.686519
## beta1   0.993982    0.000050 19734.73330 0.000000
## gamma1  0.050091    0.002589    19.35095 0.000000
## shape   6.393958    1.367361     4.67613 0.000003
##
## Robust Standard Errors:
##         Estimate  Std. Error    t value Pr(>|t|)
## mu      0.000479    0.000148     3.2427 0.001184
## ar1     0.325082    0.022873    14.2127 0.000000
## ar2     0.474015    0.027192    17.4319 0.000000
## ma1    -0.248302    0.015904   -15.6120 0.000000
## ma2    -0.625415    0.019078   -32.7813 0.000000
## omega  -0.053693    0.001912   -28.0785 0.000000
## alpha1  0.005803    0.013061     0.4443 0.656825
## beta1   0.993982    0.000058 17196.2530 0.000000
## gamma1  0.050091    0.004632    10.8131 0.000000
## shape   6.393958    1.158627     5.5186 0.000000
```

```
##
## LogLikelihood : 1980.136
##
## Information Criteria
## ------------------------------------
##
## Akaike       -6.0157
## Bayes        -5.9472
## Shibata      -6.0161
## Hannan-Quinn -5.9891
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                   0.003745  0.9512
## Lag[2*(p+q)+(p+q)-1][11]  4.235487  0.9994
## Lag[4*(p+q)+(p+q)-1][19]  8.422642  0.7321
## d.o.f=4
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                        statistic p-value
## Lag[1]                    0.1742 0.67645
## Lag[2*(p+q)+(p+q)-1][5]    8.4441 0.02284
## Lag[4*(p+q)+(p+q)-1][9]   11.6246 0.02206
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale   P-Value
## ARCH Lag[3]     12.98 0.500 2.000 0.0003149
## ARCH Lag[5]     14.11 1.440 1.667 0.0006390
## ARCH Lag[7]     14.38 2.315 1.543 0.0016384
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.5938
## Individual Statistics:
```

```
## mu     0.15453
## ar1    0.13476
## ar2    0.50224
## ma1    0.14124
## ma2    0.48699
## omega  0.09368
## alpha1 0.04498
## beta1  0.09416
## gamma1 0.25255
## shape  0.08310
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.29 2.54 3.05
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           1.8778 0.06085   *
## Negative Sign Bias  0.3597 0.71920
## Positive Sign Bias  1.2917 0.19692
## Joint Effect        4.1015 0.25071
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     13.49       0.8126
## 2    30     16.22       0.9729
## 3    40     27.32       0.9202
## 4    50     41.26       0.7761
##
##
## Elapsed time : 0.615123
```

8.3.4. Oasis Crescent Balanced High Equity Fund of Funds D

```
##
## *---------------------------------*
```

```
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(2,0,2)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error    t value Pr(>|t|)
## ar1     0.231135    0.005429    42.5778 0.000000
## ar2    -0.996165    0.006949  -143.3584 0.000000
## ma1    -0.240885    0.010380   -23.2074 0.000000
## ma2     0.994418    0.000056 17695.7207 0.000000
## omega  -3.941427    1.626714    -2.4229 0.015396
## alpha1 -0.101138    0.058227    -1.7370 0.082395
## beta1   0.623374    0.155874     3.9992 0.000064
## gamma1  0.086409    0.077557     1.1141 0.265222
## shape  12.334137    5.120311     2.4089 0.016002
##
## Robust Standard Errors:
##         Estimate  Std. Error    t value Pr(>|t|)
## ar1     0.231135    0.007316    31.5916 0.000000
## ar2    -0.996165    0.010055   -99.0673 0.000000
## ma1    -0.240885    0.015784   -15.2609 0.000000
## ma2     0.994418    0.000059 16866.0824 0.000000
## omega  -3.941427    1.387748    -2.8402 0.004509
## alpha1 -0.101138    0.063023    -1.6048 0.108539
## beta1   0.623374    0.132466     4.7059 0.000003
## gamma1  0.086409    0.066660     1.2963 0.194888
## shape  12.334137    4.627075     2.6656 0.007684
##
## LogLikelihood : 2507.489
##
## Information Criteria
## ------------------------------------
##
```

