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How Volatility and Herding of the Stock Markets in the Oceania Region Influence Investors and Policymakers: A Sector-Wise Exploration in Pre and Post-COVID Period

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Abstract

The paper probes the sector-wise presence of volatility persistence, herding behavior and corresponding implications on investors and policymakers in the Oceania region both in Pre-COVID & Post-COVID era. The inspection is based on seven identical sectors from both Australia and New Zealand using GARCH (Generalized autoregressive conditional heteroscedasticity) methods for volatility analysis and CSAD (Cross-Sectional Absolute Deviation) method for herding behavior. This paper finds the existence of herding behavior only in the consumer discretionary sector for both countries which delineates efficient market conditions for other sectors. The market is highly favorable for the investors in Food & Beverages, IT, and Healthcare sectors in both countries due to the potential growth opportunity while Real Estate and Financial sectors should be meticulously assessed in line with the alteration of macroeconomic forces. Fiscal and monetary measures along with the influx of labor forces and technological breakthroughs should be the key concentrations for the policymakers of both countries.

Keywords: volatility persistency, herding behavior, COVID-19, investors, policymakers, stock market

JEL: C15, G11, G17, G18, G41.

1. Introduction

The stability of a nation's economy may be pinned down from its endurance to a crisis period. Moreover, a nation will be regarded as stable in making the appropriate decisions in a dangerous situation. An embryonic policy can shift one nation to an abyss by making the future unstable unprecedented. Since the economy of a country is coalesced by the contribution of the very industries it confines, we, the researchers tried to fathom a way to dissect the sector-wise behavior of the stock market to prolong the strength of an economy on the verge of precariousness. As the stock market is often depicted as an excerpt for the overall industrial output, it is imperious to measure the volatility along with the herding behavior to apprehend the cardinal goal of understanding the strengths and weaknesses of an economy, especially under inauspicious situations (Zaremba et al., 2020; Audrino et al., 2020; Bai et al., 2020; Albulescu, 2021). The economy and the stock market is correlated inextricably as the repercussions of public and private organization interventions cause stock market fluctuations in rebuttal to investor expectations for the future (Hajilee et al., 2021; Baker et al., 2020; Sarkar, 2020). Generally, the relationship between the stock market and the economy is often coherent since myriad macroeconomic variables confluence with stocks of different industries representing how the real economy is doing. A soaring stock market may demonstrate better economic conditions for businesses, resulting in higher profits, while a collapsing one may indicate a recession. These patterns suggest that the economy and stock market will move in cahoots with time in which the connections may require profound investigation to enhance policymaking and investing decisions.

However, the stock market of a particular country is highly volatile to tame the results to be specific that reinforces the daily stock market return to be preposterous (Hieu et al., 2020; Dai et al., 2020). The whole civilization witnessed the aftermath of COVID-19, and the turmoil almost tried to asphyxiate the economy wherever the pandemic hit. So, the crisis period analogous to COVID-19 is uncertain, and therefore it is paramount to figure out the volatility in the stock market with a proper investigation (Li et al., 2020; Yoshino et al., 2021; Ji et al., 2020;

Ramelli & Wagner, 2020; O'Donnell et al., 2021; Mishra & Mishra, 2020). Previously, numerous researchers strived to uncover the factors affecting the stock market volatility. However, most of them were not considered industry-wise. Unlike previous research, we scrutinize the cherished industries that the investors and the public should look for by analyzing the dataset for two neighboring countries: Australia and New Zealand. Research is deficient regarding the stock markets of these two, let alone industry-wise investigation. This study also accommodates herding behavior analysis to fortify the findings. The virus has spread all over the world since it was first discovered in Wuhan, China. On January 27, 2020, Australia became the first country in Oceania to document COVID-19 infections (Georgeou & Hawksley, 2020), while New Zealand confirmed its first case of the disease in Auckland on February 28, 2020.

Individual decisions are influenced by group behavior, which is referred to as herding behavior. It is predicated on the notion that when a herd of animals moves in one direction, all the animals want to follow that group. So in the event of a crisis, it may be pertinent to incorporate herding behavior for investigating the stock market return's volatility (Arjoon et al., 2020; Kiran et al., 2020; Ferrouhi, 2021). When it comes to investing, volatility refers to how widely a security or market index's returns vary. The riskier a security is, the higher the volatility. The standard deviation or variance of returns from the same security or market index is often used to calculate volatility. Although this volatility can pose a significant investment risk, it can also form solid returns for savvy investors. There may be an opportunity even when markets fluctuate, crash, or surge. Again, the GARCH (Generalized autoregressive conditional heteroscedasticity) model is coherent for volatility analysis of the market return rather than holding onto a single ARCH model (Endri et al., 2020; Sun & Yu, 2020; Kim et al., 2021). Profuse researches are investigated to conclude the findings evaluating different versions of the GARCH model.

To fathom a very smoothed inspection from the gleaned datasets, evaluating volatility using behavioral analysis to develop a convenient prediction for investors in the New Zealand stock market will be quite appealing. Numerous researchers came upfront with various degrees of experiments to apprehend the pith of these perplexing shreds of evidence mustered from yearly information (Frijns & Indriawan, 2018; Chen et al., 2019; Lin & Quill, 2016; Gunasekarage & Wan, 2007; Yu, 2002). Though New Zealand is smaller than Australia, the index return of the stock market belies the thought of minuscule embodiment to reinforce the economy. The market movement is as salient as any major nation. In comparison to Australia, the analysis is not less cardinal as one reckons since many researchers acknowledged the market as indispensable (Chung et al., 2016; Chia, 2014; Dassanayake & Jayawardena, 2017). Moreover, the scrutinized results found in some papers prescribe striking resolution about the market during the COVID era (Brueckner & Vespignani, 2021; Alam et al., 2021; Rahman et al., 2021). As there is a dearth of research regarding the Oceania region let alone incorporating volatility and herding behavior on the same investigation, we, the researchers find it enticing to leap at this invigorating prospect so that the contribution of this paper does not go unnoticed for future exploration during the erratic period.

Furthermore, the findings of this study have critical implications for investors to arbitrate which industry to focus on and for policymakers to count on which industry during crisis moments. The research would be pivotal in understanding the significance of herding behavior during an unfavorable situation. Furthermore, investigating through GARCH and herding behavior methods is not as straightforward as in earlier studies making the research findings novel. Instead, the investigation provides several stupendous findings that will augment previous discoveries so that decision-makers will reconsider their perspective on these sectors.

To fortify the economy of a nation during capricious & vulnerable moments, it is crucial to perceive a strategy for the policymakers and the investors in the Oceania region. The core analysis is focused on executing that particular objective, and every effort has been made to contribute to the findings of other researchers working on this topic. Again, we found some research that champions our investigation on several aspects. The empirical evidence from previous studies is showcased in the second section of this study with thorough observation. The third section conveys the datasets and methodology, while the fourth section delves into the empirical findings and their implications.

2. Literature Review

Many researchers have worked on the stock market volatility over the years. In analyzing the volatility, the GARCH family has been used quite extensively (Mokni et al., 2017; Liu et al., 2017; Slim et al., 2017; Benlagha et al., 2017; Helmut, 2017; Birău et al., 2015; Oberholzer et al., 2015; Kumari et al., 2015). Consequently, numerous scholars have conducted extensive research on stock market volatility in recent years. Some of these outstanding studies deserve to be mentioned in our literature review.

Phan et al. (2021) investigate the relationship between investor sentiment and stock return based on Vietnam Stock Exchange and find a negative relationship between these two variables. They argue that investor behavior is

crucial in explaining stock price, especially which the classical financial theory fails to explain. And, that also reiterates the importance of probing stock market volatility and herding behavior of the investors. Ali et al., 2020) show a reluctance to gamble among the investors during months associated with a high chance of future volatility based on the Finnish stock market. Caporale et al. (2020) find no evidence of non-linearities in five European stock markets based on the fractional integration approach. However, they observe non-stationarity in the stock prices. Mohammad Al-Shboul and Nizar (2019) implement a long-term volatility model in assessing the Dubai Financial Market (DFM) and the Abu Dhabi Stock Exchange (ADSE). They find evidence of conditional volatility and volatility persistence in the UAE stock market. Nonetheless, there is no evidence of a leverage effect and asymmetric long memory volatility. Chen et al.(2021) present a strong impact of investor sentiment on the returns and volatility of the Chinese future energy market. They argue that noise traders like China would be more affected by investor sentiment and bring about greater volatility.

Alexandre and Xiaoli (2021) delve into the volatility patterns of oil and natural gas prices in the US concerning the economic policy uncertainty. They employ Markov-Switching GARCH models and find out significant changes in the volatility in the natural gas market between two sub-periods of the price sets before 2010 and after 2010. Neural Network Model is used in forecasting implied volatility by Liu et al. (2021). Tissaoui et al. (2021) investigate the impact of volatility on the illiquidity of the Saudi stock market through an ARDL approach. Furthermore, they use the MWC plots to ratify their findings. Engelhardt et al. (2021) study the relationship between trust and the global stock market using a sample of 47 national stock markets. They remark that high-trust countries showcase significantly lower volatility than the low-trust ones. Volatility impulse response functions are utilized in the assessment of intra-market volatility in the Athens stock market by Apostolakis et al. (2021). They argue that political uncertainty causes larger impulse responses in the Athens stock market.

Lyócsa et al. (2019) investigate the relationship between monetary policy and stock market volatility. They conclude with the evidence of increased volatility on the day of an interest rate announcement by a domestic central bank.

In the light of our research, the significance of COVID-19 cannot be overlooked at all. One of the most fundamental objectives of our research is to understand the stock market behavior during a crunch moment like this health crisis. Several contemporary researchers have come up with their findings regarding stock market volatility during the COVID-19 pandemic. And, certainly, we have to go with the temptation to mention their research works in this literature review.

Corbet et al. (2021) test the volatility spillovers of the Chinese financial market during the COVID-19 crisis by employing the volatility spillover index approach and its extensions. Wang et al. (2021) divide investor attention to COVID-19 into expected and unexpected segments and conclude that unexpected attention is of greater threat to the stock market. Oktay (2021) investigates the stock market efficiency of six different countries during the pandemic. He concludes the UK and the US market to be more deviated from efficiency compared to others. Badar (2020) shows the negative reaction of stock markets around the world during the COVID-19 pandemic. Rouatbi et al. (2021) show the COVID-19 vaccinations stabilize the stock markets around the world although a better impact in developed countries than the emerging ones. Hue and Elaine (2021) conclude multinational firms to be more resilient to economic shocks during the COVID-19.

Bakry et al. (2021) study the response of stock market volatility during the COVID-19 pandemic to government measures and the news of the development of vaccination. They conclude emerging markets experience increased volatility with government actions while developed markets experience the opposite. On the other hand, vaccination news cause increased volatility in both markets according to their research. Uddin et al. (2021) investigate the global stock market volatility during the COVID-19 pandemic and also examine the factors to reduce the volatility. They find economic resilience, level of corporate governance, and quality of health system as vital determinants to assuage the impact of the pandemic on stock market volatility. However, they argue that monetary policy is less effective during uncertain times like the COVID-19 pandemic.

In addition to the stock market volatility, we have probed the existence of herding behavior, especially during the pandemic. The motivation behind that is to comprehend investors' behavior in-depth during the pandemic. Furthermore, the necessity of drawing a line between investment and policymaking decisions on the verge of severe economic ramifications has bolstered our decision to analyze herding behavior during the pandemic. As a result, some recent studies on herding behavior have come up within our radar that need to be mentioned here.

Kizys et al. (2021) finds herding behavior during the COVID-19 pandemic and conclude government responses mitigate the herding behavior of the investors. Coskun et al. (2020) examine herding behavior in the cryptocurrency market using the cross-sectional absolute deviation (CSAD) of returns and ordinary least squares

(OLS). They conclude anti-herding behavior in the cryptocurrency market.

Choijil et al. (2021) show significant growth in research of herding behavior in financial markets over the last 30 years. Christian and Jose (2021) investigate herding behavior in European Capital Market during the COVID-19 pandemic. They conclude with the evidence of herding behavior with less informed agents following the more informed ones in the market. Wanidwaranan et al. (2020) show evidence of asymmetric herding behavior in the global capital market. Batmunkh et al. (2020) assesses herding behavior in Mongolian Stock Market under bull and bear market periods and find evidence of herding behavior in all conditions using the CSAD approach. Kumar et al. (2021) analyze herding behavior in the commodity markets of the Asia-Pacific region. They argue herding is more prominent during high volatility periods. Chang et al. (2020) also find similar evidence of herding behavior during crunch moments like Global Financial Crisis, Sars, and the COVID-19.

Last but not least, we would like to cite some studies on the stock market behavior of the region that we have selected here- the Oceania region. The reason behind selecting Australia and New Zealand was simple; to investigate the stock market of a region that has not been particularly looked at by the researchers in the past and more especially during the pandemic. Shahzad et al. (2014) investigate the volatility-volume connection in the Australian Stock Market. They present the number of trades as a pivotal driving force behind market volatility. Besides that, trades by individual investors are more impactful in terms of volatility than that of institutional investors according to their study.

