The Impact of Loadshedding on SWIX Sectors using DCC-GARCH models

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Abstract

Abstract

1. Introduction

2. Literature Review

3. Data

The aim of this project is to construct time-varying conditional correlations between different sectors of the ALSI. These co-movements between sectors are then analysed over a stratified period where South Africa was affected by load-shedding. This study utilises a series of daily returns and weights of stocks in the ALSI, which are then filtered into either the Industrial, Financial, Resource or Property sector. Sector returns are calculated on a daily level and then the entire data set is subset into months than South Africa experienced load-shedding and months where it did not. The sample period of the data is from 1 January 2014 until 31 October 2022.

The sector returns are plotted in Figure 3.1 where it is visible that the sectors show characteristics of co-movement, especially during market shocks. This is evident with the onset of COVID-19 in March of 2020 where all sectors demonstrate a significant drawback in cumulative returns. Since this downturn in 2020, the Resource sector has grown significantly while Property has not been able to recover to pre-pandemic levels.

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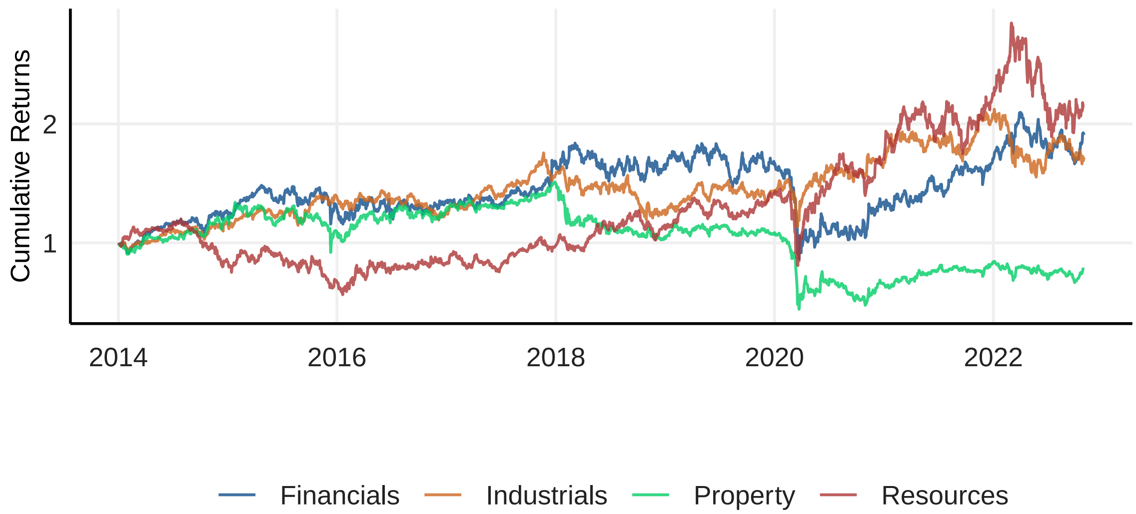

Figure 3.1: Cumulative Returns per Sector for ALSI and SWIX

3.1. Summary Statistics

Summary statistics for the series of daily sector returns are shown in Table 3.1. Resources show the largest average daily return ($\mu = 0.0005$) for the sample period, while Property shows the lowest average daily return ($\mu = 0$). The largest standard deviation belongs to the Resource sector, indicating that it has the largest volatility from a historical and static perspective. The Property sector has both the largest daily drawdown and the largest daily recovery over the sample period, at -19.35% and 15.49%. All of the sectors show negatively skewed tails, indicating that large negative returns are more likely than large positive returns for this sample period. Property exhibits a high degree of kurtosis, having its distribution concentrated around the mean. The Jarque-Bera test is used to assess whether the daily returns follow a normal distribution. The significance stars in Table 3.1 below indicate that the null hypothesis of normality in the sampled returns is rejected for all sectors at a 1% significance level.

Table 3.1: Summary Statistics and Test Scores for Sectors

	Financials	Industrials	Property	Resources
Mean	0.0004	0.0003	0	0.0005
Median	0.0006	0.0006	-0.0002	0.0004
Std.Dev	0.0161	0.0126	0.0171	0.0185
Min	-0.1227	-0.0881	-0.1935	-0.1457
Max	0.0885	0.0761	0.1549	0.1353
Skewness	-0.3902	-0.1333	-0.837	-0.1218
Kurtosis	6.3353	3.5137	26.4552	5.0679
Observations	2208	2208	2208	2208
Jarque.Bera	3758.53*	1146.21*	64776.75*	2375.19*
Ljung.Box	2100.8*	652.49*	1839.24*	1171.94
LM.GARCH	1331.899*	347.2372*	930.0183*	649.1169*

Note: This table provides summary statistics for daily returns of the sectors used in our study. Sample period: 1 January 2014 to 31 October 2022. * denotes statistical significance at 1%

3.2. Serial Autocorrelation and ARCH Effects

The Ljung-Box test is used to examine the data for serial autocorrelation over longer time periods, therefore a lag length of 10 is used. The results in Table 3.1 show that the null hypothesis of no autocorrelation can be rejected, requiring autoregressive terms in the mean equations to be fitted on all of the data. To supplement the Ljung-Box test, Figure 3.2 plots the daily returns. Figure 3.2 displays periods of volatility clustering, otherwise known as market momentum. This is a strong indication of second order persistence in the time series, pointing to autoregressive conditional heteroskedasticity (ARCH) effects and long memory that require explicit modelling of the variance components.

