# MV-Volatility modeling applied to local equities

Austin Byrne[a]

[a] *Stellenbosch University*

**Abstract**

The main aim of this study is to evaluate the volatility structure of local equities. This analysis will be achieved by making use of DCC-GARCH multivariate volatility model. Through this analysis I indetify the most volatile index/sector to be the Resource sector, while the ALSI and Industrial sector to hold the lowest volatility.

## 1. Introduction

When dealing with financial markets and portfolio creation it is paramount for an investor or risk managers to understand the risk involved in their investment decisions. Within financial markets, volatility is often evaluated as a measure of uncertainty and risk. Thus, through evaluating the volatility structure of indexes we are able to understand the risk structure involved with certain investment decisions. Furthermore, by evaluating the dynamic correlations between indexes we are able to better diversify a portfolio and reduce risk. The main objective of this project is to understand the multivariate volatility structure of local equities and thus understand the relative risk associated with certain investment decisions.

The use of Dynamic Conditional Correlation (DCC) GARCH models to evaluate market dynamics and dynamic correlations has become more frequent in portfolio creation and financial theory. Boudt, Danielsson & Laurent (2013) make use of an extension of a DCC GARCH model to forecasting the covariance matrix of the daily EUR/USD and Yen/USD return series (Boudt *et al.*, 2013). Additionally, Shiferaw (2019) run a multivariate DCC-GARCH model to evaluate time varying correlation between energy price dynamics and agricultural commodity to name a few (Shiferaw, 2019).

Understanding this topic can be vitally important for investors and portfolio managers when

[*]Corresponding author: Austin Byrne
*Email address:* 22582053@sun.ac.za (Austin Byrne)

making investment decisions. Realizing the risk exposure a portfolio is inherently exposed to is crucial when making investment decisions. Thus, by modeling the volatility of local equities an investor can make more informed investment decisions based on the intended level of risk the investors wants to take on. This project aims to achieve this analysis through a Dynamic Conditional Correlation (DCC) GARCH model capturing the market dynamics and volatility structures of local sectors and indexes. This model is renowned for its proficiency in assessing multivariate time series data, particularly its capability to capture the evolving correlations between different financial time series.

The results of this study find the Resource sector to be the most volatile with the ALSI and Industrial sector being the least volatile.

The remainder of this paper is ordered as follows: The next section covers the Data and Methodology, followed by the Results section, followed by the discussion section and lastly the Conclusion.

## 2. Data Methodology

Throughout this paper multivariate volatility modeling techniques will be used with the focus on understanding the dynamic relationships and co-movements of volatility across multiple sectors/indexes within the local equities market.

Of the MV-volatility modeling techniques that there are available, I will be utilizing the DCC-GARCH model. My aim is to use DCC models in the multivariate volatility analysis as these models are simpler and relax the constraint of a fixed correlation structure which is assumed by the CCC model, which allows for estimates of time varying correlation. I will be conducting the DCC-GARCH volatility model in R statistical package.

The data I am using holds the returns for the following indexes/sectors, ALSI, Financial Sector, Industrial Sector, jsapy index and the Resource Sector.

### *2.1. Variation in index returns*

Figure 2.1 below plots the time series analysis of each indexes returns. The importance of this plot for this analysis lies in it's ability to portray the variance structure in each indexes returns. By visualizing the return structure of an index through time we are able to identify the most volatile and thus more risky indexes.

While holding the y-axis fixed, figure 2.1 shows that the most volatile index/sector is that of the Resource sector. While the ALSI and Industrial sector appear to be the least volatile and thus lowest risk investment opportunities.

To further evaluate the return structure of the indexes/sectors in question figure 2.2 analyses the distribution of returns through a histogram plot.

