1 Introduction

Problem Statement: Estimating Volatility

The objective of this assignment is to formulate an upper bound of rolling risk calculated from the active returns of a portfolio. In order to obtain a bound, a model will be derived to estimate volatility and then the upper 5 percentile of the estimated volatilities will be used as the upper limit.

The generalized autoregressive conditional heteroscedasticity (GARCH) approach is one of the common and simpler ways to use historical data to produce estimates of current and future levels of volatilities. This model recognizes that volatilities are not constant, for instance, a particular volatility may be high or low depending on the period of time. One of goals of a GARCH model is to track the variations in the volatility through time.

Rolling risk identifies changes in the volatility of a manager’s excess returns over time. One of the goals in tracking this variation is the possibility that it may signal changes in the investment process. The project was to derive a methodology for an upper limit to the rolling risk charts. Using the natural logarithm of the monthly active returns, a GARCH model was derived to simulate a time series of volatilities in the active returns. All models and statistics were generated and calculated using Excel.
2 Methodology

2.1 Notation

The following are a list of notion that were used.

1. $u_i$: Natural logarithm of the monthly active return

2. $\sigma_n$: The volatility of the market variable on day $n$, as estimated at the end of day $n-1$

2.2 Weighting Scheme

Using a similar method to calculating variance in fundamental statistics, to estimate the current level of volatility, $\sigma_n$, will use a weighting scheme which will assign more weight to recent data.

$$\sigma_n^2 = \sum_{i=1}^{m} \alpha_i u_{n-i}^2$$ (1)

The variable $\alpha_i$ uses the amount of weight given to the observation $i$ days ago. The restrictions on $\alpha$’s are the following:

1. $\alpha_i \geq 0$

2. Choose $\alpha_i < \alpha_j$, when $i > j$, were less weight is given to older observations.

3. $\sum_{i=1}^{m} \alpha_i = 1$

To understand the approach of the GARCH, one of the assumptions in the model is that there is a weighted long-run average variance rate. Therefore (1) can be written

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^{m} \alpha_i u_{n-i}^2$$ (2)

where $V_L$ is the long-run variance rate and the $\gamma$ is the weight assigned to $V_L$.

The GARCH(1,1) model calculates $\sigma_n^2$ from the long-run variance rate, $V_L$, as well from $\sigma_{n-1}$ and $u_{n-1}$. The equation is given by

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$ (3)

where $\gamma$ is the weight assigned to $V_L$, $\alpha$ is weight assigned to $u_{n-1}^2$, and $\beta$ is the weight assigned to $\sigma_{n-1}^2$. The weights must sum up to one.

The GARCH(1,1) model is based on the fact that over time the variance tends to get pulled back to the long-run average level $V_L$. The amount of weight assigned to $V_L$ is $\gamma = 1 - \alpha - \beta$. This model is similar to the Exponentially weighted moving average model (EWMA) expect that, in addition to assigning the weights that decline exponentially to past $u^2$, it also assigns a weight to $V_L$.

In this paper, a EWMA model is generated and presented, however, the focus of this paper is to model using a GARCH(1,1) process.

The GARCH(1,1) indicates that $\sigma_n^2$ is based on the most recent observation of $u^2$ and the most recent estimate of the variance rate. The more general
GARCH\((p, q)\) model calculates \(\sigma^2_n\) from the most recent \(p\) observations on \(u^2\) and the most recent \(q\) estimates of the variance rate.

Setting \(\omega = \gamma V_L\), the GARCH(1,1) equation in (2) can be written by

\[
\sigma^2_n = \omega + \alpha u^2_{n-1} + \beta \sigma^2_{n-1} \tag{4}
\]

3 Estimating Parameters

The process used to estimate the parameters of the GARCH(1,1) model from historical data is known as the maximum likelihood method. This method involves choosing values for the parameters that maximize the likelihood of the data occurring. The problem is to estimate a variance of the returns from \(m\) observations of the variable when the underlying distribution is normal with zero mean.