Engle (1982) LM-GARCH test confirms the presence of ARCH effects in all the series using:

$$\epsilon_t^2 = \beta_0 + (\Sigma_{s=1}^{10} \beta_s \epsilon_{t-s}^2) + \upsilon_t$$

. To control for these ARCH effects, Engle (1982) showed that it is possible to simultaneously model the mean and variance equations of a series using GARCH models. This technique will be further utilized to extract the time-varying conditional correlations of our time series data.

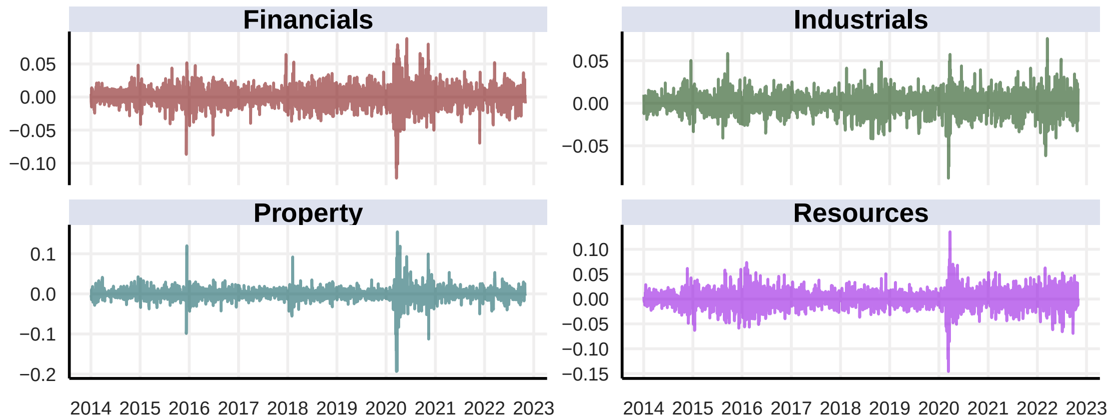

Figure 3.2: Log Returns per Sector for the SWIX

3.3. Co-Integration Tests

The next step is to test for co-integration in order to motivate the study of the time series conditional correlations. The Johansen (1988) co-integration test will be used to confirm whether there is at least one linear long-run relationship among the time series that would yield stationary residuals. The Johansen co-integration test uses a Vector Error Correction Model (VECM) approach with the form:

$$\Delta p_t = \prod p_{t-k} + \Gamma_1 p_{t-1} + \Gamma_2 p_{t-2} + ... + \Gamma_7 p_{t-7} + \mu + \delta(t) + \theta D_t + \epsilon_t \tag{3.1}$$

where p_t is a (1×4) vector of the daily returns for the sectors at time t. The Johansen test centres around the examination of the $\prod$-matrix. The $\prod$-matrix has form $\prod = \alpha\beta'$ where β is the k^{th} order co-integrating vector and α is the adjustment parameter. Below the Trace and Maximum Eigenvalue tests are used to consider the rank of the $\prod$-matrix using its eigenvalues. The rank will give an indication of long-run dependence. The Trace statistic tests whether the number of co-integrating vectors of the system is less than or equal to 4, while the Max-Eigenvalue statistic reflects separate tests used on each eigenvalue of the $\prod$-matrix. If the tests indicate that the rank of $\prod$ is statistically likely to be greater than 0, it would imply that there is co-integration and a long-run relationship between the variables.

The findings from the Trace test is that all relationships are co-integrating at the 1% significance level. The Eigenvalue test is conducted and confirms this result. This could indicate that the sectors have a common underlying factor that affects their movements. The co-integrating relationship represents correlation between the time series processes in the long term and validates the necessity to study these co-movements.

3.4. Unconditional Coerrelation

Table 3.2 gives the unconditional correlation of returns of the sectors for the entire period as well as for the unconditional correlation for the period where South Africa experienced load-shedding.

These static estimates of historic correlation are often used in practice but have many limitations. The unconditional correlations are limited by the sample period and do not account for any changes. Therefore they do not accurately reflect the relationships between the time series at specific points in time. In this section, it has been observed that the time series data of the sector returns display both first and second order serial autocorrelation. Thus the static estimates of correlation are misleading when the mean persistence and conditional heteroskedasticity is not controlled for. Static estimates of correlation also fail to take into account the dynamic nature of the underlying correlations. In the next section the underlying correlations conditional on past information will be studied.

Table 3.2: Static Unconditional Correlation

	Financials	Industrials	Property	Resources
Financials	1.0000	0.5779	0.6855	0.5005
Industrials	0.5096	1.0000	0.5267	0.5171
Property	0.6212	0.3557	1.0000	0.4156
Resources	0.3770	0.4679	0.2746	1.0000

Note: This table provides correlation for daily returns of the different sectors over the whole period (bottom left) and just the periods of load-shedding (top right).

4. Methodology

4.1. DCC Model

The goal of this study is to examine the dynamic correlations between the Industrial, Financial, Property and Resource sectors of the ALSI as well as to understand how these correlations change over time. To achieve this goal, the DCC (Dynamic Conditional Correlation) model is used. The DCC model is a statistical model that is commonly used to analyse the correlations between multiple time series data. It consists of two components: a GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model, which is used to model the variance of the time series data, and a dynamic conditional correlation model, which is used to model the correlations between the time series.

To estimate the DCC model the maximum likelihood estimation procedure is used. This involves specifying the functional form of the model, including the functional form of the GARCH and dynamic conditional correlation components. Then estimating the parameters of the model that maximize the likelihood of the data given the model. The DCC model has been widely used in the literature to study dynamic correlations in financial markets.

