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.

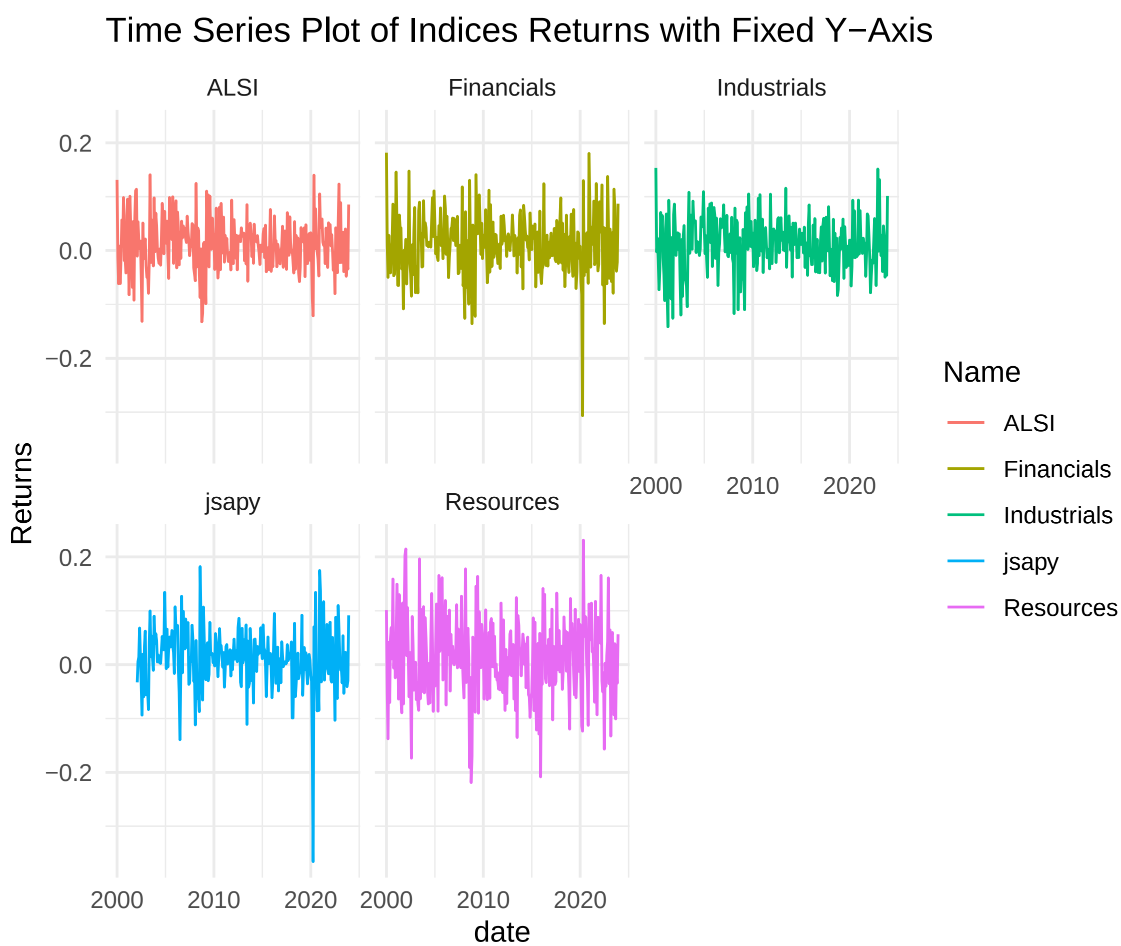

Figure 2.1: Time Series Analysis of Returns

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.

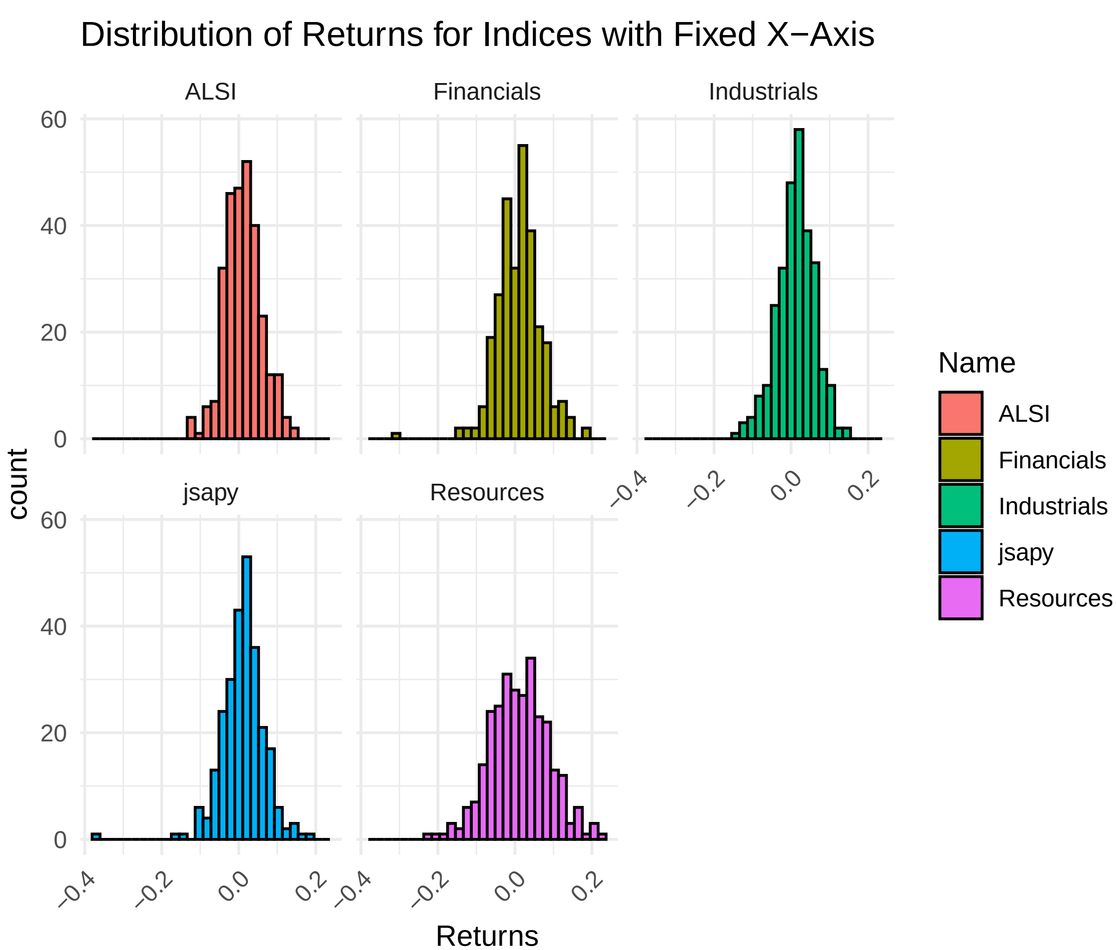

Figure 2.2: Distribution of Returns

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

References

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

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Appendix

Appendix A

Some appendix information here

Appendix B