Dynamic Correlations Between the U.S. Equity Market and Australian Sector Indices and Their Regime Differences: Evidence from DCC-GARCH with Wavelet–Changepoint Segmentation

Ruixin Huang
School of Economics & School of Mathematics and Statistics, University of Sydney, New South Wales, Sydney, 2050, Australia
huangruixin84@gmail.com

ABSTRACT

This study observes the time-varying linkage relationship between the US stock market and the three industry indexes in Australia, and wants to see if this correlation has different laws at different stages. We use the daily index data from Yahoo Finance to calculate the logarithmic rate of return, and also use ADF and KPSS test to check the stationarity of the data. The division of stages is automatically determined by a data-driven method: firstly, an American volatility proxy index is decomposed by wavelet, and then combined with the detection of PELT mutation point, and finally two breakpoints are found, which divides the whole sample period into three stages. Then, we estimate a DCC-GARCH model to find out the dynamic correlation between the American market and each Australian industry. The results show that there has always been a positive linkage between them, and the ranking of strong and weak industries is very stable: Consumer Discretionary has the strongest connection with the American market, followed by Industrials, and Consumer Staples has the weakest correlation. On the whole, the average correlation in different stages does not change much, but the tail linkage and related volatility in the middle stage will become stronger, which means that the effect of diversification will become worse when the markets are more closely linked. We use the thick-tailed DCC model with multivariate T distribution innovation to test the robustness, and the results are consistent with the previous ones, and the information criterion is better than the Gaussian benchmark model.

Keywords: Dynamic correlation; DCC–GARCH; regime segmentation; wavelets; changepoint detection; diversification

1. INTRODUCTION

Diversified investment in the world is very important for us to build a portfolio; But its effect depends on the stability of the links between different markets. In fact, when the market is particularly uncertain, the correlation between them often becomes stronger, and as a result, when we need to diversify risks most, its benefits become less. As a major information and pricing center, American stock market can influence other markets through global risk appetite, capital flow and information transmission. Australia is closely related to the global financial market, but its various industry indexes are different in terms of economic periodicity and the impact of global demand. Therefore, the linkage between the performance of various industries in the US market and Australia may not only change with time, but also vary from industry to industry.

This paper will study two issues. First, how will the correlation between the US stock market and different industry indexes in Australia change over time? Second, will these correlations show different "patterns", which are meaningful in economics and persist in all industries? In order to avoid using static correlation measurement method or selecting time period subjectively, we combine data-driven pattern division with a framework called Dynamic Conditional Correlation (DCC).

The contribution of this research is threefold. First, it systematically studies the dynamic correlation between American market and three industries in Australia-Consumer Staples, Consumer Discretionary and Industries, and finds that the ranking order of these industries has been quite stable. Secondly, it uses a method called wavelet–change point segmentation to find the dividing line of different patterns from the data, thus reducing the problem of randomly selecting time periods. Thirdly, it uses a threshold-based high-synchronous frequency measurement method to evaluate the tail linkage, and links the observed phenomenon with a practical problem: when the benefits of investment diversification may decrease.

The rest of this paper is arranged like this. Section 2 reviews the related research on time-varying dependence, volatility modeling and state transition. Section 3 introduces the construction method of data and variables. Section 4 explains the empirical methods, including stationarity test, state division, DCC-GARCH estimation and tail synchronization measurement. Section 5 shows the main results. Section 6 reports the robustness test using thick-tailed DCC model. Section 7 is a summary.

2. LITERATURE REVIEW

Many studies have found that the dependence between countries and different industries will change with time, not be fixed. In times of crisis, the correlation between them tends to become stronger, which makes the effect of cross-market diversification worse. This common phenomenon urges people to establish some econometric models, so that conditional variance and correlation coefficient can also change dynamically.

We usually use GARCH models to describe the dynamic changes of volatility, which can capture the phenomenon that volatility will gather together and continue. But in the case of multivariable, it is difficult to simulate the whole conditional covariance matrix because the dimension is too high. DCC framework provides a simple and common solution, which separates conditional variance (estimated by univariate model) from conditional correlation (dynamic simulation). Therefore, DCC-GARCH model is especially suitable for research and analysis of the linkage relationship between different markets and industries over time.

