Question Two

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```r
library(tidyverse);library(gt);library(tbl2xts);library(PerformanceAnalytics);library(lubridate);library
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.2 --
## v ggplot2 3.4.0     v purrr   1.0.1
## v tibble  3.2.1     v dplyr   1.1.3
## v tidyr   1.3.0     v stringr 1.5.0
## v readr   2.1.4     v forcats 0.5.2

## Warning: package 'tibble' was built under R version 4.2.3

## Warning: package 'dplyr' was built under R version 4.2.3

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

## Warning: package 'gt' was built under R version 4.2.3

## Loading required package: xts

## Warning: package 'xts' was built under R version 4.2.3

## Loading required package: zoo

## Warning: package 'zoo' was built under R version 4.2.3

##
## Attaching package: 'zoo'
##
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
##
##
## ######################### Warning from 'xts' package ##########################
## #                                                                             #
## # The dplyr lag() function breaks how base R's lag() function is supposed to  #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or       #
## # source() into this session won't work correctly.                            #
```

```
## #                                                                            #
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop          #
## # dplyr from breaking base R's lag() function.                                #
## #                                                                            #
## # Code in packages is not affected. It's protected by R's namespace mechanism #
## # Set `options(xts.warn_dplyr_breaks_lag = FALSE)` to suppress this warning.  #
## #                                                                            #
## ###############################################################################
##
## Attaching package: 'xts'
##
## The following objects are masked from 'package:dplyr':
##
##     first, last
##
##
## Attaching package: 'PerformanceAnalytics'
##
## The following object is masked from 'package:graphics':
##
##     legend
##
## Loading required package: timechange
##
## Attaching package: 'lubridate'
##
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union

## Warning: package 'RcppRoll' was built under R version 4.2.3

## Warning: package 'rugarch' was built under R version 4.2.3

## Loading required package: parallel
##
## Attaching package: 'rugarch'
##
## The following object is masked from 'package:purrr':
##
##     reduce
##
## The following object is masked from 'package:stats':
##
##     sigma

## Warning: package 'forecast' was built under R version 4.2.3

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```r
list.files('/code',full.names = T, recursive = T) %>%
    as.list() %>%
    walk(~source(.))
```

Question Two

```r
setwd("C:/Users/tashe/Desktop/Financial Econometrics Exam")
```

The article speaks about investors and their intentions to move their portfolio holdings towards USD Indexes, as the "opportunity" to obtain higher returns is attractive. The Rand has depreciated over the years and investors looking at similar indexes compared to their local portfolio, believe that if they switch to a currency appreciating against the Rand, they can increase their portfolio returns.

```r
#Data
Indexes <- readr::read_rds("data/Cncy_Hedge_Assets.rds")
ZAR <- readr::read_rds("data/Monthly_zar.rds")
```

The data sets are based on two different time lines/periods. This means that we first need to convert the Indexes to a monthly basis.

```r
Indexes <- Indexes %>%
    mutate(Year = format(date, "%Y"), Month = format(date, "%B")) %>%
    group_by(Year,Month) %>%
    filter(date == last(date)) %>%
    ungroup()

#Now we can join both Data sets.
combo <- left_join(Indexes, ZAR %>% select(date, value), by = "date")
combo <- combo %>%
    na.locf(value, na.rm = T, fromLast = FALSE, maxgap = 3) #Using the last known dollar value.
```

Now we can convert the US Global Indexes to ZAR value.

```r
combo <- combo %>%
    mutate(MSCI_ACWI = MSCI_ACWI*value,
           Bbg_Agg = Bbg_Agg*value) %>%
    select(date:ALBI)
```

Now the data is in an appropriate format. We have the local Index; *ALBI* and *J433*, and the Global Index; *Bbg_Agg* and *MSCI_ACWI*. Let's first take a look at the movement of the ZAR.USD value over time.