Mai et al. (2016) study the relationship between aggregate volatility risk and stock returns of the Australian Stock Market. They find a negative relationship between these two variables only when the market volatility is increasing. Jayawardena et al. (2016) use the Heterogeneous Autoregressive (HAR) model to forecast stock volatility of the Australian Stock Market based on overnight information. They find the predictive power of overnight information higher than that of the market-opening period. Frino et al. (2011) employ the Pseudo-Halt methodology to find the impact of trading halts on stock price and volume volatility of the Australian Stock Exchange. They conclude that trading halts raise both price and volume volatility.

Rahman et al. (2021) investigate the response of the Australian Stock Market to the COVID-19 announcement and find a negative reaction to the pandemic. They conclude that the pandemic causes a great disaster to the smallest, least profitable, and value portfolios. Naidu et al. (2021) ratify the adverse effect of COVID-19 on the stock returns of various sectors in Australia. Bedford et al. (2021) probe the impact of innovation on future stock returns and profitability of Australian firms. They conclude that innovative firms would yield higher future profitability but not higher future stock returns.

Having brought up pertinent contemporary research works, it is of paramount importance that we illustrate the novelty and difference of this study from previous research. Furthermore, we would like to draw our contribution to previous studies as well to depict the significance of this study. First, to the best of our knowledge, this paper would be the first research work to investigate sector-wise stock market volatility and herding behavior of Australia and New Zealand. And the first to do so during the COVID-19 pandemic. In addition, a comparative scenario of the stock market depicted between these two countries would give researchers so much to contemplate in the future. The paper inquest stock market volatility and herding behavior in conjunction which is nearly unexampled in previous studies. Moreover, a massive deficiency of the study on the stock market of the Oceania region is pretty much palpable in both the past and contemporary papers. All in all, we believe, this paper has the potential to unveil so many novel findings that it may extend and contribute remarkably to earlier research works in numerous directions. Besides that, this study may have crucial implications for both the investors and policymakers of Australia and New Zealand. Investors would obtain a comprehensive idea of which sector to invest in or not; especially in the aftermath of the pandemic. Likewise, policymakers might get a thorough understanding of which sector to intervene in or not.

We have partitioned our research data into three sub-samples; Full period, Pre-COVID, and Post-COVID. This has been done primarily to draw a meticulous comparison of the stock market behavior in normal and crisis periods. In evaluating volatility persistence, we have employed the GARCH (1,1) model. The GARCH-M (1,1) model has been exerted to capture the risk-return relationship. Furthermore, asymmetric GARCH models such as EGARCH (1,1) and TGARCH (1,1) have been utilized to measure the leverage effects seen in stock returns. On the other hand, herding behavior has been assessed by the cross-sectional absolute deviation (CSAD) approach. In the following sections, detailed explanations of all the methods and findings have been employed.

3. Data, Scope, and Method

Modeling market return through GARCH & CSAD (Herding Behavior) analysis is quite a strenuous process yet we extract the datasets from some secondary sources according to our categorical analysis. We picked up 7

common sectors for both countries that can essentially manipulate the market return with the most effective news impacts. The datasets are mostly gleaned for the analysis of the aftermath of the shock and the verdict to make a relation between variance and return along with the herding psychology.

3.1 Data Selection, Collection & Timeframe

We, the researchers, mustered all data from similar industries in Australia and New Zealand from 01/04/2015 to 09/02/2021 to create an efficacious comparison. We trifurcate the data into panels: Panel-A (whole period), Panel-B (pre-COVID), and Panel-C (post-COVID), where the required information can be conglomerated into an eccentric resolution. For Australia the Panel-B is regarded from 01/04/2015 to 24/01/2020 as the initial COVID case was found on 24th January 2020 and Panel-C is considered from 27/01/2020 to 09/02/2021 and for New Zealand, the same data are panelized according to the first COVID case found on 28th February 2020 (Panel B: 01/04/2017 to 02/28/2020 & Panel C: 03/02/2020 to 09/02/2021). Moreover, there are some companies whose data are not found properly from the considered full period yet to make the comparison worthwhile we take the same period for the Australian industries and the similar one for the New Zealand separately.

As for the Australian industries, we oust out Idp Education Ltd (Data found till Nov 27, 2015), Kogan.com Ltd (Data found till Jul 08, 2016), and Pointsbet Holdings Ltd (Data found till Jun 13, 2019) from Consumer Discretionary sector. Similarly, Ampol Ltd (ALD) (Data found till Apr 26, 2018) and Viva Energy Group Ltd (Data found till Jul 16, 2018) are withdrawn from the Energy sector along with Netwealth Group Ltd (Data found till Nov 21, 2017), Virgin Money PLC (Data found till Feb 05, 2016), Zip Co Ltd (Data found till Jan 30, 2015) and HUB24 Ltd

Table 1. Comparison of considered sectors

Sectors	Criteria	Australia	New Zealand
Consumer Discretionary	*Expenditure*	**48.8% of GDP (Sep,21)**	**57.5% of GDP (Jun,21)**
Energy	*Consumption*	**8,891 kWh per year**	**8,229 kWh per year**
Financial Institutions	*Contribution*	**47.36% of GDP**	**41.3% of GDP**
Food & Beverages	*Contribution*	**11% (2018)**	**34% (2020)**
IT	*Growth*	**5.9% (2021)**	**5.7% (2021)**
Health Care	*Expenditure*	**$ 4,919 per capita**	**$ 4,212 per capita**
Real Estate	*Growth*	**11.7%**	**19.3%**

Note. In this table, the reason is portrayed why we consider the sectors which can impact mostly on the economy. For New Zealand, Fishing & Agriculture hold the most important due to the extent of the surrounding ocean area but the number of companies is pretty few during the data collection period to make a statement about the sector's contribution and the similarity of the criteria is incomparable with Australia.

Source: (*Australia Private Consumption: % of GDP, 1959 – 2021 | CEIC Data*.; *Energy Consumption in Australia*.; *Food and Beverage Industry Tops $71.7 Billion*.; *Gartner Forecasts IT Spending in Australia to Grow 6.5% in 2022, IBISWorld - Industry Market Research, Reports, and Statistics*; *New Zealand GDP | 2021 Data | 2022 Forecast | 1960-2020 Historical | Chart | News*; *New Zealand IT Spending on the Rise, Set to Reach $14.7 Billion by 2022*; *New Zealand's Consumption*; *NZ Tech Spending to Grow by 5.7% to $13.8B*).

From the Financial Institutions sectors. A2 Milk Company Ltd (A2M) (Data found till Apr 01, 2015), Costa Group Holdings Ltd (CGC) (Data found till Jul 27, 2015), Inghams Group Ltd (ING) (Data found till Nov 08, 2016) & United Malt Group Ltd (UMG) (Data found till Mar 25, 2020) are withdrawn from Food & Beverages sector. Again, Afterpay Touch Group Ltd (APT) (Data till May 05, 2016), Link Administration Holdings Ltd (LNK) (Data till Oct 28, 2015), Megaport Ltd (MP1) (Data till Dec 18, 2015), Nuix Ltd (NXL) (Data till Dec 07, 2020) & Wisetech Global Ltd (WTC) (Data till Apr 12, 2016) are separated from IT sector while Scentre Group Ltd (Data till July 26, 2014), 360 Capital Industrial Fund (Data till Dec 14, 2012), Charter Hall Long WALE REIT (Data till Nov 09, 2016), National Storage REIT (Data till Dec 20, 2013), Shopping Centres Australasia Group (Data till Nov 27, 2012), Unibail Rodamco Westfield (Data till Jun 01, 2018) & Waypoint REIT Ltd (Data till Aug 04, 2016) are expunged from Real Estate Sector. Since Energy, Food & Beverages, and IT sectors maintain a fewer number of companies after the withdrawals we assume it can restrain us from more exquisite results while Real Estate, Consumer Discretionary, and Financials Institutions envelop the void though having some withdrawals. Though Australia is bigger than New Zealand regarding land mass and population genre, we can compare both countries by the considered sectors. Facts are shown in Table 1.

As for the New Zealand industries, we evict Savor Ltd, NZ Automotive Investments Ltd., Millennium and Copthorne Hotels NZ Ltd., Just Life Group Ltd., Good Spirits Hospitality Ltd., Colonial Motor Company Ltd., CDL Investments NZ Ltd., etc. from the consumer discretionary calculation due to the unavailability and

limitation of data. Likewise, we have excluded Blackwell Global Holdings Ltd. and Ascension Capital Ltd. In the financial sector. Similarly, Synlait Milk, Seeka Ltd., and Scales Corporation Ltd. from the food & beverages sector, Oceania Healthcare Ltd. and Truscreen Ltd. from the healthcare sector, Plexure Group Ltd. and Serko Ltd. from the IT sector are excluded due to data limitation. Lastly, Goodman Property Trust and CDL Investment NZ Ltd. are excluded from the Real Estate sector measurement.

3.2 Data Analysis and Modeling

For share market yields volatility assessment, the ARCH paradigm should be described before evaluating the GARCH model. Time series variability can be modeled using an ARCH (autoregressive conditionally heteroskedastic) framework. Variables that are prone to change and volatility are described using ARCH frameworks. When there are short moments of higher fluctuation, ARCH models are most commonly employed.

"For this reason, ARCH methods are commonly described as estimates for a specific sort of parameter, such as the rate of progress in investments or equity markets over time. As a result, the parameter in these cases is either the percentage gained or lost since the last time, or the logarithm of the proportion of this time's values to last time's values."

$$y_t = \frac{(x_t - x_{t-1})}{x_{t-1}} \quad (1)$$

$$log\left(\frac{x_t}{x_{t-1}}\right) = log(x_t) - log(x_{t-1}) \quad (2)$$

There is no need to focus on just one of these variables. With periods of heightened or decreased variation, an ARCH model could be useful. It's possible that residuals from an ARIMA framework could have this quality (Endri et al., 2020; Kim et al., 2021).

Conditional volatility can be modeled using GARCH models. They're useful in situations where a time series' volatility is a function of previous levels of volatility, a phenomenon known as volatility clustering.

"The Autoregressive Conditional Heteroskedasticity (ARCH) and its extension (GARCH) methods are the most extensively employed to cope with heteroskedasticity in time - series data. GARCH models are classified into two categories: symmetric structures (such as GARCH (1,1) and GARCH-M (1,1)) and asymmetric structures (such as EGARCH (1,1) and TGARCH (1,1). Each of these models has a separate equation for the conditional mean and a separate expression for the conditional variance. Since NSE (National Stock Exchange) returns are heteroskedastic, the GARCH models discussed previously are employed in this work to estimate NSE returns."

3.2.1 Symmetric GARCH Models

3.2.1.1 GARCH (1,1) Model

"The model involves the joint estimation of the mean equation and the conditional variance equation. The mean equation is specified as follows:

$$R_t = \mu + \varepsilon_t \quad (3)$$

Where, R_t is return at the time, t, $\mu$is the mean of the returns and ε_t is the residual return at time t. The return for a month will depend on returns in previous periods (autoregressive component) and the innovation terms in previous periods (moving order component). A GARCH model is typical of the following form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \quad (4)$$

Where, σ_t^2 is the conditional variance at time t, α_0 is the mean of unconditional variance (long-run average variance), ε_{t-i}^2 is the previous residual(ARCH term), σ_{t-i}^2 is the previous variance (GARCH term), α_i is the ARCH parameter and β_i is the GARCH parameter. For this model to be well defined and conditional variance to be positive, the parameters must satisfy the following constraints:$\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$." (Bollerslev, 1986; Taylor, 1987)

3.2.1.2 GARCH-M (1,1) Model

"The model is based on the GARCH model. The mean and the variance of the GARCH-M(1,1) are specified:

the mean equation: $R_t = \mu + \lambda\sigma_t^2 + \varepsilon_t$ (5)

the variance equation:$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2$ (6)

The parameter λ is called the risk premium parameter. This is predicated on the premise that an investment with a higher riskiness would, on general, yield a greater yield. The approach then enables for the conditional mean to be determined by the conditional variance. The connection between variance and yield can be examined using this approach."

3.2.2 Asymmetric GARCH Models

If "bad news" has a significantly larger impact on volatility than "good news" of the same magnitude in financial markets, then asymmetric specification such as GARCH or GARCH-M is not appropriate, because only squared residuals ε_{t-i}^2 enter the equation, and the signs of the residuals or shocks do not affect conditional volatility (in other words, by squaring the lagged error in GARCH, the sign is lost). In other words, the paradigm presupposes that both positive and negative news have the same effect. Yet, a fundamental feature about financial volatility is that negative news (shocks to the system) has a greater impact on volatility than positive news (positive shocks). Such inequities in stock returns are widely linked to leverage effects, in which negative shocks cause the company's value to decline, expanding the debt-equity ratio and increasing the likelihood of insolvency (debt-equity proportions are vital predictors of the chance of default in credit scoring methods). This makes shareholders, who carry the residual risk of the firm, perceive their future cash flow stream as being relatively riskier. To account for the leverage effects observed in stock returns, the asymmetric models which include: [EGARCH (1,1) and TGARCH (1,1)] are employed.