Another study is about structural mutation and institutional change. This idea is also consistent with the general direction of studying structural changes and dynamics under different systems in time series analysis. [1][5] Many studies define institutions according to external events, but this may be a bit subjective and may not match the structural changes of the data itself. The change point detection method provides a more data-based method, which can find out the time point when the statistical characteristics change. Wavelet method is very useful here, because it can decompose a signal into different time scales and help us separate those components that may better reflect the change of medium-term volatility. Therefore, by combining wavelet features with change point detection, a more objective system division boundary can be obtained.

Finally, diversification theory tells us that whether it is useful to hold assets in different markets depends on the dependence structure between them. If under some systems, the correlation between assets becomes stronger, or synchronous movements occur more often in extreme cases, then the benefits of diversification will decrease. This makes us not only look at the average correlation, but also study how extreme situations change together under a specific system.

3. DATA

Every day's index data is obtained from Yahoo Finance. The representative of American market is S&P 500 index, and the representative of Australian industry is three S&P/ASX 200 industry indexes, which represent Consumer Staples, Consumer Discretion and Industrials. Our sampling time is from March 1, 2016 to March 1, 2026. Because the holiday arrangements in the American and Australian markets are different, we only kept the days when all the indexes were traded together, so we aligned the price data and finally got 2,211 synchronized daily income data. [9]

The income is calculated with the adjusted closing price by taking their logarithmic difference and expressing it as a percentage. For simplicity, some basic statistical information of income data will not be written here. Based on the stationarity diagnosis results of ADF and KPSS test, you can ask us for it if you need it.

4. METHODOLOGY

4.1 Return construction

The daily log returns are calculated according to the adjusted closing price, and the result is expressed as a percentage. This transformation is helpful for us to model and understand volatility, and it is also in line with the common practice in intellectual finance.

4.2 Stationarity tests: ADF and KPSS

We use two tests to check whether the data is stationary: one is Augmented Dickey-Fuller test, which assumes that the data has a unit root; The other is KPSS test, which assumes that the data is stationary. At the same time, these two tests can complement each other, which makes it easier for us to understand the data and facilitate the establishment of the model later. [3][7]

4.3 Data-driven regime segmentation: wavelet decomposition and PELT changepoints

In order to objectively determine different periods, we use the absolute return series of S&P 500 index as a proxy index of American volatility. We use a wavelet transform method called LA8 filter to extract the second level of detail components to represent the medium-scale fluctuation of the proxy index of volatility. Then, we use PELT algorithm and set a minimum time limit to detect the change points of mean and variance. This method found two dividing points: February 21, 2017 and October 16, 2024, which divided the whole sample into three stages. Table 1 lists the start and end time of each stage and the number of observations contained in it. [8][6]

Table 1. Data-driven regime breakpoints and phase sample sizes

Item	Value
Sample period	2016-03-01 to 2026-03-01
Breakpoint 1	2017-02-21
Breakpoint 2	2024-10-16
Phase 1 obs.	217
Phase 2 obs.	1705
Phase 3 obs.	289

4.4 DCC–GARCH model

We use DCC (1,1) model to analyze four return series (American index plus three Australian industries). Conditional variance uses univariate sGARCH (1,1) process, while conditional correlation changes according to the setting of DCC. The benchmark hypothesis is the innovation of multivariate normal distribution. We focus on three time-varying correlations between the American index and each Australian industry. [4][2]