```
## Akaike       -7.6290
## Bayes        -7.5674
## Shibata      -7.6293
## Hannan-Quinn -7.6051
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                    0.05272  0.8184
## Lag[2*(p+q)+(p+q)-1][11]   6.52188  0.1908
## Lag[4*(p+q)+(p+q)-1][19]  12.85558  0.1195
## d.o.f=4
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      0.202  0.6531
## Lag[2*(p+q)+(p+q)-1][5]     4.521  0.1959
## Lag[4*(p+q)+(p+q)-1][9]     5.955  0.3034
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]     6.117 0.500 2.000 0.01339
## ARCH Lag[5]     6.368 1.440 1.667 0.04920
## ARCH Lag[7]     6.472 2.315 1.543 0.11253
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.3923
## Individual Statistics:
## ar1    0.09666
## ar2    0.14939
## ma1    0.07102
## ma2    0.11346
## omega  0.16144
## alpha1 0.23407
```

```
## beta1  0.16285
## gamma1 0.68145
## shape  0.60248
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.1 2.32 2.82
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.0518 0.2933
## Negative Sign Bias  0.8735 0.3827
## Positive Sign Bias  0.2444 0.8070
## Joint Effect        1.2933 0.7307
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     12.69       0.8538
## 2    30     18.88       0.9244
## 3    40     39.41       0.4514
## 4    50     44.31       0.6633
##
##
## Elapsed time : 1.044708
```

8.3.5. Allan Gray Tax-Free Balanced Fund A

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(2,0,2)
```

```
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error    t value Pr(>|t|)
## ar1    -0.886711    0.005895  -150.4167 0.000000
## ar2    -0.967115    0.003128  -309.1505 0.000000
## ma1     0.926601    0.000819  1131.0529 0.000000
## ma2     1.007177    0.000093 10857.2407 0.000000
## omega  -0.452845    0.001988  -227.8019 0.000000
## alpha1 -0.058364    0.022922    -2.5462 0.010890
## beta1   0.957780    0.000409  2344.1451 0.000000
## gamma1  0.087792    0.003086    28.4517 0.000000
## shape  16.593129    9.261943     1.7915 0.073207
##
## Robust Standard Errors:
##         Estimate  Std. Error   t value Pr(>|t|)
## ar1    -0.886711    0.010235  -86.6380 0.000000
## ar2    -0.967115    0.005761 -167.8787 0.000000
## ma1     0.926601    0.001035  894.9172 0.000000
## ma2     1.007177    0.000252 3992.7728 0.000000
## omega  -0.452845    0.007871  -57.5313 0.000000
## alpha1 -0.058364    0.023532   -2.4802 0.013131
## beta1   0.957780    0.000673 1422.9646 0.000000
## gamma1  0.087792    0.004579   19.1729 0.000000
## shape  16.593129    9.952360    1.6673 0.095464
##
## LogLikelihood : 2605.244
##
## Information Criteria
## ------------------------------------
##
## Akaike       -7.9275
## Bayes        -7.8658
## Shibata      -7.9278
## Hannan-Quinn -7.9036
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
```

```
##                          statistic p-value
## Lag[1]                      0.7776  0.3779
## Lag[2*(p+q)+(p+q)-1][11]    2.5163  1.0000
## Lag[4*(p+q)+(p+q)-1][19]    6.5978  0.9393
## d.o.f=4
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.9295  0.3350
## Lag[2*(p+q)+(p+q)-1][5]    1.7337  0.6825
## Lag[4*(p+q)+(p+q)-1][9]    2.6565  0.8140
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.1833 0.500 2.000  0.6686
## ARCH Lag[5]    1.5520 1.440 1.667  0.5787
## ARCH Lag[7]    1.6841 2.315 1.543  0.7838
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.1222
## Individual Statistics:
## ar1    0.21132
## ar2    0.15063
## ma1    0.03965
## ma2    0.10654
## omega  0.19833
## alpha1 0.11689
## beta1  0.19980
## gamma1 0.20711
## shape  0.13952
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.1 2.32 2.82
## Individual Statistic:     0.35 0.47 0.75
```

```
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           0.8096 0.4185
## Negative Sign Bias  0.9178 0.3590
## Positive Sign Bias  0.3996 0.6896
## Joint Effect        1.5936 0.6608
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     13.61       0.8059
## 2    30     20.07       0.8908
## 3    40     29.64       0.8603
## 4    50     36.53       0.9061
##
##
## Elapsed time : 0.688906
```