```r
ZAR_plot <- ZAR %>%
    ggplot()+
    geom_line(aes(date, value), color = "blue", lwd = 0.6) +
    ylab("Rand per USD")+
    xlab("Date")+
    labs(title = "USD to ZAR movement",
         subtitle = "Currency fluctuations")+
    fmxdat::theme_fmx()
```

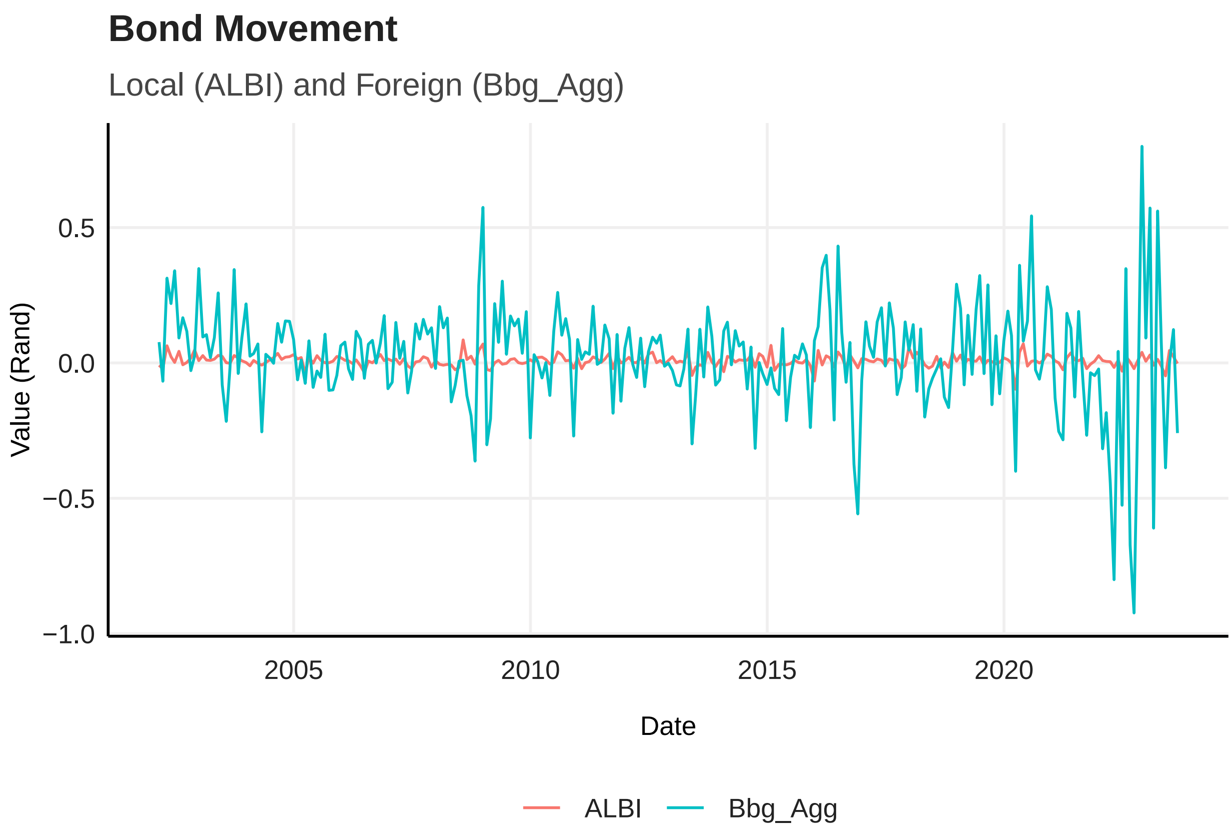
```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
fmxdat::finplot(ZAR_plot)
```

As we can see the ZAR has been out-shined by the USD, especially over the last 2 decades, which could cause some investors to lean more towards holding foreign assets.

Let's assess and compare the local to foreign Indexes. First let's take a look at the bonds.

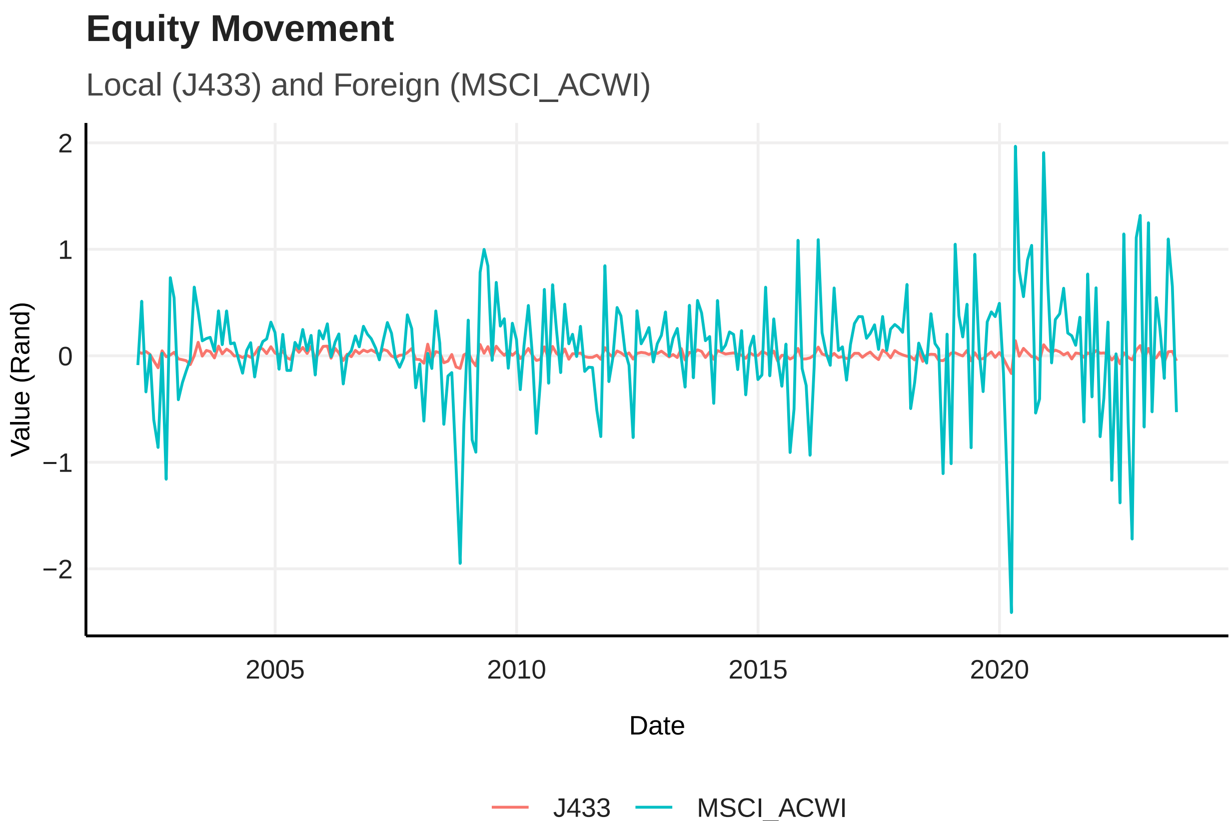
```
#Let's directly compare the bonds
Bond_plot <- combo %>%
    select(date, Bbg_Agg, ALBI) %>%
    gather(Type, value, -date) %>%
    ggplot()+
    geom_line(aes(date, value, color = as.factor(Type)))+
    ylab("Value (Rand)")+
    xlab("Date")+
    labs(title = "Bond Movement",
         subtitle = "Local (ALBI) and Foreign (Bbg_Agg)")+
    fmxdat::theme_fmx()
Bond_plot
```



We note that the movement of the local listing, in red, is much more stable around zero. This means that the returns are considered safe and this is the perception that people have about bonds. The global bond index, in teal, is much more volatile.

Let's take a look at the equity market.