3.2.2.1 EGARCH (1,1) Model

"To capture the leverage effects, the logarithm of the conditional variance is modeled as:

$$\log(\sigma_t^2) = \alpha_0 + \beta_1 \log(\sigma_t^2) + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} + \gamma \left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) \quad (7)$$

The leverage effect term (γ) is denoted as 'RESID(−1)/@SQRT(GARCH(−1))' in the output of Eviews. The termγ, accounts for the presence of the leverage effects, which makes the model asymmetric. If γ = 0, then the model is asymmetric. If γ is negative and statistically different from zero, it indicates the existence of the leverage effect."(Nelson, 1991).

3.2.2.2 TGARCH (1,1) Model

"The specification of the conditional variance for the TGARCH (1,1) model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta_1 \sigma_{t-1}^2 \quad (8)$$

Where, d_t is a dummy variable, that is, $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 1$ if $\varepsilon_t \geq 0$. The coefficient γ in the model captures the asymmetric effect if $\gamma > 0$. The α_0, α_1, and β_1 are the parameters of the conditional variance equation that will be estimated. In the model, the good news ($\varepsilon_t \geq 0$) and bad news ($\varepsilon_t < 0$) have different effects on the conditional variance; good news has an impact of α_1, while bad news has an impact of $\alpha_1 + \gamma$. If $\gamma > 0$, bad news increases volatility, and we say that there is a leverage effect. If $\gamma \neq 0$ the news impact is asymmetric. The criteria to accept the null hypothesis of no leverage effect in the TGARCH model is that γ coefficient must be negative. In other words, if the γ coefficient is not negative there is evidence of leverage effects in the series (Glosten et al., 1993; Zakoian, 1994).

3.2.2.3 Herding Behavior (CSAD) Model

There are two ways to calculate asset returns. We won't go into detail about the discrete returns, but the continuously compounded yields will be used in our analysis. So long as the profits are modest (tends to occur with daily yields) A comparison can be drawn between the performance of continuous compounding and that of discrete yields. Let the daily return $r_t$be defined as follows

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right) \quad (9)$$

Where, p_t is the closing price of a security in time t, $p_{(t-1)}$ is the closing price of the security at t−1. The cross-sectional average stock of N returns ($r_{m,t}$) is calculated by taking an average of all individual stock returns on day t as per the following equation:

$$r_{m,t} = \frac{\sum r_t}{N} \quad (10)$$

Where, r_t is the observed stock return of the firm at time t, and N is the number of firms included in the industry index. As a modification of the Christie and Huang (1995) method, Chang et al. (2000) propose another CSAD (Cross-Sectional Absolute Deviation), an empirical method for the detection of herding towards average, which is statistically defined as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |r_t - r_{m,t}| \quad (11)$$

Where, $CSAD_t$ is a proxy that indicates the distance from the market average return, how much of the stock returns are dispersed around the average return, N is the total number of stocks in the industry index, r_t is the

return of the stock on day t and the variable $r_{m,t}$ is the cross-sectional average market return at day t. Sinceherding would increase the correlation of stock returns, the presence of herding in the market would transform the linear relationship between individual stock return and market return based on the capital asset pricing model into a non-linear relation (Mertzanis & Allam, 2018). Following the Lee et al. (2013) study, we examine the herding behavior using the modified regression model as per the following equation:

$$CSAD_t = \alpha + \gamma_1 r_{m,t} + \gamma_2 |r_{m,t}| + \gamma_3 r_{m,t}^2 + \varepsilon_t \quad (12)$$

where, $r_{m,t}$ is the cross-section average return of sample on day t and is used to account for asymmetric behavior under different market conditions; $|r_{m,t}|$ is the absolute market return at day t, used to account for the magnitude and not the direction of the market; $r_{m,t}^2$ is the squared value of the equally weighted portfolio $r_{m,t}$, captures the non-linear relationship that would arise because of the herding behavior in the market. According to Chang et al. (2000), the presence of a significantly negative coefficient γ_3 confirms the existence of herding behavior while a statistically positive γ_3 indicates anti herding behavior.

4. Empirical Results and Discussion

In this section, we briefly present our analysis of the data and discuss the findings from our modeling effort.

4.1 Descriptive Statistics and Graphical Presentation of the Data

If we look at the descriptive statistics, in the case of Australia, we can see that the average of Energy Sector is in the negative form at Panel A while Financials portray the same in Panel B and Panel C with larger standard deviation. Again Real Estate sector espouses a negative mean with a lower standard deviation as well in Panel C (Table 2).

Table 2. Descriptive analysis

Timeline	*Industries*	*Australia*				
		Mean	*St. Dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera*
Panel:A Full Period	***Consumer Discretionary***	*0.034717*	*0.683748*	*-1.868768*	*19.80697*	*20800.44*
	Energy	*-0.006332*	*1.377785*	*-1.385308*	*15.82669*	*12082.72*
	Financials	*0.011291*	*1.395492*	*-0.174583*	*34.19976*	*68310.56*
	Food & Beverages	*0.050728*	*1.259698*	*-0.044823*	*6.685513*	*953.6383*
	IT	*0.102329*	*0.925081*	*-0.38718*	*6.730645*	*1018.634*
	Health Care	*0.075334*	*0.84055*	*-0.207075*	*5.125452*	*329.0163*
	Real Estate	*0.021593*	*1.604707*	*-0.132809*	*33.64842*	*65914.3*
Panel:B Pre-COVID	***Consumer Discretionary***	*0.065394*	*0.571601*	*-0.011114*	*3.933681*	*46.44752*
	Energy	*0.027059*	*1.318897*	*0.144606*	*5.956501*	*469.9069*
	Financials	*-0.069284*	*1.713143*	*-1.368063*	*25.26329*	*26792.24*
	Food & Beverages	*0.151207*	*1.239248*	*0.739592*	*6.065638*	*616.9611*
	IT	*0.162026*	*0.875047*	*0.226608*	*4.716384*	*167.811*
	Health Care	*0.086042*	*0.785136*	*-0.043179*	*4.090494*	*63.72075*
	Real Estate	*0.052432*	*2.019365*	*-0.195477*	*23.45573*	*22289.9*
Panel:C Post-COVID	***Consumer Discretionary***	*0.014327*	*0.743796*	*-1.111569*	*7.287921*	*394.6423*
	Energy	*0.071822*	*1.310921*	*-0.983663*	*11.63272*	*1326.169*
	Financials	*-0.004673*	*0.77548*	*-0.578242*	*7.027933*	*297.0854*
	Food & Beverages	*0.194983*	*1.288363*	*0.414479*	*4.705061*	*60.80536*
	IT	*0.090426*	*1.190938*	*-0.606448*	*6.937446*	*287.1536*
	Health Care	*0.04619*	*0.8767*	*-0.14114*	*5.145472*	*79.2162*
	Real Estate	*-0.014028*	*0.77862*	*-2.396783*	*16.78461*	*3603.145*

Note. In this table, descriptive statistics are employed for investigation.

Table 2. Descriptive analysis (continue)

Timeline	*Industries*	*New Zealand*				
		Mean	*St. Dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera*
Panel:A Full Period	***Consumer Discretionary***	*0.000195*	*0.078027*	*-0.062916*	*8.009674*	*1214.825*
	Energy	*-0.000559*	*0.012249*	*-1.35647*	*19.76262*	*14741.66*
	Financials	*0.000311*	*0.010573*	*-0.112023*	*24.7862*	*25237.61*
	Food & Beverages	*0.00028*	*0.050192*	*0.017095*	*16.58131*	*9553.142*
	IT	*0.000367*	*0.100088*	*-0.069846*	*7.711885*	*1139.771*
	Health Care	*0.000686*	*0.011144*	*1.67597*	*26.5963*	*30318.12*
	Real Estate	*0.000286*	*0.006171*	*-4.103732*	*62.76246*	*193317.3*

Panel:B	***Consumer Discretionary***	*-0.000125*	*0.078367*	*0.009286*	*8.14166*	*825.0551*
Pre-COVID	***Energy***	*-0.000646*	*0.008833*	*0.498909*	*13.9529*	*4082.455*
	Financials	*0.000204*	*0.010416*	*0.082284*	*35.7216*	*38055.53*
	Food & Beverages	*0.000516*	*0.061161*	*0.002102*	*11.33539*	*2388.33*
	IT	*5.09E-05*	*0.097642*	*-0.043873*	*8.05536*	*861.7322*
	Health Care	*0.000232*	*0.009029*	*-0.353294*	*5.24532*	*197.1576*
	Real Estate	*0.000344*	*0.003172*	*-0.086671*	*3.413117*	*7.167121*
Panel:C	***Consumer Discretionary***	*0.001044*	*0.078034*	*-0.17581*	*7.582528*	*366.1354*
Post-COVID	***Energy***	*-0.000389*	*0.017041*	*-1.642909*	*13.67849*	*2168.864*
	Financials	*0.000527*	*0.010891*	*-0.460292*	*6.24338*	*200.3431*
	Food & Beverages	*-0.000186*	*0.01055*	*0.351471*	*10.57208*	*1007.215*
	IT	*0.000972*	*0.104735*	*-0.112218*	*7.130062*	*300.8118*
	Health Care	*0.001594*	*0.014444*	*2.371977*	*26.10217*	*9896.001*
	Real Estate	*0.000167*	*0.009782*	*-3.112133*	*30.19749*	*13557.92*

Following that, a normality test was performed to evaluate the pattern in the datasets. All the sectors in Australia during Panel A depict long-left tail (negative skewness) and leptokurtic (kurtosis>3). All sectors maintain leptokurtic through all three Panels while Energy, Food & Beverages, & IT sectors delineate long-right tail due to positive skewness during Panel B.

All the sectors in New Zealand during Panel A depict long-left tail (except the Healthcare and Food & Beverages sector) and leptokurtic (kurtosis>3). All sectors maintain leptokurtic through all three Panels while Consumer Discretionary, Energy, Financials and Food & Beverages sectors in Panel B and Healthcare and Food & Beverages sectors in Panel C elucidate long-right tail due to positive skewness.

Figure 1 & 2 also shows a graphical representation of time plotting, where upward trends for some variables can be seen. As a result, it became unavoidable for us to conduct Unit Root Tests and take the necessary steps to eliminate all of those trends.

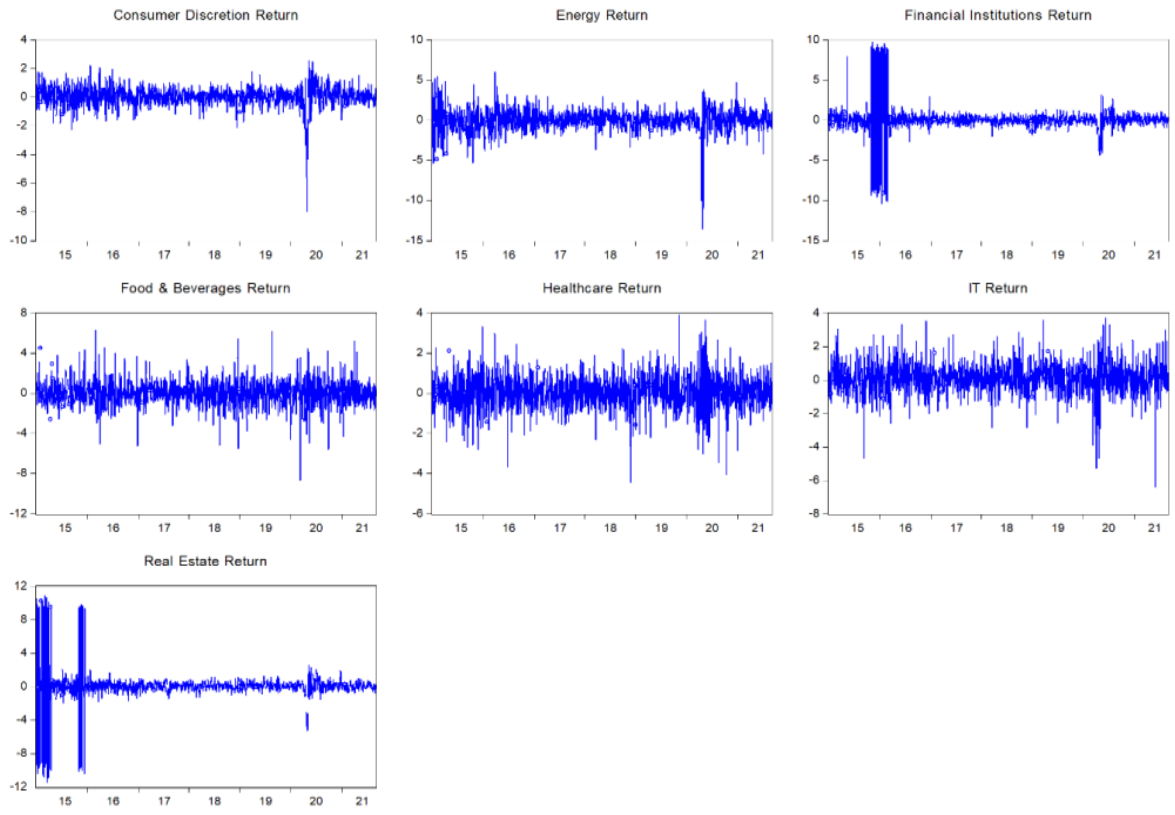

Figure 1. Time Plots of the selected sectors returns for Australia

Note. In this figure the rate of changes of stock returns of different industries are plotted for the whole period of our investigation which shows the volatility clustering.