This study will use the sector daily returns, a 1×4 stochastic vector $\{r_t\}$. The DCC model is specified as follows:

$$r_{it} = \mu_{it} + \epsilon_{it} \tag{4.1}$$

$$\epsilon_{it} = \sqrt{H_{it}}.\eta_i \text{ with } \epsilon_{it} \sim N(0, H_t) \text{ and } \eta_i \sim N(0, I). \tag{4.2}$$

Where μ_t is the unconditional AR(1)-mean equation, ϵ_t the vector of ordinary residuals, H_t the $N \times N$ conditional covariance matrix and η_i the standardised residuals.

Various MV-GARCH models have been proposed to model the covariance process, H_t, in Equation 4.2. The DCC model will be used in this paper which allows the covariance matrix to be separated into different univariate volatility equations and their respective conditional correlations.

The covariance matrix in the DCC-Model is defined as follows:

$$H_t = D_t R_t D_t \tag{4.3}$$

with $D_t = diag(\sqrt{h_{11,t}}...\sqrt{h_{NN,t}})$ and $h_{ii,t}$ taking the functional form of the univariate GARCH model specified. The dynamic conditional correlation structure is then given by the following equation:

$$Q_{ij,t} = (1 - \theta_1 - \theta_2).\bar{Q} + \theta_1(\epsilon_{i,t-1}\epsilon^{'}_{j,t-1}) + \theta_2(Q_{ij,t-1}) \tag{4.4}$$

where $Q_{ij,t}$ is the unconditional variance between different series i and j, $\bar{Q}$ is the unconditional covariance between the series estimated in the univariate GARCH specification and estimation step.

The scalar parameters θ_1 and θ_2 must satisfy both the non negativity assumption $\theta_1 \geq 0$ and $\theta_2 \geq 0$ as well as the assumption that $\theta_1 + \theta_2 < 1$. The second step the requires only the estimate of θ_1 and θ_2 using a likelihood function. Equation **??** expresses the unconditional variance matrix, $Q_{ij,t}$, as a standard GARCH-type equation, so that we can derive the dynamic conditional correlation matrix, R_t, between any two series as:

$$R_t = Q_{ij,t}^{*-1}.Q_{ij,t}.Q_{ij,t}^{*-1} \tag{4.5}$$

with $Q^*_{ij,t}$ a diagonal matrix with the square root of the diagonal elements of $Q_{ij,t}$ as its entries, such that $Q^*_{ij,t} = Diag(Q_t)^{1/2}$. This process can be thought of intuitively as multiplying both sides of Equation **??** by the inverse of Diagonal matrix D_t. The dynamic conditional correlation matrix, $R_{ij,t}$ will therefore have entries in the bivariate framework as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}.q_{jj,t}}} \tag{4.6}$$

$$= \frac{(1-\theta_1-\theta_2)\bar{q} + \theta_1 \epsilon_{i,t-1}\epsilon'_{j,t-1} + \theta_2 q_{ij,t-1}}{((1-\theta_1-\theta_2)\bar{q_i} + \theta_1 \epsilon^2_{i,t-1} + \theta_2 q_{ii,t-1}).((1-\theta_1-\theta_2)\bar{q_j} + \theta_1 \epsilon^2_{j,t-1} + \theta_2 q_{jj,t-1})} \tag{4.7}$$

Following the methodology of Engle (2002), the DCC model is estimated by maximising the log-likelihood function for Equation 4.1 as:

$$L(\theta,\phi) = -\frac{1}{2}\sum_{t=1}^{T}(ln(2\pi) + ln(|D_t R_t D_t|) + \epsilon'_t (D_t R_t D_t)^{-1}\epsilon_t) \tag{4.8}$$

and using the fact that $H_t = D_t R_t D_t$, Equation 4.8 can be simplified as:

$$L(\theta,\phi) = -\frac{T}{2}ln(2\pi) - \frac{1}{2}.\sum_{t=1}^{T}(2.ln\,|D_t| + \epsilon'_t (D_t D_t)^{-1}\epsilon_t) - \frac{1}{2}\sum_{t=1}^{T}(ln\,|R_t| + \epsilon'_t (R_t^{-1})\epsilon_t) \tag{4.9}$$

The second step is then to maximise the correlation part by using the maximised value in the equation above to solve:

$$L_C(\theta, \phi) = -\frac{1}{2}\sum_{t=1}^{T}(ln\,|R_t| + \epsilon_t^{'}(R_t^{-1})\epsilon_t) \tag{4.10}$$

The two-stage DCC estimation procedure outlined above has parameter estimates that are both consistent and asymptotically normal. Cappiello, Engle & Sheppard (2006) find a clear limitation of the DDC, that the dynamics of the conditional correlation do not account for asymmetric effects. This means that although the model accounts for the magnitude of past shocks' impact on future conditional volatility and correlation, it does not differentiate between positive and negative shock effects. This limitation will not be resolved in this study. [1]

After the GARCH model is fit at a univariate level, the dynamic conditional correlation series will be fit for each bi-variate relationship. This dynamic structure of the returns of each sector pair of Resources, Financials, Property and Industrials will be explored further.

4.2. Univariate Specification

The first stage in building the DCC model framework consists of fitting univariate GARCH specifications to each series of returns. The univariate GARCH model fit on the data is the GJR-GARCH [glosten1993relation]. Table **??** below contains the chosen univariate GJR-GARCH fit.