```
Equity_plot <- combo %>%
    select(date, J433, MSCI_ACWI) %>%
    gather(Type, value, -date) %>%
    ggplot()+
    geom_line(aes(date, value, color = as.factor(Type)))+
    ylab("Value (Rand)")+
    xlab("Date")+
    labs(title = "Equity Movement",
         subtitle = "Local (J433) and Foreign (MSCI_ACWI)")+
    fmxdat::theme_fmx()
Equity_plot
```

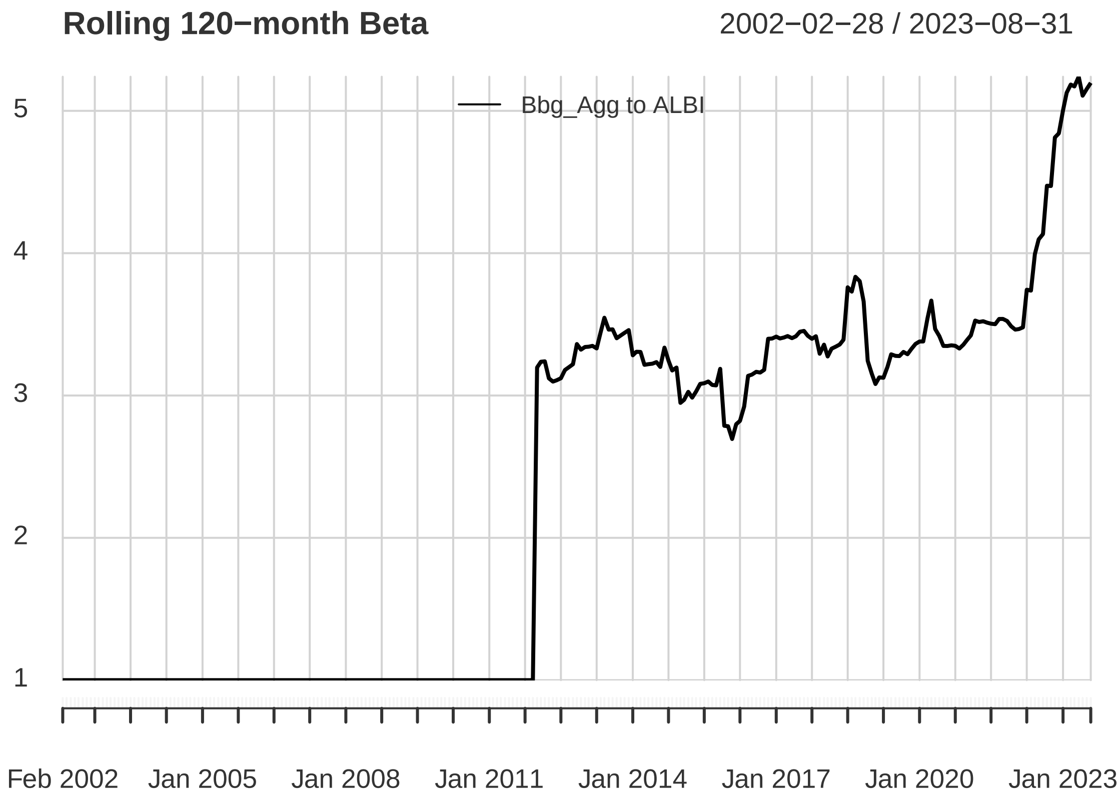


Again, the local equity movement, in red, is significantly lower than the global equity movement, in teal.

However, these direct comparisons must not be the only metric utilised when formulating an argument for holding off-shore assets to increasing the portfolio exposure. We note that there is more opportunity to make significantly larger gains, but there is also a great deal of loss that can occur. The idea is to obtain the most growth and leverage the USD appreciation over holding Rand Indexes.

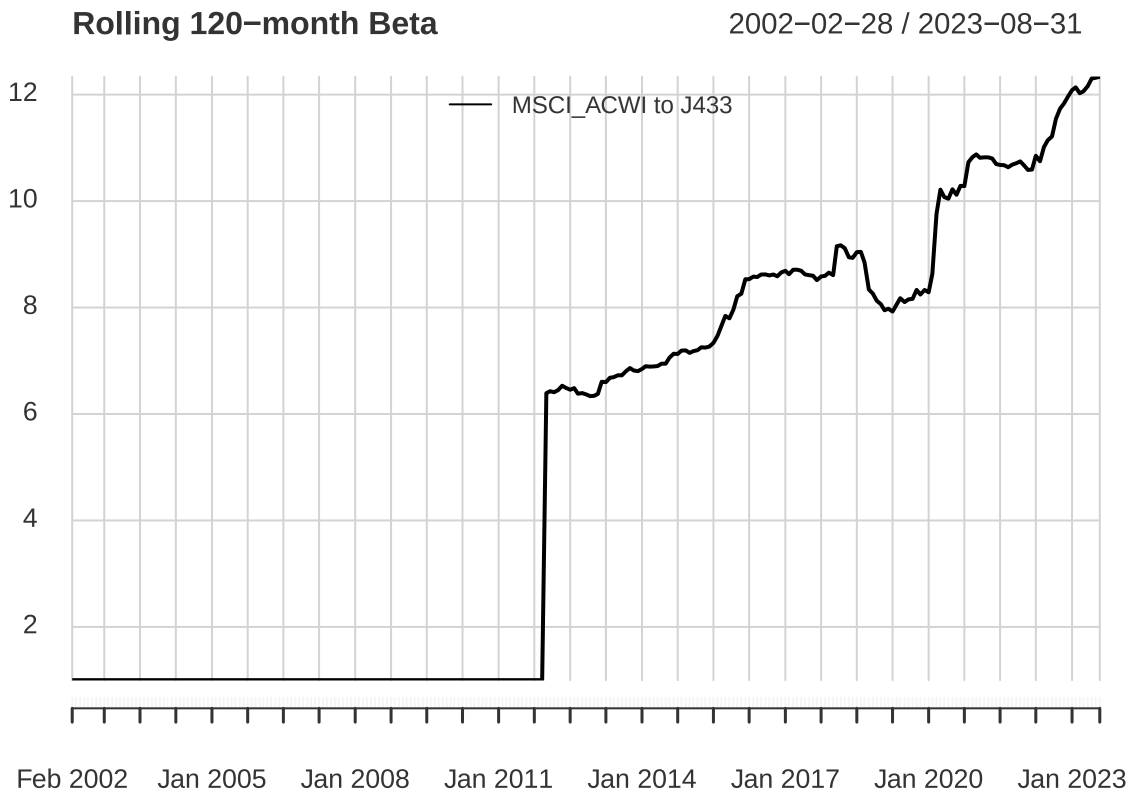
Let's look at the Rolling 120-day Beta, as this information will indicate the volatility of the Index movements.