8.3.6. Coronation Balanced Plus Fund A

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(1,0,2)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error    t value Pr(>|t|)
## mu      0.000214    0.000126     1.7043 0.088320
## ar1     0.938763    0.013566    69.1993 0.000000
```

```
## ma1    -0.835801    0.000340 -2456.9711 0.000000
## ma2    -0.124992    0.000698  -179.1878 0.000000
## omega  -1.019102    0.260039    -3.9190 0.000089
## alpha1 -0.086249    0.030792    -2.8010 0.005094
## beta1   0.903338    0.024665    36.6237 0.000000
## gamma1  0.199287    0.053086     3.7540 0.000174
## shape  23.564511   18.479347     1.2752 0.202245
##
## Robust Standard Errors:
##         Estimate  Std. Error    t value Pr(>|t|)
## mu      0.000214    0.000129     1.6636 0.096198
## ar1     0.938763    0.011777    79.7116 0.000000
## ma1    -0.835801    0.000277 -3022.7314 0.000000
## ma2    -0.124992    0.000848  -147.4541 0.000000
## omega  -1.019102    0.190347    -5.3539 0.000000
## alpha1 -0.086249    0.032595    -2.6460 0.008144
## beta1   0.903338    0.018092    49.9292 0.000000
## gamma1  0.199287    0.056543     3.5245 0.000424
## shape  23.564511   16.597517     1.4198 0.155677
##
## LogLikelihood : 2521.733
##
## Information Criteria
## ------------------------------------
##
## Akaike       -7.6725
## Bayes        -7.6108
## Shibata      -7.6728
## Hannan-Quinn -7.6486
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.2376  0.6259
## Lag[2*(p+q)+(p+q)-1][8]    1.9051  1.0000
## Lag[4*(p+q)+(p+q)-1][14]   6.0298  0.7460
## d.o.f=3
## H0 : No serial correlation
##
```

```
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.1552  0.6936
## Lag[2*(p+q)+(p+q)-1][5]    1.3313  0.7813
## Lag[4*(p+q)+(p+q)-1][9]    3.6998  0.6401
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]   0.09872 0.500 2.000  0.7534
## ARCH Lag[5]   2.53571 1.440 1.667  0.3646
## ARCH Lag[7]   3.00882 2.315 1.543  0.5119
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.028
## Individual Statistics:
## mu     0.09344
## ar1    0.03143
## ma1    0.02925
## ma2    0.02964
## omega  0.70754
## alpha1 0.26128
## beta1  0.69172
## gamma1 0.05216
## shape  0.24613
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.1 2.32 2.82
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          1.30198 0.1934
## Negative Sign Bias 0.03351 0.9733
## Positive Sign Bias 0.89152 0.3730
```