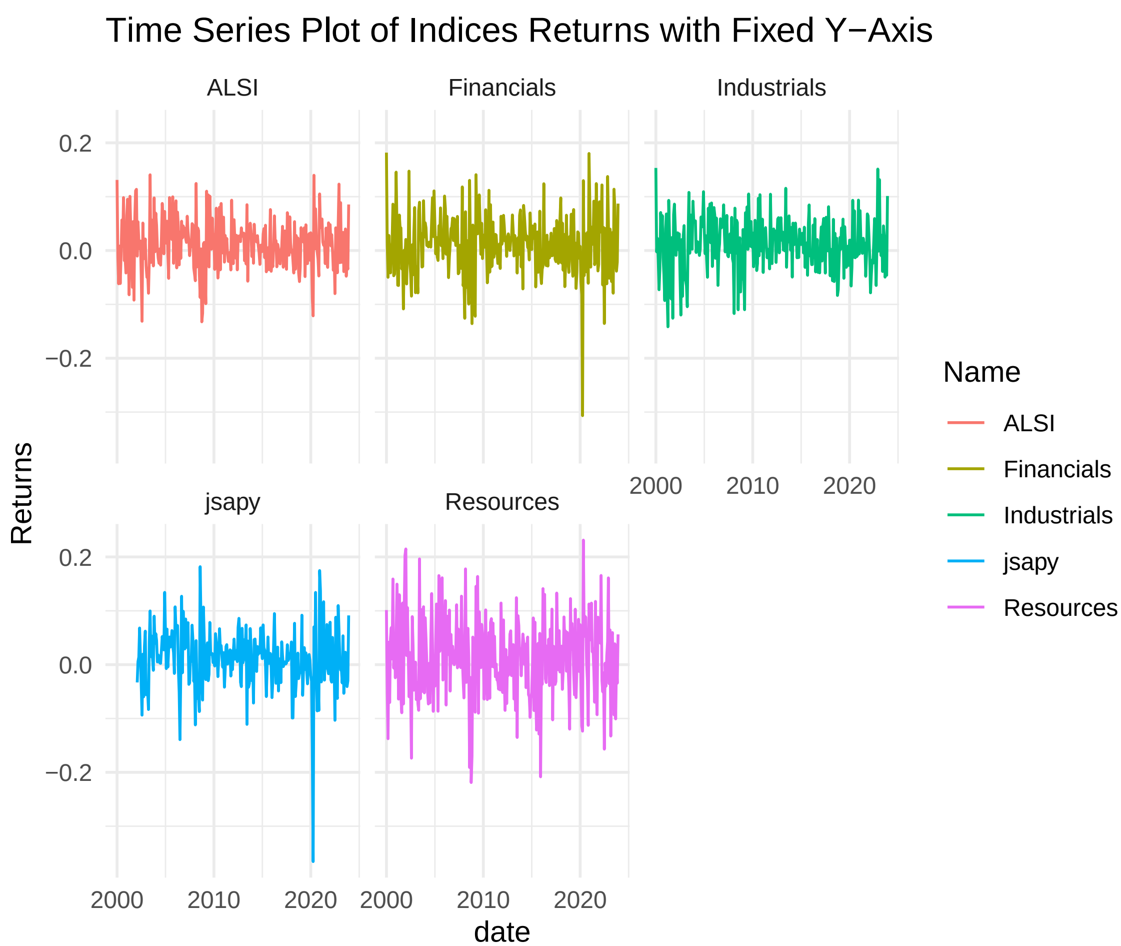


Figure 2.1: Time Series Analysis of Returns

*2.2. Analyzing the Distribution of Returns*

Through figure 2.1 we have identified the resource sector as the most volatile and thus most risky investment option, while the ALSI and industrial sector to be the least volatile. To build on this analysis I run a histogram plot of the return structure. Through this plot we are able to identify any fat tails or skewness in returns as well as identify the index/sector with the widest variation in returns.

The results of figure 2.2 below are inline with that found in figure 2.1 above. The resource sector once again appears to be the most volatile with the ALSI and industrial sector appearing to be the least volatile.

Following the analysis of figures 2.1 and 2.2 we have now obtained a better understanding of the return structure and volatility of the indexes/sectors in question. Thus, we are now able to proceed to the multivariate volatility analysis using the DCC-GARCH model. However, Before I fit any GARCH models to my data I need evaluate the presence of any ARCH effects. If there are no ARCH effects present, it does not make sense to run any GARCH models for this volatility analysis. To test for ARCH effects I perform the McLeod-Li test. This test checks for auto regressive conditional heteroskedasticity (ARCH) in the time series data (Wang, Van Gelder, Vrijling & Ma, 2005). If present the p-values will be very close to 0, indicating that the volatility within the variables changes over time. Thus, it is viable to use GARCH models. This test is done in the next section.