Define \(v_i = \sigma^2_i\) as the variance estimated for day \(i\). Assume that the probability distribution of \(u_i\) conditional on the variance is normal. The parameters that best fit the model are the ones that maximize

\[
\prod_{i=1}^{m} \frac{1}{\sqrt{2\pi v_i}} \exp\left(-\frac{u_i^2}{2v_i}\right) \tag{5}
\]

Taking logarithms of (5), the maximization problem reduces to

\[
\sum_{i=1}^{m} \left[-\ln(v_i) - \frac{u_i^2}{v_i}\right] \tag{6}
\]
4 Summary

To formulate an upper bound on annualized active risk of a given portfolio based on historical data to be used for control and tracking purposes of volatility in risk management. The current approach to an upper bound is using an accepted standard of rolling risk calculated from the active returns of a portfolio. In order to obtain a bound, a model will be derived to estimate and track volatility over time and then the upper 5 percentile of the estimated volatilities will be used as the upper limit.

A common approach to model volatility is using a generalized autoregressive conditional heteroscedasticity (GARCH) model. This model assumes that the returns at time, t, has a normal distribution. In this paper, a GARCH(1,1) is estimated on each of the portfolios that we wish to track the volatility of the active returns. This was one of the reasons why this model was chosen. It will help to indicate a control limit and track the variation in the active returns. Other motivating factors include, the model’s assumptions related to mean reversion, distribution of the weights on recent observations, and the ability to estimate the parameters in the model.

The critical parameter in risk management is volatility. The ability to track, create an upper bound, and forecast volatility would be a significant improvement in analyzing and controlling risk. Unfortunately, volatility is not an easy phenomenon to predict or forecast. One class of models which have proved successful in forecasting volatility in many situations is the GARCH family of models. The model, with certain assumptions, attempts to keep track of the variations in the volatility through time.

The GARCH(1,1) indicates that predicted variance rate is based on the most recent observation of the squared average and the most recent estimate of the variance rate. The more general GARCH(p,q) model calculates variance rate from the most recent p observations on squared average and the most recent q estimates of the variance rate. This family of models also assumes that over time, the variance tends to get pulled back to a long-run average level. The GARCH(1,1) model can be viewed as a mean-reverting stochastic model where the variance has a drift that pulls it back to the long-run variance at a certain rate.

4.1 Advantages of GARCH

A common phenomenon in volatility is clustering, in which there are periods of high and low variance in the data, and where large changes tend to be clustered around large changes, and small tend to be followed by small. The aim of a GARCH model is to encompass this volatility clustering as well as the leptokurtic behavior in the tails of the distribution of the underlying data; therefore, the tail distribution of the GARCH process is heavier than that of a normal distribution. The proof lies in the details regarding the 4th moment of the model. Along with the ability to model the volatility evolution, the model also assigns weights that decline exponentially to past observations in the data. Therefore more recent shock has more impact on the model. This may be an advantage.
over using rolling risk for 5 year data. Analyzing both a GARCH(1,1) model and a rolling risk of the data, it can be illustrated that the shock to the data can be view more so in the model. Also, the impact of the shock will dissipate earlier in the model. Furthermore, because of the recent events, this model also encompasses the "black swan" events, which refer to a sudden large, unexpected movement in the data.

4.2 Disadvantages of GARCH

A common disadvantage to standard GARCH models exist since they cannot model asymmetries of the volatility with respect to the sign of past shocks. Therefore they have an effect on the level, but no effect on the sign. Bad news which is identified by a negative sign has the same influence on the volatility as good news, a positive sign if the absolute values are the same. In the data, bad news has a larger effect on volatility than good news. This, so called, Leverage-Effect, can be modeled using extensions to the GARCH, such as a threshold GARCH, which models the asymmetry in volatility. TGARCH may be a consideration for future volatility models.

4.3 Summary of Parameter Estimation

In estimating the parameters of the GARCH(1,1) model from the dataset, the technique of the maximum likelihood estimation was implemented. On a given day, the returns for the next day are assumed to be conditional distributed as a normal random variable with mean zero and a variance rate. Assuming that the returns are independent, the joint distribution can be factored as the product of marginal densities. Thus, the joint distribution can be expressed as the likelihood function. Values for the parameters of the model that produces the maximum value of the log-likelihood function are the MLEs of the parameters. The method used in this paper, uses this approach for each dataset to obtain the values of the parameters which maximizes the MLEs for each of the GARCH(1,1) models. Using Excel, the method is implemented and tested for each model.

4.4 Testing of Model

Several tests were run on the data and the model to support this application of the GARCH model. For each of the datasets, the log active returns was tested for Normality using the Jarque-Bera tests, other tests can be implemented as well, such as the Sharpio-Wilk test.