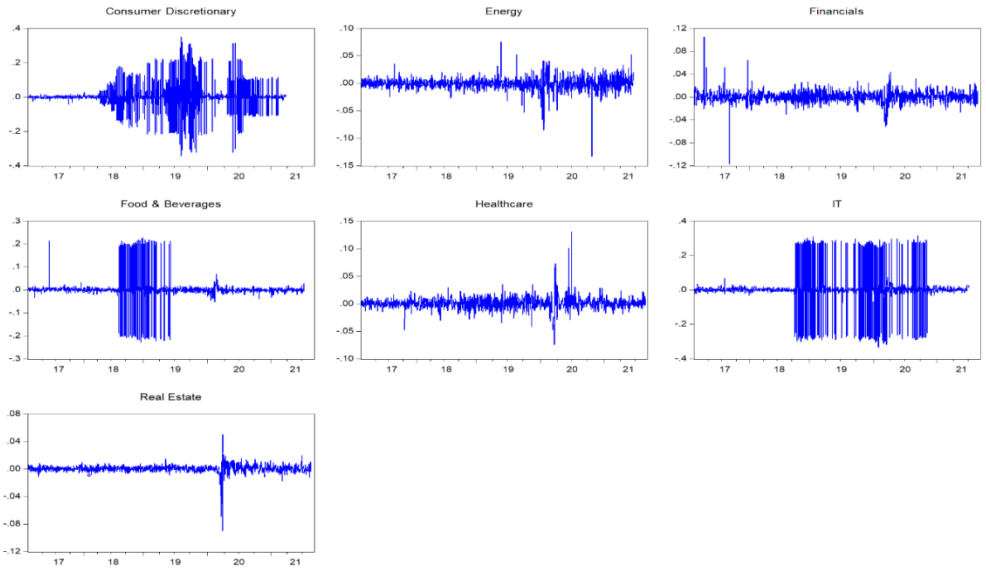

Figure 2. Time Plots of the selected sectors returns for New Zealand

Note. In this figure the rate of changes of stock returns of different industries are plotted for the whole period of our investigation which shows the volatility clustering.

4.2 Unit Root test (Augmented Dickey-Fuller (ADF) & Phillips-Perron (PP)Test (Level & 1st Difference)

Table 3 displays summary results from Augmented Dickey-Fuller (ADF) & Phillips-Perron (PP) tests for all sectors at the level and 1st difference for all three panels. Appendix A contains detailed results for each test, as well as t-statistics, R-squared, adjusted R-squared, and other test parameters. The null hypothesis for all the sectors in Australia was rejected at a significance level of 1%. Table 3 explains there is no unit root in the data set as well as no trend with continuity which corroborates the tenability of the datasets.

Table 3. Summary results from the unit root test (at level & 1st Difference)

Timeline	***Industries***	***Australia***				***New Zealand***			
		PP		***ADF***		***PP***		***ADF***	
		At Level	***At First Difference***	***At Level***	***At First Difference***	***At Level***	***At First Difference***	***At Level***	***At First Difference***
Panel: A Full Period	***Consumer Discretionary***	*-37.5586****	*-629.7989****	*-11.3166****	*-18.2719****	*-105.1403****	*-380.1477****	*-13.68687****	*-16.6989****
	Energy	*-42.5562****	*-983.1896****	*-17.4002****	*-20.9185****	*-37.6411****	*-352.8342****	*-22.71983****	*-18.51895****
	Financials	*-55.9553****	*-235.2451****	*-7.8358****	*-19.9302****	*-38.54291****	*-715.5256****	*-37.96446****	*-20.83722****
	Food & Beverages	*-39.7318****	*-592.4066****	*-39.7357****	*-19.2269****	*-90.21936****	*-420.7552****	*-9.08312****	*-21.68109****
	IT	*-39.4643****	*-495.8146****	*-37.9348****	*-20.8577****	*-125.3842****	*-426.2538****	*-17.16545****	*-18.29384****
	Health Care	*-41.1613****	*-812.1075****	*-41.1603****	*-20.1641****	*-33.98408****	*-281.0147****	*-22.33432****	*-18.44988****
	Real Estate	*-58.4892****	*-305.9291****	*-9.6233****	*-20.187****	*-33.48291****	*-336.9442****	*-9.351395****	*-28.2983****

Note. (*) Significant at the 10% level. (**) Significant at the 5% level. (***) Significant at the 1% level. (no) Not Significant. Probability-based on MacKinnon's (1996) one-sided p-values. Since there is no unit root in this dataset, we concur our dataset to be validated for further investigation for GARCH modelling.

4.3 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

For this analysis, we used four types of GARCH models to interpret the market volatility with variance. Table 4 portrays the main features of volatility analysis along with the robustness, longevity, intensity, and news impacts on the pattern.

For the conciseness of our paper, we have illustrated the volatility analysis of the Consumer Discretionary sector only in this section. Further explanations on all the other sectors derived from the datasets given in the appendices (Table A1-A.6) which have been delineated in the sector-wise exploration section.

As per analysis, we, the researchers, found the AIC (Akaike Info Criterion), SIC (Schwarz Criterion), HQ (Hannan-Quinn Criterion) values for Consumer Discretionary for all Panel are lower than +5 which means the

calculation is pretty robust. The volatility analysis for the other sectors is given in Appendix: Table A1-A6. From all the analysis it can be formulated about the robustness of the calculation.

Since serial autocorrelation of the squared returns must be present on the volatility analysis, we need to capture the p-value tends to 0. For Australia, from Table 4, the p-value for Panel A and Panel C comes closer to 0 ((1-p) value for both are 0.9993 & 0.9986 respectively), which depicts there is a volatility clustering for the analysis in Full Period and the Post-COVID time and the model is approximately 99% valid for all three panel due to significant values. (GARCH (1,1) explanation)

The value of (α_1+β) is closer to 1 except for EGARCH (1,1) in all three panels which elucidates volatility is not persistent or is not going to be volatile for the long term.

We know taking the high risk can provide a high return in the market in short term but from GARCH-M (1,1), we find the value of λ (Risk Premium) is not significant in all three panels which unfolds the truth about having no crucial relationship between variance and return.

For EGARCH (1,1), the model is 71.86% valid in Panel B. α_1 (ARCH Effect) delineates the size effect of the news while γ (leverage Effect) does the significant effect of the shock. As α_1 is significant, the size of the impact on the news will also be momentous. Since γ is negative and statistically different from zero, it indicates the existence of the leverage effect for all three panels. As all three γ are negative, the volatility is inversely proportional with the news effect e.g. positive news will decrease the volatility while negative news will increase the volatility.

Model is 77.28% valid in Panel B. Moreover, γ is significant in all three panels from TGARCH (1,1) perspective which institutes volatility is asymmetric and positive news has more impact than that of negative news.

Similarly, for New Zealand, from table 4, the p-value for Panel A and Panel B comes closer to 0 for GARCH (1,1) and TGARCH (1,1), implying the robustness of models. The value of (α_1+ β) is above 1 in both the full and pre-COVID periods, showing persistent volatility in these periods. However, the post-COVID period doesn't possess persistence in the sector. GARCH-M (1,1) shows signs of risk-return trade-off in the post-COVID period. And, lastly, the leverage effect is present in all three timeframes of the study for the consumer discretionary sector. For further illustration, please refer to the results of all the sectors in the appendices given in the supplementary data.

Table 4. Volatility Analysis of Consumer Discretionary Sector

			Australia			
Timeline	***Particulars***	***Parameter***	***GARCH(1,1)***	***GARCH-M(1,1)***	***EGARCH(1,1)***	***TGARCH(1,1)***
Panel:A Full Period	***Mean Equation***	***μ***	*0.042898****	*0.03874****	*0.033737****	*0.037272****
			(0.9993)		*(0.9905)*	*(0.9961)*
		λ (Risk Premium)	-	*0.014845*	-	-
	Variance Equation	***α_0 (Constant)***	*0.008211****	*0.008135****	*-0.129467****	*0.007760****
		α_1 (ARCH Effect)	*0.084996****	*0.084605****	*0.137551****	*0.050496****
		β (GARCH Effect)	*0.891661****	*0.892257****	*0.981111****	*0.902319****
		γ (Leverage Effect)	-	-	*-0.040673****	*0.048255****
		α_1+ β	*0.976657*	*0.976862*	*1.118662*	*0.952815*
Panel:B Pre-COVID	***Mean Equation***	***μ***	*0.024873**	*-0.066901****	*0.016142*	*0.018357*
			(0.905)		*(0.7186)*	*(0.7728)*
		λ (Risk Premium)	-	*0.341968*	-	-
	Variance Equation	***α_0 (Constant)***	*0.001224****	*0.001055****	*-0.021750****	*0.000188*
		α_1 (ARCH Effect)	*0.020451****	*0.017585****	*0.025072****	*0.000852*
		β (GARCH Effect)	*0.974473****	*0.977815****	*0.998752****	*0.987686****
		γ (Leverage Effect)	-	-	*-0.020069****	*0.019572****
		α_1+ β	*0.994924*	*0.9954*	*1.023824*	*0.988538*
Panel:C Post-COVID	***Mean Equation***	***μ***	*0.088802****	*0.103086****	*0.067668****	*0.075871****
			(0.9986)		*(0.988)*	*(0.9935)*
		λ (Risk Premium)	-	*-0.045171*	-	-
	Variance Equation	***α_0 (Constant)***	*0.013924****	*0.014130****	*-0.157732****	*0.014389****
		α_1 (ARCH Effect)	*0.123250****	*0.124186****	*0.172428****	*0.056606*
		β (GARCH Effect)	*0.846272****	*0.844904****	*0.973308****	*0.862446****
		γ (Leverage Effect)	-	-	*-0.069508****	*0.091950****
		α_1+ β	*0.969522*	*0.96909*	*1.145736*	*0.919052*

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates the existence of volatility clustering.

Table 4. Volatility Analysis of Consumer Discretionary Sector (continue)

			New Zealand			
Timeline	***Particulars***	***Parameter***	***GARCH(1,1)***	***GARCH-M(1,1)***	***EGARCH(1,1)***	***TGARCH(1,1)***
Panel:A Full Period	***Mean Equation***	***μ***	*-0.000901** (0.9875)*	*0.520386****	*-0.000361 (0.6992)*	*-0.00059* (0.9154)*
		λ (Risk Premium)	*-*	*0.091545****	*-*	*-*
	Variance Equation	***α_0 (Constant)***	*0.000000884****	*0.002005****	*-0.111491****	*0.000000409**
		α_1 (ARCH Effect)	*0.069197****	*0.186655****	*0.155732****	*0.124608****
		β (GARCH Effect)	*0.938171****	*0.293953****	*0.998502****	*0.938207****
		γ (Leverage Effect)	*-*	*-*	*0.066898****	*-0.090842****
		α_1+ β	*1.007368*	*0.480608*	*1.154234*	*1.062815*
Panel:B Pre-COVID	***Mean Equation***	***μ***	*-0.00079*** (0.9683)*	*-0.001083***	*-0.000284 (0.5947)*	*-0.000408 (0.7594)*
		λ (Risk Premium)	*-*	*0.029981*	*-*	*-*
	Variance Equation	***α_0 (Constant)***	*0.000000357***	*0.000000275*	*-0.08353****	*0.00000004*
		α_1 (ARCH Effect)	*0.057596****	*0.056609****	*0.126189****	*0.09243****
		β (GARCH Effect)	*0.954445****	*0.955664****	*0.999578****	*0.974475****
		γ (Leverage Effect)	*-*	*-*	*0.078305****	*-0.097292****
		α_1+ β	*1.012041*	*1.012273*	*1.125767*	*1.066905*
Panel:C Post-COVID	***Mean Equation***	***μ***	*-0.001249 (0.2993)*	*0.545593****	*-0.005215 (0.6995)*	*-0.002197 (0.46)*
		λ (Risk Premium)	*-*	*0.094749****	*-*	*-*
	Variance Equation	***α_0 (Constant)***	*0.0000324****	*0.002181****	*-5.312519****	*0.0000365****
		α_1 (ARCH Effect)	*0.071146****	*0.329622****	*-0.18611**	*0.027469*
		β (GARCH Effect)	*0.915113****	*0.144958*	*0.023745*	*0.913718****
		γ (Leverage Effect)	*-*	*-*	*-0.770194****	*0.071418**
		α_1+ β	*0.986259*	*0.47458*	*-0.162365*	*0.941187*

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates the existence of volatility clustering.