```
gt <- combo %>%
    gather(Index, Returns, -date) %>%
    tbl_xts(tblData = ., cols_to_xts = Returns, spread_by = Index)
PerformanceAnalytics::chart.RollingRegression(Ra = gt$Bbg_Agg , Rb = gt$ALBI, width=120,attribute = c("]
```



This rolling regression further supports that the global bond market holds higher risk compared to the ALBI.

```
PerformanceAnalytics::chart.RollingRegression(Ra = gt$MSCI_ACWI , Rb = gt$J433, width=120,attribute = c
```

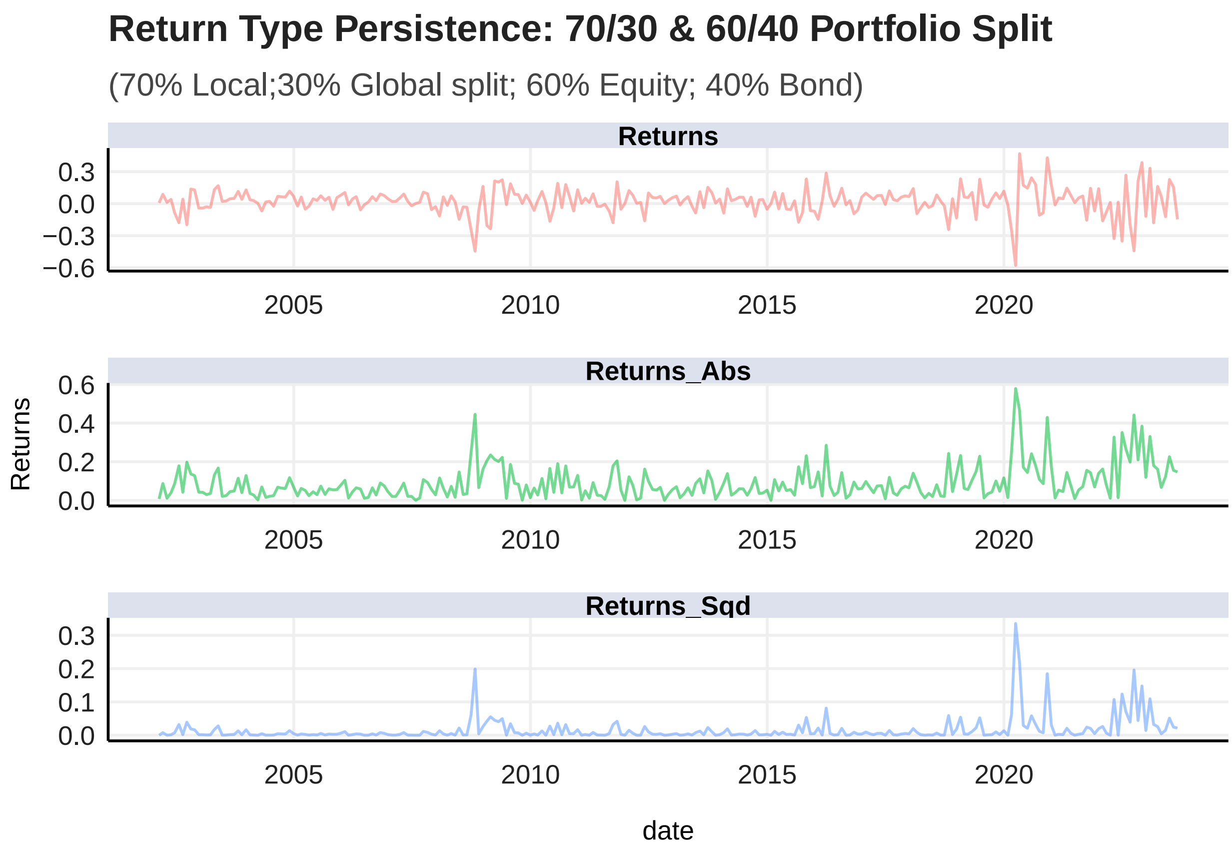


This rolling regression also indicates that the global equity market displays higher risk to a portfolio.

The returns process for the portfolio, with the constraints implemented, will be investigated below.