The underlying assumption in a GARCH model is that volatility changes over time. Periods of volatility are correlated within the same group, as discussed earlier with the effect of volatility clustering. To examine the effectiveness of the model, this paper studies the structure of the autocorrelations. If the GARCH model is working well, it should remove the autocorrelation. The Ljung-Box
statistic test was used to validate the model for the variance rate. The plots of the series autocorrelations are also presented in hopes to show that the autocorrelations for all lags are small, and show no pattern. Overall, the goal is to show that the GARCH model accounts for the evolution of the volatility in active returns and is effective in eliminating the autocorrelation in squared returns.

4.5 Summary of Results

For each of the following portfolios, a GARCH(1,1) model is present and tested with the corresponding control limit. 1. (FRSGDAN004A0) - Domestic Equities 2. (FRSGFAY001A0) - Fixed Income Investment Grade vs Target 3. (SMTT10) - Total Fund ABAL Wgt 4. (FRSGNNU003A0) Foreign Equities For all but 1, (FRSGNNU003A0) Foreign Equities, the GARCH(1,1) model was able to remove the autocorrelations in the squared returns. For this particular portfolio, the number of data points was less than all others, n=200, which may have been a contributing factor as to why the GARCH was not able to remove the autocorrelations.

In conclusion, I believe the overall goal is to capture the shocks to the volatility before the event occurs, instead of waiting for the series to identify an alert by passing the UCL. Analyzing the periods during which the process modeled using the GARCH(1,1) was out-of-control, (above the 95% bounds), displays large movements in the one month active returns before the signaled alert. This can be seen during a certain time range of the data that was used in this paper. This may be a future application to this model in practical usage.

4.6 FAQ:

• Why the GARCH(1,1) approach was taken?

The reason a GARCH process is used to model volatility can be addressed by viewing the strengths of the model and how this correlates with the behaviors, assumptions, and characteristics of a time series of financial data. The advantages, which were summarized before, will provide a model which enable to track volatility evolution.

• Why the estimated volatilities may be more substantial than actual values?

The argument has been brought up as to why use the estimated volatilities from the GARCH(1,1) model versus the actual risk generated from the data for that given time period/range. To answer to why the model may be more beneficial than the actual values lies in the weighting scheme of the observations that helps to build the GARCH(1,1) model. Using the actual risk calculated from the variance of historical data is an unbiased estimator of the variance rate. In that formula there is an equally weighted shock to past observations. Calculating rolling risk for 5 years, distributes
the weight equally for each of the observations for the past 5 years, a factor that has lead to issue of independence. Whereas, in a GARCH model, the estimated volatilities from the model are built upon the same dataset, however, the model places more weight on recent data. This scheme reaffirms the previously discussed advantages to the model.

- Interpretation of the control limit derived in the GARCH(1,1)

The GARCH model is derived from the assumption that the data of asset returns follows a normal distribution with zero mean and the distribution of the returns conditional on the variance is also normal. There exists two random variables in the model, the returns and the variance rate. For example, the variance of X when drawing from a population of (X,Y) that yields Y is a constant term. For example, if X is height and Y is weight of a certain population of people, to understand the conditional distribution of X given Y, then consider the variance of the height of people in a sample given a weight is constant of that sample. Using this assumption that the probability distribution of the returns conditional on the variance is normal leads into the explanation as to why the upper five percentile of the estimated volatilities was used as a control limit. Using a similar approach as in quality control charts and the using the assumptions of normality, the processes can be within certain control limits. I purpose that a certain number of the estimated volatilities should be within certain bounds as the accepted norm behavior. The upper control bound calculated from the upper five percent signify the upper 5 percent of estimated volatilities that are extremes within the dataset. There has been research in this area to develop control schemes for this type of data, either using constant control limits or time-varying limits. Creating and substantiating time-varying control bounds can investigate for further analysis, however, for ease of implementation, a constant control limit was taken for preliminary analysis. Furthermore, analyzing the periods during which the process modeled using the GARCH(1,1) was out-of-control, (above the 95% bounds), displayed large movements in the one month active returns before the signaled alert. (http://darkwing.uoregon.edu/ yfang/JAS1999.pdf)
5 Results for (FRSGDAN004A0) - Domestic Equities

The GARCH(1,1) model and Rolling Risk of (FRSGDAN004A0) - Domestic Equities is presented below.

\[ \sigma^2_n = 0.00000074 + 0.2083 \sigma^2_{n-1} + 0.7196 \sigma^2_{n-1} \] (7)

Because \( \gamma = 1 - \alpha - \beta \), then \( \gamma = 0.0772 \), thus \( \omega = \gamma V_L \), so \( V_L = 0.0000102 \).