The Univariate GARCH model includes:

Mean equation:

$$r_t = \mu + a_1.r_{t-1} + \epsilon_t \tag{4.11}$$

Volatility equation:

$$\epsilon_t = \sqrt{h_t}.\eta_t, \quad \text{where}\eta_t \sim N(0,1) \tag{4.12}$$

where r_t is the daily return for a sector at time t, μ is the unconditional mean of the time series and a_1 is the coefficient for the autoregressive term in the mean equation. The conditional variance at time

[1] In order to account for these effects the Asymmetric Dynamic Conditional Correlation (ADCC) was created, for more information follow @cappiello2006asymmetric or @engle1995multivariate

t, h_t, is modeled as a function of the variance at previous time periods and the error term at previous time periods. The random error term, ϵ_t, is multiplied by the square root of the conditional variance to ensure that the variance is always positive. The standardized error term, η_t, has a mean of 0 and a standard deviation of 1. Equation 4.12 specifies the relationship between the error term ϵ_t and the conditional variance h_t.

The GJR-GARCH model is a variant of the GARCH model that can effectively capture fat tails, excess kurtosis, and leverage effects, allowing for more flexibility in modeling the time-varying variance. In the GJR-GARCH(1,1) model, the variance at time t is modelled as:

$$h_t^2 = \beta_0 + \beta_1(|\epsilon_{t-1}| - \gamma\epsilon_{t-1})^2 + \beta_2 h_{t-1}^2 \tag{4.13}$$

This model combines elements of both the ARCH and GARCH models, and different model specifications can be obtained by varying the parameters γ and β_1. For example, setting $\gamma = 0$ results in a GARCH model.

The parameter γ in GJR-GARCH model reflects the leverage effect, which refers to the phenomenon where the magnitude of the response of the variance to a shock depends on the sign of the shock. A positive value of γ indicates that negative shocks tend to have a larger impact on the variance than positive shocks of the same magnitude, while a negative value of γ indicates the opposite. This model specifications allow the GJR-GARCH model to capture different responses of the variance to positive and negative shocks, which can be important for accurately modelling time series data that exhibits asymmetry.

Table 4.1 shows that the returns series for all sectors display strong persistence in volatility and both ARCH and GARCH effects, as measured by $(\alpha_1 + \beta_2)$. This indicates volatility clustering. The statistical significance of the β_2 parameter for all sectors in the GJF-GARCH model indicates a strong presence of conditional heteroskedasticity. This is consistent with the results of Engle (1982) LM-GARCH test run in section 3 and confirms the presence of ARCH effects. This further suggests that the static measures of return correlations between sector returns in the last section are not reliable.

The main takeaway from Table 4.1 comes from the α_1 and β_2 parameters, which can be used to assess the persistence of volatility in the time series. α_1 measures the contribution of past shocks to the current variance, while β_1 measures the contribution of the past variance to the current variance. A positive value of α_1 indicates that positive shocks tend to be followed by more volatility than negative shocks of a similar magnitude, while a negative value of α_1 indicates the opposite. Table 4.1 shows that Financials and Industrials have a negative value for α_1 indicating an asymmetry where negative shocks have a larger impact on volatility than positive shocks. Property and Resources both have positive values for α_1. Similarly, a positive value of β_2 indicates that high levels of volatility tend to persist over time, while a negative value of β_2 indicates that high levels of volatility tend to dissipate over time. All sectors have a significant and positive β_2. All sectors also have a positive and significant γ indicating that negative shocks tend to have a larger impact on the variance than positive shocks of the same magnitude.

To estimate the time-varying DCC model, the next step is to extract the standardized residuals from the estimated GJR GARCH model and maximize the log-likelihood function. This allows for the estimation of the time-varying conditional correlations between the sectors of the ALSI.

Table 4.1: Univariate GJR GARCH Coefficients

Sector	a_0	a_1	β_0	β_1	β_2	γ	Skewness	Shape
Financials	0.0003	-0.0044	0.0000	0.0241	0.9176	0.0906	0.9546	8.0904
	0.2075	0.8405	0.2271	0.0980	0.0000	0.0001	0.0000	0.0000
Industrials	0.0002	-0.0084	0.0000	0.0057	0.9017	0.1295	0.9117	8.8658
	0.2538	0.6971	0.0000	0.1845	0.0000	0.0000	0.0000	0.0000
Property	-0.0001	0.0005	0.0000	0.0374	0.8854	0.1012	1.0024	5.4217
	0.6317	0.9809	0.0527	0.0000	0.0000	0.0000	0.0000	0.0000
Resources	0.0003	0.0066	0.0000	0.0169	0.9444	0.0626	0.9554	10.3411
	0.3851	0.7588	0.4273	0.2334	0.0000	0.0001	0.0000	0.0000

Note: This table provides the univariate GJR GARCH model coefficients with the p-values underneath.

5. Results

In order to understand the dynamics of the different sectors of the ALSI the DCC models are analysed. The DCC model separates the variance and the correlation structure into two distinct components: the GARCH component, which models the variance of each time series, and the dynamic conditional correlation component, which models the correlations between the time series. This allows the DCC model to capture both the direct and indirect effects of one time series on the variance of another time series. Additionally, the DCC model allows for the dynamic correlations between time series to vary over time.

5.1. *Whole Period*

Table 5.1: .....

	Estimate	Std. Error	t value	Pr(>|t|)
[Financials].omega	0.0000	0.0000	0.6434	0.5199
[Financials].alpha1	0.0241	0.0248	0.9719	0.3311
[Financials].beta1	0.9176	0.0471	19.4922	0.0000
[Industrials].omega	0.0000	0.0000	5.3197	0.0000
[Industrials].alpha1	0.0057	0.0071	0.8065	0.4199
[Industrials].beta1	0.9017	0.0092	98.1795	0.0000
[Property].omega	0.0000	0.0000	0.6647	0.5062
[Property].alpha1	0.0374	0.0397	0.9403	0.3471
[Property].beta1	0.8854	0.0178	49.6809	0.0000
[Resources].omega	0.0000	0.0000	0.3505	0.7260
[Resources].alpha1	0.0169	0.0301	0.5623	0.5739
[Resources].beta1	0.9444	0.0479	19.7292	0.0000
[Joint]dcca1	0.0266	0.0047	5.6699	0.0000
[Joint]dccb1	0.9515	0.0090	105.1736	0.0000

Note: This table displays the fit of the dynamic conditional correlations of daily returns of different sectors within the ALSI over the full period of this study.