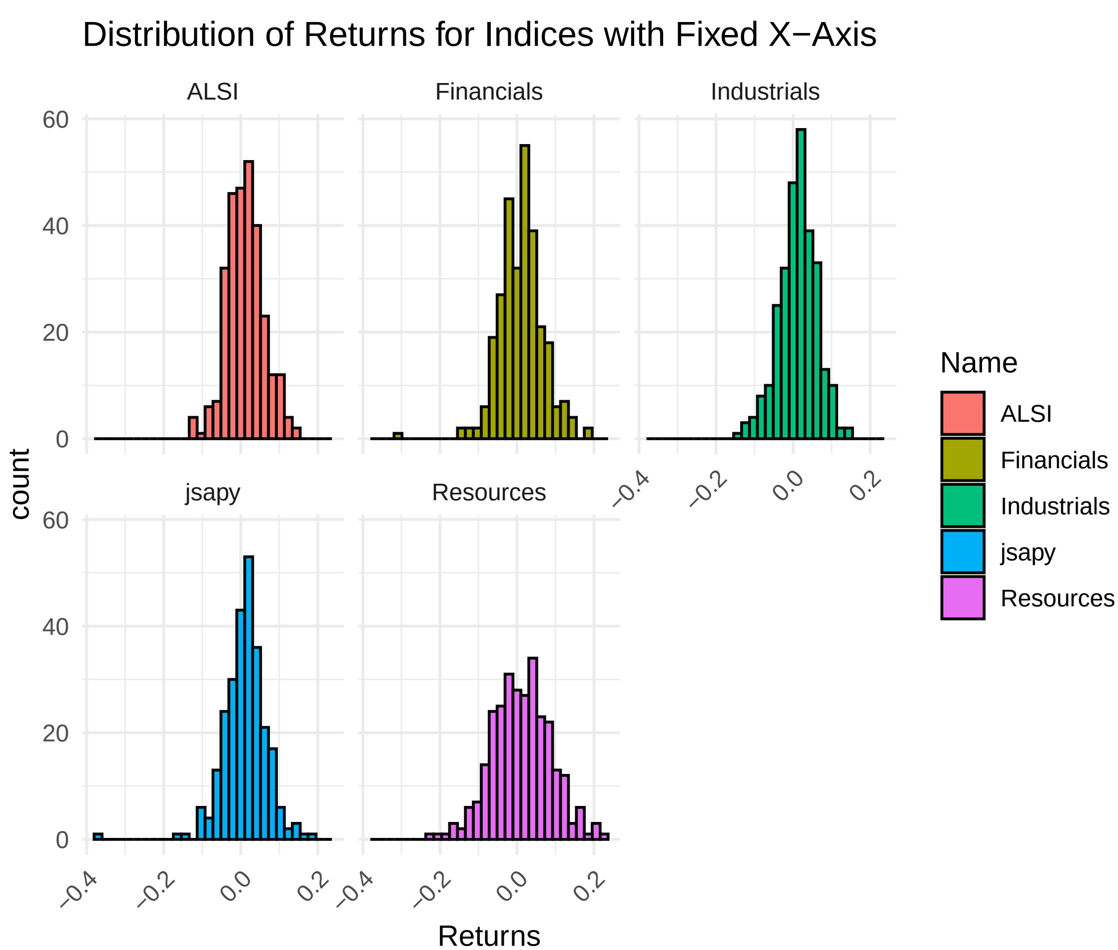


Figure 2.2: Distribution of Returns

### *2.3. Testing for ARCH Effects*

The results in table 2.1 below provide evidence of ARCH effects. All p-values are close to zero which indicates that there is statistical significance indicating that the volatility between the variables change over time. Thus, it is viable to make use of a GARCH model to conduct the volatility analysis.

In the next section I will make use of the DCC-GARCH model to plot the Dynamic Conditional Correlation plots and report the results.

Table 2.1: McLeod-Li Test Results for Autoregressive Conditional Heteroskedasticity

| Test | TestStatistic | PValue |
|---|---|---|
| Q(m) of squared series (LM test) | 44.88386 | 0.0000023 |
| Rank-based Test | 108.25550 | 0.0000000 |
| Q_k(m) of squared series | 341.50090 | 0.0001048 |
| Robust Test (5%) | 321.42970 | 0.0015293 |

## 3. Results

In the following section I plot a volatility comparison plot with the purpose of further understanding which index/sector inherently is exposed to the most volatility. Furthermore, I run the Dynamic Conditional Correlation plots for each index/sector.