4.4 Herding Behavior Analysis

Suppose one family starts camping near a riverside and another family is trying to set up the camp near that river. Then after some days it can be seen there will be more than 20 families make their camp tents which can be metaphorical of following the herd. In terms of erratic moments, humans are most afraid of nature and start to follow the herd for the guidance of the crowds to confirm sure-shot which can be a vital tool for survival but escaping the reality by trailing the herd too often can be dicey (Steinbeck, 1939). People do what others do instead of using their information to make a concrete decision as they ponder the other people who have done their research. So this phenomenon is crucial in this pandemic era in which humans are going through affecting the investors' decision on the stock market thus making a country's economy highly incalculable for the time being. In this research, we have done behavioral analysis with the same trifurcation as it is done in the previous section for volatility to root the motivation for the most dependent sectors infecting the economy. Since people follow the decision of the other in an uncertain period, they ignored their information obliging the opinion of the other by distorting the signal chain which in reality is suicidal as the others are also following their previous versions. This is also called informational cascades which can explain everything from standard conformity to fads, booms & crashes like the one that happened in the 2008 financial crisis (Kabir, 2018). The herding analysis of the curated samples is shown in Table 5. As we, the researchers follow the CSAD model, the coefficient γ_3 delineates the herding behavior in the analyzed sector. Moreover, it can be said from Table 5 that, only the consumer discretionary sector in Australia depicts herding behavior in Panel-C while herding can be found in all 3 panels from the same sector in New Zealand. No other sector provides any evidence of herding in both Australia and New Zealand. Detailed discerning is done in the next section.

Table 5. Summary of Herding Behavior Analysis

Timeline	Industries	Australia				New Zealand			
		α	γ_3	F-Stat	Adj. R^2	α	γ_3	F-Stat	Adj. R^2
Panel :A Full Period	**Consumer Discretionary**	1.051231*** (44.34443)	0.049849*** (3.910322)	234.4078***	0.29149	0.003012*** (3.309330)	**-1.663785***** (-13.27862)	8484.240***	0.956012
	Energy	1.180667*** (33.62282)	0.011789*** (2.199966)	242.2670***	0.296907	0.005704*** (19.14267)	5.050004*** (9.618939)	485.6166***	0.540495
	Financials	0.910623*** (42.94772)	0.143032*** (33.59170)	8759.097***	0.939062	0.006843*** (25.21822)	9.061596*** (17.64879)	536.3756***	0.555729
	Food & Beverages	0.942177*** (28.40132)	0.173230*** (17.03493)	455.2372***	0.442193	0.006943*** (19.16442)	3.335036*** (16.61022)	35956.72***	0.988517
	IT	1.411555*** (47.12544)	0.182983*** (10.82265)	271.5641***	0.322652	0.002294*** (4.056927)	0.014466 (0.090185)	45058.66***	0.990903
	Health Care	1.364092*** (45.75248)	0.324566*** (13.27341)	284.2540***	0.335508	0.008299*** (26.81037)	6.780677*** (12.35762)	644.6523***	0.599126
	Real Estate	0.695926*** (33.51934)	0.119858*** (29.74712)	11625.44***	0.953492	0.004722*** (31.87200)	-0.617181 (-0.887088)	348.1153***	0.449758
Panel:B Pre-COVID	**Consumer Discretionary**	1.063068*** (56.16074)	0.120007*** (2.762468)	70.24177***	0.137957	0.002819*** (2.500120)	**-1.635884***** (-10.63506)	5665.959***	0.957842
	Energy	1.165628*** (27.54183)	0.059215*** (3.772064)	173.6989***	0.284029	0.005186*** (18.24897)	11.57095*** (10.12051)	312.0097***	0.535599
	Financials	0.892239*** (49.80600)	0.169786*** (45.38945)	16919.44***	0.975064	0.006178*** (19.84730)	8.689632*** (16.40444)	571.5350***	0.667655
	Food & Beverages	0.950956*** (25.58021)	0.189802*** (13.67092)	292.8267***	0.402061	0.004561*** (9.766263)	1.526591*** (5.671503)	34094.31***	0.992008
	IT	1.376138*** (46.92209)	0.186657*** (7.514212)	140.8135***	0.245367	0.002075*** (3.683435)	0.085367 (0.448447)	48319.76***	0.994457
	Health Care	1.351311*** (47.94695)	0.341778*** (13.60252)	210.8520***	0.330206	0.008081*** (21.76752)	14.03917*** (5.289444)	226.6884***	0.442507
	Real Estate	0.653649*** (36.86982)	0.144726*** (39.28653)	22999.33***	0.981465	0.005243*** (34.11767)	43.87671*** (3.869503)	28.98620***	0.089322
Panel:C Post-COVID	**Consumer Discretionary**	1.321392*** (19.51169)	**-0.037390*** (-1.532749)	89.62595***	0.397498	0.003309*** (2.138610)	**-1.708023***** (-7.843693)	2813.400***	0.952258
	Energy	1.485869*** (17.25845)	0.018806** (1.990885)	68.38188***	0.331307	0.009158*** (12.75340)	5.905337*** (7.044350)	155.7384***	0.520879
	Financials	1.096157*** (16.26755)	0.030859 (0.637889)	108.8213***	0.44282	0.007641*** (12.80154)	4.462710* (1.596572)	38.90146***	0.208363
	Food & Beverages	0.961853*** (12.62758)	0.161277*** (9.078155)	144.3530***	0.507709	0.009473*** (16.47966)	-0.442977 (-0.203762)	84.52959***	0.368736
	IT	1.548644*** (19.20994)	0.116658*** (3.574567)	88.63083***	0.388381	0.003179*** (2.539363)	0.055697 (0.196025)	9282.637***	0.984688
	Health Care	1.408051*** (17.11681)	0.219559*** (3.780616)	75.10201***	0.353818	0.009570*** (14.73612)	7.299265*** (8.260523)	299.5323***	0.671062
	Real Estate	0.937225*** (14.61026)	-0.003477 (-0.086983)	152.1543***	0.532569	0.006374*** (17.38763)	-0.748943 (-0.663491)	132.2789***	0.485118

Note. In this table, herding behavior analysis has been made through the CSAD model. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. A statistically positive γ_3 indicates anti herding and a statistically negative γ_3 indicates herding behavior. Value of t-statistics are given in brackets ().

4.5 Sector-Wise Exploration

In this section, we are going to probe into the sector-wise results (Tables A1-A6-Appendix) with volatility & herding behavior interpretation for both Australia and New Zealand.

4.5.1 Consumer Discretionary Sector

In Australia's case, the overall shrinking volatility persistence in all three panels can be ascribed to the 8-10% dip in 2020 household consumption which is expected to be recovered by 2022 (Where next for retail and consumer?, 2022). Again, the risk premium factor derived from GARCH-M (1,1) model is not significant in all three panels

rendering no crucial relationship between risk and return. Lastly, both EGARCH (1,1) and TGARCH (1,1) models tally with the existence of the leverage effect in the consumer discretionary sector. Both of the models imply the greater impact of good news on volatility as a consumer is being cost-conscious and more likely to approach shopping at discounted retail stores which challenges the increased competition through online businesses.

This sector in Australia depicts anti-herding behavior in two periods of our analysis except for Panel-C. Access to regular and available information regarding the consumer sector is viable for Panel A & Panel B. Panel-C suggests the herding behavior at 10% level as local purchasing trend continues after pandemic with 46% while online purchasing is 38% showing not much difference, implying a sense of perplexity among the investors (Australia: consumer online commerce behavior changes after COVID-19 2020 | Statista, 2022). So in the Post-COVID era investors tend to follow the others most likely in retail, tourism, and online shopping.

While the overall and pre-COVID volatility persistence could be attributed to the competitiveness possessed by the consumer discretionary sector, especially by services like hotels, restaurants, leisure pertinent to the tourism sector, apparel as well as the retailing sector in New Zealand (IN RETAIL (NEW ZEALAND): COVID-19 special edition 3 - McGrathNicol, 2021). Accordingly, for the same reasons, the risk premium factor derived from GARCH-M (1,1) model is significant in the post-COVID era, but not in the pre-COVID era representing the compensation of risk by return in this sector in the post-pandemic. Lastly, both EGARCH (1,1) and TGARCH (1,1) models accord with the existence of the leverage effect in the consumer discretionary sector. Both of the models imply the greater impact of good news on volatility in the full and pre-COVID periods. Albeit, the impact of bad news supplants that of good news on volatility in the post-COVID era which supports the panic buying and consumption displacement during the crisis period (Lins & Aquino, 2020).

The result shows evidence of herding behavior in the consumer discretionary sector of New Zealand at the 5% level in all three panels of our investigation which means the consumer discretionary sector has always been associated with the herding behavior in New Zealand. This implies the chance to manipulate the market by the investors and attain abnormal and irrational gains from the consumer discretionary sector, all in all compromising the market efficiency (Amirat & Alwafi, 2020). Nevertheless, the rationale behind the herd behavior in this sector is the notion of unrelenting reliability on products like pharmaceuticals and supermarket retailing along with the strong businesses of New Zealand such as hotels, restaurants, and leisure-related to the tourism sector that makes the investors somewhat deviated from their analysis and reliant on what others are doing.

4.5.2 Energy Sector

For Australia, the energy sector exhibits the same scenario as the consumer discretionary sector due to no persistency in volatility among the three panels. Oil prices fell by more than half since their peak amid the pandemic though this effect has been transitory. With the market's excess supply, natural gas prices are following the trend. Accordingly, GARCH-M (1,1) the risk premium factor is not significant in all three panels representing no crucial relationship between risk and return although effective energy policy has been taken regarding climate change and renewable sources (Abbott & Cohen, 2019; Nelson et al., 2019). Consequently, the leverage effect exists in all panels due to policy reassurance and more renewable energy integration for further aggrandizement of the energy sector to protect from the probable bad impact of negative news. Energy sector illustrates anti-herding behavior in all three panels although unpredictable price dropping in the oil and gas sector forces people to follow the crowd rather than clustering effective information in the post-COVID period in Australia (Byrne, 2022).

For the full period and pre-COVID era, volatility persistence is present in the energy sector of New Zealand. This can be ascribed to the enhanced credit flow in the renewable energy sector of New Zealand in producing electricity before the COVID-19 pandemic (Wang & Yang, 2017). Consequently, the leverage effect is present in both the full and pre-COVID periods due to the growing economic involvement of the market players. Whereas, this asymmetric nature of the market fades away as the extension of the energy market discontinues in the aftermath of the pandemic. The energy sector of New Zealand depicts anti-herding behavior in all three periods of our analysis. The access to timely and accurate information regarding energy stocks assists the investors to act upon their analysis rather than market consensus (Dhall & Singh, 2020).

4.5.3 Financial Sector

Volatility in this sector of Australia is persistent both in the full and pre-COVID periods as the banking sector faces expected and some unexpected loss during the pandemic period which affects heavily in our full period analysis. Cash earnings increased to $26.8 billion, up from $17.4 billion a year ago and in line with pre-pandemic levels. ("Banking Matters", 2022). The EGARCH (1,1) and TGARCH (1,1) model delineates signs of the leverage effect in the pre-COVID and post-COVID periods despite not providing any clear evidence that can differentiate the impact between good and bad news. Nevertheless, the whole period doesn't show any asymmetric effect according

to these models. This can be ascribed to the best market condition of the financial sector after the pandemic which affects highly the whole period. The model depicts no evidence of herding in the post-COVID era and anti-herding behavior in the other two periods. The stronghold of befitting financial institutions along with variations across the regions can be accredited to the absence of herding behavior in this sector mostly contributed to the major four banks of Australia.

All the 3 panels represent the non-persistence of volatility in the financial sector of New Zealand, providing evidence of New Zealand's sound financial system even amid the crisis. In terms of the Risk Premium Factor, the Financial sector in New Zealand possesses a risk-return trade-off in both pre and post-COVID era, but not in the case of the full period. This implies that return in this sector suffices the risk separately concerning the deviation of the market in different periods. The financial sector holds anti-herding behavior in all 3 panels according to the model just like the energy sector because of the convenience and appropriateness of accessing information about the sector.

4.5.4 Food & Beverages Sector

In Australia, we do not find any persistency in volatility during all the panels investigated for this sector which claims the sector to be unwavering during the pandemic. Around half of the domestic pork, consumption is imported, while almost all fresh fruit and vegetables devoured in Australia are domestically sourced (Greenville et al., 2022). Again, the risk factor is not crucially significant with the return according to GARCH-M (1,1) as it is already explained that this sector is not affected that much as other sectors ache. This sector shows evidence of anti-herding behavior in all 3 periods. This can be assigned to the many alternatives in the Australian market and the myriad of domestic sources rich in this category did not give any happenstance to be affected by the COVID-19.