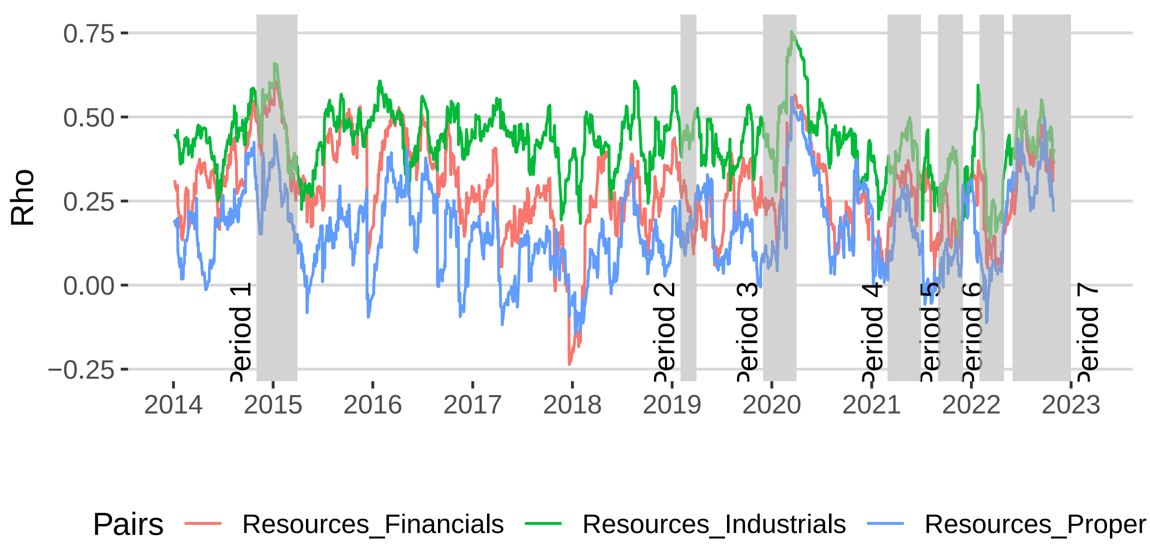

Figure 5.1: Dynamic Conditional Correlations: Resources

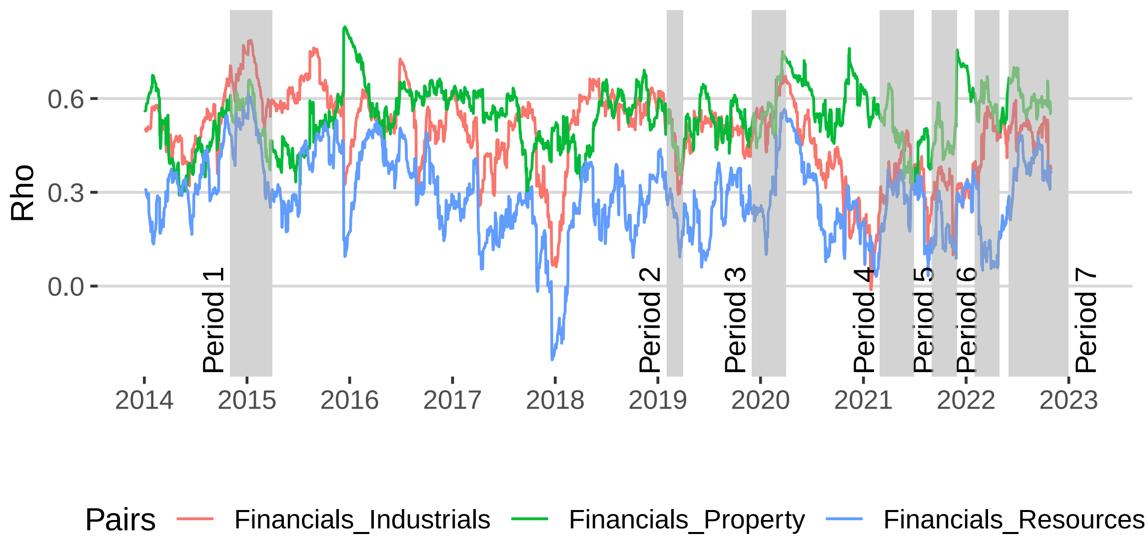

Figure 5.2: Dynamic Conditional Correlations: Financials

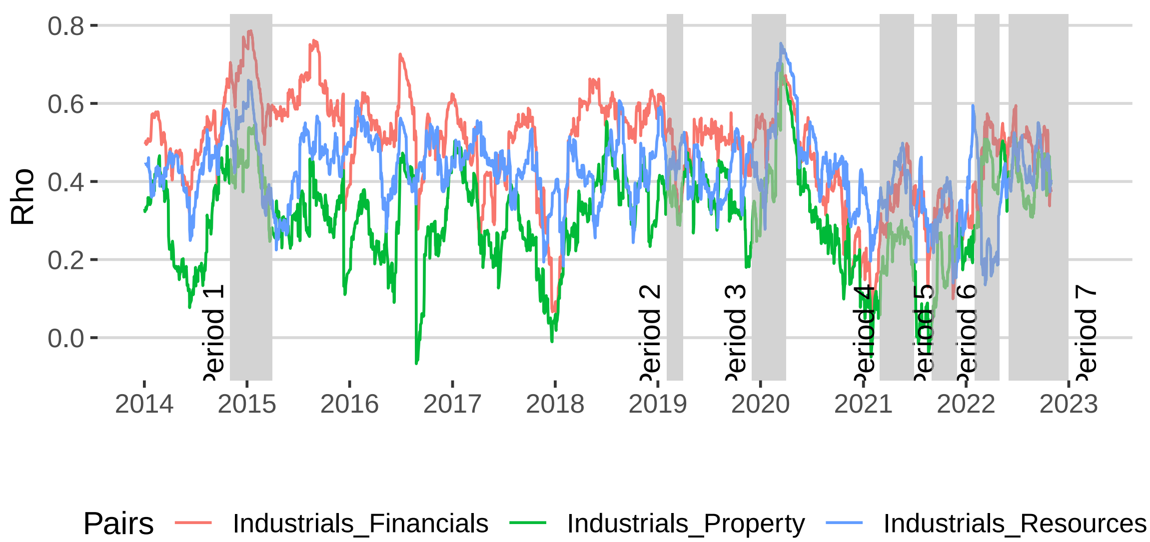

Figure 5.3: Dynamic Conditional Correlations: Industrials

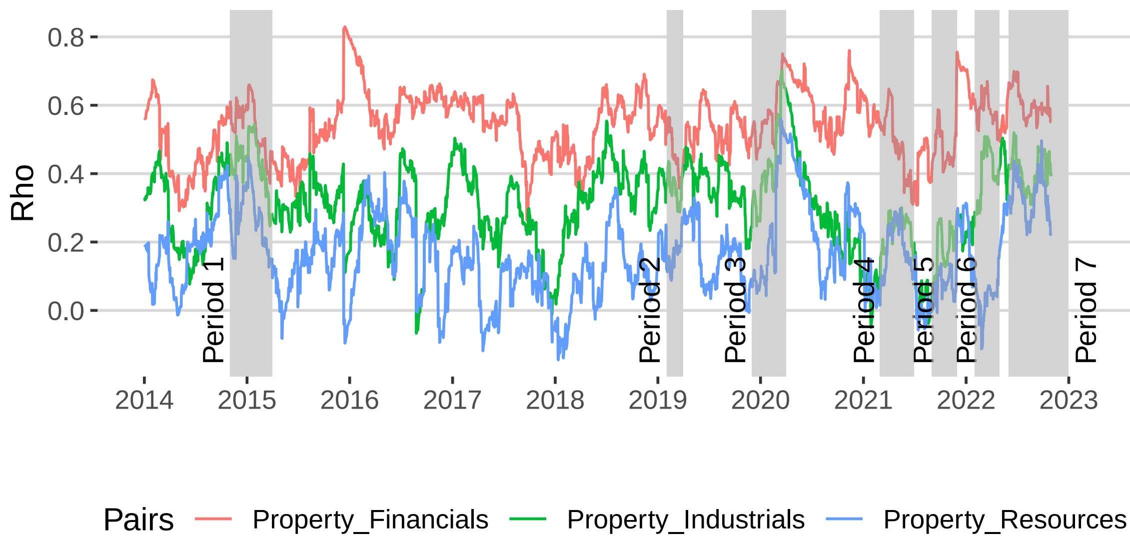

Figure 5.4: Dynamic Conditional Correlations: Property

	Mean	Std.Dev	Min	Max
Financials -> Industrials	0.4856	0.1342	-0.0124	0.7865
Financials -> Resources	0.5443	0.0949	0.2640	0.8294
Financials -> Property	0.2869	0.1331	-0.2362	0.6137
Industrials -> Resources	0.3089	0.1252	-0.0669	0.7016
Industrials -> Property	0.4283	0.0969	0.1348	0.7545
Resources -> Property	0.1646	0.1257	-0.1447	0.5596

Note: This table provides summary statistics of the dynamic conditional correlations of daily returns of different sectors within the ALSI over the entire period of this study.

5.2. Load Shedding Period

	Estimate	Std. Error	t value	Pr(>|t|)
[Financials].omega	0.0000	0.0000	2.6464	0.0081
[Financials].alpha1	0.0000	0.0758	0.0000	1.0000
[Financials].beta1	0.7239	0.0818	8.8533	0.0000
[Industrials].omega	0.0000	0.0000	18.2457	0.0000
[Industrials].alpha1	0.0000	0.0143	0.0000	1.0000
[Industrials].beta1	0.8280	0.0183	45.1670	0.0000
[Property].omega	0.0001	0.0000	3.1694	0.0015
[Property].alpha1	0.0687	0.0954	0.7200	0.4716
[Property].beta1	0.5314	0.1099	4.8351	0.0000
[Resources].omega	0.0000	0.0000	2.5240	0.0116
[Resources].alpha1	0.0000	0.0279	0.0000	1.0000
[Resources].beta1	0.7978	0.0585	13.6449	0.0000
[Joint]dcca1	0.0247	0.0102	2.4348	0.0149
[Joint]dccb1	0.9275	0.0314	29.5384	0.0000

Note: This table displays the fit of the dynamic conditional correlations of daily returns of different sectors within the ALSI over the periods that encounter loadshedding in this study.

