

## Question 6: MSCI Funds

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```
knitr::opts_chunk$set(  
  echo = FALSE,  
  fig.height = 5,  
  fig.pos = "H",  
  fig.width = 6,  
  message = FALSE,  
  warning = FALSE  
)  
  
# Note: Include = FALSE implies the code is executed, but not printed in your pdf.  
# warning and message = FALSE implies ugly messages and warnings are removed from your pdf.  
# These should be picked up when you execute the command chunks (code sections below) in your rmd, not ;  
  
# load packages  
pacman::p_load("MTS", "robustbase")  
pacman::p_load("tidyverse", "devtools", "rugarch", "rmgarch",  
  "forecast", "tbl2xts", "lubridate", "PerformanceAnalytics",  
  "ggthemes", "ks")  
pacman::p_load("tidyverse", "rugarch", "rmgarch")  
  
#load Packages  
library(tidyverse)  
library(tbl2xts)  
library(rugarch)  
  
# load data, and see how this can be stored and later called from your 'data' folder.  
msci <- read_rds("data/msci.rds")  
bonds <- read_rds("data/bonds_10y.rds")  
comms <- read_rds("data/comms.rds")
```

## Introduction

This report investigates how the return profiles of different asset classes (Equities, Commodities, Real Estate and Bonds) have increased in their convergence over time by explaining co-movements between different asset classes using a multivariate GARCH model.

## Data

I begin by selecting specific assets from the data sets provided and follow an approach similar to the practical. I select the MSCI\_ACWI index to represent Equities, the BCom\_Index to represent Commodities, the MSCI\_RE to represent Real Estate and the US\_10Yr to represent bonds. I calculate returns for the daily price data before combining the data to perform the analysis, followed by log scaling and centering the data. This was tricky to accomplish in one go so I split it up into its parts, wrangled the data and then combined the data.

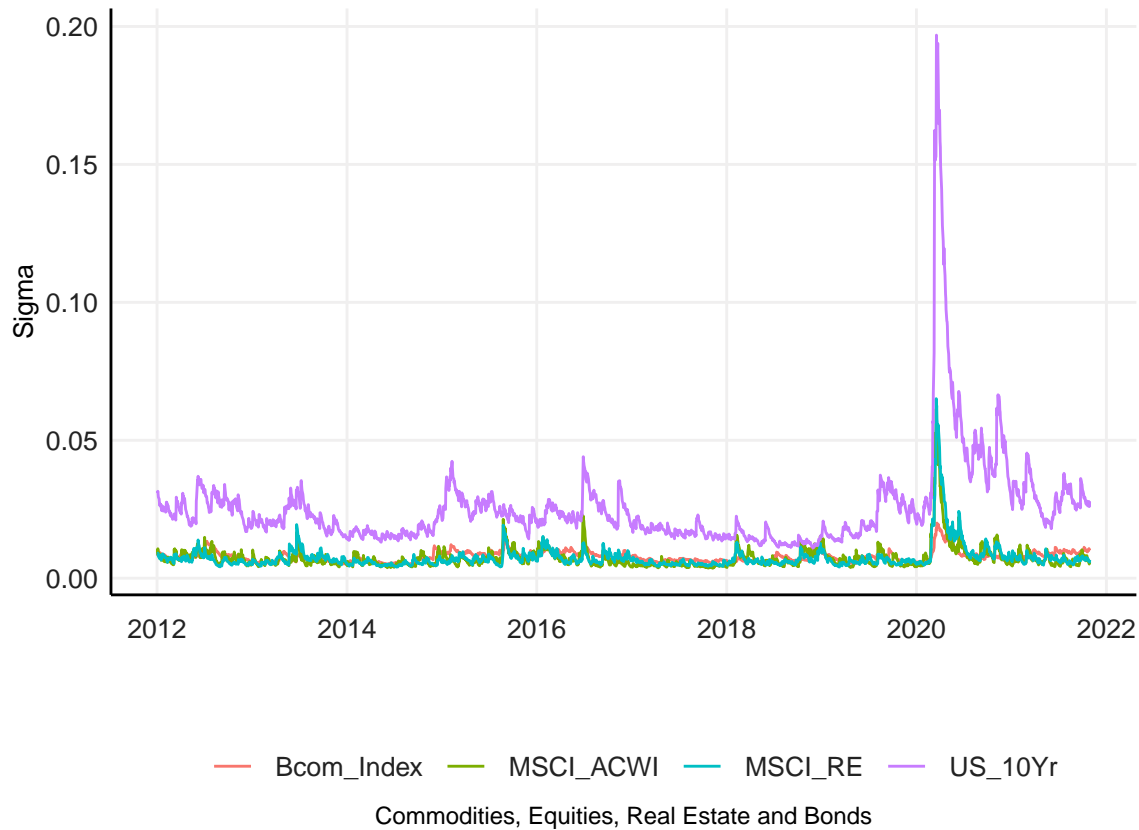
## DCC Model

I follow the practical code closely to render the model. I amend code and nested functions inside one another to keep the working document neat. I plot the estimates of volatility for each series from from 'dccPre'.