The long-run average variance per month implied by the model is 0.0000102. The volatility of \( \sqrt{0.0000095} = 0.0032 \) or 0.32% per month.

Below are three graphs with the 5-year Rolling Risk with a modeled GARCH process for (FRSGDAN004A0) - Domestic Equities.

As a comparison, a graph below with the 5-year Rolling Risk with a modeled EWMA process for (FRSGDAN004A0) - Domestic Equities is presented. The same method was used to maximize the likelihood function, however, initial values were \( \omega = 0 \), \( \alpha = 1 - \lambda \), and \( \lambda = 0.97 \).
6 Significance of Model for (FRSGDAN004A0) - Domestic Equities

The GARCH model assumes that volatility changes with the passage of time. There may exist periods of relatively high and low volatility. Thus, can expect when \( u_i^2 \) to be high, then \( u_{i+1}^2 \) is high, also when \( u_i^2 \) is low, this implies \( u_{i+1}^2 \) to be low. Analyzing the autocorrelation structure of \( u_i^2 \), will help determine if the autocorrelation were removed by the GARCH model.

If assume that \( u_i^2 \) do exhibit autocorrelation, then if the GARCH model is working well, the autocorrelation should be removed. To test the GARCH model, will examine the autocorrelation structure of \( \frac{u_i^2}{\sigma_i^2} \). If this is less significant using a Ljung-Box Statistic test, then the model of \( \sigma_i \) has explained the autocorrelations in \( u_i^2 \).

Below is the autocorrelations for \( u_i^2 \) and for \( \frac{u_i^2}{\sigma_i^2} \) for a lag length of \( k = 36 \) for (FRSGDAN004A0) - Domestic Equities

![Autocorrelation plots](Image)

For \( K = 36 \), if the Ljung-Box Statistic = \( Q > \chi_{1-\alpha,K} \), then then there is statistical evidence to say at least one of the first \( K \) autocorrelations is non-zero.

For \( K = 36 \), zero autocorrelations can be rejected with 99.75% confidence when the Ljung-Box statistic, \( Q \), is greater than \( \chi_{0.0025,36} = 64 \).

Model 1 From the dataset for (FRSGDAN004A0) - Domestic Equities, the Ljung-Box statistic for \( u_i^2 \) series, \( Q = 131.652 \). This is strong evidence of autocorrelation. For the \( \frac{u_i^2}{\sigma_i^2} \) series the Ljung-Box statistic, \( Q = 57.596 \), suggesting
that the autocorrelation has been removed by the GARCH model. Model 2

From the dataset for (FRSGDAN004A0) - Domestic Equities, the Ljung-Box statistic for $u_i^2$ series, $Q = 132.57$. This is strong evidence of autocorrelation.

For the $\frac{u_i^2}{\hat{\sigma}_i^2}$ series the Ljung-Box statistic, $Q = 58.837$, suggesting that the autocorrelation has been removed by the GARCH model.
7 Results for (FRSGFAY001A0) - Fixed Income Investment Grade vs Target

The GARCH(1,1) model and Rolling Risk of (FRSGFAY001A0) - Fixed Income Investment Grade vs Target is presented below.

Below are two graphs with the 5-year Rolling Risk with a modeled GARCH process for (FRSGFAY001A0) - Fixed Income Investment Grade vs Target.
8 Significance of Model for (FRSGFY001A0) - Fixed Income Investment Grade vs Target

The GARCH model assumes that volatility changes with the passage of time. There may exist periods of relatively high and low volatility. Thus, can expect when \( u_t^2 \) to be high, then \( u_{t+1}^2 \) is high, also when \( u_t^2 \) is low, this implies \( u_{t+1}^2 \) to be low. Analyzing the autocorrelation structure of \( u_t^2 \), will help determine if the autocorrelation were removed by the GARCH model.