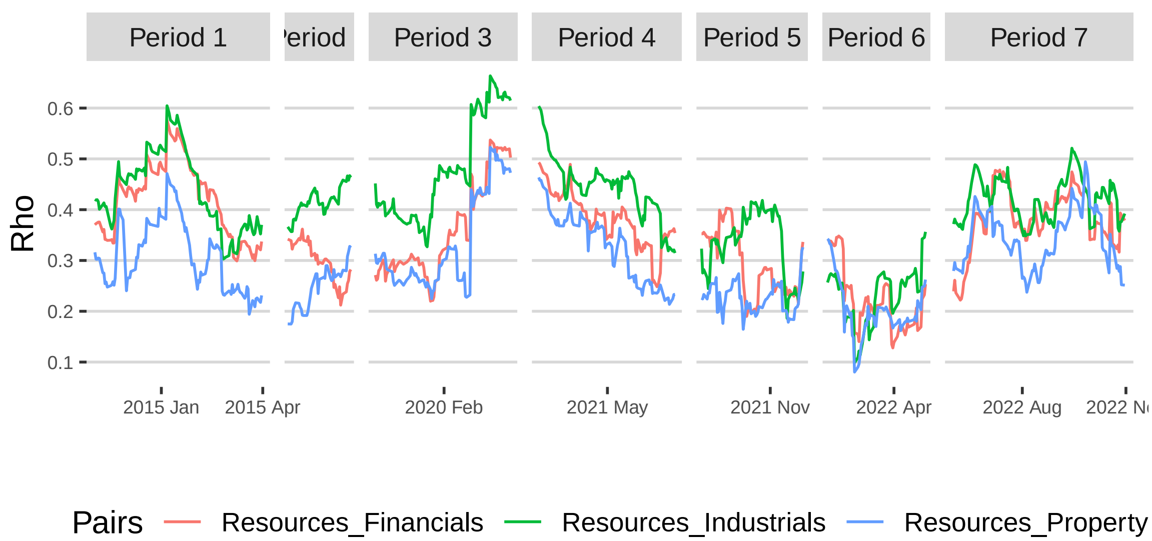

Figure 5.5: Dynamic Conditional Correlations: Resources

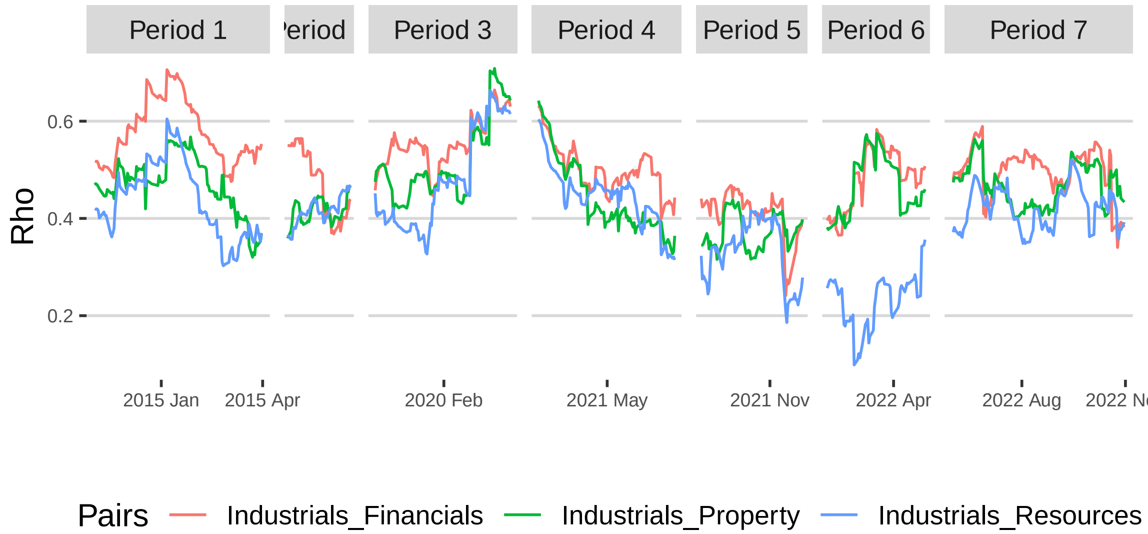

Figure 5.6: Dynamic Conditional Correlations: Industrials g

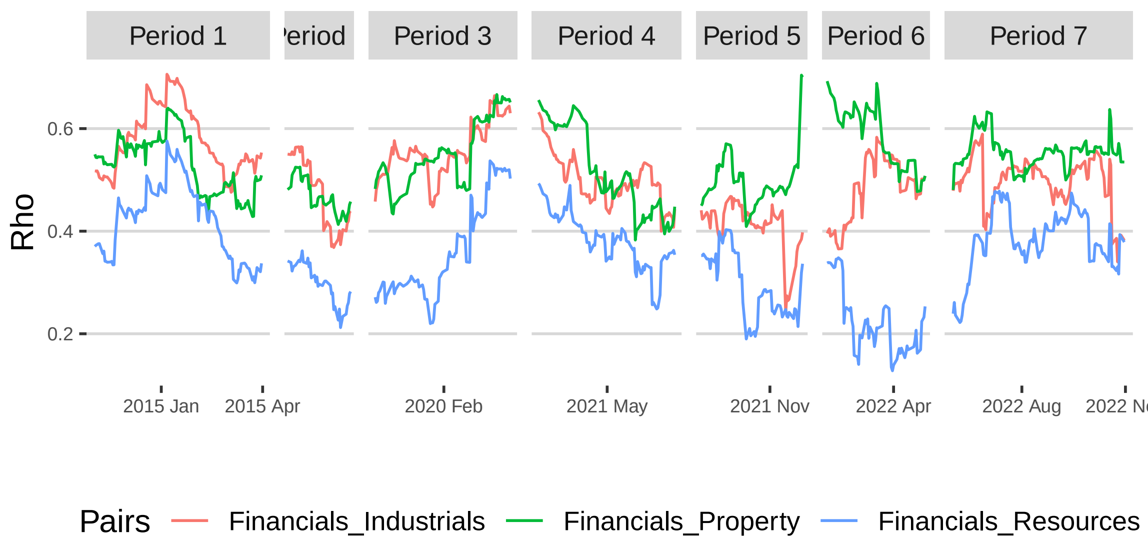

Figure 5.7: Dynamic Conditional Correlations: Financials

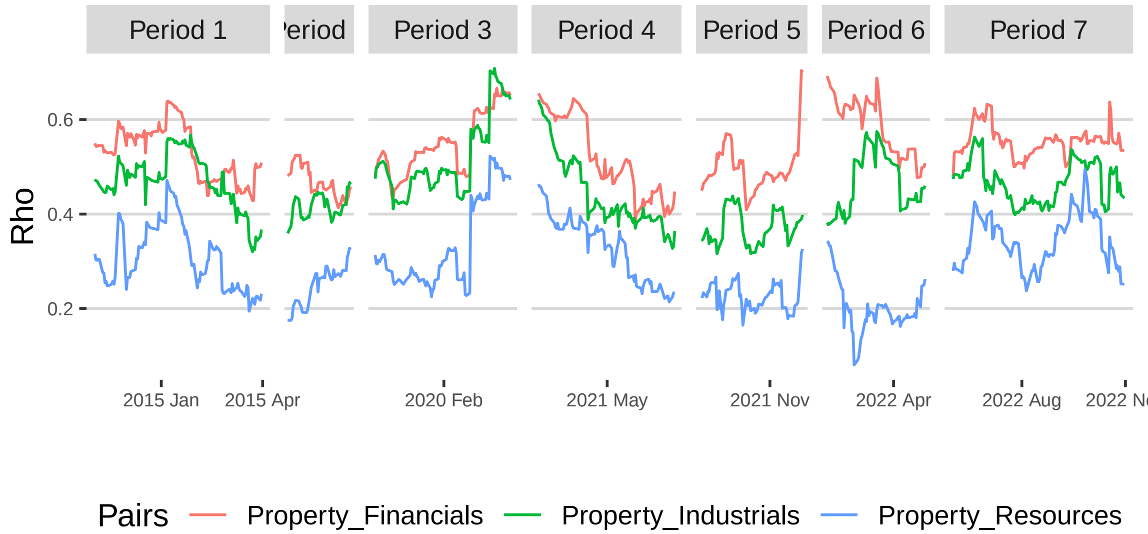

Figure 5.8: Dynamic Conditional Correlations: Property

	Mean	Std.Dev	Min	Max
Financials -> Industrials	0.5077	0.0763	0.2413	0.7059
Financials -> Resources	0.5344	0.0655	0.3827	0.7042
Financials -> Property	0.3516	0.0914	0.1279	0.5758
Industrials -> Resources	0.4565	0.0730	0.3156	0.7085
Industrials -> Property	0.4050	0.1006	0.0987	0.6634
Resources -> Property	0.2957	0.0824	0.0803	0.5228

Note: This table provides summary statistics of the dynamic conditional correlations of daily returns of different sectors within the ALSI over the periods that encounter loadshedding in this study.

The results from the Dynamic Conditional Correlations (DCC) model show that the volatility of sector returns exhibit strong co-movements, as observed in the Table **??** and illustrated in the Figure **??**. The DCC model, which extracts the underlying process and removes noise from the data, reveals lower correlations compared to the static correlations presented in section **??**. The minimum and maximum values of the correlations tend to occur during times of endogenous and exogenous shocks to the market. This suggests that the market is highly interconnected and exhibits volatility clustering, as found in section **??**.