```
## Sample mean of the returns:  -0.0001532192  0.0006273741 -0.000122789 -0.0001327623
## Component:  1
## Estimates:  3e-06  0.183428  0.782732
## se.coef   :  0  0.021974  0.022599
## t-value   :  5.585021  8.347446  34.636
## Component:  2
## Estimates:  2e-06  0.136209  0.826154
## se.coef   :  0  0.017766  0.022081
## t-value   :  4.61807  7.666786  37.41462
## Component:  3
## Estimates:  5e-06  0.079257  0.914998
## se.coef   :  2e-06  0.010207  0.01074
## t-value   :  3.076316  7.764681  85.19931
## Component:  4
## Estimates:  1e-06  0.049531  0.936488
## se.coef   :  0  0.006571  0.008666
## t-value   :  3.466549  7.537786  108.0608
```

## Volatility of Returns for the past decade

Different Asset Classes



The 'dccPre' function is used to fit the univariate GARCH models to each series in the data and a standard univariate GARCH(1,1) is run which produces the error term and sigma, which is then used to calculate the standardized residuals used to estimate the DCC model.

The DCC model is then run and the estimates of time-varying correlation are produced.

```
## Sample mean of the returns: -0.0001532192 0.0006273741 -0.000122789 -0.0001327623
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## se.coef : 0 0.021974 0.022599
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## Component: 4
## Estimates: 1e-06 0.049531 0.936488
## se.coef : 0 0.006571 0.008666
## t-value : 3.466549 7.537786 108.0608
```

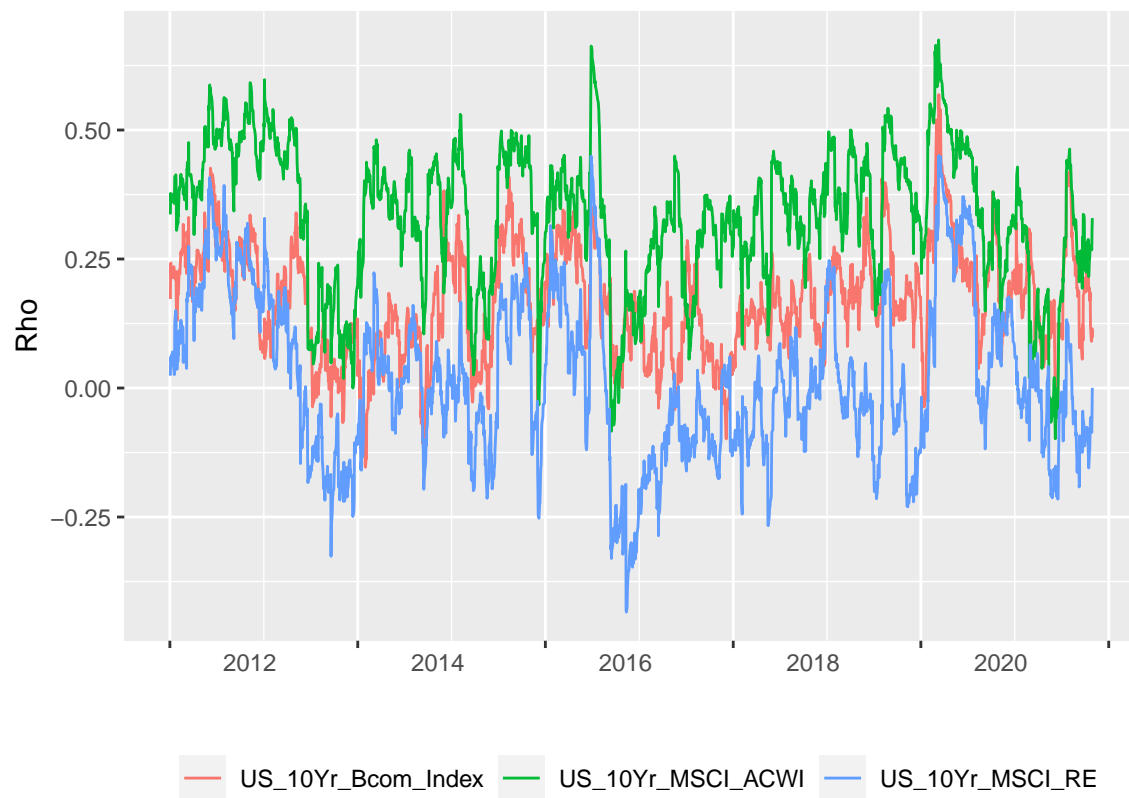
```
## Estimates: 0.9439883 0.02805751 7.628358
## st.errors: 0.009865406 0.004106348 0.4391585
## t-values: 95.68672 6.832717 17.3704
```

## Co-movements of Assets

I now plot line graphs that illustrate how co-movements between different asset classes have changed over the last 10 years. I don't want to include the GFC, as all asset classes were responding similarly at the time.

To produce the Dynamic Conditional Correlations graphs for the four asset classes I nest the renaming function from the practicals inside of a graphing function, so that it can be reused simply by changing the input names.