Volatility in this sector is persistent both in the full and pre-COVID periods for New Zealand. This can be attributed to the excellent growth along with myriad investments in this sector over the last 10 years. New Zealand has been one of the key players in the world economy in this sector, both in production and export. Investors find the food and beverages sector fascinating for investment due to its premium quality in terms of food safety and nutritional standards. Consequently, the risk in this sector is compensated in the pre-COVID era, but not in the post-COVID period according to the findings of the GARCH-M (1,1) model. The full and pre-COVID period of this sector provides evidence of anti-herding behavior due to the structured and well-guided nature of the food and beverages sector in New Zealand. The post-COVID period shows no evidence of herding or anti-herding behavior because of the altering situation of the market in the pandemic.

4.5.5 IT Sector

There is no persistency in volatility at all in all three panels of our analysis regarding the IT sector of Australia evincing stability in the technology firms during the pandemic era but not the growth. Accordingly, the IT market holds a risk-return trade-off according to the GARCH-M (1,1) model. Again, evidence of the leverage effect is found in all three panels with bad news having a larger impact on volatility. The model musters evidence of anti-herding behavior in all 3 periods. The accessibility to appropriate information is quite efficient and effective to control the anti-herding nature as the IT sector is booming anyhow in this pandemic.

Volatility persistence in all 3 panels in the IT sector of New Zealand isn't that surprising because of the immense growth rate and capital investment in the sector. Likewise, the IT market holds a risk-return trade-off according to the GARCH-M (1,1) model. Moreover, evidence of the leverage effect is found in the pre-COVID era with bad news having a larger impact on volatility. However, in the post-COVID period, the sector is symmetric due to the transitional situation during the pandemic. The IT sector shows no evidence of herding behavior in any of the periods analyzed. This is because of the precise information, sound infrastructure, and market competitiveness of the sector.

4.5.6 Healthcare Sector

From GARCH (1,1) model, it is discernible volatility isn't persistent during each panel of data in the healthcare sector of Australia showing healthcare systems' continuous performance over the crisis and the stability around sooner inoculation but uncertainty in this sector remained the same. However, the sector doesn't exhibit any evidence of risk-return trade-off in all three panels of analysis which could be attributed to the obvious precariousness associated with the industry, especially during the pandemic. This sector holds evidence of anti-herding behavior in all 3 periods. Australia shows a greater quick venture in this sector with response to the pandemic and the populous is highly concerted in this spectacle but the severity of border lockdown, neutralizing local movements affect the whole scenario in the post-pandemic era with a lesser supply of healthcare labors.

According to the GARCH (1,1) model, volatility isn't persistent in the full and pre-COVID era in the healthcare sector. Nonetheless, it shows evidence of persistence in the post-COVID era. The uprising demand for healthcare products and services during the pandemic both domestically and internationally is the fundamental source of the volatility persistence. However, the sector doesn't provide any evidence of risk-return trade-off both in the pre and post-COVID periods which could be attributed to the obvious uncertainties associated with the industry, especially during the pandemic. The model provides evidence of anti-herding behavior in all 3 periods. This can be ascribed to the many alternatives that are available in the market with a high level of competitiveness.

4.5.7 Real Estate Sector

For Australia, according to GARCH (1,1), volatility is not persistent in Panel-C and Panel-A but Panel-B displays a long-term persistency in volatility. "According to the Population Statement released by the Australian Government, Australia's population is expected to grow from 25.36 million in June 2019 to 28.43 million in June 2030. Interestingly, due to a variety of factors, including positive net interstate migration, Queensland and Western Australia are likely to have slightly higher dwelling stocks ("Australia's residential property market post-COVID-19 - KPMG Australia", 2021). The EGARCH (1,1) and TGARCH (1,1) models reveal evidence of shock and leverage effect in all the panels discussed with a greater impact of bad news on volatility than good news during the pandemic. The model suggests anti-herding behavior in the full and pre-COVID era but it shows no evidence of herding behavior in the post-COVID period due to the lower price of the properties than that of in the pre-COVID era. The housing market experienced a -2.1% trough decline from a peak in 2020, before rocketing to 12.2% in the first six months of 2021 (Owen, 2022).

While in New Zealand volatility isn't persistent in all 3 periods in this sector, albeit the size of the impact of volatility is much higher in the post-COVID era according to the ARCH effect coefficient (α_1). The point is the sector was massively hit in the 1st half of 2020 because of the global supply chain disruption when the COVID-19 was at its zenith. Yet, the sector had been revitalized from the middle of 2020, thanks to the strong COVID protocol as well as robust demands generated in the sector just after the respite. For this quick recovery, the real estate stocks have been able to get back to a steady-state despite being battered by the pandemic in the first half of 2020. The EGARCH (1,1) and TGARCH (1,1) models manifest evidence of the asymmetric effect in the post-COVID period, but not in the pre-COVID era, with a greater impact of bad news on volatility than good news during the pandemic. The model shows no evidence of herding behavior in both the full and post COVID period, but presents signs of anti-herding behavior in the pre-COVID era. In essence, diversified investment opportunities in the real estate sector prevent the investors from herding behavior.

5. Concluding Remarks

Australia was pioneering in all the sectors before the pandemic and again responded too fast to shun the uncertainty in the economic zone yet failed to triumph having no casualties. Though non-persistence in the volatility and anti-herding behavior is found in the pre-COVID era, herding mentality can be observed in the consumer sector with significant leverage effect after the pandemic which can be ascribed to the changes of the habit of the customer in the long term with significant changes in priorities and spending criteria. ("The Australian Consumer in 2021", 2022). Innovation in the reusable and sustainable product is mandatory to keep up with the new digitally centered consumers and more investments centric policy in retail, the tourism sector will suffice the stronghold in this sector. The same things happen in the energy sector having a greater impact on bad news. Fiscal policy such as stimulus package can bolster the sector which the government is trying to imply by $500 million renewable energy fund in Queensland as the whole country shifting electricity to green future ("COVID-19 and renewable energy policy in Australia: the path forward", 2022). Though IT sector delineates stability according to the investigation, the reluctance of influx in the number of tech professionals and proficient labor forces by issuing stern isolation protocol hinders the betterment. Over the last two decades, Australia's IT industry has faced numerous conflicts, along with a lack of relevant government policies, partisan politics, a lack of government involvement in the sector, and ambiguity about creating policy on taxation and grants for research and development. The most important thing will be a consistent policy to facilitate successful student education in science, technology, engineering, mining, and math, as well as an adequate supply of IT graduates. There are far too few software developers graduating from tertiary institutions to meet industry demands (Galbally, 2022). Policymakers must link-up between supply availability, affordability, proximity, and environmental impact. The policy to uphold the usage of renewable energy is expected to increase GDP by more than $13 billion and allow an additional $6b in consumption by Australians ("Utility of the future A customer-led shift in the electricity sector", 2022). The success of these policies of innovative energy creation will require a massive number of skilled and unskilled laborers. In that case, the isolation and migration policies need to be revisited to augment the inflow of potential labor force in Australia. The Food & Beverages sector did not get the hindrance as the other sector faced

due to the plethora of domestic supply of the vegetables and other dairy products. This sector sustained in the very pandemic moment which backed up the devastated economy then. Yet attention is required as technology will flourish towards the next decade. Deploying cutting-edge technologies to boost efficiency, embracing digital transformation, and establishing an early warning system to track current and emerging risks can assist management in learning to separate noise from macro trends of changing stakeholder expectations. Diversifying and decentralizing operations, including investing in passive non-yield dependent income such as wind and solar farms, tourism, carbon offset farming, or biodiversity credits, allows businesses to disentangle revenues from weather conditions. (Favaro et al., 2022) The Healthcare sector faced the same issue as in the IT industry, the depletion of outsourced health professionals during the pandemic. During the pandemic financial industries scuffled but with the proper management and the wary intrusion of the major four banks of Australia buttress the industry at that time. After the COVID-19 populous seems to be dependent and have a belief in the banking system. Reserve bank of Australia injected extra liquidity for the functioning of the financial institutions, waned the cash rate twice from 0.25% to 0.1% in the face of inflation of about 3.5% ("Supporting the Economy and Financial System in Response to COVID-19", 2022). Reserve bank of Australia also reduced the lending rate for housing from 3.5% to 2.56% which is beneficial to depressed families ("Lenders' Interest Rates", 2022). As the lending rate is lowered, people will try to consume more in housing which eventually will surge the market price of real estate due to the increased rate of demand with a lower supply of housing properties.

Historically, New Zealand is a country with sustainable growth and investment in most industrial sectors it operates. This flow of money fosters volatility persistence in the consumer discretionary, food and beverages, and the energy sector in the overall period of our investigation. However, the post-COVID period in these sectors reduces volatility persistence. It's therefore clear that these three sectors could not sustain their growth in investment during the COVID-19, implying a need for a fresh infusion of money in these sectors. The policymakers have to make sure that these sectors don't lose their financial strength in the aftermath of the pandemic. New Zealand has nonetheless gone through a significant change in its monetary indicators. As a result, the money supply increases along with the increase in demand and salary pressures. These forces caused inflation to go up steadily during the pandemic. To control inflation, the interest rate had to be raised, which could be a massive hindrance in the further investments in the consumer discretionary, food & beverages, and the energy sector in New Zealand. The policymakers need to be wary of that situation as these sectors will be pivotal in the future financial strength of the country, and hence, they require investments. Policies need to be revised to allocate further money flow in these sectors. For investors, these areas of financing are very promising as their immense growth can indicate where New Zealand might go in a few years. However, one key area of concern would be the evidence of herding behavior found in the consumer discretionary sector in all three panels of our study. This implies this sector isn't assessed objectively by the investors. Hence, the investors might need to revisit their approach in this sector and be cautious of manipulation resulting from the herding behavior. The consumer discretionary sector also shows a reduction of the confidence in the investors in the post-pandemic period as the impact of bad news is greater than the positive ones, which further corroborates the requirement for increasing the market efficiency in the sector. In terms of the financial sector, the stock market is in a saturated condition. The non-volatility persistence shows a sound economic infrastructure. Yet, the stagnancy of the industry could be costly in the coming days. A fresh inflow of capital, particularly in technological innovation, is required to boost the financial scenario. Anti-herding behavior has been observed in the sector, showing an augmented and efficient flow of information. The policymakers need to retain this position to further sustain the risk-return trade-off in the industry, fostering investors' confidence in the financial stocks. The investors who want to hold a low-risk investment in their portfolio, this sector would be their potential target. However, this low-risk is so far converting in lower return, which might impede investors' interest in the post-pandemic circumstances. Hence, the policymakers need to concentrate on technology and innovation in the financial arena to raise more capital inflow in this sector to break the stagnant position of this sector. For the investors, the thriving IT and healthcare sector will be a key focus to generate higher returns in the coming days. The investments and demands in these sectors are inflating day by day. Moreover, the market demand seems to be augmented even further with the pandemic. As a result, share prices also go up in these sectors. Hence, investors should capitalize on the immense growth stage of both sectors. However, the policymakers should be cautious about maintaining the credit inflow in the long run, given that no risk-return trade-off can be found in the healthcare sector. In terms of real estate, the share price in the sector has been on the rise for several years. The increased demand and lower interest rates over the years for houses caused the growth in the industry. However, the interest rates won't be the same because of the rising inflation in the post-COVID period. The hike in the price-to-income ratio will pull the rising demand down in the post-COVID era as the interest rate goes up. As a result, the macroeconomic forces will control the sector in the future. Moreover, herding behavior isn't present in the industry. Overall, the sector won't be luring many investors

soon with no risk-return trade-off found in this study and the reduced demand and stock price in the coming days. The policymakers may take steps that augment the income level of the people in New Zealand. A higher income to price ratio might reinvigorate the sector by fostering increased demand in the future.