```
garch_data <- combo %>%
    gather(Index, Returns, -date) %>%
    mutate(Log_Returns = log(abs(Returns))) %>%
    mutate(Scale_Log = (Log_Returns - mean(Log_Returns, na.rm = T)))

garch_data <- left_join(garch_data,
          garch_data %>% tbl_xts(., cols_to_xts = "Log_Returns", spread_by = "Index") %>%

      PerformanceAnalytics::Return.clean(., method = c("none", "boudt", "geltner")[2], alpha = 0.01) %>%

      tbl2xts::xts_tbl() %>% gather(Index, CleanedRet, -date) ,
    by = c("date", "Index"))

Local <- c("ALBI","J433")
Global <- c("MSCI_ACWI", "Bbg_Agg")

#Weights split. This is to see how the Calculation was done.
# Local: 0.7.
#Local Equity = 0.7*0.6 = 42%
# Local Bonds: 0.7*0.4 = 28%
#Global: 30%
# Global Equity: 0.3*0.6 = 18%
# Global Bonds = 0.3*0.4 = 12%
```

```r
garch_data_wt <- garch_data %>%
    mutate(weight = ifelse(Index == "J433", 0.42,
                           ifelse(Index == "ALBI", 0.28,
                                  ifelse(Index == "MSCI_ACWI", 0.18, 0.12)))) %>%
    tbl_xts(.,cols_to_xts = weight, spread_by = Index)

garch_data_retxts <- garch_data %>%
    tbl_xts(., cols_to_xts = "Returns", spread_by = "Index")