If assume that \( u_t^2 \) do exhibit autocorrelation, then if the GARCH model is working well, the autocorrelation should be removed. To test the GARCH model, will examine the autocorrelation structure of \( \frac{u_t^2}{\sigma_t^2} \). If this is less significant using a Ljung-Box Statistic test, then the model of \( \sigma_t \) has explained the autocorrelations in \( u_t^2 \).

Below is the autocorrelations for \( u_t^2 \) and for \( \frac{u_t^2}{\sigma_t^2} \) for a lag length of \( k = 36 \) for (FRSGFY001A0) - Fixed Income Investment Grade vs Target.

For \( K = 36 \), zero autocorrelations can be rejected with 99.75% confidence when the Ljung-Box statistic, \( Q \), is greater than \( \chi_{0.0025,36} = 64 \).

Model 1 From the dataset for (FRSGFY001A0) - Fixed Income Investment Grade vs Target, the Ljung-Box statistic for \( u_t^2 \) series, \( Q = 184.848 \). This is strong evidence of autocorrelation. For the \( \frac{u_t^2}{\sigma_t^2} \) series the Ljung-Box statistic, \( Q = 68.099 \), suggesting that the autocorrelation has not been removed.
by the GARCH model. Model 2 From the dataset for (FRSGFAY001A0) - Fixed Income Investment Grade vs Target, the Ljung-Box statistic for $u_t^2$ series, $Q = 184.89$. This is strong evidence of autocorrelation. For the $\frac{u_t^2}{\sigma_t^2}$ series the Ljung-Box statistic, $Q = 62.688$, suggesting that the autocorrelation has been removed by the GARCH model.
9 Results for (SMTT10) - Total Fund ABAL Wgt

The GARCH(1,1) model and Rolling Risk of (SMTT10) - Total Fund ABAL Wgt is presented below.

Below are two graphs with the 5-year Rolling Risk with a modeled GARCH process for (SMTT10) - Total Fund ABAL Wgt.
10 Significance of Model for (SMTT10) - Total Fund ABAL Wgt.

The GARCH model assumes that volatility changes with the passage of time. There may exist periods of relatively high and low volatility. Thus, can expect when \( u^2_i \) to be high, then \( u^2_{i+1} \) is high, also when \( u^2_i \) is low, this implies \( u^2_{i+1} \) to be low. Analyzing the autocorrelation structure of \( u^2_i \), will help determine if the autocorrelation were removed by the GARCH model.

If assume that \( u^2_i \) do exhibit autocorrelation, then if the GARCH model is working well, the autocorrelation should be removed. To test the GARCH model, will examine the autocorrelation structure of \( \frac{\sigma^2_i}{\sigma^2_i} \). If this is less significant using a Ljung-Box Statistic test, then the model of \( \sigma_i \) has explained the autocorrelations in \( u^2_i \).

Below is the autocorrelations for \( u^2_i \) and for \( \frac{\sigma^2_i}{\sigma^2_i} \) for a lag length of \( k = 36 \) for (SMTT10) - Total Fund ABAL Wgt.

For \( K = 36 \), if the Ljung-Box Statistic = \( Q > \chi_{1-\alpha,K} \), then then there is statistical evidence to say at least one of the first \( K \) autocorrelations is non-zero.

For \( K = 36 \), zero autocorrelations can be rejected with 99.75% confidence when the Ljung-Box statistic, \( Q \), is greater than \( \chi_{0.0025,36} = 64 \).

Model 1 From the dataset for (SMTT10) - Total Fund ABAL Wgt, the Ljung-Box statistic for \( u^2_i \) series, \( Q = 287.326 \). This is strong evidence of autocorrelation. For the \( \frac{\sigma^2_i}{\sigma^2_i} \) series the Ljung-Box statistic, \( Q = 69.769 \), suggesting that the autocorrelation has not been removed by the GARCH model. Model 2 From
the dataset for (SMTT10) - Total Fund ABAL Wgt, the Ljung-Box statistic for \( u_i^2 \) series, \( Q = 289.144 \). This is strong evidence of autocorrelation. For the \( \frac{u_i^2}{\hat{\sigma}_i^2} \) series the Ljung-Box statistic, \( Q = 41.014 \), suggesting that the autocorrelation has been removed by the GARCH model.
11 Results for (FRSGNNU003A0) Foreign Equities

The GARCH(1,1) model and Rolling Risk of (FRSGNNU003A0) Foreign Equities is presented below.