The market in Australia is quite saturated and well established before the pandemic while it is nascent in the New Zealand region. As a comparison, we found the consumer discretionary, food & beverages, and energy sector are highly prospective sectors in terms of investment opportunity for both countries shortly while financial institutions that are adequately sound in both countries hold the key to sustaining the economy. Again, the IT sector in both countries is growing rapidly implying the digitization of everything from supply chain to delivery system. Furthermore, in the case of real estate, the housing price in Australia is still burgeoning and with the lower interest rate, this is expected to sustain in the coming days. While, in New Zealand, the rising interest rate imposed to control the inflation rate is expected to cause a reduced demand in the housing sector which will eventually shrink the housing price. Both fiscal and monetary policy needs to be rectified for this specific sector. Health sector could be a boon to both countries' economies if investments in innovation and technology with proper monitoring thrive in these sectors. In the erratic moment during the COVID, populous along with the investors were nonplussed about the economy, but as it is convalescing from the near abyss, the policymakers should concert in the homogenous alternatives to mushroom and bolster it to fortify the concerning laws for shielding the economy against such volatile period. So a pragmatic approach can be apprehended. A compendium on the understanding of sector-wise implications for both investors and policymakers is presented below:

Table 6. Comparison summary

	For Investors		**For Policymakers**	
Sectors	Australia	New Zealand	Australia	New Zealand
Consumer Discretionary	Favorable due to the Stability and Potential Growth	Favorable due to the growth opportunity	Enhancing money flow and information	Same as Australia
Energy	Favorable due to the potential growth in renewable energy	Viability dependent on future policies	Fiscal measures supporting renewable sources of energy	Sustaining the enhanced credit flow in the post-COVID period
Financials	Favorable	Favorable for the investors not willing to take risks	Control the inflation rate	A fresh inflow of capital in innovation and technological breakthroughs
Food & Beverages	Highly Favorable	Highly Favorable	Enhancing money flow and information	Same as Australia
IT	Highly Favorable	Highly Favorable	Fostering skilled labor force	Sustaining the enhanced credit flow in the post-COVID period
Healthcare	Highly Favorable	Highly Favorable	Fostering skilled labor force	Sustaining the enhanced credit flow in the post-COVID period
Real Estate	Favorable	Unfavorable due to supply-demand gap	Control the inflation rate to sustain the purchasing power of people	Augmenting income level

Note. Implications for Investors and the Policymakers of both Australia and New Zealand are shown in this table.

For future researchers, one possible extension of this investigation can be a probe into the influence of macroeconomic forces such as inflation and interest rate on different sectors in both the stock markets. Sectors like real estate and financial need to be assessed in light of macroeconomic variables to further corroborate the findings of this study. Furthermore, the implications of different fiscal measures on different sectors of the stock markets in both countries, especially during the pandemic can be explored to capture the sector-wise response of both economies. Lastly, other variants of the GARCH family can be implemented to scrutinize the sector-wise volatility persistence along with more widened datasets.

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None.

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Appendix

Table A1. Volatility analysis of energy sector

			Australia			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.039120*	0.040281	0.011568	0.020858
			(0.8922)		(0.358)	(0.594)
		λ (Risk Premium)	-	-0.001041	-	-
	Variance Equation	**α_0 (Constant)**	0.041526***	0.041562***	-0.116010***	0.034826***
		α_1 (ARCH Effect)	0.110115***	0.110145***	0.154947***	0.036606***
		β (GARCH Effect)	0.863519***	0.863464***	0.979752***	0.894617***
		γ (Leverage Effect)	-	-	-0.061267***	0.083462***
		α_1+ β	0.973694	0.973609	1.134699	0.931223
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.043738*	0.048451	0.029861	0.035798
			(0.8942)		(0.7143)	(0.8033)
		λ (Risk Premium)	-	-0.004572	-	-
	Variance Equation	**α_0 (Constant)**	0.017763***	0.017800***	-0.065688***	0.016768***
		α_1 (ARCH Effect)	0.054960***	0.055052***	0.083295***	0.018105**
		β (GARCH Effect)	0.928330***	0.928215***	0.988436***	0.942309***
		γ (Leverage Effect)	-	-	-0.030312***	0.043722***
		α_1+ β	0.98329	0.983267	1.071731	0.960414
Panel:C Post-COVID	**Mean Equation**	**μ**	0.032174	0.021962	-0.033200	-0.002584
			(0.3996)		(0.4428)	(0.0341)
		λ (Risk Premium)	-	0.006675	-	-
	Variance Equation	**α_0 (Constant)**	0.119065***	0.121545***	-0.133741***	0.114157***
		α_1 (ARCH Effect)	0.196271***	0.197248***	0.205188***	0.050507***
		β (GARCH Effect)	0.759687***	0.757502***	0.960824***	0.800167***
		γ (Leverage Effect)	-	-	-0.118275***	0.180669***
		α_1+ β	0.955958	0.95475	1.166012	0.850674

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A1. Volatility analysis of energy sector (continue)

			New Zealand			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	-0.000323 (0.7308)	-0.000119	-0.000446 (0.8569)	-0.000372 (0.7958)
		λ (Risk Premium)	-	-2.291029	-	-
	Variance Equation	**α_0 (Constant)**	0.000000165***	0.000000163***	-0.13069***	0.000000216***
		α_1 (ARCH Effect)	0.011123***	0.011014***	0.089442***	0.007659***
		β (GARCH Effect)	0.989269***	0.98941***	0.992779***	0.989286***
		γ (Leverage Effect)	-	-	-0.020296***	0.005251**
		α_1+ β	1.000392	1.000424	1.082221	1.061124
Panel:B Pre-COVID	**Mean Equation**	**μ**	-0.000396 (0.8805)	0.001222**	-0.000365 (0.7603)	-0.000331 (0.8150)
		λ (Risk Premium)	-	-27.69745***	-	-
	Variance Equation	**α_0 (Constant)**	-0.0000000854***	-0.000000057**	-0.334055***	-0.000000105***
		α_1 (ARCH Effect)	-0.003107**	-0.004279***	0.114803***	-0.001216***
		β (GARCH Effect)	1.006955***	1.007697***	0.973238***	1.007357***
		γ (Leverage Effect)	-	-	-0.060526***	-0.00442***
		α_1+ β	1.003848	1.003418	1.088041	1.006141
Panel:C Post-COVID	**Mean Equation**	**μ**	-0.000367 (0.3768)	-0.000477	-0.000206 (0.2070)	-0.000264 (0.2643)
		λ (Risk Premium)	-	0.44613	-	-
	Variance Equation	**α_0 (Constant)**	0.0000957***	0.0000958***	-3.314958***	0.0000965***
		α_1 (ARCH Effect)	0.448195***	0.45064***	0.520642***	0.577336***
		β (GARCH Effect)	0.310277***	0.308437***	0.644641***	0.281096***
		γ (Leverage Effect)	-	-	-0.03499	-0.160864
		α_1+ β	0.758472	0.759077	1.165283	0.858432

Table A2. Volatility analysis of financial sector

			Australia			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.042178*** (0.9996)	-0.577348	0.006262 (0.3881)	0.020011* (0.8976)
		λ (Risk Premium)	-	0.384649	-	-
	Variance Equation	**α_0 (Constant)**	0.003206***	1.000436	-0.131829***	0.005364***
		α_1 (ARCH Effect)	0.118795***	0.150000	0.178082***	0.173333***
		β (GARCH Effect)	0.896901***	0.600000	0.993705***	0.910721***
		γ (Leverage Effect)	-	-	-0.106826***	0.006294
		α_1+ β	1.015696	0.75	1.171787	1.084054
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.037924*** (0.9936)	-2.066829	-0.00434 (0.2392)	0.008988 (0.4833)
		λ (Risk Premium)	-	1.331666	-	-
	Variance Equation	**α_0 (Constant)**	0.002063**	1.020377	-0.120130***	0.004301
		α_1 (ARCH Effect)	0.115728***	0.150000	0.167799***	0.206635***
		β (GARCH Effect)	0.905792***	0.600000	0.994135***	0.911768***
		γ (Leverage Effect)	-	-	-0.130846***	-0.001629
		α_1+ β	1.02152	0.75	1.161934	1.118403
Panel:C Post-COVID	**Mean Equation**	**μ**	0.055683** (0.967)	0.063006	0.040863 (0.8563)	0.044460* (0.8895)
		λ (Risk Premium)	-	-0.01776	-	-
	Variance Equation	**α_0 (Constant)**	0.020932***	0.020517***	-0.228834***	0.024163***
		α_1 (ARCH Effect)	0.174013***	0.172855***	0.244235***	0.127877**
		β (GARCH Effect)	0.781563***	0.783797***	0.962777***	0.788637***
		γ (Leverage Effect)	-	-	-0.074086***	0.087465**
		α_1+ β	0.955576	0.956652	1.207012	0.916514

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A2. Volatility analysis of financial sector (continue)

			New Zealand			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.000449 (0.874)	0.00027	0.00021 (0.5045)	0.000316 (0.6933)
		λ (Risk Premium)	-	1.843612	-	-
	Variance Equation	**α_0 (Constant)**	0.0000201***	0.00002***	-1.907245***	0.0000172***
		α_1 (ARCH Effect)	0.152635***	0.151737***	0.228132***	0.031474*
		β (GARCH Effect)	0.686977***	0.688499***	0.80904***	0.743256***
		γ (Leverage Effect)	-	-	-0.092329***	0.17068***
		α_1+ β	0.839612	0.840236	1.037172	0.77473
Panel:B Pre-COVID	**Mean Equation**	**μ**	-0.0000289 (0.1150)	0.015129***	0.0000958 (0.1981)	0.0000453 (0.0887)
		λ (Risk Premium)	-	0.001507***	-	-
	Variance Equation	**α_0 (Constant)**	0.000000188***	0.00000021*	-14.17448***	0.0000301***
		α_1 (ARCH Effect)	-0.004233***	-0.001074*	-0.14926***	0.008866
		β (GARCH Effect)	1.001733***	0.997864***	-0.557288***	0.625776***
		γ (Leverage Effect)	-	-	0.092974***	0.261106***
		α_1+ β	0.9975	0.99679	-0.706548	0.634642
Panel:C Post-COVID	**Mean Equation**	**μ**	0.001101** (0.9862)	0.002835***	0.001063** (0.9809)	0.001033** (0.9776)
		λ (Risk Premium)	-	-18.23567**	-	-
	Variance Equation	**α_0 (Constant)**	0.00000264***	0.0000016***	-0.294828***	0.00000345***
		α_1 (ARCH Effect)	0.003328	-0.032911***	0.053361	0.003402
		β (GARCH Effect)	0.958997***	1.00957***	0.973326***	0.934374***
		γ (Leverage Effect)	-	-	-0.028935*	0.030575
		α_1+ β	0.962325	0.976659	1.026687	0.937776

Table A3. Volatility analysis of food & beverages sector

			Australia			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.051123* (0.9346)	0.017759	0.048498* (0.925)	0.052158* (0.929)
		λ (Risk Premium)	-	0.023911	-	-
	Variance Equation	**α_0 (Constant)**	0.514335***	0.521520***	-0.166144***	0.511924***
		α_1 (ARCH Effect)	0.226853***	0.230007***	0.435081***	0.230657***
		β (GARCH Effect)	0.463219***	0.456025***	0.596376***	0.465386***
		γ (Leverage Effect)	-	-	0.008264	-0.009181
		α_1+ β	0.690072	0.686032	1.031457	0.696043
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.042488 (0.8336)	0.002238	0.040069 (0.8213)	0.046491 (0.8572)
		λ (Risk Premium)	-	0.03005	-	-
	Variance Equation	**α_0 (Constant)**	0.659516***	0.689787***	-0.138366***	0.628178***
		α_1 (ARCH Effect)	0.205053***	0.209184***	0.399170***	0.219757***
		β (GARCH Effect)	0.344756***	0.319667***	0.485921***	0.371601***
		γ (Leverage Effect)	-	-	0.039824	-0.041297
		α_1+ β	0.549809	0.528851	0.885091	0.591358
Panel:C Post-COVID	**Mean Equation**	**μ**	0.069239 (0.7158)	0.006739	0.053312 (0.5873)	0.059548 (0.6179)
		λ (Risk Premium)	-	0.038738	-	-
	Variance Equation	**α_0 (Constant)**	0.539832***	0.544834***	-0.185564***	0.547515***
		α_1 (ARCH Effect)	0.308167***	0.321642***	0.514434***	0.269738***
		β (GARCH Effect)	0.466653***	0.454921***	0.681382***	0.462541***
		γ (Leverage Effect)	-	-	-0.046411	0.076171
		α_1+ β	0.77482	0.776563	1.195816	0.732279

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A3. Volatility Analysis of Food & Beverages Sector (continue)

			New Zealand			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	-0.000649*** (0.9903)	0.001718	-0.002371*** (1.000)	-0.000511 (0.6051)
		λ (Risk Premium)	-	0.000269	-	-
	Variance Equation	**α_0 (Constant)**	0.0000107***	0.0000107***	-0.26029***	0.0000122***
		α_1 (ARCH Effect)	0.149347***	0.148512***	0.281319***	-0.000165
		β (GARCH Effect)	0.872107***	0.872653***	0.984733***	0.901453***
		γ (Leverage Effect)	-	-	-0.065852***	0.15957***
		α_1+ β	1.021454	1.021165	1.266052	0.901288
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.000736** (0.9639)	1.460204***	-0.00157** (0.9508)	0.000358 (0.2968)
		λ (Risk Premium)	-	0.235352***	-	-
	Variance Equation	**α_0 (Constant)**	0.0000172***	0.001677***	-0.253256***	0.0000164***
		α_1 (ARCH Effect)	0.117681***	0.04634**	0.186989***	0.000444
		β (GARCH Effect)	0.890224***	0.137942*	0.975564***	0.904959***
		γ (Leverage Effect)	-	-	-0.127782***	0.165739***
		α_1+ β	1.007905	0.184282	1.162553	0.905403
Panel:C Post-COVID	**Mean Equation**	**μ**	-0.000757* (0.9423)	-0.00141*	-0.000681 (0.8832)	-0.000671 (0.8932)
		λ (Risk Premium)	-	9.008081	-	-
	Variance Equation	**α_0 (Constant)**	0.0000088***	0.00000739***	-0.837442***	0.0000089***
		α_1 (ARCH Effect)	0.173403***	0.147387***	0.29114***	0.228076***
		β (GARCH Effect)	0.733288***	0.771722***	0.934243***	0.727842***
		γ (Leverage Effect)	-	-	0.040736	-0.095159
		α_1+ β	0.906691	0.919109	1.225383	0.955918