### *3.1. Volatility Comparisson*

Figure 3.1 below represents the volatility comparison plot. Through evaluating this plot it is once again evident that the resources sector is consistently the most volatile index/sector. Furthermore, post 2020 their is a significant spike in the volatility in the Financials sector and the jsapy, thus suggesting the Financials Sector and jsapy index are the most sensitive to large shocks in the economy, such as the COVID-19 pandemic. Additionally, the Industrial sector remains the least volatile along with the ALSI.

Now that I have further strengthened my understanding of the nature of volatility for each index/sector, I will now focus my analysis on the conditional correlations in the next section.

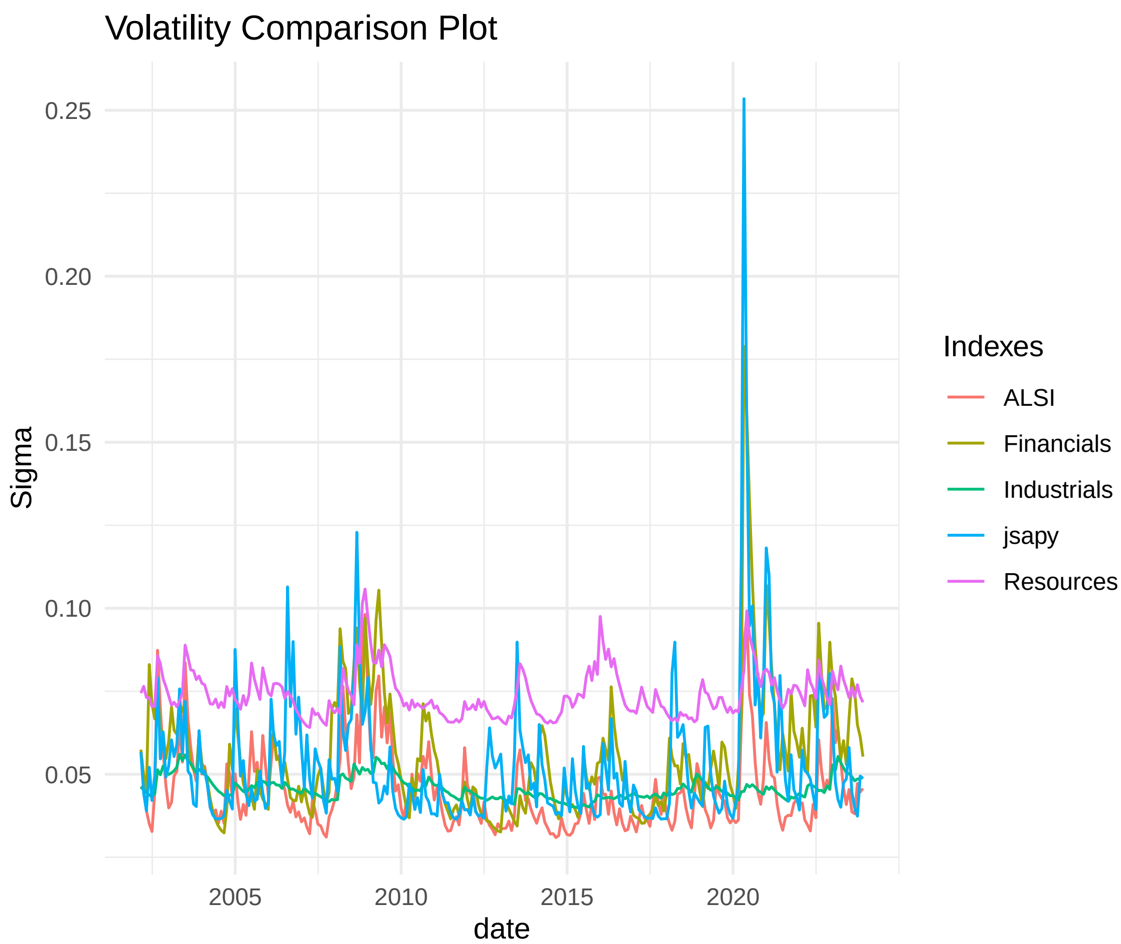


Figure 3.1: Volatility comparisson plot

### *3.2. Dynamic Conditional Correlations*

In this section I plot the Dynamic Conditional Correlation plots for each index/sector. Through these plots we are able to identify which index's/sectors are correlated over time. This is important information when creating optimal portfolios, ensuring diversification and reducing risk for portfolio managers and investors alike.