Portfolio_dis_weight <- rmsfuns::Safe_Return.portfolio(garch_data_retxts, weight = garch_data_wt, geomet

#Create plots
Portfolio_dis_weight_plot <- cbind(Portfolio_dis_weight, Portfolio_dis_weight^2, abs(Portfolio_dis_weig
colnames(Portfolio_dis_weight_plot) = c("Returns", "Returns_Sqd", "Returns_Abs")


Portfolio_dis_weight_plot <-
Portfolio_dis_weight_plot %>%
    xts_tbl() %>%
gather(ReturnType, Returns, -date)

ggplot(Portfolio_dis_weight_plot) +
geom_line(aes(x = date, y = Returns, colour = ReturnType, alpha = 0.5)) +

labs(title = "Return Type Persistence: 70/30 & 60/40 Portfolio Split",
     subtitle = "(70% Local;30% Global split; 60% Equity; 40% Bond)") +
facet_wrap(~ReturnType, nrow = 3, ncol = 1, scales = "free") +
guides(alpha = "none", colour = "none") +
fmxdat::theme_fmx()
```



We can see that there are still pockets of heteroskedasticity between the periods.The squared residuals show some persistence, which supports the use of GARCH model to further support against holding off-shore stock with the intent of outperforming the Rand.

Fitting GARCH

```
library(rugarch)
#ARMA 1 process
garch11 <-

  ugarchspec(

    variance.model = list(model = c("sGARCH","gjrGARCH","eGARCH","fGARCH","apARCH")[1],

    garchOrder = c(1, 1)),

    mean.model = list(armaOrder = c(1, 0), include.mean = TRUE), #Armaorder specifies AR1

    distribution.model = c("norm", "snorm", "std", "sstd", "ged", "sged", "nig", "ghyp", "jsu")[1])

garch1 = ugarchfit(spec = garch11,data = Portfolio_dis_weight )
```

The LogLikelihood value of 215.1396 provides an indication that the model is of good fit.

Let's look at the persistence of variance>

```r
persistence(garch1)
```

```
## [1] 0.9570032
```

This value is less than 1, which is required. Now, more interestingly, let's look at the volatility model fit.

```r
infocriteria(garch1)
```

```
##
## Akaike       -1.622700
## Bayes        -1.554035
## Shibata      -1.623426
## Hannan-Quinn -1.595092
```

We note that the levels of criteria that can be used. Let's look at another volatility fit model.

```r
gjrgarch11 = ugarchspec(variance.model = list(model = c("sGARCH","gjrGARCH","eGARCH","fGARCH","apARCH")

                                              garchOrder = c(1, 1)),

                        mean.model = list(armaOrder = c(1, 0), include.mean = TRUE),

                        distribution.model = c("norm", "snorm", "std", "sstd", "ged", "sged", "nig", "gl

garch2 = ugarchfit(spec = gjrgarch11, data = as.matrix(Portfolio_dis_weight))
infocriteria(garch2)
```