### Dynamic Conditional Correlations: US\_10Yr



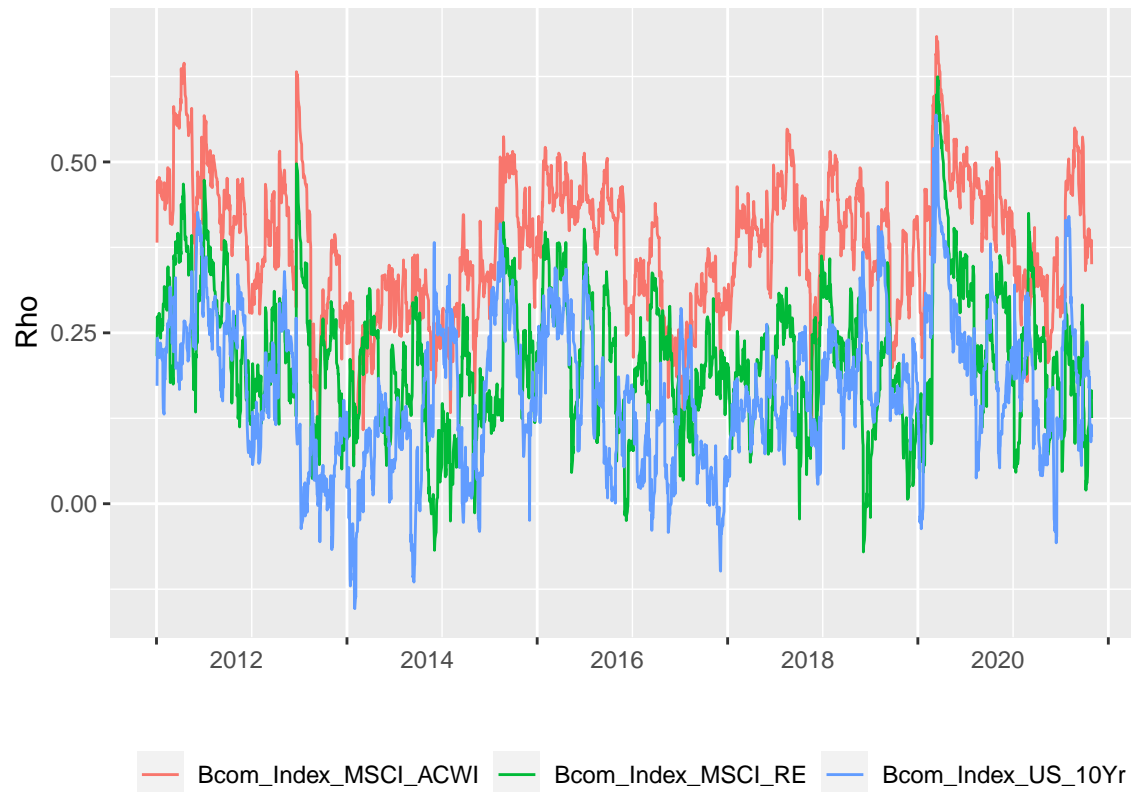
Commodities, Equities, Real Estate and Bonds

From

the Dynamic Conditional Correlations: US\_10Yr graph, in the last two years of the period the other three asset classes (equities, real estate and commodities) see to be moving similarly to the US 10 Year Treasury bond. This is not surprising as bond prices are underpinned by interest rates and interest rate changes have significant effects on asset classes.

## Dynamic Conditional Correlations: Bcom\_Index

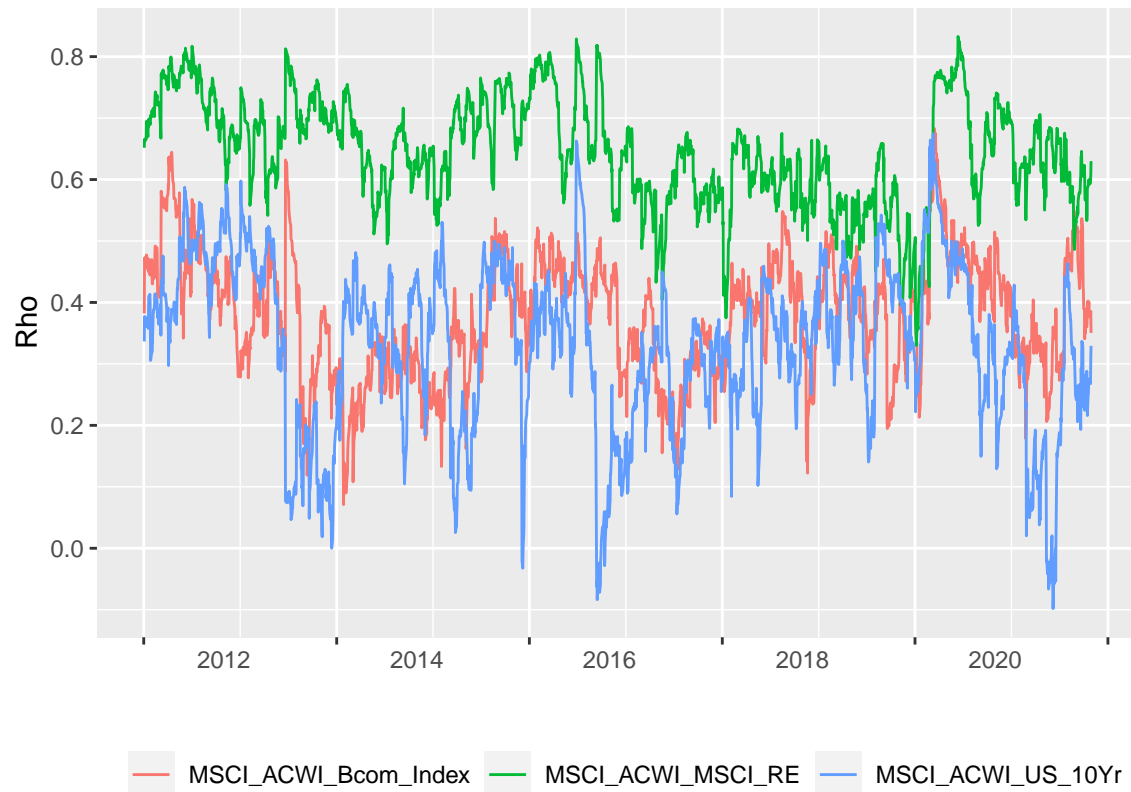
Plot of Total Cases and Deaths per Continent



Commodities, Equities, Real Estate and Bonds

From, Dynamic Conditional Correlations: Bcom\_Index graph, commodities have a less correlated than other asset classes as can see the bonds-commodities relationship oscillates just above zero.