Figure 3.2 represents the Dynamic Conditional Correlations plot for both the Resources sector and jsapy index. Figure 3.3 represents the Dynamic Conditional Correlations plot for the Financial and Industrial sector. Lastly, Figure 3.4 represents the Dynamic Conditional Correlations plot for the ALSI.

Figure 3.2 illustrates the Resource sector has a high dynamic correlation with the ALSI with a correlation above 0.5 throughout the entire time frame. Furthermore, the Resources sector has the lowest dynamic correlation with the jsapy index. Additionally, Figure 3.2 illustrates that the jsapy index has a high dynamic correlation with the Financial sector and lowest dynamic correlation with the Resource sector.

Figure 3.3 illustrates that the Financial sector holds a high dynamic correlation with the jsapy index, ALSI and the Industrial sector. While holding a low dynamic correlation with the Resource sector. Furthermore, Figure 3.3 illustrates that the Industrial Sector holds a strong dynamic correlation with the ALSI and holds its lowest dynamic correlation with the Resource sector and jsapy.

Lastly, Figure3.4 illustrates that the ALSI holds a strong dynamic correlation with the Industrial and Resource sector while holding its lowest dynamic correlation with the jsapy index.

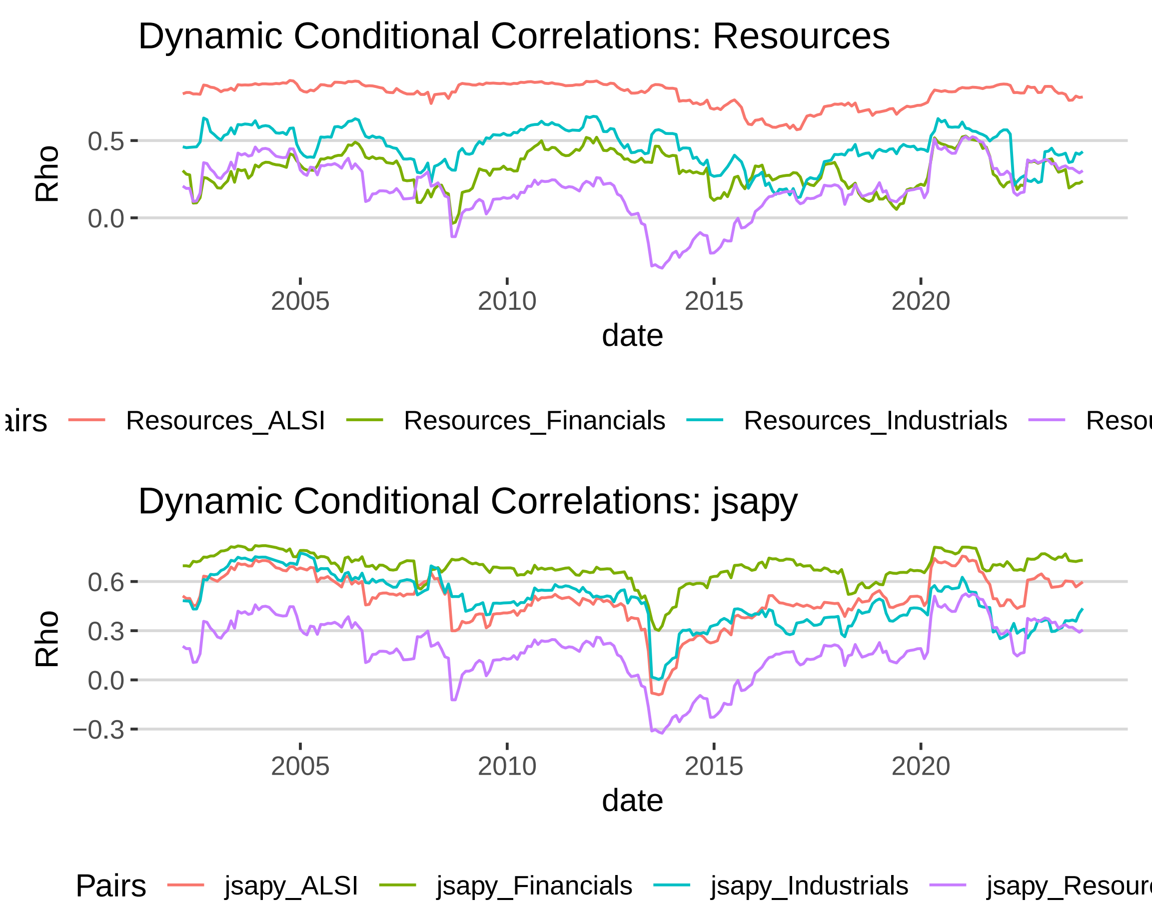


Figure 3.2: Dynamic Conditional Correlations: Resources and jsapy

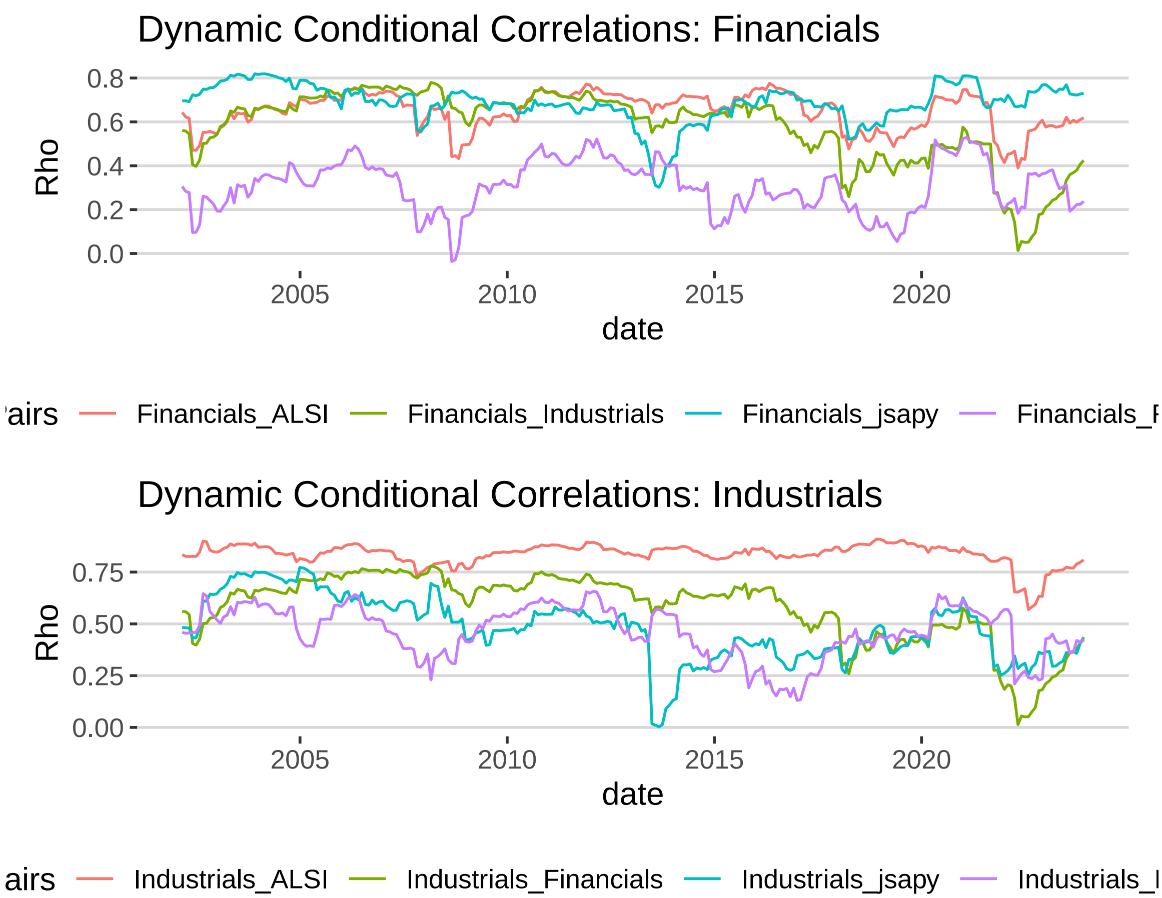


Figure 3.3: Dynamic Conditional Correlations: Financials and Industrials

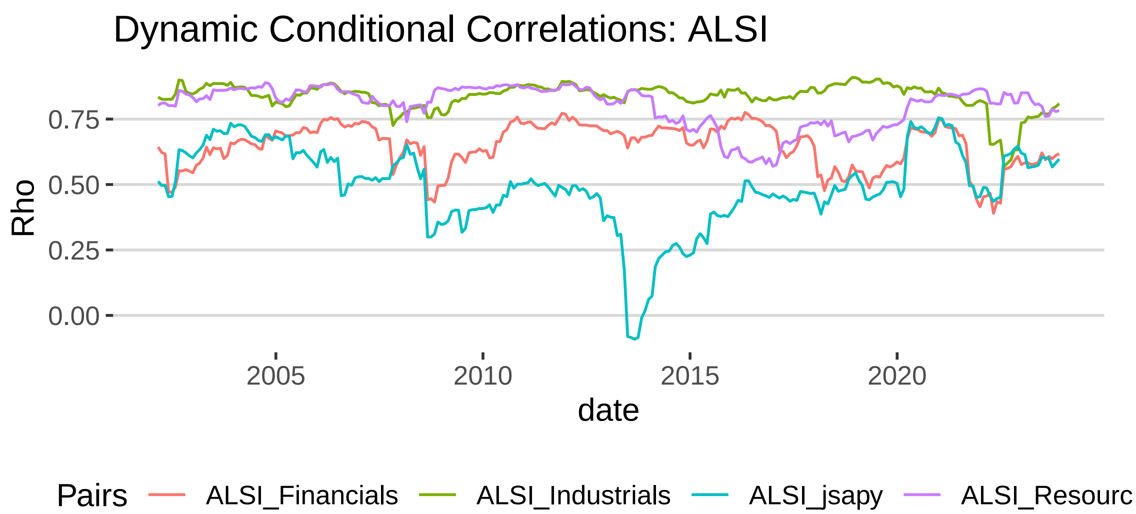


Figure 3.4: Dynamic Conditional Correlations: ALSI