4.5 Tail synchronization frequency

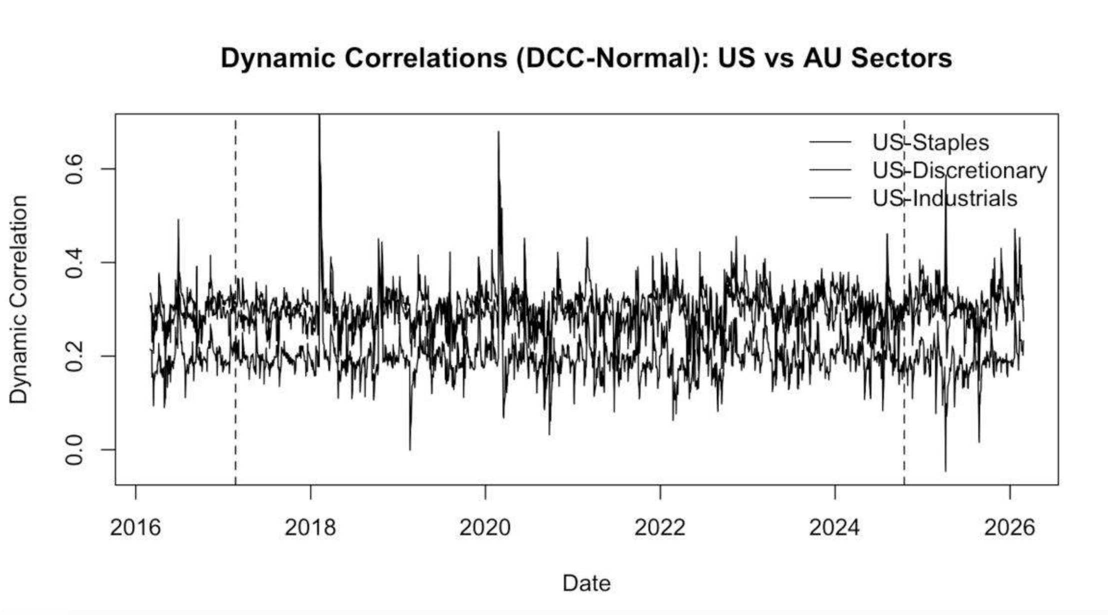
In order to measure the tail linkage, we define the situation that the dynamic correlation exceeds a certain threshold as a high synchronization event. When the thresholds are set to 0.5, 0.6 and 0.7, we calculate the overrun frequency of each U.S.-sector combination in the stage. This index can complement the interval comparison based on the mean, because it can highlight the prevalence of abnormally high dependence.

5. EMPIRICAL RESULTS

5.1 Time-varying correlations

Figure 1 shows the dynamic correlation of estimation under Gaussian DCC model, in which the vertical line represents two institutional breakpoints. The correlation is generally positive, but it fluctuates and occasionally peaks. In the whole sample, Consumer Discretionary plate has the strongest linkage with American market, followed by Industrials, and Consumer Staples usually has the weakest correlation.

Figure 1. Dynamic conditional correlations (DCC–Normal) between the U.S. equity market and Australian sector indices. Vertical dashed lines mark data-driven regime breakpoints (2017-02-21 and 2024-10-16).



5.2 Regime-level summaries

Table 2 shows the summary of dynamic correlation in different stages, including average, standard deviation, maximum and 95th percentile. The ranking of each sector remains stable at each stage. Although there is little difference in the average correlation level in different States, the variation of dispersion degree and tail characteristics is more obvious. This shows that the difference between different States is more reflected in the intensity and variability of coordinated motion than just the difference in average dependence.

Table 2. Phase summary of dynamic correlations (DCC-Normal)

Pair	Phase	Mean	SD	Max	Q95
US-Staples	Phase1	0.195855	0.038049	0.429274	0.259365
US-Staples	Phase2	0.193864	0.045816	0.68787	0.25723
US-Staples	Phase3	0.182228	0.039192	0.293154	0.239055
US-Discretionary	Phase1	0.310243	0.036471	0.49171	0.363122
US-Discretionary	Phase2	0.314306	0.045669	0.718782	0.378144
US-Discretionary	Phase3	0.325512	0.041088	0.587238	0.383776
US-Industrials	Phase1	0.283967	0.031808	0.451608	0.324748
US-Industrials	Phase2	0.286452	0.046259	0.7115	0.347283
US-Industrials	Phase3	0.298884	0.040989	0.453366	0.373046

5.3 High synchronization frequencies

Table 3 reports threshold-based synchronization frequencies under the Gaussian DCC specification. High-correlation events are generally more concentrated in the middle phase, especially at higher thresholds, indicating stronger tail comovement during this regime. However, at the lower threshold, the U.S.–Discretionary pair also shows a relatively higher exceedance frequency in the final phase, suggesting that elevated comovement can re-emerge when a less stringent definition of “high correlation” is used. Overall, the pattern implies that diversification benefits may deteriorate in regimes where the likelihood of strong synchronization increases.