Table A4. Volatility Analysis of IT Sector

			Australia			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.126002*** (1.00)	0.255273***	0.110874*** (1.00)	0.112278*** (1.00)
		λ (Risk Premium)	-	-0.164284	-	-
	Variance Equation	**α_0 (Constant)**	0.178904***	0.175833***	-0.157648***	0.132411***
		α_1 (ARCH Effect)	0.110297***	0.108400***	0.166734***	0.020160**
		β (GARCH Effect)	0.677411***	0.682338***	0.853807***	0.759524***
		γ (Leverage Effect)	-	-	-0.087619***	0.121020***
		α_1+ β	0.787708	0.790738	1.020541	0.779684
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.115435*** (1.00)	-0.074580	0.120093*** (1.000)	0.120183*** (1.00)
		λ (Risk Premium)	-	0.265301	-	-
	Variance Equation	**α_0 (Constant)**	0.301236*	0.371272*	-0.168299***	0.182119***
		α_1 (ARCH Effect)	0.077515**	0.075435**	0.116154***	0.011751
		β (GARCH Effect)	0.508512**	0.413504	0.763343***	0.691777***
		γ (Leverage Effect)	-	-	-0.072730***	0.091426***
		α_1+ β	0.586027	0.488939	0.879497	0.703528
Panel:C Post-COVID	**Mean Equation**	**μ**	0.117060** (0.9686)	0.284606**	0.089691* (0.9017)	0.091914* (0.8951)
		λ (Risk Premium)	-	-0.163286	-	-
	Variance Equation	**α_0 (Constant)**	0.434604***	0.386652***	-0.227213***	0.377424***
		α_1 (ARCH Effect)	0.306546***	0.265367***	0.333534***	0.106001***
		β (GARCH Effect)	0.360825***	0.428181***	0.783660***	0.448016***
		γ (Leverage Effect)	-	-	-0.130711***	0.270690***
		α_1+ β	0.667371	0.693548	1.117194	0.554017

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A4. Volatility Analysis of IT Sector (continue)

			New Zealand			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.004823*** (1.00)	-5.209939***	0.016181*** (1.00)	0.002713*** (1.00)
		λ (Risk Premium)	-	-0.995292***	-	-
	Variance Equation	**α_0 (Constant)**	0.00000226**	0.001904	-5.147383***	-0.000000137
		α_1 (ARCH Effect)	0.126284***	1.971017***	0.657314***	0.027224***
		β (GARCH Effect)	0.911878***	-1.469777	0.059661	0.919352***
		γ (Leverage Effect)	-	-	0.118723	0.21297***
		α_1+ β	1.038162	0.50124	0.716975	0.946576
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.005137*** -1	0.137029***	0.001083 (0.8657)	0.002614*** (0.9999)
		λ (Risk Premium)	-	0.030103	-	-
	Variance Equation	**α_0 (Constant)**	0.00000209	0.012155***	-0.061092***	-0.00000028
		α_1 (ARCH Effect)	0.136807***	-0.253215***	0.089537***	-0.001156
		β (GARCH Effect)	0.916437***	0.983189***	0.997964***	0.94291***
		γ (Leverage Effect)	-	-	-0.125026***	0.221752***
		α_1+ β	1.053244	0.729974	1.087501	0.941754
Panel:C Post-COVID	**Mean Equation**	**μ**	0.002664*** (0.9982)	1.11571***	0.020083*** (1.00)	0.002842*** (0.9980)
		λ (Risk Premium)	-	0.213536***	-	-
	Variance Equation	**α_0 (Constant)**	0.000000623	0.002954***	-6.701392***	0.0000012
		α_1 (ARCH Effect)	0.080557***	-0.048583***	1.076107***	0.096824***
		β (GARCH Effect)	0.920444***	0.502328***	-0.211643***	0.920406***
		γ (Leverage Effect)	-	-	0.015412	-0.043646
		α_1+ β	1.001001	0.453745	0.864464	1.01723

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A5. Volatility Analysis of Healthcare Sector

			Australia			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.076663*** (0.999)	0.074598	0.074324*** (0.9998)	0.076684*** (0.9991)
		λ (Risk Premium)	-	0.003219	-	-
	Variance Equation	**α_0 (Constant)**	0.046914***	0.046917***	-0.067185***	0.046927***
		α_1 (ARCH Effect)	0.071666***	0.071681***	0.078165***	0.071780***
		β (GARCH Effect)	0.861798***	0.861781***	0.981228***	0.861755***
		γ (Leverage Effect)	-	-	-0.018457***	-0.000172
		α_1+ β	0.933464	0.933462	1.059393	0.933535
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.082830*** (0.9997)	0.057502	0.082854*** (0.9998)	0.079941*** (0.9995)
		λ (Risk Premium)	-	0.040744	-	-
	Variance Equation	**α_0 (Constant)**	0.223500***	0.226456***	-0.035418***	0.285251***
		α_1 (ARCH Effect)	0.091474***	0.092095***	0.039996***	0.071760**
		β (GARCH Effect)	0.560490***	0.555288***	0.989196***	0.457468***
		γ (Leverage Effect)	-	-	-0.009857	0.050584
		α_1+ β	0.651964	0.647383	1.029192	0.529228
Panel:C Post-COVID	**Mean Equation**	**μ**	0.058718 (0.8384)	0.041394	0.062168 (0.8485)	0.059658 (0.8187)
		λ (Risk Premium)	-	0.024315	-	-
	Variance Equation	**α_0 (Constant)**	0.039873**	0.039253**	-0.165404***	0.039686**
		α_1 (ARCH Effect)	0.111541***	0.109776***	0.202759***	0.113642***
		β (GARCH Effect)	0.845943***	0.848218***	0.958826***	0.846938***
		γ (Leverage Effect)	-	-	-0.021035	-0.005805
		α_1+ β	0.957484	0.957994	1.161585	0.96058

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A5. Volatility Analysis of Healthcare Sector (continue)

			New Zealand			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A	**Mean**	**μ**	0.000524**	-0.0000641	0.000622**	0.000516**
Full Period	**Equation**		(0.9665)		(0.9853)	(0.9568)
		λ (Risk Premium)	-	7.858798**	-	-
	Variance	**α_0 (Constant)**	0.00000433***	0.00000419***	-0.439675***	0.00000432***
	Equation	**α_1 (ARCH Effect)**	0.135337***	0.130722***	0.218009***	0.133042***
		β (GARCH Effect)	0.833758***	0.838655***	0.969717***	0.834177***
		γ (Leverage Effect)	-	-	-0.009945	0.004036
		α_1+ β	0.969095	0.969377	1.187726	0.967219
Panel:B	**Mean**	**μ**	0.000466	0.001418*	0.000504*	0.000453
Pre-COVID	**Equation**		(0.8858)		(0.9027)	(0.8592)
		λ (Risk Premium)	-	-12.73051	-	-
	Variance	**α_0 (Constant)**	0.0000138***	0.0000169***	-2.657752***	0.000014***
	Equation	**α_1 (ARCH Effect)**	0.178451***	0.198058***	0.37403***	0.172992***
		β (GARCH Effect)	0.664189***	0.60866***	0.749666***	0.660326***
		γ (Leverage Effect)	-	-	-0.014879	0.013542
		α_1+ β	0.84264	0.806718	1.123696	0.833318
Panel:C	**Mean**	**μ**	0.000951**	0.000409	0.00079*	0.000778*
Post-COVID	**Equation**		(0.9708)		(0.9356)	(0.9178)
		λ (Risk Premium)	-	7.00449	-	-
	Variance	**α_0 (Constant)**	0.0000021***	0.00000218***	-0.259829***	0.00000173**
	Equation	**α_1 (ARCH Effect)**	0.175328***	0.173041***	0.294918***	0.131957***
		β (GARCH Effect)	0.835596***	0.835147***	0.994737***	0.840949***
		γ (Leverage Effect)	-	-	-0.040545	0.097858*
		α_1+ β	1.010924	1.008188	1.289655	0.972906

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A6. Volatility Analysis of Real Estate Sector

			Australia			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A	**Mean**	**μ**	0.031020***	0.029364***	0.018189*	0.018018*
Full Period	**Equation**		(0.9969)		(0.9271)	(0.8994)
		λ (Risk Premium)	-	0.008051	-	-
	Variance	**α_0 (Constant)**	0.00566***	0.005723***	-0.208522***	0.006197***
	Equation	**α_1 (ARCH Effect)**	0.160838***	0.161226***	0.263020***	0.080713***
		β (GARCH Effect)	0.838374***	0.837743***	0.992635***	0.847005***
		γ (Leverage Effect)	-	-	-0.078105***	0.138013***
		α_1+ β	0.999212	0.998969	1.255655	0.927718
Panel:B	**Mean**	**μ**	0.030673***	-3.991797	0.016623	0.016685
Pre-COVID	**Equation**		(0.989)		(0.8401)	(0.8048)
		λ (Risk Premium)	-	2.252839	-	-
	Variance	**α_0 (Constant)**	0.004558***	1.163863	-0.199925***	0.005583***
	Equation	**α_1 (ARCH Effect)**	0.158502***	0.150000	0.257688***	0.072797***
		β (GARCH Effect)	0.847193***	0.600000	0.994654***	0.853804***
		γ (Leverage Effect)	-	-	-0.073976***	0.150586***
		α_1+ β	1.005695	0.75	1.252342	0.988538
Panel:C	**Mean**	**μ**	0.031641	0.037888	0.014858	0.019215
Post-COVID	**Equation**		(0.8533)		(0.4891)	(0.6111)
		λ (Risk Premium)	-	-0.030389	-	-
	Variance	**α_0 (Constant)**	0.013763**	0.013779**	-0.284515***	0.011648***
	Equation	**α_1 (ARCH Effect)**	0.178457***	0.178535***	0.287089***	0.091763***
		β (GARCH Effect)	0.777481***	0.777439***	0.956670***	0.806945***
		γ (Leverage Effect)	-	-	-0.090771***	0.129802***
		α_1+ β	0.955938	0.955974	1.118662	0.898708

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

Table A6. Volatility Analysis of Real Estate Sector (continue)

			New Zealand			
Timeline	**Particulars**	**Parameter**	**GARCH(1,1)**	**GARCH-M(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
Panel:A Full Period	**Mean Equation**	**μ**	0.000423*** (1.00)	0.000341***	0.000358*** (0.9998)	0.000375*** (0.9997)
		λ (Risk Premium)	-	6.12845	-	-
	Variance Equation	**α_0 (Constant)**	0.000000912***	0.000000922***	-0.552599***	0.000000883***
		α_1 (ARCH Effect)	0.160672***	0.161261***	0.25684***	0.113129***
		β (GARCH Effect)	0.794624***	0.79337***	0.967843***	0.806465***
		γ (Leverage Effect)	-	-	-0.051013***	0.069517***
		α_1+ β	0.955296	0.954631	1.224683	0.919594
Panel:B Pre-COVID	**Mean Equation**	**μ**	0.000416*** (0.9998)	0.000801*	0.000412*** (0.9998)	0.000412*** (0.9998)
		λ (Risk Premium)	-	-39.546	-	-
	Variance Equation	**α_0 (Constant)**	0.00000144**	0.00000154*	-1.694958**	0.00000147**
		α_1 (ARCH Effect)	0.088302***	0.091044***	0.171384***	0.075319*
		β (GARCH Effect)	0.768286***	0.755278***	0.864801***	0.766485***
		γ (Leverage Effect)	-	-	-0.01245	0.022331
		α_1+ β	0.856588	0.846322	1.036185	0.841804
Panel:C Post-COVID	**Mean Equation**	**μ**	0.000468* (0.9141)	0.000188	0.00036 (0.8389)	0.000364 (0.8032)
		λ (Risk Premium)	-	8.944812	-	-
	Variance Equation	**α_0 (Constant)**	0.00000348***	0.00000367***	-0.520426***	0.00000377***
		α_1 (ARCH Effect)	0.207413***	0.214275***	0.214062***	0.089756**
		β (GARCH Effect)	0.709366***	0.696998***	0.965537***	0.730483***
		γ (Leverage Effect)	-	-	-0.094502***	0.160256***
		α_1+ β	0.916779	0.911273	1.179599	0.820239

Note. (*) Significant at the 10% level, (**) Significant at the 5% level, (***) Significant at the 1% level, (no) Not Significant. (1-p) values are obtained on the brackets. (***) in the μ for mean equation illustrates existence of volatility clustering.

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