## 4. Discussion

In the above analysis I have evaluated the overall volatility of each index/sector and compared the results with each other. Furthermore, I have evaluated the dynamic correlations between each index/sector. With these results one can identify which indexes/sector hold the highest risk and which indexes/sectors to combine in a portfolio to induce diversification and risk mitigation.

Through my analysis it is evident that the Resource sector holds the highest volatility and thus highest risk while the ALSI and Industrial sector hold the lowest volatility and thus lowest source of risk. Thus if you were attempting to build a low risk portfolio you would hold a high proportion of the ALSI and Industrial sector. If this were the case and you intended to impose some diversification into your portfolio we could evaluate the Dynamic Conditional Correlation plots for the ALSI and Industrial sector.

With respect to the ALSI investing in the jsapy index would provide for increased diversification in your portfolio. This addition to the portfolio could be warranted as the jsapy index holds average volatility and thus average risk. Therefore, by introducing the jsapy to the portfolio we are increasing the diversification while not exposing the portfolio to a great deal of risk. With respect to the Industrial Sector investing in the Resource sector would induce diversification although increasing risk through the highly volatile Resource Sector.

Therefore, a portfolio that holds a large portion in the ALSI and Industrial sector with slight investment in the jsapy and even slighter investment in the Resource sector will provide for a low risk, diversified investment portfolio.