Table 3. Extreme co-movement frequency by threshold (DCC-Normal)

Threshold	Phase	US-Staples	US-Discretionary	US-Industrials
0.5	Phase1	0.0	0.0	0.0
0.5	Phase2	0.002932551	0.005865103	0.005865103
0.5	Phase3	0.0	0.0103806228	0.0058651026
0.6	Phase1	0.0	0.0	0.0
0.6	Phase2	0.001173021	0.0029325513	0.0029325513
0.6	Phase3	0.0	0.0	0.0
0.7	Phase1	0.0	0.0	0.0
0.7	Phase2	0.0	0.0005865103	0.0005865103
0.7	Phase3	0.0	0.0	0.0

6. ROBUSTNESS CHECKS

6.1 Heavy-tailed DCC specification

To account for fat-tailed behavior in financial returns, we re-estimate the model using multivariate t innovations with univariate Student-t specifications. Table 4 compares fit criteria across the Gaussian and t-based DCC models. The heavy-tailed model achieves improved information criteria and a higher log-likelihood, supporting its empirical relevance. [4]

Table 4. DCC model fit summary and information criteria (lower is better)

Model	Distribution	No. parameters	Log-Likelihood	Akaike	Bayes	Shibata	Hannan-Quinn
DCC-Normal	mvnorm	24	-11044.46	10.01218	10.07406	10.01194	10.03478
DCC-t	mvt	29	-10671.38	9.679223	9.754001	9.678884	9.70654

6.2 Robustness of regime summaries and tail frequencies

Figure 2 and Table 6 present dynamic correlations and regime summaries under the DCC–t specification. The main qualitative findings remain unchanged: correlations are positive, sector ranking is stable, and regime differences manifest primarily through volatility and tail behavior. Table 5 reports threshold-based synchronization frequencies under the t specification, confirming that high-synchronization events are most pronounced in the middle phase, consistent with the baseline analysis.

Table 5. Extreme co-movement frequency by threshold (DCC-t)

Threshold	Phase	US-Staples	US-Discretionary	US-Industrials
0.5	Phase1	0.0	0.0	0.0
0.5	Phase2	0.006451613	0.0117302053	0.0123167155
0.5	Phase3	0.0	0.0103806228	0.0
0.6	Phase1	0.0	0.0	0.0
0.6	Phase2	0.002346041	0.0064516129	0.0052785924