Below are two graphs with the 5-year Rolling Risk with a modeled GARCH process for (FRSGNNU003A0) Foreign Equities.
12 Significance of Model for (FRSGNNU003A0) Foreign Equities.

The GARCH model assumes that volatility changes with the passage of time. There may exist periods of relatively high and low volatility. Thus, we can expect when $u_i^2$ is high, then $u_{i+1}^2$ is high, also when $u_i^2$ is low, this implies $u_{i+1}^2$ to be low. Analyzing the autocorrelation structure of $u_i^2$, will help determine if the autocorrelation were removed by the GARCH model.

If assume that $u_i^2$ do exhibit autocorrelation, then if the GARCH model is working well, the autocorrelation should be removed. To test the GARCH model, will examine the autocorrelation structure of $\frac{u_i^2}{\sigma_i^2}$. If this is less significant using a Ljung-Box Statistic test, then the model of $\sigma_i$ has explained the autocorrelations in $u_i^2$.

Below is the autocorrelations for $u_i^2$ and for $\frac{u_i^2}{\sigma_i^2}$ for a lag length of $k = 12$ for (FRSGNNU003A0) Foreign Equities. The lag was changed from the other charts due to the shorter time period of the data.

For $K = 36$, if the Ljung-Box Statistic = $Q > \chi_{1-\alpha,K}$, then then there is statistical evidence to say at least one of the first $K$ autocorrelations is non-zero.

For $K = 36$, zero autocorrelations can be rejected with 99.75% confidence when the Ljung-Box statistic, $Q$, is greater than $\chi_{0.0025,12} = 30.3$.

Model 1 From the dataset for (FRSGNNU003A0) Foreign Equities, the Ljung-Box statistic for $u_i^2$ series, $Q = 84.643$. This is strong evidence of autocorrelation. For the $\frac{u_i^2}{\sigma_i^2}$ series the Ljung-Box statistic, $Q = 30.507$, suggesting that the
autocorrelation has not been removed by the GARCH model. Model 2 From the dataset for (FRSGNNU003A0) Foreign Equities, the Ljung-Box statistic for \( u_i^2 \) series, \( Q = 84.155 \). This is strong evidence of autocorrelation. For the \( \sigma^2_i \) series the Ljung-Box statistic, \( Q = 39.666 \), suggesting that the autocorrelation has not been removed by the GARCH model.

13 Conclusion

13.1 Benefits of GARCH

Usually the spike of standard deviation or volatility is caused by some (black swan) event. This means the spike usually occurs at a very short time (less than a month) and the subsequent month volatility comes back down to normal. The GARCH can perfectly capture this type of event. Since it’s pretty much like the exponentially weighted rolling standard deviations, only with an additional assigned weight to a long-run average volatility, the black swan event effect disappear quickly to reflect the going-back-to-normal situation. However, the rolling risk has time lags (the longer the rolling, the bigger the lags) which tend to show periods of higher risk after the black swan event. This makes it harder to identify if the market is still in panic mode.

Both GARCH and rolling risk depends on historical data so they are ex-post measures. One of the reasons a GARCH\(1,1\) model was chosen for this project, the method is a common and popular tool to measure the the implied volatility of S&P 500 index, the VIX. This is ex-ante measure that reflect the market expectation of the future volatility. Research has shown that the future volatility can be more closely replicated by GARCH than the regular rolling risk. For the each of the four possible datasets of monthly active returns, the GARCH\(1,1\) is significant in modeling 3 of the 4 portfolios. The next stage is to focus on the actual results of the model. An investigation will continue to make the connection between an alert and movements in the series of the 1 month rolling returns.
13.2 Summary-Preview

The goal is to capture the shocks to the volatility before the event occurs, instead of waiting for the series to identify an alert by passing the UCL. Analyzing the periods during which the process modeled using the GARCH(1,1) was out-of-control, (above the 95% bounds), displays large movements in the one month active returns before the signaled alert. This may be an application to this model for future usage. For instance, the GARCH process for (FRSGNNU003A0) Foreign Equities.
This is also seen in the GARCH process for (FRSGFAY001A0) - Fixed Income Investment Grade vs Target.