## 5. Conclusion

To conclude, throughout this study I evaluate the return structure and volatility of the ALSI, Financial Sector, Industrial Sector, jsapy index and the Resource Sector. Furthermore, by making use of the DCC-GARCH volatility model I was able to establish the dynamic conditional correlation for each index/sector in question.

The results found the Resource sector to be the most volatile and thus most risky while finding the ALSI and Industrial sector to be the least volatile and thus lowest risk options of the available indexes/sectors. Through evaluating the respective dynamic correlations it is found that the most optimal portfolio construction could potentially be, a portfolio that holds a large portion in the ALSI and Industrial sector with slight investment in the jsapy and even slighter investment in the Resource sector as this portfolio would induce a low risk and well diversified portfolio.

The limitations to the study are that we only focus on the ALSI, Financial Sector, Industrial Sector, jsapy index and the Resource Sector, thus the results are only limited to these indexes/sectors.

## References


Boudt, K., Danielsson, J. & Laurent, S. 2013. Robust forecasting of dynamic conditional correlation GARCH models. *International Journal of Forecasting*. 29(2):244–257.

Shiferaw, Y.A. 2019. Time-varying correlation between agricultural commodity and energy price dynamics with bayesian multivariate DCC-GARCH models. *Physica A: Statistical Mechanics and Its Applications*. 526:120807.

Wang, W., Van Gelder, P.M., Vrijling, J. & Ma, J. 2005. Testing and modelling autoregressive conditional heteroskedasticity of streamflow processes. *Nonlinear processes in Geophysics*. 12(1):55–66.