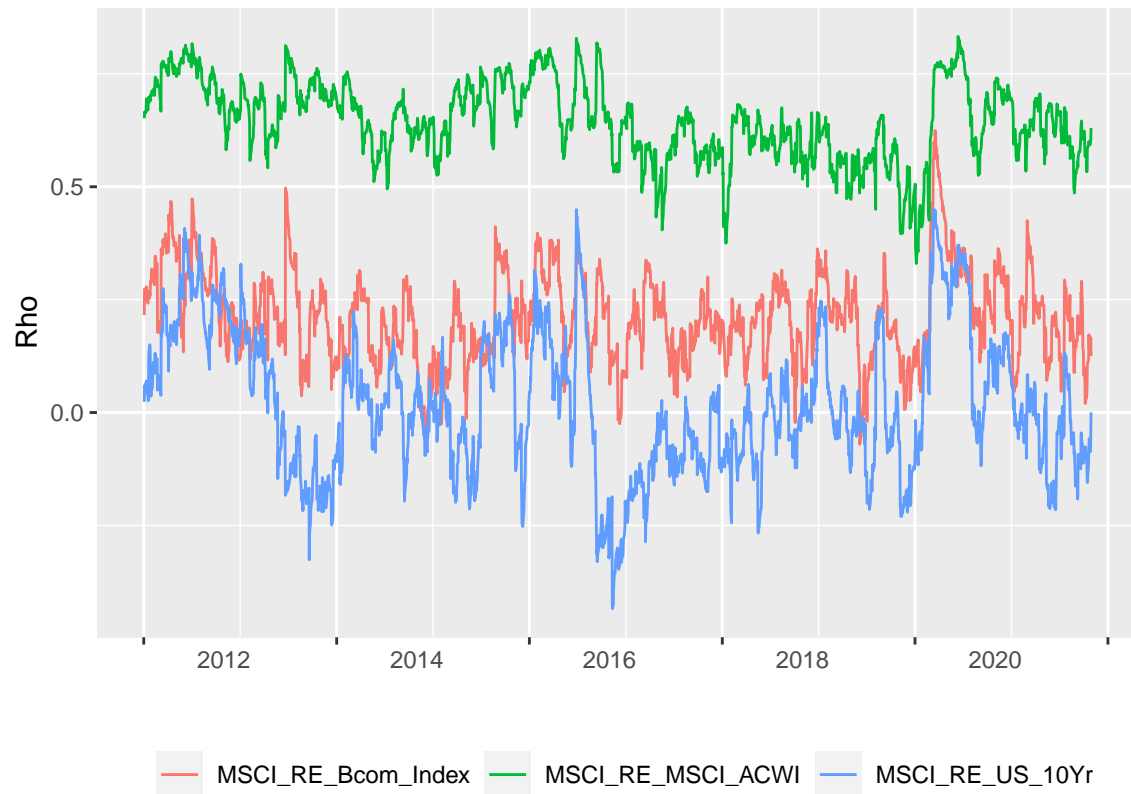
## Dynamic Conditional Correlations: MSCI\_ACWI



Commodities, Equities, Real Estate and Bonds

From the Dynamic Conditional Correlations: MSCI\_ACWI graph, the All Country World Index and the Real Estate assets are more correlated than the other assets classes. This may be because of a common factor such as the availability of credit, which would lead to increased housing and equity prices as demand for these assets would increase where the supply of credit facilities increases.

## Dynamic Conditional Correlations: MSCI\_RE



Commodities, Equities, Real Estate and Bonds