```
##
## Akaike       -1.735452
## Bayes        -1.639321
## Shibata      -1.736862
## Hannan-Quinn -1.696801
```

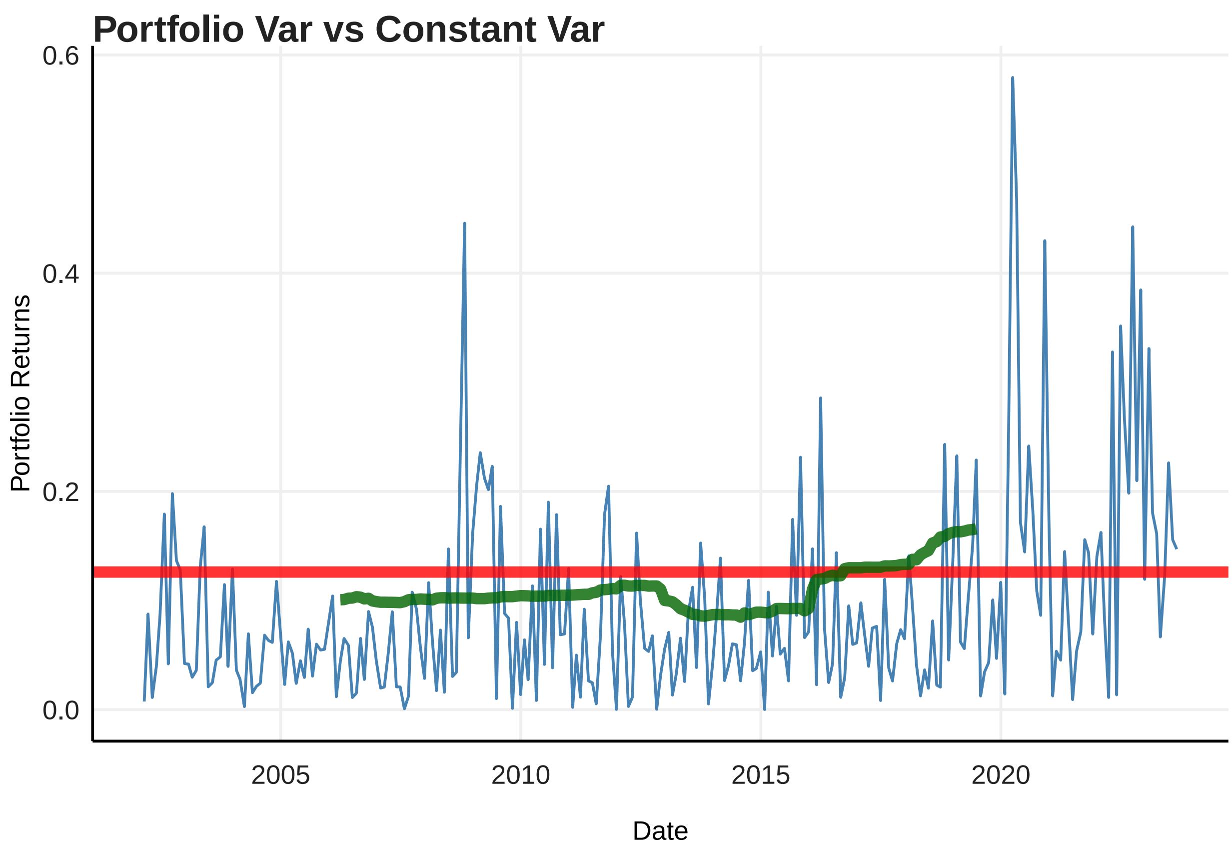
So the garch1 model is a better fit for the portfolio insights.

Let's look at a better indicator of the true volatility of the portfolio returns.

```r
pacman::p_load(RcppRoll)  # Great for fast estimation

back = 100

Portfolio_dis_weight <- Portfolio_dis_weight %>%
    xts_tbl()

 Portfolio_dis_weight %>%
     mutate(Constant_var = sd(portfolio.returns)) %>%
     mutate(sqrtRet = sqrt(portfolio.returns^2)) %>%
mutate(Roller = roll_sd(portfolio.returns, n = back, fill = NA)) %>%
ggplot() +
geom_line(aes(date, sqrtRet), color = "steelblue") +
geom_hline(aes(date, yintercept = mean(Constant_var)), color = "red",
```

```r
    alpha = 0.8, size = 2) +
geom_line(aes(date, y = Roller), color = "darkgreen", alpha = 0.8,
    size = 2) +
     xlab("Date")+
     ylab("Portfolio Returns")+
fmxdat::theme_fmx() +
labs(title = "Portfolio Var vs Constant Var")
```

```
## Warning in geom_hline(aes(date, yintercept = mean(Constant_var)), color =
## "red", : Ignoring unknown aesthetics: x

## Warning: Removed 99 rows containing missing values (‘geom_line()‘).
```



This graph shows that utilising the constant variance as a proxy of risk is not suitable, as the red line displays the true nature of variance over time.

With all of the above information, we are able to get a better understanding of why hedging against the Rand is not a suitable strategy - especially if we are strictly looking at the USD to ZAR exchange rate over the years.