```
## Joint Effect       2.45018 0.4844
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     13.43       0.8160
## 2    30     26.21       0.6145
## 3    40     42.22       0.3335
## 4    50     52.86       0.3273
##
##
## Elapsed time : 0.534945
```

8.3.7. Kagiso Islamic Balanced Fund A

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(0,0,1)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      0.000340    0.000174  1.95032 0.051138
## ma1     0.053607    0.042965  1.24768 0.212147
## omega  -9.999999    3.398815 -2.94220 0.003259
## alpha1 -0.012028    0.065541 -0.18351 0.854396
## beta1   0.071391    0.314736  0.22683 0.820557
## gamma1  0.408089    0.099367  4.10688 0.000040
## shape   6.666648    1.796230  3.71147 0.000206
##
## Robust Standard Errors:
```

```
##          Estimate  Std. Error  t value Pr(>|t|)
## mu       0.000340    0.000174  1.95915 0.050095
## ma1      0.053607    0.047427  1.13030 0.258352
## omega   -9.999999    4.031662 -2.48037 0.013125
## alpha1  -0.012028    0.077721 -0.15476 0.877014
## beta1    0.071391    0.376417  0.18966 0.849576
## gamma1   0.408089    0.110515  3.69262 0.000222
## shape    6.666648    1.743721  3.82323 0.000132
##
## LogLikelihood : 2614.758
##
## Information Criteria
## ------------------------------------
##
## Akaike       -7.9626
## Bayes        -7.9147
## Shibata      -7.9628
## Hannan-Quinn -7.9440
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.1338  0.7146
## Lag[2*(p+q)+(p+q)-1][2]    0.1501  0.9996
## Lag[4*(p+q)+(p+q)-1][5]    1.4229  0.8651
## d.o.f=1
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.7907  0.3739
## Lag[2*(p+q)+(p+q)-1][5]    4.5848  0.1896
## Lag[4*(p+q)+(p+q)-1][9]    7.6654  0.1496
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
```

```
## ARCH Lag[3]    0.9064 0.500 2.000  0.3411
## ARCH Lag[5]    3.7404 1.440 1.667  0.1989
## ARCH Lag[7]    4.8779 2.315 1.543  0.2372
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.4352
## Individual Statistics:
## mu     0.05379
## ma1    0.16929
## omega  0.36692
## alpha1 0.09195
## beta1  0.37269
## gamma1 0.12778
## shape  0.27150
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.69 1.9 2.35
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          0.44672 0.6552
## Negative Sign Bias 0.98126 0.3268
## Positive Sign Bias 0.02813 0.9776
## Joint Effect       0.97007 0.8085
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     11.17       0.9181
## 2    30     15.12       0.9840
## 3    40     26.71       0.9325
## 4    50     41.26       0.7761
##
##
## Elapsed time : 0.4941418
```

8.3.8. Old Mutual Balanced Fund A

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(0,0,2)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error   t value Pr(>|t|)
## ma1     0.120755    0.031166    3.8746 0.000107
## ma2    -0.051063    0.037280   -1.3697 0.170780
## omega  -0.628558    0.004950 -126.9898 0.000000
## alpha1 -0.116951    0.022369   -5.2283 0.000000
## beta1   0.941678    0.000194 4845.7528 0.000000
## gamma1  0.070535    0.012281    5.7432 0.000000
## shape  13.935498    6.654379    2.0942 0.036244
##
## Robust Standard Errors:
##         Estimate  Std. Error   t value Pr(>|t|)
## ma1     0.120755    0.024962    4.8375 0.000001
## ma2    -0.051063    0.032783   -1.5576 0.119331
## omega  -0.628558    0.006140 -102.3744 0.000000
## alpha1 -0.116951    0.023779   -4.9183 0.000001
## beta1   0.941678    0.000178 5278.2385 0.000000
## gamma1  0.070535    0.011418    6.1776 0.000000
## shape  13.935498    6.411594    2.1735 0.029744
##
## LogLikelihood : 2625.119
##
## Information Criteria
## ------------------------------------
##
```

```
## Akaike       -7.9943
## Bayes        -7.9463
## Shibata      -7.9945
## Hannan-Quinn -7.9757
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.1254  0.7232
## Lag[2*(p+q)+(p+q)-1][5]    0.4507  1.0000
## Lag[4*(p+q)+(p+q)-1][9]    2.0535  0.9822
## d.o.f=2
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                    0.01524 0.90176
## Lag[2*(p+q)+(p+q)-1][5]   4.99499 0.15349
## Lag[4*(p+q)+(p+q)-1][9]   8.67693 0.09458
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]  0.001145 0.500 2.000 0.97300
## ARCH Lag[5]  7.741082 1.440 1.667 0.02316
## ARCH Lag[7]  8.929129 2.315 1.543 0.03244
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.0234
## Individual Statistics:
## ma1    0.07803
## ma2    0.07336
## omega  0.14620
## alpha1 0.13677
## beta1  0.14628
## gamma1 0.06038
```

```
## shape  0.09625
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.69 1.9 2.35
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           0.7986 0.4248
## Negative Sign Bias  0.4307 0.6668
## Positive Sign Bias  0.3936 0.6940
## Joint Effect        1.8350 0.6073
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     16.11       0.6496
## 2    30     22.36       0.8050
## 3    40     41.98       0.3431
## 4    50     57.44       0.1909
##
##
## Elapsed time : 0.325119
```