When examining the dynamic correlations between sectors in Figure **??**, it is clear that the co-movements between these assets are relatively low.

6. Conclusion

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Appendix

6.1. No Loadshedding Results

	Estimate	Std. Error	t value	Pr(>|t|)
[Financials].omega	0.0000	0.0000	0.5307	0.5956
[Financials].alpha1	0.0308	0.0202	1.5247	0.1273
[Financials].beta1	0.9319	0.0296	31.4997	0.0000
[Industrials].omega	0.0000	0.0000	0.1620	0.8713
[Industrials].alpha1	0.0203	0.0968	0.2099	0.8337
[Industrials].beta1	0.9021	0.0823	10.9579	0.0000
[Property].omega	0.0000	0.0000	0.4572	0.6475
[Property].alpha1	0.0594	0.0502	1.1813	0.2375
[Property].beta1	0.8878	0.0279	31.7715	0.0000
[Resources].omega	0.0000	0.0000	0.4453	0.6561
[Resources].alpha1	0.0393	0.0206	1.9053	0.0567
[Resources].beta1	0.9418	0.0283	33.2911	0.0000
[Joint]dcca1	0.0279	0.0061	4.5714	0.0000
[Joint]dccb1	0.9440	0.0143	65.8566	0.0000

Note: This table displays the fit of the dynamic conditional correlations of daily returns of different sectors within the ALSI over the periods that do not encounter loadshedding in this study.

	Mean	Std.Dev	Min	Max
Financials -> Industrials	0.4809	0.1287	0.0128	0.7520
Financials -> Resources	0.5440	0.0877	0.2343	0.8391
Financials -> Property	0.2744	0.1260	-0.2475	0.5506
Industrials -> Resources	0.2642	0.1138	-0.1141	0.5330
Industrials -> Property	0.4384	0.0794	0.1904	0.6814
Resources -> Property	0.1434	0.1158	-0.1522	0.5349

Note: This table provides summary statistics of the dynamic conditional correlations of daily returns of different sectors within the ALSI over the periods that do not encounter loadshedding in this study.