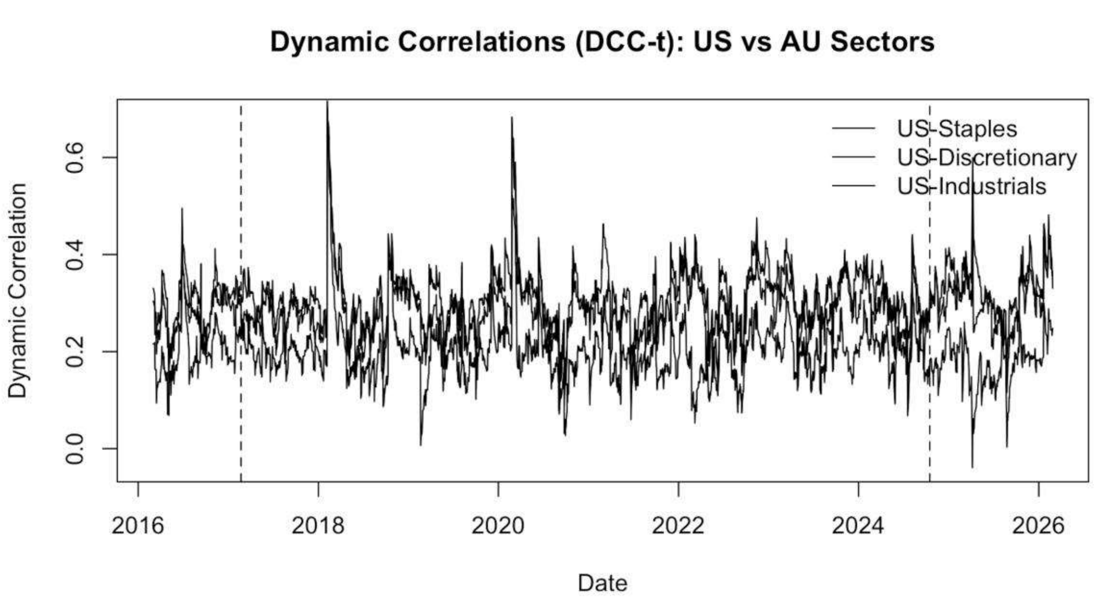
Table 5. (continued) Extreme co-movement frequency by threshold (DCC-t)

Threshold	Phase	US-Staples	US-Discretionary	US-Industrials
0.6	Phase3	0.0	0.0	0.0
0.7	Phase1	0.0	0.0	0.0
0.7	Phase2	0.0	0.0005865103	0.0005865103
0.7	Phase3	0.0	0.0	0.0

Table 6. Phase summary of dynamic correlations (DCC-t)

Pair	Phase	Mean	SD	Max	Q95
US-Staples	Phase1	0.199933	0.055212	0.444355	0.281771
US-Staples	Phase2	0.196312	0.061564	0.690327	0.282924
US-Staples	Phase3	0.172698	0.05085	0.298673	0.250145
US-Discretionary	Phase1	0.301681	0.055072	0.495153	0.377331
US-Discretionary	Phase2	0.308896	0.064767	0.71591	0.40286
US-Discretionary	Phase3	0.329278	0.055756	0.599355	0.415515
US-Industrials	Phase1	0.278052	0.043744	0.451755	0.336986
US-Industrials	Phase2	0.281296	0.064919	0.700061	0.374144
US-Industrials	Phase3	0.303716	0.057582	0.481261	0.403153

Figure 2. Dynamic conditional correlations (DCC–t) between the U.S. equity market and Australian sector indices. Vertical dashed lines indicate the data-driven regime breakpoints (2017-02-21 and 2024-10-16).



7. CONCLUSION

This paper investigates dynamic correlations between the U.S. equity market and Australian sector indices using DCC–GARCH models and data-driven regime segmentation. Using synchronized daily index returns from 2016 to early 2026, two breakpoints are identified via wavelet decomposition of a U.S. volatility proxy combined with PELT changepoint detection, yielding three regimes. DCC estimates indicate persistently positive comovement with a stable sector ranking, in which Consumer Discretionary is most closely linked to the U.S. market and Consumer Staples the least. The comparison of Regime shows that the average correlation changes little, but in the middle regime, the fluctuation of tail linkage and correlation becomes more obvious, which means that when the synchronization between markets is strengthened, the benefits of diversification may decrease. The robustness test using the thick-tailed DCC model gives consistent results and better information criteria, which enhances the credibility of these findings.

REFERENCES

[1] Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1–22.
[2] Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. The Review of Economics and Statistics, 72(3), 498–505.
[3] Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427–431.
[4] Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339–350.
[5] Hamilton, J. D. (1994). Time series analysis. Princeton University Press.
[6] Killick, R., Fearnhead, P., & Eckley, I. A. (2012). Optimal detection of changepoints with a linear computational cost. Journal of the American Statistical Association, 107(500), 1590–1598.
[7] Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54(1–3), 159–178.
[8] Percival, D. B., & Walden, A. T. (2000). Wavelet methods for time series analysis. Cambridge University Press.
[9] Yahoo Finance. (n.d.). Historical market data. Yahoo Finance database.